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A sharing economy for residential communities with PV-coupled battery storage: Benefits, pricing and participant matching

Sarah Henni *, Philipp Staudt, Christof Weinhardt

Karlsruhe Institute of Technology, Kaiserstrasse 12, 76131 Karlsruhe, Germany

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ABSTRACT

The transition of the energy sector towards more decentral, renewable and digital structures and a higher involvement of local residents as prosumers calls for innovative business models. In this paper, we investigate a sharing economy model that enables a residential community to share solar generation and storage capacity. We simulate 520 sharing communities of five households each with differing load profile configurations and find that they achieve average annual savings of 615€ as compared to individual operation. Using the gathered data on electricity consumption in a sharing community, we discuss a fixed pricing approach to achieve a fair distribution of the profits generated through the sharing economy. We further investigate the impact of prosumers' and consumers' load profile patterns on the profitability of the sharing communities. Based on these findings, we explore the potential to match and coordinate suitable communities through a platform-based sharing economy model. Our results enable practitioners to find optimal additions to an energy sharing community and provide new insights for researchers regarding possible pricing schemes in energy communities.

1. Introduction

On the path to a more sustainable future, efforts are made worldwide to decarbonize the electricity supply through a transition from large centralized power plants towards many smaller distributed energy resources (DERs). The German energy transition is an example for this transformation: In 2018, 37.8% of Germany's electricity consumption came from renewable sources such as wind and solar generation [1]. A large share of the over 1.6 million currently installed photovoltaics (PV) systems is comprised of small panels with less than 10 kilowatt peak (kWp) generation capacity each [2]. These systems are mostly installed on rooftops of residential homes, illustrating the shift towards an increasingly decentralized electricity supply. A challenge that comes with this transition is the increasing volatility of the electricity supply that needs to exactly match demand at all times to ensure system stability. The expansion of intermittent DERs must therefore be accompanied by extensive demand and generation flexibility measures, especially in the low and medium voltage distribution grids that most DERs are connected to. In distribution grids, battery energy storage systems (BESSs) can help to resolve congestion and shift excess generation to times with more demand. As with the expansion of PV plants, the driving impulse for the increasing adoption of BESSs comes from residential applications. In the course of decreasing system costs and subsidies for the joint purchase of a PV system and a BESS, an increasing installation of residential BESSs can be observed in Germany. In 2019, one BESS was installed for every two PV systems under 10 kWp, accumulating to 160,000 installations [3,4]. This potential of storage capacity should be further exploited through innovative business models targeted at local residents, for example leveraging the potential of peer-to-peer energy sharing. However, it is unclear how different households with different load patterns can contribute to such an energy sharing community and what benefit can be expected. This makes it more difficult to establish such communities as both prosumers with or without batteries as well as consumers are unaware of the corresponding opportunities. Part of this problem is the establishment of a pricing approach that is perceived as fair among the participants who invest in hardware (prosumers) and participants who profit from said hardware (consumers). In this paper, we show the potential financial benefit of an average community, we suggest different pricing approaches and discuss their distributional consequences and we evaluate the characteristics of different households in regards to their contribution to the financial success of an energy sharing community. We thus expand the extant literature with an in-depth analysis of the benefits of local energy sharing communities.

Due to current regulation, increasing self-consumption is the only feasible option for residential users to profit from a BESS. It is, therefore, questionable whether small-sized storage systems can already be operated economically without subsidy programs. One issue is the

* Corresponding author.
E-mail address: sarah.henni@kit.edu (S. Henni).

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limited number of operating hours that is associated with the joint utilization of PV plants and BESSs. Over the course of a typical day, the storage unit is charged during sunshine hours and then discharged after sunset, usually allowing little more than one full charge–discharge cycle per day [5]. Residential BESSs are usually sized to match a households' electricity consumption with the bottleneck being the consumption during the night. Losses with regards to utilization arise when a household's load during the hours without PV generation is not sufficient to fully discharge the storage unit until the generation of the PV system starts again the next day. Similarly, when the electricity generation throughout the day is not sufficient to charge the BESS to its maximum, its capacity is not fully utilized. The profitability of a BESS is thus not only dependent on a household's overall electricity consumption but also on the distribution of the load throughout the day. To enhance the utilization rate of BESSs and to subsequently further incentivize local investments in storage capacity, we propose a sharing economy model that allows a residential community to share excess PV generation, stored electricity and storage capacity. In this paper, we furthermore contribute to the understanding of a sharing economy in energy markets and explain how under-utilization in residential energy communities can be overcome through a sharing economy model. Aside from the possible financial savings of the community, this approach also allows consumers to participate in the sharing of locally generated electricity without having to invest in the capital-intensive infrastructure themselves. This development can be desirable from a system's perspective as well, since increased local consumption may reduce peak loads and thus relieve the distribution grids [6]. Correspondingly, sharing approaches in the electricity sector have the potential to promote decentralized structures and to subsequently assist the transition towards a more sustainable energy system [7]. To accelerate this development, we propose a platform-based sharing economy model to identify and match suitable communities and investigate financial benefits, fair revenue distribution as well as matching between prosumers and consumers. In the course of this study, we answer the following research questions:

- What are the average financial benefits of a sharing economy business model for a residential community that engages in peer-to-peer sharing of local electricity generation, stored electricity and storage capacities in a setting with privileged self-consumption?
- What is the impact of different pricing schemes on the distribution of the financial benefits among the participants of a residential peer-to-peer network?
- How can suitable participants for a sharing economy be described and matched into a community based on electricity consumption profile characteristics?

To answer these questions, we first transfer the sharing economy theory into the context of the energy sector regarding the application of sharing solar generation and storage capacity. We investigate the potential profits of a sharing community depending on load profile patterns of different participants by simulating 520 sharing communities based on empirical demand profiles. Based on the results of the simulation, we discuss a fair pricing approach for the shared goods and propose a solution for the coordination of communities. Finally, we analyze how communities can be set up most profitably.

2. Related work

In this section, we provide an introduction into the literature on the theory of the sharing economy and its application to the energy sector. In the first paragraph of the literature review, we elaborate on the relevance of sharing economy approaches in the energy sector, shedding light on potential business models and current use cases. In the second part, we review similar previous research and address the current regulation on sharing electricity and storage in residential neighborhoods and subsequently derive the research gap that we aim to fill with this study.

2.1. The sharing economy in the electricity sector

Platform-based sharing economy companies such as Airbnb and Uber have gained significant attention in recent years by challenging traditional business models. Through these platforms, existing but under-utilized assets are deployed much more efficiently, while end-users gain direct control of services and products which they previously had no access to [7,8]. On the other hand, the unprecedented changes in the energy sector require ground-breaking innovative business models and hands-on solutions that further drive the transition from large power plants towards decentral and renewable generation [9]. Whereas traditionally, consumers would get their electricity from a large supplier, nowadays, an increasing number generates part of their consumption autonomously through DERs. These so-called prosumers are able to partially supply themselves with self-generated local electricity, making them less dependent on large utilities [10]. Combined with an increasing availability of technology such as smart meters, new digital solutions can emerge in this setting. Thus, platform-based sharing economies are expected to have a significant impact on the energy sector by increasing utilization rates of assets and by enabling peer-to-peer (P2P) access to energy related products and services [8].

A sharing economy can be categorized along the four dimensions shared good, market orientation (e.g., profit or nonprofit, global or local, online or offline), market structure (e.g., consumer-to-consumer or business-to-consumer) and industry sector (e.g., mobility, energy supply) [11]. In the setting of this paper this translates to, (1) the shared good is storage capacity that is shared (2) for profit (3) between residential neighbors (4) in the energy sector. The emergence of sharing economy activities in the context of the energy sector has previously been investigated by [11] who finds that sharing economy business models offer the opportunity to accelerate the energy transition as they share the key properties of decentralization, digitalization and increased P2P interaction. The author derives six key characteristics of a sharing economy and transfers them to the energy domain. In line with [8], the relevance of digital energy platforms to increase P2P interaction is highlighted. The leverage of digital technologies allows a more efficient coordination of the increasingly fluctuating and volatile energy supply through DERs. The aspect of shared values, in particular, is seen as an important driver for developments in the energy sector that in some cases may even outweigh cost advantages. Another feature is the better use of under-utilized capacities, often through granting access to capital-intensive resources that previously had to be owned in order to be utilized. The author of [11] further points out the similarity to prominent sharing economy platforms like Uber and Airbnb with high private capital investment. This aspect is supported by the findings in [7], where the authors apply the characteristics and dimensions provided in [11] to three case studies and find that one of the main drivers for sharing economy models in the energy sector is the investment of private capital in other assets than real estate, especially in DERs and BESSs, combined with the increasing independence from utilities. One barrier to these developments, which is identified in [7], is missing financial incentives for local energy generation, partially caused by regulatory and bureaucratic hurdles for sharing approaches. One distinctive feature of the sharing economy in the energy sector is the reversal of the principle *Access instead of ownership* in the case of DERs for the prosumers. Whereas in the past, most households were pure consumers who obtained their electricity from large central power plants (and thus without ownership), nowadays many participate in electricity generation themselves through owning PV generation systems.

In contrast to other sharing economies, sharing in the energy sector poses some unique challenges. Since electricity is a homogeneous good and its flows cannot be physically traced from point A to B, electricity sales need to be coordinated through balancing software that coordinates transfers and hardware that can realize the related physical flows [12]. This is especially important when introducing a sharing economy business model between households as granular balances of generation and load have to be documented and billed. Further, electricity supply and demand need to be balanced at all times, i.e., any generation at any given time must be either consumed directly or stored in a storage system. Nevertheless, renewable electricity generation from DERs is not considered an under-utilized resource since it can also be fed into the electricity grid in order to be transmitted and consumed elsewhere [7,11].

2.2. Residential sharing of solar generation and storage systems

With high electricity prices and comparably low feed-in-tariffs, increasing self-consumption is the most profitable way to benefit from residential solar generation. As PV adoption rates rise, the idea of sharing excess electricity generation with neighbors to increase self-consumption is investigated by a number of authors. Due to the fluctuating nature of solar generation with large peaks during the day, storage technologies can help in further aligning the electricity generation with a household's load. However, residential storage systems such as lithium-ion batteries are still costly and therefore only barely profitable for individual usage [5]. Thus, larger central storage capacity is seen as an opportunity to supply entire communities more independently while benefiting from economies of scale [13,14]. However, community storage is not yet widely applied due to a number of regulatory and bureaucratic barriers [6]. Meanwhile, about 160,000 PV storage systems are already installed in Germany, with rapidly increasing numbers. We therefore explore the opportunity of connecting these existing assets by investigating a sharing economy model for individual residential PV and storage systems.

The implementation of a sharing economy model for residential storage systems is interpreted differently. The authors of [15] investigate the utilization of storage systems for several business models such as peak-shaving of industrial load and self-consumption for buildings. Thus, sharing in this context means distributing a storage system's capacity amongst different purposes, not users. In contrast to that, in this study, we investigate the P2P sharing of solar generation and storage capacity amongst residential households within a neighborhood in spatial proximity as suggested by [16]. An extensive overview of trends and challenges in P2P sharing literature is provided in [17], identifying the regulatory framework as key enabler but also barrier of real-world P2P implementations. The main motivational factors for the participants in a P2P network are cost savings and emission reductions [18]. However, grid operators may also benefit from such a scheme due to the possibility of balancing electricity supply and demand, e.g., by reducing peak demand in a grid section and thus avoid infrastructure investments [17,19]. Network losses due to flexible power dispatch of prosumers participating in a P2P network can be neglected [20]. A number of authors investigate possible operating models as well as the financial benefits of sharing PV generation, stored electricity and storage capacity in a residential neighborhood. The authors of [21] compare four operation paradigms for a community of five households with a PV and BESS each, ranging from a central coordination through the utility to a distributed operation by the end-users to a naïve charge–discharge strategy and selfish control with no coordination between the households. While the centralized approach yields the best results in terms of financial gains, it is by far the most computationally expensive. In [22], the maximization of PV self-consumption in a neighborhood with six households through electricity sharing with and without a BESS being installed in each household is investigated. The simulation is carried out with demand data from Austrian households over four weeks in winter and summer each. The authors of [23] introduce a tool for a smart neighborhood simulation and illustrate the benefits of battery sharing in terms of reduced amortization times over the system's lifetime. In [24], different community sizes within a distribution grid area consisting of 500 households are simulated using synthetic load profiles in order to improve grid stability and to investigate the ideal community size for BESS sharing in terms of additional self-consumption. What is missing in the existing literature, is an investigation of the impact of different configurations of household load profiles on the profitability and the simulation of sharing communities over a longer period of time than just a few weeks.

Another aspect that is insufficiently addressed in the previously presented publications, is the distribution of the profits that are generated through the sharing of electricity amongst neighbors. This could be resolved through either a trading or a cost sharing mechanism [16]. The former requires participants to constantly make decisions to adapt to the market conditions. These can also be determined by an intelligent agent and be based on a participant's preferences and forecasts on consumption and generation patterns. In further research, the analysis of prosumers' decision making is often approached with a game theoretic models [25]. In the context of sharing PV generation and storage on a household level, game theoretic approaches have been applied to demonstrate (theoretical) financial and ecological benefits, to design pricing and profit distribution schemes and to show equilibria of different trading mechanisms [18,19,26–28]. There are several pilot projects on local energy markets with P2P trading in place today [29], but they mostly do not include storage systems. Instead, projects with storage sharing at community level are often designed around a large storage system and handle the sharing by assigning fractions of the storage system to the community members [6]. However, (game-theoretic) P2P trading approaches as described by [25] and [29] have their limitations. They assume that prosumers are willing to participate to some extent in the trading of energy in order to make profits or increase a community's independence from the grid. Even if the decisions are made by an intelligent agent, information about the participants' preferences and forecasts on load and generation might be needed. Given that electricity is a low-involvement product that most people have no or little experience with and given that financial margins for trading electricity are small, this could pose a high entrance barrier for local energy sharing communities. In fact, studies on end-users' participation in energy efficiency measures have shown that only for a vanishingly small proportion of the participants, behavioral efforts could be observed and even this group is significantly less motivated beyond the initial euphoria of the first weeks [30,31]. It has also been shown that the understanding of electricity consumption is very low in residential households in general [32]. It is therefore questionable whether inexperienced participants would understand the consequences of their participation and their actions in an energy trading mechanism. At the very least, it has to be assumed that the participation in a complex trading scheme could pose an entrance barrier for many residents. Based on these premises, we design a sharing economy model that requires no active participation in trading. Instead of a trading mechanism, we propose the deployment of an "agreed cost-sharing mechanism" as previously suggested by [16]. Profits are generated by maximizing a community's overall self-consumption through an automatic energy management system and prices for the shared goods are set through a platform so that the mechanism results in a subjectively fair revenue distribution.

From the findings above, we derive the necessity of a comprehensive analysis of the theoretical and practical potentials of a sharing economy model for residential PV generation and storage capacity. We transfer the existing theory to this use case and demonstrate the concept and investigate financial benefits through the simulation of a sharing economy model for 520 different communities, using empirical load profiles from Chicago households. We then discuss a fair revenue distribution based on the gathered data and shed light on the contribution of the individual participants in the sharing economy based on their load profile properties. Previous work has either only investigated operation modes and financial benefits or trading and sharing mechanisms, often with little empirical data on residential load profiles and only over short periods of time. Additionally, we investigate the possibility of matching and coordinating profitable energy sharing communities based on their load profile characteristics.

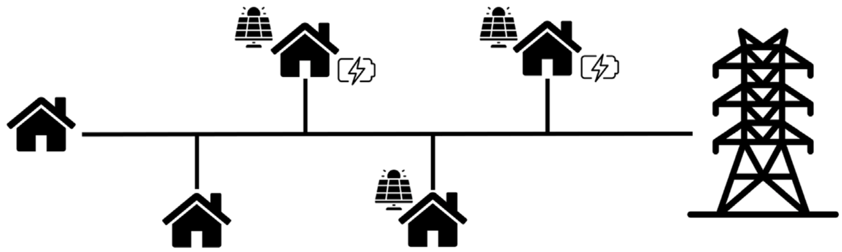

Fig. 1. Sharing community setup: Two battery-prosumers (PV + BESS), one prosumer (PV) and two consumers are locally connected through the distribution grid and jointly connected to the national grid.

2.3. Regulation of local energy communities

Regarding the use case of sharing local PV generation and storage capacity, the general findings on possible barriers in the energy sector are confirmed by an overview on current pilot projects and the corresponding business models conducted in [6]. The authors find that many pilot projects face regulatory barriers, especially if they rely on the public grid instead of an isolated microgrid setup. They conclude that sharing storage may remain a niche phenomenon if no regulatory adjustments are made. As of today, in many countries, the regulation poses great obstacles for residential PV and storage sharing. In Germany, for instance, self-consumption of PV generation is free of taxes and levies for all PV plants up to 10 kWp while selling excess generation to a neighbor through the public grid is fully burdened with fees of around 23 ct/kWh [33]. With the current electricity price being close to 31 ct/kWh and with a fixed feed-in-tariff for electricity from PV plants up to 10 kWp of around 10 ct/kWh [34], this renders electricity sharing amongst neighbors unprofitable. It is possible to avoid part of the charges by registering a so-called “customer installation“, in which case fees related to grid usage of up to 12 ct/kWh must not be paid [35], rendering a profit window for energy sharing of about 10 ct/kWh. On the European level, the importance of citizen involvement in the transition of the energy sector towards a decentralized structure has been recognized. In the 2019 directive on common rules for the internal market for electricity, the European Union emphasizes the importance of so-called “Citizen Energy Communities” that engage in energy generation, distribution, storage or efficiency services, laying the course for political changes [36]. Thus, it is important to carefully choose the regulatory framework when investigating the potential benefits of a sharing economy model. The authors of [12], for example, employ a time-of-use tariff as it already exists in many areas of the United States. Some studies are based on the current regulation but allow for somewhat more freedom when it comes to sharing, assuming free-of-charge self-consumption and include feed-in-tariffs for excess generation that is fed into the grid [22–24]. Instead of fixed feed-in-tariffs, some authors employ real-time-pricing schemes that reflect fluctuations in spot market prices [14] or incentive prices to enhance self-consumption during hours of high generation [21]. In the following, we present a sharing economy model for the described setup with preferential treatment of self-consumption within a community.

3. Deriving a sharing economy model for local electricity and storage sharing in a residential peer-to-peer network

Applying the principles derived in [11], we specify the unique features of a sharing economy model for locally generated and stored electricity and storage capacity. Fig. 1 shows an exemplary configuration of a local sharing community. Participants can be owners of a PV installation (prosumers) and a BESS (battery-prosumers) or merely participate with their electricity load as consumers who do not own assets but instead participate by buying excess electricity from the prosumers and battery-prosumers. All participants are connected to each other through the public grid.

In Tables 1 and 2, we transfer the dimensions and characteristics of a sharing economy as described in [11] to a residential sharing economy for solar generation and storage capacity.

Two aspects are especially worth noting regarding the use-case at hand. In the context of local electricity generation, *access instead of ownership* and *under-utilized resources* can be interpreted differently, depending on the value that is ascribed to the (geographical) origin of electricity. If a value is ascribed to a local origin, then both of the mentioned principles apply to a sharing economy model in a local community. Local electricity can indeed be under-utilized and *access instead of ownership* applies for consumers who can buy locally generated electricity from a neighbor instead of investing in a PV system of their own. In research, it is debated whether consumers are willing to pay a surplus on local electricity [38–40]. Of course, in this context, local electricity also contains the notion of renewable generation. It can thus be difficult to differentiate whether consumers actually value the geographical origin of the electricity (and the independence that comes with it) or simply the underlying generation technology. Therefore, in our model, we do not assume that participants in a sharing economy are willing to pay more for local electricity than the current electricity price. In this setting, while *access instead of ownership* is reversed in the case of DERs, it applies for storage systems if the regulatory framework allows it. For consumers, on the other hand, it then applies for both DERs and BESSs.

For the deployment of a sharing economy model, we propose a platform solution to match and coordinate communities in the spirit of [41]. The benefits of a well-matched community are shown in the results of the case study in Section 5. The platform could be operated by producers and distributors of BESSs as an additional service to their customers and they can provide information and the possibility to simulate the sharing mechanism for community members. A comparable approach can be observed in the business model of the sonnenCommunity implemented by the German battery manufacturer SonnenGmbH [7]. This community is a virtual P2P platform, which allows its participants to share excess PV generation with other members. Through the intelligent connection of DERs and BESSs, electricity can be exchanged between community members during peak generation times. In contrast to the sharing economy model proposed in this paper, community members do not have to live in spatial proximity and can therefore not benefit from regulatory schemes implemented for local energy communities.

4. Simulating a sharing economy model for a residential neighborhood

To demonstrate the theoretical concept explained in the last section, we simulate a sharing economy model for PV generation and storage capacity within a residential community. For the simulation, we choose the setting of five households as shown in Fig. 1 consisting of two battery-prosumers, one prosumer and two consumers. A similar setting is implemented in [21] to compare operation strategies and the authors of [24] show that 98% of the efficiency of a large sharing community is already achieved with five participating households. While previous

Table 1
Dimensions of a sharing economy model for local solar generation and storage capacity as described in [11].

Shared good	Market orientation
(Local) Electricity from solar generation: A (battery-)prosumer may share excess PV generation with neighbors that have excess demand at the same time. *Storage capacity*: A BESS can be shared in two ways: A neighbor can buy stored electricity from a battery-prosumer and she can store her own excess solar generation in a battery-prosumer's storage if there is capacity available.	*Profit-oriented*: Participants in the community share electricity at lower costs than what they would have to pay for electricity from the grid. We assume that no fees have to be paid for self-consumption of locally generated electricity. The shared electricity has to be priced so that no participant suffers economic disadvantages. A small annual fee could be charged by the service provider.
Market structure	Industry sector
Consumer-to-Consumer Other settings are perceivable, e.g, Business-to-Consumer if, for example, the platform provider offers additional services or owns BESS capacities.	*Energy supply* Within the sector of energy supply, the provision of energy (i.e., electricity) and capacity (i.e., storage capacity) has to be distinguished.

Table 2
Transferring the principles of the sharing economy derived in [11] to the case study of a local energy sharing community.

Aspect	Application in case study
Platform-based	A platform is needed for the matching and coordination of communities and for the provision of information. The platform operators are service providers and do not need to own any assets.
Leverage of digital technologies	Digital coordination mechanisms are key to manage the interaction of electricity supply and demand as well as storage operation within a sharing community. Digital technologies such as smart meters are necessary for the measurement of the electricity flows that are provided to the coordination algorithm.
C2C/P2P-interaction	The sharing economy is made possible through P2P interaction. Local (battery-) prosumers share their decentral electricity generation and storage capacities with other (battery-)prosumers or consumers. Information, energy and money are exchanged through the digital platform.
Access instead of ownership	*(Battery-)Prosumers* : Ownership (of DER, BESS) instead of access (to electricity supply from central power plants) *Prosumers*: Access (to storage capacity) instead of ownership (of BESS) *Consumers*: Access (to local electricity and storage capacity) instead of ownership (of DER, BESS).
Under-utilized resources	Shared good *electricity* : Not applicable for renewable electricity generation per se. (Locally) Unused electricity is fed into the grid and utilized elsewhere. Exception: Sharing can prevent losses of electricity if PV generation would have to be curtailed during peak hours due to insufficient grid capacities. Shared good *local electricity*: Principle is applicable when a value is attributed to the use of local energy, for example to increase independence from utilities. Shared good *storage capacity* : Higher utilization rate if shared in energy communities.
Shared values	The energy transition is widely supported in the public [37]. "Green" energy supply and self-sufficiency have non-monetary value [38].

studies often perform these simulations on limited empirical data and over short periods of time, we compare the results of 520 different sharing communities over one year with a 30-minute time resolution. Since the utilization rate of a BESS largely depends not only on a household's overall consumption but also on the load pattern throughout the day, we use different combinations of household load patterns for each community. We then simulate the 520 sharing communities twice: During the first simulation, we keep all other parameters constant to explore the effects of different load patterns on the utilization rate of a PV-coupled BESS for different household configurations. We use real load profiles from a Chicago dataset containing 100,000 household load profiles in 30-minute intervals and scale them to the average annual consumption of a single-family home in Germany which is 4000 kWh. The sizes of the PV and storage systems for each household are chosen to correspond to typically installed systems in German households so that the resulting community could exist as of today (Table 3). We use PV generation data from a research campus in southern Germany and scale the data so that it corresponds to the generation of an 8 kWp solar installation with 950 full load hours, which is a typical output for a residential PV system in Germany [42]. Losses in battery components are chosen to correspond to the performance of current household storage systems [4]. In the second simulation, we keep the original absolute loads of the households in our datasets. Instead, we scale the size of the PV plant and BESS capacity and power so that the ratio of load to capacity and power remains the same as in the first simulation. So, for example, a household with an annual load of 5000 kWh would have a 10 kWp PV plant and a 7.5 kWh/4.375 kW BESS installed. This approach may result in BESS and PV configurations that are not realistic (as sizes come in discrete rather than continuous steps), but it allows us to specifically investigate and compare the effect of the absolute load vs. the load pattern on the profitability of the energy sharing community.

Table 3
Assumptions for the sharing community with all parameters constant.

	Assumption	Corresponds to
Annual household load	4000 kWh	Single family home with 3–4 residents [43]
PV generation capacity	8 kWp	Commonly installed residential PV plant in Germany [2]
Usable (not nominal) BESS capacity	6 kWh	Commonly installed size and corresponding to assumed annual load [4,44]
BESS charging capacity	3.5 kW	Current systems in the market predominantly range between 0.4 and 0.6 kW/kWh [4]
Efficiency	95%	Charging/discharging performance of current systems [4]

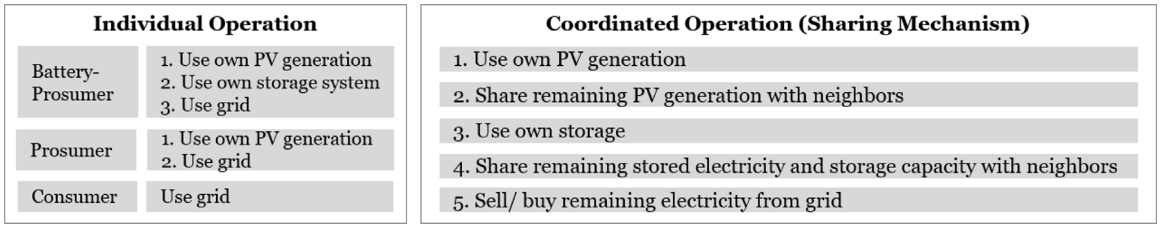

Fig. 2. Principles of community electricity supply during individual operation (no sharing between neighbors) and coordinated operation (sharing of PV and BESS with neighbors).

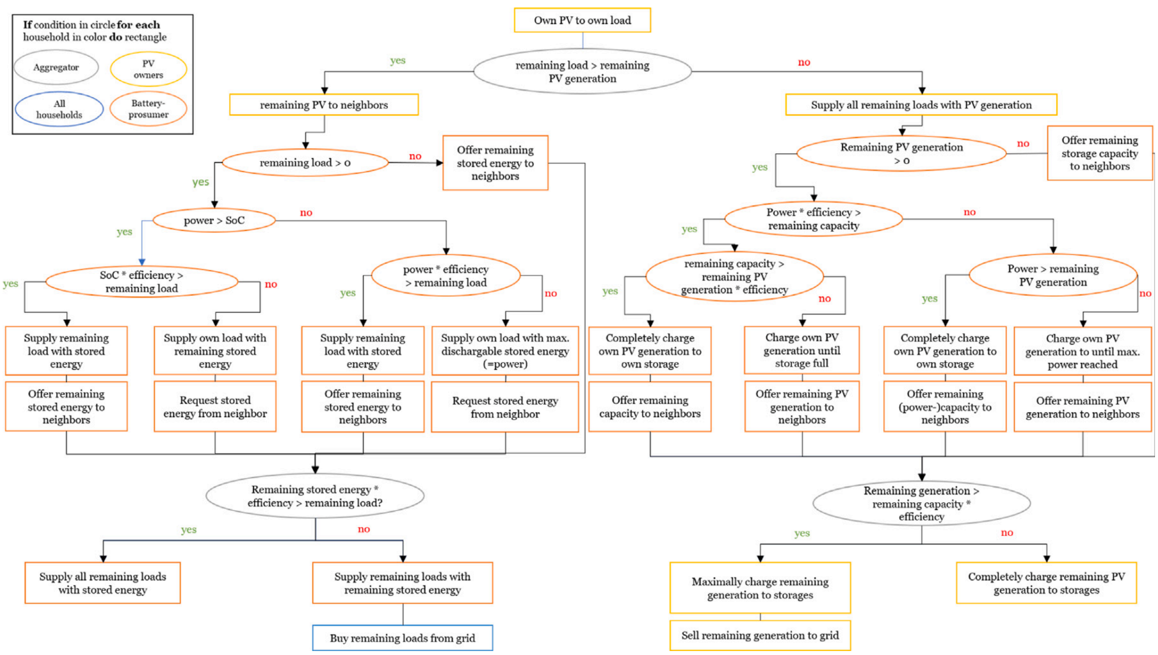

Fig. 3. Sharing algorithm of the coordinated community operation at each time step.

The five households for each of the 520 communities are randomly drawn from the original dataset. We design two operating strategies for each community: One, where the households operate individually to maximize self-consumption without sharing electricity or storage capacity and one coordinated strategy that maximizes the community's self-consumption overall. For both strategies, the sum of the households' resulting electricity bills is calculated and compared to investigate a community's combined profit from a sharing economy model. The distribution of the revenues among the residents is addressed separately in Section 5.1. We choose a regulatory framework similar to the German regulation as of today, with an electricity price of 30 $\frac{ct}{kWh}$, and a feed-in-tariff of 10 $\frac{ct}{kWh}$, for solar generation [34]. We assume that all electricity generated within the community can be shared without additional costs. This means that every additional self-consumed kWh yields savings of 20 cents. The simulation is carried out over one year of household consumption and PV generation data. In the individual operation strategy, each household follows a greedy strategy as described in Fig. 2. (Battery-)Prosumers will first directly consume as much PV generation as possible, then use the storage system (if existent) to store excess electricity or supply remaining loads and then resort to the public grid as a last option for remaining load or excess generation. The annual electricity cost of a household is then determined according to Eq. (1) where buy_t^h and $sell_t^h$ is the electricity that a household h from the set of all households in a community C buys from or sells to the grid at time step t for the fixed electricity price p^{el} and the fixed feed-in-tariff p^{fit}. The overall electricity costs of the community $Cost^c$ are determined by adding the costs of all households in the community according to Eq. (1). Note that the upper limit for annual electricity costs for a single household is 1200€ if the entire consumption of 4000 kWh is supplied by the grid at 30 $\frac{ct}{kWh}$, which applies to all consumers in the individual operating strategy. For (battery-)prosumers, the annual costs can be negative if more money is earned through feed-in than spent on electricity supply from the public grid, i.e., instead of paying a bill they may receive a payment at the end of the year.

$$Cost^c = \sum_{h \in C} Cost^h \quad Cost^h = \sum_{t \in T} buy_t^h * p^{el} - \sum_{t \in T} sell_t^h * p^{fit} \tag{1}$$

The coordinated operation strategy for the sharing community as depicted in Fig. 3 schedules all electricity flows so that a maximum overall self-consumption is ensured. The color scheme illustrates which actions apply to the respective types of households. Similar algorithms have been previously presented in [22] and [23] with only battery-prosumers as participants. For this control strategy, no forecast is needed as it is beneficial under a uniform electricity tariff to immediately maximize self-consumption at any given time step. At each time step, (battery)-prosumers first supply their own load with as much PV self-generation as possible. Then, the sharing economy operator (which can be implemented as a simple information system) compares the community's overall remaining load and excess PV generation. At any timestep, each household sends information about remaining load, excess PV generation and remaining storage capacity to the operator. After the operator compares the overall remaining load and solar generation, any remaining generation is shared with neighbors that have remaining loads. In case there is more remaining load than PV generation in the community, the PV generation is distributed proportionally according to the remaining load of the respective neighbors,

Table 4
Parameters for the characterization of load pattern (sources [39–48] and own extensions).

Parameter	Equation	Explanation
Night impact	$P^i_{night} = \frac{1}{3} * \frac{\frac{1}{N} * \sum_{n \in N} E^i_{d,n}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $N = \{1, \dots, 12\} \cup \{46, 47\}$	The share of the consumption during night hours n in N of the total daily consumption.
Lunch impact	$P^i_{lunch} = \frac{1}{8} * \frac{\frac{1}{L} * \sum_{l \in L} E^i_{d,l}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $L = \{22, \dots, 26\}$	The share of the consumption during lunch hours l in L of the total daily consumption.
End of work impact	$P^i_{EoW} = \frac{1}{6} * \frac{\frac{1}{EoW} * \sum_{e \in EoW} E^i_{d,e}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $EoW = \{32, \dots, 38\}$	The share of the consumption during end of work hours e in EoW of the total daily consumption.
Daily minimum demand	$P^i_{min} = \min_{t \in T} E^i_{d,t}$	Minimum of the daily load profile.
Summer/winter ratio	$P^i_{SWR} = \frac{\sum_{s \in SM} \sum_{t \in T} E^i_{s,t}}{\sum_{w \in WM} \sum_{t \in T} E^i_{w,t}}$	The ratio of the total demand in summer months SM to the total demand in winter months WM.
Daily non-uniformity coefficient	$P^i_{NUC} = (\frac{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}{\max_{t \in T} E^i_{d,t}})$	Describes the maximal variation in regards to the average load
PV correlation	$P^i_{PV} = \frac{cov(E^i_d, PV_d)}{\sigma_{E^i_d} * \sigma_{PV_d}}$	The Pearson correlation coefficient of the load profile with a generation profile of a photovoltaic system PV_d

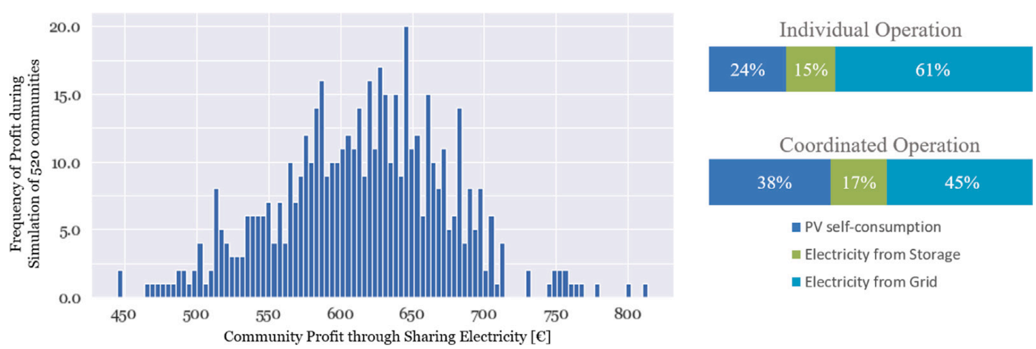

Fig. 4. Community profit distribution for 520 sharing communities (left), sources of electricity supply in average community (right).

and vice versa (this is important with regards to payments in the sharing economy model). The community charges their storage capacity only after as much PV generation as possible is consumed directly. This is advantageous because the usage of storage is associated with costs due to cyclic degradation. Thus, it would be cost-inefficient for the community as a whole to store electricity instead of sharing it with a neighbor that has immediate load to supply. Each battery-prosumer will first make use of personal storage capacity before remaining capacity or stored electricity is offered to neighbors. The community buys from the public electricity grid in order to supply remaining load or feed in excess PV generation after as much PV generation as possible has been consumed or stored directly. At any time step, the algorithm ensures that the utilization of storage is within the restrictions of the maximum power capacity of the BESS and that no more electricity is charged or discharged than the current State of Charge (SoC) allows. The resulting electricity costs are calculated for the community as a whole according to Eq. (1). The overall community profit from the sharing mechanism is then determined as the difference between the community's electricity costs during individual and coordinated operation. For the comparison of overall profits from an energy sharing economy model, the electricity streams between the individual members of the community are not relevant and therefore handled as a "blackbox" for now. The flows and the resulting consequences for the pricing and payment of the shared goods are addressed in Section 5.1.

4.1. Characterizing participants based on load profile properties

In this study, we aim to not only assess the possible profits of a sharing economy for PV generation and battery storage, but we also determine the impact of the individual participants of the energy sharing community and their characteristics on said profitability. This has not yet been explored in the literature: On the one hand, there is a range of literature dealing with the characterization and classification of electricity load profiles by means of describing parameters (i.e., maximum daily load, summer–winter ratio), clustering or pattern mining (see for example [45–54]). But these findings have not yet been applied to the literature on the economics of local energy sharing communities described at the beginning of this paper. Therefore, in this study, we apply the findings of the research on load profile characterization to find out which characteristics of participants' load profiles are beneficial for the proposed sharing community. To this end, Table 4 shows a collection of describing parameters that we calculate for each load profile in our simulations where l corresponds to half an hour during the day (i.e., l = 22 refers to 11 am).

In Section 5.2, we derive statements about the suitability of various participants for a sharing community. Since we keep the overall electricity consumption constant during the first simulation, the discovered relationships can be fully attributed to the pattern of the respective household's load profile. In the second simulation, we compare the effects of the load patterns to the effect of changes in absolute load. In total, we identified 15 parameters during our investigations, but for the sake of comprehensibility, we present here only those for which an impact on the community's performance could be found. Each of the parameters in Table 4 is calculated for every day of the load profile and then the median of all resulting values is used to describe a "median" day of the load profile. This approach compresses the annual load profile to a few values, thus a lot of information is lost in the process. In order to keep some information, we distinguish between six

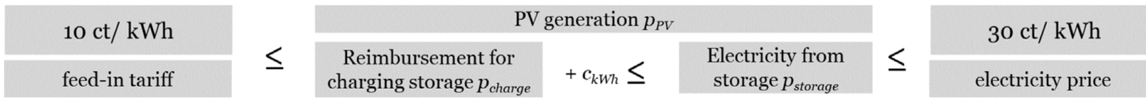

Fig. 5. Upper and lower bounds for fair pricing of PV generation (p_{PV}), charging storage (p_{charge}) and buying electricity from storage ($p_{storage}$) when considering the marginal costs of storage c_{kWh}.

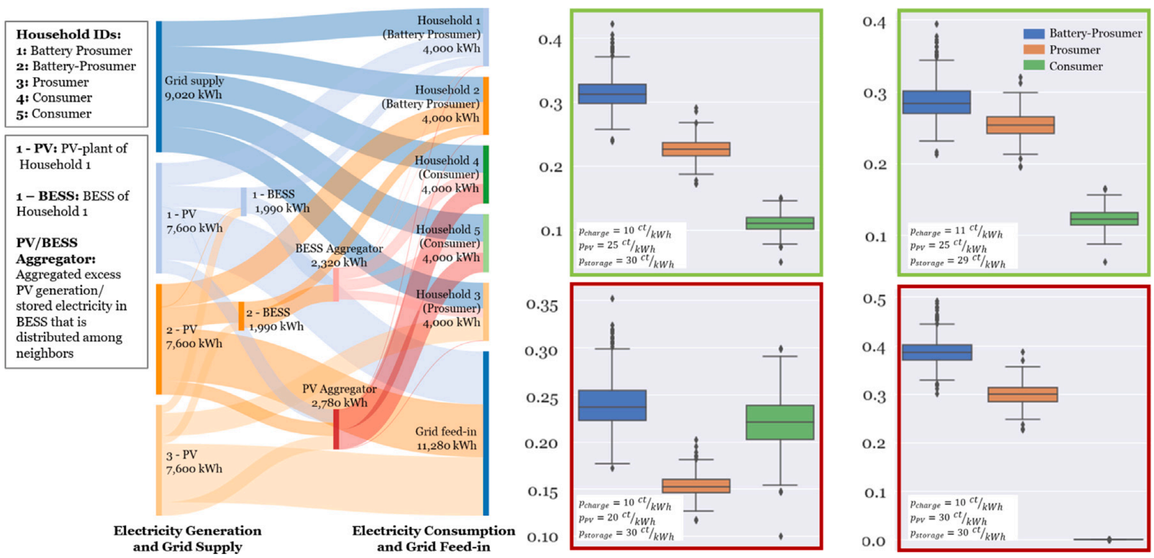

Fig. 6. Electricity flows in the average sharing community (left). Distribution of community profits amongst household types in percentages considering different pricing schemes for shared electricity (right).

different "median" days: First, we differentiate between *workdays* (Mo–Fr) and *weekends* (Sa, Su). Second, we account for seasonal effects by distinguishing between *summer* (June–September), *winter* (December–March) and *spring/autumn* (April, May, October and November). For each household, we thus obtain 90 parameters that are then used to build a random forest regression to determine the interaction of load profile properties and community profits. The used method and our results are described in Section 5.2.

5. Results: Community profit, revenue distribution and participant matching

For 520 communities consisting of five households each, we simulate a sharing economy model and compare the annual electricity costs with the case of individual operation of the assets. Fig. 4 (left) shows the distribution of profits over the 520 simulations. The community that profits least from the sharing of electricity and storage capacity has annual savings of 445€, the most profitable sharing economy community yields annual savings of 813€. On average, 615€ are saved through the sharing of electricity and storage capacity amongst five households. By keeping all other system parameters constant, the results show the effect of different load pattern configurations on the profitability of a sharing community. The results show the financial potential of a sharing economy model in residential communities. A further finding is the effect of a sharing mechanism on the utilization rates of the assets in the community. Fig. 4 (right) shows the proportional origin of the annual electricity consumption, averaged over all 520 communities. Since annual household consumption is scaled to 4000 kWh each, the communities consisting of five households have an annual electricity consumption of 20,000 kWh. During individual operation, almost two thirds of the electricity is supplied from the grid. On average, an additional 3208 kWh are self-consumed in a sharing community. The largest effect between individual and coordinated operation can be observed in the electricity that is directly consumed from solar generation. The sharing of the storage systems accounts for only 430 kWh out of the additional self-consumption. While this might not seem much, it can be explained by a number of factors. First, we assume that the storage systems are dimensioned to match the annual consumption of a single household, since we want to explore the sharing potential for already existing PV and storage systems. Larger community storage systems might lead to higher savings. Second, as previously explained, the joint operation of a solar installation and a BESS has an upper limit of approximately one cycle per day meaning 365 cycles per year. When comparing the utilization rates of the BESS in individual and coordinated operation, we thus have to consider the additional cycles per year that are achieved through means of the sharing economy model. This number increases from approximately 280 cycles per year in the individual scheme to around 320 cycles per year in the coordinated operation for each of the two storage systems employed in the communities. Given that the solar generation is limited on many days during the year, this number suggests that in a sharing community as configured in this simulation, a nearly maximal utilization rate of BESSs for self-consumption is achieved. The increased rate of utilization is thus an incentive for storage owners to participate in a sharing scheme as proposed here. Nevertheless, the bulk of the profits is generated through the additional direct self-consumption, a result that is partly attributable to the addition of the pure consumers to the sharing community. Although these consumers do not bring private capital in the form of technology into the community, they are presumably an important factor in the economics of the sharing economy business model and should therefore be encouraged to participate through financial incentives. Nonetheless, it can be argued that higher initial investments justify higher profit shares for (battery)-prosumers. In the next section, we examine different price configurations and discuss how they encourage the respective types of households to participate in the sharing community.

5.1. Distributional fairness through a fixed pricing approach

During the simulation, all shared electricity flows at each time step are recorded to track the amount of electricity that is shared between the respective households in the community. Fig. 6 (left) shows this for the average community over one year. There are three flows that have to be reimbursed differently: First, electricity from a (battery-)prosumer's solar panels can be directly consumed by a neighbor at the price p_{PV}. Second, stored electricity from a battery-prosumer's BESS that is consumed by another customer ($p_{storage}$) and third, electricity from solar generation that is sold to a battery-prosumer to be stored in her BESS. Note that for the latter, the battery storage owner pays p_{charge} to the (battery-)prosumer who provides the electricity. We propose to choose fixed values for each of these prices. This is a contrasting approach to a trading mechanism, but, as previously argued, it offers decisive advantages. A fixed pricing mechanism is de facto "business as usual" for the majority of electricity consumers. However, the fixed prices of the shared goods have to be chosen carefully and thus we demonstrate the effects of different pricing configurations in this setting. We argue that some conditions have to be met to result in a "fair" profit sharing outcome. The concept of fairness is quite ambiguous in research and for more differentiation on fairness consider [55]. In this paper, we stipulate that distributional fairness is achieved if (i) larger investments result in larger profit shares, (ii) additional consumption of locally generated electricity is rewarded (i.e., profit share of consumers > 0), and (iii) no household is penalized for participating in the sharing economy community (i.e., the profit from participating in the community has to be larger than during individual operation). To ensure that no household suffers economic disadvantages from participating, certain limits apply to the three previously described prices (compare Fig. 5). All have to be above the feed-in-tariff so that there is no incentive to feed electricity into the public grid instead of sharing it. Similarly, consuming local electricity should always be advantageous and thus $p_{storage}$ and p_{PV} should be less than the grid electricity price. The price that is paid for stored electricity $p_{storage}$ has to be at least as high as the price that the owner pays for storing electricity (p_{charge}) plus the (marginal) costs of storing an extra kWh in the BESS c_{kWh}. The marginal costs c_{kWh} are difficult to determine. In general, the levelized costs of storage can be calculated using the overall system costs and dividing it by the capacity and the achievable cycles during a lifetime. For lithium-ion batteries, the authors of [56] find this value to be between 0.36 and 0.69 $\frac{\$}{kWh}$. As system costs have decreased significantly in the last years, one German online information portal claims that levelized costs can be as low as 15 $\frac{ct}{kWh}$ for small-sized BESSs currently in the market, even without considering subsidies [57]. However, it could also be argued that in the case of under-utilized storage capacity, the marginal costs are zero because without the sharing economy model, the storage system would never reach full cycle times before reaching its calendaric end of life of up to 20 years. Either way, considering the initial investment costs, for the revenue distribution, we stipulate that a battery-prosumer receives a larger profit share than a prosumer, and that a prosumer in turn receives a larger share than a consumer. Subsequently, in the investigated pricing schemes for a sharing economy model, c_{kWh} is set sufficiently high to ensure these conditions. The configuration of the prices can then be reduced to two decisions: *How much is storage worth* (setting c_{kWh})? and *How much is local consumption being rewarded* (setting p_{PV})?

The flows from the PV and BESS owners to the consumers in Fig. 6 (left) show that consumers are responsible for requesting the majority of shared direct self-consumption and stored electricity, again underlining the importance of consumers for the overall profitability. Interestingly, roughly one third of stored electricity is consumed by the respective BESS owner and two thirds are shared with neighbors. This is due to the implementation of the algorithm without forecasts that enables the provision of stored electricity to supply a neighbor's load at time step t without considering whether the storage owner might need it for personal demand in time step $t + x$. However, it is also beneficial for the storage owner to sell this electricity rather than consuming it later.

The four exemplary pricing configurations in Fig. 6 (right) illustrate the effects of setting p_{PV} and c_{kWh}. When the two parameters are set to their respective upper limits (bottom right), (battery)-prosumers receive the maximally possible profits at the expense of the consumers. This scheme is not feasible under our fairness principles as it provides no incentive for a consumer to participate in the sharing economy model. A contrary effect is created if the p_{PV} is set significantly lower at 20 $\frac{ct}{kWh}$ (bottom left). In this setting, a consumer is rewarded more than the prosumer, which contradicts the guideline that we previously set that higher investments should yield higher profit shares. We therefore conclude that the price for PV generation has to be somewhere in between 20 and 30 $\frac{ct}{kWh}$ in our setup to reward consumption without marginalizing initial investments in technology. A possible fair revenue distribution scheme is thus illustrated in the top left graph where p_{PV} is set at 25 $\frac{ct}{kWh}$. With an average of around 615€ annual profits for a sharing community, each of the two battery-prosumers receives around 185€, the prosumer receives around 120€ and each of the consumers 60€. In this initial feasible revenue distribution scheme, we set the reward for an investment in a storage system as high as possible with $c_{kWh} = 20\frac{ct}{kWh}$ since we argue that a battery-prosumer should receive a larger share of the profit than a prosumer. The effect of a slight reduction in c_{kWh} on this ratio is shown in the graph in the upper right corner. While the profit share of the consumers does not change substantially, in the average sharing community, the gap between battery-prosumers and prosumers is gradually closing. This could be justified by the observation that the majority of profits comes from additional PV self-consumption rather than stored electricity as seen in Fig. 4. As shown with the examples in Fig. 6 (right), there is more than one set of fixed prices that would ensure distributional fairness as previously defined. Note that while we always refer to the outcome of the pricing configurations on the average sharing community, the boxplots show that the distribution of profits can differ significantly in individual cases. However, the choice of prices can also serve to incentivize individual participants to shift their electricity load in benefit of the sharing community. In a platform-based sharing economy model, the pricing configuration should be considered individually for each sharing community as it is a crucial design element of the initial setup. In general, fair pricing and revenue distribution needs to be further investigated, possibly by undertaking field studies on residential preferences and willingness to participate in a sharing economy model as proposed here.

5.2. Matching communities: Suitability of participants based on load profile properties

In this section, we want to investigate how to predict the profitability of a sharing community based on the participants' load profile properties. We find that there is a dependency between the performance of battery-prosumers during individual operation and the community profits in a sharing economy (Fig. 7 left). As previously mentioned, (battery-)prosumers can have negative electricity costs and during our simulation, this was always the case for the battery-prosumers. The figure shows that when the two battery-prosumers in the community perform poorly in individual operation, i.e., their positive cashflow is small when they operate by themselves, the sharing community's profit tends to be larger. No such relationship could be found for the one prosumer (without BESS) in the community. It is an interesting finding that battery-prosumers with poorer individual performance would have a greater incentive to participate in a sharing economy. Since they contribute the largest investments to the community, their willingness to participate is crucial for the formation of sharing communities.

The overall profits of a sharing community can be attributed to the additional self-consumption from (a) PV generation (direct self-consumption) and (b) stored energy. We therefore split the overall additional self-consumption of each sharing community into these two

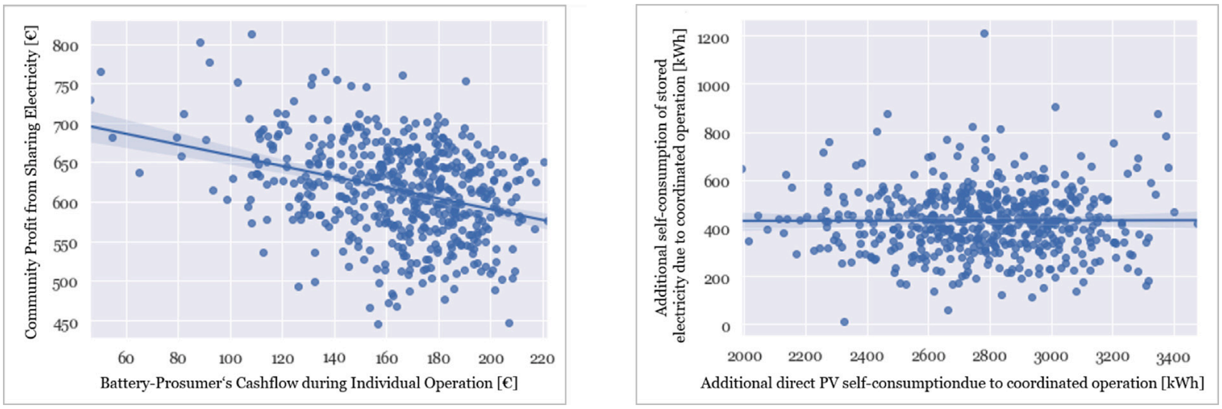

Fig. 7. The two battery prosumer's (average) cashflow during individual operation compared to the community profit from sharing electricity (coordinated operation) (left). Relationship of a community's additional self-consumption from PV generation and stored electricity (right).

parts. We find that there seems to be no dependency between additional self-consumption from PV and BESS (Fig. 7 right), and we will investigate if we can predict either of these values from participants' properties. Therefore, we want to investigate how we can predict the three target variables (1) additional (direct) PV self-consumption, (2) additional self-consumption of stored energy and (3) overall community profit in a sharing economy, using only the attributes of participants' load patterns. We use the load profile properties described in Section 4.1 and obtained 90 descriptive parameters for each household. We train a random forest regression using the *RandomForestRegressor* method of the Python package sckit-learn. We average each of the 90 parameters for three sets of participants: (i) the two battery-prosumers, (ii) the two consumers and (iii) all community participants. We then use them as input to predict our three target values. In addition, we train one more tree with the input parameters of battery-prosumers and consumers combined, resulting in 180 input parameters. The maximum depth of the regression tree is set to 12. To evaluate the overall performance of the regression, we split the 520 households in a training (n = 450) and test (n = 70) set. We then calculate the mean squared error (MSE) for the predictions on the test set and compare it to a naive benchmark [58]. As naive benchmark prediction, we use the average of the respective target value for each community (e.g., €615 for the community profit).

The resulting improvements of the MSE when compared to our naive benchmark are shown in Table 5. We find that we can improve the MSE for all target values significantly when using the participants' load profile pattern parameters as input. Interestingly, we can improve our prediction of additional self-consumption from storage by over 40% using the battery-prosumers' parameters as input, but achieve virtually no improvement when using the consumers' parameters. For additional direct PV self-consumption, it is the other way around: Our prediction improves by almost 80% with the consumers' parameters as input and only 9% using the battery-prosumers' parameters. The average over all households taken together yields the worst results which shows that too much information is lost by averaging over all households. We achieve the best results for additional PV self-generation and community profit when combining the battery-prosumers' and consumers' parameters, however the improvements are marginal. From the results we derive that one has to take a closer look at different participants depending on the target of a sharing economy. If the aim is to increase the utilization of PV-coupled BESSs, then it is best to include suitable battery-prosumers while the properties of the other participants are less important. On the other hand, if the main goal is to increase direct PV self-consumption and overall profitability, the properties of the consumers that are added to the sharing economy are decisive. It should be noted that we also performed all of the predictions with the load pattern parameters of the prosumer (both individually and in combination with the other participants) but no improvements could be achieved in any scenario. We conclude that the properties of the single prosumer are of very little importance compared to the other participants in our scenario.

Following our results in Fig. 7 and Table 5, it seems that battery-prosumers that perform worse on their own than others, i.e., their load profile leads to a low BESS utilization, profit from joining or establishing a sharing community. To better understand the results and the importance of individual features in predicting the target values, we use the Shapley Additive Explanation (SHAP) introduced by [59]. The SHAP value is more robust than classic feature importance measures as it avoids inconsistencies such as giving higher importance to features that are used earlier in a tree split. For each observation, the SHAP value calculates the marginal contribution of each feature to the target variable. This impact can be calculated both globally (i.e., the overall average impact of the parameter on the model output) and locally (i.e., the impact of the parameter on the output for each observation in the data set), which increases the transparency for the interpretation of the features' impact. Fig. 8 shows the ten highest global and local SHAP values in the case of predicting additional self-consumption from storage with the battery-prosumer's load profile parameters. We can see that the *daily minimum demand* in summer and spring/autumn on weekends has a strong negative effect on the target value. This means that battery-prosumers with **high** minimum daily demands on weekends perform **better** on their own. Our explanation of this observation is as follows: A high daily minimum demand speaks for a relatively less "peaky" load profile. Households with a more even consumption spread throughout the day might make better use of the surplus generation that is stored in the BESS during the day. Notably, both of the two most important features are on the weekend. We suspect that this is the case because most households exhibit a "beneficial" pattern for BESS utilization during the workdays anyway: Standard load profiles typically have high demand in the evening hours. Therefore, the behavior on weekends makes the difference between overall better or worse BESS utilization. Interestingly, the *PV correlation* of battery-prosumers load profile during summer and on workdays in spring/autumns has a positive effect on additional self-consumption from storage. This is surprising because higher demand during PV generation hours should lead to less available surplus generation to be stored in the BESS. This apparent contradiction can be partially explained by looking at the right side of the diagram. The local SHAP values on the right show the impact of the input parameters on each observation in the dataset, i.e., the individual communities. The impact of the *PV correlation* for example is left-skewed: While low value have a high (negative) impact on the target value, high values have a less pronounced positive impact. From this we can deduce that especially low *PV correlation* leads to less additional self-consumption from BESS in a sharing community. This could be explained by the fact that households that exhibit a contradicting pattern to PV generation have high BESS utilization rates

Table 5
Improvement in MSE when using participants' load profile properties to predict the performance of the sharing community.

Input properties	Target value		
	Additional (direct) PV self-consumption	Additional self-consumption from storage	Community profit
Benchmark (average)	100% (MSE = 74,283)	100% (MSE = 13,165)	100% (MSE = 3710)
Battery prosumers	91.1%	56.9%	98.8%
Consumers	22.9%	98.4%	30.6%
All households	82.9%	86.7%	79.5%
Consumers + Battery prosumers	22.3%	60.7%	25.5%

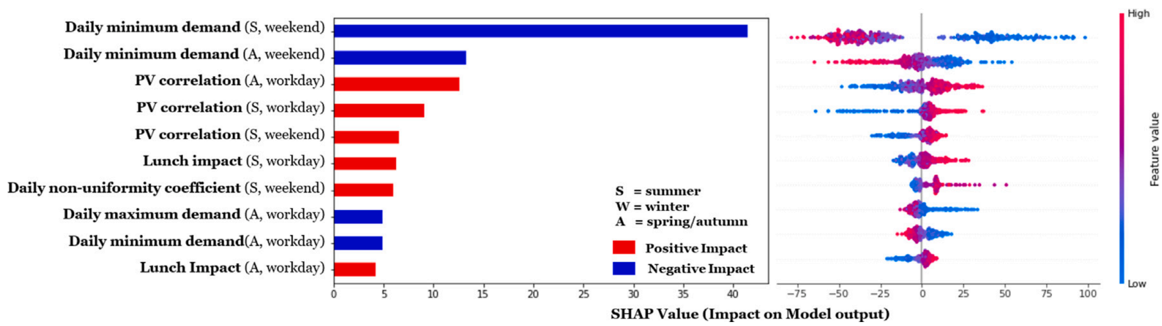

Fig. 8. Global (left) and local (right) SHAP values of the ten highest battery-prosumer feature impacts on additional self-consumption from storage in a sharing community.

anyway, meaning that there is not much room for improvement by means of a sharing economy.

The participation of consumers in a sharing economy community has not been the focus in previous research, as they do not own any energy-related technologies that would justify their participation in the community. Therefore, the contribution of their electricity demand and load pattern to the profitability of a sharing community has not yet been extensively analyzed. This might immensely influence the profitability of the sharing economy model and utilization rates of storage systems. The authors of [23] find that in a community consisting of only battery-prosumers, internal trading is very low and could be increased by adding consumers. This relationship is also evident in the flow diagram in Fig. 6 (left), where it can be seen that consumers are responsible for most of the energy exchange within the peer-to-peer network. The results of our prediction further emphasize the importance of consumers in a sharing economy for PV-coupled BESSs. The load profile properties of the consumers explain the majority of additional self-consumption from PV and ultimately community profit in our simulation. Fig. 9 shows the top ten most important features for the identification of suitable consumers. Unsurprisingly, the *PV correlation* in summer on workdays is the most important feature. Yet, the *PV correlation* in summer on **weekends** is *not* among the top ten parameters. We suspect that this is the case because it is more unusual for a household to correlate with PV generation during the week than on the weekend. On workdays, standard load profiles usually have relatively low demand during the day. Both *PV correlation* and the closely related parameter *lunch impact* appear for all seasons on workday in the ten most important parameters. Twice among the top three is the *summer–winter ratio*. Here, a high value corresponds to higher additional PV self-consumption. Since our dataset consists of households from the USA, there are many load profiles with high demand in summer, indicating an air-conditioning system which is likely reflected in this parameter.

When adding the parameters of battery-prosumers to the input features, we achieve a 5% improvement of community profit prediction. However, the ten most important parameters (compare Fig. 10) are congruent with Fig. 9, only slightly differing in the importance order. Only the sixteenth parameter, *end of work impact* in summer on weekends, belongs to the battery-prosumers. A high value indicates a relatively high demand in the late afternoon and evening hours. These households might have a better performance on their own due to high BESS utilization rates and thus profit less from entering a sharing community.

In summary, we can conclude that the choice of suitable participants impacts a sharing community's profit immensely and should therefore be considered when matching a community. Different properties are relevant for the respective choice of battery-prosumers and consumers for them and others to profit most from an energy sharing economy. Since all other parameters of the community's configuration are kept constant in our simulation, a causal relationship between the identified load profile properties and target values can be concluded. These features can therefore be utilized to match sharing communities with high profit potentials. The identification of relevant parameters is of high practical relevance as well: Since the load profile pattern parameters that were used in this study can be intuitively explained by certain behavior known to the household, they can be approximated even without data of load profile measurements. A promising next research question would be to link specific behavior or work patterns to the relevant load profile parameters that were identified in this study.

5.3. Comparing the impact of changes in absolute load on community profit and additional self-consumption

During the simulation, we deliberately set all community and household parameters to the same values to explore causal relationships between the load profile patterns and the performances of sharing communities. However, in practice, this will likely not be the case for households that could potentially be connected in a sharing economy. We thus ran the simulation of the 520 sharing communities a second time, this time with the original absolute annual loads of the households in the dataset. Our objective with this is to quantify the impact of absolute loads, compared to the effect of load patterns, on the target values of the performance of a sharing economy. In order to retrieve comparable results to our first simulation, we scaled the PV plant and BESS so that the relation between absolute load of a (battery-)prosumer and installed technology would be the same as in the first simulation. This means that for example a battery-prosumer with an annual load of 6000 kWh would operate a 9 kWh BESS and a 12 kWp solar plant. Obviously, there will be a dependency between absolute loads of (battery)-prosumers and resulting community profit

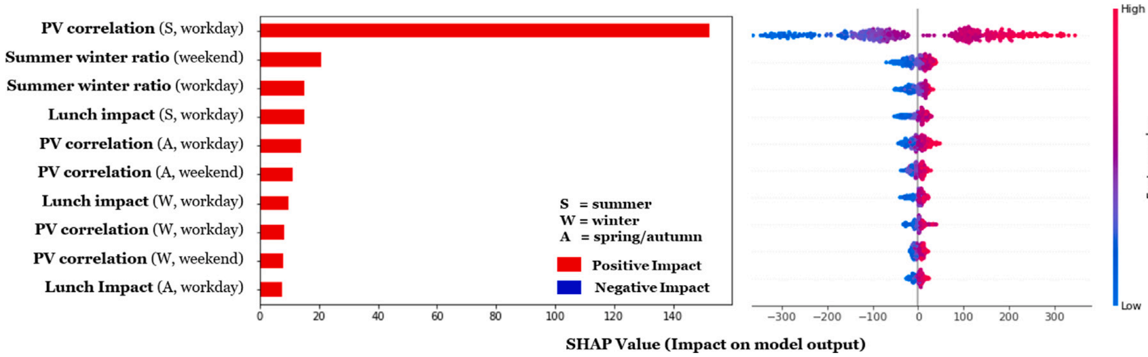

Fig. 9. Global (left) and local (right) SHAP values of the ten highest consumer feature impacts on community profit from sharing electricity.

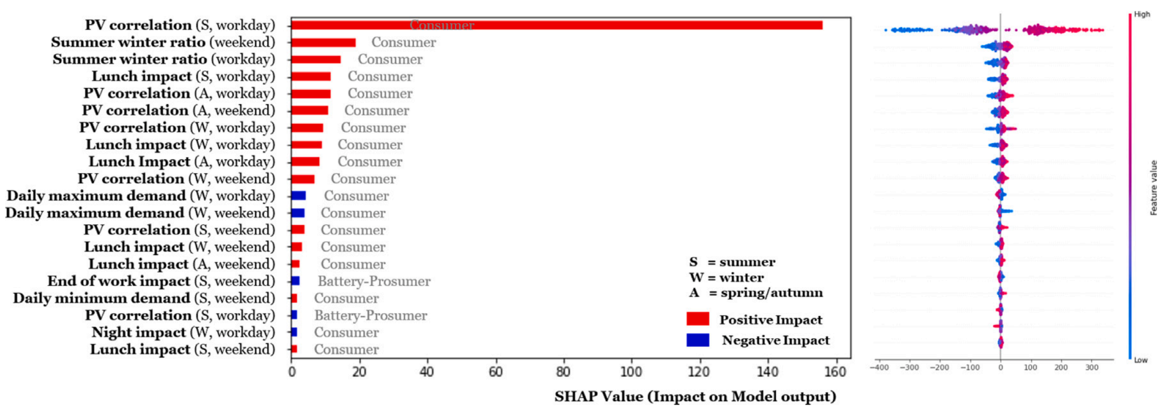

Fig. 10. Global (left) and local (right) SHAP values of combined consumer and battery-prosumer feature impact on community profit from sharing electricity.

and self-consumption from PV and BESS. For this reason, we look at relative instead of absolute changes in community profits during the evaluation. Furthermore, instead of predicting absolute additional self consumption, we now define our target values as (1) additional self-consumption from storage **per installed kWh** and (2) additional (direct) PV self-consumption **per installed kWp**. This is plausible because larger PV plants and BESSs cause larger investments and thus more self-consumption does not automatically result in a more profitable investment. However, in this simulation, the annual loads of the households relative to each other may vary substantially. Furthermore, the load of the consumers is not considered during the sizing of PV plants and BESSs and is therefore expected to have a large effect on the simulation outcomes.

For the prediction of our three target values, we again use the 90 load pattern parameters and add the absolute load as additional input parameter. Fig. 11 shows a selection of SHAP values for the prediction of our target values. We find that additional self-consumption from storage per kWh can again be best explained using the battery-prosumers parameters, achieving a 23% improvement compared to the benchmark MSE. Fig. 11 (right) shows the corresponding SHAP values which indicate that the absolute load is not among the parameters that are decisive for increasing BESS utilization. Similar to the previous results, the most important parameters are *daily minimum demand* and *PV correlation*. On the other hand, for the prediction of the relative community profit, the absolute load is by far the household feature with the most impact. Here, we achieve the best results when using both the consumers' and battery-prosumers' parameters as input, resulting in an 84% improvement compared to the benchmark prediction. The annual load of the consumers has the largest impact on the relative gain, closely followed by the annual loads of the battery-prosumers. Notably, the latter effect is negative, indicating that battery-prosumers with low annual load profited more from joining a sharing community, possibly because they were matched with (relatively) larger consumers that increased self-consumption.

In summary, we see large effects of absolute changes in annual loads on the profitability of a sharing community. It is worth noting that the households in our dataset had quite large annual demand in general. Even though we only used single family households without electric heating, the average annual electricity consumption in our data subset was around 7500 kWh, ranging from around 2000 kWh to more than 12,000 kWh. We suspect that this is due to the origin of the data that stems from American households which evidently have higher electricity consumption than average European households possibly caused by an higher market penetration of air conditioning devices. It is therefore plausible that in many residential neighborhoods in Europe, the spread in annual electricity consumption is not as pronounced and therefore effects of load pattern changes will have a great impact as shown in this study.

6. Discussion

For the first simulation, we set all technological parameters as well as overall consumption to fixed values in order to explore the effects of differing load patterns. The storage units are sized to resemble a BESS that is commonly installed in a residential household as of today. It is however also conceivable that with the appropriate regulatory framework, a sharing economy model as proposed incentivizes the installation of larger community storage units. To get a first idea of the impact of larger storage systems, we repeat the first simulation with larger storage units with a capacity of 8 kWh and a power output capacity of 4.6 kW each while all other parameters and load profiles remain the same as before. Fig. 12 shows the origin of annual community electricity consumption in a direct comparison of the two storage system sizes and averaged over all 520 communities.

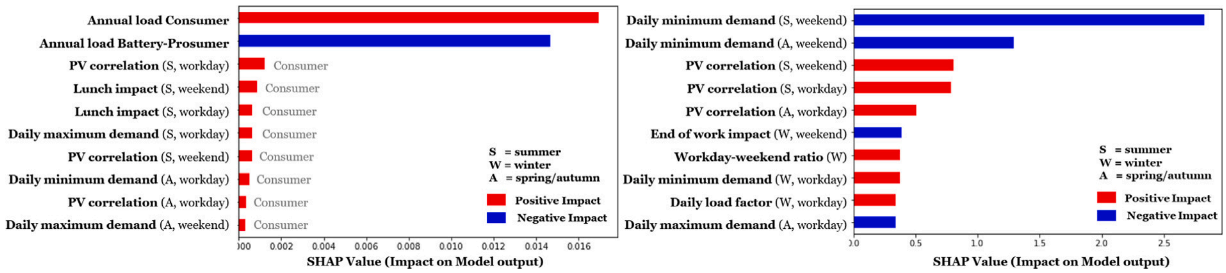

Fig. 11. Left: Ten highest SHAP values for the prediction of relative community profit using consumer and battery-prosumer parameters. Right: Ten highest SHAP values for the prediction of additional self-consumption from storage per kWh using battery-prosumer parameters.

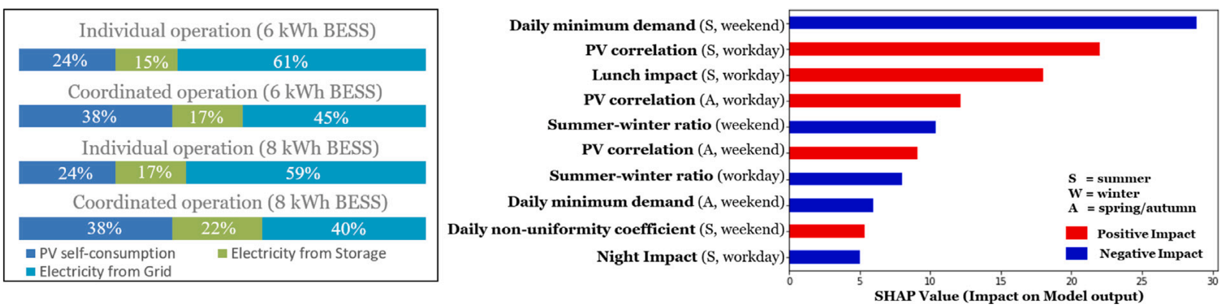

Fig. 12. Left: Comparison of sources of community electricity supply in average community for 6 kWh and 8 kWh BESSs. Right: Ten highest SHAP values for the prediction of additional self-consumption from storage with battery-prosumers parameters.

The direct PV self-consumption remains the same in both cases as no adjustments are made to the size of the PV plant. During the individual operation, the share of the consumption of stored electricity is slightly larger than with smaller storage systems. A more significant difference can be observed in the additional self-consumption from storage in the coordinated sharing community where 22% instead of 17% of stored electricity are now consumed. However, the utilization rate of the larger storage units in the coordinated operation decreased from 320 to 307 annual cycles. This could still be sufficient to justify the installation of the larger storage units as it might benefit from smaller specific system costs [60]. To find out which of the load profile properties affect battery utilization with a larger storage, we repeat the prediction of the additional self-consumption from storage. We again achieve the best results when using only the battery-prosumers load pattern parameters, improving the naive benchmark by 54% (compared to only a 43% improvement with smaller storage units). The most important features for determining battery-prosumers that profit from entering a sharing community (shown in Fig. 12 (right)) are similar as with the smaller storage unit (compare with Fig. 8), except that now the summer–winter ratio appears among the most important features. As we argued before, a high summer–winter ratio might indicate the presence of an air-conditioning system. The impact of this attribute is right-skewed and has a negative impact on the target value, indicating that the absence of an air-conditioning system leads to higher additional self-consumption from storage in a sharing community, but not the other way around. This observation could be easily used in practice to identify suitable candidates for a sharing community.

We assume a fixed electricity price and feed-in tariff as is they are common in many countries today. However, as we argued before, from a system's view, BESS are a flexibility measure that could complement grid capacities, and other tariffs might incentivize consumption at certain times. Investigating other regulatory frameworks such as time-of-use tariffs or real-time-pricing of electricity could thus yield interesting additional insights.

7. Conclusion

In this paper, we provide a comprehensive examination of the theoretical and practical potentials of a sharing economy business model for a residential community that engages in the sharing of solar generation and storage capacity. First, we address the theory on sharing economy, highlighting the potential that is attributed to its application in the energy sector. Through the simulation of 520 communities, we show that a sharing community with five households as configured in the case-study yields average annual profits of €615 that vary individually with the load patterns of the participating households. We suggest a fixed pricing approach that considers fairness aspects to distribute the generated revenues amongst the participants within the energy sharing economy. Finally, we show that the selection of suitable participants, based on load profile properties, can enhance the potential revenues and also the incentive to participate in sharing local electricity. In this regard, we further differentiate between the impact of load patterns and absolute load. Building upon these findings, a platform-based sharing economy model could accelerate the implementation of local energy communities. The sharing economy is thus becoming an important component in energy economics and should be further investigated.

CRediT authorship contribution statement

Sarah Henni: Conceptualization, Methodology, Software, Validation, Visualization, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Philipp Staudt:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Christof Weinhardt:** Conceptualization, Supervision, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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