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Optimized PV-coupled battery systems for combining applications: Impact of battery technology and geography

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ABSTRACT

Interest in residential batteries to supply photovoltaic (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 open-source optimization framework to determine the best-suited battery technology depending on the size and 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 Geneva (Switzerland) and Austin (United States). 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 Austin is lithium nickel cobalt aluminum oxide (NCA) as for Geneva lithium nickel manganese cobalt oxide (NMC) batteries reach in average a higher net present value than NCA-based batteries. However, NCA-based batteries could be a more promising alternative when applications are combined.

1. Introduction

The modularity of solar photovoltaics (PV) is enabling the installation of substantial amounts of generation capacity embedded in the distribution network or even in the consumption centers. In 2016, installations in the residential sector of the United States (U.S.) represented 67% of the new PV installations with a nominal power lower than 2 MW [1], while in Germany for the same year, 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 consumers' interest in increasing the amount of self-generated PV that they consume in-home (this is referred 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 13–24% when battery storage is included in the system, using an elementary charging approach [7].

In parallel, battery costs, especially for lithium-ion technologies, 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

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List of abbreviations.

PV	Photovoltaics
FiT	Feed-in Tariff
PVSC	PV self-consumption
PVCT	Avoidance of PV curtailment
DLS	Demand load-shifting
DPS	Demand peak shaving
NMC	Lithium nickel manganese cobalt oxide
NCA	Lithium nickel cobalt aluminum oxide
LFP	Lithium iron phosphate
LTO	Lithium titanium oxide
ALA	Advanced lead-acid
VRLA	Valve-regulated lead-acid
FT	Flat tariff
DT	Double tariff
NPV	Net present value
LCOES	Levelized cost of energy storage
LVOES	Levelized value of energy storage
SOC	State of charge
DoD	Depth of discharge

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. Previous studies have focused on capital and operational expenditures associated with the design [12] and operation [13–16] of PV-coupled battery systems. The influence of solar resource, demand profiles, jurisdiction and electricity prices across geographies has been evaluated for PV self-consumption individually [16,22]. In addition to cost improvement, the simultaneous provision of various applications has been presented as an alternative strategy to increase the economic attractiveness of energy storage technologies thereby enabling accelerated deployment [17,18]. The combination of different storage applications has already been investigated at the distribution and transmission networks [17,19,20] and for different battery technologies [21]. However, despite the fact that behind-the-meter systems are anticipated to represent a major business opportunity for stationary storage, previous research on the simultaneous provision of various applications by these systems is scant. For example, previous authors investigated either various types of applications or geographical dependence and/or using a technology-agnostic approach [12–16,18,23–31]. Therefore, various battery technologies available in the market have not been evaluated with the same method and for the full combination of consumer applications.

The main aim of this work is to determine the best-suited battery technology for various combinations of applications. For this, we develop an open-source optimization framework using linear programming to solve the management problem of a PV-coupled battery system. The model is robust and can consider different combinations of applications (*e.g.* PV self-consumption and demand load shifting), tariff structures, export prices and battery characteristics such as aging, efficiency, lifespan and cycles. Moreover, we evaluate which additional, currently unexploited economic benefit can be reaped by combining applications and compare different battery sizes. Our model can be used by consumers and utility companies to explore different batteries and electricity tariffs for a given demand, PV generation and combination of applications. Importantly, the comparison of our results for Geneva (Switzerland) and Austin (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 geographies.

Considering the relevance of these research questions and in order to promote the use of our model by other peers, we also make our model and data open. With this, we contribute towards openness in energy research, which is lagging behind other fields [32]. Open-source energy models permit more meaningful collaboration among academics and allow to engage the public. Therefore, they are important for energy policy communication and benefit not only academics but the public in general [32,33]. In the interest of transparency, and to boost collaboration and science reproducibility in the energy field, this work joins other open-source efforts such as openmod, renewables-ninja [34] and the Linux Foundation Energy.

The remainder of this paper is structured as follows. The materials and methods are presented in the next section. Section 3 gives the optimization results as a function of the combination of applications, battery technology and geography. Section 4 presents the implications of our results and finally the main conclusions are presented in Section 5.

2. Material and methods

Fig. 1 is a schematic representation of our method. In first place, we specify the input data for electricity demand and PV generation in Section 2.1. The applications and their combinations are subsequently defined as a function of the electricity tariff structure in Section 2.2. Then, the battery technologies, system topology, components and techno-economic indicators are presented in Sections 2.3, 2.4 and 2.5.

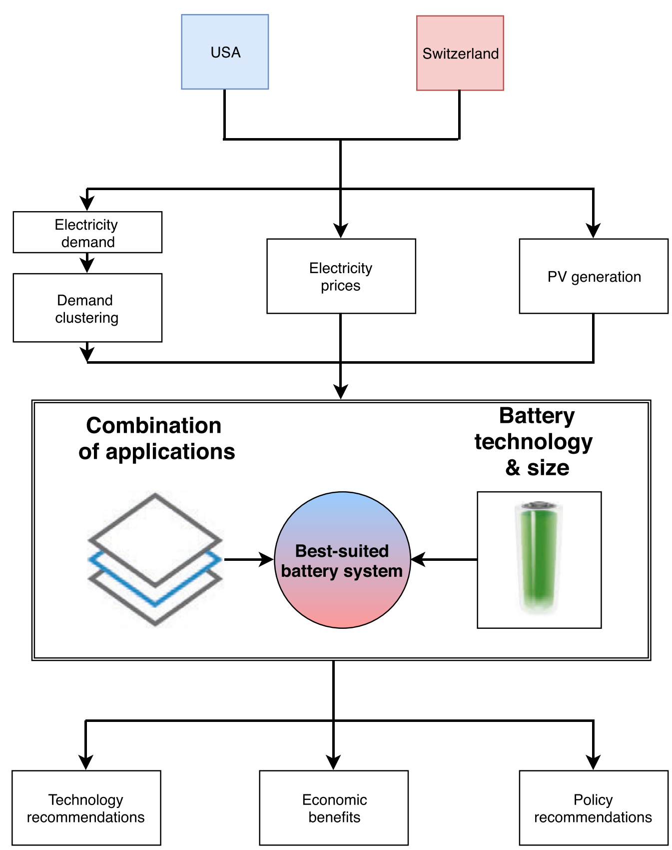

Fig. 1. Schematic representation of the modeling approach proposed.

Finally, Section 2.6 describes the schedule optimization. Across the study we use USD as common currency for both geographies.[1]

2.1. Demand and PV generation

We use electricity consumption data with 15-min 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 geographies. 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 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 geographies are used to model PV generation. We focus on the median PV size of the empirical distribution across Switzerland (i.e. 4.8 kW_p) [35] and Texas (i.e. 5 kW_p) [36] for our baseline results (*i.e.* unchanged PV size), while alternative scenarios including the 25th (i.e. 3.2 and 3.15 kW_p for Geneva and Austin respectively) and 75th percentiles (i.e. 6.9 and 6.4 kW_p for Geneva and Austin respectively) are shown in Section 4 of the SI.

2.2. 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.

Electricity prices used in this study are based on available tariffs which are offered by the local utility companies in the two geographies. Both, single tariffs and double tariffs (also called Time-of-Use tariffs, which have a peak and off-peak periods) are considered in the analysis. In Geneva, double tariffs are applied all-year-round, while in Austin, they are applied only in summertime. The PV 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 Electric Reliability Council of Texas day-ahead market (ERCOT southern load zone) and from the European Power Exchange day-ahead market for Switzerland (EPEXSPOT). 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. 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 [37]. As a first attempt to include them we assume low capacity tariffs applied to large consumers by the local utilities in the two geographies (*i.e.* around 10 USD/kW/month), taking a more conservative approach than other studies (*e.g.* see Ref. [31]). In order to ensure that the tariffs are revenue neutral in average for all the households evaluated (*i.e.* the consumer bill remains similar), the per-kWh rates are reduced by 20% in Geneva and 30% in Austin whenever the capacity tariff is used. 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.

On-grid batteries can perform up to 15 applications depending on the discharge duration, scale and stakeholder [38]. Consumer applications refer to those which help consumer to minimize the electricity bill, with the number of relevant applications depending on the bill structure. Considering the various components of a household electricity bill, a residential battery can perform the applications shown in Fig. 2:

PV self-consumption (PVSC): PV surplus electricity is stored in a battery and used later on to meet the local electricity demand when it is higher than PV generation (see Fig. 2 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. 2 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. 2 c.). The battery charges from the grid when retail 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 electricity peaks which can result in distribution network upgrading as well as expensive electricity supply (see Fig. 2 d.). The main driver is therefore the presence of a capacity-based component in the electricity tariff.

Back-up power is excluded from this study 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 min in 2016) [39]. However, we acknowledge that in some geographies back-up power is the main motivation for battery installation (*e.g.* Hawaii).

2.3. Battery technologies

Battery technologies widely differ in cost, aging, lifetime and round trip efficiency [38], and we compare here six representative technologies 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 ultracapacitor into a conventional lead-acid cell, increasing efficiency and cycle life. ALA batteries are currently in the demonstration phase and hence costs are currently higher than for conventional lead-acid batteries. The selected representative products are compared with the most likely values found in the market according to Schmidt et al. [40] (see

[1] Exchange rates used: 1 USD/CHF and 1.18 USD/EUR.

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

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

[a] When the capacity tariff is applied, the Double tariff is reduced by 20% in Geneva and 30% in Austin.
[b] 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.
[c] We use real hourly wholesale price for ERCOT and EPEXSPOT markets. The price shown in the table is the average wholesale price.

2.4. PV-coupled battery system

This study focuses on the investment in a residential 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 (*i.e.*, coupled on the direct current side) since a lower investment is required and the overall efficiency of stored PV electricity is higher than in AC-coupled topologies (*i.e.*, coupled on the alternating current side) [51]. Moreover, the prevention of PV curtailment is possible (for further information see Section 1.4 of supplementary information). Since manufacturers claim no operational costs required for residential battery technologies, we set them to zero [43,47]. Installation costs are considered for the inverter and battery and are assumed to be high for both countries, equal to USD 2000, based on Ref. [52].

2.5. Techno-economic indicators

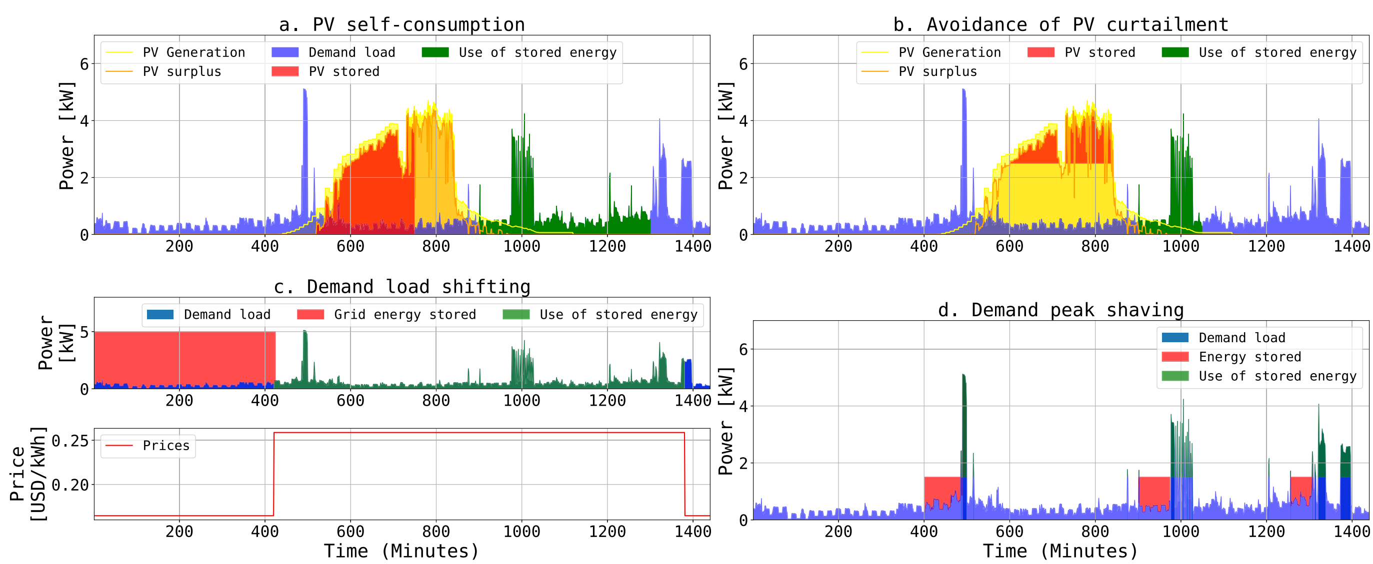

Fig. 2. Schematic representation of the four applications analyzed in this study. a. PV self-consumption, b. Avoidance of PV curtailment, c. Demand load shifting and d. Demand peak shaving. This figure is explanatory and does not fully represent the model constraints or approach, which are suitably explained in Section 2.6. The horizontal scale corresponds to the minutes throughout the day.

the values presented in Section 1.5 of the SI).

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 the type of cathode material. Other relevant values for the techno-economic assessment of PV-coupled battery systems, such as the inverter and converter efficiencies, discount rate and costs are given in Table 3. Three currently available battery sizes were assessed, small (3 kWh), medium (7 kWh) and large (14 kWh). Moreover, battery aging is modeled on a daily basis using the maximum between 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[2] for every technology. The cyclic aging is then given by the number of cycles per day at the given depth of discharge (DoD), divided by the maximum number of cycles at a given DoD [49]. Further details and a detailed example of the aging model utilised for this study are presented in Section 2 of the SI).

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.

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

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

[2] 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.

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

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	[41–43]
	NCA	8000 @ 100%	20	92.5%	650	1*C	1	1	0	0.047 & 0.05	[44]
	LFP	6000 @ 100%	20	94%	980	2*C	1	1	0	0.024 & 0.05	[41,42,45]
	LTO	15000 @ 100%	25	96.7%	1630	4*C	1	1	0	0.003 & 0.04	[46], personal communication
Lead-acid	VRLA	1500 @ 50%	10	85%	330	0.1*C	0.5	1	0.5	0.236 & 0.1	[12,47]
	ALA	4500 @ 70%	15	91%	750	1*C	0.7	0.9	0.2	0.06 & 0.07	[41,42,48]

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

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

Component	Units	Value	Reference
Charge controller efficiency	%	98	[50]
Inverter efficiency	%	94	[50]
Bi-directional inverter cost	[USD/kW]	600	[51]
Bi-directional inverter lifetime	years	15	[1]
Balance of plant cost	[USD/kW]	100	[13]
Installation costs	[USD]	2000	[52]
Operation and maintenance costs	[USD/kW]	0	[43,47]
Discount rate	%/a	4	[17]
End of life (EoL)	%	70	[53]
Inverter load ratio (ILR)	p.u.	1.2	[54]

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

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

wCAPEX are the capital expenditures (in USD), OPEX are the operational expenditures (in USD), r is the discount factor, E_{dis} is the energy discharged from the battery and N is the lifetime of the project (*i.e.*, the same as the inverter which in this study is considered to be 15 years). The cash flows of the PV-coupled battery system are represented as $CF_{PV-Batt}$, whileCF_{Batt} are the cash flows due to the battery only, and CF_{PV} are the cash flows due to the PV system.

2.6. Optimization of the battery schedule

The management problem of a PV-coupled battery system is solved by Mixed Integer Linear Programming, using Pyomo, an open-source tool for modeling optimization applications in Python [55] and solved with CPLEX. 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. Battery aging was treated as an exogenous parameter, calculated on daily basis and was not subject to optimization. Ffor further information, we invite the reader to see section 2 of the SI. The temporal resolution of the input data and simulation is 15 min, with this value providing a reasonable compromise between the modeling real performance and computational speed [56]. 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 [53] and when the battery lifetime exceeds the inverter lifetime, the residual value of the battery is considered using straight-line depreciation [57]. Replacement is considered when the battery cannot match the inverter lifetime which is taken as the project lifetime, we take a conservative 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 the same electricity prices for all years across battery lifetime. The model objective function is given by Eq. (5), while constraints, variables and parameters are also presented below, with the full list of model parameters and variables given in Table 4. The validation of the model can be found in Section 3 of the SI. The model and the U.S. data (the Swiss data is confidential) are publicly available in https://github.com/alefunxo/Basopra.

Table 4
List of model parameters and variables.

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	%

$$Min\left(\overbrace{\sum_{i=0}^{t}\left(E_{grid_i}*\pi_{import_i} - E_{PV-grid_i}*\pi_{export_i}\right.}^{\text{Energy - basedtariff}} + \left.\left(\underbrace{P_{max-day}*\pi_{capacity}*PS}_{\text{Power-basedtariff}}\right)\right)\right) \tag{5}$$

where the energy-based tariff is given by E_{grid_i} which is the electricity drawn from the grid, π_{import_i} is the import price (*i.e.*, retail price), $E_{PV-grid_i}$ is the PV-electricity exported to the grid, π_{export_i} is the export price (*i.e.*, the wholesale price in this study). All these variables have the sub-index i representing every time step (i.e., 15-min step for this study) from 0 to t (*with t equals to day corresponding to 96 steps in a day*). As for the power-based tariff, it is given by $P_{max-day}$, which is the maximum power required from the grid for the day, $\pi_{capacity}$ which is the capacity tariff (*i.e.*, in USD/kW/day) and PS is a boolean variable which indicate the use of demand peak shaving in the combination of applications. The objective function is subject to the constraints introduced below.

Subject to:

Battery constraints:

$$SOC_{min} \le SOC_i \le SOC_{max} \tag{6}$$

$$E_{char_i} = E_{PV-batt_i} + E_{grid-batt_i} \tag{7}$$

$$E_{dis_i} \le (SOC_{i-1} - SOC_{min})*C_{batt}^{nom} \tag{8}$$

where, SOC_{min} and SOC_{max} are the minimum and maximum states of charge and SOC_i is the state of charge at the instant i, below and above which the battery is never discharged and charged respectively. E_{char_i} the energy charged into the battery, $E_{PV-batt_i}$ is the PV energy flow to the battery and $E_{grid-batt_i}$ is the grid energy flow to the battery. E_{dis} is the electricity discharged from the battery and C_{batt}^{nom} is the nominal capacity of the battery.

Energy balance constraints:

$$E_{grid_i} = E_{grid-load_i} + E_{grid-batt_i} + E_{loss-inv-grid_i} \tag{9}$$

$$E_{PV_i} = E_{PV-load_i} + E_{PV-batt_i} + E_{PV-grid_i} + E_{PV-curt_i} + E_{loss-conv_i} + E_{loss-inv-PV_i} \tag{10}$$

$$E_{load_i} = E_{PV-load_i} + E_{grid-load_i} + E_{dis_i}*\eta_{inv} \tag{11}$$

$$SOC_i = \frac{(SOC_{i-1}*C_{batt}^{nom} + E_{char_i} - E_{dis_i} - E_{loss-batt_i})}{C_{batt}^{nom}} \tag{12}$$

$$E_{dis_i} = E_{batt-load_i} + E_{loss-inv-batt_i} \tag{13}$$

The energy balance constraints verify that all the energy flows sum up to the total energy provided by the grid (E_{grid_i}), the PV system (E_{PV_i}) and to cover the household demand (E_{load_i}), as well as to define the state of charge and the energy discharged from the battery. The energy flows are represented using the convention $E_{from-to}$, for instance, $E_{PV-grid}$ is the energy from the PV system injected into the grid. The losses are represented using the convention $E_{loss-device-dueto}$, for instance, $E_{loss-inv-PV}$ represents the losses in the inverter due to PV electricity flows. The efficiencies are represented using the convention η_{device}, where the device can be the converter (η_{conv}), the inverter (η_{inv}) or the battery (η_{batt}).

Efficiency losses constraints:

$$E_{loss-conv_i} = \left(E_{PV-load_i} + E_{PV-batt_i} + E_{PV-grid_i} + E_{loss-inv-PV_i}\right)*(1 - \eta_{conv}) \tag{14}$$

$$E_{loss-biinv_i} = E_{loss-inv-PV_i} + E_{loss-inv-grid_i} + E_{loss-inv-batt_i} \tag{15}$$

$$E_{loss-inv-PV_i} = \left(E_{PV-load_i} + E_{PV-grid_i}\right)*(1 - \eta_{inv})/\eta_{inv} \tag{16}$$

$$E_{loss-inv-grid_i} = E_{grid-batt_i}*(1 - \eta_{inv})/\eta_{inv} \tag{17}$$

$$E_{loss-inv-batt_i} = E_{dis_i}*(1 - \eta_{inv}) \tag{18}$$

$$E_{loss-batt_i} = E_{char_i}*(1 - \eta_{batt}) \tag{19}$$

Efficiency losses constraints account for the losses of the converter (Eq. (14)), the losses in the inverter (Eq. (15)), losses in the inverter due only to the PV (Eq. (16)), the losses in the inverter due to grid charging (Eq. (17)), the losses in the inverter due to the energy discharged from the battery (Eq. (18)), and the losses in the battery (Eq. (19)). Energy flows are, for convention, considered after the inverter, and to calculate the converter losses, we consider the losses in the bi-directional inverter due to the PV energy flows (see Fig. 7 of the SI). The PV curtailed is not taken into account as losses and it is assumed to be curtailed at the converter.

Power constraints:

$$P_{char_i} \le P_{max-char} \tag{20}$$

$$P_{dis_i} \le P_{max-dis} \tag{21}$$

$$P_{PV_i} \le P_{conv} \tag{22}$$

$$P_{PV-grid_i} + P_{PV-load_i} + P_{dis_i} + P_{loss-inv-PV_i} + P_{loss-inv-batt_i} \le P_{inv} \tag{23}$$

$$P_{grid-batt_i} + P_{loss-inv-grid_i} \le P_{inv} \tag{24}$$

Power variables are designated using P and follow the same conventions previously presented. The battery maximum charging and discharging power are represented by $P_{max-char}$ and $P_{max-dis}$. P_{conv} and P_{inv} represent the converter and inverter rating.

Application selection:

$$P_{PV-grid_i} \leq P_{limit} \quad \forall \quad i \quad if \quad PVCT = 1 \tag{25}$$

$$E_{grid-batt_i} = 0 \quad \forall \quad i \quad if \quad DLS = 0 \tag{26}$$

$$P_{grid_i} \leq P_{max-day} \quad \forall \quad i \quad if \quad DPS = 1 \tag{27}$$

Since the model allows to select from a pool of applications (*i.e.*, PV self-consumption, avoidance of PV curtailment, demand load shifting and demand peak shaving), when one of the applications is selected the corresponding constraint is applied (except for PVSC which is applied by default and includes all the constraints mentioned above). Thus, when PVCT is selected, a constraint to the power feed-in $P_{PV-grid_i}$ is applied (see Eq. (25)), and when demand load shifting is not applied (*i.e.*, DLS = 0), the battery cannot charge from the grid. Finally, when demand peak shaving is applied (*i.e.*, DPS = 1), a constraint on the maximum power drawn from the grid P_{grid_i} is applied (see Eq. (27)), which is then limited to the minimum ($P_{max-day}$), as a result of the optimization.

3. Results

Since we aim to determine the best-suited battery technology for various combination of applications and analyze the impact of geography and size, we present first the results for a typical battery size of 7 kWh depending on the battery technology, geography and for different combinations of applications (see Table 5). PV self-consumption is common across all combinations since this application is the baseline for residential batteries. Depending on the combination of applications, different tariff structures are needed, thus combinations of tariffs are done (*e.g,* if demand peak shaving is combined with PV self-consumption, then a flat tariff is combined with a capacity tariff, see the combination 2 in Table 5). 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 (4.8 kW_p for Geneva and 5 kW_p for Austin). Results for other PV sizes and alternative combinations of applications are given in Sections 4 and 5 of the SI.

3.1. Levelized cost

Fig. 3 displays the levelized cost of energy storage for six battery technologies and five combinations of applications in Geneva and Austin. 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 Austin offer lower cost per kWh since they are heavily cycled, (*i.e.* the average battery in Austin supplies 62% more electricity throughout its lifetime than in Geneva). As for Geneva, the LCOES also clearly decreases as household electricity consumption increases (demand data for both countries is analyzed in Section 1.1 of the SI). 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 Geneva where the battery use increases on average by 23% 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 Austin 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 in average by 14% in Geneva and by 9% in Austin.

Additionally, Fig. 3 shows the optimization results for the most likely values for every technology in terms of battery pack cost, calendric and cycle lifetime, DoD and round-trip efficiency according to Ref. [40] (except for ALA, for which there is no public data available beyond the proposed manufacturer, for further information see Section 1.5 of the SI). These values are very close to the chosen manufacturer. The greater difference corresponds to LTO chemistry, mainly due to the great cost's deviation (1650 USD/kWh is the average cost and 1060 USD/kWh is the most likely cost [40]).

3.2. Levelised value

Fig. 4 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 25% and 15%, respectively) because in both cases, less electricity is supplied by the battery due to a shallower DoD. 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 3.4). On the other hand, the cash flow is significantly lower for VRLA-based batteries due to low DoD (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 Geneva (*i.e.* in average 0.21 USD/kWh), compared to Austin. (*i.e.* in average 0.09 USD/kWh), due to higher electricity prices. Furthermore, when excluding demand peak shaving, batteries in households with higher demand create slightly more value per-kWh due to a higher self-

Table 5
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.

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

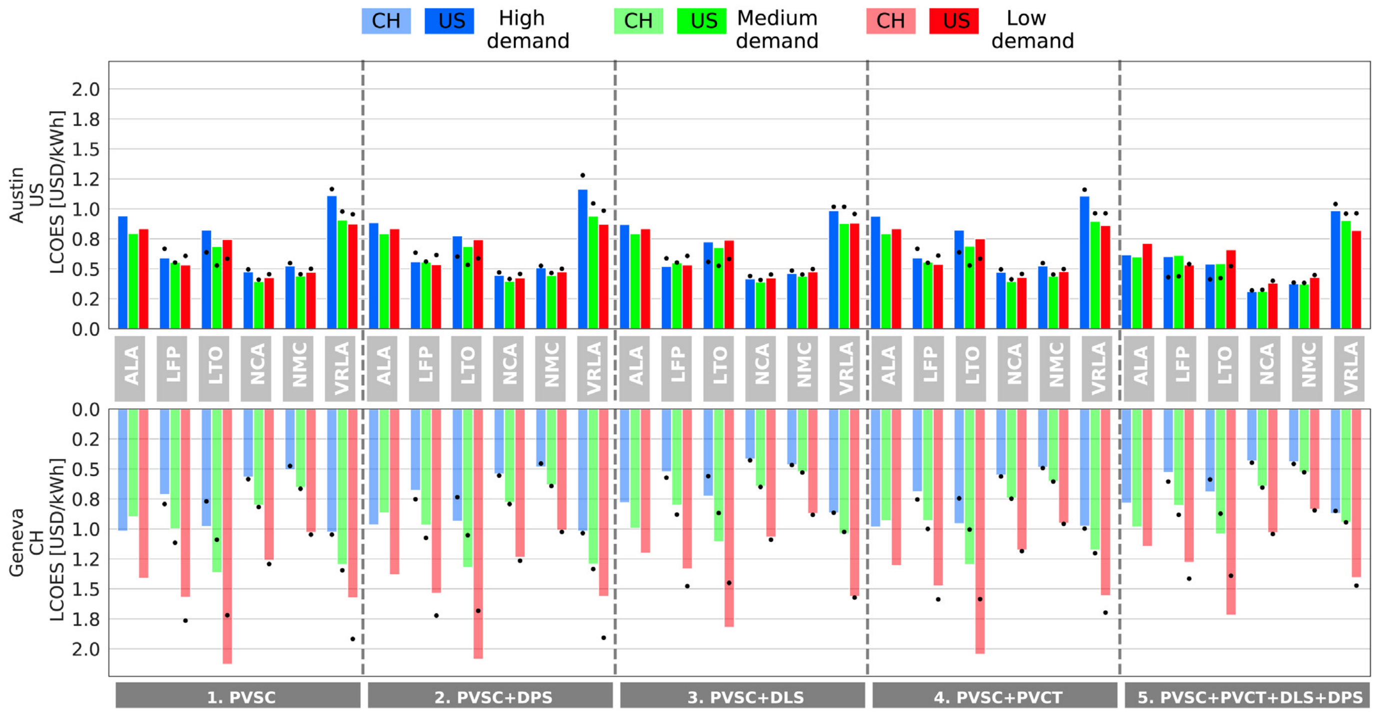

Fig. 3. Levelized cost of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for Auxtin, U.S. (top) and Geneva, Switzerland (bottom). The size of the PV system correspond to the median installed capacity across both geographies (*i.e.* 4.8 for Geneva and 5 kW_p for Austin). The black point in the graph corresponds to the optimization results for the most likely values for every technology in terms of battery pack cost, calendric and cycle lifetime, depth of discharge and round-trip efficiency according to Ref. [40] (except for advanced lead-acid, for which there is no public data available beyond the proposed manufacturer). Note that for the LCOES the lower is the bar the better are the results.

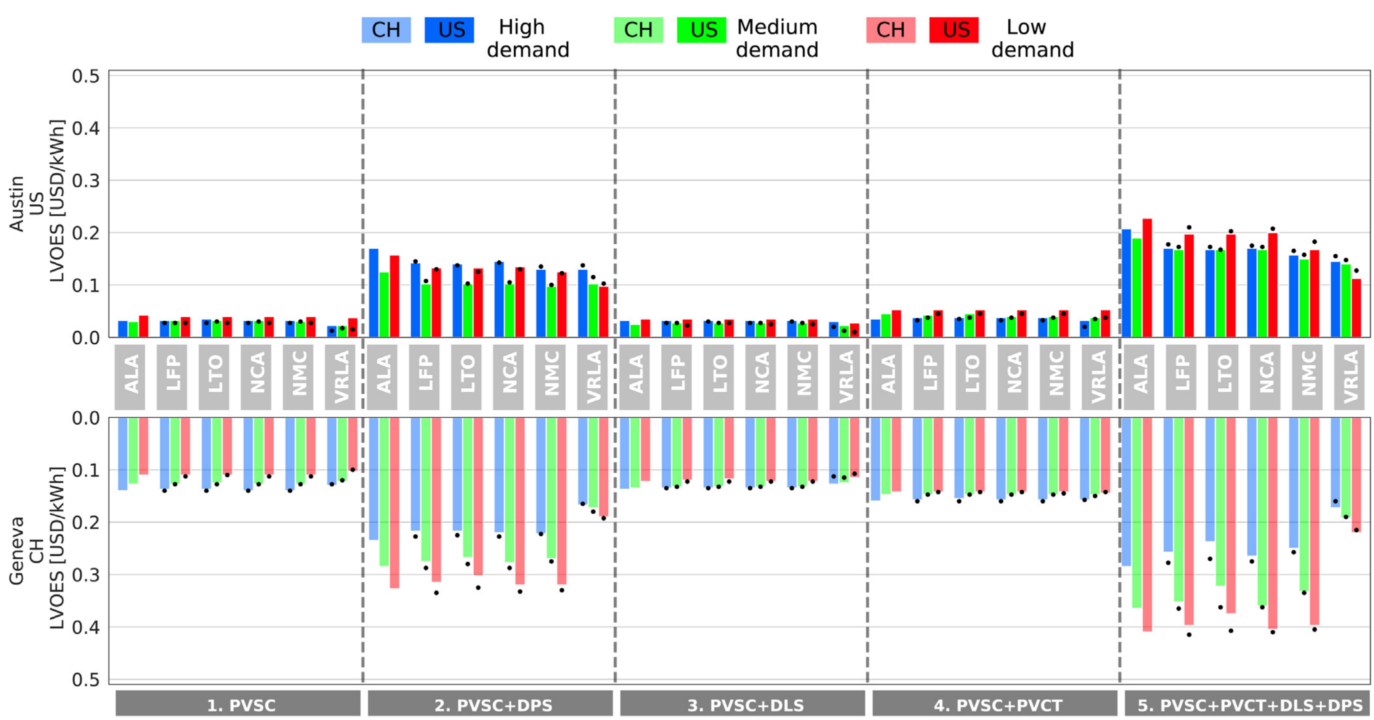

Fig. 4. Levelized value of energy storage of a 7 kWh battery for all battery technologies depending on the type of combination of applications for Austin, U.S. (top) and Geneva, Switzerland (bottom). The size of the PV system correspond to the median installed capacity across both geographies (*i.e.* 4.8 for Geneva and 5 kW_p for Austin). The black point in the graph corresponds to the optimization results for the most likely values for every technology in terms of battery pack cost, calendric and cycle lifetime, depth of discharge and round-trip efficiency according to Ref. [40] (except for advanced lead-acid, for which there is no public data available beyond the proposed manufacturer). Note that for the LVOES the higher is the bar the better are the results.

consumption. On the other hand, when demand peak shaving is included, batteries in Geneva 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 27% higher). This improvement is due to the synergies between demand load shifting and demand peak shaving (see Section 4 of the SI). Demand peak shaving is the application adding most value per-kWh, equal to 0.11 and 0.15 USD/kWh in the U.S. and Switzerland, respectively, owing to the importance of the capacity tariff in the final bill (even if the bill is revenue neutral when it is added as discussed in Section 2.2). The LVOES obtained when the optimization is run with the most likely values for every technology remains very similar (see the black points in Fig. 4).

3.3. NPV

Fig. 5 displays the NPV for all battery technologies depending on the type of combination of applications for Geneva and Austin. 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 not positive economic case yet. However, we can see that the profitability is markedly improved for most technologies by combining applications. Since the battery operation adds more value in Geneva than in Austin, 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 only 3 months before the project lifetime, which includes a supplementary investment to replace the battery and therefore further reduces the NPV (the same applies to high demand households for full combination of applications in Austin). In terms of applications, the combination of PV self-consumption with

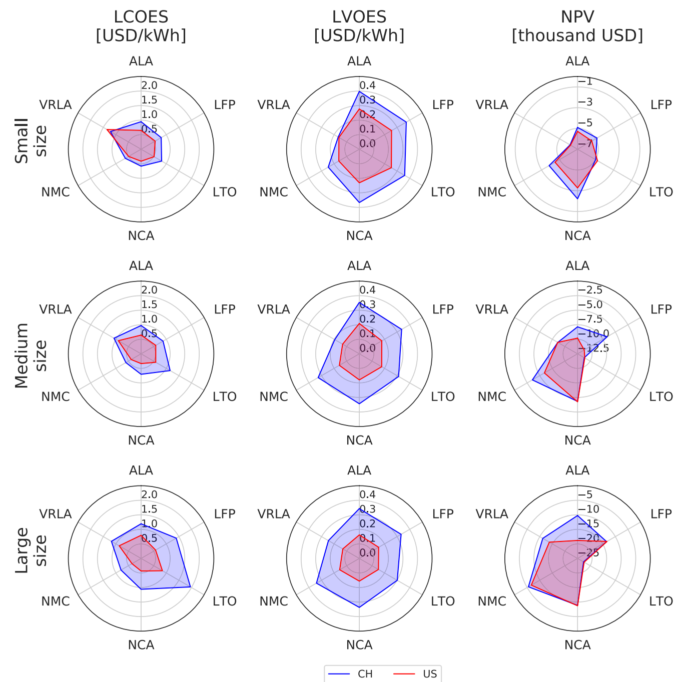

Fig. 6. Comparison of the average LCOES (left), LVOES (middle) and NPV (right) for various battery technologies performing simultaneously all consumer applications in Austin, U.S. (red) and Geneva, Switzerland (blue) depending on the type of annual electricity demand, namely small (top), medium (middle) and large (bottom). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

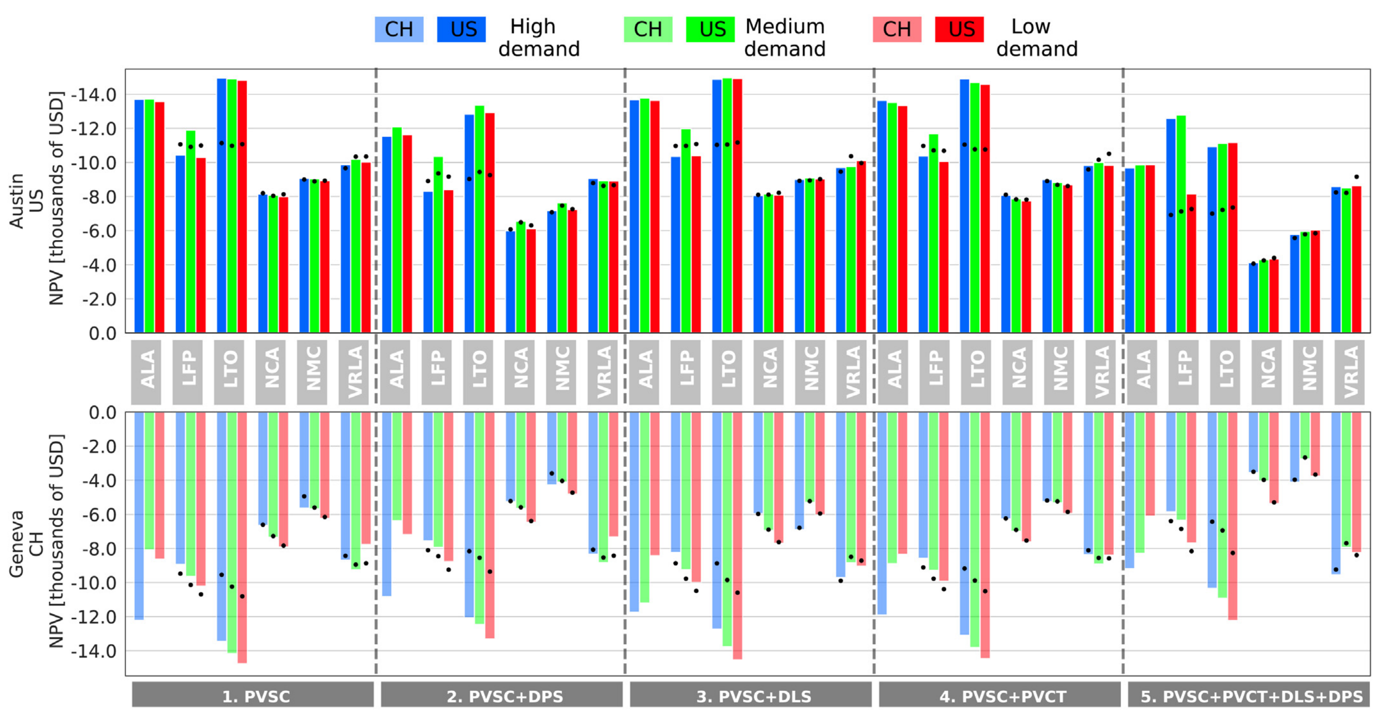

Fig. 5. Net present value of a 7 kWh battery for all battery technologies depending on the type of combination of applications for Austin, U.S. (top) and Geneva, Switzerland (bottom). The size of the PV system correspond to the median installed capacity across both geographies (*i.e.* 4.8 for Geneva and 5 kW_p for Austin). The black point in the graph corresponds to the optimization results for the most likely values for every technology in terms of battery pack cost, calendric and cycle lifetime, depth of discharge and round-trip efficiency according to Ref. [40] (except for advanced lead-acid, for which there is no public data available beyond the proposed manufacturer). Note that the y-axis presents negative NPV for both countries, thus the lower is the bar the better are the results.

demand peak shaving increases the NPV on average by 15%, which can be improved 6% more when demand load-shifting is included. The NPV obtained when the optimization is run using the most likely values for every technology remains very similar (see the black points in Fig. 4). The greater difference corresponds to LTO chemistry, mainly due to the great cost's deviation (1650 USD/kWh is the average cost value while 1060 USD/kWh is the most likely cost value[40]).

3.4. Impact of battery size

Fig. 6 displays the average levelized cost, levelized value and NPV across the three groups of consumers (see Section 1.1.1 of the SI), 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 Austin, lower levelized cost is reached. The per-kWh cost difference between the two countries increases when the battery size increases. In Geneva, a large battery incurs higher per-kWh cost due to relatively low number of cycles and higher capital expenditure. In contrast, in Austin, large batteries reduce further the levelized cost.

VRLA and NMC-based batteries increase their added value when the battery size increases. 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 Austin and very competitive with NMC-based batteries in Geneva for medium-sized batteries, while for large-sized batteries NMC chemistry get the best NPV. Overall, the NPV results of Fig. 6 indicate that batteries in Geneva are on average 13% (10% for small sizes, 16% for medium sizes and 12% for large sizes) more attractive than in Austin, due to higher value added as a result of higher electricity prices.

4. Discussion

Based on our experiments for Geneva and Austin, we find that NCA and NMC are the best-suited battery technologies for various combinations of applications including PV self-consumption, avoidance of PV curtailment, demand load shifting and demand peak shaving. When all the applications are combined, NCA is the best-suited battery technology in Austin, which is representative of geographies with high irradiance, households with high electricity consumption, low electricity prices and where the use of air conditioning is extended. On the other hand, NMC-based batteries reach in average a NPV 7% higher than NCA-based batteries in Geneva, where electricity consumption and irradiance are lower, electricity prices higher and where there is no air conditioning in summer. The household demand marginally affects the profitability of PV-coupled battery systems and the NPV difference is less than 10% (2% in the U.S. and 8% in Switzerland, on average) among the three consumption brackets for all technologies and combinations of applications. On the other hand, geography impacts the battery's economic viability and the NPV of battery systems in Geneva are on average 16% higher than in Austin, mainly due to higher electricity prices.

Despite significantly increasing the NPV, batteries simultaneously performing several applications are not profitable yet under existing

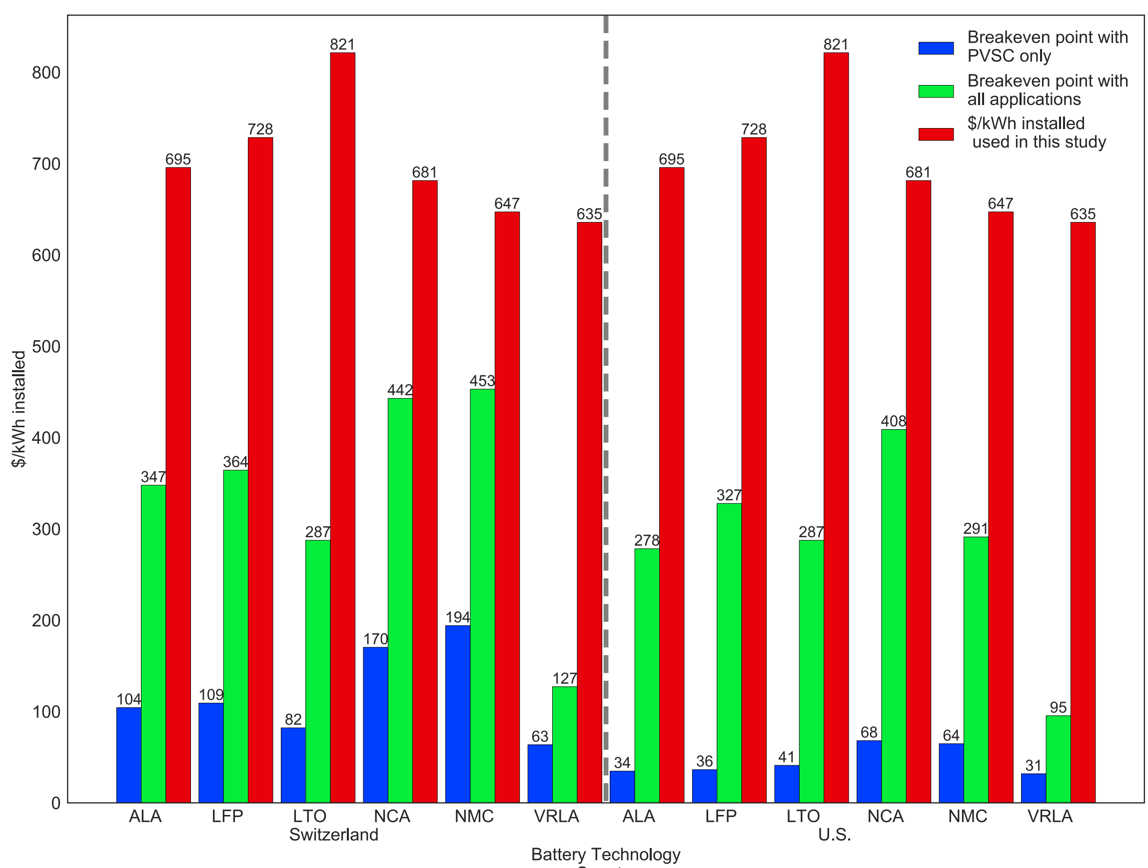

Fig. 7. Break-even point of a 7 kWh battery for all battery technologies depending on the type of combination of applications, PV self-consumption only (blue), the full combination of applications (green) and for comparison, the installed cost per kWh used in this study (red), for the U.S. (right) and Switzerland (left). The size the PV system correspond to the median installed capacity across both geographies. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

market conditions. However, further (expected) reductions in battery costs, together with the combination of 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 the number of cyle of batteries but when demand peak shaving is not included in the combination, it barely increases the NPV, even in Switzerland where a 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 geographies. However, with (installed) cost reductions of 55%, medium size 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. For instance, NCA-based batteries are more suitable than NMC-based ones when combining applications mainly due to higher charge and discharge rates, number of cycles and extended lifespan, even if their cost 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, batteries require further cost reductions regardless of battery technology. Installation costs (including permitting, inspection, interconnection, overhead, profit and installation labor) in Geneva and Austin are assumed to be $ 2000 in this study [51,52] but may reduce with increasing installation experience (learning by doing) and market competition. Fig. 7 displays the break-even point of a 7 kWh battery performing only PV self-consumption, and performing all four applications depending on the battery technology and geography. The current total 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 35% reduction in total costs to be profitable in Switzerland and 40% in the U.S. NMC-based batteries in Switzerland require a 30% reduction on total 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 83% in the total cost per-kWh-installed, compared to today's cost, is required. On the other hand, when all applications are combined, a reduction of only 52% is required. In the case of the U.S., further reductions are needed (93% if only PV self-consumption is addressed and 60% if all applications are combined). According to IRENA, the total costs of lithium-ion batteries' will be reduced by 60% on current levels by 2030 [38], 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 even shorter if electricity prices increase as projected.

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 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 DoD 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 already established and other criteria such as their material criticality is far lower compared to lithium-ion batteries [58]. 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.

5. Conclusions

The aim of this study is to determine the best-suited battery technology for various combination of applications including PV self-consumption, avoidance of PV curtailment, demand load shifting and demand peak shaving for Austin (U.S) and Geneva (Switzerland), which are two geographies with different solar irradiance levels, electricity prices and electricity demand profiles. Our analysis takes into account three battery sizes, namely 3 kWh, 7 kWh and 14 kWh and based on our tests, we conclude that NCA and NMC are the best-suited batteries in both geographies and for all the combinations of applications, being NCA slightly better in the U.S.

Moreover, emerging from the present study, we point to four key factors that influence the economic profitability of a PV-coupled battery system and assess their intrinsic uncertainty: (a) The low influence of annual household demand, which in this study varies from 4.9% in Austin to 2.2% in Geneva; (b) the rather high impact of the geography since the NPV is 18% higher in Geneva than in Austin, whose uncertainty is medium since the environmental factors (e.g., solar irradiance and temperature) are widely known but there is rather high uncertainty in the electricity bill structure; (c) the medium impact of battery technology which depends not only on the technical characteristics, which are already appropiate for residential applications, but as well on battery costs which are still high for the same niche and whose uncertainty is rather high; and (d) the impact of the combination of applications, which can be marked, especially when demand peak shaving is included, 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 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 [59]. 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.

The open-source model used in this study is publicly available in https://github.com/alefunxo/Basopra, and could be used for other geographies with different solar irradiance levels, demand profiles, tariff structures as well as alternative storage technologies.

Conflicts of interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2019.06.003.

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