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Photovoltaic systems coupled with batteries that are optimally sized for household self-consumption: Assessment of peak shaving potential

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HIGHLIGHTS

- Optimal sizing of PV-coupled batteries from household's economic perspective.
- Batteries can be commercially viable with appropriate self-consumption benefits.
- Collaboration between different stakeholders economically attractive.
- Batteries that are optimally sized for self-consumption have a large peak shaving potential.
- Pre-charging of batteries is key to realize peak shaving potential batteries.

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ABSTRACT

As the share of renewable energy sources in the energy mix is increasing, new challenges arise regarding the grid integration. This research focuses on a solution for one of these challenges, namely the employment of batteries to address the mismatch in electrical power between electricity supply from photovoltaic systems and household electricity demand. Herein, the optimal sizing of batteries for household self-consumption is combined with peak shaving at district level, whereas previous studies only looked at these questions in isolation. Our analysis makes use of a unique set of power measurement data from 79 households in the Dutch city of Amersfoort, in 295 evenly distributed days, with a resolution of 10 s. By using simulation of batteries and Net Present Value analysis, the average optimal storage size for self-consumption in the case of net metering abolishment for households with photovoltaic systems was determined to be 3.4 kWh. Large differences were observed between different households; photovoltaic system size, total net metered consumption and specific characteristics of load profiles resulted into optimal storage sizes in the range of 0.5–9 kWh. The impact of these optimally sized batteries on neighborhood peak demand was assessed and found to be limited, corresponding to a decrease of 5.7%. The peak shaving potential was further assessed under different control strategies of the batteries. Results show that the impact could be amplified to a decrease of 22% or 51% when the batteries are controlled by using heuristics or by assuming perfect foresight together with a power minimization algorithm, respectively. The findings of this paper emphasize the importance of collaboration between households and other stakeholders, such as distributed system operators and retailers in transitioning to a sustainable power system.

1. Introduction

One of the viable options to cut greenhouse gas emissions in order to combat climate change is to generate electricity from renewable energy sources. Photovoltaics (PV)[1] are expected to play an important role in this [1]. The global generation capacity of PV systems has increased from approximately 7 GW in 2006 to about 300 GW at the end of 2016 [2]. At the same time, a significant growth in electricity consumption due to electrification of the transport system and residential heating is expected [3,4]. As these trends will predominantly take place in the residential sector, this will pose challenges for the operation of low voltage (LV) electricity grids. Batteries installed in households could alleviate some of these challenges, by shaving peaks and filling valleys in the household demand profiles [5].

Several scholars have assessed the economic value that can be created by using storage in the smart grid context, i.e., by providing flexibility services to the electricity system, by addressing the power quality, reducing the negative effects of renewable energy, reducing the

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[1] All abbreviations are included in a nomenclature, which can be found in Appendix A.

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peak demand and system costs [6]. Furthermore, batteries can be used for market optimization; for instance by combining self-consumption with minimizing costs on the day-ahead market [7], or control battery operation on the day-ahead market and in the imbalancement settlement system in an economically optimal way [8]. Malhotra et al. [9] stated that demand charge reduction, residential solar integration and frequency regulation are the most attractive grid-connected applications, whereas load following, renewable energy integration and ancillary services are the most attractive island-mode and microgrid services [9]. Another review study on energy systems in island-mode reported that PV-diesel-battery systems were proven to be competitive, feasible and having positive environmental impact [10]. Collectively, these studies outline a critical role for batteries in the integration of PV-generated electricity. Increasing self-consumption of households can decrease the stress on the grid by limiting the maximum feed-in of PV-generated electricity [11,12]. Storage is reported to increase self-consumption by 13–24% for battery sizes of 0.5–1.0 kWh per kWp of PV system size [13]. With sufficient self-consumption incentives, the coupling of PV and batteries can become an attractive option from a households' economic perspective [14,15].

While using batteries to increase self-consumption limits the impact of PV-generated electricity to the grid, several other studies have investigated the role batteries in reducing the peak power demand of a household or neighborhood. For instance, in a fast-charging infrastructure for electric vehicles (EVs) batteries can allow for efficient fast-charging with reduced impact on the main grid [16]. In a DC microgrid, batteries are especially suitable as they can operate on DC, just like PV electricity production and EV charging [17]. Research on the exact peak shaving potential of PV-battery systems is still inconclusive. De Oliveira e Silva and Hendrick [18] found that the peak power consumption does not decrease when a battery is added to the PV system. This is in contrast to Fares and Webber [19], who found that peak power on neighborhood level can be reduced by 8–32%. The difference largely depends on geography: households in the United States [19], which have consumption peaks in summer due to the use of air conditioning versus households in Belgium [18], where consumption peaks occur in winter when there is much less solar irradiation. In different climatological conditions peak shaving can also occur in the winter [20]. Our research aims to present a generic solution by addressing also the peak shaving potential under low solar irradiation conditions.

There are several limitations in current literature about the coupling of PV systems with batteries. Firstly, many studies focus on single households [12,14,18], or small samples of households [11,21–23], regarding the consumption or PV generation profiles. A disadvantage of these approaches is that they lack the statistical power to determine the differences that exist between households. Furthermore, for peak shaving, aggregation of many households is essential as problems for grid operators mostly arise at neighborhood or district level. Secondly, most studies make use of synthesized generation or consumption profiles instead of measured data, and only a few studies [15,19] are exceptions to this. For PV generation profiles, sometimes solar irradiation is used as the only input [24], occasionally combined with temperature [25,26]. In practice, PV-generated electricity depends on many more factors, such as tilt and orientation of the PV system [27], and the output can be influenced by location-specific shadow impacts, especially in residential areas [28]. Thirdly, most studies use measurements with a resolution of 15 min to one hour. Beck et al. [29] found that these time resolutions could be insufficient: for households with large amounts of electricity consumption or production exceeding 2 kW, using 15 min resolution data results in substantial errors (> 5%) in determining self-consumption. Furthermore, for determining peak power demand, which plays an important role in this research, higher time resolutions are also preferred [13]. Lastly, all reviewed studies have a single focus, particularly maximizing self-consumption or minimizing household electricity costs, whereas our study is focused on whether batteries can be used for additional applications in support of multi-revenue business models.

The aim of this paper is thus to determine the economically optimal battery size for high self-consumption for a large variety of PV households in the Netherlands, while assessing the potential of these batteries for consumption peak shaving.

The novel contributions of this research address five aspects. Firstly, this study adds new results to the body of literature on optimal storage sizing by determining the influence of many different technical and economic factors. Secondly, we provide insight in the impact on optimal storage size due to differences between individual household production and consumption profiles by making use of a large set of 79 households. Thirdly, we assess the peak shaving potential by mutually combining optimal sizing of batteries from a household's economic perspective with peak shaving on neighborhood level, which reflects a realistic future use case. Fourthly, we present two novel pre-charging algorithms which are employed for determining both the minimum and maximum peak shaving potential. When grid assets are mainly dimensioned to transport PV-generated electricity, this leads to a low utilization rate of these assets [30]. Our approach of coupling a battery to a PV system and pre-charging the battery on days with low PV surplus (i.e. more production than consumption) leads to more efficient use of distribution grid capacity because of two separate factors: a lower distribution grid capacity is needed and the utilization rate of the distribution grid capacity is increased. Lastly, a unique empirical dataset of 79 households with PV systems and very high time resolution (10 s) of net power measurement data underlies all results.

The paper is organized as follows: in Section 2, the mathematical model is presented, followed by an explanation of how the battery size for optimal self-consumption is determined, a description of the pre-charging algorithms, an overview of battery technologies and possible impact of battery degradation, and a description of the input data and the assumptions underlying this research. Section 3 presents the results regarding the optimal storage sizing and the peak shaving potential, including a sensitivity analysis. The paper ends in Section 4 with conclusions and recommendations.

2. Methods

2.1. Model description

The simulation model was developed in MATLAB. Fig. 1 shows a simplified flow chart representing all steps that were undertaken in the model, for each household, and various storage sizes. It is similar to the model reported in Ref. [19], with the main difference being the input; net power (P_{net}) in this study compared to separate consumption and generation profiles in [19]. In case of either surplus production and a non-fully charged battery, or residual load (i.e. more consumption than production) and a non-empty battery, the battery can be used to prevent import from or export to the grid. Then, the resulting power from/to the grid (P_{grid}) is either zero or $P_{net}-P_{rated}$ (in case of battery power constraint violation). P_{rated} is defined as the power of a battery charged or discharged with a C-rate of 1 (i.e. P_{rated} is 1 kW per kWh of battery size), and is thus dependent on the battery size in kWh; η is the one-way charging/discharging efficiency of the battery. The energy in the battery E_{bat} at time t can be calculated according to Eq. (1):

$$E_{bat}(t) = E_{bat}(t-1) - \begin{cases} P_{net} * \eta * \Delta t & \text{if } P_{net} \leqslant P_{rated} \\ P_{rated} * \Delta t & \text{else} \end{cases} \tag{1}$$

This is formulated for surplus production; in case of residual load P_{net} is divided by η.

This model was used to first determine the optimal storage size. Storage sizes were stepwise increased at an interval of 0.5 kWh. Per household and per storage size, the energy consumed from the grid was determined. The benefits of storage could then be determined by

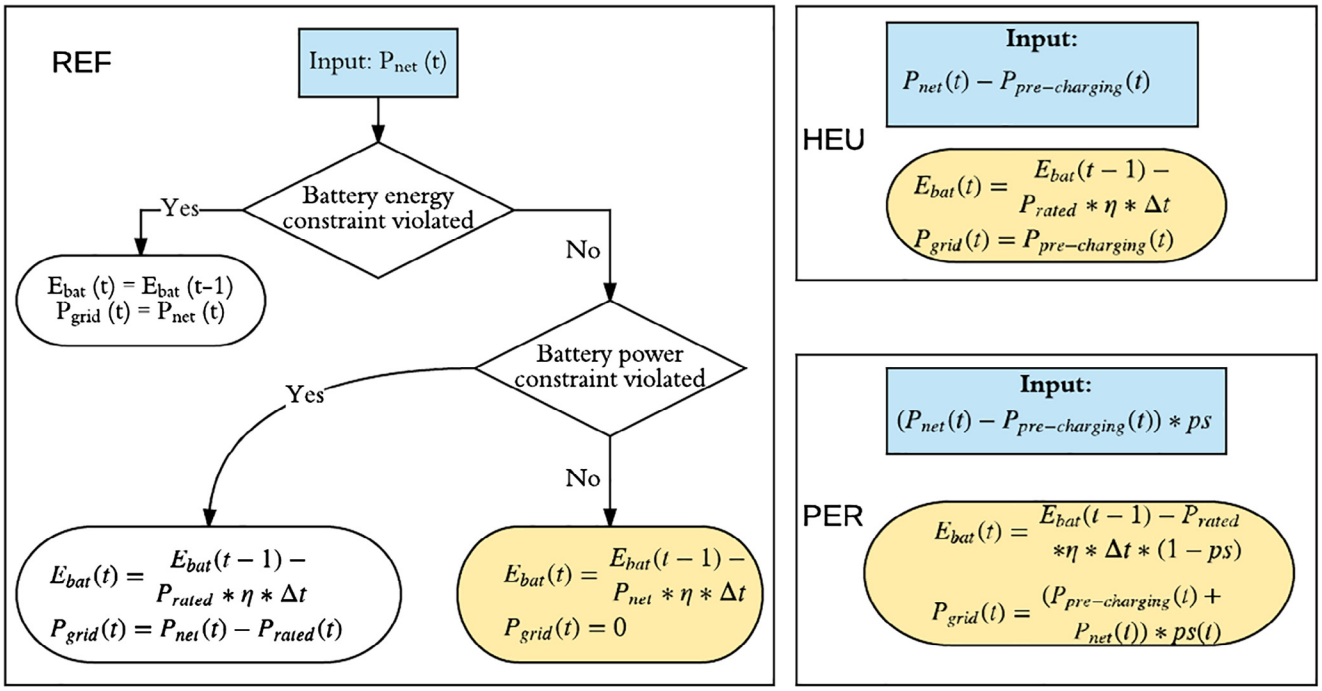

Fig. 1. Flow chart of battery use without control (left, REF). For the battery control algorithms (right) the colored blocks change to respective formulae. HEU aims to determine the minimum potential of optimal-sized batteries for peak shaving, PER the maximum potential (see text and Table 1 for details of the algorithms).

multiplying the difference in energy consumed from the grid with and without battery by the difference between the feed-in tariff (FIT) and the retail electricity price. Subsequently, the Net Present Value (NPV) of household j and battery size s was calculated according to Eq. (2):

$$NPV_{s,j} = -C_{bat} * 3.5 * (s/3.5)^{SF} + \sum_{y=0}^{L} B_{s,j} * CF * (1 + PDI)^{y}/(1 + r)^{y} \quad (2)$$

With

s = Battery size (kWh)
$B_{s,j}$ = Benefits of storage (€/year) of household j with battery size s
CF = Correction factor
C_{bat} = Investment costs battery (€/kWh)
PDI = Price difference increase; increase Δ *Electricity price* in (%/year)
r = Discount rate
L = Lifetime battery
SF = Scale factor
y = time (years).

Regarding the scale factor, 3.5 kWh is chosen as the reference storage size. The Correction factor (CF) was included to convert the benefits to yearly benefits; this factor is 365/295 (see Section 2.3). The optimal storage size s_{opt} was defined as the storage size with the highest NPV for that specific household. See Table 2 for the values used for each parameter/variable.

Subsequently, the impact on the peak power consumption and evening energy use in winter was determined by simulation using three cases: (a) a reference case denoted as REF, where batteries were not controlled, (b) a minimum potential case, where batteries were controlled using a heuristics algorithm (HEU), and (c) a maximum potential case, where batteries were controlled to minimize peak power assuming perfect information forecasting (PER), see also Fig. 1.

Table 1 shows the differences between HEU and PER algorithms. The rationale behind the HEU algorithm was that the highest energy use of households in the Netherlands occurs in winter, especially in the evening hours after work, while during nights there is still much capacity on the grid for extra consumption. Hence, the battery could be pre-charged during those nighttime hours. The advantage of using heuristics is that the battery would require little additional software and no digital communication (hence this would already work in a non-smart grid). In the PER algorithm, the batteries were ensured to be fully charged at 14:00 every day and a power limit was set on the aggregated power consumption of the neighborhood.

Table 1
Characteristics of two battery control algorithms.

	Heuristics algorithm (HEU)	Minimization of power algorithm, perfect information forecasting (PER)
Pre-charging hours	0:00–6:00	0:00–14:00
Months	November to March	All
Battery use switched on	17:00	When aggregated neighborhood power is above certain threshold.
Pre-charging amount	Fixed, Proportional to battery size	Variable, required to have a full battery at 14:00

When P_{net} would surpass this power limit, the power consumed from the grid was corrected to the power limit by a "power stabilizer" (*ps* in Fig. 1), and the remaining proportion of the demand was taken from the battery in such a way that P_{grid} would equal the power limit. The power limit was stepwise decreased in different model runs in order to find the lowest possible maximum power consumption.

2.2. Battery technology and degradation

Most prominent battery technologies for household applications are lead-acid (LA) batteries, high temperature batteries (e.g. NaS or NaNiCl, flow batteries and lithium-ion batteries (LiBs) [31]. All technologies have their own specific characteristics and accompanying advantages and disadvantages. Based on the review studies of Mahlia et al. [5] and Yekini Suberu et al. [32], the following facts are relevant for household applications. The LA battery technology is the oldest technology for

household and commercial applications. Being a mature technology, LA batteries are relatively cheap. Most significant disadvantages entail the low cycle depth and fast battery degradation. The most used high temperature battery is the NaS battery. Advantages of this battery are the high energy density, high efficiency, low maintenance and high cycle life. However, safety can be an issue for these batteries because of the high operating temperature, possible explosion when in contact with air and corrosion in insulators caused by the challenging chemical environment. Flow batteries hold some significant advantages against conventional batteries. For instance, the separation of power and energy constraints enables the easy optimization of the configuration, the batteries are safe and have a long life time. However, these advantages are accompanied by high investment costs, and moreover the complex system requirements and related high maintenance costs which make them less attractive for small scale storage applications (e.g. households) [5].

LiBs have rapidly become the most prominent technology for mobile consumer electronics [31]. Advantages are the high energy density, efficiency, cycle depth and cycle life. The most important disadvantage is the high investment costs, although these are rapidly declining in recent years [33,34]. As lithium-ion is the battery chemistry with the highest investments in recent years [35], and prominent home batteries such as the LG Chem and the Tesla Powerwall use this technology, lithium-ion is the technology of choice in our research. Within the LiB family, currently the three most prominent chemistries are Nickel-Cobalt-Aluminum-Oxide (NCA), Nickel-Manganese-Cobalt (NMC) and Lithium-Iron-Phosphate (LFP) [36]. From these, the NCA battery has the lowest costs, while the LFP performs best on cycle life time [31]. A promising new technology is Lithium-Titanate-Oxide (LTO). The LTO-battery potentially has excellent cycle life characteristics, but currently is in the research phase and is more expensive compared to the other LiB chemistries [36]. In this research, we use the NMC battery of the Tesla Powerwall as a reference technology. We perform a sensitivity analysis on the critical battery parameters to ensure that our results are also applicable to other battery technologies.

The cyclic degradation of a battery can be approximated with a linear function of the energy throughput of the battery [37]. This relationship is moderated by many variables, of which the three most important are C-rate, temperature and depth of discharge:

- **C-rate:** High C-rates result in faster degradation [37]. However, this mainly holds for very high C-rates, i.e. 3.5C and higher, whereas the difference in degradation between 0.5C and 2C has been found to be negligible [17]. In our research, we assume a C-rate of 1C which varies between 0.5C and 2C in the sensitivity analysis
- **Temperature (T):** In general, higher operating temperatures lead to increased battery degradation [38,39]. However, at low C-rates capacity loss is shown to be similar for T = 10 °C and T = 22 °C [37]. Degradation is accelerated at higher temperatures of T ≥ 34 °C and especially at T = 46 °C [37]. As ambient temperatures generally are not that high in the Netherlands, and household battery systems are expected to be in moderate space conditions, we assume that high temperatures have a negligible influence in our research. Moreover, the power requirements for batteries in stationary applications are not very stringent which results in uncomplicated heat management [40]. In this regard it is also relevant to mention that next to very high temperatures, also very low temperatures can lead to acceleration of battery degradation [41]; this is due to lithium plating and dendrite formation [42]. The most effective operating temperature for lithium-ion batteries (LFP batteries in this case) is determined to be 13 °C [43]. As batteries are installed inside households, it is unlikely that operating temperature would drop far below this temperature. Therefore we choose to also omit this temperature effect in our degradation model.
- **Depth of discharge:** Higher cycle depth leads to faster degradation [44]. As this can be an issue in our research, we monitor the modelled degradation resulting from the different algorithms employed in our research by using rainflow cycle counting. This method was first introduced by Amzallag et al. [45] and applied to batteries by Stroe et al. [46]. The method records and counts every half cycle, i.e. when operation of battery alters from charging to discharging or vice versa, the state of charge (SOC) of the battery and the depth of cycle (DOC) of that half cycle. This shows how the algorithm translates to operation of the batteries and gives insight in the battery degradation, for which especially the DOC and number of (half) cycles are important indicators [47].

2.3. Input data

Data was obtained from the "*Smart Grids: Profit for all*" [48] project in the neighborhood Nieuwland of the city Amersfoort, the Netherlands. More details about the measurement data can be found in [49]. Measurement equipment was supplied by Net2Grid [50]. In this district 500 small (0.8–4.4 kWp) PV systems were installed between 1999 and 2001 totaling 1.3 MWp [51]. For 100 households, the power interaction with the grid was measured every 10 s. The data concerned net metered power; hence consumption and production could not be analyzed individually. The period of measurement was November 2013 to October 2014. While a full year of measurements was aimed for, three problems regarding data quality were encountered. Firstly, data were missing due to communication issues for 68 days, spread out over the 12-month period. It was assumed that the remaining 295 days were representative of a year. Secondly, data for individual households was found to be often incomplete. The criterion for excluding a household from the analysis was whether more than a month of the remaining data was missing. As a result, 21 households were kept outside of the research. The remaining 79 households had an average residual load of 2637 kWh (standard deviation (SD) is 1120) and an average surplus production of 797 kWh (SD = 638) over the 295 days. For households with substantial surplus production (> 50 kWh), the average derived system size was 2.4 kWp (SD = 0.74), which is well in line with previous analysis of the PV systems in Nieuwland [51]. Multiple linear regression was performed to determine the impact of these variables on the optimal storage size. The PV system size was derived from the data by taking the 99.995 percentile value of surplus production, assuming (a) the highest surplus production values could be outliers or influenced by the cloud edge/cloud enhancement effect [52] and (b) of the 2.5 million data points per households, there are enough values with simultaneous occurrence of peak production and minimal consumption.

Table 2 shows the most important input parameters of this research. Since all parameters are under substantial uncertainty, sensitivity analyses have been performed; minimum and maximum input values for the sensitivity analyses are also shown in this table.

The cost of the battery was determined by extrapolating the expected 8% annual cost decline starting from 300 €/kWh in 2014 to 2020 based on [34], resulting in a base material costs of 180 €/kWh. We assumed that these costs are also obtainable for residential storage of size 3.5 kWh as the (marginal) scale effect of larger batteries (as in

Table 2
Input parameters.

	Min	Base	Max	Based on
C_{bat} (€/kWh)	130	**234**	494	[34]
SF		**0.9**		[53]
Self-consumption benefits (€/kWh)	0.04	**0.16**	0.28	Net metering abolishment, [14]
PDI	0%	**1%**	3%	[54]
r	2%	**4%**	8%	[14]
$1-\eta$	4%	**8%**	20%	[55]
L (years)	10	15	20	See below
C-rate	0.25	1	2	[37,56]

EVs) [53] could approximately be offset by cost savings accompanying the much lower power, weight and volume requirements of residential batteries. To obtain the battery costs, we assumed the installation costs would add 30% to the material costs. To reflect the fact that smaller systems may require higher installation costs per kWh than larger systems, we implemented a scale factor of 0.9 over the total costs, based on [53] and the fact that batteries are modular, see Eq. (2). The self-consumption benefits, i.e. the difference between the retail electricity price and FIT, is completely dependent on the electricity pricing scheme; as a base, this is estimated to be €0.16/kWh. This was estimated to increase by 1% per year, as the Dutch government announced it would pay investments in renewable energy by increasing existing energy taxes [54]. In our model, the battery was DC-coupled to the PV system; we used the same setup as shown in [44]. Following the example of [55], we took the Tesla Powerwall efficiency of 92% as the reference (i.e. 8% losses), which when combining with a roundtrip inverter efficiency of 96% results in an 88% total round trip efficiency. Constant efficiency and a C-rate of 1 were assumed, following the example of [56]. Regarding lifetime, Tesla guarantees 80% of remaining capacity after 10 years for the Powerwall. As the battery will also be usable with lower capacity remaining [44], we assumed the lifetime to be 15 years.

3. Results and discussion

This section is structured as follows: In Section 3.1, optimal sizes of batteries for household self-consumption are determined. This is done to provide insight in the factors that determine the optimal storage size, and simultaneously serves as input for Section 3.2 where simulations are performed and the results are analyzed, thus adding to the knowledge of the peak shaving potential. Sections 3.3 and 3.4 are focused on the external validity of the research. In Section 3.3 insights are provided in how the batteries are operated under different charging/control algorithms and how this impacts battery degradation. In Section 3.4 various sensitivity analyses are performed and recommendations are drawn.

3.1. Determining optimal storage size

As explained in Section 2.1, the NPV was determined for various storage sizes for all households. Fig. 2 shows the relationship between increasing the storage size and the NPV for three individual households.

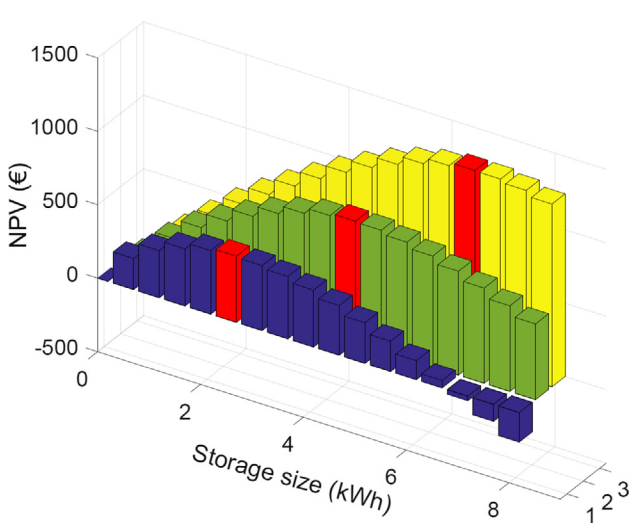

Fig. 2. Storage size vs. Net Present Value for three different households (colored blue, green and yellow). Red bars represent the optimal storage size for that specific household. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

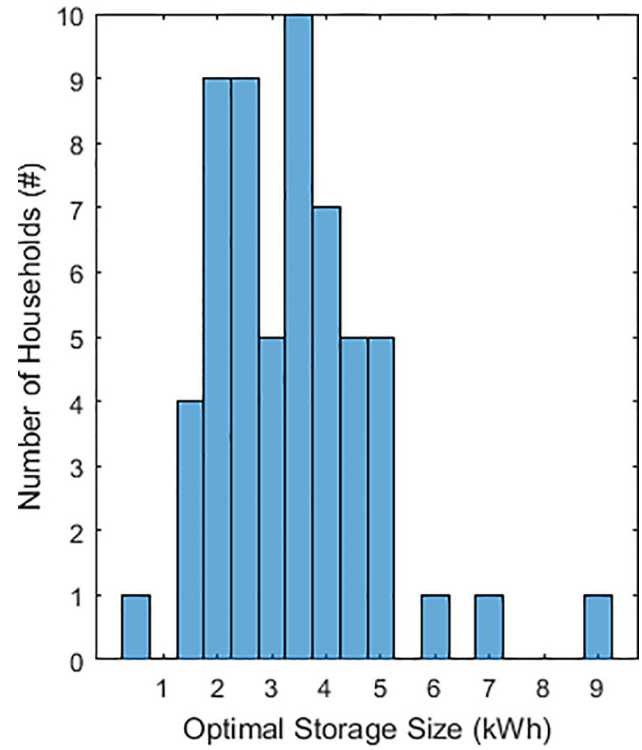

Fig. 3. Histogram of frequency of optimal storage sizes.

The optimal storage size is defined as the storage size with the highest NPV for that household (i.e. the red bars in Fig. 2). The maximum NPV coincides with the storage size where the marginal discounted benefits of increasing the battery size equals the marginal costs of increasing the battery size. Although individual differences are apparent, all curves show a similar pattern: with increasing storage size, the NPV first exhibits a rather steep increase, followed by a diminishing incline until a maximum is reached and finally a gradual decline in NPV is observed. This is explained by the fact that a rather small battery in a household is per definition more often fully charged with PV-generated electricity and therefore has a higher utilization rate compared to a larger battery for the same household.

A histogram of optimal storage sizes of all investigated households is shown in Fig. 3. A positive NPV was found for 58 out of the 79 households. The optimal sizes for a battery ranged from 0.5 to 9 kWh, with an average of 3.36 kWh (SD = 1.49) and mode and median both of 3.5 kWh. The NPV values ranged from 72.0 € to 1.74 k€, with an average of 697€ (SD = 296). The profitability index, i.e. present value per euro invested [57], ranged from 1.1 to 2.0. Note that from an economic point of view the Tesla Powerwall 2 with a size of 13.5 kWh appears to be too large for the Dutch market if it is only used to increase self-consumption: only three households would have a positive NPV for the Powerwall 2, even when the price would drop to the cost assumption made in this research.

Our findings are in line with previous research [56], that found an optimal storage size of 0.75 kWh per MWh of consumption, when combined with a PV system of size 1 kWp per MWh of consumption. A higher optimal storage size was found by [14], mainly due to the assumption of a larger difference between FIT and retail electricity price. Note that both above-mentioned studies describe results for one typical household with PV, whereas our research also encompasses the substantial differences that exist among different households.

Fig. 2 also shows that increasing the storage size somewhat above optimal does not result in major decreases in NPV. More details are shown in Fig. 4, in which the average decreases in NPV are depicted when battery sizes would be increased by different amounts. These

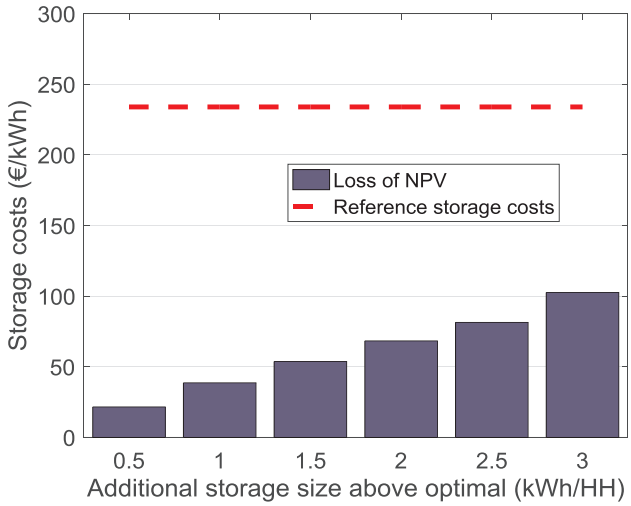

Fig. 4. Investment opportunities for external parties. The y-axis represents the average decrease in NPV per kWh, i.e. 'storage costs', if all battery sizes would be increased by the value on the x-axis.

decreases are small compared to the assumed reference storage cost of 234 €/kWh. Therefore, this presents an attractive investment opportunity in the case that a second party would be willing to compensate the decrease in NPV of a larger than optimal battery, e.g. in exchange for allowance to operate the battery to provide other ancillary services. Besides, recent research shows that consumers might be convinced to purchase a larger than optimal battery for non-financial benefits such as increased self-sufficiency/decreased grid dependency [58].

Furthermore, by analyzing household characteristics that determine the optimal storage size, it becomes apparent that the optimal storage size has the highest correlation with the total surplus production: $r(56) = .85$, $p < .001$. The correlation with the derived PV system size is also relatively high, with $r(56) = .75$, $p < .001$. The correlation with the yearly net metered consumption is found to be insignificant; $r(56) = -.14$, $p = .15$. Multiple linear regression was used to predict the optimal storage size (s_{opt}, in kWh) by using derived PV system size (*PV Size*, in kWp) and net metered consumption (*NC,* in MWh/year), as these variables are readily available for most households, also without a smart meter. This results in the empirical relationship depicted in formula (3).

$$s_{opt} = -0.032 - 0.187 * NC + 1.51 * PV\ Size \tag{3}$$

The adjusted R^2 of this model is 0.579; further statistical details are shown in Table 3. The MATLAB prediction slice plot is included as an interactive graph in the online version of this article. Larger PV system sizes result in larger optimal storage sizes. Remarkably, the statistically significant negative regression coefficient of NC suggests that, given certain PV systems size, lower net metered consumption is expected to result in larger optimal storage sizes. This can also be seen in Fig. 5. For lower values of net metered consumption, fewer dark blue markers (representing low optimal storage size) are visible than in the area with similar PV system size but high values of net metered consumption. The figure also shows that not all variance in optimal storage sizes can be explained by PV system size and net metered consumption, as households with similar values of these variables can have very different optimal storage sizes. Two of the largest optimal storage sizes (6 kWh and 7 kWh; red markers with PV size of ~3 kWp and NC of ~1 MWh/year) have a PV system size and NC that are similar to households with smaller optimal storage sizes. This finding suggests that the residents of these two households are more often not at home during the day, resulting in more days with high surplus PV electricity production (i.e. low self-consumption). This results in a need for larger batteries – even though the PV system size and the yearly NC is similar to other households.

Table 3
Multiple linear regression. Dependent variable is optimal storage size (kWh).

	Regression coefficient	Standard Error	p (one-sided)
Intercept	−.032	.46	.47
Net Metered Consumption (MWh/year)	−.187	.10	.038
Derived System Size (kWp)	1.51	.17	< .001

These results indicate that the empirical model needs to be handled with care. Firstly, because 42.1% of the variance is still unexplained, and is thus dependent on specific consumption and production profiles. This finding also stresses the importance of having smart meters (or sub-metering) with high time resolution to enable a more thorough analysis in order to provide tailored advice for each household. In addition, this has important implications for research by stressing that studies about households should always take a sufficiently large sample of households into account. Secondly, because the economic assumptions also have a high impact on the optimal storage size. This is explored more in-depth in the sensitivity analysis in Section 3.4.

In this section we determined the optimal storage size for each individual household. Furthermore, we saw how this optimal storage size is influenced by the PV system size, the yearly surplus of PV and the yearly net-metered consumption. In the next section, we will do simulations with these optimally sized batteries to determine the peak shaving potential of the batteries in this neighborhood.

3.2. Simulations with optimal-sized batteries

The total storage capacity in the investigated neighborhood, under the condition of optimally sized batteries, is 195 kWh, thus an average of 2.47 kWh per household including the households with a negative NPV (21 out of 79). Figs. 6–8 show the impact on the aggregated neighborhood power to/from the grid and battery content of the non-controlled (REF) and the batteries controlled by the heuristics (HEU) and perfect information power minimization algorithms (PER). See Table 1 and Fig. 1 for details on cases. Batteries are a natural partner for PV regarding peak shaving in summer: batteries are charged during the day with surplus PV electricity, and this electricity is used in the evening hours.

Fig. 6 illustrates this concept: the neighborhood is a net producer of electricity from around 10:00 to just before 18:00. This surplus of PV-generated electricity is fed into the grid in the case without batteries, whereas in the REF case this electricity is used to charge the batteries in the neighborhood. Electricity from these batteries is then used in the evening hours resulting in much lower peak power demand. In winter, when electricity consumption peaks, batteries have only a marginal impact on the consumption pattern if they are not pre-charged. As there is little surplus of PV-generated electricity, the batteries are not charged and the peak cannot be shaven. Fig. 7 shows a comparison between the case without batteries and the HEU case. In the HEU case, the batteries are pre-charged during the night resulting in higher power consumption in these hours. From 06:00 to 17:00 the power consumption of the case without batteries is roughly the same as in the HEU case, however in the HEU case, after 17:00, the peak consumption of the neighborhood is shaven to some extent. Note that in reality, the heuristics would probably have to be designed differently to prevent large voltage fluctuations. However, much of the energy content of the batteries is already used from ~17:00 to 19:00, which results in batteries being depleted too early and a new consumption peak occurring around 20:00. Fig. 8 shows the same day but for the case of the PER algorithm. In this case, batteries are also pre-charged; power consumption in the PER case is higher than in the case without batteries, however not as high as in the HEU case because in the PER case the batteries are still

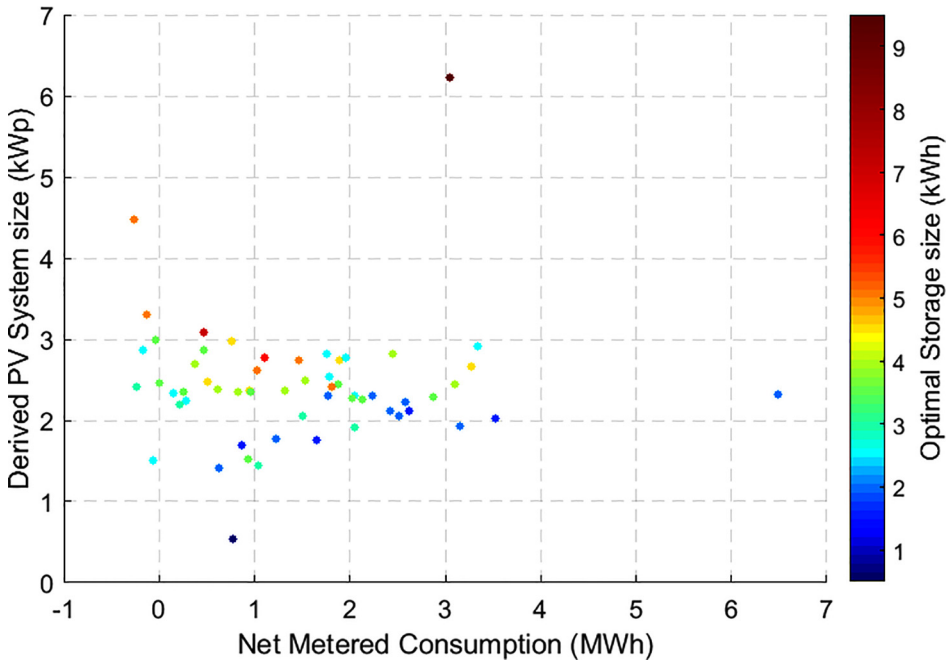

Fig. 5. Relationship between net metered consumption, PV system size and optimal storage size.

partly charged as a result of the previous day. As in the PER case batteries are discharged at such rates that the neighborhood aggregated power does not exceed a certain threshold, and energy from the batteries is used in a more efficient way resulting in the maximum peak shaving capabilities.

Due to the high time resolution of the data, the impact on peak power demand could be determined very accurately. Over the year, the neighborhood net peak power consumption decreases from the original 111.4 kW to 105.1 kW (−5.7% compared to original) for the REF case, to 86.8 kW (−22%) for the HEU case and to 54.9 kW (−51%) for the PER case, i.e., the maximum peak shaving potential. The maximum peak shaving potential found in this research is much higher than in previous research such as [18,19], despite having a relatively low battery capacity per household; 2.5 kWh in this research, compared to 7 kWh in [19] and 25 kWh in [18]. This finding stresses the importance of the specific algorithm used for determining the peak shaving potential. These results have relevant practical implications, for example when designing grids in new neighborhoods or upgrading existing grids in residential areas. Peak shaving can have various benefits, such as lower grid (re)investment costs, lower generation capacity investment costs and lower marginal electricity costs.

Fig. 9 shows boxplots of the four-hour peak energy use for the four cases over the 295 days. It is apparent that the upper quartile (Q4) of the REF case is similar to the case without batteries; this is in line with previous findings about the peak power shaving considering that Q4 mostly represents the winter months and the non-controlled batteries have little impact then. The batteries in the REF case result in lower peak energy use in Q1 to Q3 than the case without batteries. The PER case yields similar results in Q1 and Q2 as the REF case, but lower in Q3 and Q4. This is due to the design of the algorithm: batteries only come into action when the neighborhood consumption exceeds a certain limit, which does not happen on many days. Using heuristics seems most preferable under the objective of achieving the lowest energy demand during evening hours.

Resulting load duration curves are shown in Fig. 10, which shows that the power minimization algorithm has a very large impact, but for a small proportion of the time (~6%), whereas the heuristics algorithm has lower consumption than non-controlled batteries for the 13% of peak consumption of both other cases. Due to charging and discharging losses, the utilization of batteries increases the total net electricity consumption compared to the case without batteries; an increase of 2.8%, 3.6% or 1.1% for non-controlled batteries, batteries controlled by

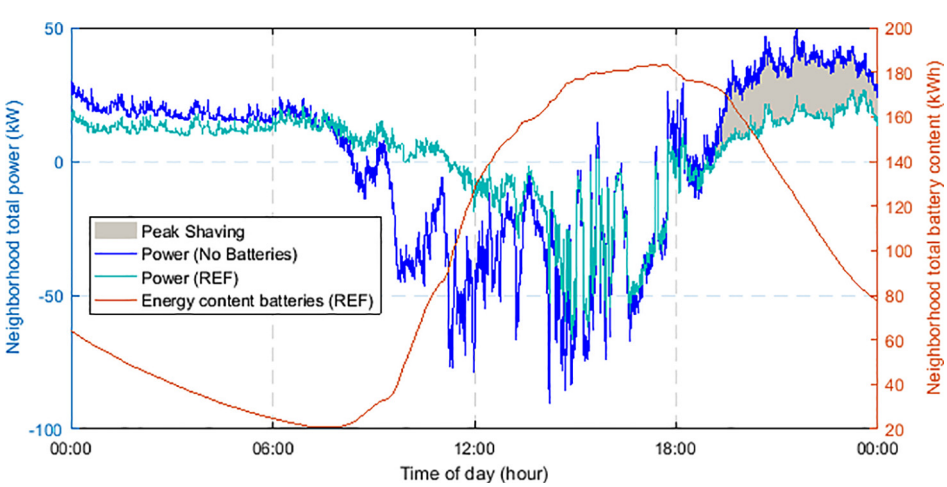

Fig. 6. Demonstration impact battery REF case on a summer day (3 August 2014). The blue graphs on the primary y-axis shows the neighborhood electricity power without batteries and the REF case. When the power is below zero, the neighborhood is a net producer of electricity, hence the simulated batteries are charged in the REF case. The aggregated battery energy content (orange line) is shown on the secondary y-axis. The electricity stored in the batteries is used in the evening, resulting in lower peak consumption when using batteries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

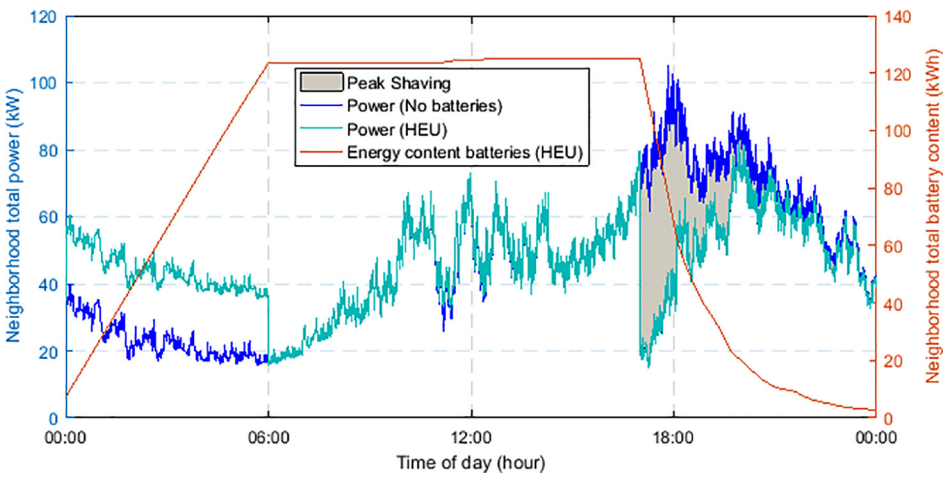

Fig. 7. Demonstration HEU case on a winter day (28 November 2013). Blue lines indicate the households' aggregated power without batteries and in the HEU case. Orange line indicates the households' aggregated battery content. In the HEU case, batteries are pre-charged from 00:00 to 06:00 and switched on at 17:00, resulting in lower electricity consumption from the grid in the evening. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

heuristics and batteries controlled by the power minimization algorithm, respectively. These load duration curves can serve as input for stakeholders such as grid operators and energy retailers to determine which of the cases is preferable from their perspective.

In this section we determined the peak shaving potential of batteries in different use cases. We saw that the PER case led to the highest peak power shaving, while the HEU case led to the largest peak shaving potential. In the next section we provide more insight on the operation of the batteries in the different cases and give an indication of the battery degradation in each of these cases.

3.3. Rainflow cycle counting

Rainflow cycle counting was used both to give insights on the impacts of the different algorithms on the battery behavior and to monitor battery degradation indicators. By far most cycle depths are below 2% in all scenarios. This can be detected due to the high time resolution of data; for example, when a cloud temporarily blocks direct sunlight this can result in a micro-cycle, or when a household appliance is switched on resulting in a household shifting from being a net producer to a net consumer.

Fig. 11 shows per case the cycles with Depth Of Cycle (DOC) > 2%. In the REF case, most cycles have low DOCs and SOCs. Other notable bars are at a SOC of 100% and low DOC values, and at a DOC of 100% and SOC of 0% (which represents a full discharge). Charging from 0% to 100% occurs less frequently, which is in line with the intermittent nature of PV electricity generation and possible alternation with net consumption when household appliances are switched on. The rainflow cycle chart of the HEU case looks similar to the REF case, while the most notable difference is the large bar in the middle of the chart: this represents the pre-charging from SOC of 0% to SOC of ~60% during winter nights. This also results in fewer cycles around a SOC of 0%, as the batteries are more often not empty. In the PER case, most cycles occur close to a SOC of 100%, which indicates batteries are often not fully discharged. This is an indication that the capacity of the batteries in the PER case are not used to their full potential, which is a logical consequence of the algorithm design; batteries are switched on only when the aggregated neighborhood power exceeds a certain limit. This occurs only a small proportion of the time (see Fig. 10).

Table 4 shows the average battery capacity reduction of all batteries, based on aging assumptions of [44]. Calendric aging (1.33% per year in both reference and strong aging) accounts for the largest part of aging. In the PER case the capacity fade is lowest, again because the batteries are often not fully discharged, which results in lower energy throughput and cycle depths. The battery capacities in the HEU case are only marginally faster reduced than the non-controlled batteries.

3.4. Sensitivity analyses

The most important limitations of this research are due to the uncertainty of the economic parameters and the external validity given that the research is essentially a case study. Both issues are addressed by making use of different sensitivity analyses. Fig. 12 shows the impact of the various input parameters on the average optimal storage size (see

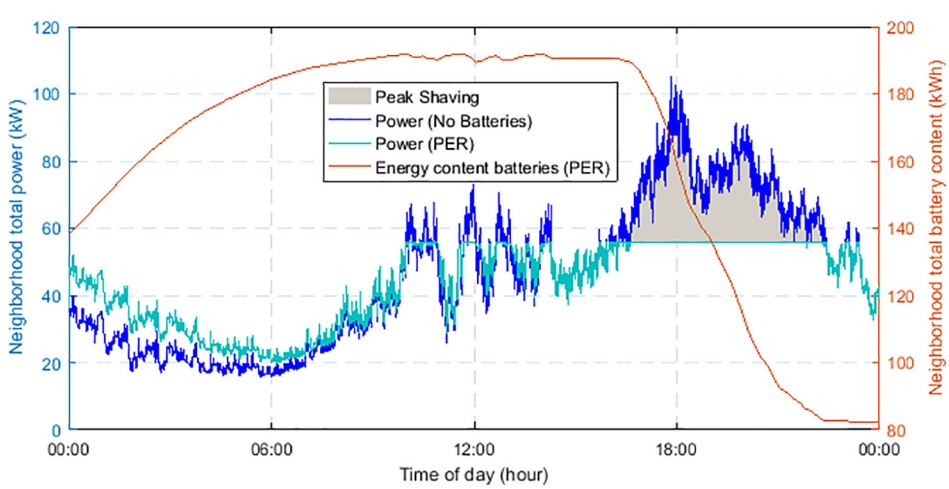

Fig. 8. Demonstration PER case (28 November 2013, same day as Fig. 7). Peak consumption in the evening is minimized because batteries are only used when neighborhood power exceeds a certain limit.

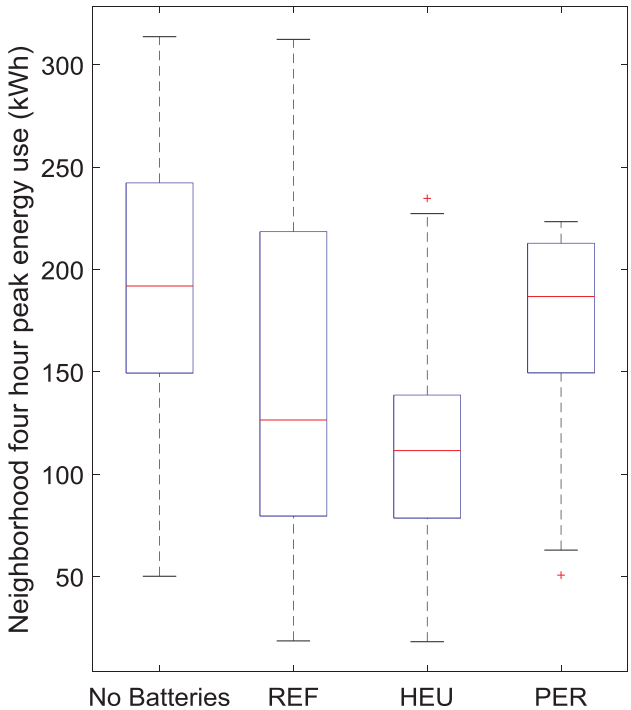

Fig. 9. Boxplots of the evening four-hour peak energy use over the 295 days for the four cases.

Table 2 for initial values). The optimal storage size is quite robust for the variables self-consumption benefits increase, discount rate and efficiency. Lifetime and battery costs have larger impact, but the largest impact comes from the self-consumption benefits. This is an important result from a policy perspective, as these benefits can be controlled by policies, thereby directly influencing the amount of residential storage. The relationship between the C-rate and optimal storage is particularly interesting. For very low C-rates ($\leq$ 0.1) the average optimal storage size goes to zero: batteries are not capable to store enough PV generated electricity to obtain a business case. However, C-rates between 0.25 and 0.75 have a moderate positive effect on the average optimal storage size, because power rates increase with battery size. Hence, battery producers may be inclined to manufacture batteries with relatively low C-rates, also because lower C-rates (i.e. lower power requirements for the batteries) represent cost savings. However, this would have important implications to the maximum peak shaving potential, as is shown in Fig. 13. If batteries would have a C-rate of 0.25, then the theoretical maximum peak shaving decreases from 51% to 33%. The other variables have a similar effect on peak shaving potential as on optimal storage. The peak shaving potential cannot increase much above the found 51%, because the average power of the day with the largest consumption serves as asymptote. On the other hand, even for pessimistic values of the parameters there is still substantial peak shaving potential (> 30%).

In the last sensitivity analysis, shown in Fig. 14, the amount of storage available in the neighborhood is varied in two ways: first, by multiplying all battery *sizes* by a certain factor (depicted as "Size per battery" in Fig. 14), and second by multiplying the *number* of batteries by a certain factor (depicted as "Amount of batteries" in Fig. 14). The results on the minimum peak shaving potential (HEU) are especially robust. This is because the new consumption peak (86.8 kW, see Section 3.2) occurs on a winter day at 2PM, when batteries are not used as a result of the algorithm design. Therefore, this peak shaving potential is less dependent on the amount of storage in the neighborhood: this peak shaving can be obtained by using just a part of the storage capacity (see Fig. 11b), but cannot be increased when the storage capacity is increased. The maximum peak shaving potential (PER) is more sensitive to varying the amount of storage. Especially the number of batteries has a large impact; hence, it is preferable to have a large number of small batteries, rather than a few large batteries. This is due to the assumption in this research that households can only use electricity from their own battery. An implication of this finding is that it can be attractive to have community energy storage, so that a larger number of households can use the stored electricity when needed.

4. Conclusions

In this study the optimal sizing of batteries for PV self-consumption at household level was combined with determining the peak shaving potential of these optimal-sized batteries at neighborhood level, for a case study in the Netherlands. We have shown that, given certain economic conditions, it can be attractive for PV system owners to couple their system with batteries in case net metering scheme is abolished or not in force. In the Netherlands, the net metering will be abolished and be replaced by an as of yet unknown support scheme in 2020 [59]. If these batteries are operated in a controlled manner, then these can have a large peak shaving potential. This impact is robust for lower amount of storage capacity in the neighborhood, and has a limited effect on battery degradation. In addition, our analysis has shown

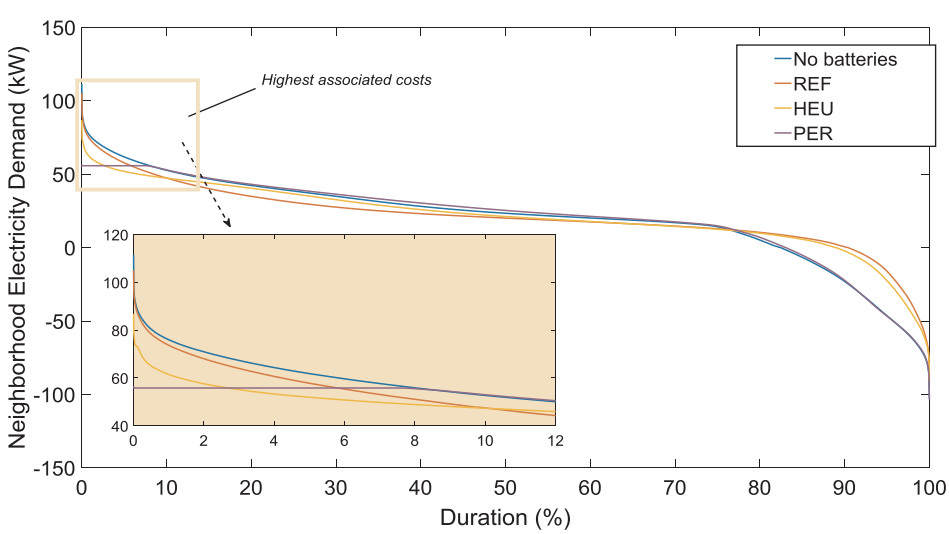

Fig. 10. Load duration curves of neighborhood of No Batteries, REF, HEU and PER cases). The HEU and PER case perform best in the peak demand area associated with the highest cost.

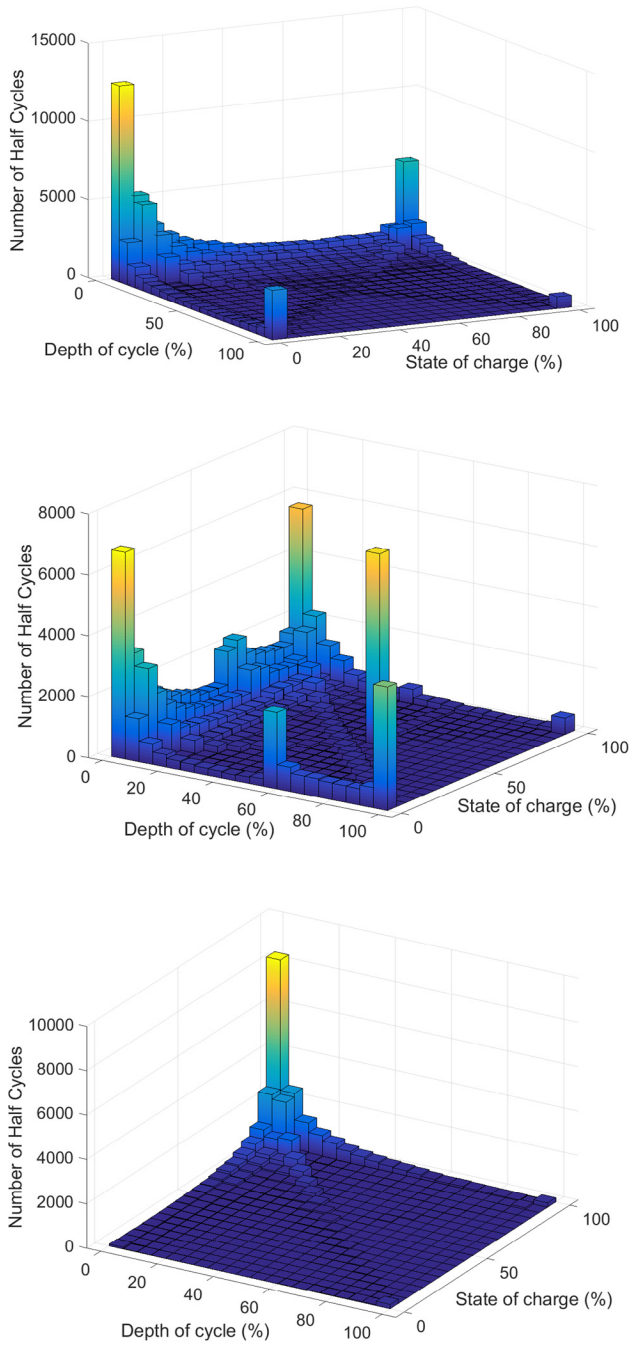

Fig. 11. a–c. Rainflow cycle counting chart of all 58 batteries (REF (upper, 11a), HEU (middle, 11b), PER (lower, 11c)). Charts of individual batteries would largely lead to a similar picture, as the algorithm works the same for every battery within a use case. For visual purposes, micro-cycles (DOC < 2%) are not depicted, as their amounts dwarf the other cycles.

Table 4
Average battery capacity fade per year resulting from calendric and cycle aging for the different cases. Aging assumptions are based on [44].

	REF	HEU	PER
Reference aging	1.57%	1.67%	1.38%
Strong aging	1.74%	1.89%	1.42%

the importance of several preconditions for realizing this peak shaving potential, both from battery and policy design perspectives. Firstly, as consumption peaks occur in winter, we propose to pre-charge batteries

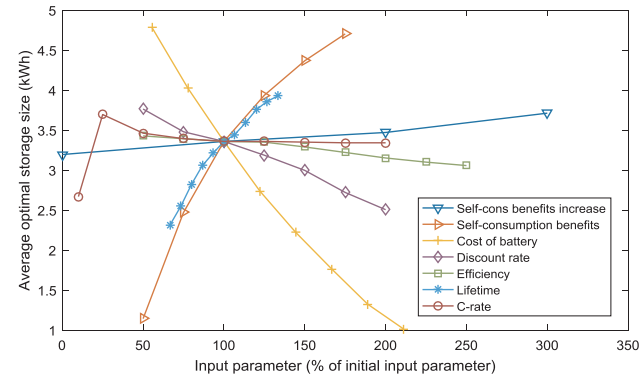

Fig. 12. Sensitivity analysis on average optimal storage size. See initial values in Table 2.

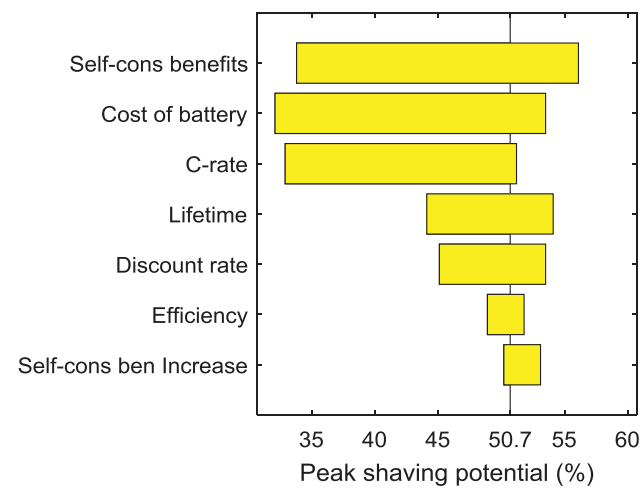

Fig. 13. Tornado diagram from impact of different battery parameters on the maximum peak shaving potential of the neighborhood, i.e. PER case. See Table 2 for maximum and minimum values.

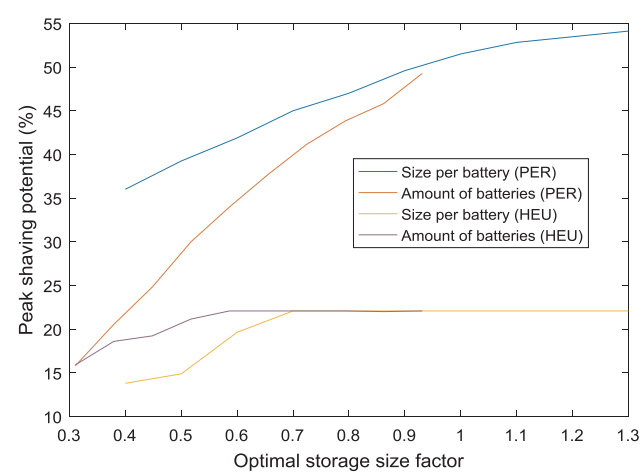

Fig. 14. Impact of varying the number of batteries in the neighborhood [from 18 (optimal storage size factor = 0.31) to base value 58 (factor = 1.0) on peak shaving potential of heuristics (HEU) and perfect information power minimization (PER)] and varying the battery sizes (from on average 0.4 * 3.4 kWh to 1.3 * 3.4 kWh) on peak shaving potential of both algorithms.

from the grid instead of solely from PV-generated electricity as it is found to be more beneficial. Secondly, some technical characteristics of batteries, such as the C-rate, can be unimportant for one purpose, but very important for a second purpose. Lastly, it is important that joint

investment, e.g. by house owners and grid operators, is made possible; since our economic analysis revealed that NPVs do not decrease much when battery sizes are increased above the economic optimal for self-consumption, making collaboration between different stakeholder very attractive.

A key policy priority should therefore be to encourage this joint investment. This can be done for example by enabling differentiated network tariffs. Another policy recommendation is to investigate alternative compensation mechanisms for replacing the net metering scheme in the case of abolishment. The findings of this study support the argument that a subsidy for batteries could both compensate a PV owner and result into substantial additional societal benefits, however, this option should be investigated further to take other compensation options into account.

Recommendations for future research are to replicate this study for different locations. As we have shown, individual consumption and production profiles have significant influence; performing similar research in different climatological conditions and with different consumption profiles may yield valuable new insights. In addition, this research can be enhanced with a laboratory setup, for example by focusing on the impact of the different algorithms on the voltage level in the LV grid. Furthermore, we advise designing a hybrid algorithm that optimizes between self-consumption and peak shaving objectives. Our research focused on the minimum and maximum potential for peak power shaving of batteries, however the employed algorithms both have disadvantages: the heuristics algorithm fails to capture the full peak shaving potential of the battery, while the impact of the power minimization algorithm may hamper self-consumption. Future research may address a different combination of ancillary services, for example using the batteries to operate on the markets for operating reserves. Lastly, different storage configurations can be explored, for example the possibility to use the battery of a neighbor, or to have community energy storage instead of individual batteries.

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Appendix A

A.1. Nomenclature

Abbreviations	
DC	Direct current
FIT	Feed-in Tariff
HEU	Batteries controlled using heuristics algorithm
LA	Lead-acid
LFP	Lithium-Iron-Phosphate
LiB	Lithium-ion battery
LTO	Lithium-Titanate-Oxide
LV	low voltage
NCA	Nickel-Cobalt-Aluminum-Oxide
NMC	Nickel-Manganese-Cobalt
PER	Batteries controlled using minimization of power algorithm, using perfect information forecasting
PV	Photovoltaic
REF	Reference case (no control battery)
SD	Standard deviation
T	Temperature
Indices	
j	Household
s	Battery size in NPV calculation [kWh]
t	Time step in battery operation
y	Time in NPV calculation [years]
Parameters	
C_{bat}	Investment costs battery [€/kWh]
CF	Correction factor
C-rate	Power to energy ratio battery [kW/kWh]
η	One-way efficiency battery [%]
L	Lifetime of battery [years]
PDI	Price difference increase [%/year]
R	Discount rate [%]
SF	Scale factor [–]
Variables	
B	Benefits of storage [€/year]
DOC	Depth of Cycle [%]
E_{bat}	Energy content of battery [kWh]
NC	Net-metered consumption [MWh/year]
NPV	Net present value [€]

P_{grid}	Power to/from grid [kW]
P_{net}	Net power (consumption − production) [kW]
$P_{pre-charging}$	Additional power from grid to charge battery in times with few solar insolation [kW]
P_{rated}	Maximum charge/discharge power battery [kW]
ps	Power stabilizer [%]
s	Battery size [kWh]
SOC	State of Charge [%]
s_{opt}	Optimal storage size [kWh]

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2018.04.023.

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