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SPECIAL ISSUE PAPER

Providing primary frequency control with residential scale photovoltaic-battery systems

A techno-economic simulation study of a virtual power plant

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Abstract Decentralized photovoltaic (PV) battery systems have recently received great attention from consumers around the world. PV battery systems allow consumers to reduce their dependence on the local electricity supplier at lower or equivalent costs. However, the profitability of PV battery systems depends greatly on the local meteorological conditions and the local electricity retail tariff. In central European countries, PV battery systems generate and store less electricity in winter months due to lower irradiation. The battery, in particular, can be reserved to provide ancillary services during winter months and thereby improves the overall systems economics. In this study, a large dataset consisting of individual load profiles is used to simulate a virtual power plant which provides ancillary services during battery idle times. The results show that participants with large batteries can greatly increase their overall systems economics by participating in reserve markets. However, participants with small battery capacities may not be able to recover the additional costs for communication with the virtual power plant and are thus not suitable candidates to provide grid stabilizing services (ancillary services).

Keywords Photovoltaics · Stationary battery storage · Self-consumption · Frequency regulation · Virtual power plant

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1 Introduction

A significant number of photovoltaic (PV) systems have been deployed in the last decade due to attractive policies (e.g. feed in tariffs in Germany, FiT), which resulted in massive manufacturing scale up and subsequent PV module price reductions. In 2015, 7.4 % of the net German electric energy demand is covered by approximately 1.5 million PV installations [5], which corresponds to an installed capacity of approximately 40 GW. The ongoing reduction of manufacturing costs of PV modules have recently led to decreased FiTs. In Germany, the FiTs for residential scale installations are below the retail rate (currently between 0.0853 and 0.1231 €/kWh [5]) and are guaranteed over time period of 20 years. Therefore, end consumers may choose to operate the PV system in a so called self-consumption mode, where rooftop PV modules fuel directly the electric energy demand of a building (behind the meter). In self-consumption mode, the cost of PV are in direct competition with the local retail price rather than with the generation costs of a particular power plant alone. Hence, a PV installation can create a monetary value whenever its levelized cost of electricity (LCOE) is below the local retail tariff [9]. Self-consumption and grid-independence can be increased by adding battery storage to the system. Although currently rather expensive, also Lithium-ion battery costs have started to decline and are assumed to follow a similar learning curve as seen for PV panels as manufacture scales up. A further driver of battery cost reduction is the increasing demand of electric vehicles (EVs) which causes a consequent scale up of battery manufacturing (e.g. Gigafactories) [1,13,23].

In central European countries, PV-battery systems operate mainly in spring, summer and fall months if their sole purpose is to increase self-consumption. During idle times in winter, they can be used to provide additional services like peak shaving, arbitraging, grid upgrade-deferral or ancillary services and thereby increasing the economics of the overall system [14].

In this article we study the superposition of two operating modes: self-consumption and primary frequency control (PFC). PFC can lead to additional revenues and increase the overall system economics. The goal of this contribution is to asses and identify feasible conditions for which self-consumption coupled with PFC can lead to increased economic performance.

2 Primary frequency control with battery systems

In a liberalized market the transmission grid operator (TSO) organizes the following ancillary services as part of its legal obligations: Frequency control (primary control, secondary control, tertiary control), voltage support, etc. Throughout this article we focus only on primary frequency control (PFC) as batteries are well suited to provide this type of service.

Electricity or electrical energy cannot be stored in large quantities by conventional means. For this reason, at any given point in time, the amount of electricity produced must correspond precisely to the amount being consumed. This balance guarantees the secure operation of the electricity grid at a constant frequency of 50 Hz. Unforeseen fluctuations between the feeding-in and withdrawal of electrical energy in the grid must be balanced out at short notice, which is done by the suppliers of control energy increasing or reducin g power plant output. In the concurrence of an imbalanced grid, primary frequency control (PFC) is invoked to stabilize the frequency followed by secondary and tertiary control which restores the frequency to its nominal value of 50 Hz (+/−50 mHz death band) [22].

TSOs across Europe may require different requirements for the provision frequency regulation. We follow here the requirements and guidelines for the TSO of Switzerland (Swissgrid AG). Swissgrid organizes weekly tenders for the provision of primary frequency control. The minimum bidding reserve is ±1 MW with a maximum allowance of ±25 MW per tenderer. The successful tenderer is then obligated to reserve the offered capacity at the offered price during one week with a lead time of 45 s and a maximum duration of 15 min per invocation. The successful tenderer is paid as bid.

Battery systems are well suited to provide this kind of service for two main reasons. Firstly, batteries can react orders of magnitudes faster than traditional power plants. This may become an important advantage as the required reaction time may decrease significantly with increasing share of renewable [24]. Secondly, batteries can provide power reserves (up and down regulating power) without producing energy, effectively decoupling power from energy provision [7]. Single household units with rooftop PV systems combined with batteries cannot provide PCR alone but in combination with other rooftop PV-battery installations when aggregated in a virtual power plant (VPP). In this study, a large dataset of 4232 load profiles is assumed to represent individual participants of a VPP. All load profiles are simulated in self-consumption mode with an ex post evaluation of battery idle times. In idle mode, each individual battery participates in PCR provision within the VPP. This set up allows to resolve and compare additional revenues from the PCR market with additional expenditures for VPP communication/hardware on a household level.

3 Literature review

The flexibility of electricity storage units is known to cover a large range of the electricity value chain. Thus, the combination of different use cases for stationary storage units to generate additional revenues has been vastly discussed in the academic literature. Malhorta et al. [11] present a literature review on stationary battery storage applications, their profitability and use cases. Based on expert interviews from industry and academia, the authors identified three trends for possible use cases. These include demand charge reduction, residential solar integration (increase of self-consumption) and frequency regulation. Megel et al. [12] studied the situation in which large batteries are used to overcome transformer bottlenecks (peak shaving) in low-voltage grids. In that situation, transformers overload (and subsequently overheat) in periods of large demand or large PV generation. However, these events occur rarely, resulting in a mostly inactive battery. The inactive battery can be used for PFC when not providing the peak shaving reduction service. The authors find that the profits generated by a battery providing both peak-shaving and PFC services are almost equal to the sum of the profits from two identical battery sets, where one provides only the local service and the other only the PFC system service. In addition to stationary batteries, batteries in electric vehicles may also be used to provide ancillary services, as proposed by Vaya and Anderson [25]. They compared charging costs for plug-in electric hybrids (PHEV) with revenues that could generated from primary frequency control in different market settings. The authors conclude that charging costs may be offset by the revenues from the capacity reserve market. The work of Steber et al. [20] is dedicated to different control strategies for individual storage units and market settings. The analysis focuses on the first virtual power plant pre-qualified for the PCR market in the German control area TenneT in 2015. The paper discusses the uncertainty of the regulation for the provision of PCR services in terms of the hold-back time of the reserve capacity. They also show that appropriate control strategies can be used to provide both PCR and self-consumption service in parallel by dedicating a minimum and upper storage level for PCR. The control strategy has been validated with a simulation which demonstrated that the loss in grid independence is small when incorporating PCR with different hold-back time durations.

Existing research, however, has not addressed how different PV battery configurations and individual load profiles affect economic performance. Households with large financial returns on additional investments in VPP infrastructure (mainly communication with VPP) are identified and discussed. In this article, a virtual power plant (VPP) represented by a set of individual load profiles is techno-economically simulated. The economic benefits resulting from VPP participation are shown for each individual member.

4 Methods and data

4.1 Hypothetical setup and general approach

This article uses 4232 real load profiles with a duration of one calendar year that are assumed to represent a virtual power plant. Each load profile corresponds to a single building which can be equipped with a PV-battery system as shown in Fig. 1.

The system is sized to maximize the independence from the grid by maintaining positive definite net present value without taking any revenues from PFC markets into account (baseline mode). The optimization procedure that maximizes the grid independence has already been developed in previous contributions [17,18]. For completeness and for the sake of clarity, the relevant content developed in [17,18] is briefly outlined in Sects. 4.2, 4.3. Once all load profiles have been processed with the system configuration that maximizes grid independence, the state of charge (SoC) over time and all energy flows between the system components (Fig. 1) can be quantified. In particular, the energy that flows into and out of the battery is used to determine the number of cycles over a given time horizon. The threshold number of cycles within a particular time window is used throughout this work to define the battery idle times where the battery can be used for PFC services. Battery idle times are defined in terms of a weekly cycle threshold number (i.e., whenever the cycle number throughout a week is lower than the threshold value $N_{\max}$. In practice, this requires a predictive element in the PFC control strategy. However, throughout this work we assume perfect information and forecast for future cycle numbers. During idle times, the batteries are assumed to be fully reserved for the PFC service and cannot be accessed for the self-consumption service. However, self-consumption is not completely turned off during idle times, since some of the demand may be directly covered by PV generation (without storing energy intermediately in the battery). The revenues from the capacity reserve markets are calculated per household according to the capacity provisioned. Thus, participants that offer lower capacity receive proportionally smaller revenues from the primary reserve market.

4.2 Unit simulation model

A simulation framework has been built to assess the economic viability of PV-battery systems for self-consumption applications. That model is described in detail in previous articles [17,18]. The framework is capable of modelling the fundamental physical processes taking place in each component of a PV-battery system for a given load profile with a temporal resolution of 30 min. The most important input and out variables of the simulation model are summarized in Table 1.

A brief overview of the modelling approach from [17,18] is given in the remainder of this subsection.

4.2.1 PV modules

The current-voltage characteristic and its deviation from the standard testing conditions (STC) is calculated for each time step in the simulation using so called translation equations [16]. The electronic properties of a commercially available

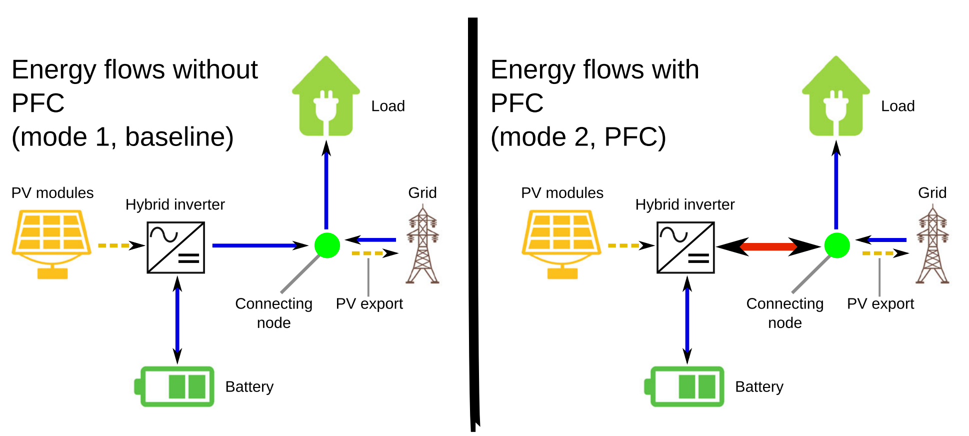

Fig. 1 Technical setup and energy flows between the components in self consumption (baseline) and PFC mode. The difference between the two modi is, that the battery takes also energy from the grid, which is used for down regulation (negative regulating power)

Table 1 Overview of the simulation input and output variables

Simulation inputs
- Load profiles - El. properties of PV modules - Installed PV and battery capacity - Module orientation and tilt - Weather data (sol. irradiation and temp.) - Investment cost and tariffs
Simulation outputs
- Battery state of charge over time - Degree of self-sufficiency - Net present value (NPV) - Internal rate of return (IRR) - Levelized cost of electricity (€/kWh)

mono-crystalline PV module is taken as input data. The model is sensitive to ambient temperature and solar radiation.

4.2.2 Battery storage

Many battery models have been discussed in the literature [4]. Often they are very detailed and can determine voltage-current relations on the cell level. However, these models are often restricted to a certain battery type or chemistry and require often complicated estimation of parameters. For the simple estimation of the economic viability of operation modes it is sufficient to model the battery using a simple energy balance with a given energy capacity.

4.2.3 Battery ageing

In this article, we do not restrict ourselves to certain a battery type or chemistry, but set certain requirements regarding the maximum number of cycles. The battery (for example Li-Ion) should be able to endure $N_c = 4000$ cycles before its capacity fades to 80 % of its initial capacity (theoretical end of life, EoL). It is assumed that the EoL can be determined by the total energy throughput, which can be obtained by cycling the battery $N_c = 4000$ times. At the EoL, the battery is assumed to be replaced at the expense of the end consumer/owner of the installation. The maximum discharge depth (DoD) allowed to reach $N_c = 4000$ is assumed to be 80 %.

4.2.4 Inverter and battery discharging/charging losses

Inverter losses typically depend on the voltage level and the converted power. For the sake of simplicity, throughout this work, we assume that the inverter has an average efficiency of 95 %. The battery discharging and charging efficiency are also assumed to be constant at 95 %. The roundtrip efficiency of the battery is therefore 90.3 % before the inverter and 81 % after the inverter (AC–AC roundtrip efficiency), respectively.

4.3 Load and weather data

Half-hourly load data from a large smart-meter pilot project in Ireland is used [2]. The dataset contains 4232 load profiles from participants all over Ireland collected during 75 weeks. Each load profile has been cropped to represent a full year with 17,520 data points per load profile or consumer, respectively.

Hourly solar radiation data (direct and diffuse radiation) and temperature data is used for the location of Zurich, Switzerland [26] for a typical meteorological year (TMY). The data is preprocessed to using solar azimuthal and elevation angles to project the radiation on any arbitrarily oriented surface [16].

4.4 PFC market data

The TSO of Switzerland (Swissgrid) provides historic bidding data for PFC services. A complete dataset for the year of 2014 has been used. For each week of the year 2014 bids for a certain amount of regulating power are given. Since the bidding process and the price formation itself are not modelled in this article, an average weekly price is taken as a reference value for each week of the year 2014 as shown in the upper plot of Fig. 2. The plot below shows the provisioned capacity in MW for every week of the year 2014. The maximum provisioned capacity for PFC in 2014 was 92 MW.

4.5 Cash-flow analysis

Once all physical state variables are known over time, the energy flows between all system components can be deter-

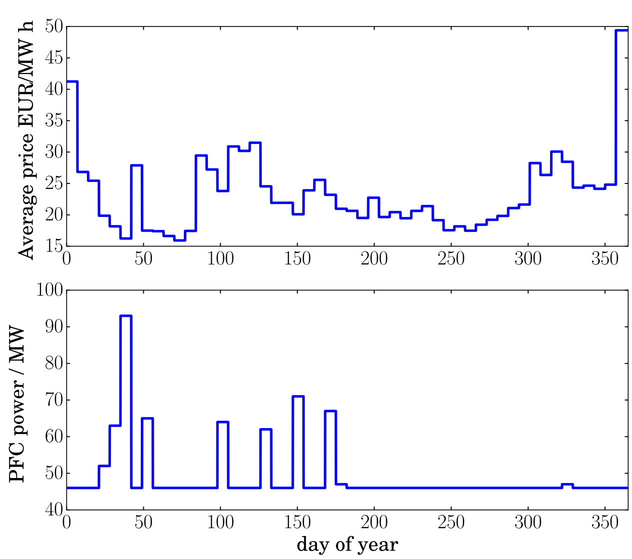

Fig. 2 Primary frequency control prices and reserved capacity for the year 2014 in the Swiss control area [reference]

mined. The cost savings from the energy supplied from the PV modules or battery systems can be compared against the initial investment costs. This is done using the discounted cash- flow method which allows to derive a number of economic key performance factors such as net present value (NPV) or levelized cost of electricity (LCOE). The cash-flow model automatically determines the battery EoL and accounts for battery replacement costs. All economic calculations are performed by ignoring any upfront incentives such as cash-boni, subsidized feed-in tariffs or tax benefits. In the model that considers self-consumption plus PFC, the revenues from the reserve capacity market (by providing PFC) are considered in addition to the cost savings from PV-generated electricity.

5 Simulation study

5.1 Simulation study setup

Using a simulation study, we aim to compare two operational modes: self consumption (baseline) against self-consumption with PFC provision within a virtual power plant. For each consumer (load profile), the system is sized by maximizing the grid independence while maintaining a positive net present value of the PV battery system in the baseline operational mode. For each consumer (load profile), idle times of the battery system are identified. During these time windows, the system is allowed to participate in PFC provision to generate additional revenues from the PFC market. Additional investment costs for hardware and communications necessary to participate in PFC markets are taken into account.

5.2 Probabilistic input variables

In order to test the two operation modes under realistic conditions, we assign to each load profile in the dataset a fixed orientation and tilting angle using a given probability distribution. Thus, each consumer is assumed to live in an independent house with defined orientation and tilting angle of the building. The seed used for drawing the random numbers from the tilt and orientation angle distributions has been set to a constant, which ensures the reproducibility of this work. The probability distribution for the orientation is assumed to follow a normal distribution [10] with location parameter loc $= \mu = 180^{\circ}$, and scale parameter scale $= \sigma = 50^{\circ}$. For the tilt angle of the PV module a Gompertz distribution is taken (loc = 0, scale = 12, shape = 0.03) as Fig. 3 shows.

Once the module orientation is assigned, a Monte-Carlo-simulation starts where randomized combinations of the installed PV capacity (kWp) and battery storage capacity (kWh) are simulated. Both the PV installed capacity and the battery storage capacity is drawn from a continuous and uniform probability distribution $U(a, b)$ within the specified upper a and lower bounds b.

With reference to Table 2, uniform random numbers for the PV installed capacity are drawn between 0.26 kWp (corresponds to one PV module) and 30 kWp (maximum

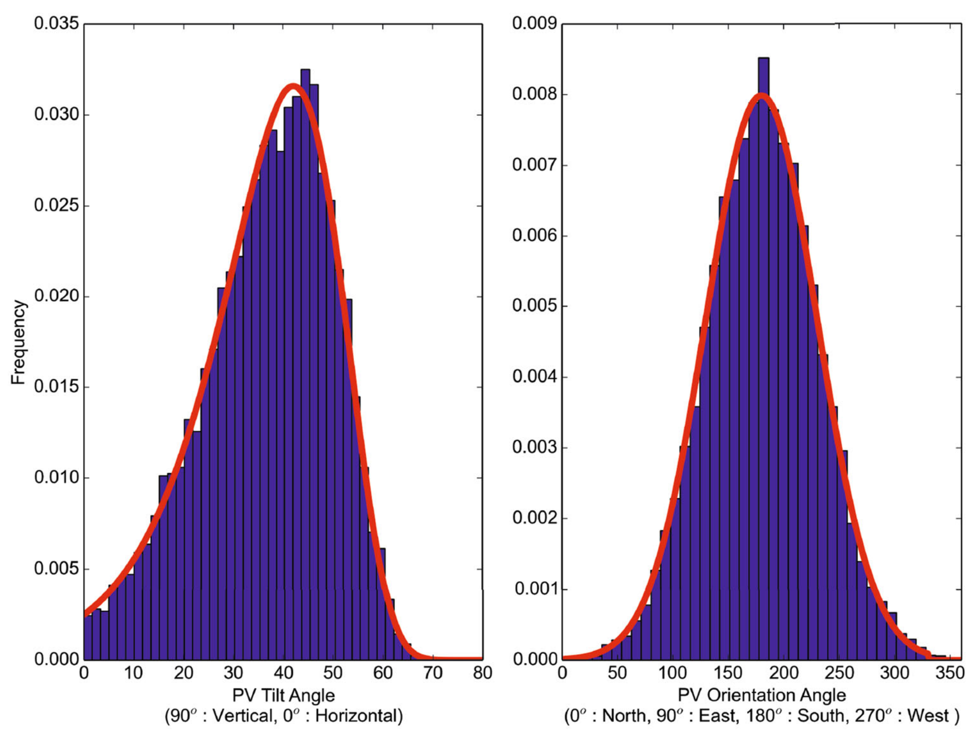

Fig. 3 Probability distribution function for panel tilt and orientation

Table 2 Upper and lower bound limits for the draw of randomly generated PV installed power and battery capacity

Installed PV capacity (kWp)	$a > 0.26$	$b \leq 30$
Battery storage capacity (kWh)	$a > 0.00$	$b \leq 20$

installed PV capacity that is legally allowed to operate in self-consumption mode). The installed battery capacity is uniformly sampled between 0 kWh and 20 kWh. Each of the two variables are sampled 256 times. The 256 combinations are forwarded to the unit simulation, which cannot be executed on normal personal computers due to the large number of consumers in the dataset and the large number of repetitions per consumer (256). More than 1 million cases must be simulated (256 × 4232). Code parallelization has been applied to split-up the problem to multiple cores. The simulation code is currently executed using the super computer called Brutus of ETH Zurich, which allows to utilize up to 128 CPUs in parallel.

5.3 Deterministic input parameters

The deterministic input parameters are summarized in Table 3 and have been mainly adopted from [17,18]. Note that subsidies are excluded from the economic calculation. Furthermore, the price for additional hardware and communication has been priced with 1200 €and corresponds to a commercially available product [3]. The VPP must be operated and managed by a third party aggregator. Margins from PFC market transactions in favor of the third party aggregator are not taken into account.

5.4 Aggregation of simulation results

The Monte-Carlo-simulation generates 256 cases per consumer for each output variable, which must be aggregated in a meaningful way. The aggregation strategy consists in combining the installed PV power and the battery capacity that maximizes grid independence, while maintaining a NPV of greater or equal to zero.

5.5 VPP simulation and revenues from PFC market

Once the optimization has identified the system configuration which yields maximum grid independence with NPV ≥ 0, battery idle times are identified for each consumer k. The battery is defined to be in idle mode based on the average weekly cycle number in week j for each participant k. In

Table 3 Deterministic input parameters

	Value	Comment
PV module properties		
Open circuit voltage/short circuit current	37.8V/9.8A	CAP
Max. power point voltage/current	30.7V/8.5 A	
Voltage/current temperature coefficient (at STC)	0.06/−0.31 %/K	
Module surface area	1.63 m^2	
Battery properties		
Battery life cycles	4000	CAP
Max. depth of discharge (DoD)	80 %	
Inversion efficiency		
Inverter efficiency	95 %	CAP
Charge/discharge efficiency	95 %	
Economic parameters		
Specific plant costs incl. installation excl. battery	2000 €/kWp	[8]
Battery costs	500 €/kWh	[13,15]
Battery replacement costs	200 €/kWh	
Discount factor	3 % p.a.	
El. price escalation rate	2.5 % p.a.	[21]
Incentives (cash-bonus)	0 €/kWp	
Tariffs (based on Zurich, Switzerland)		
High/low tariff rate (high tariff: 6 am to 10 pm Mo-Sa)	0.24/0.12 €/kWh	
Feed in Tariff (FiT)	0 €/kWh	
VPP costs		
Hardware and communication cost	1200 €	[3]

CAP commercially available product

order to compute the weekly number of cycles for participant k, the energy transferred from the battery (B) to the load (L) in week j, defined as $W^{j,k}_{B\rightarrow L}$, must be calculated first. The cycle number in week j, can be understood as the ratio between $W^{j,k}_{B\rightarrow L}$ and the available battery capacity $E^k_{bat}\cdot$DoD. Therefore, the average cycle number over each participant in the VPP is given by

$$\bar{N}_j = \frac{1}{n_u}\sum_{k=1}^{n_u}\frac{W^{j,k}_{B\rightarrow L}}{E^k_{bat}\cdot \mathrm{DoD}} \tag{1}$$

with $n_u = 4232$ the size of the VPP (i.e. number of participants). The battery is fully assigned to PFC mode whenever the weekly average number of cycle is below the threshold $N_{\max}$. During weeks where the relation $\bar{N}_j \leq N_{\max}$ holds, the battery remains charged at half capacity to provide up and downward regulating power. In this article, we define $N_{\max} = 4$; more simulations are needed to find the optimal value of $N_{\max}$. It is assumed the that the battery technology can be charged or discharged at a specific rate $\lambda = 1.0$ kW per kWh battery capacity, which applies to the commonly used $LiFePO_4$ chemistry and is frequently used for stationary battery applications.

As stated in Sect. 2, the capacity needs to be provisioned for a time window of maximum $\Delta t_{\mathrm{PFC}} = 15$ min. At all times, the battery must thus be able to maintain a constant charging/discharging rate for a maximum of 15 min without over or undercharging the battery (red regions in Fig. 4). This implies, with reference to Fig. 4, that the battery should be charged at an SoC of 50 % in order to provide up and downward regulation. However, deviations from 50 % SoC are possible by using the security margins as shown in Fig. 4. In case of a fully activated reserve capacity, the charged or discharged energy in the time interval of Δt_{PFC} =15 min is given by $\lambda \cdot E_{bat} \cdot \Delta t_{\mathrm{PFC}}$ and cannot exceed $E_{bat} \cdot \mathrm{DoD}/2$, where E_{bat} is the rated battery capacity in kWh. Mathematically, this leads to the inequality

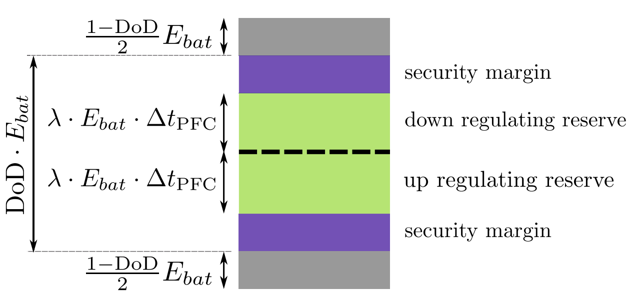

Fig. 4 Schematic representation of reserved storage capacity for PFC. The *center portion* of the battery is reserved for PFC. The *blue portions* may be used to provide the self-consumption service. However, in this article, parallel operation of PFC and self-consumption mode is not considered. Consequently, the *blue portions* are assumed to represent security margins for the reserve capacity (color figure online)

$$\lambda \cdot E_{bat} \cdot \Delta t_{\mathrm{PFC}} \leq E_{bat} \cdot \mathrm{DoD}/2 \tag{2}$$

$$\lambda \leq \mathrm{DoD}/(2 \cdot \Delta t_{\mathrm{PFC}}) \tag{3}$$

$$\lambda \leq 1.6\ \mathrm{h}^{-1} \tag{4}$$

This conditions holds for the chosen technology $\lambda = 1\ \mathrm{h}^{-1}$.

The VPP, consisting of the 4232 individual load profiles can deliver a significant contribution for total demand of PFC in the Swiss control area. Many degrees of freedom exist for the optimal distribution of the reserve capacity among the individual participants. However, the focus in this article is on the individual household, and the additional profit it can generate by participating in the VPP. Each consumer participating in the VPP will be remunerated according to the provided capacity, which permits an individual analysis of a household participating in the VPP. Note, that the third party aggregator may claim a significant portion of the revenues generated from the PFC market. However, in this article, the third party aggregator generates only income from the additional communication units necessary to operate the VPP. Any margins or fees from PFC market revenues are not taken into account and are directly forwarded to the PV battery system owner.

6 Simulation results

The optimal PV battery system configuration is quantified for the case of self consumption only (baseline). Given that no subsidies in any form have been taken into account, the optimization in the baseline scheme yields relatively small system components (small PV modules and batteries) [18] which only lead to modest end user autonomy factors. In fact, approximately 78 % of the consumers analyzed for the location of Zurich, Switzerland, can reach a NPV of larger or equal to zero. The remaining 22 % cannot reach a NPV of larger or equal to zero due to small annual demand or non-beneficial load profile shape [18]. Via a post-processing step, the idle times of each end user is identified using $N_{\max} = 4$. This implies that the VPP reserves capacities for PFC when its average cycling number in week j is smaller or equal than $N_{\max} = 4$. Revenues from PFC markets are assigned according to Fig. 2. The system economics is for each participant re-evaluated using the discounted cash flow method. The case where self-consumption and PFC is combined can be compared in terms of NPV and IRR as shown in Figs. 5 and 6. It is clearly observable that the participation in PFC markets results in net economic benefits as the histogram moves towards higher net present values when providing capacity for PFC.

From an investors perspective, it is more meaningful to relate the cash flows to the capital expenditure and report an average return, which is known as the internal rate of return (IRR). The IRR for baseline and PFC is shown in Fig. 6.

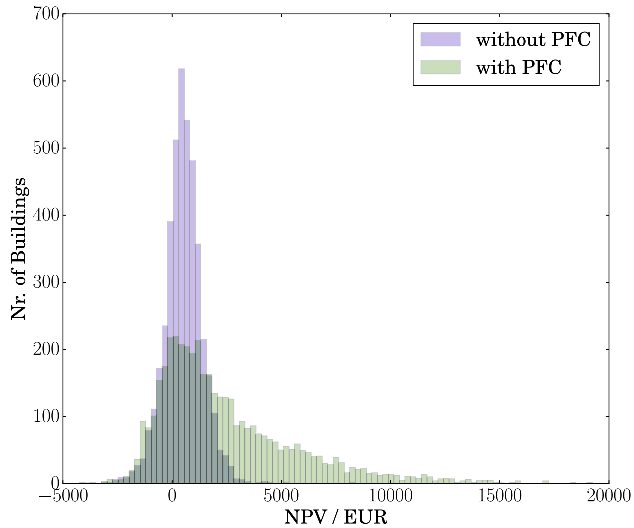

Fig. 5 Histogram of the net present value (NPV) in self-consumption mode in comparison with self-consumption mode with the provision of primary frequency control (PFC). The revenues from the PFC markets move the histogram to higher net present values

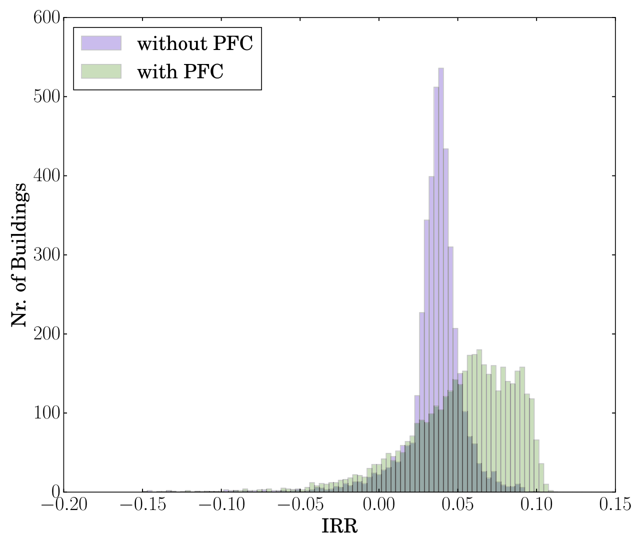

Fig. 6 Histogram of the internal rate of return (IRR) in self-consumption mode in comparison with self-consumption mode with the provision of primary frequency control (PFC). The revenues from the PFC markets move the histogram to higher values of IRR

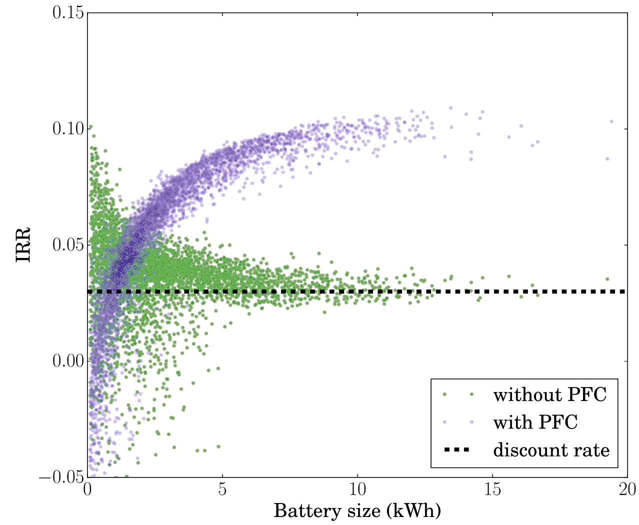

Fig. 7 Battery size versus internal rate of retunr (IRR) in self-consumption only mode, in comparison with self-consumption mode with the provision of primary frequency control (PFC). Larger batteries can provide more power for PFC, which results in larger returns for larger batteries in that case

The IRR clearly benefits from the provision of capacity for PFC and reaches a maximum IRR of approximately 10 %. The battery size is a determinant for the additional revenues that an individual household can generate within a VPP as the battery size directly correlates to the maximum capacity the battery can provide (through the factor λ). Thus, the individual economic performance within a VPP correlates with the IRR as shown in Fig. 7; each data point in Fig. 7 refers to an individual consumer in self-consumption only mode (baseline, green dots) and self-consumption combined with PFC. It can be inferred from Fig. 7 that batteries tend to have a higher IRR in baseline mode than in self-consumption plus PFC mode. For larger batteries, the situation is very different: In the baseline mode they come with lower IRR than smaller batteries, as it is more difficult to amortize the larger investment costs over time. Small systems fail to amortize the additional investment costs for communication with the VPP, as their share of revenue from the VPP is too small. A system with larger battery size can provide more power for PFC and can thus receive a larger share of the VPP revenue. Note that the provision of PFC capacities result in a reduced performance in the self-consumption mode. While the PV systems alone can still cover portions of the buildings load, the battery system is assumed to remain in standby mode while providing PFC reserves, which results in a reduction of the grid independence factor. Figure 8 shows the grid independence factor in baseline mode (self-consumption only) in comparison with self-consumption and PFC reserve provision. It is clearly observable that the higher the grid independence factor is in the baseline, the more it reduces the grid independence factor when providing PFC. Consumers with larger grid independence also have larger batteries, which then suffer from a proportionally larger loss in independence when providing PFC capacities. On average, the grid independence factor is reduced by less than 2.0 %.

7 Conclusions and discussion

This analysis shows that capacity reserve markets are an attractive way to increase the economics of PV battery systems and offer a way to utilize the system in time periods

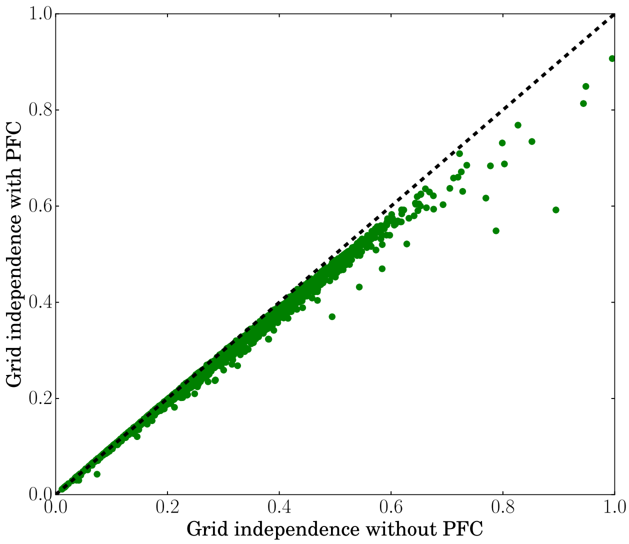

Fig. 8 Comparison of grid independence in self-consumption mode and in self-consumption mode plus PFC. PFC provision potentially reduces the grid independence factor, because the battery is reserved for PFC in certain weeks of the year

during which the system is rarely used for self-consumption operation (mainly winter). The main finding is, that owners of large battery systems can greatly improve the economics of their PV battery system. By contrast, smaller PV battery installations have smaller return for PFC applications because the additional costs necessary for VPP communication are more difficult recovered with lower revenues from the PFC market. This is in contrast to the situation where the system is only used for self-consumption (baseline); in that case larger systems become less economical because of their higher capital expenditure. The revenues from PFC markets may lead to favorable investment conditions in distributed PV battery systems. However, the risk of falling PFC market price during the long project duration is non-negligible and must be better understood to give conclusive investment recommendations. Furthermore, a widespread adoption of the VPP concept is limited by the maximum reserve capacity of approximately ±100 MW (for Switzerland).

The parallel operation of self-consumption and PFC is feasible and may give additional flexibilities and potentially larger revenues. However, there might be significant losses in grid independence and self-consumption, which was most likely the primary operating mode or use case of the system. Depending on the system ownership, conflicts of interest may arise between the end user and the VPP aggregator, as the latter receives more flexibility and opportunities to realize additional profits.

The threshold $N_{\max}$, which defines the maximum, weekly average cycle number for VPP to operate in PFC mode, has been set to $N_{\max} = 4$ for the purpose of this analysis. This may be a reasonable choice, considering the battery is cycled once per day under ideal conditions. For a particular week, this would imply that the battery is in idle time if it is used less than 4 out of 7 days. However, the proper value must be discussed by repeating the techno-economic evaluation for different values of $N_{\max}$. It is clear that the grid independence decreases with increasing $N_{\max}$, therefore a pareto-optimal choice may be found for $N_{\max}$. This will be subject to future investigations.

In this article, the system is sized in self-consumption mode only. Revenues from PFC markets were completely ignored in the sizing of the system. The system configuration may change significantly towards larger battery capacities by incorporating these PFC revenues in the sizing procedure and provide larger grid independence for the end user, while maintaining a positive NPV. This will be the focus of future analysis.

Based on the large dataset which hypothetically could form a VPP, a maximum reserve capacity of more than ±50 MW could be generated. However, the maximum allowance is ±25 MW per bid. This indicates that either the size of the VPP must be lowered or the dedicated storage and power capacity per participant must be lowered while maintaining the size of the VPP. The latter option allows for more local control flexibility and reduces losses in terms of grid independence. It is unlikely that virtual power plants of this size (4232 participants) are in the near future realistic since only 6000 storage units have been sold in Germany in the year 2013 [6]. Note, the presented economic figures are independent of the size and design of the VPP, since all revenues from the reserve capacity markets are assigned based on the individually reserved capacity per week.

8 Limitations

A number of limitations currently exist and represent a certain degree of uncertainty in the results and figures presented.

1. Price development of PFC markets: The economics of the PV battery system is quantified for a time horizon of 20 years. The prices for PFC services are adopted which correspond to the year 2014. In our analysis, PFC prices from 2014 have been used. Changes in the price levels within the next 20 years are very likely. However, there is currently no consensus whether prices rise or fall. On the one hand, some energy economics articles claim that the demand for capacity markets or frequency control will grow to balance out the increased and stochastic share of renewables in the power system [19,24]. On the other hand, it can be argued that the imminent market adoption of residential scale battery systems will put pressure on the market for frequency regulation, which may result in price drops [19] due to over capacities in the market.

2. Risk adjusted discount factor: Due to unexpected PFC price development, end users and the VPP aggregators will likely experience different returns on their investment. To compensate for this risk, a risk adjusted discount factor must be used which is not implemented here. Alternatively, different scenarios for the price development could be formed to better quantify this risk.
3. Advanced control algorithms: It is technically possible to provide the local self-consumption service in parallel with PFC. This may result in flexibilities for power provision, locally and within the VPP. The aggregator might use such flexibilities to place PFC capacities during periods of high prices (e.g. low hydro power lake levels) in order to maximize profits. Technical aspects regarding the design of control algorithms have not been taken into account in this work. Furthermore, a predictive controller is needed to predict the average cycle number one week ahead. This requires reliable forecasting of future demand and weather conditions. In this article, perfect future knowledge is assumed (i.e. no forecasting errors).
4. Further battery degradation: The actual time series for the requested PFC power is not taken into account. Therefore, additional charging and discharging processes in PFC modes are not modelled. Depending on the frequency of TSO-calls, the battery may be subject to additional degradation. However, the additional charging/discharging processes for the actually requested power is due to the 15 min limitation greatly reduced and it can be assumed that additional battery degradation effects are very small.
5. Third party aggregator margins: The third party aggregator must operate and manage the VPP in an entrepreneurial way. However, no third party aggregator profits are taken into account other than the additional upgrade that enables communication with the Aggregator. Thus, the presented investment figures might be significantly reduced depeding on the aggregators business model.

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