ASSESSING THE BENEFITS OF DECENTRALISED RESIDENTIAL BATTERIES FOR LOAD PEAK SHAVING

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Highlights

- A performance metric was developed to assess the benefits of load peak shaving
- A photovoltaic and battery system for a test house in Northern Ireland was assessed
- Peak Shaving management strategies help to shave peaks by 98%
- To maximise the benefits of peak shaving a bigger battery size is needed
- Peak shaving incentive tariff is necessary to justify the cost in larger batteries

Abstract

The deployment of distributed, behind-the-meter batteries operating on a peak-shaving mode, could benefit the electricity network, by providing an optimal and location-specific services, increasing the penetration of intermittent renewable sources, and deferring costly network upgrades. However, the quantitative assessment of the benefits of load peak-shaving and its impact on the distribution network remains a challenge. The present paper introduces a metric of five indexes to evaluate the technical performances of load peak shaving. This metric is applied on a case study, based on a photovoltaic and battery system application for a test house in Northern Ireland, whose electricity demand is representative of the average UK demand profile. Two peak shaving strategies are compared with a more usual self-consumption mode, and the impact of the battery size is evaluated. Peak-shaving management strategies show promising performance by reducing peaks by more than 98%, while still decreasing the yearly consumption by 15%, and avoiding 75% of the photovoltaic-generated energy to be exported back to the grid. The economic analysis compared the net present values achieved under two different tariff policies. Using peak-shaving incentivising tariff remunerating customers £0.24 per kWh of peak shaved allowed to maintain profitability with a capacity cost of up to £400/kWh, compared to only £150/kWh for a usual flat tariff scheme. Such an incentive is a step forward in promoting customers to purchase a larger battery and to operate it in a way that benefits the grid operator.

Keywords

Peak Shaving; Integrated Battery; Energy Storage Control Strategies; Decentralized Control; Domestic Sector.

Nomenclature

Acronyms

BTM	Behind the Meter
LV	Low Voltage
NPV	Net Present Value
PBP	Payback Period
PV	Photovoltaic
PS	Peak-Shaving
SC	Self-Consumption

Constants

λ	Proportionality factor used to define the battery charging rate (W)
$Capa$	Battery Capacity (Wh)
T	Electricity rate (£/kWh)

Th_D Discharge threshold (W)

Th_C Charge threshold (W)

Variables

F_{PV} Forecasted PV generation (W)

F_{ND} Forecast profile of the Net Demand (W)

$I_{\{condition\}}$ Profile (vector) containing 1s in indices corresponding to timesteps for which $\{condition\}$ is true and 0s everywhere else

M_i , $i = 1 \dots 5$ Performance metrics parameters

$\widehat{M}$ weighted average of the performance metrics parameter

P_{com} Power command signal generated by an algorithm and used as an input by the battery model (W)

P_{ND} House Net Demand (Electricity consumption minus photovoltaic exports) (W)

P_L House Load (Net Demand plus Battery contribution) (W)

P_{Batt} Battery power output (W)

P_{Batt}^{MAX} battery rated (maximal) power (W)

P_{PV} PV generation (W)

R Revenues (£/year)

SOC State of Charge

SOC_{ref} Reference State of charge

$X(t)$ Value (scalar) of any time-dependent variable X taken at timestep t

$X([t_1, t_2])$ Profile (column vector) consisting in all the values of X between times t_1 and t_2

1 Introduction

1.1 Context of this work

Storage is often presented as the missing piece to the integration of renewables and other Low Carbon Technologies, thanks to the flexibility it can provide by reducing the need for synchronisation between production and generation of electricity [1]. Electricity storage can also help reduce losses in transmission and distribution networks through properly managed local use of stored energy. From the customers' perspective, owning a storage asset can allow to take advantage of differential tariffs or other incentives, in particular when coupled with on-site PV generation (often referred to as 'prosumerism') [2].

The literature indicates that electricity storage has a greater potential when located closer to loads, and further away from generation, as its benefits affect more regions of the network [3], however, the complexity of a large-scale deployment and the lack of data lead to immature business cases and subsequent lack of investment. Robust numerical modelling describing the impacts of low-voltage (LV) connected Battery Energy Storage Systems, BESS, is necessary to disrupt the present situation [4]. The reason for this stems from the variety of possible ways to control energy storage systems. Moreover, the effect on the electricity network can potentially be either beneficial or damaging, depending on the timing and intensity of charging and discharging patterns. The operation strategies implemented by battery controllers shape the impact on the grid. In this paper, the focus is put on decentralised peak-shaving (PS) control: batteries respond to the local power consumption in the house – as opposed to responding to an aggregator or price signals.

The term "peak-shaving" may refer to different concepts in the literature. We refer to "Peak Shaving" (PS) as the reduction in demand peaks, which are caused by electrical appliances within the household, as defined in [5]. Domestic demand peaks are created by the switching on and off of some appliances for seconds or minutes, causing the power consumption to spike at values significantly higher than the base load. Figure 1 gives an example of a demand profile over 24 hours, on which the spikes are identifiable (highlighted in red) compared to the base load values (in blue). Demand peaks cause electrical current peaks within the cables, where the losses are proportional to the square of the

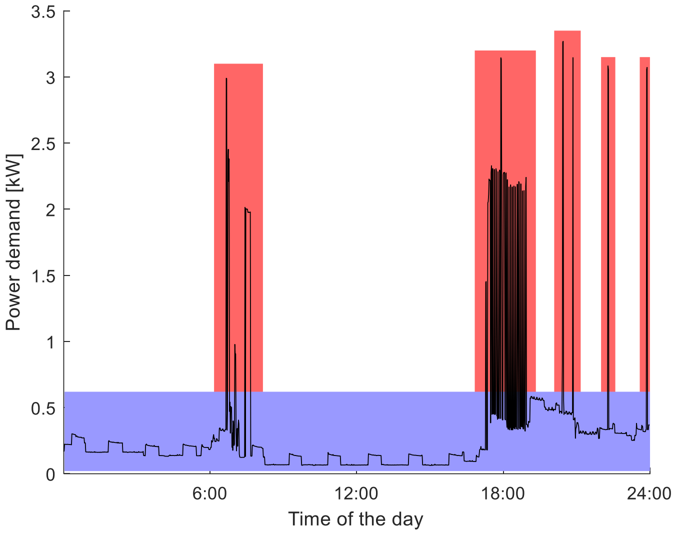

Figure 1 - Example of a demand profile for a single house, for 24 hours. Peaks are highlighted in red, and the baseload in blue.

electrical current (doubling the current increases the losses fourfold) [6]. Additionally, spikes are associated with voltage drops in the cables, and voltage unbalance in three-phase networks [7]. Finally, peaks are difficult to predict accurately, and therefore to manage. PS entails discharging a battery whenever such peaks are detected. As a result, if a battery is providing PS from behind the meter (BTM) of a customer, the grid does not “see” peaks anymore and therefore is not subjected to their negative impacts.

1.2 Literature review

Batteries represent a substantial capital investment, usually paid by the customer. Hence, maximising the financial benefits for the owner translates into minimising the payback period (PBP) value for the investment of the battery and PV system. This is done by using a Self-Consumption (SC) operation strategy to reduce the electricity imported from the grid, or by taking advantage of differential tariffs. Many of the articles related to the economic viability of BTM batteries are based on optimising the value of a cost function, for given tariffs and battery costs, constrained by the size of the battery using linear [8,9], convex [5] or dynamic [10] optimisation. The challenge is that such operation strategies can lead to negative impact on the grid: a pure SC strategy, means charging the battery whenever the PV panels are producing excess energy, but when the battery becomes full while the sun is still shining, excess PV starts spilling back to the grid, cause potential voltage swings [11]. Additionally, differential tariffs can cause a rebound effect, as illustrated in [12], where in order to remove peaks occurring during high electricity price, other peaks are generated during the times of cheap electricity by charging the battery. In contrast, it was shown that grid relief can be achieved without negatively affecting the quantity of renewable energy self-consumed (and therefore, customers' benefits) by applying a PS battery managing strategy [13].

A PS strategy consists of discharging the battery when the demand exceeds a certain threshold to "shave" the peaks and charging it otherwise. This approach is used in [14], and in [15] however a perfect forecast is used to define the threshold value in both cases, which is limiting the significance of the results. The perfect forecast assumption is often made, either explicitly [16] or implicitly [5], but it is obviously impractical, especially with high time resolution. A few publications address this challenge, such as [17] where a "live" response is implemented in addition to the response to the perfect forecast.

The PS threshold used in [18] adapts to the live consumption by increasing its value if the battery cannot meet the peak demand, however no mechanisms are presented to correct the threshold downwards when the demand decreases. Moreover, the study is limited to on one single day, containing one single peak, which is highly restricts any generalisation to more complex situations. In [19], the threshold is defined as the average of the power demand until the present time step. Using the average value is reasonable proxy for the threshold, however a "correction factor" should be added to account for the efficiency of the battery being lower than 100%, and for the fact that the average consumption in the future can be different to that of the past.

An interesting approach to bypass these challenges is introduced in [20], were the threshold is defined as 2kW and kept constant, but the charging strategy is based on the State Of Charge (SOC) value. More specifically, the battery is charged or discharged proportionally to the difference between a reference "target" SOC value (set to 50%) and the actual SOC of the battery. Therefore, the battery state is always “stabilised” towards this SOC target, to have enough room for absorbing PV-produced electricity, and enough capacity to shave potential coming peaks. The limitation of this approach lies in the choice of the target SOC that depends on the PV size, season, consumption habits, and other factors and its optimal value may change throughout battery operation. The present paper suggests a novel way to adjust the target SOC during the year.

Looking at the literature about PS for BTM batteries, a second challenge is the lack of a methodology to quantify the PS performance and therefore correctly assess the impact of using BTM batteries into the grid. In [21], the term “peak reduction” is widely used but never defined. It may refer to the difference between highest value of the profile before and after peak-shaving, however such definition works only if there is clearly a unique peak during the period considered. The approach in [22] is to look at a number of houses and the change in their After Diversity Maximum Demand (ADMD) after peak shaving as a performance indicator. Although the method helps to assess the impact on the grid, it fails to provide ‘per-household’ information on how the battery is performing. A similar issue is found in [23], where a method is given to assess the peak-shaving reduction potential of a substation, based on the shape of its load-duration curve (LDC). However, the indices introduced are defined for the characteristics of a substation and are not applicable directly to the LDC of a residential profile. In [24], only one peak was considered, leading to a straightforward way to judge the performance of the algorithm, but such method becomes unusable for a domestic load profile, containing up to tens of peaks during a single day. The method provided by [25] goes further in this direction, by defining peak reduction as the lowest threshold exceeded less than 1%, 1.5%, and 2% of the time in a residential profile, and then the performance is based on the number of times this limit has been violated, despite the use of a battery. This method indicates that the cumulated duration of peaks matters, but the chosen values of 1, 1.5 or 2 percent are arbitrary, and condition the performance results.

From this literature, it can be observed that a correct assessment of PS performance should evaluate the following aspects:

i) The peak magnitude [22–24].

ii) Their cumulated duration [23,25].

In addition, it is important that the algorithm maintain high performance regarding:

iii) The PV energy that a battery stores for later use on site (and which would have been spilled back to the grid, if no battery was present). Publications traditionally focus on self-consumption rate, defined in [26], or self-sufficiency ratio [27].

iv) The total energy consumed is required, in order to ensure that PS is not provided at the expense of very high total energy demand.

1.3 Scope of the study

The review presented above identifies a double gap in the literature for domestic peak shaving:

- A peak-shaving management strategy that does not require to use a threshold based on a perfect forecast to operate. It means a control method that fits the requirements of a domestic load profile that is characterised by high peak-to-mean ratio and high randomness in the peak occurrence timing.
- A methodology to quantify the performance of PS battery management strategies and their impact on the distribution network.

This paper addresses the double gap identified by describing and developing PS management strategies which can be easily integrated into battery controllers and by defining metrics and parameters to accurately quantify the technical performance achieved by the PS management strategies and the impact on the grid.

The study adopts a ‘bottom-up’ approach, focussing on a single house, equipped with Photovoltaic (PV) panels and a battery. This choice is motivated by three factors: first, a distributed, autonomous configuration is the simplest and cheapest strategy in terms of deployment of communication infrastructure. Secondly, BTM peak-shaving should lead to positive effects at all voltage levels, through reduction power flows, therefore substantial reduction of losses; of voltage fluctuation, and of phase imbalance, bringing about congestion relief and creating the opportunity for investment deferral [22]. Finally, financial and incentive mechanisms would be necessary in order to ensure that decentralised batteries benefit the network. Focusing the study at single house level will help understand which form these incentives should have, and this paper suggest a potential tariff scheme, made for PS incentivising.

1.4 Structure of the paper

The paper is organised as follows: Section 2 describes the methodology, which is then applied in a case study defined in Section 3. The results obtained are exposed and discussed in Section 4, and Section 5 concludes this paper.

2 Methodology

This section describes the PS strategies implemented, the new metrics proposed to assess the use of PS management strategies for BTM batteries and the economic parameters used to assess the benefits of PS.

2.1 Peak-shaving management strategies

Peak shaving entails drawing energy from the battery rather than from the grid when demand peaks above a certain threshold Th_D (Discharge threshold). If the power discharged by the battery is equal to the difference between the Net Demand Power P_{ND} and Th_D , the grid will not 'see' the peak. The value chosen for the discharge threshold is $Th_D = 1kW$. It corresponds to the transition between peak and non-peak values of the profile and can be identified as the inflection point in the LDC, shown in Figure 2.

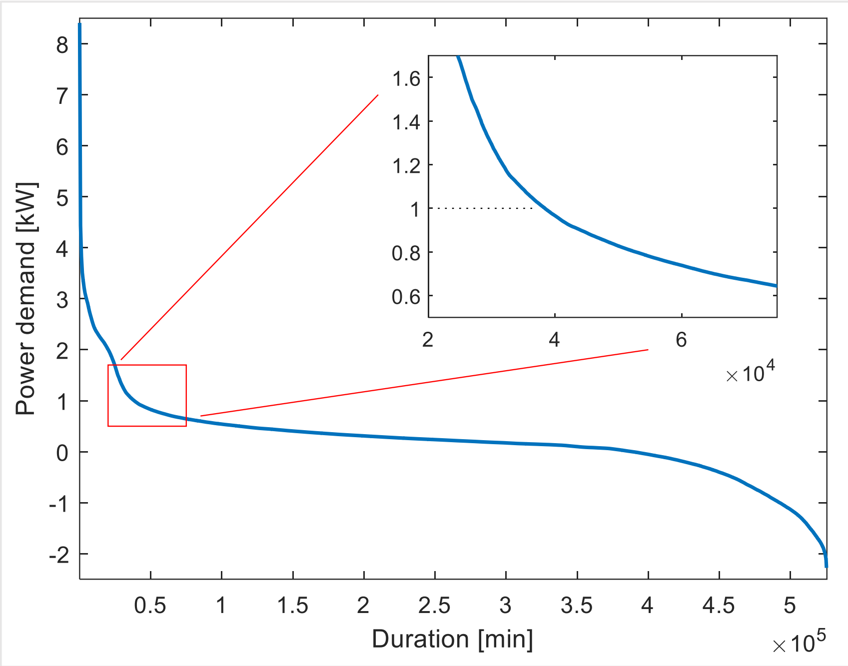

Figure 2 – Load Duration Curve (LDC) of the considered profile. The PS threshold Th_D is found at the slope decrease, representing the difference between peak and non-peak demand.

The "Peak-shaving" part itself is straightforward, provided enough energy is stored in the battery when needed. However, since the spikes are impossible to accurately predict, the challenge is ensuring that enough charge is present in the battery when needed. Therefore, a 'smart' PS management strategy is in fact a smart charge recovery strategy. In the following, two control strategies are studied, and the term "peak-shaving" is maintained, rather than "charge recovery" for consistency.

2.1.1 Reference SOC Algorithm

This algorithm was introduced in [20], for voltage fluctuation limitation. The general functioning of this algorithm was not changed and is presented below. The only changes were made to the values of the parameters used. The control method consists of operating the battery so that its SOC tends towards a reference (or target) value, set to $SOC_{ref} = 50\%$ (value used in the original publication). A charge, Th_C, and discharge threshold, Th_D, are also defined, and the values chosen for this study are respectively $Th_C = 0\ kW$ and $Th_D = 1\ kW$ (as opposed to respectively +2kW and -2kW in the original paper). The choice of Th_D is explained previously in section 2.1, and it is defined as the limit found in the yearly LDC between base load and peak (inflection point). Th_C is chosen equal to 0 in order to have a straightforward comparison with the self-consumption algorithm.

At any time-step, the decision to charge or discharge the battery and at which power rate is made, depends on the following cases:

1. If the net power demand, P_{ND}, exceed the demand threshold: $P_{ND}(t) > Th_D$, the battery discharges to make up for the difference (it should be noted that P_{ND} is defined positive when power flows into the house). The power command signal, P_{com} sent to the battery, is defined by equation (1).

$$P_{com}(t) = Th_D - P_{ND}(t) \tag{1}$$

   The resulting load (power drawn from the grid) should become equal to the threshold value, Th_D, unless the peak exceeds what the inverter can provide, or the battery is empty.

2. If the charging threshold, Th_C is exceeded,: $P_{ND}(t) < Th_C$. The battery will charge in order to absorb the difference, and equation (2) gives the power command in this case.

$$P_{com}(t) = Th_C - P_{ND}(t) \tag{2}$$

   The resulting load becomes equal to the charging threshold, Th_C.

3. If the net demand is between the thresholds: $Th_C < P_{ND}(t) < Th_D$, the battery charges or discharges in order to make the SOC tend towards the target value. The power command is obtained by multiplying the SOC difference by proportion coefficient λ as in equation (3).

$$P_{com}(t) = \lambda\left[SOC_{ref} - SOC(t-1)\right] \tag{3}$$

   As introduced in [20], the coefficient λ is defined such that the maximum possible SOC difference would lead to the battery maximum power output P_{Batt}^{MAX}, described in equation (4).

$$\lambda = \frac{P_{Batt}^{MAX}}{\max\left(SOC_{ref} - 0\% , 100\% - SOC_{ref}\right)} \tag{4}$$

2.1.2 Reference SOC estimation using Forecast

The second algorithm has been proposed by the authors to improve the “Reference SOC” algorithm described in the previous subsection. Having a fixed SOC_{ref} value may lead to sub-optimal performance. For example, in a day with little PV production, but a large number of peaks, a value of 50% (as defined in [20]) may lead to the battery running flat too early to shave enough peaks, meaning that a proportion of the battery capacity is not used. The solution implemented here consists of using forecasts for the coming 24h period to adapt the SOC value. If a small number of peaks is expected, the SOC_{ref} value is reduced, in order to provide more capacity for PV charging, and if a large number is expected, then the value is raised to ensure sufficient charging can be achieved during non-peak times. Equation (5) gives the formula used for calculating the value for SOC_{ref}.

$$SOC_{ref} = 0.2 + 0.6 * \frac{E_{PS}}{Capa} \tag{5}$$

Where E_{PS} is the total amount of energy required to shave the peaks forecasted in the following 24-hour period, defined in equation (6), and $Capa$ is the battery capacity.

$$E_{PS} = I_{F_{ND} > Th_D}^{T}([t, t + 24h]) * (F_{ND}([t, t + 24h]) - Th_D) \tag{6}$$

Where $I_{F_{ND} > Th_D}$ is a vector composed of ‘1’ in index corresponding to timesteps the condition $F_{ND} > Th_D$ is true and ‘0’ elsewhere, over the period $[t, t + 24h]$ and F_{ND} is the forecasted net demand.

The constant 0.2 and factor 0.6 in equation (5) are linear corrections, that maintains SOC_{ref} within the range 20%-80%, thereby reducing the impact of forecast inaccuracy by always leaving some capacity for unexpected PV charging and Peak shaving.

A ‘light’ forecast model was sought for computational efficiency, since the model is run for a full one-year period, with a one-minute resolution. Different forecast models have been investigated among three main categories: i) persistent types use past consumption profiles with minimum treatment, ii) ARIMA models apply statistical tools to past profiles, taking advantage of possible correlations, and iii) artificial intelligence-based models use neural networks to “learn” to from past time series and extrapolate predictions [28]. These methods were benchmarked in [29], specifically for their application in household electricity consumption forecasting, with very high granularity (down to one second). The study concludes that more advanced forecasting methods (ARIMA models or neural network models) do not generally produce better performance than simpler persistence forecasts [29]. In practice, publications claim to have developed methods that systematically beat the persistence model, based on neural networks [30] or probabilistic methods [31], but the simple fact that the persistence model is used as a benchmark in these publications gives an indication of its performance.

Based on this conclusion, a persistence forecast model was chosen for the present study. The forecast demand is defined as the previous same weekday as a forecast profile, in order to account for weekly variations. (e.g. if the current day is a Wednesday, the demand profile of the previous Wednesday is used as a forecast profile). This forecast model is very quick to run and therefore allows the forecast to be updated at every timestep, hence reducing the effect of inaccuracies. Moreover, it can be implemented in a controller which only requires keeping in memory the previous 7 days of demand and PV generation.

2.2 Performance metrics definition

The graph of a peak-shaved profile usually gives an idea of how well the PS algorithm performed, (e.g. Figure 8 in the results section) but a quantification is necessary in order to accurately compare and evaluate results. The following introduces a metric composed of 5 parameters which aims to provide a comprehensive comparison of the performance of different aspects of peak shaving.

As detailed in the literature review, the change in peak magnitude is obviously an important aspect to measure [22–24]. The first metrics parameter gives an estimation of the peak reduction achieved by the PS algorithms. Since many peaks are typically present on a domestic consumption profile, it is not practically possible to look at a single peak's reduction. M_1 is defined as the ratio between the sum of the average squared peak after and before PS:

$$M_1 = \frac{I_{P_L > Th_D}^T * [(P_L - Th_D)^2]}{I_{P_{ND} > Th_D}^T * [(P_{ND} - Th_D)^2]} \tag{7}$$

Where $I_{\{condition\}}$ is a vector composed of '1' in index corresponding to timesteps where the $\{condition\}$ is true, and are zeros elsewhere. P_L is the vector of the load profile, and P_{ND} the net demand profile. M_1 can be seen as a standard deviation change, calculated with respect the Th_D instead of the mean value, and considering only values higher than Th_D.

In addition to the decrease in peak height, it is relevant to consider the cumulated duration for which the threshold is exceeded [23,25]. Parameter M_1 provides an indication of the 'vertical' reduction in peaks, similarly, parameter M_2 provides their 'horizontal' reduction, by quantifying the duration spent exceeding the threshold. More precisely, M_2 is defined as the ratio between the duration exceeding the threshold after PS and before PS:

$$M_2 = \frac{I^T * I_{P_L > Th_D}}{I^T * I_{P_{ND} > Th_D}} \tag{8}$$

In terms of PV energy management, publications typically focus on the customers side, using SC ratio [26], or self-sufficiency ratio [27]. In our case, the focus is on the grid side, therefore parameter M_3 calculates the increase in energy used on site, that would have been exported to the grid if there were no battery. Mathematically:

$$M_3 = 1 - \frac{I_{P_L < 0}^T * P_L}{I_{P_{ND} < 0}^T * P_{ND}} \tag{9}$$

Due to energy conversion efficiencies lower than 100%, some energy is lost during the process of charging and discharging a battery. This extra energy will appear in the electricity bill, and moreover, will have to be somehow produced. A PS algorithm could not be qualified as performant if it was causing large increases in energy. Parameter M_4 quantifies the change in relative energy consumption variation:

$$M_4 = \frac{I^T_{P_L>0} * P_L - I^T_{P_{ND}>0} * P_{ND}}{I^T_{P_{ND}>0} * P_{ND}} \tag{10}$$

Finally, in order to determine the overall performance of an algorithm, parameter $\widehat{M}$ is defined as an average of the M_i

$$\widehat{M} = \frac{(1 - M_1) + (1 - M_2) + M_3 + \left(1 - \sigma(M_4)\right)}{4} \tag{11}$$

Where: σ is a sigmoid function defined as $\sigma(z) = \frac{1}{1+e^{-z}}$

$\widehat{M}$ is not strictly speaking an average or even a weighted average. Simple operations were added to parameters M_1, M_2 and M_4 so that each term of $\widehat{M}$ tends towards 1 with high performance, and 0 when the performance is poor. The sigmoid function is used to maintain values of M_4 between 0 and +1, for comparison with the other parameters.

Table 1 summarises the metrics parameter and how to read them.

Name	Feature measured	Definition	Best Performance	Worst performance
$\boldsymbol{M_1}$	Profile flatness	$M_1 = \frac{I^T_{P_L > Th_D} * [(P_L - Th_D)^2]}{I^T_{P_{ND} > Th_D} * [(P_{ND} - Th_D)^2]}$	$M_1 \rightarrow 0$	$M_1 \rightarrow 1$
$\boldsymbol{M_2}$	Peak duration	$M_2 = \frac{I^T * I_{P_L > Th_D}}{I^T * I_{P_{ND} > Th_D}}$	$M_2 \rightarrow 0$	$M_2 \rightarrow 1$
$\boldsymbol{M_3}$	Exported Energy	$M_3 = 1 - \frac{I^T_{P_L < 0} * P_L}{I^T_{P_{ND} < 0} * P_{ND}}$	$M_3 \rightarrow 1$	$M_3 \rightarrow 0$
$\boldsymbol{M_4}$	Change Energy Demand	$M_4 = \frac{I^T_{P_L > 0} * P_L - I^T_{P_{ND} > 0} * P_{ND}}{I^T_{P_{ND} > 0} * P_{ND}}$	$M_4 \rightarrow -\infty$	$M_4 \rightarrow +\infty$
$\boldsymbol{\widehat{M}}$	Average Performance	$\widehat{M} = \frac{(1 - M_1) + (1 - M_2) + M_3 + \left(1 - \sigma(10 * M_4)\right)}{4}$	$\widehat{M} \rightarrow 1$	$\widehat{M} \rightarrow 0$

Table 1 - Summary of the metrics' definition

2.3 Economic study parameters

The economic analysis is based on Net Present Value (NPV) calculations using equation (12).

$$NPV(C_0, N) = -C_0 + \sum_{k=1}^{N} \frac{R}{(1+i)^k} \tag{12}$$

C_0 is the battery initial investment, $C_0 = Capacity\ cost\ [£/kWh] * Capa\ [kWh]$. N is the number of years considered and i the discount rate (a value of 5% is chosen). R is the yearly revenue. The revenue normally varies from year to year, but in this case only one year of measurements was available. It was therefore assumed that R is the same from one year to another. The economic calculations here only for the battery system: it is assumed that the PV panels are already present, and their economics is not assessed. Equations (13) and (14) detail the calculations of R for flat tariff and PS incentive tariff respectively. They are calculated by working out the difference between the cost of electricity (with the flat tariff or with PS incentive tariff respectively) compared to what electricity would have costed if no battery was installed (i.e. by looking at the net demand).

$$R_{Flat} = R_{Flat,Load} - R_{Flat,ND} \tag{13}$$

$$R_{PSIT} = R_{PSIT,Load} - R_{Flat,ND} \tag{14}$$

R_{Flat} and R_{PSIT} are the annual net revenues with a flat tariff and a PS incentive tariff respectively. $R_{Flat,Load}$ and $R_{PSIT,Load}$ are the gross revenues obtained with a flat tariff, when considering the battery operation with a flat tariff and the PS incentive tariff respectively. $R_{Flat,ND}$ is the gross revenue that would have been obtained with a flat tariff if no battery was operated.

To determine the influence of the capital cost of the battery on its economic viability, the PBP was calculated for a range of C_0 values. The PBP measures the time it takes for the NPV to become positive after an investment. It is given in years, and can be found using equation (15), in which the NPV is calculated from equation (12).

$$N_{pay\ back\ period} = \min(N \mid NPV(C_0, N) > 0) \tag{15}$$

Two tariff schemes were considered for the NPV calculation. The first one is the usual flat tariff, for which a constant price is given for each unit of electricity consumed. The value was fixed to £0.17/kWh as it represents the regulated tariff in Northern Ireland, where the house is located [32]. The second tariff was created for the purpose of the study, as a peak-shaving incentive policy. It was inspired by the GB Renewable Heat Incentive Tariffs (RHI) which aimed to incentivise the production of renewable heat by paying the customer for each unit of renewable heat produced (typically by a heat pump) [33]. With the PS incentive tariff, the customer is remunerated for each kWh coming out of the battery that is used to reduce peaks and is charged at a higher rate for the peaks generated (when the load cannot be maintained below the peak threshold Th_D). The rest of the billing is the same as for regular flat tariffs of 0.14 £/kWh to incentivise customers to remain under the threshold limit. During peak times the amount of energy above the threshold is charged at £0.24/kWh, and the incentives for shaving peaks is £0.24/kWh of peak reduced.

Name		Charge
Flat Tariff		$T_{flat} = -£0.17/kWh$
Exported Feed-in Tariffs		$T_{FiT} = £0.05/kWh$
Peak-Shaving Incentive Tariff	Off-Peak:	$T_{OffPeak} = -£0.14/kWh$
	Peak:	$T_{Peak} = -£0.24/kWh$
	Peak reduction:	$T_{PS} = £0.24/kWh$
Exported Feed-in Tariffs		$T_{FiT} = £0.05/kWh$

Table 2 - Summary of the values used for electricity cost calculations

Exported Feed-in Tariffs were also considered for both cases, and a value of £0.05 per kWh exported is used, reflecting previous support schemes [34]. Table 2 summarises the values used for the different tariffs.

3 Case study

The PS battery management strategies have been applied to one of the test houses located in Northern Ireland (Fig.6). These houses are mid-terraced, energy inefficient design, built according to 1900 standards, and represent 28% of the UK housing stock. The house considered is inhabited by a family of three, comprising two adults and a teenager [35]. Monitoring equipment is located in the guard chambers and measures the electricity consumption with one-minute resolution. The house is equipped with a retrofitted air-source heat pump, and a backup gas boiler for heating[36,37] However, the electricity consumption of the heat pump was measured separately, therefore the data used corresponds to the electricity consumption without any electrical heating.

3.1 Data collection

Figure 3 - Test Houses at Ulster University, Jordanstown Campus [36]. The electricity consumption of house 64 was used for the present study.

The data collected covers one full year: from January 1st, 2018 at 00:00, to December 31st, 2018 at 23:59, at a resolution of 1 minute. The energy consumption throughout that year was 4,044kWh making it a typical medium consumer in the UK [38]. It was assumed that the house is equipped with a 2kWp PV panel on its rooftop, oriented with a 32° tilt angle and -40° azimuth angle. Its generation profile for the 1-year period was generated by TRNSYS [35]. The net demand profile was thus obtained by subtracting the PV profile to the house demand profile.

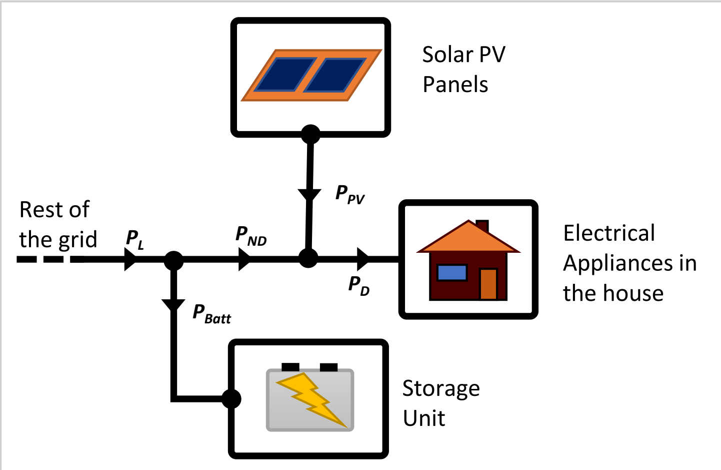

Figure 4 - Lay out of the simulation model analysed and sign convention for the power flows

Figure 4 displays the lay-out considered and summarises the sign convention used for the different power flows. The power values are positive when flowing towards the house, except for the battery P_{Batt}.

3.2 Battery model description

A "bucket" model has been used to model the battery. This choice comes from the simplicity of the model, which only captures essential aspects of the battery, leading to a computationally efficient result [39]. The model used is described in Figure 5.

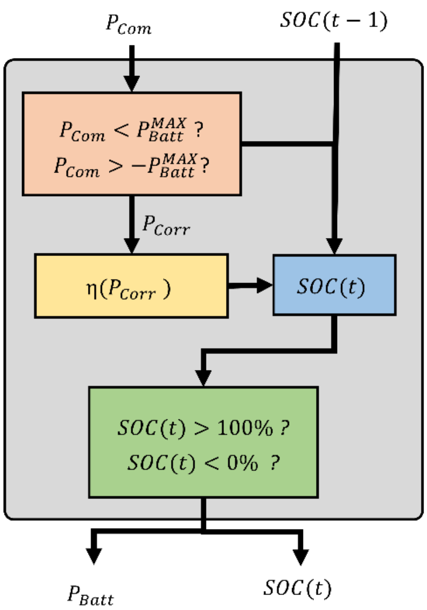

Figure 5 - Illustration of the function principle of the battery model

The model takes as an input the command power P_{com}, calculated using one of the algorithms defined in section 2.1., and the SOC of the battery at the previous time step. It calculates the actual battery output power, and the updated SOC, based on internal efficiency and power and energy limitations. The efficiency of the energy transfers is modelled by a linearized inverted curve, show in Figure 3. The points A, B, C and D were tuned during the validation process.

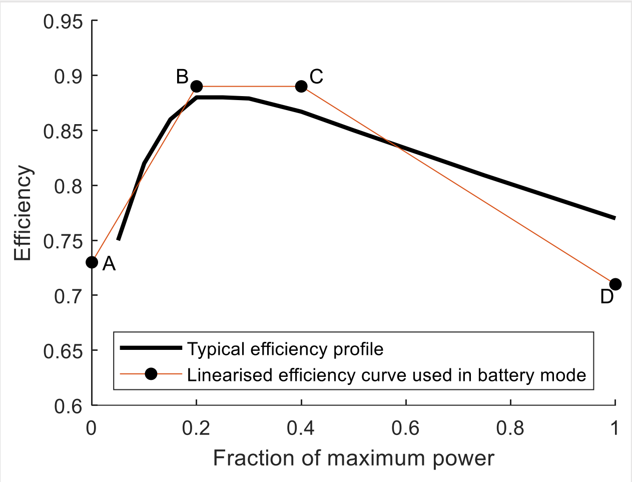

Figure 6 – Typical and linearized efficiency curves.

3.3 Battery model validation

The operating data of a 4kWh, 2kW battery operating in one of the test houses was collected and used for the validation of the battery model. By looking at the operation data, it could be seen that the battery is programmed to charge when the net demand becomes lower than minus 33W and discharge when the house consumption reaches values higher than 33W. This operation algorithm was modelled using MATLAB to generate the power command, $P_{com}(t)$ of each time step based on the house consumption. The model was fed with the net demand measurements for 178 days (from August 2019 to February 2020). The validation was done by comparing the power output and SOC of the real battery, to those of the battery model. The points A, B, C and D of the efficiency curve (Figure 6) were adjusted to fit the model to the actual battery used. The values used are show in Table 3.

Point	A	B	C	D
% of $\boldsymbol{P_{Batt}^{MAX}}$	0%	20%	40%	100%

Efficiency	0.73	0.89	0.89	0.71

Table 3 - Tuning of the efficiency curve

	SOC	Power output
RMSE	0.36%	0.11W
R^2	0.994	0.972

Table 4 - Statistical results obtained for 178 days of comparison

The quality of the model was assessed by calculating the root mean squared error (RMSE) and the R^2 values for power profiles and SOC profiles. The values obtained are summarised in Table 4.

To illustrate the results, Figure 7 shows a scatter of the SOC values measured on the real battery, against the SOC values obtained with our model (blue dots). The intensity of the bleu denotes the density. The values are concentrated around a straight line of equation $y = x$ (in black). Additionally, the average SOC values obtained with the model are plotted in red, for each measured SOC. This red curve almost superimposes the $y = x$ line. To conclude, the SOC and power outputs are very close to each other in the modelled and measured results, which make this model suitable to be used for our application.

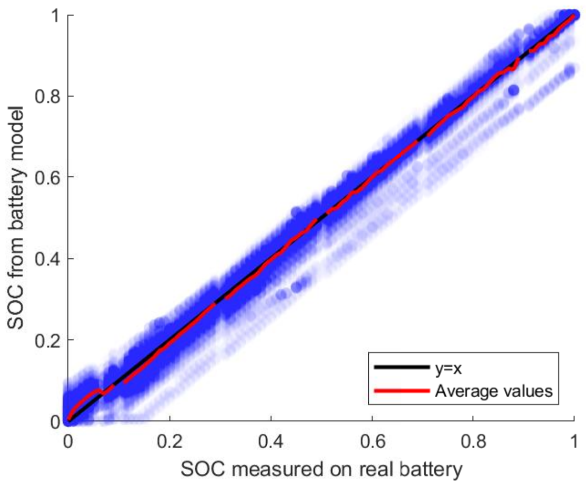

Figure 7 - Comparison of the SOC measured for the real battery, and the SOC obtained from the battery model, for the 178-day period.

4 Results and discussion

The PS battery management strategies are compared to the commonly used SC strategy for 7 different battery sizes, from small 2kWh / 1kW to large 15kWh / 11kW. First, the technical performance results are presented and discussed, followed by an evaluation of the technical analysis.

4.1 Technical performance results

Figure 8 shows a 3-day snapshot of the results for the three algorithms (SC at the top ; fixed SOC_{ref} in the middle and forecasted SOC_{ref} at the bottom), where for clarity only 3 battery sizes are reported: 2kWh, 8kWh and 15kWh. The detailed results for each M parameter and all three algorithms are shown in Figure 9.

4.1.1 SC control method

To start with, the commonly used SC algorithm presents good energy managements with higher values of parameters M_3 (avoided PV exports) low negative values for M_4 (change in net energy demand). More than 90% of the PV exports are avoided, and the demand is reduced by 25% for an 8kWh battery, or larger (Figure 9). This is visible on Figure 8, where all the PV energy generated is stored in the battery, as indicated by load profiles remaining equal to zero during sunny hours. However, the peak reduction performances of the SC algorithms are very poor across all battery capacities. This is expressed by parameter M_1 and M_2 (reduction in peak magnitude and duration respectively) in Figure 9. Their values remain higher than 70%, indicating that the peaks were not significantly reduced. These results are partly explained by the first day shown in Figure 8 which was chosen for being particularly cloudy. For all three sizes represented, the battery did not charge, hence was not able to provide any peak shaving in the evening time (indicated by all the curves superimposing the net demand). The remainder of the explanation comes from the discharge threshold being equal to 0kWh. Consequently, when the PV panels stop producing electricity, the profile remains flat and equal to zero only for few hours as the battery is discharging, until the battery runs flat after a few hours, and is unable to shave any more peak.

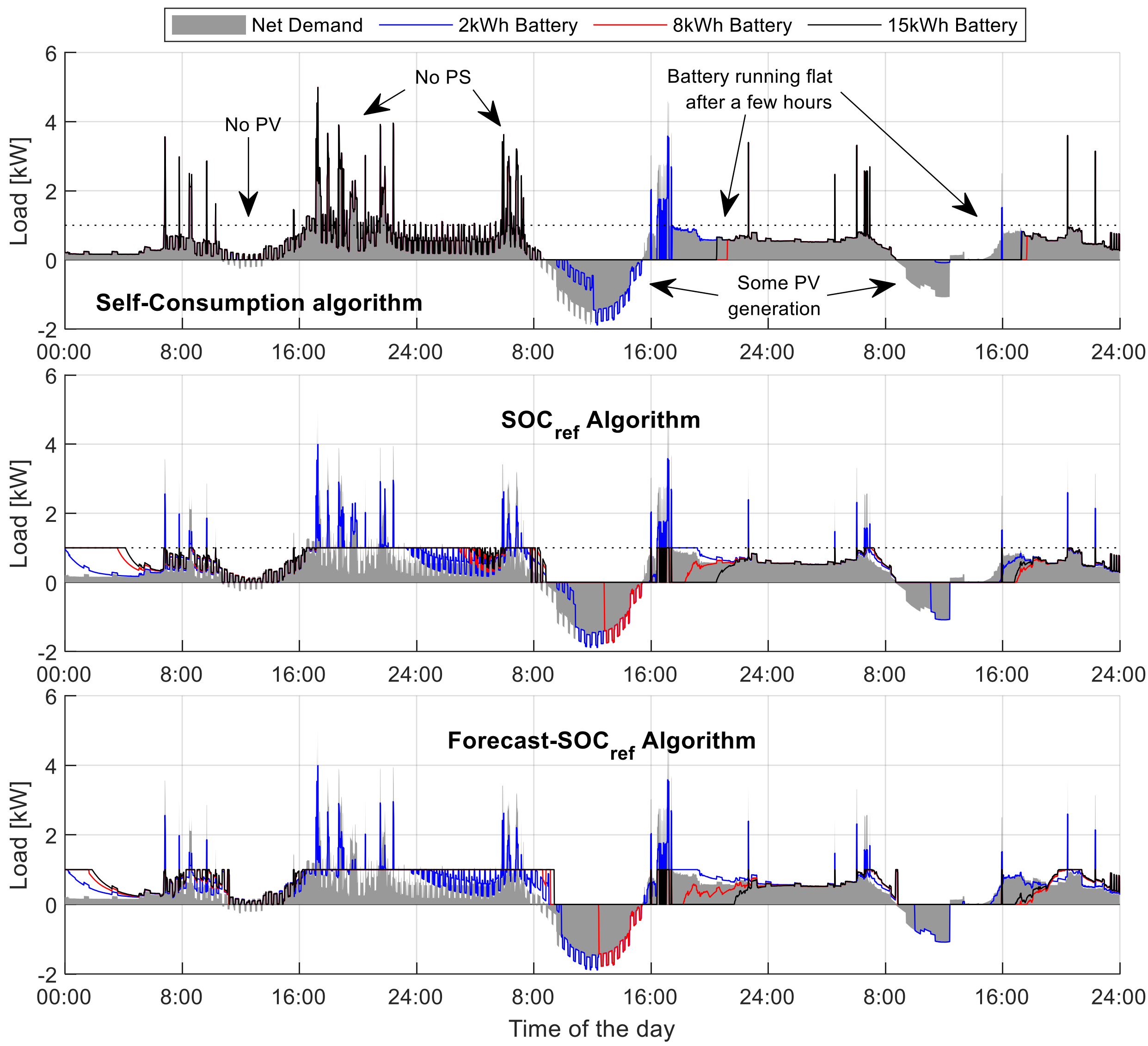

Figure 8 - Profiles for the 3 algorithms (SC: top, SOC_{ref}: middle, forecast-SOC_{ref}: bottom) over the 3-day period February 13-15th 2018. For each graph, the Net Demand is shown in grey (Household demand including PV, excluding any battery), the total load including a 2kWh battery (blue), an 8kWh battery (red) and a 15kWh battery (black)

4.1.2 PS control methods

The two PS management strategies show good peak shaving performance for batteries 8kWh batteries and larger: parameters M_1 and M_2 indicated that close to 0% of the peak magnitude and duration remains after PS. The less performant results obtained with smaller batteries are partly explained by the lower inverter rated which directly constraints the magnitude reduction of a peak. (e.g. for a peak of 6kW, the best that an inverter rated at, say 2kW can do is to reduce the peak to 4kW, even if the battery is fully charged). Figure 8 (middle and lower graphs) shows numerous partly shaved peaks for the 2kWh battery (blue curves), all reduced by exactly 1kW (inverter rating). The low capacity itself explains the rest of the poor PS performance of the PS algorithms for small sizes. The battery runs flat before all evening peaks can be shaved. For similar reasons, the energy performance of the PS algorithms is not satisfactory at low battery sizes but catches up with the SC algorithm for larger batteries. Figure 9 shows more than 70% of PV exports are avoided (parameter M_3) and the energy consumption is reduced by more than 16% (Parameter M_4).

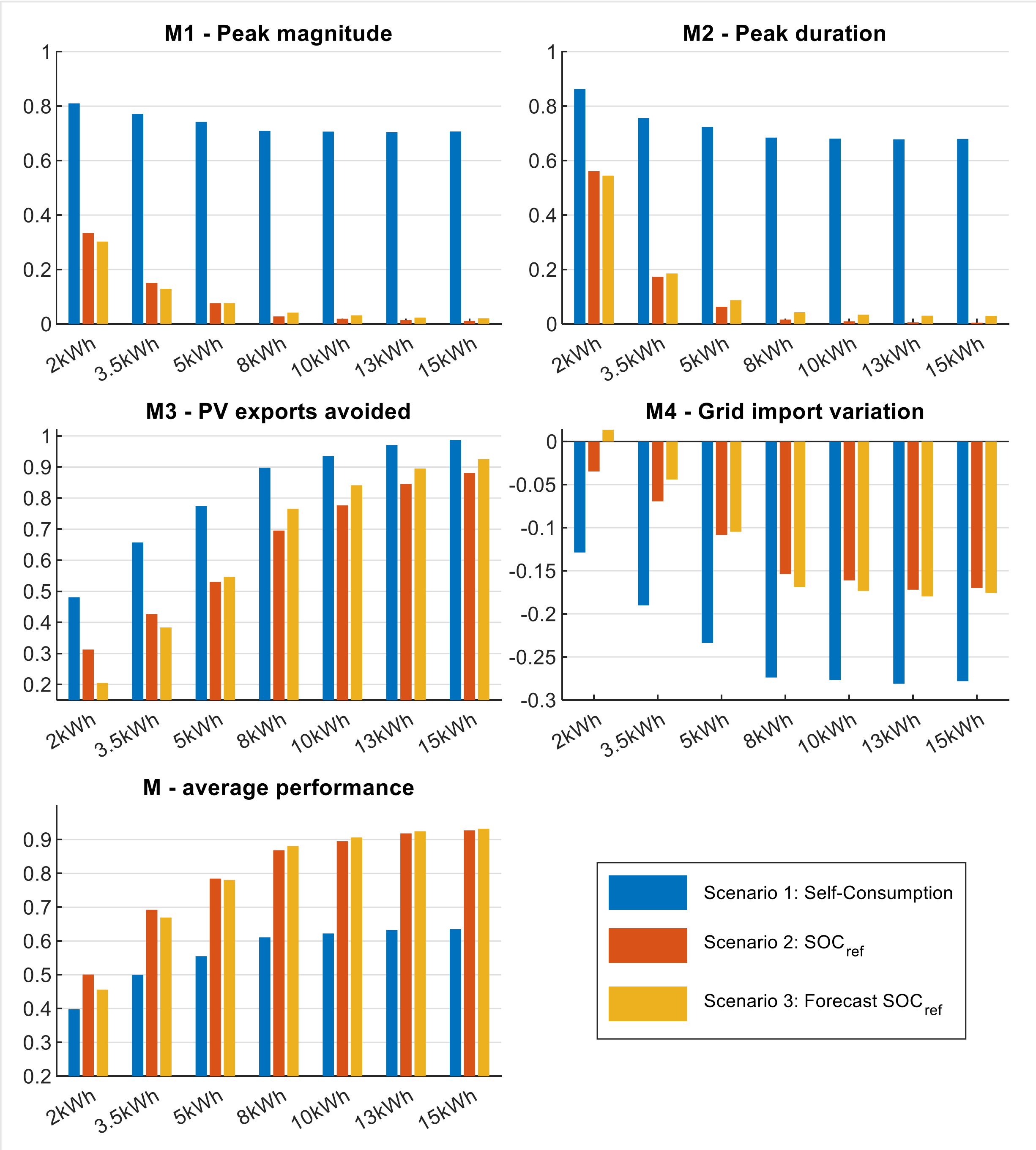

Figure 9 - Performance comparison for each M-parameter (each graph representing one parameter) and for each Algorithm: SC in blue, SOC_{ref} in red, and forecast- SOC_{ref} in orange.

4.1.3 Global performance

The performance of all management strategies for each M-parameter tend to individually improve with larger battery capacities. This trend is visible in parameter $\widehat{M}$ (Figure 9) showing the global performance of all three algorithms. Due to the very modest results of the SC method for parameters M_1 and M_2, its resulting global performance are about half as high as those of the other algorithms. This poor performance by the SC algorithm is observed in the LDC shown in Figure 10 where the curve remains very close to the Net Demand LDC for values above the discharge threshold. Good PV management performance are also visible on the left-hand side zoom, showing the SC algorithm (in red) letting very little amounts PV exported back to the grid (negative values).

The two PS algorithms show similar results for all the M-parameters, including $\widehat{M}$. Using the fixed SOC_{ref} yields slightly better for lower battery sizes and remaining while using forecast improves the results obtained for 8kWh capacities and higher. These differences are partly explained by coincidence: the difficulty to accurately forecast peaks leads to alternatively good and poor anticipation of the coming peaks yielding overall neglectable improvement obtained by adding forecast. The slightly higher performance of the forecast-based algorithm with larger batteries is

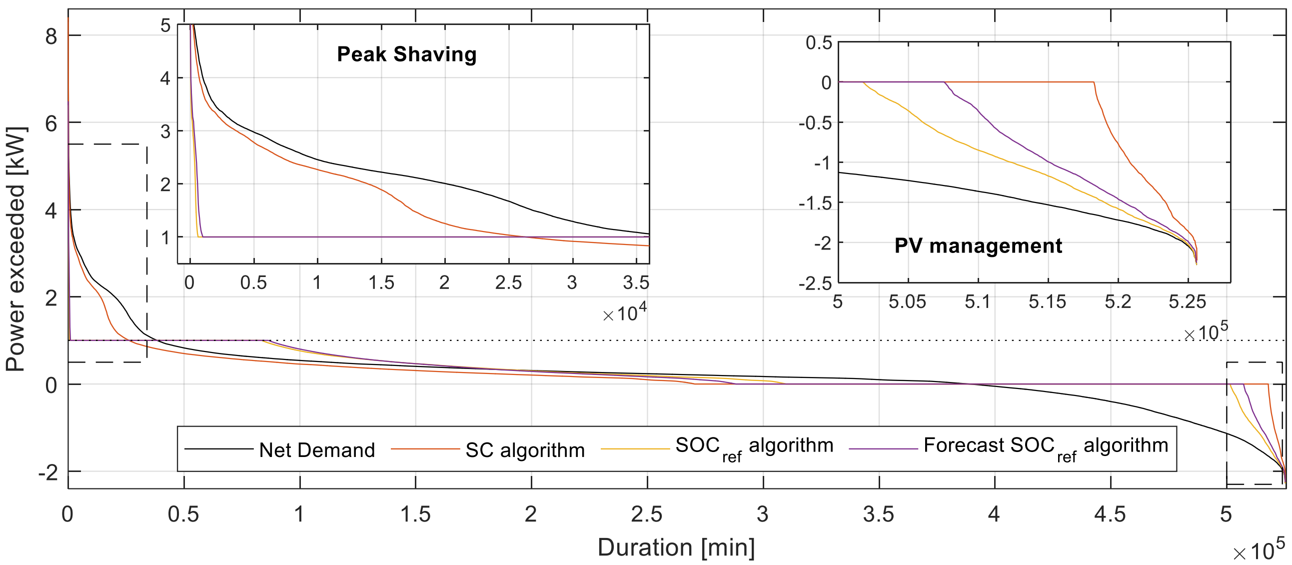

Figure 10 - Duration curves of the 3 algorithms for an 8kWh battery, and the net demand (before battery contribution).

explained by the lower susceptibility of the energy performance (M_3 and M_4) to forecasting inaccuracies. If the battery capacity is large enough, there is still room for PV charging as long as the forecasting error remains small enough. This can be observed on the LDCs Figure 10, where the zoom on the PS part (right hand side) shows a very small advantage of the SOC_{ref} algorithm on reducing peaks, whereas the forecast SOC_{ref} method provides more PV exports reduction, as seen on the corresponding zoom (left hand side).

Due to this similarity between the two PS algorithms, the economic analysis that follows only considers the SOC_{ref} algorithm, compared to the SC method.

4.2 Economic analysis

4.2.1 Results for a flat tariff

Figure 11 shows the NPV in case of flat tariff for the SC and PS management strategies. The different colours correspond to different battery sizes, and the line type to the algorithm. The investment period is limited to 10 years, as most batteries have a lifespan of around this duration, therefore if the PBP is reached after 10 years, the replacement and/or maintenance costs will make it

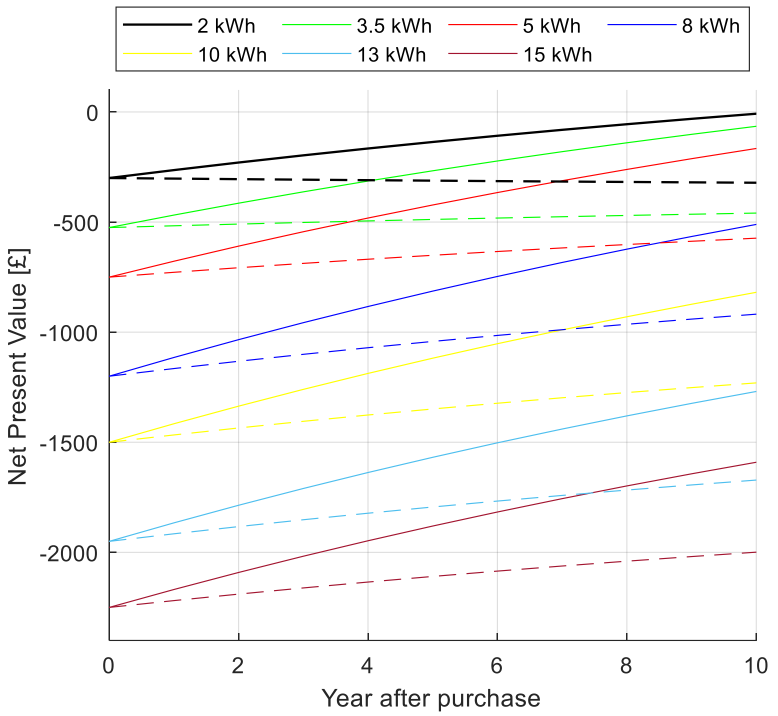

Figure 11 – Net Present Values (£) obtained with a flat tariff, for the first 10 years of investment, for all the battery sizes considered in the study (from 2kWh until 15kWh). SC algorithm in solid lines and PS algorithm in dashed lines

impossible to ever reach profitability. The NPV curves are shifted downwards as the capacity size increases, although it can be noticed that higher battery capacities perform slightly better, as indicated by a steeper slope, but not enough to cover the increasing investment cost.

For the case under analysis Figure 11 indicates that the only viable case is for a 2kWh battery following a SC strategy, purchased at a capacity cost of 150£/kWh. This capital cost is unrealistically low, which means that it is currently not profitable to use battery combined with PV units for the residential sector at the current battery cost. This result is important, since it implies that the customer will not have any direct interest in purchasing a larger battery and use a battery management strategy that would benefit the grid.

4.2.2 Peak-shaving incentive tariff

First, the assumption that only a 5kWh and an 8kWh batteries should be kept for the economic analysis is assessed. This assumption comes from looking at parameter $\widehat{M}$, Figure 9, indicating that the increase in performance for larger batteries than 8kWh is neglectable, therefore making the additional investment unworthy. In Figure 12, the NPV curves for a 3.5, 5, 8 and 10kWh batteries for $C_0 = £150/kWh$ are plotted in solid lines for the PS incentive tariff, and in dashed line with the flat tariff.

Increasing the battery size from 3.5 to 5kWh leads to an increase of 0.7 years in the PBP at this capacity cost, for an increase from about 0.68 to 0.78 in parameter $\widehat{M}$ (Figure 9). On the other hand, increasing from 8 to 10kWh size leads to reaching breakeven about 1.5 year later, for an increase in performance from 0.87 to 0.9: a significantly lower increase in performance for a larger increase in PBP. For this reason, the economic study is restrained to 5kWh and 8kWh battery sizes.

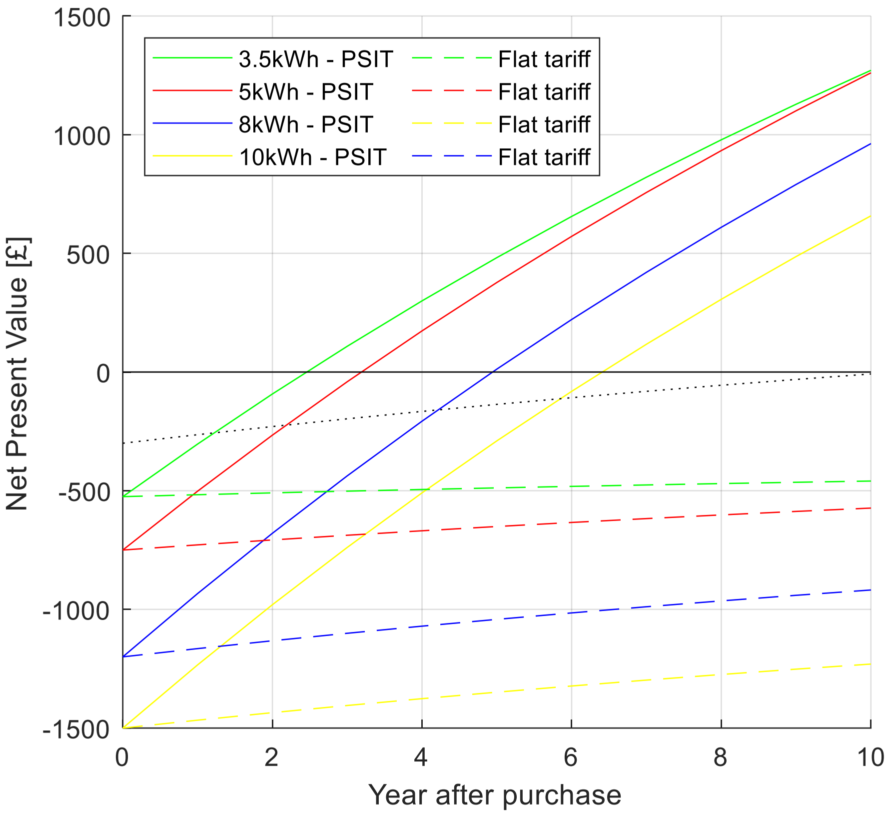

Figure 12 -Net Present Values (£) obtained with a Peak-Shaving algorithm, for the first 10 years after purchase, for battery sizes ranging from 3.5kWh to 10kWh. Solid lines correspond to the application of the PS incentive tariff, and dashed lines to the flat tariff

The results displayed in Figure 12 prove the capability for the PS incentive tariff to promote the purchase of a larger battery and operate it in PS mode. For all battery sizes considered, the NPV curves are significantly steeper than with the flat tariff, which substantially shortens the PBP. The PBP is graphically found as the intercept between an NPV curve and the line $y = 0$. The NPV curve of a 2kWh battery operating in SC mode, with flat tariff is also represented in dotted black line for comparison.

Nevertheless, the results are obtained for an initial capacity cost of £150/kWh, which is unrealistically low. In the following, the impact of the investment capacity on the PBP is evaluated.

4.2.3 Impact of capacity cost on payback period

The graph of Figure 13 was obtained by varying the C_0 value from £0/kWh until £500/kWh in steps of 10, and measuring the intercept between the corresponding NPV curve and the $y = 0$ axis (as in Figure 11 and Figure 12), which defines the PBP. The value of this PBP is represented in the vertical axis of Figure 13 and the C_0 value that lead to this result in the horizontal axis.

The results are presented for PSIT and flat tariff (in solid and dashed lines respectively), for the two selected battery sizes, 5kWh and 8kWh (in red and blue, respectively). The curve obtained for a 2kWh battery operating on self-consumption mode, with a flat tariff is also shown in Figure 13, as comparison.

The first observation is that using a flat tariff with the PS algorithm reduces significantly the system's economic viability. The very steep curves obtained for both battery when using a flat tariff sizes (dashed lines, overlapping each-other on the graph) show that even with an unrealistic low capital investment under £50/kWh it would still take more than 10 years to reach breakeven point. This very low economic viability can seem to be in contradiction with the results obtained for parameters M_3 and even more, M_4 (Figure 9). These parameters indicated that the PS algorithm still

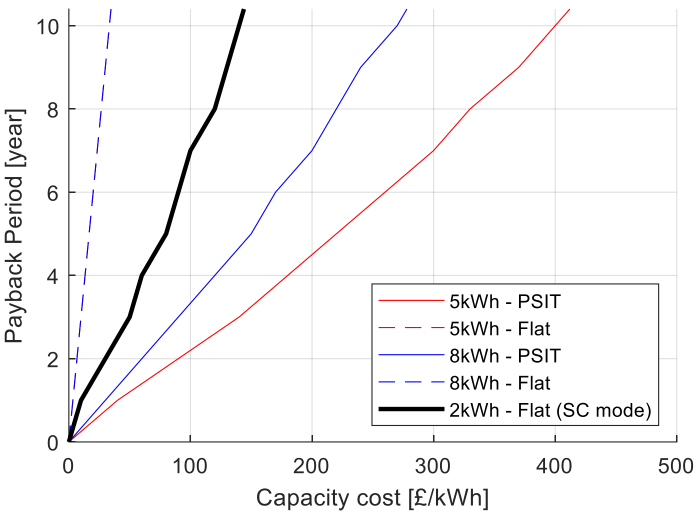

Figure 13 – Payback period (in year) against Capacity cost (in £/kWh) for the 5 and 8kWh, both with PS incentive tariff, and Flat tariff. Results obtained for a 2kWh battery in Self-Consumption (SC) mode with a flat tariff are also displayed

provides a good level of self-consumption: between 55% and 75%, and of energy savings: more than 10% to 20% for 5kWh and 8kWh batteries respectively. This saved energy should lower electricity costs, and hence, higher NPV. The poor performance is explained by two aspects: i) the decrease in the total energy consumption does not make up for the increase in capacity costs (compared to a

2kWh battery for example) and ii) the PS algorithm charges the battery when the SOC is low, and not only when the PV is generating energy. Therefore, part of the energy used to provide performant peak-shaving is charged from the grid, leading to a net increase in demand.

Overall, these effects make it almost impossible for a battery to be profitable with a flat tariff, when operating on PS mode. Using the PS incentive tariff, on the other hand, substantially increase the profitability of the system, as indicated by much lower slopes for both battery sizes, when using this tariff. A capacity cost of £150/kWh was hardly enough to make a small 2kWh battery profitable after 10 years, when operating on SC mode, whereas the PBP is reduced to 5 and 3.25 years for the PS mode with PSIT tariff, with 8 and 5kWh batteries respectively. It means that the battery owner would return from his investment in 10 year even with a capacity cost increased to £270/kWh for an 8kWh battery, and to £400/kWh for a 5kWh unit. Such capacity costs correspond to total investments of £2160 and £2000, which are more realistic battery prices [40].

5 Conclusion

Residential behind-the-meter storage presents strong potential for providing many ways to support to the electricity network [4]. This paper presents two peak-shaving (PS) strategies that can be integrated into battery controllers in order to provide peak shaving and compared them with a self-consumption (SC) strategy. A novel metric of parameters that can be used in order to assess the impact of PS strategies is also proposed. The algorithms are tested against empirical data from a domestic setting, with a one-minute resolution, over a one-year period.

The PS algorithms introduced reduced peaks down to less than 5% of their initial magnitude and duration. Moreover, the PS algorithms still maintained good levels of energy management: from 70% to 90% of exports avoided, and a decrease in overall consumption by up to 16%. Although the SC strategy leads to the best performance in terms of energy management, avoiding more than 90% of exports and decrease in total consumption by more than 26%, there capability of peak-shaving proved to be very poor.

The economics of integrating a battery to an existing photovoltaic system was studied. After establishing that using a flat tariff with a simple self-consumption mode makes it nearly impossible to be viable, a PS incentive tariff is studied. We show that such tariff substantially reduces the payback period for a given capacity cost. It would allow for a customer to purchase a 5kWh battery at £400/kWh, and still reach profitability in less than 10 years. The payback period would be reached within the same duration for a 2kWh battery with flat tariff, at a cost of £150/kWh or lower. Therefore, the PS incentive tariff introduced has the potential to incentivise customers to provide PS to the grid, while maintaining satisfactory energy management performance.

The Northern Irish context in particular could benefit from such a policy. It presents very high levels of renewables integrated (small-scale wind farms), while remaining largely electrically isolated from the rest of the European network. The resulting low inertia, combined with a long and stringy network, and low industrial base demand leads to a "peaky", domestic-driven load profile [44], in which promoting PS can have important benefits.

Load peaks cause voltage fluctuations, ohmic losses, phase imbalances, and uncertainty on the electricity network, particularly in long radial low voltage sections, typical for low density populations such as Northern Ireland. Providing peak shaving will help address these challenges by reducing the burden imposed by the integration of renewables and low carbon technologies. Moreover, since Northern Ireland consumed 3TWh of electricity in 2017 [41], assuming that 28% of the houses were equipped with PV and Battery systems, the 15% reduction in consumption achieved in this paper would lead to 126GWh of energy saved annually. With a carbon intensity of 480gCO_2/kWh [42], this represents 60,480 tons of avoided CO_2 avoided.

This study focused on providing and measuring PS at the level of one single house. Further work should be undertaken to assess the exact benefit that a network operator can hope to obtain from a fleet of PS domestic batteries. The relationship between features of individual versus aggregated load profiles are not straightforward, and only thorough analyses could conclude on the large-scale benefits of PS. Such studies could also identify the business opportunities for grid operators, of providing tariff policies such as the PS incentive tariff. Furthermore, the decentralised control methods presented in this paper should be compared with centralised and distributed methods. The coordination of storage units may improve technical performance, but would lead to increased costs and complexity, for which the net benefit is yet to be quantified.

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Author Contributions

Corentin Jankowiak: Writing original draft, editing. Aggelos Zacharopoulos: Supervision and review. Caterina Brandoni: Supervision, review and editing. Patrick Keatley: Supervision, review and editing. Paul MacArtain: Review and editing. Neil Hewitt: Funding acquisition, review.

Conflicts of Interest

The authors declare no conflict of interest.

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