Optimization of PV-coupled battery systems for combining applications: impact of battery technology and location

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Summary

Interest in residential batteries to supply PV electricity on demand is increasing, however they are not profitable yet. Combining applications has been suggested as a way to increase their attractiveness, but the extent to which this can be achieved, as well as how the different value propositions may affect the optimal battery technology, remain unclear. In this study, we develop an optimization framework to determine the best-suited battery technology and size depending on the applications combined, including PV self-consumption, demand load-shifting, demand peak shaving and avoidance of PV curtailment. Moreover, we evaluate the impact of the annual demand and electricity prices by applying our method to representative dwellings in Switzerland and the U.S. Our results indicate that the combination of applications help batteries to become close to break-even by improving the net present value by up to 66% when compared with batteries performing PV self-consumption only. Interestingly, we find that the best-suited battery technology in the U.S. is NCA as for Switzerland NMC-based batteries reach in average a higher net present value than NCA-based batteries and could be a more promising alternative in future. This highlights the importance for policy makers to avoid lock-in in a particular policy which may be suboptimal in the long term.

Keywords: PV, energy storage, battery, lithium-ion, electricity demand, combination of applications

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1 Context & Scale

The projected transition to a low carbon energy sector faces some intrinsic challenges world-wide. Further integration of distributed renewable supply from intermittent sources such as solar and wind energy will lead to increased imbalance between demand and supply. This imbalance across time calls for new technological solutions such as energy storage, primarily decentralized in the case of solar. Current high costs of various electricity storage technologies is the most serious drawback for their further deployment to increase the value of renewable energy technologies. The simultaneous provision of various energy applications could potentially be a key driver for the further implementation of storage technologies across the energy sector. Here, we focus on residential batteries and devise a method for optimally combining energy storage applications in order to minimize the electricity bill of consumers. We inform about the best-suited battery technology depending on the combination of applications and location. Finally, we determine the break-even point depending on the applications provided and show how the combination of applications can relax the cost requirements of battery technologies.

1. Introduction

The modularity of solar photovoltaics (PV) is enabling the installation of substantial amounts of generation capacity embedded in the distribution network close to domestic electricity demand. In 2016, new installations in the residential sector of the United States (U.S.) represented 67% of the PV installations with a nominal power lower than 2 MW[1], while in Germany for the same year, new PV installations in the residential sector accounted for 50% of the total number of installations[2]. This PV development has been facilitated by the rapid decrease in cost of PV modules during the last decade, (*e.g.* in Germany and the U.S. the price of installed rooftop systems has declined by 60% and 55% respectively since 2009)[1,3]. In parallel with these cost declines, retail electricity prices have risen steadily for the last decade across many countries (*e.g.* by 78% in Spain, 52% in Germany, and 48% in the U.K. since 2007)[4], while the subsidies for PV electricity fed to the grid, referred to as feed-in tariffs (FiT), have markedly declined (*e.g.* by 71% in Germany since 2009)[5]. Additionally, FiT are being restricted, for example, there is a cap on the installed capacity that can profit of the FiT in Australia and Switzerland[6]. Furthermore, the stochastic nature of the solar energy resource prevents PV systems from supplying electricity on demand as is possible with many other conventional technologies such as fossil plants and hydro storage. All of these factors are significantly increasing residential consumers interest in increasing the amount of self-generated PV that they consume in-home (this refer to as PV self-consumption) by using battery systems[6]. Typical rates of PV self-consumption which ranges between 20 and 40% for residential consumers can be increased by 13 to 24% when battery storage is included in the system, using an elementary charging approach[7].

In parallel with this increased consumer interest, battery costs, especially lithium-ion tech-nologies, are following a similar trend as experienced by PV systems and the International

Renewable Energy Agency (IRENA) reported a cost reduction of 65% since 2010 for lithium-ion batteries[8]. To encourage battery development, dedicated subsidies have been implemented[9,10]. In Germany, more than 30000 new residential PV-coupled battery systems have benefited from the federal program since 2013 and in 2017, half of every small PV system was installed with a coupled battery as a result of government economic incentives[10]. Home battery storage is still an emerging market but some projections estimate that households and businesses may account for nearly 60% of installed storage capacity worldwide by 2040[11].

Due to its great potential, many authors have investigated key factors impacting on PV-coupled battery systems' profitability[12–16]. However, there is wide consensus that PV-coupled battery systems performing PV self-consumption are not yet profitable in any location[16,17]. In addition to cost improvement, the simultaneous provision of various applications is an alternative strategy to increase the economic attractiveness of energy storage technologies thereby enabling accelerated deployment[18]. The combination of different storage applications has already been investigated at the distribution and transmission networks[18–20] and for different battery technologies[21]. However, despite the fact that behind-the-meter systems are anticipated to represent major business for stationary storage, previous research applied to these systems is scant.

On-grid batteries can perform up to 15 applications depending on the discharge duration, scale and stakeholder[22]. Consumer applications refer to those which help consumer to minimize the electricity bill, with the number of relevant applications depending on the bill structure. In this study we include all potential consumer applications except back-up power, namely, PV self-consumption, avoidance of PV curtailment, demand load-shifting and demand peak shaving (see Fig. 1). Back-up power is excluded since we focus on distribution areas with a high level of grid stability (for both utilities referred in this study, the number of minutes of power failure experienced by a typical customer in a year was below 100 minutes in 2016)[23]. These consumer applications are described as follows: PV self-consumption, the prime application for residential batteries, uses the battery to store PV surplus electricity for later consumption (see Fig. 1 a.). Avoidance of PV-curtailment applies where grid regulators seek to maintain grid stability through feed-in limitations, thus above a threshold PV power cannot be injected to the grid. The PV excess is stored in the battery and can be used at a later time (see Fig. 1 b.). Demand load-shifting uses the battery to exploit varying tariff differentials (see Fig. 1 c.), shifting electricity consumption to times with low price. Finally, demand peak-shaving uses energy stored in the battery to reduce the maximum power drained from the grid (in kW) during a specified period, to mitigate demand electricity peaks (see Fig. 1 d.).

The influence of solar resource, demand profiles, jurisdiction and electricity prices across locations has only been evaluated for PV self-consumption individually[16,24]. Other authors investigated various types of applications but without geographical dependence and/or using a technology-agnostic approach[12–17,25–30]. Therefore, various battery technologies available in the market have not been evaluated with the same method and for the full combination of consumer applications. Battery technologies widely differ in cost, aging, lifetime and round trip efficiency[22], and we compare here six representative products of different technologies
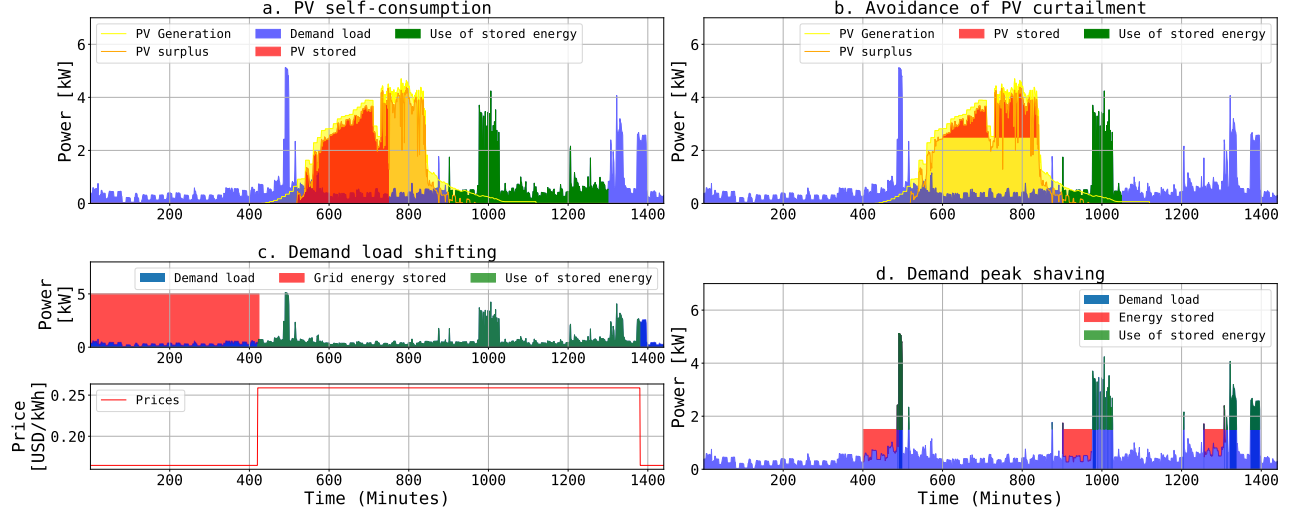
Fig. 1: Schematic representation of the four applications analyzed in this study. a. PV self-consumption, b. Avoidance of PV curtailment, c. Demand load shifting and d. Demand peak shaving.

within both the lithium and lead-acid families. Within lithium-ion technologies, we include the most common technologies in grid applications, namely lithium nickel manganese cobalt oxide (NMC) and lithium iron phosphate (LFP). Additionally, we include lithium nickel cobalt aluminum oxide (NCA) which have relative competitive installation costs, and lithium titanium oxide (LTO) that is the more thermally stable technology and has extremely high cycle lifetime[8]. As for lead-acid we include traditional valve-regulated lead-acid (VRLA) and advanced lead-acid (ALA). The latter incorporates an ultra-capacitor into a conventional lead-acid cell, increasing efficiency and cycle life. Advanced lead-acid batteries are currently in the demonstration phase and hence costs are currently higher than for conventional lead-acid batteries. Further information on battery technology specifications is given in Section 1.4 of the Supplementary Information.

The aims of this work are to develop an optimization framework to determine the best-suited battery technology and size for various combination of applications; and secondly, evaluate which additional, currently unexploited economic benefit can be reaped by combining applications. Our open-source model uses Linear Programming to solve the management problem of a PV-coupled battery system and is flexible enough to consider different combinations of applications, tariff structures, export prices and battery characteristics such as aging. Our results can help various stakeholders interested in PV and battery technologies, such as consumers, utility companies, manufacturers and policy makers in designing deployment strategies for battery storage located behind the meter. Importantly, the comparison of our results for Switzerland and Texas (U.S.) allow us to understand whether or not the optimal technology and break-even point for the various combinations of applications is geographically dependent in view of the different pricing structures, annual electricity demand and irradiance of the two locations.

These two geographies are selected because interestingly, they have experienced dissimilar penetration of space cooling and energy efficiency technologies and as a result, U.S. house-

holds have higher average electricity demand compared to Swiss households (3.7 times higher) and offer very different electricity demand profiles (see Section 1 and Figs. 2 and 3 of the Supplementary Information). In the same way, both locations have disparate electricity prices. In the analysis we consider both, single tariffs and double tariffs (which are applied all year-round in Switzerland and only in summertime in the U.S.). Likewise, capacity tariffs applied to residential consumers are considered (*i.e.* to bill the peak electricity demand -in USD/kW-during a billing period), since their implementation is being widely suggested following the penetration of air conditioning, heat pumps and electric vehicles[31] (for further information on electricity tariffs see Section 1.3 of the Supplementary Information). The export price is assumed to be the wholesale electricity price as is the case for traditional electricity generators. The remainder of this paper is structured as follows. Section 2 gives the optimization results as a function of the combination of applications, battery technology and geography. Section 3 presents the implications of our results and the main conclusions. The methods are presented at the end of the document.

2. Results

We use three key performance indicators to compare battery technologies. The levelized cost (LCOES) and levelized value (LVOES) quantify the cost and value respectively associated with the battery discharge throughout the entire lifetime. Thirdly, net present value is used to analyze the profitability of the project (see Section Methods). Since we aim to analyze the impact of geography and the combination of applications on the best-suited battery technology, we present first the results for a typical battery size of 7 kWh depending on the battery technology, location and for different combinations of applications and tariff structures (see Table 1). PV self-consumption is common across all combinations since this application is the baseline for residential batteries. Afterward, we evaluate the impact of the battery size. All results are based on a representative (median of the distribution) fixed PV size in each geographical region (see Section 1.2 in the Supplementary Information). Results for other PV sizes and alternative combinations of applications are given in Sections 4 and 5 of the Supplementary Information.

2.1. Levelized cost

Fig. 2 displays the levelized cost of energy storage for six battery technologies and five combinations of applications in Switzerland and the U.S. Three major observations can be made. First, NCA and NMC-based batteries offer lower levelised cost for all combinations, the former due to an elevated lifespan and a high number of cycles, while for the latter the reason is a combination of low cost (technology with the lowest cost after VRLA) and a reasonable compromise between number of cycles and lifespan. Secondly, batteries performing in the U.S. offer lower cost per kWh since they are heavily cycled, (*i.e.* the average battery in the U.S. supplies 48% more electricity throughout it's lifetime than in Switzerland). As for Switzerland, the LCOES also clearly decreases as household electricity consumption increases (demand data for both countries is analyzed in Section 1.1 of Supplementary Information).

Combination name	Applications				Electricity tariff structure			
	PV Self-consumption (PVSC)	Avoidance of PV curtailment (PVCT)	demand-load shifting (DLS)	Demand peak shaving (DPS)	Flat tariff (FT)	Double tariff (DT)	Capacity tariff	Feed-in limit
Combination 1 (Baseline scenario)	ON	OFF	OFF	OFF	ON	OFF	OFF	OFF
Combination 2	ON	OFF	OFF	ON	ON	OFF	ON	OFF
Combination 3	ON	OFF	ON	OFF	OFF	ON	OFF	OFF
Combination 4	ON	ON	OFF	OFF	ON	OFF	OFF	ON
Combination 5	ON	ON	ON	ON	OFF	ON	ON	ON

Table 1: Various combination of applications and the respective electricity tariff structure compared in this study. If the application indicator is ON, it means that the referred application is included in the combination, same is valid for the electricity tariff structure indicators.

These results have important implications for the energy transition since residential batteries cycle more for consumers with large electricity consumption and consumers with low consumption could group themselves under communities battery schemes in order to reach lower costs.

Finally, in terms of combination of applications, demand load-shifting increases the use of the battery, reducing the levelized cost, particularly in Switzerland where battery use increases on average by 15% when demand load-shifting is included. This is mainly due to the double tariff structure which is applied all year-round and low PV surplus in winter, in contrast to the U.S. where there is a relatively high PV surplus in winter and the double tariff is applied only during summertime. Accordingly, demand load-shifting reduces the LCOES by 7-43% in Switzerland and by 2-17% in the U.S.

2.2. Levelised value

Fig. 3 displays the levelized value for all battery technologies depending on the combination of applications. The differences among technologies regarding added value per-kWh for combinations that do not include demand peak shaving is relatively small (i.e. less than 9% for both countries). Conversely, ALA-based and VRLA-based batteries add more and less value per-kWh respectively than other battery chemistries when demand peak shaving is included (on average 27% and 17%, respectively) because in both cases, less electricity is supplied by the battery due to a shallower depth-of-discharge. However, in the case of ALA-based batteries, the battery is used mostly for demand-peak shaving since it is the application that adds most value and this technology offers significant discharge rating (see Section 1.4 of the Supplementary Information). On the other hand, the cash flow is significantly lower for VRLA-based batteries due to low depth-of-discharge (50%), efficiency (85%) and crucially the limited power characteristics (*i.e.* maximum charge and discharge power of 0.1*C) leading to lower levelized value.

In terms of geography, more value per-kWh is added in Switzerland (*i.e.* in average 0.23 USD/kWh), compared to the U.S. (*i.e.* in average 0.1 USD/kWh), due to higher electricity
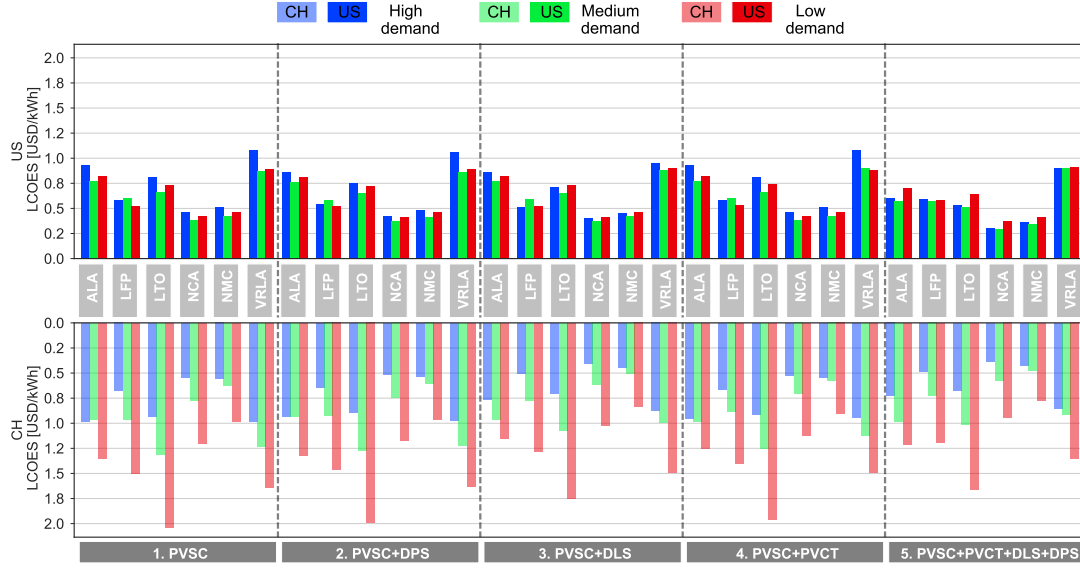
Fig. 2: Levelized cost of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the median installed capacity across both locations.

prices. Furthermore, when excluding demand peak shaving, batteries in households with higher demand create slightly more value per-kWh due to a higher self-consumption. On the other hand, when demand peak shaving is included, batteries in Swiss households with lower demand create more value per-kWh, due to a higher relative influence of the capacity tariff, *i.e.* the battery is primarily used for demand peak shaving.

The addition of applications such as demand load shifting (combination 3) or avoidance of PV curtailment (combination 4) to the baseline scenario (PV self-consumption referred to as combination 1) adds only marginal value, however when the four applications are combined, the results are significantly better than the combination of PV self-consumption and demand peak shaving (*i.e.* value per-kWh is on average 15% higher). This improvement is due to the synergies between demand load shifting and demand peak shaving (see Section 4 of the Supplementary Information). Demand peak shaving is the application adding most value per-kWh (*i.e.* 0.14 and 0.3 USD/kWh in the U.S. and Switzerland, respectively), owing to the importance of the capacity tariff in the final bill.

2.3. NPV

Fig. 4 displays the net present value for all battery technologies depending on the type of combination of applications for Switzerland and the U.S. It can be seen that due to high costs (as well as reduced cycle life, depth-of-discharge and lifespan in the case of VRLA) there is no positive economic case. However, we can see that the profitability is markedly improved for most technologies by combining applications. This is particularly the case for NCA and
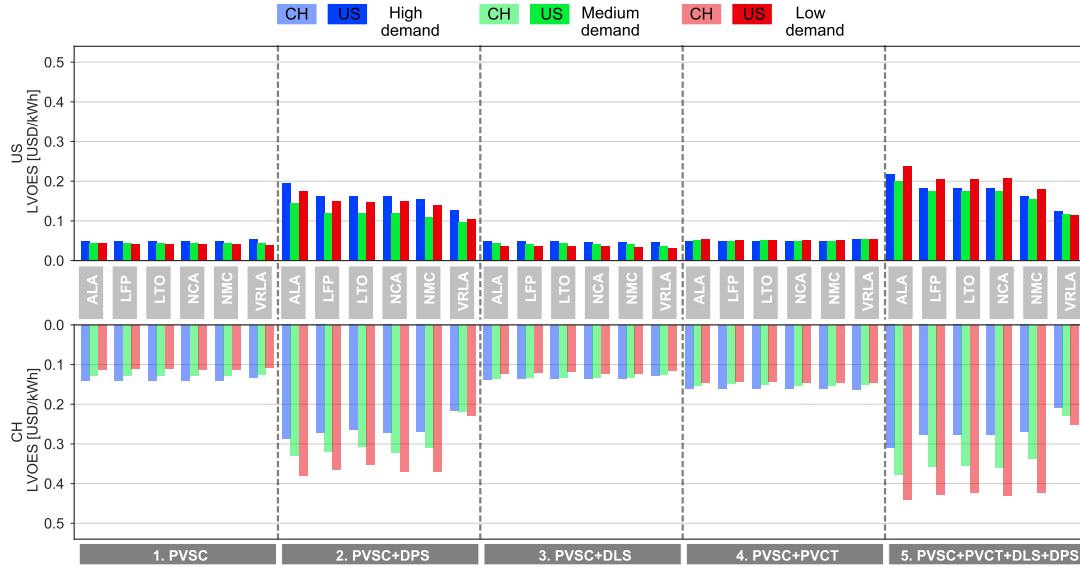
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Fig. 3: Levelized value of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the median installed capacity across both locations.

NMC-based batteries if demand peak shaving is included due to their better power response. Since the battery operation adds more value in Switzerland than in the U.S., the NPV is higher as a result. In the U.S., similar NPV across the consumption brackets is present, with the clear exception of medium demand households using LFP-based batteries. This exception is due to a replacement battery for consumers 3 months before the project lifetime in this consumption bracket, which includes a supplementary investment to replace the battery and therefore further reduces the net present value (the same applies to high demand households for full combination of applications in the U.S.). In terms of applications, the combination of PV self-consumption with demand peak shaving increases the NPV on average by 22%, which can be improved 7.6% more when demand load-shifting is included.

2.4. Impact of battery size

Fig. 5 displays the average levelized cost, levelized value and net present value across the three groups of consumers (see Methods Section and Section 1.1.1 of Supplementary Information), for small (*i.e.* 3 kWh), medium (*i.e.* 7 kWh) and large (*i.e.* 14 kWh) batteries performing simultaneously all consumer applications depending on the battery technology. Since batteries are heavily cycled in the U.S., lower levelized cost is reached. The per-kWh cost difference between the two countries increases when the battery size increases. In Switzerland, a large battery incurs higher per-kWh cost due to relatively low number of cycles and higher capital expenditure. In contrast, in the U.S., large batteries reduce further the levelized cost.

VRLA and NMC-based batteries increase their added value when the battery size increases.
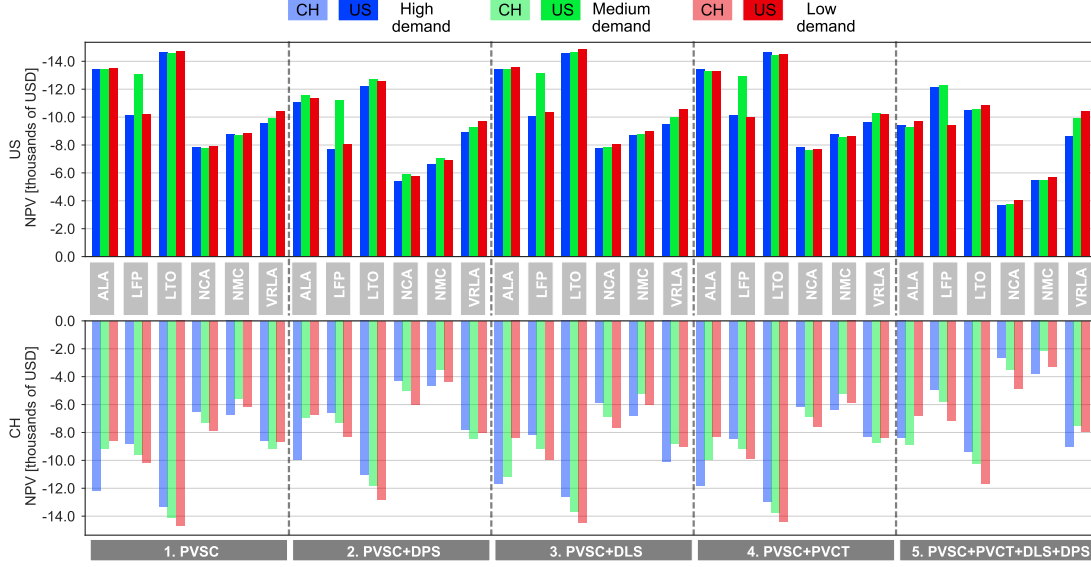
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Fig. 4: Net present value of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the median installed capacity across both locations.

This is due to their lower charge and discharge rates (0.1*C and 0.4*C, respectively) which means that they need a large energy capacity to provide significant power, while added value decreases with battery size for other chemistries with larger charge and discharge rates. For small size batteries, NCA-based batteries have better results in both countries, whereas VRLA batteries reach worst results for the full combination of applications. NCA-based batteries are preferred in the U.S. and very competitive with NMC-based batteries in Switzerland for medium-sized batteries, while for large-sized batteries NMC chemistry get the better net present value. Overall, the net present value results of Fig. 5 indicate that batteries in Switzerland are on average 30% (29% for small sizes, 36% for medium sizes and 25% for large sizes) more attractive than in the U.S., due to higher value added as a result of higher electricity electricity prices.

3. Discussion

Based on our work, we find that the best-suited battery technology in the U.S. is NCA as for Switzerland NMC-based batteries reach in average a net present value 18% higher than NCA-based batteries. The household demand marginally affects the profitability of PV-coupled battery systems and we find the NPV difference among the three consumption brackets for all technologies and combinations of applications is less than 5% (4.9% in the U.S. and 2.2% in Switzerland, on average). On the other hand, geography impacts the battery's economic viability markedly and the net present value of Swiss battery systems are on average 30% more attractive than in the U.S., mainly due to higher electricity prices.
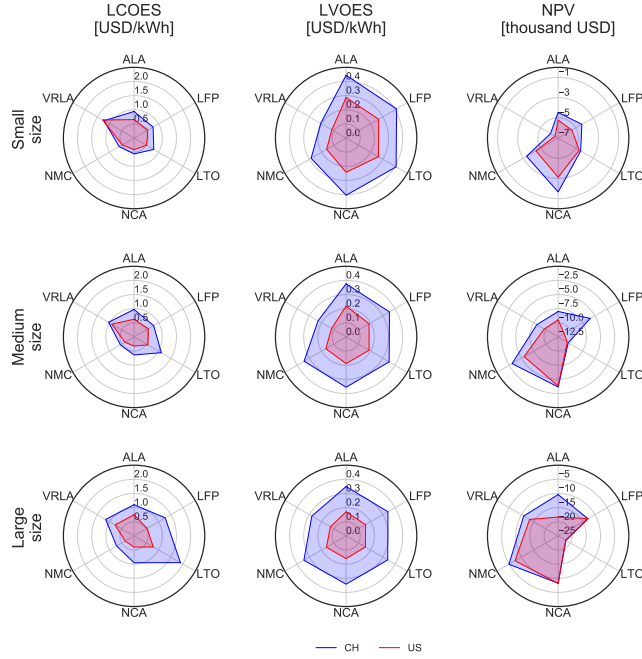
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Fig. 5: Comparison of the average LCOES (left), LVOES (middle) and NPV (right) for various battery technologies performing simultaneously all consumer applications in the U.S. (red) and Switzerland (blue) depending on the type of annual electricity demand, namely small (top), medium (middle) and large (bottom).

Despite significantly increasing the NPV, batteries simultaneously performing several applications are not yet profitable under existing market conditions. However, further (expected) reductions in battery costs, together with combining battery applications may hold the key towards household battery profitability. In particular, adding demand peak shaving to PV self-consumption brings clear benefits compared to the baseline scenario (PV self-consumption only), especially for NCA and NMC-based batteries (up to 66% higher NPV). It is expected that demand peak-shaving would also introduce other benefits for the wider energy system, since electricity peaks are typically met by more costly or carbon-intense generators across many countries (this is not however the case of Switzerland where hydropower is used for this purpose). Moreover, distribution system operators could also defer or even save investment in infrastructure. Thus demand peak shaving is an application which provides synergies for the consumer, utility companies and distribution system operators. Demand load-shifting increases battery use but when demand peak shaving is not included in the combination, it barely increases the net present value, even in Switzerland where double tariff is applied all year-round. Being a regulation-based application, the avoidance of PV curtailment is more interesting from the grid perspective than from the consumer perspective.

In the residential electricity market, small battery sizes offer the best economic case. Despite a higher annual electricity demand in Texas compared to Geneva, larger battery capacities are not economically justified and a small size battery (3 kWh in this study) obtains the best results in both locations. However, with (installed) cost reductions of 55%, medium size

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batteries will get more economically attractive than small size batteries in both countries. From a market perspective, further cost reduction of lithium-ion technologies may result in more market competition for NMC-based batteries which have the strongest position in the market at the moment. This is an important message for policy makers in order to avoid technological lock-in which may inhibit the development of other chemistries that could be better for the residential sector in the future. For instance, NCA-based batteries are more suitable than NMC-based ones when combining applications mainly due to higher charge and discharge rates, cycles and extended lifespan, even if the price is higher, thus a cost reduction of NCA-based batteries can compromise the leader position of NMC-based batteries in the residential market.

In order to reach economic profitability, battery systems require further cost reductions regardless of battery technology. Installation costs (including permitting, inspection, interconnection, overhead, profit and installation labor) in Switzerland and the U.S. are assumed to be $ 2000 in this study[32,33] but may reduce with increasing installation experience (learning by doing) and market competition. Fig. 6 displays the break-even point of a 7 kWh battery performing PV self-consumption only as well as all four applications depending on the battery technology and location. The current installation cost per kWh considering battery, inverter and installation are also given for reference purposes. When all applications are combined, NCA-based batteries are closest to profitability. They require only 25% reduction in installed costs to be profitable in Switzerland and 35% in the U.S. NMC-based batteries in Switzerland require a similar reduction on installed costs, however, in the U.S. this increases up to 55%. Due to higher electricity prices, profitability may be reached first in Switzerland even if PV self-consumption is the only application, however, on average a reduction of 81% in the cost per-kWh-installed, compared to today's cost, is required. On the other hand, when all applications are combined, a reduction of 47% is required. In the case of the U.S., further reductions are needed (93% if only PV self-consumption is addressed and 59% if all applications are combined). According to IRENA lithium-ion batteries', installation costs will be reduced by 60% on current levels by 2030[22], thus residential batteries may reach profitability (without subsidies) in both countries in the next decade if all applications are combined. This break-even period may be however shorter if electricity prices increase.

NCA-based batteries already have the appropriate characteristics to combine applications and expand their deployment. LFP-based batteries have suitable technical characteristics but a high number of cycles must be ensured. On the other hand, LTO-based batteries can be considered as over-designed for household needs which leads to higher cost, and if they are over-sized, entail a higher cost than other battery types. NMC-based batteries are expected to lead the cost decline due to their leader position in the market, however, technical specifications, mainly calendar life, will need further development if manufacturers want to keep their dominant position in a near future with residential batteries performing several applications simultaneously. Advanced lead-acid batteries have competitive characteristics and performance, however, shallow depth-of-discharge and high costs, penalize them when compared with lithium-ion technologies. Therefore, only aggressive cost reductions and significant technical improvements could lead to increase their market share. The environmental dimension can be an important asset for this technology since its recycling process has been
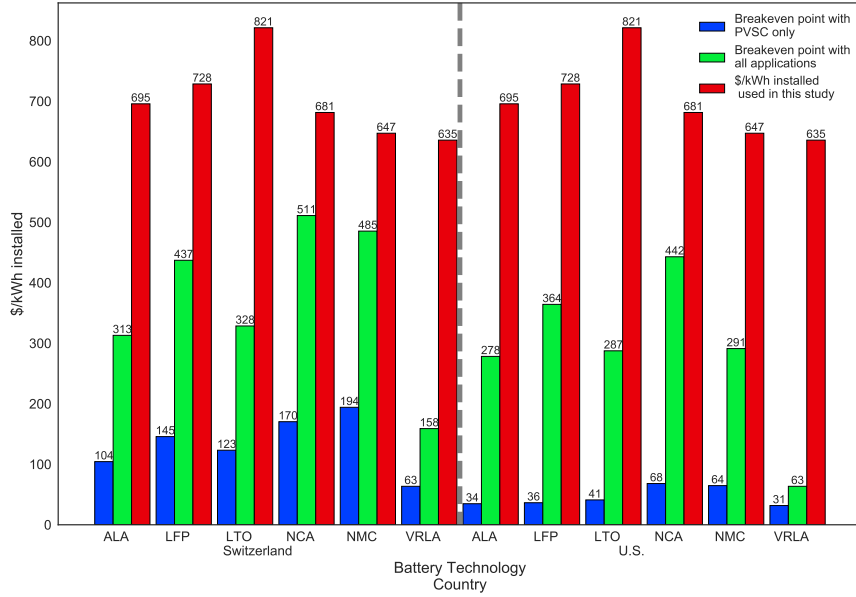
Fig. 6: Break-even point of a 7 kWh battery for all battery technologies depending on the type of combination of applications, PV self-consumption only (blue), the full combination of applications (green) and for comparison, the installed cost per kWh used in this study (red), for the U.S. (right) and Switzerland (left). The size the PV system correspond to the median installed capacity across both locations.

already established and other criteria such as their material criticality is far lower compared to lithium-ion batteries[34]. Finally, already-mature traditional lead-acid batteries, which have limited margin for improvement, are clearly less attractive for exploiting additional applications which appears to be a strategy that cannot be ignored.

Jülch has previously addressed key factors that influence the economic profitability of a PV-coupled battery system performing only PV self-consumption (see Fig. 7)[35] (in blue). Emerging from the present study, we contribute with four additional factors: (a) The low influence of annual household demand, which in this study varies from 4.9% in the U.S. to 2.2% in Switzerland; (b) the rather high impact of location (*i.e.* 30% higher NPV in Switzerland than in the U.S.), whose uncertainty is rather low since the electricity bill structure and environmental factors are widely known; (c) the medium impact of battery technology which depends not only on the technical characteristics, which are already good for residential applications, but as well on battery costs which are still high for the same niche and whose uncertainty is rather high; (d) the impact of the combination of applications, which can be marked, especially with demand peak shaving, but there is rather high uncertainty since the number of applications depends on local regulation by utility companies and policy makers.

Although our study proposes a robust framework to quantify the attractiveness of batteries and the proposed models are rich in technology details, it is not without limitations, which in turn call for future research. Other forecast strategies different to perfect forecast could be introduced in the optimization framework, with this reducing the revenue. In addition, the
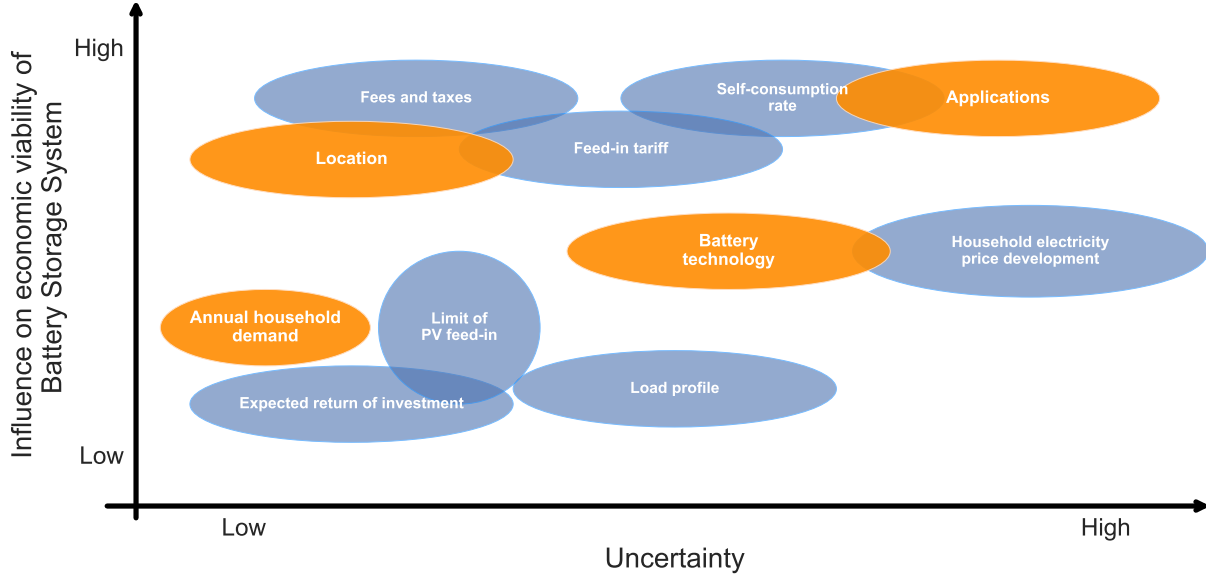
Fig. 7: Influence of different factors on economic viability of the battery storage system linked to the uncertainty, based on[35]. The factors in orange are assessed in this study.

design of future electricity tariffs including time-of-use and capacity components is still a topic under investigation. In particular, capacity tariffs are expected to become more widespread since they offer great cost reflectivity as well as revenue variability for network businesses in the face of current and expected disruptions and conduct to flexibility[36]. Additionally, while the scope of the research presented in this paper is limited to electricity demand in dwellings, future research should also incorporate heat and transport demand and the trade-offs of different low carbon technologies such as residential batteries, heat pumps and electric vehicles. Finally, the proposed optimization framework could be extended to more geographies.

Methods

Demand and PV generation

We use electricity consumption data with 15-minute temporal resolution monitored in single dwellings in Western Switzerland (636 dwellings) and Austin, Texas (308 dwellings) during the year 2015. Considering this amount of data, we opt to form representative consumer groups in order to reduce the computational time required. To generate these representative consumer groups, we employ clustering to produce groups of consumers with similar behaviors. We split the consumers according to their annual consumption into three separate groups, *i.e.* a low, medium and high consumption group in both locations. Finally, within these three groups we cluster based on the average daily load profile. We opt to produce four clusters in each consumption bracket, noting that the selecting the number of clusters in highly dimensional data is a difficult task. From each cluster we select the household that is

closer to the centroid which is subsequently optimized. The results presented in this study are the average of the four representative households of each cluster per consumption bracket. For further information see Section 1.1 of Supplementary Information (SI).

Environmental variables including outdoor temperature and horizontal solar irradiance monitored across both locations are used to model PV generation. We focus on the median PV size of the empirical distribution across Switzerland[37] and Texas[38] for our baseline results (*i.e.* unchanged PV size), while alternative scenarios including the 25th and 75th percentile are shown in Section 4 of the Supplementary Information. For further information see Section 1.1 of the Supplementary Information.

Electricity tariff and battery applications

The operation of a residential battery as well as the number of applications it can deliver depends on the tariff structure. Since there is not a market mechanism incentivizing the export of electricity from residential batteries to the main grid, this case is not considered either.

Electricity prices used in this study are based on available tariffs which are offered by the local utility companies in the two locations. Both, single tariffs and double tariffs (with a peak and off-peak periods) are considered in the analysis. In Switzerland, double tariffs are applied all-year-round, while in the U.S. they are applied only in summertime. The export price is assumed to be the wholesale electricity price as is the case for traditional electricity generators. This is already the case in Switzerland for installations which are on the waiting list to be granted a one-off subsidy for the capital investment in PV[6] and this is expected to become a widespread policy as a consequence of falling cost of PV technology. We use 2015 wholesale electricity prices from the day-ahead market for Texas (ERCOT southern load zone) and Switzerland (EPEXSPOT). It is important to note that, apart from the electricity price, electricity bills include other fixed costs as well, such as taxes and grid usage.

Capacity tariffs, which bill the peak electricity demand (*i.e.* in USD/kW) during a billing period, have been widely applied for large consumers, typically belonging to the secondary and tertiary economic sectors. For residential customers capacity tariffs have only being marginally applied (*e.g.* by the Arizona Public Services in the U.S.), although their implementation is being suggested following the penetration of air conditioning, heat pumps and electric vehicles[31]. As a first attempt to include them we assume capacity tariffs applied to large consumers by the local utilities in the two locations. Finally, following the example in Germany, a (physical) feed-in limit of 50% of the nameplate PV-system capacity for both countries is assumed as a preventive measure to keep the power system stable during periods of high PV production[12].

Considering the various components of an electricity bill, a battery can perform the following applications:

PV self-consumption (PVSC): PV surplus electricity is stored in a battery and used later

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on to meet local demand when it is higher than PV generation (see Fig. 1 a.). The main driver is the price difference between the electricity imported from the grid (*i.e.* retail price) and the electricity exported to the grid (*i.e.* FiT or wholesale price as in this study).

Avoidance of PV curtailment (PVCT): In some regions with substantial PV penetration, a feed-in limit is set above which PV power cannot be injected to the grid to keep grid stability (see Fig. 1 b.). Electricity dissipation is typically done using the PV inverter[12]. Batteries can prevent this PV curtailment by storing this electricity and meeting local demand later on. The implementation of PV curtailment is determined by regulation.

Demand load-shifting (DLS): A battery is used to exploit varying tariff differentials (see Fig. 1 c.). The battery charges from the grid when prices are low (off-peak periods) and it discharges when they are high (peak periods). The existence of varying-price tariffs is a prerequisite for demand load-shifting.

Demand peak-shaving (DPS): The discharge of a battery is used to reduce the maximum power drained from the grid (in kW) used during a specified period. Demand-peak shaving can be used to mitigate demand electricity peaks which can result in distribution network upgrading as well as expensive electricity supply (see Fig. 1 d.). The main driver is therefore the presence of a capacity-based component in the electricity tariff.

PV-coupled battery system

This study focuses on the combined investment in a PV-coupled battery system; more specifically, we analyze the techno-economic implications of adding a battery system when purchasing a new PV system that would otherwise be installed on its own. We consider a DC-coupled topology since a lower investment is required and the overall efficiency of stored PV electricity is higher than in AC-coupled topologies[33]. Moreover, the prevention of PV curtailment is possible (for further information see Section 1.5 of supplementary information). Since manufacturers claim no operational costs required for residential PV and battery technologies, we set them to zero[39,40]. Installation costs are considered for the inverter and battery and are assumed to be high for both countries (*i.e.* \$ 2000).

Techno-economic indicators

Three complimentary indicators are used to analyze the techno-economic performance of batteries coupled with PV systems, *i.e.* the PV system is excluded in the analysis since we are interested in the decision of adding a battery. The levelized cost of energy storage, LCOES (USD/kWh) quantifies the cost associated with the total electricity supplied by the battery throughout the life of the system (see Eq. 1). The second indicator is the levelized value of energy storage, LVOES (USD/kWh). It quantifies the revenue associated with the battery discharge throughout the life of the system (see Eqs. 2 and 3). Finally, the net present value (NPV) calculated as the sum of the discounted cash flows over the lifetime of the battery system (Eq. 4) is used to appraise the overall impact of the system configuration

and operation for each combination (geography, technology, consumer type and combination
of applications) on the economic profitability of residential batteries.

$$LCOES = \frac{\sum_{i=0}^{N} \frac{CAPEX}{(1+r)^i} + \sum_{i=1}^{N} \frac{OPEX}{(1+r)^i}}{\sum_{i=1}^{N} \frac{E_{dis}}{(1+r)^i}} \tag{1}$$

$$LVOES = \frac{\sum_{i=1}^{N} \frac{CF_{Batt_i}}{(1+r)^i}}{\sum_{i=1}^{N} \frac{E_{dis}}{(1+r)^i}} \tag{2}$$

$$CF_{Batt_i} = CF_{PV-Batt_i} - CF_{PV_i} \tag{3}$$

$$NPV = \sum_{i=1}^{N} \frac{CF_{Batt_i}}{(1+r)^i} - \sum_{i=0}^{N} \frac{CAPEX}{(1+r)^i} \tag{4}$$

Optimization of the battery schedule

The management problem of a PV-coupled battery system is solved by Linear Programming,
using Pyomo, an open-source tool for modeling optimization applications in Python[41] and
solved with CPLEX. The model parameters and variables are presented in the Section 1.5
of Supplementary Information. The battery schedule is optimized for every day (*i.e.* 24 h
optimization framework) and we assume perfect day-ahead forecast of the electricity demand
load, solar PV generation and wholesale prices in order to determine the maximum economic
potential regardless of the forecast strategy used. Aging was treated as an exogenous param-
eter, calculated on daily basis and was not subject to optimization (for further information
see section 2 of the Supplementary Information). The temporal resolution of the input data
and simulation is 15 minutes , with this value providing a reasonable compromise between
the modeling real performance and computational speed[42]. The model objective function
have two components, namely the energy and power components of the electricity bill. As
the tariff structure depends on the applications considered, a boolean parameter activates
the power-based factor of the bill when is necessary.

Every optimization was run for one year and then the results are linearly-extrapolated to
reach the battery end of life. We assume 30% of capacity depletion as the end of life[43] and
when the battery lifetime exceeds the inverter lifetime, the residual value of the battery is
considered using straight-line depreciation[44]. Replacement is considered when the battery
cannot match the inverter lifetime which is taken as the project lifetime, we take a conser-
vative approach maintaining the same cost in the future discounted to the present, due to
the high uncertainty linked to future battery costs for different battery technologies. The
analysis is done with same electricity prices for all years across battery lifetime. The model
objective function, constraints, variables and parameters can be found in Section 1.6 of the
Supplementary Information, as for the validation of the model is in Section 3 of the Sup-
plementary Information. The model and the U.S. data (the Swiss data is confidential) are
publicly available in `https://github.com/alefunxo/`.

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4. Acknowledgement

5. Author contributions

A.P.B. formulated and verified the model, performed the research, analyzed the data and wrote the paper; D.P. designed and coordinated the study; D.P. and M.P. supervised the research; E.B. verified the model and designed the demand clustering; M.C.G. provided guidance on the demand clustering and the manuscript preparation. All authors gave their final approval for publication.

6. Additional information

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Optimization of PV-coupled battery systems for combining applications: impact of battery technology and location

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1. Supplementary methods and material

Fig. 1 is a schematic representation of our method. In first place, we specify the input data for electricity demand and PV generation (Sections 1.1 and 1.2). The applications and their combinations are subsequently defined along with the respective electricity tariff structure (Section 1.3). Then, the battery technologies, system topology and components are presented (Sections 1.4 and 1.5). Thirdly, our schedule optimization is described (Section 1.6). Across the study we use USD as common currency for both locations[a].

1.1. Demand datasets

Two demand datasets covering Austin, Texas in the U.S. and a western Swiss city with 15-minute smart meter data covering the whole year 2015 were used in this study. For Austin the data were obtained from the Pecan Street project, for 308 households, as for the 636 Swiss dwellings data confidentiality agreements apply, however we treated the data as if it was from Geneva. In terms of average yearly electricity consumption the American households use 3.7 times more electricity than Swiss households from the datasets. The two cities present a completely different consumption behavior, while in Austin there is a clear seasonality with

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  Email address:* David.Parra@unige.ch (David Parra)
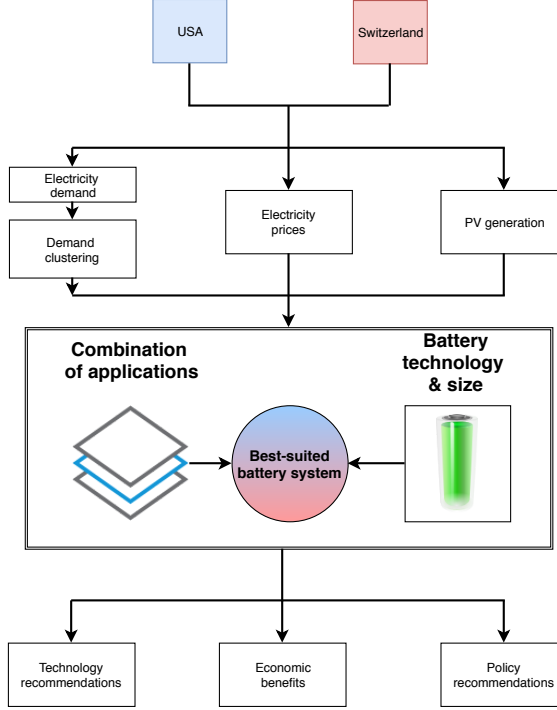[a]Exchange rate used: 1 USD/CHF.

Fig. 1: Schematic representation of the modeling approach proposed.

a summer peak that is the double of winter or fall consumption, in Geneva summer is the less electricity-demanding season and winter and fall present comparatively only 16% more electricity demand. In terms of monthly average consumption, in Austin, excluding summer months, the average consumption is 837 kWh/month and almost two times greater during summer months. On the other hand, in Geneva a clear mean of 274 kWh/month is maintained all year-round with a slightly lower consumption in spring and fall (see Fig. 2).

1.1.1. Demand clustering

Rather than run individual simulations for all the household consumers, which would lead to very long simulation times, we instead aim to find representative consumers which exemplify typical consumption patterns within the data in both countries. Therefore, for both the U.S. and Switzerland we create groups of consumers with similar behavior in terms of the shape and overall magnitude of their average daily load profiles. From each group, we then select the consumer whose load is closest to the centroid of the group, designating that consumer as the representative from that group. Simulations are run for each representative consumer.

To generate the representative consumer groups, we employ a clustering method. In the literature, a range of clustering methods have been employed to form consumer segments (for a review of the clustering techniques applied to electricity load data see[1]), however k-means is the most commonly used clustering framework and has been used in a range of studies regarding household load profiles[2–5]. Therefore, we form our consumer groups using k-means clustering.
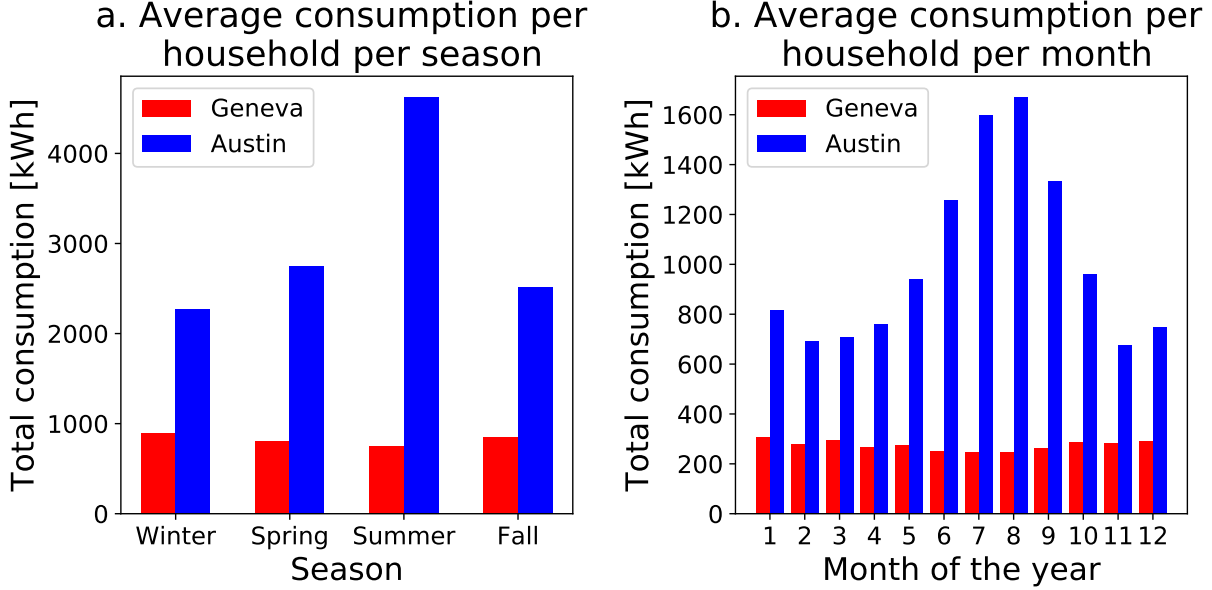
Fig. 2: Average consumption per household in both locations, Geneva, Switzerland is shown in red while Austin, Texas is presented in blue. a. Per season and b. Per month.

When clustering daily load profiles, previous work typically normalizes the load profiles, bringing the daily shapes to a similar scale for pattern recognition[2,3], as described by Eq. 1:

$$e_c(t) = \frac{l_c(t)}{\sum_{t=1}^{t=24} l_c(t)} \tag{1}$$

Where $e_c(t)$ is the normalized load at time t and $l_c(t)$ is consumer cs load at time t before normalization.

While this approach is successful for forming groups of load profiles with similar shapes independent of consumption magnitudes, in this work we also want to study the effect of differing levels of overall consumption. Therefore, first we look at the distributions of total yearly consumption in both locations and form groups with similar consumption levels. As shown in Fig. 3, we see that there are several consumers with abnormally high consumption in both locations (above 7500 kWh in Switzerland is considered an outlier and above 25000 kWh in the U.S. is considered an outlier) and we do not consider these consumers, since our ultimate aim is to find representative consumers. We then split the remaining consumers whose consumption is within our defined normal range into 3 separate groups, i.e., a low consumption group, a medium consumption group and a high consumption group in both locations. The low consumption group is defined by consumers in the 0th to 33rd percentiles, the medium consumption group is defined by consumers in the 34th to 66th percentiles, and the high consumption group contains consumers with yearly consumption greater than the 67th percentile.
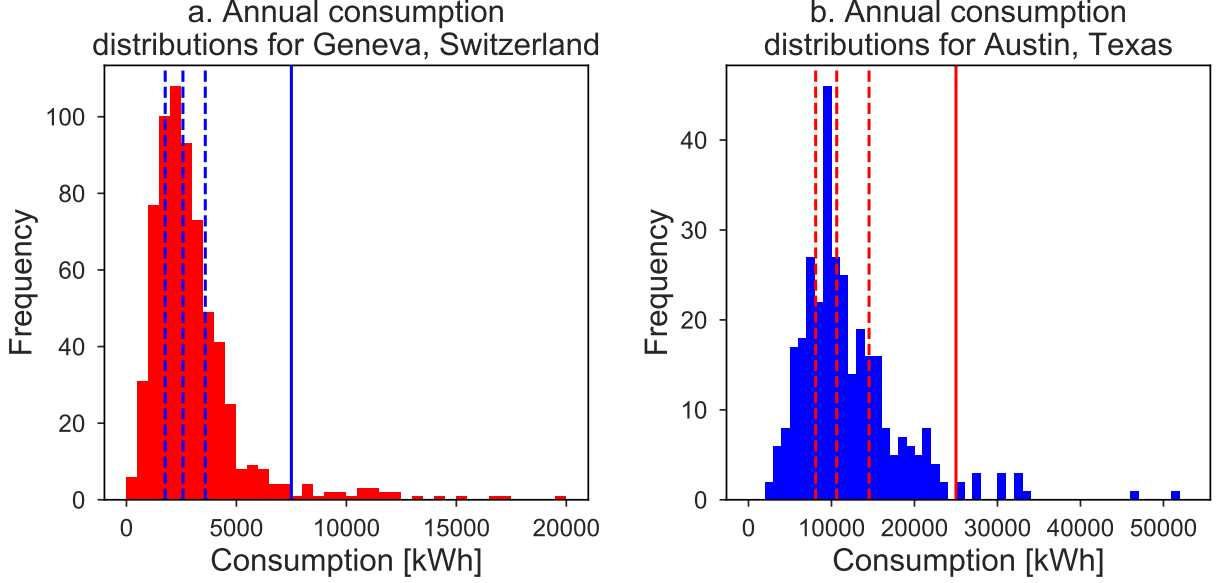
Fig. 3: Electricity consumption in a. Geneva, Switzerland and b. Austin, Texas. The dashed lines represent the dataset first, second (median) and third quartiles and the continuous line marks the limit to outliers.

After forming the consumption brackets based on overall consumption, we further subdivide these by clustering according to the load shape. Within the 3 consumption brackets the normalized consumer average daily load profiles are clustered to form 4 subgroups in each bracket. We use the k-means clustering method, which randomly assigns an initial set of centroids, and then iteratively moves these to minimize the objective function shown in Eq. 2.

$$J = \sum_{j=1}^{K} \sum_{i=1}^{n_j} \sqrt{\sum_{t=1}^{t=24} (e_{i,j}(t) - \zeta_j(t))^2} \qquad (2)$$

Here, j indexes the clusters from 1 to K and i indexes the load shapes assigned to cluster j, where n_j is the total number of shapes in cluster j. $e_{i,j}$ is the i-th load shape assigned to cluster j and ζ_j is the centroid of cluster j. As can be seen we minimize the Euclidean distance metric between centroids and the normalized load profiles.

Since we cluster average daily load profiles, we ultimately produce groups with similar average behaviors, recognizing that there may be significant deviation away from the average daily load shape for an individual on any given days[2,3]. We opt to produce 4 clusters in each consumption bracket, noting that the selecting the number of clusters in highly dimensional data where it is not known is a difficult task. However, to provide some justification we look at the variance explained by the cluster centroids compared to the total variance in the data. Fig. 4 shows the elbow plots for both locations, and illustrates that in general the additional variance accounted for through by an extra cluster diminishes below 5-7% after adding more
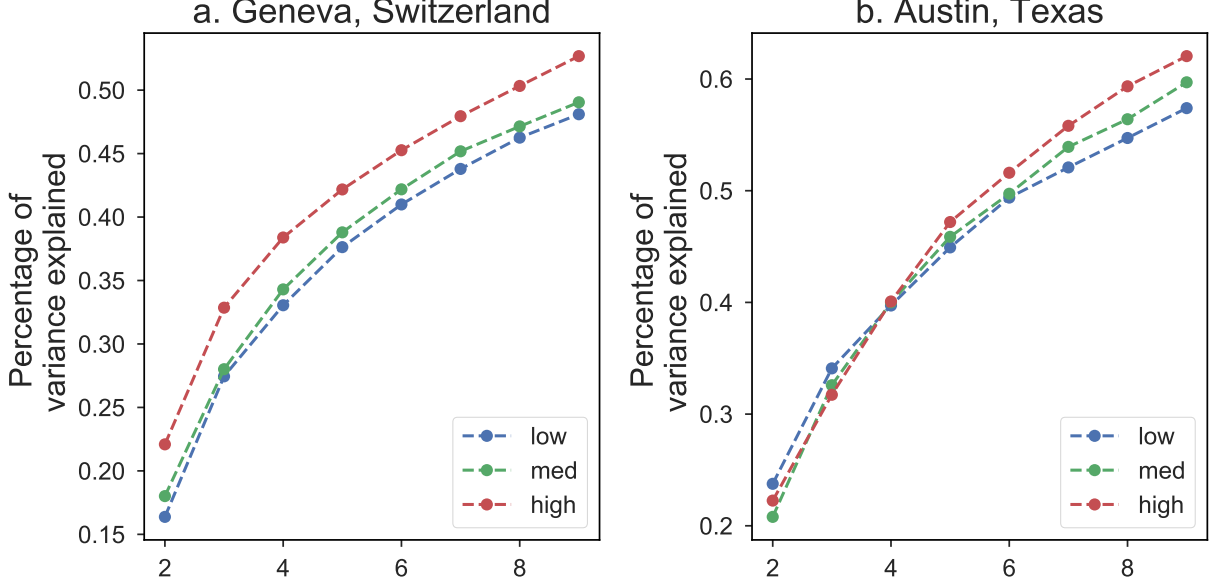
Fig. 4: Percentage of the variance explained in function of the number of clusters used for a. Geneva, Switzerland and b. Austin, Texas for the three electricity consumption brackets (high, medium and low).

than four clusters.

1.2. PV generation

Environmental variables including outdoor temperature and horizontal solar irradiance monitored across both locations are used to model PV generation. We simulate PV generation using a standard one-diode model and PV panel input data with a nominal efficiency of 18.6%, representative of the current state of the art[6]. The model also includes a maximum power point tracker system, as is the case of most PV systems, to maximize the output regardless of the environmental conditions. The PV system's installed capacity is modeled based on the empirical distribution across Switzerland[b] and Texas[c] (see Section 1.3 of the supplementary information). We finally focus on the median PV size of the distributions for our baseline results (i.e. unchanged PV size), while alternative scenarios including the 25th and 75th percentile are shown in Section 5 of the supplementary information.

In order to do a comprehensive comparison, hereon in this section we refer to a generation profile generated for each location using a PV installation of 1 kW_p of nominal power. In terms of yearly generation, a PV system in Austin generates 15% more electricity than the same PV system in Geneva. The capacity factor in Austin is 18.8% while in Geneva is 16.3%, being these values congruent with related literature[7]. We assume the same generation for every PV system for every household in this study being then adjusted according to the

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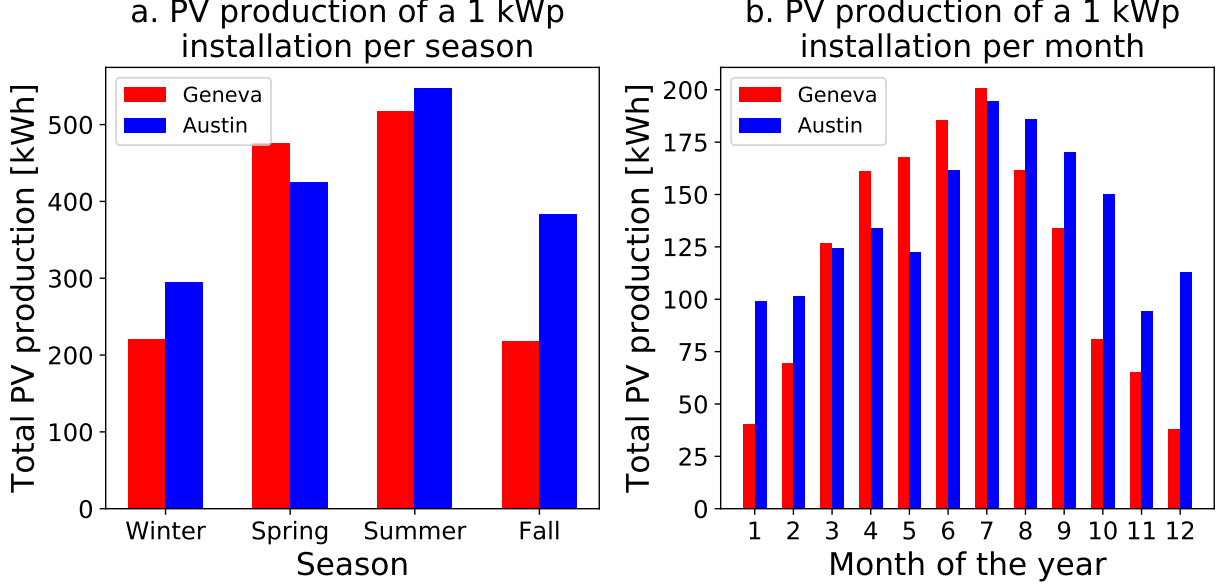[b]Swiss Federal Office of Energy
[c]https://openpv.nrel.gov

Fig. 5: Electricity generation of a 1 kW_p PV installation in both locations, Geneva, Switzerland is shown in red while Austin, Texas is presented in blue. a. Per season and b. Per month.

PV size distribution in each location. Fig. 5 presents the differences per season and per month between the two locations, as can be observed throughout the year Austin have more generation than Geneva, except during spring when the PV system in Geneva produces 11% more electricity than in Austin. As for fall and winter, a PV system in Austin produces 75% and 34% more electricity than the same PV system in Geneva, respectively. In summer the difference is less than 6%.

The distribution of PV sizes for both locations and the first, second and third quartiles are presented in Fig. 6. Since A limit of 10 kW_p of nominal power for residential systems is usually used by national reports[8,9], we selected the same limit for this study. We take into account all the country installations under the mentioned threshold, as for USA we take only Austin installations under the same threshold. For both datasets the three quartiles are very close, the first quartile is 3.15 kW_p and 3.2 kW_p for Austin and Geneva, respectively, as for the third quartile Austin presents a smaller system size (6.4 kW_p) than Geneva (6.9 kW_p). The medians are again very close, being only 0.2 kW greater in Austin (5 kW_p) than in Geneva.

1.3. Electricity tariff and battery applications

The operation of a residential battery as well as the number of applications it can deliver depends on the tariff structure. In this study we include all existing consumer applications, excluding back-up power since we focus on distribution areas with a high level of grid stability (for both utilities referred in this study, the number of minutes of power failure experienced
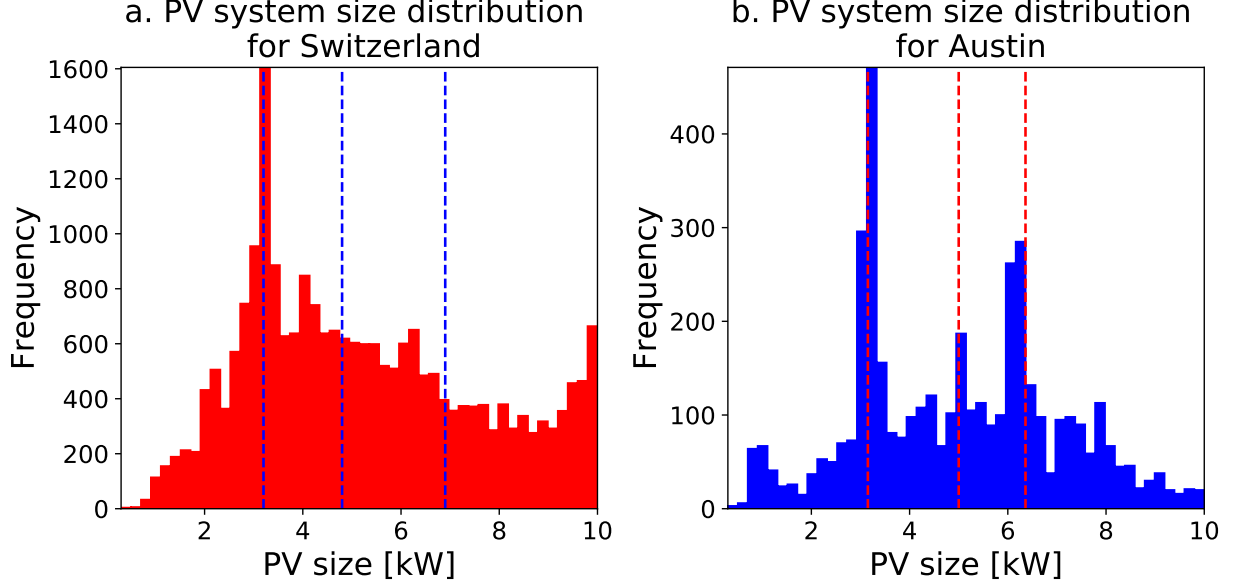
Fig. 6: PV system size distribution smaller than 10 kW_p for a. Switzerland (22807 data points) and b. Texas (4295 data points). The dashed lines represent the dataset first, second (median) and third quartiles.

by a typical customer in a year was below 100 minutes in 2016[d]). Since there is not a market mechanism incentivizing the export of electricity from residential batteries to the main grid, this case is not considered either.

Energy tariffs are based on Electricit vitale Bleu for households in Geneva and on TOU for residential customers in Austin. Both, single tariffs and double tariffs (with a peak and off-peak periods) are considered in the analysis. In Switzerland, double tariffs are applied all-year-round, while in the U.S. they are applied only in summertime. The export price is assumed to be the wholesale electricity price as is the case for traditional electricity generators. This is already the case in Switzerland for installations which are on the waiting list to be granted a one-off subsidy for the capital investment in PV[9] and this is expected to become a widespread policy as a consequence of falling cost of PV technology.

We use 2015 wholesale electricity prices from the day-ahead market for Texas (ERCOT southern load zone) and Switzerland (EPEXSPOT). In general, Swiss export prices are larger than prices in Texas with average daily prices of 0.04 USD/kWh and 0.027 USD/kWh respectively. However, the differences among average electricity prices per season indicate a general trend in Geneva where spring and summer months are usually low (around 0.033 USD/kWh) while fall and winter prices are around 0.047 USD/kWh (see figure 7). As for Austin, prices are similar among winter, spring and fall (around 0.024 USD/kWh), however in summer prices are larger (0.035 USD/kWh in average) but can be as high as 2.25 USD/kWh. It is important to note that, apart from the electricity price, electricity bills include other fixed costs as well,

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[d]For the utility in Texas, the number of minutes of power failure amounted to 95.6 minutes (which is 30% lower than the average in the U.S.[10]) while it was only 7.8 minutes in the canton of Geneva.
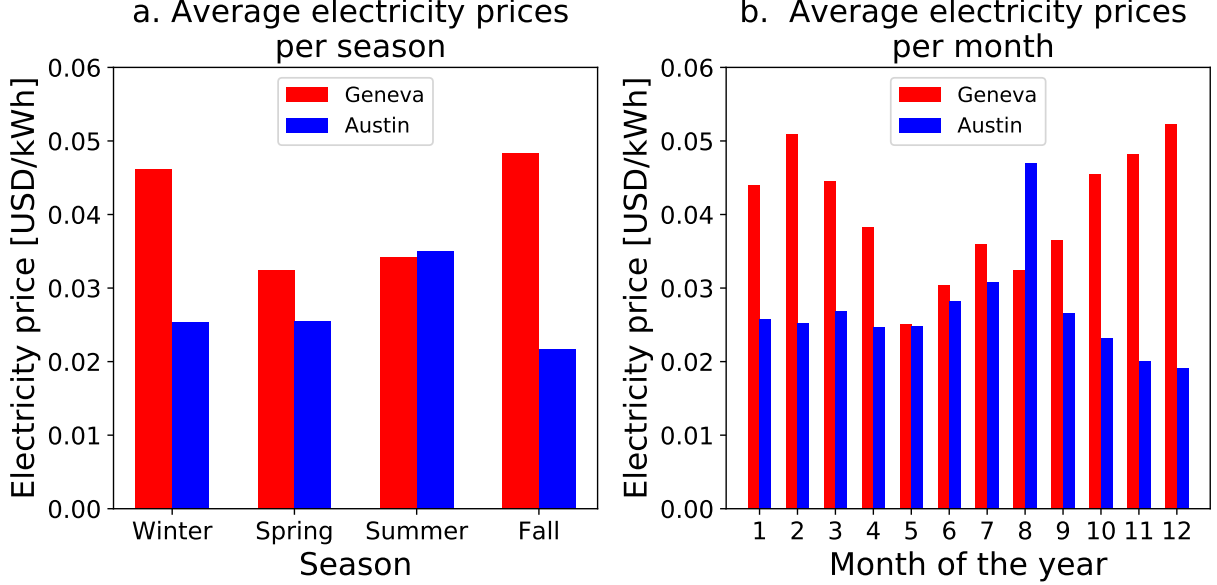
Fig. 7: Electricity prices in both locations, Geneva, Switzerland is shown in red while Austin, Texas is presented in blue. a. Per season and b. Per month.

such as taxes and grid usage.

Capacity tariffs, which bill the peak electricity demand (i.e. in USD/kW) during a billing period, have been widely applied for large consumers, typically belonging to the secondary and tertiary economic sectors. For residential customers capacity tariffs have only being marginally applied (e.g. by the Arizona Public Services in the U.S.), although their implementation is being suggested following the penetration of air conditioning, heat pumps and electric vehicles[11]. As a first attempt to include them we assume capacity tariffs applied to large consumers by the local utilities in the two locations. Finally, following the example in Germany, a (physical) feed-in limit of 50% of the nameplate PV-system capacity for both countries is assumed as a preventive measure to keep the power system stable during periods of high PV production[12]. Table 1 provides the input data for every battery application depending on the tariff structure.

1.4. Battery technologies

We compare and optimize the operation of the most deployed battery technologies for residential applications, including the two main families, lithium-ion and lead-acid. A total of six different technologies are analyzed: for the lithium family, these include lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), lithium iron phosphate (LFP), and lithium titanium oxide (LTO) batteries; and for the lead-acid family, we consider traditional valve regulated lead-acid (VRLA) and advanced lead-acid (ALA) batteries. The technical and economic battery input data required by the model were collected from publicly available data-sheets and personal communication with representative manufacturers. Table 2 presents the key specifications for the six battery technologies defined by

Name		Units	U.S.	Switzerland	Based on
Flat Tariff		USD/kWh	0.073	0.22	Energy
Double Tariff	On-peak[a]	USD/kWh	0.183	0.24	Energy
	Off-peak	USD/kWh	0.056	0.152	Energy
Export price		USD/kWh	0.027[b]	0.047[b]	Energy
Capacity tariff		USD/kW/month	10.14	9.39	Power
Feed-in limit		$\%kW_{p-PV}$	50%	50%	Regulation

[a] In the U.S. on-peak time is only from June to September from 1 p.m. to 7 p.m. on weekdays. In Switzerland, on-peak time is all year-round from 7 a.m. to 10 p.m. on weekdays and from 5 p.m. to 10 p.m. on weekends.
[b] We use real hourly wholesale price for ERCOT and EPEXSPOT markets. The price shown in the table is the average wholesale price.

Table 1: Various electricity tariffs components depending on the bill structure and for the two locations used in this study to test various battery applications.

Technology	Cathode Material	Cycles @ DoD	Maximum lifetime [years]	Roundtrip Efficiency	Energy Costs [USD/nominal kWh]	Maximum charge/ discharge rate [kW]	ΔSOC	Maximum SOC	Minimum SOC	Cycle & calendar aging factor per year[a]	Reference
Li-ion	NMC	5000 @ 100%	15	91.8%	410	0.4*C	1	1	0	0.059 & 0.07	14–16
	NCA	8000 @ 100%	20	92.5%	650	1*C	1	1	0	0.047 & 0.05	17
	LFP	6000 @ 100%	20	94%	980	2*C	1	1	0	0.024 & 0.05	14,15,18
	LTO	15000 @ 100%	25	96.7%	1630	4*C	1	1	0	0.003 & 0.04	19, personal communication
Lead-acid	VRLA	1500 @ 50%	10	85%	330	0.1*C	0.5	1	0.5	0.236 & 0.1	12,20
	ALA	4500 @ 70%	15	91%	750	1*C	0.7	0.9	0.2	0.06 & 0.07	14,15,21

[a] The cycle aging factor is given for a 50% depth-of-discharge. For further information please refer to the section 2 of the supplementary information.

Table 2: Battery specifications for the six technologies compared in this study. SOC denotes the state of charge.

the type of cathode material. Three currently available battery sizes were assessed, small (3 kWh), medium (7 kWh) and large (14 kWh). Moreover, aging is modeled on a daily basis for the first year using the maximum among the daily calendar factor and the daily cyclic factor. The former is calculated as the multiplicative inverse of the calendar lifetime, whereas the cyclic aging factors are based on Woehler curves[e] for every technology. The cyclic aging is then given by the number of cycles per day at the given depth of discharge (depth-of-discharge), divided by the maximum number of cycles at a given depth-of-discharge[13]. Further details are presented in Section 2 of the Supplementary Information.

1.5. PV-coupled battery system

The DC-coupled system used in this study is illustrated in Fig. 8 and it includes an integrated inverter with a buck-boost charge controller with a maximum power point tracking system and a bi-directional inverter (required to charge from the grid). An inverter loading ratio (i.e. the ratio between the inverter rating and the PV rating, referred to as ILR) of 1.2 is

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[e]The Woehler curves show the number of remaining cycles of a battery as a function of depth of discharge until the end of lifetime. This curve is given by some battery manufacturers in data sheets.

Component	Units	Value	Reference
Charge controller efficiency	%	98	[23]
Inverter efficiency	%	94	[23]
Bi-directional inverter cost	[USD/kW]	600	[24]
Bi-directional inverter lifetime	years	15	[8]
Balance of plant cost	[USD/kW]	100	[25]
Installation costs	[USD]	2000	[26]
O&M	[USD/kW]	0	[16,20]
Discount rate	%/a	4	[27]
End of life (EoL)	%	70	[28]
ILR	p.u.	1.2	[22]

Table 3: Values selected for the technical and economic assessment of PV-coupled battery systems.

considered for this study[22]. Other technical and economic characteristics of the PV-coupled battery system considered in this study are shown in Table 3.

DC-coupled topology allows to select a smaller inverter (i.e. increase the ratio between the inverter rating and the PV rating beyond 1) and store otherwise clipped energy[29]. Likewise, this topology prevents from curtailing PV export exceeding a regulatory threshold as in Germany where PV generators with a installed capacity of maximum 30 kW must be able to reduce the feed-in power in case of network overload or limit the power supply of the PV-system to the grid to 70% of installed capacity which can be enforced to 50% if a storage installation is funded by the government subsidy program[30,31][fg].

DC -coupled systems require a single power conversion to store energy (through the charge controller), whereas AC-coupled systems require two power conversions (from the PV array through the PV inverter and then through a bi-directional inverter to the battery). Therefore, in applications where PV output storage is frequent, DC-coupled systems are generally more efficient than AC-coupled systems. In the DC-coupled system, the efficiency of the charge controller is set at 98% while that from the bi-directional DC/AC inverter is set at 95%[23]. Thus, the DC/AC efficiency from the PV system to the grid or to the demand load is 93%. On the other hand, when PV electricity is stored, one must consider battery roundtrip efficiency,

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[f]9 subsection 2

[g]In the literature curtailed and clipped energy are often interchangeable, however in this work we use the term clipped energy to refer to wasted energy due to technical restrictions (e.g. inverter rating) while curtailed energy is used when we refer to wasted energy due to legal restrictions.
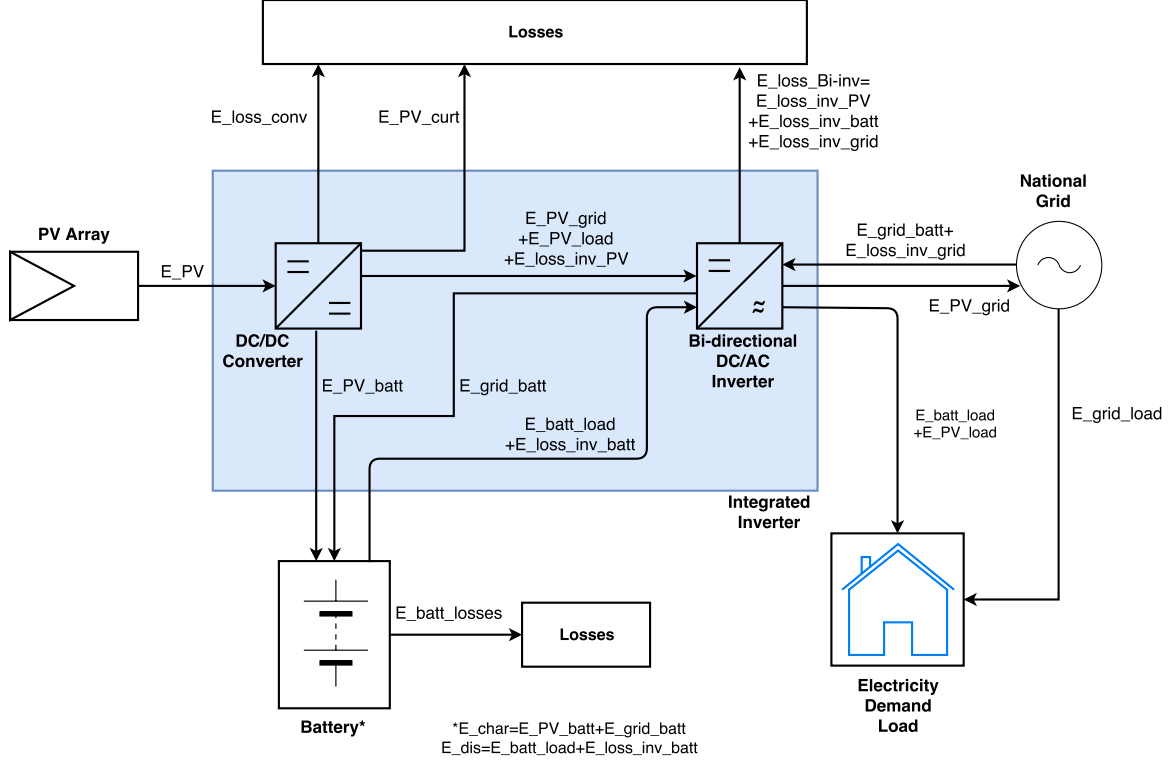
Fig. 8: DC-coupled PV-battery system with integrated inverter used in this study. Arrows indicate the direction of possible energy flows between the individual components.

therefore lowering efficiency depending on battery technology, for instance, it goes down to 79% for the VRLA. As for grid charging, the AC-AC efficiency (i.e. grid-to-battery-to-load efficiency) is within a range of 76% (for VRLA) to 87% (for LTO).

1.6. Optimization of the battery schedule

The model objective function have two components, namely the energy and power components of the electricity bill. As the tariff structure depends on the applications considered, a boolean parameter activates the power-based factor of the bill when is necessary. The objective function and constraints are presented below.

$$Min(\overbrace{\sum_{i=0}^{t}(E_{grid_i} * \pi_{import_i} - E_{PV-grid_i} * \pi_{export_i})}^{\text{Energy-based tariff}} + (\underbrace{P_{max-day} * \pi_{capacity} * PS}_{\text{Power-based tariff}})) \qquad (3)$$

Subject to:
Battery constraints:

$$SOC_{min} \leq SOC_i \leq SOC_{max} \qquad (4)$$

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$$E_{char_i} = E_{PV-batt_i} + E_{grid-batt_i} \qquad (5)$$

$$E_{dis_i} \leq (SOC_{i-1} - SOC_{min}) * C_{batt}^{nom} \qquad (6)$$

Energy balance constraints:

$$E_{grid_i} = E_{grid-load_i} + E_{grid-batt_i} + E_{loss-inv-grid_i} \qquad (7)$$

$$E_{PV_i} = E_{PV-load_i} + E_{PV-batt_i} + E_{PV-grid_i} + E_{PV-curt_i} + E_{loss-conv_i} + E_{loss-inv-PV_i} \qquad (8)$$

$$E_{load_i} = E_{PV-load_i} + E_{grid-load_i} + E_{dis_i} * \eta_{inv} \qquad (9)$$

$$SOC_i = \frac{(SOC_{i-1} * C_{batt}^{nom} + E_{char_i} - E_{dis_i} - E_{loss-batt_i})}{C_{batt}^{nom}} \qquad (10)$$

$$E_{dis_i} = E_{batt-load_i} + E_{loss-battinv_i} \qquad (11)$$

Efficiency losses constraints:

$$E_{loss-conv_i} = (1 - \eta_{conv}) * (E_{PV-load_i} + E_{PV-batt_i} + E_{PV-grid_i}) \qquad (12)$$

$$E_{loss-biinv_i} = E_{loss-inv-PV_i} + E_{loss-inv-grid_i} + E_{loss-inv-batt_i} \qquad (13)$$

$$E_{loss-inv-PV_i} = (E_{PV-load_i} + E_{PV-grid_i}) * (1 - \eta_{inv}) \qquad (14)$$

$$E_{loss-inv-grid_i} = E_{grid-batt_i} * (1 - \eta_{inv}) \qquad (15)$$

$$E_{loss-inv-batt_i} = E_{dis_i} * (1 - \eta_{inv}) \qquad (16)$$

$$E_{loss-batt_i} = E_{char_i} * (1 - \eta_{batt}) \qquad (17)$$

Power constraints:

$$P_{char_i} \leq P_{max-char} \qquad (18)$$

$$P_{dis_i} \leq P_{max-dis} \qquad (19)$$

$$P_{PV-grid_i} + P_{PV-load_i} + P_{dis_i} + P_{loss-biinv_i} \leq P_{inv} \qquad (20)$$

$$P_{PV-grid_i} + P_{PV-batt_i} + P_{PV-load_i} + P_{loss-conv_i} \leq P_{inv} \qquad (21)$$

$$P_{grid-batt_i} + P_{loss-inv-grid_i} \leq P_{inv} \qquad (22)$$

Application selection:

$$P_{PV-curt_i} \leq P_{limit} \quad \forall \quad i \quad if \quad PVCT = 1 \qquad (23)$$

$$E_{grid-batt_i} = 0 \quad \forall \quad i \quad if \quad DLS = 0 \qquad (24)$$

$$P_{grid_i} \leq P_{max-day} \quad \forall \quad i \quad if \quad DPS = 1 \qquad (25)$$

Modeling parameters	Name	Units	Modeling variables	Name	Units
Converter efficiency	η_{conv}	%	PV generation fed to the load	$E_{PV-load}$	kWh
Inverter efficiency	η_{inv}	%	PV generation exported to the grid	$E_{PV-grid}$	kWh
Inverter rating	P_{inv}	kW	PV generation injected to the battery	$E_{PV-batt}$	kWh
Battery Efficiency	η_{batt}	%	PV generation curtailed	$E_{PV-curt}$	kWh
Maximum discharge power	$P_{max-dis}$	kW	Energy lost due to converter efficiency	$E_{loss-conv}$	kWh
Maximum charge power	$P_{max-char}$	kW	Total energy lost due to bi-directional inverter efficiency	$E_{loss-binv}$	kWh
Battery nominal capacity	C_{batt}^{nom}	kWh	PV energy lost due to bi-directional inverter efficiency	$E_{loss-PVinv}$	kWh
Battery lifetime	N	years	Grid energy lost due to bi-directional inverter efficiency	$E_{loss-gridinv}$	kWh
Battery maximum state of charge	SOC_{max}	%	Battery energy lost due to bi-directional inverter efficiency	$E_{loss-battinv}$	kWh
Battery minimum state of charge	SOC_{min}	%	Energy lost due to battery efficiency	$E_{loss-batt}$	kWh
Retail prices	π_{import}	USD/kWh	Energy drained from the battery	E_{dis}	kWh
Export prices	π_{export}	USD/kWh	Energy injected to the battery	E_{char}	kWh
Capacity tariff	$\pi_{capacity}$	USD/kW	Energy delivered from the battery to the load	$E_{batt-load}$	kWh
Feed-in limit	P_{limit}	%	Energy imported from the grid to the battery	$E_{grid-batt}$	kWh
Combination of applications	[PVCT, PVSC, DLS, DPS]	Boolean array	Energy imported from the grid to the load	$E_{grid-load}$	kWh
Load demand	E_{load}	kWh	Energy drained from the grid	E_{grid}	kWh
PV generation	E_{PV}	kWh	Maximum power drained from the grid	$P_{max-day}$	kW
Optimization time framework	t	minutes	Power related to any energy parameter	$P_x = E_x/\Delta t$	kW
Temporal resolution	Δt	fraction of hour	State of charge	SOC_i	%

Table 4: List of model parameters and variables.

2. Aging

Battery aging and durability are parameters with a great uncertainty for battery energy storage technologies[32]. In this paper, we model battery aging process through the battery capacity depletion since it limits the battery lifetime. The aging behavior is typically divided in two, calendar aging (when the battery is standby) and cycle aging (when the battery is used)[13]. We acknowledge the battery aging process is non-linear, particularly in the first hundreds of cycles, but as pointed out in earlier papers, capacity losses can be assumed to be linear without compromising lifetime predictions markedly[12,13] and this approach is followed in this study. Furthermore, previous studies have reported that one of the two aging factors dominates (typically cycle aging for small batteries) in typical operation conditions[13], thus the model can be simplified across the different technologies through the use of the maximum of both, see Eq. 26. The aging factor is calculated in daily basis.

Typically a 20% reduction of the initial capacity is applied to define the end of life (EoL) of a battery[13], especially for industrial application since under this value the manufacturers do not guarantee the battery performance. However, lower values are often stated for residential applications which are less demanding[12,28], in this study we use a 30% capacity depletion as EoL.

Calendar losses have been previously modeled using the Arrhenius formula since they are mainly dependent on the battery temperature[28]. However, the temperature is controlled by the battery management system in new models available in the market. Therefore, the proposed model neglects its effect on the battery aging. Eq. 27 defines daily calendar aging as the multiplicative inverse of the battery calendar lifetime.

As for the cyclic aging, we use a similar approach as the presented by Magnor et al.[13] which is based on Woehler curves[h] for different battery technologies. We extend this method to other technologies adapting the maximum number of cycles performed by the battery. The cyclic aging is then given by the number of cycles per day at the given DoD, divided by the maximum number of cycles at a given DoD, as indicated by Eqs. 28 and 29.

$$aging_d = max(cyc_d, cal_d) \tag{26}$$

$$cal_d = \frac{1}{Batt_{cal-life}} \tag{27}$$

$$DoD^\star = \frac{\sum_{i=1}^{t} E_{dis_i}}{E_{batt}^{nom}} \tag{28}$$

$$cyc_d = \frac{N_{cycles_d}^{DoD^\star}}{N_{max}^{DoD^\star}} \tag{29}$$

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[h]The Woehler curves show the number of cycles of a battery as a function of depth of discharge until the end of lifetime. This curve is given by most battery manufacturers in data sheets.
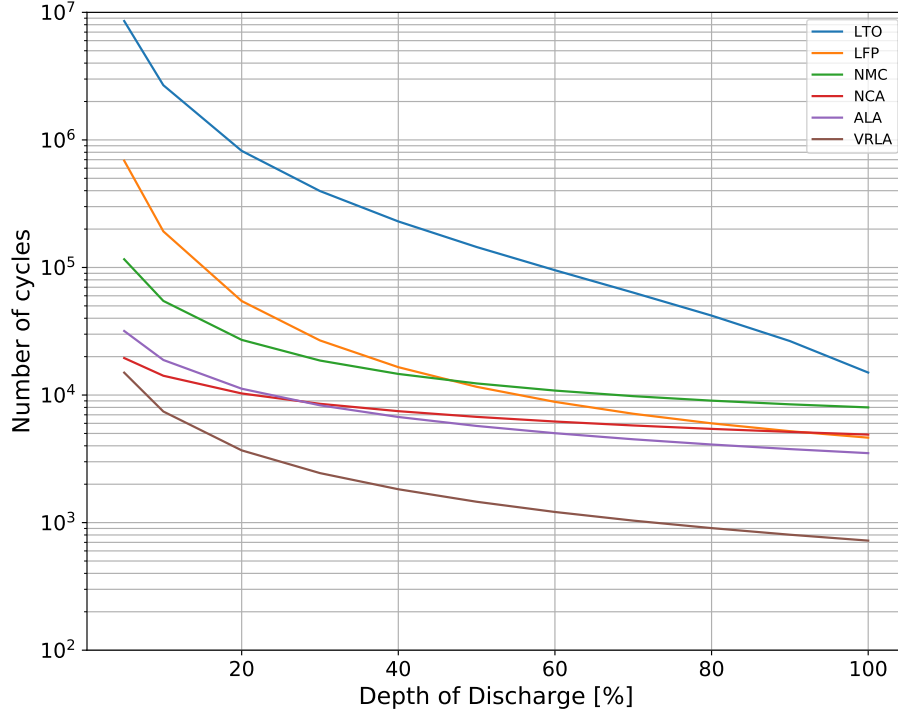
Fig. 9: Woehler curves for every technology used in this study.

The Woehler curves used in this study are displayed in Fig. 9 and the equation that mathematically describes every curve is presented in Table 5. Each curve is based on manufacturers' datasheets.

Technology	Number of cycles as a function of DoD	Reference
LTO	$\exp\left(\frac{\log(DoD)-\log(771.51)}{-0.604}\right) - 45300$	[33]
LFP	$\exp\left(\frac{\log(DoD)-\log(70.869)}{-0.54}\right) + 1961.37135$	[34]
NCA	$\exp\left(\frac{\log(DoD)-\log(1216.7)}{-0.869}\right) + 4449.67011$	[17]
NMC	$\exp\left(\frac{\log(DoD)-\log(1E8)}{-2.168}\right)$	[35]
ALA	$\exp\left(\frac{\log(DoD)-\log(37403)}{-1.306}\right) + 330.656417$	[36]
VRLA	$\exp\left(\frac{\log(DoD)-\log(667.61)}{-0.988}\right)$	[20]

Table 5: Number of cycles for every technology used in this study.

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3. Model validation

In order to validate the model, some test scenarios with intuitive solutions for the optimum schedule of operation of the battery are considered. The three scenarios are run with a LFP battery with a large capacity (100 MWh) and efficiency of 100%. The demand is considered to be constant at 100 kW.

In the first case, presented in figure 10, the time-series test price presents a single time slot with a low price of 10 USD/kWh and a peak price of 100 USD/kWh. The battery charging and discharging limits are set at 2*C. The output is as expected a schedule where the battery is charged in the low-price time slot and discharged afterwards.
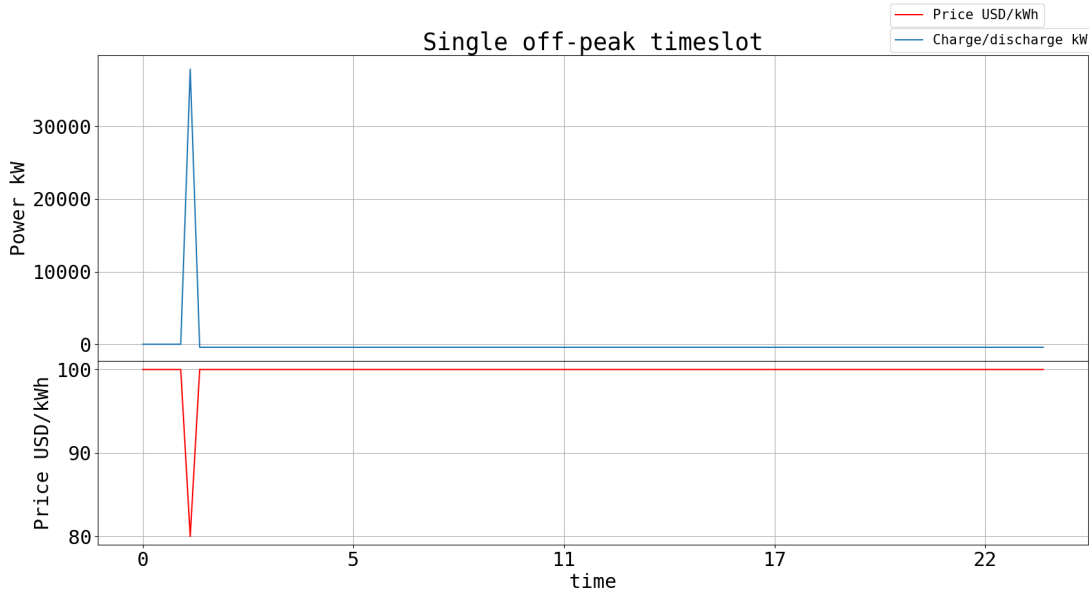
Fig. 10: Result for optimization of the single off-peak time slot test case. The output schedule for charge (positive y-axis) and discharge of the battery with the given price input.

In the second test, shown in figure 11 the time-series test price is a square wave varying between 100 USD/kWh and 10 USD/kWh. The battery charging and discharging limits are set at 100 kW. Therefore, we would expect the optimized result to output a schedule that charged when the prices are low, then discharged to cover the demand when the prices are high. The figure of the model results is an excellent fit with the expected schedule. A positive power flow means the battery is charging.

In the last test, shown in figure 12 the time-series test price is a sinus wave varying between 50 USD/kWh and -50 USD/kWh. The battery charging and discharging limits are set at 100 kW. Therefore, we would expect the optimized result to output a schedule that charged when the prices are lower than 0 USD/kWh, then discharged to cover the demand when the prices are high. We can see how at the end of the day, the battery charges only when prices are strictly below 0 USD/kWh, since the battery does not charge if it does not need the energy before the end of the day.
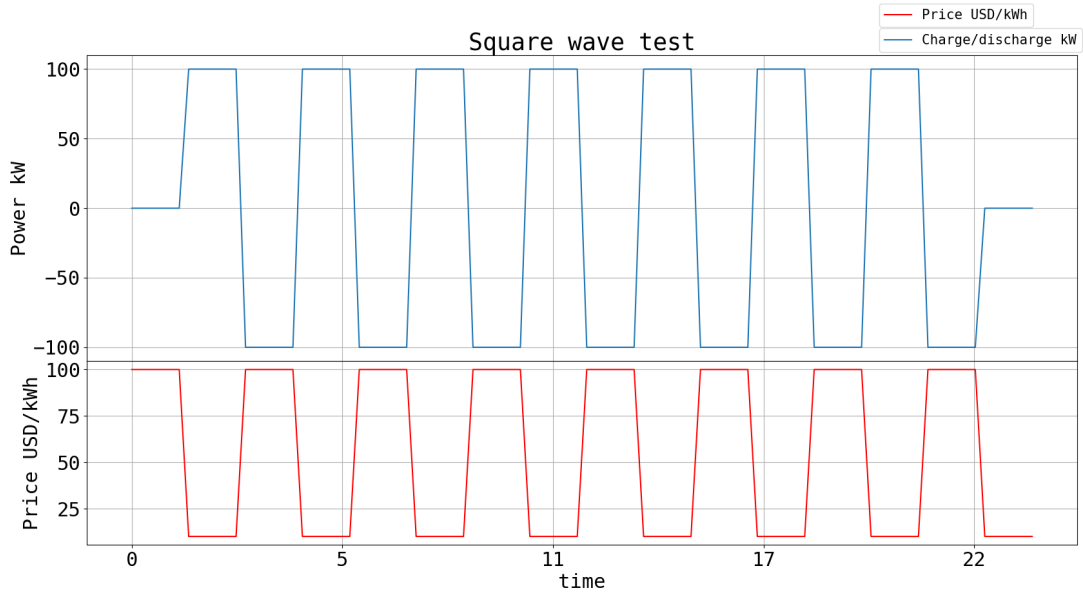
16

Fig. 11: Result for optimization of the square wave price test case. The output schedule for charge (positive y-axis) and discharge of the battery with the given price input.
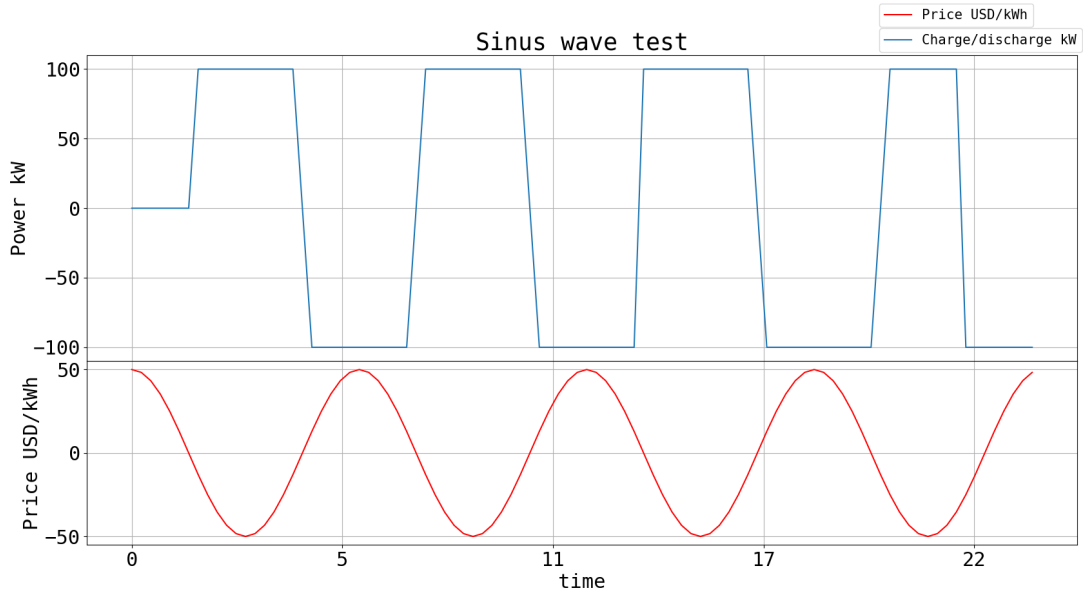

Fig. 12: Result for optimization of the sinus wave price test case. The output schedule for charge (positive y-axis) and discharge of the battery with the given price input.

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4. Other combinations of applications

Results are presented here for a typical size of 7 kWh depending on the battery technology and for both locations. Since we aim to analyze the impact of geography, battery technology and size on the attractiveness of the combination of applications, our baseline results are based on a representative (median) fixed PV size in each geographical region. Three additional combinations of applications are analyzed besides the five presented in the main paper. In order to give the reader a point of comparison, PV self-consumption only and the full combination of applications are as well deployed.

The main result drawn from Figs. 13,14 and 15 is the influence of demand load shifting when combined with PV self-consumption and demand peak shaving, which helps to reduce the levelized cost and slightly enhance the added value. At the end it results in an improved NPV which is significantly higher than the scenario where avoidance of PV curtailment is combined with the same two applications.
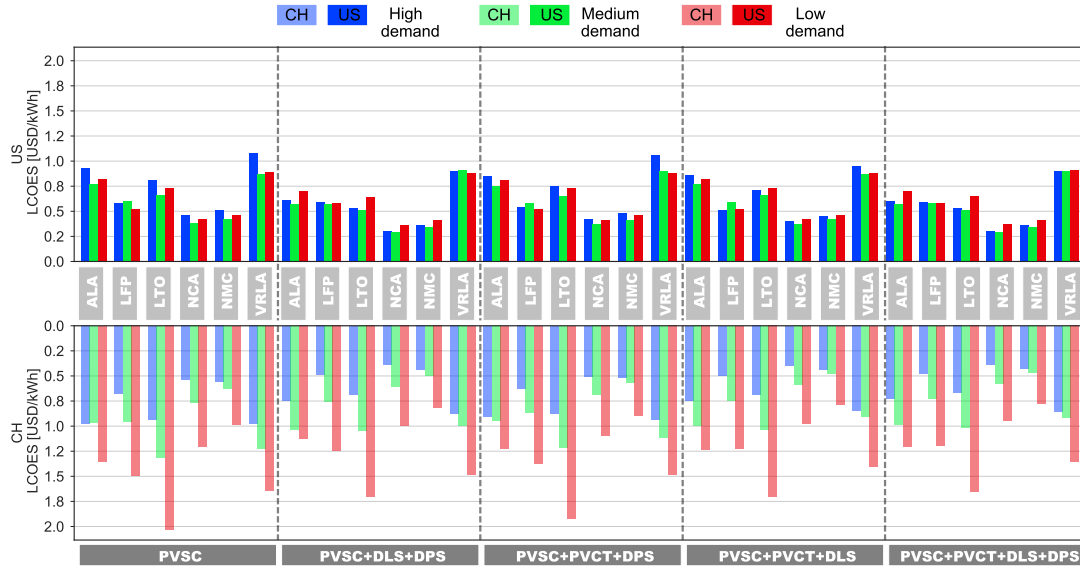

Fig. 13: Levelized cost of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the medium installed capacity across both locations.
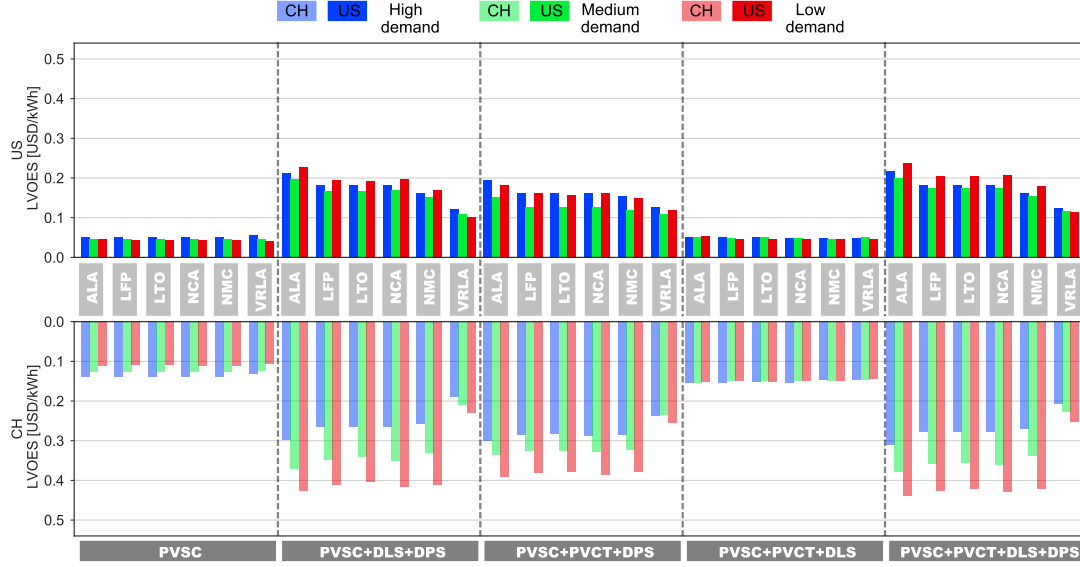
18

Fig. 14: Levelized value of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the medium installed capacity across both locations.
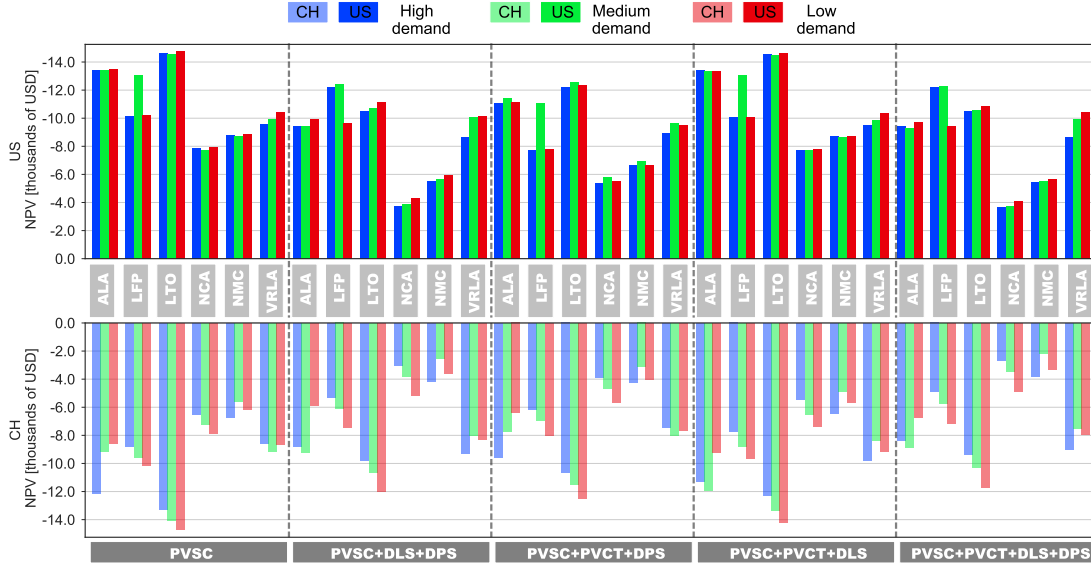

Fig. 15: Net present value of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for the U.S. (top) and Switzerland (bottom). The size the PV system correspond to the medium installed capacity across both locations.

5. PV size impact

Fig. 16 displays the average LCOES, LVOES and NPV across the three groups of consumers, for the 25th, median and 75th quartiles of the PV size distribution for Switzerland and Fig 17 for the U.S., for a 7 kWh battery performing simultaneously all consumer applications depending on the battery technology.

In general, the combination of applications reaches smaller levelized cost, higher levelized value and higher NPV for all batteries, with the exception of LFP-based batteries in the U.S. when median PV size is assessed (due to replacement near the end of life). Moreover, the difference between a battery performing PV self-consumption only and one performing all the applications simultaneously is higher as the PV size raises for the levelized value and the NPV, as for the levelized cost the difference diminishes with PV size.
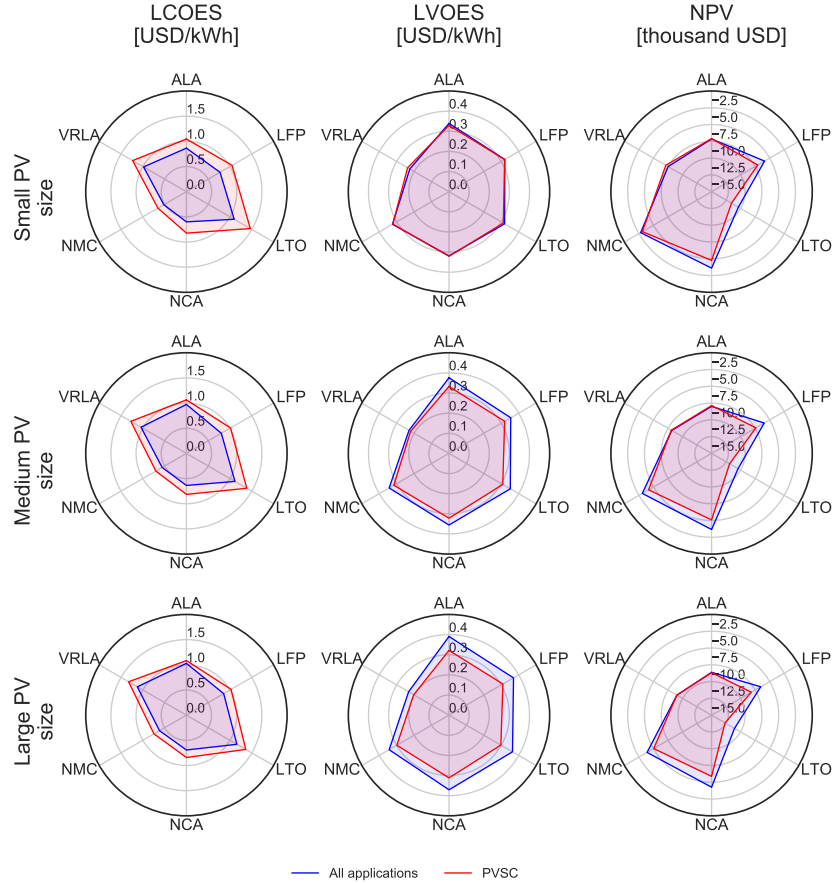

Fig. 16: Comparison of the average LCOES (left), LVOES (middle) and NPV (right) for various battery technologies and a 7 kWh battery performing only PV self-consumption (red) and all consumer applications simultaneously (blue) in Switzerland, depending on the size of PV, namely small (top), medium (middle) and large (bottom).
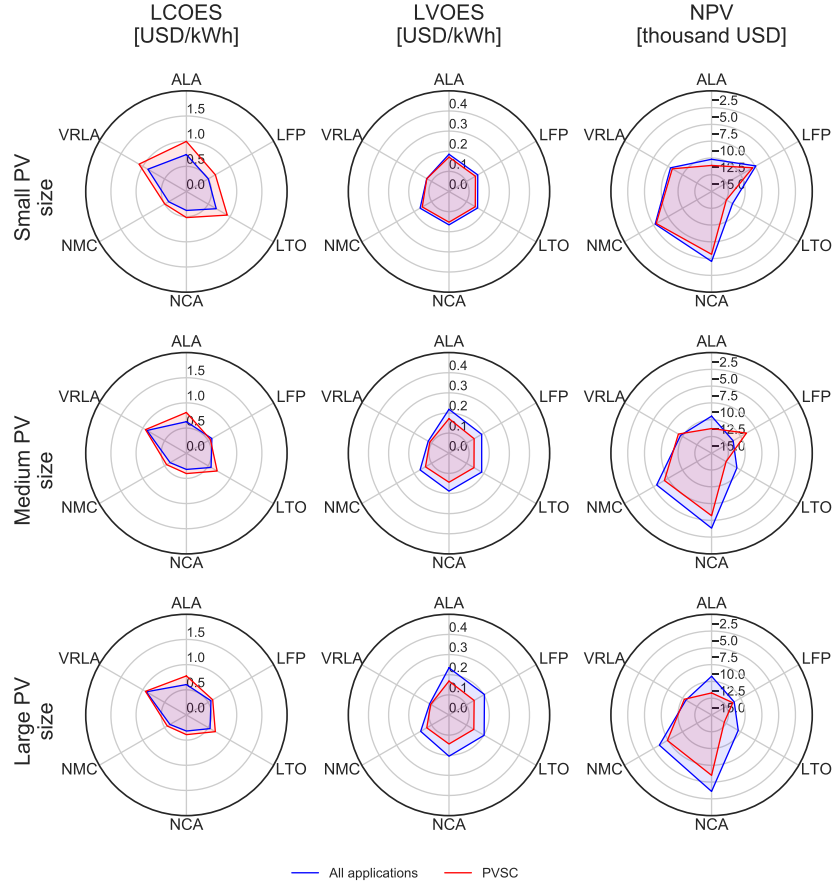
Fig. 17: Comparison of the average LCOES (left), LVOES (middle) and NPV (right) for various battery technologies and a 7 kWh battery performing only PV self-consumption (red) and all consumer applications simultaneously (blue) in the U.S., depending on the size of PV, namely small (top), medium (middle) and large (bottom).

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