

The potential for peak shaving on low voltage distribution networks using electricity storage

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ABSTRACT

Co-location of energy storage with demand provides several benefits over other locations, while still being able to provide balancing services to the grid. One of these additional benefits is deferral of distribution infrastructure reinforcement, allowing increased load growth. This paper considers the potential of electricity storage for peak shaving on distribution networks, focusing on residential areas. A demand model is used to synthesise high resolution domestic load profiles, and these are used within Monte Carlo analysis to determine how much peak shaving could be achieved with storage. An efficient method of finding the potential peak shaving using electricity storage is developed for this purpose. It is shown that moderate levels of storage capacity can deliver significant demand reductions, if suitably coordinated and incentivised. With 2 kWh of battery storage per household, the peak demand at low voltage substations could potentially be halved. The effects of PV capacity, household size and C rates are considered. With 3 kW PV per house, 4.5 kWh of batteries could keep peak flows at the same level as before the addition of PV. It is also shown that 3 kWh of battery storage per household could allow provision of all heating from heat pumps without increasing the peak demand.

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1. Introduction

1.1. The benefits of distributed energy storage

To deal with the increasing penetration of variable renewables associated with decarbonisation of the energy system, as well as increasingly simultaneous load from heat pumps and electric vehicle charging, flexibility is becoming increasingly important. There are four main approaches to providing flexibility in a low carbon energy system: flexible generation (such as gas with CCS), interconnection to other countries and regions, demand response (such as smart charging of electric vehicles), and finally energy storage, on which this paper focuses.

Of the many candidate electricity storage technologies, batteries are of particular interest at small- and medium-scales due to their relatively high energy density, lack of geographic constraints, low noise levels, and low maintenance requirements. The drive to develop lithium-ion batteries for electric vehicles and portable electronics has led to dramatic cost reductions in recent years [1],

and it is widely expected that prices will continue to fall in future [2].

Co-location of energy storage with demand, for example by installing it in towns and cities (such as within houses [3] or at substations), can provide a number of key benefits over other locations. These benefits include peak shaving of both import and export (e.g. from embedded solar) and hence deferred infrastructure reinforcement, provision of backup power, power quality improvements, and increased self-consumption of embedded generation. Storage co-located with demand can also provide most of the benefits that can be provided by storage located elsewhere, such as reserve, footroom,¹ and frequency response.

In many cases, the benefits of operating storage are spread across a number of stakeholders. For example, self-consumption of rooftop solar photovoltaics (PV) using battery storage in a domestic property can lower the householder's electricity bills. It is possible, though not guaranteed, that this operation may consequently reduce peak flows on the local distribution network, thus benefitting the distribution network operator (DNO) and

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¹ Footroom is the ability of the system to absorb decreases in demand/increases in generation.

Nomenclature	
γ	Demand threshold
η_c	Charging efficiency of the storage, between 0 and 1
η_d	Discharging efficiency of the storage, between 0 and 1
d	Raw power demand (i.e. with no embedded generation or storage), ≥ 0
e	Energy contained in the storage, ≥ 0
E_{\max}	Maximum allowable energy level in the storage, > 0
E_{\min}	Minimum allowable energy level in the storage, ≥ 0
N	Number of houses
p	Net power demand, after taking account of embedded generation and storage
$P_{c,\max}$	Maximum allowable charging power of the storage, > 0
$P_{d,\max}$	Maximum allowable discharging power of the storage, > 0
s	Output from the embedded generation (e.g. rooftop solar PV), ≥ 0
t	Time
u	Charging power of the storage, or discharging power if negative
ADMD	After diversity maximum demand
C-MADEnS	Consortium for Modelling and Analysis of Decentralised Energy Storage
CREST	Centre for Renewable Energy Systems Technology
DNO	Distribution network operator
HH	Household
HW	Hot water
PV	Photovoltaic
wd	Weekday
we	Weekend

subsequently other electricity consumers in the distribution area (by lowering future distribution charges). It may also reduce peak demands at a national level, thus reducing the country's generation capacity requirements and potentially displacing use of CO₂-emitting peaker plants, as well as providing footroom and lowering ramp rates in demand.

This paper describes an investigation into the potential of demand co-located electricity storage for peak shaving in low voltage distribution networks. Peak shaving could make it possible to defer reinforcement of distribution infrastructure as load growth occurs, e.g. from implementation of electric heating or electric vehicle charging. This paper is primarily concerned with the technical potential for peak shaving using storage, which is unaffected by price policy, therefore we do not consider price policy or economics here. The proportion of the technical potential that is achieved in reality depends upon the price policy that is implemented, but currently there are no real incentives for domestic peak shaving in the UK and many other parts of the world. This research is one element of the modelling work that forms part of a wider initiative looking at the role and value of energy storage within cities, within a research project titled 'Consortium for Modelling and Analysis of Decentralised Energy Storage' (C-MADEnS, www.c-madens.org).

1.2. Summary of previous work

Many recent studies have considered the use of energy storage for peak shaving. Luthander et al. [4] investigated the effects of storage and solar PV curtailment on peak shaving, showing that curtailment in particular can be used to halve peak PV export with less than a 7% annual loss in self-consumption. This study however has the limitation that the storage was operated simply to maximise self-consumption, rather than focusing on peak shaving explicitly.

A number of studies focus on control algorithms and pricing/incentive schemes for peak shaving, often in combination with some other goal (such as self-consumption of solar PV). Zheng et al. [5] developed a simple dispatch strategy for residential peak shaving from building-based energy storage, and investigated the economics of various storage technologies operating under a Con Edison demand tariff that charges consumers according to their maximum power demand during a one-month billing period. For the storage dispatch strategy, a "demand limit" was set, and the storage acted to try and maintain the household's power demand at the demand limit. By optimising the storage capacity and demand limit, it was found that annual profit from using storage can reach around 40% of the household's electricity bill, and that allowing occasional breaches of the intended demand limit increase profit.

Leadbetter and Swan [6] conducted investigations into the optimal sizing of battery storage systems for residential peak shaving, with results suggesting that typical system sizes should range from 5 kWh/2.6 kW for homes with low electricity usage, up to 22 kWh/5.2 kW for homes with high usage and electric space heating. Peak shaving of between 42% and 49% was reported in five regions of Canada. They also found that very little cycling is required for peak shaving, and that as such the system's life is limited by the calendar life of the batteries.

Hayes et al. [7] investigated individualised price policies to incentivise demand management, with the goal of reducing system demand peaks in such a way that the price tariffs seen by consumers are individualised and non-discriminatory. These exploit the demand awareness obtained from advanced metering infrastructure. Through a case study of residential users with energy storage in a typical European distribution network, the individualised price policy approach is shown to have advantages over a global price policy, where many users in the same network region are given the same price policy. These advantages included increased load factor, improved voltage and line loading conditions, and reduced network losses.

Others have focused on the effect of time-of-use tariffs on load shifting in residential areas with energy storage. Graditi et al. [8] considered the economics of electrochemical storage systems (including batteries and flow batteries) responding to time-of-use tariffs in Italy, focusing on their use within public institutions. Through case studies it is shown that at current costs, the use of battery storage systems is only economically feasible if there is a significant difference between the high and low prices in the tariff. Reductions in battery costs, and the introduction of support policies, will improve the economics of storage.

In the UK, much of the recent research into small-scale energy storage has been carried out within projects funded through Ofgem's Low Carbon Networks Fund. Yunusov et al. [9] used smart meter data to assess the impact of battery storage location (i.e. position on the feeder as well as whether on one or all three phases) on performance for peak shaving and phase balancing, focusing on two real low voltage networks. Some of the same authors have also considered real-time optimisation of DNO-owned storage being used for peak reduction, developing storage controllers that take into account demand forecasts and consumer

clustering [10]. Load forecasting in storage controllers for peak shaving has also been proposed by Reihani et al. [11] among others. Pudjianto et al. [12] also investigated smart control of electric vehicle charging, heat pumps and network voltage regulators to reduce network investment, showing that between 2010 and 2050 the costs of network reinforcement in the UK could reach up to £36bn if we maintain passive distribution network and passive demand approaches, and that these costs could be reduced significantly by taking advantage of smart demand technologies.

Others have carried out work on similar themes to those featured in this paper. In a very similar approach to that presented here, Navarro et al. [13] used the CREST Demand Model within Monte Carlo analysis, in their case to understand the likelihood of voltage issues arising with varying penetrations of solar PV on two low voltage networks in the north-west of England, showing the relationship between PV penetration and voltage issues to be roughly exponential.

Aside from having energy storage devices within (or on the outside of) domestic properties, there are several other approaches to providing householders with some energy storage capacity. Two particularly interesting concepts are 'cloud energy storage' [4,14] (also proposed in Germany as 'Die Strombank' [15]), whereby householders and enterprises can rent out a portion of a large storage device in the local area, and virtual power plants [16], whereby small distributed energy storage units are operated by an aggregator to provide larger levels of generation and load, allowing revenue through provision of services such as Short Term Operating Reserve (which requires a minimum of 3 MW) [17]. Whether such systems would act to perform peak shaving is dependent upon the incentive schemes put in place.

As well as being considered for distribution networks, energy storage is also being studied for use within transmission networks. Aguado et al. [18] developed an optimisation algorithm for making decisions on the suitability, size and placement of battery storage systems for transmission network expansion. This required the modelling of new lines and batteries in the transmission network. Results show how the deferral of the construction of new transmission lines is feasible in a market-driven environment if batteries are attached to certain nodes.

Later on in this paper we examine how electricity storage can be used to reduce the impact of heat pumps. Others have also researched active control of heat pumps [19], showing that active control can lower peak loads and increase self-consumption of embedded renewables generation, but also that active control increases the electricity consumption of the heat pump by 8–12%. Here we assume that regular heat-driven control is used, however future work could look at how to combine active control of a heat pump with the control of local energy storage in order to maximise socioeconomic benefits in areas with high penetrations of heat pumps.

While many studies have looked at control strategies and pricing schemes for peak shaving with energy storage, there is no clear understanding of the potential of the technology: what is the maximum possible peak shaving that can be achieved? This is an important question from a policy and planning perspective. Without a good understanding it is difficult to account for the potential of storage in the planning of future networks and generating capacity.

The answer is highly dependent upon profiles of demand and local generation, so for example the potential peak shaving at an industrial estate will be different to the potential peak shaving in a residential street. Even in residential areas, the penetration of active energy technologies such as heat pumps, electric vehicles, and solar PV, will have an effect on peak flows on the distribution infrastructure, and on the potential for peak shaving using energy storage. Domestic electricity consumption accounted for 30% of

electricity demand in the UK in 2016 [20], more than any other sector, and domestic consumption patterns are well-understood and reasonably consistent across a country such as the UK, so we have focused on storage in residential areas here. We consider the effects of heat pump and solar PV penetration by including them in the analysis at certain points.

Many previous studies are also limited in that they have only considered single household demand peaks. We have set out to address this by considering the aggregated peak import and export at the secondary substation level. Secondary substations, also known as final distributions substations, transform electricity from medium voltage down to low voltage, for final distribution to homes and businesses. We focus on the aggregated benefits of storage when connected to the distribution network, and we do not investigate the placement of storage (which has been previously investigated by others, e.g. [9,18,21]).

1.3. Objectives

Investigations by partners on the C-MADeN research project have shown that a lack of appropriate incentives for storage, along with simple control algorithms that do not monitor household import and export, can lead to home batteries being uneconomical [22]. The work presented here has taken a different approach, investigating the possible benefits of small-scale storage to the local distribution network. It is hoped that provision of these benefits could be suitably monetised.

This paper sets out to answer the following key questions:

1. What is the maximum possible peak shaving that is achievable using battery storage in residential areas, both from demand and export of solar PV?
2. Can battery storage in residential areas help to alleviate the impacts of heat pumps?

By answering these questions we are also answering a fundamental question of whether peak shaving using battery storage in residential areas is worth pursuing, as well as providing a basis against which the performance of control systems and incentive schemes can be compared. We will explore how a range of factors influence the achievable peak shaving, including storage capacity, maximum charging and discharging rates, household size, and the penetration of active energy technologies such as solar PV and heat pumps.

To accomplish our objectives, an existing, well-validated demand model [23] is used to synthesise household-level electricity demands, heat demands, and solar generation. To determine the maximum possible peak shaving achievable using battery storage in residential areas (the first question), we develop a novel method of finding the maximum peak shaving that can be achieved using a given energy storage device, assuming there is perfect foresight of the local demand and generation. We use this method with the synthesised demand data. While perfect foresight of demand is not possible in reality, the method of finding the maximum peak shaving that is developed in this paper could be used with forecasted demand patterns in a real storage control system.

Economic aspects are not considered in this paper. It is anticipated that the methods and results that are presented here will be used by others to determine the economic effects of alleviating stress on distribution networks using energy storage. This would involve in-depth assessment of the costs of upgrading transmission and distribution infrastructure to cope with energy technologies such as rooftop solar PV, heat pumps, and electric vehicles [24].

The paper is laid out as follows. Section 2 describes the methodology, including the demand model and how we determine the maximum possible peak shaving. Section 3 looks at the average household electricity demands generated by the demand model, as well as the effect of aggregation on peak demand. Section 4 evaluates the potential peak import and export reductions on existing networks, both with and without solar PV, and the effect of heat pumps is investigated in Section 5. Finally, Section 6 presents our conclusions, explores possible policy implications from the work, and discusses the next steps.

2. Methodology

Before giving detailed descriptions of the different steps of the methodology, we first explain the general process of finding the possible effects of electricity storage on peak import and export at a low voltage substation. For any given combination of PV capacity, storage capacity, and heat pump penetration, the process shown in Fig. 1 is followed to find the ‘After Diversity Maximum Demand’ [25] (ADMD, explained in Section 2.1) with and without storage. A very similar process is followed to find the possible effects of storage on peak export from solar PV.

To generate datasets for use in this analysis, the demand profiles of aggregations of 100 houses are found using the CREST Demand Model. This is a typical number of houses connected to a secondary substation in the UK. The household sizes and building types are assigned randomly based on UK distributions [26]. To account for the time it takes for energy storage to reach what might be considered as steady-state operation, each demand profile consists of two weeks of net demands (raw demands minus generation

from rooftop solar PV), one week in summer and one week in winter. When analysing peak demands, the storage starts the two week period full (100% state of charge), and when analysing peak export, the storage starts the period empty. In each case, five weekdays are followed by two weekend days. We focus on mid-summer and mid-winter because in residential areas with rooftop solar PV, import and export peaks are most likely to occur in mid-summer and mid-winter, respectively, when outside temperatures and day lengths are near their extremes.

In almost all of the analyses presented here, 150 different aggregations of 100 houses are used, and in each analysis, the peak flows to and from the aggregation are averaged over the 150 aggregations. Each of the 150 aggregations is a different set of houses. Choosing the number of aggregations is a trade-off between accuracy and computational time: the more aggregations that are used, the closer the average results will be to reality, however if too many aggregations are used then the computational time becomes problematic. 150 aggregations provide reasonable accuracy while allowing results to be generated in a reasonable time.

In this work it is assumed that the electricity storage installed in an area is coordinated in its operation. This could be because the storage is operated by a DNO or aggregator. The storage could be a single device (e.g. within a substation) or a number of smaller devices (e.g. street-side or in-home). It is assumed that the storage is operated purely with the goal of minimising the ADMD or peak export of the group of houses being served by the substation.

2.1. Quantifying peak flows

In areas with low levels of embedded generation, infrastructure requirements have traditionally been evaluated using the concept of ‘After Diversity Maximum Demand’ (ADMD) [25]. For a group of houses/dwellings being fed from a substation in such areas, the expected peak power demand of the whole group over a long period of time is what sets the required capacities of the substation equipment and the cables running to each house. ADMD is the peak power demand of the group divided by the number of houses in the group, and is given by

$$\text{ADMD} = \frac{1}{N} \max_t \left(\sum_{i=1}^N p_{i,t} \right) \quad (1)$$

where N is the number of houses and $p_{i,t}$ is the demand of house i at time t . ADMD is typically expressed in kW, so values of $p_{i,t}$ are specified in kW. The time resolution of demand data should ideally be high enough that demand peaks are not averaged out with lower demands in neighbouring time intervals. For $p_{i,t}$ we have used data at one minute resolution for two weeks of a year in this work, one week in mid-winter and one week in mid-summer, i.e. the times when peak import and peak export (from solar PV) are most likely to occur, respectively. ADMD typically reduces to less than 2 kW for large groups of houses (e.g. >20 houses) [25]. The way that a curve of ADMD against N flattens out as N is increased can be explained by the law of large numbers.

In areas with high levels of embedded generation, peak export can again be expressed on a per-household level, using the same method as used for ADMD. In this paper, peak export is therefore expressed as peak export per household, even though most of the analyses are conducted with aggregations of 100 households.

2.2. Generating household net demand data

In order to understand the effect of introducing electricity storage within residential distribution networks, data describing demand profiles of domestic properties is required. Many demand

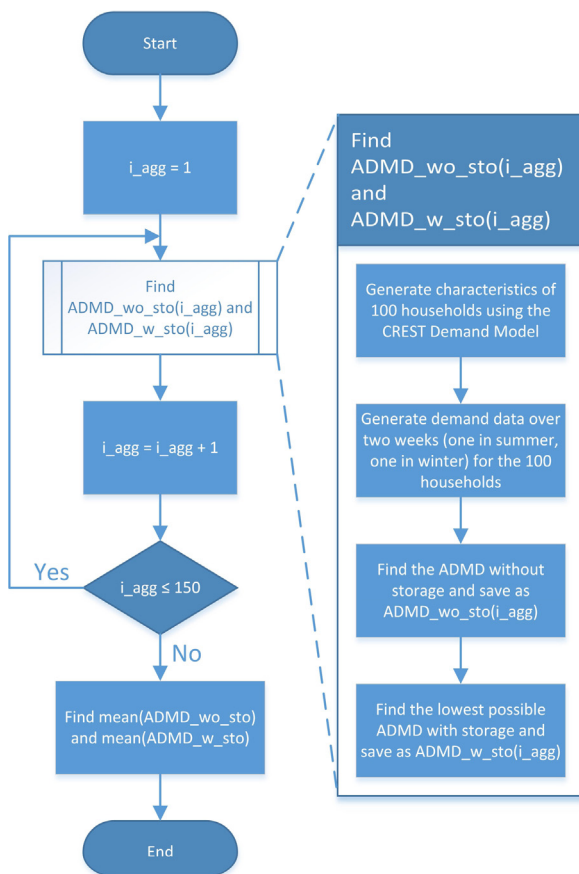


Fig. 1. Finding the After Diversity Maximum Demand (ADMD) for aggregations of 100 households with and without storage (ADMD_w_sto and ADMD_wo_sto, respectively).

models exist (e.g. [27,28]), but here the CREST Demand Model [23] has been used. The CREST Demand Model uses time use survey logs taken by thousands of UK householders as part of the UK Time Use Survey [29], along with data on appliances found in UK households, to stochastically synthesise a realistic load profile based upon many parameters (some of which are listed further below). The resulting demand data is at one minute resolution, and can be aggregated over a number of households.

The CREST Demand Model is an integrated thermal-electrical model, with sub-models for occupancy, irradiance, external temperature, electrical demand (itself comprising sub-models for lighting and appliance demand), thermal demand, solar PV, and solar thermal collectors. Being an integrated model, many of the different sub-models are interlinked, so for example a change in irradiance will affect four sub-models: solar thermal collector, solar PV, thermal demand (changing passive solar gains), and electrical demand (for lighting in actively occupied dwellings). Several of the sub-models have been separately validated, and the whole model has been validated by comparing its output with independent empirical data. The CREST Demand Model is an open-source development, and its authors make clear that it is primarily for application in low voltage network and urban energy analyses, exactly the type of analysis presented in this paper.

Using the CREST Demand Model it is possible to generate net demand profiles for households at one minute resolution, based upon many parameters. The following parameters are of particular interest in this work:

- Number of residents
- Month of the year
- Weekday/weekend
- Installed solar panel area
- Solar panel efficiency
- Solar panel angle and elevation

At the time of writing, the CREST Demand Model does not have a multiple day feature, so in order to simulate multiple consecutive days, separate days were modelled while maintaining the same household and appliance properties between days. Therefore within the resulting data there is some discontinuity in demand at midnight, however as this is not a time when the distribution network is under stress, this does not impact significantly on our results.

2.3. Modelling heat pumps

In Section 5, we consider the effects of heat pumps on peak power flows in areas with electricity storage, therefore it is necessary to generate realistic electricity demands resulting from use of heat pumps. As mentioned above, the CREST Demand Model includes a thermal sub-model, generating realistic heat demands based upon the synthesised occupancy and irradiance profiles. For an individual household, the heat demand profile has a characteristic ‘spikiness’, due to thermostat deadbands (set in the CREST Demand Model at 2 °C for space heating and 5 °C for hot water) and the thermal inertia inherent in buildings. Heat pumps produce heat over longer periods than gas boilers, so have a less spiky demand profile; for the analysis shown in Section 5, we configured the CREST Demand Model such that the heating unit can provide up to 10 kW of heat, typical for an air source heat pump [30], and included a 125 l domestic hot water tank. The energy demands for space and water heating have been converted into electricity demands by using a heat pump coefficient of performance of 3. This is within the typical range of 2–4 [31]. In the heat pump analyses, only the winter data was used. This is because heating demands in summer are very low, so introducing electric heating into residential areas increases the likelihood that peak electricity demands will occur in winter.

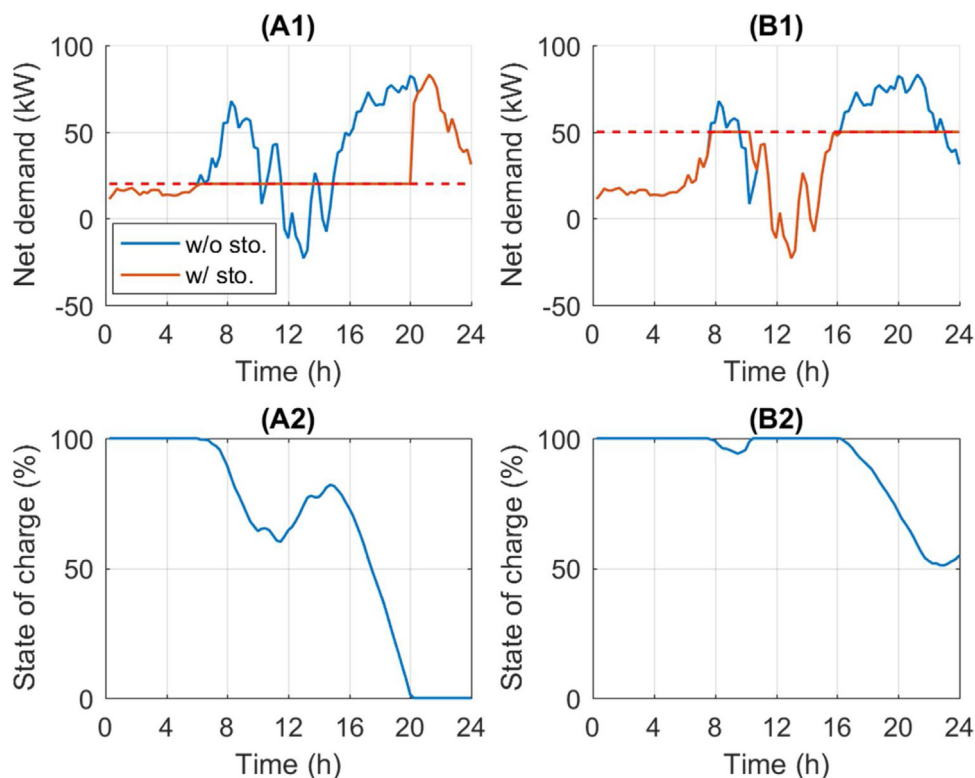


Fig. 2. Net demands over 24 h for an aggregation of 100 houses with solar PV and battery storage, for two demand thresholds (shown with dashed lines): (A) demand threshold of 20 kW, (B) demand threshold of 50 kW.

2.4. Finding the maximum possible peak shaving using storage

The extent to which a given storage device can be used to reduce ADMD is dependent upon how it is used for other services, such as grid balancing and electricity price arbitrage, and the effectiveness of the control system. In reality, forecasts of demand and local generation would be used alongside voltage/current monitoring within a controller using an algorithm such as model predictive control or stochastic receding horizon control, in order to maximise the potential of the storage. However, it is possible to put an upper limit on the potential of a given storage device in reducing peak demands, assuming full knowledge of demands in advance (i.e. ex-post analysis), using the novel method presented in this subsection. The same method can also be used to find the maximum reduction in peak export from embedded generation, but a description is given here for reducing peak demands.

To find the maximum achievable reduction, a “demand threshold” is first set. A storage schedule is determined by stepping through each discrete time interval and doing the following: whenever demand is lower than the demand threshold, try to charge the storage in order to bring the net demand up to the demand threshold, and whenever demand is higher than the demand threshold, try to discharge the storage in order to bring the net demand down to the demand threshold. The demand threshold is used in the same way as the demand limit implemented by Zheng et al. in their economic analysis of storage operating under demand tariffs [5]. Fig. 2 shows an example of the effect of two different demand thresholds on net demand over the course of 24 h in an area of 100 households with solar PV and battery storage.

A “perfect” storage device with instantaneous response and infinite storage capacity, charging power capacity, and discharging power capacity, would always produce a perfectly flat net demand profile when being used to reduce peaks as much as possible, however with a real storage device this will not be the case. The resulting net demand profile, and in particular the resulting ADMD, is dependent upon the demand threshold: as shown in Fig. 2(A1 and A2), a low demand threshold will tend to keep the storage at a low state of charge, meaning that peaks may be missed because the storage is empty; as shown in Fig. 2(B1 and B2), a high demand threshold will tend to keep the storage at a high state of charge and under-utilise the device. Using a bounded optimisation algorithm (such as MATLAB’s *fminbnd* function) it is possible to search for the demand threshold that gives the greatest reduction in ADMD. The resulting ADMD is the lowest that could possibly be achieved using that storage device.

To be clear, we solve the following optimisation problem:

$$\min_{\gamma} \text{ADMD} = \max_t(p_t) \quad (2)$$

where γ is the demand threshold and p_t is the net demand of an aggregation of households at time t , given by

$$p_t = d_t - s_t + u_t \quad (3)$$

d_t is the total raw demand of the aggregation (i.e. the total demand if there were no solar PV or storage), s_t is the total power coming from the solar PV panels installed within the aggregation, and u_t is the total power going into the storage installed within the aggregation (or being discharged from the storage, if negative).

The power into storage, u_t , is calculated using a time-stepping approach. For each time t in turn, we determine if the storage will be charged or discharged by comparing the net demand without storage (i.e. $d_t - s_t$) with the demand threshold γ , and calculate the value of u_t accordingly.

If $d_t - s_t \leq \gamma$, then the storage will be charged, and u_t is given by

$$u_t = \min(P_{c,\max}, (E_{\max} - e_t)/(\eta_c \Delta t), \gamma - (d_t - s_t)) \quad (4)$$

where $P_{c,\max}$ is the charging power capacity of the storage, E_{\max} is the maximum allowable energy level in the storage, e_t is the energy level in the storage at the current time, and η_c is the charging efficiency of the storage.

Otherwise, the storage will be discharged, and u_t is given by

$$u_t = -\min(P_{d,\max}, (e_t - E_{\min})\eta_d/\Delta t, (d_t - s_t) - \gamma) \quad (5)$$

where $P_{d,\max}$ is the discharging power capacity of the storage, E_{\min} is the minimum allowable energy level in the storage, and η_d is the discharging efficiency of the storage.

We initially set $e_1 = E_{\max}$. Once u_t has been determined, e_{t+1} is then calculated as follows, ready to be used as e_t in the next time step.

$$e_{t+1} = \begin{cases} e_t + u_t \eta_c \Delta t, & u_t \geq 0 \\ e_t + \frac{u_t \Delta t}{\eta_d}, & u_t < 0 \end{cases} \quad (6)$$

As mentioned above, γ^* can be found using bounded optimisation, since we know that

$$0 \leq \gamma^* \leq \max_t(d_t - s_t) \quad (7)$$

2.5. Assumed storage characteristics

Throughout this paper it is assumed that the storage has charging and discharging efficiencies of 92.2%, giving a round-trip efficiency of 85%. This is typical for battery storage [8,32], but higher efficiencies are also achievable. It is also assumed that the full storage capacity can be used (i.e. 100% depth of discharge). In reality, battery storage is typically not used with 100% depth of discharge, however manufacturers typically quote “useable storage capacity” or “effective storage capacity”, which is equivalent to what we have used. Degradation is not considered, though it could be considered in future work in this area.

3. Average demand profiles and ADMD

The average UK household electricity demand, as synthesised by the CREST Demand Model, is shown against time of day in Fig. 3. Peak and trough values are shown in Table 1. Morning and evening peaks are clear, with both being higher in winter than in summer. Also clear is that the evening peak is wider during winter than during summer. These increases are all related to increased

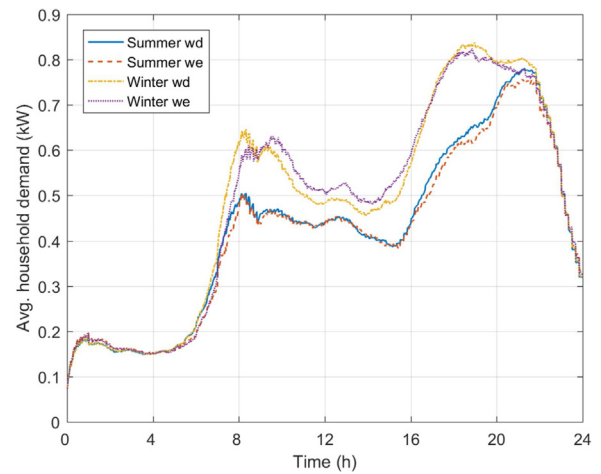


Fig. 3. Average UK household electricity demand against time of day for weekdays and weekends in mid-July and mid-January, as synthesised by the CREST Demand Model. No solar PV. Demands averaged over 5 weekdays and 2 weekends in each season, for 15,000 households.

Table 1

Daily peaks and troughs of average UK household electricity demand as generated by the CREST Demand Model (and shown in Fig. 3).

	Summer Weekday		Summer Weekend	
	Time	Demand (kW)	Time	Demand (kW)
Overnight trough	04:00	0.15	04:00	0.15
Morning peak	08:15	0.50	08:15	0.50
Afternoon trough	15:15	0.39	15:15	0.39
Evening peak	21:15	0.78	21:15	0.76

	Winter Weekday		Winter Weekend	
	Time	Demand (kW)	Time	Demand (kW)
Overnight trough	04:00	0.15	04:00	0.15
Morning peak	08:15	0.65	09:30	0.63
Afternoon trough	13:45	0.46	14:15	0.48
Evening peak	19:00	0.84	18:45	0.82

lighting and heating demands in winter (while we are assuming that the heating system is a gas boiler, there are electrical loads associated with pumps in the heating system). The maximum average demand is shown to be 0.84 kW; this is not the same as the average peak demand ('After Diversity Maximum Demand', as explained above), which is higher. The maximum average demand is very similar to the 0.91 kW found in smart meter trials conducted within the Customer-Led Network Revolution project run by Northern Powergrid [33]. The shape of the curve, including time of maximum average demand, is also very similar.

It should be noted that the average demand values rise from zero at midnight at the start of the day. This is because the demand model does not have a multiple day feature, as explained in Subsection 2.2. Since the distribution network is not under stress at midnight, this is not an issue and does not affect the results shown later in the paper. Since the fact that the demand starts the day at zero is simply a consequence of the lack of a multiple day feature in the demand model, the demands before 01:00 were disregarded when picking out the overnight troughs shown in Table 1.

The mean ADMD for a range of aggregation sizes is shown as a curve in Fig. 4, and the error bars show standard deviation of the ADMDs over 150 repetitions. (Most of the results shown in this paper are the average results from 150 different aggregations. Each aggregation is a new set of houses.) The reason for the shape of the curve is as follows: while each house might have its own annual peak demand of over 10 kW (e.g. an electric shower, kettle and

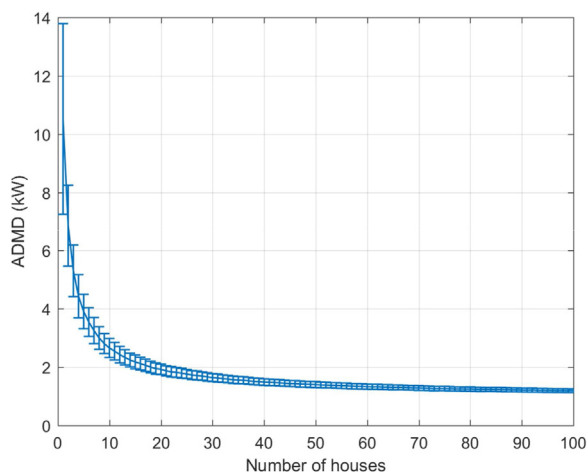


Fig. 4. ADMD against number of houses in the aggregation, as found using the CREST Demand Model. Results averaged over 150 different aggregations. Bars show standard deviations.

washing machine all operating at the same time), the chances of every house in a large group of houses all requiring such high powers at the same time is very low. From Fig. 4 it is clear that with a moderate number of households, ADMD settles down to a level of just over 1 kW. Clearly this level is dependent upon various factors including household size (i.e. number of residents) and wealth; being based on the CREST Demand Model, the results shown are representative of the UK average.

4. Peak shaving on existing networks

This section considers the possible peak shaving that can be achieved using electricity storage in various scenarios. Each of the different subsections looks at the effect of varying a different key parameter; these are rooftop solar PV capacity, household size, and the storage C rates. A C rate is the measure of the rate at which a battery is charged (or discharged) relative to the energy storage capacity of the battery. For example, a discharging C rate of 0.5C means that the discharging current in A is 0.5 times the storage capacity in Ah, so the battery will take 2 h to be fully discharged from full. In this work we use kW and kWh, but the concept remains the same.

4.1. Varying solar PV capacity

Using the method laid out in Section 2, the maximum possible peak demand reduction from using energy storage is found. Fig. 5 shows the lowest possible ADMD when using battery storage in residential areas; in much of this paper, storage capacity is expressed on a per-household level, but it is assumed that the storage takes the form of a single device (e.g. at the substation) or multiple smaller devices (e.g. within homes or on the street-side) which are coordinated in their operation, for example through control by an aggregator. From these results it is clear that significant reductions in peak electricity demand on a low voltage feeder can be achieved using battery storage, assuming that the storage is coordinated and suitably incentivised in its operation. With a 2 kWh battery per household (a reasonably small domestic battery [34]), the peak electricity demand of a group of houses could be halved. Therefore in areas where electricity storage is adopted, increased load growth could potentially be possible without the need for infrastructure reinforcement. This load growth could take the form of more houses attached to a feeder, or

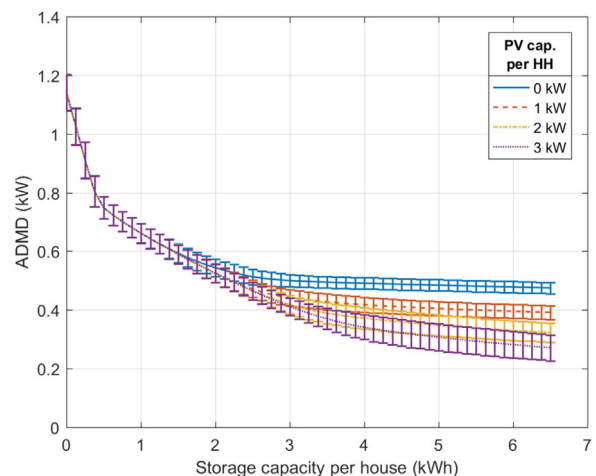


Fig. 5. Lowest possible ADMD against battery storage capacity per house, on an aggregation of 100 houses with varying penetrations of solar PV. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C. Results averaged over 150 different aggregations. Bars show standard deviations.

increased consumption within existing houses, for instance due to the introduction of electric vehicles or heat pumps. The latter is considered further in the next section of this paper.

It is evident from Fig. 5 that with storage capacities below approximately 1.5 kWh per house, the potential for peak shaving of demand is independent of the size of any installed solar PV. With storage capacities above 1.5 kWh per house, greater reductions in peak demand are possible with higher PV capacities. This is because, with large amounts of electricity storage, the evening demands of the aggregation can be reduced to such an extent that peak demands sometimes occur earlier in the day, so that solar PV's effect of depressing daytime demand becomes noticeable.

The general flattening out of the curves as storage capacity is increased is simply related to the fact that there is a limit to how much storage capacity is worthwhile in any given application. The curves all exhibit clear elbows at ~ 0.4 kWh. They are approximately linear up to this point, then become nonlinear with greater storage capacities. This is because, with small storage capacities, storage capacity is not a limiting factor; instead, the discharge power is the limiting factor on the peak shaving that can be achieved, with the storage simply being used at the well-spaced, short periods of highest demands. Therefore the effect of storage on peak demands scales linearly with discharge power (e.g. a discharge power of 0.2 kW can reduce peak demands by 0.2 kW). With higher storage capacities than ~ 0.4 kWh, peak demands can be reduced to such an extent that storage capacity becomes the limiting factor. Increased storage capacities then give diminishing returns as there are more and more times when the storage is empty. The positions of the elbows would change with different maximum C rates. The curves are specific to UK domestic electricity demands; they would change shape in areas with substantially different electricity usage patterns.

Bars are used in Figs. 5 and 6 to show standard deviations of the results. It is clear that uncertainty in the potential peak shaving is increased with high levels of PV capacity and storage capacity. Standard deviation bars are not shown in the rest of the charts in this paper in order to enhance clarity.

Fig. 6 shows the lowest possible maximum absolute power flows when using battery storage for both positive and negative peak shaving. This shows the effect of solar PV on peak flows, particularly where there is little or no storage and >1 kW of PV per

house (so that reverse flows start to dominate). It also shows that larger installed storage capacities, such as greater than 2 kWh per house, are most beneficial in areas with higher penetrations of solar PV.

As mentioned above, the results presented in this section are developed based on the assumption that the storage is coordinated and suitably incentivised in its operation. This paper is mostly concerned with the maximum possible peak shaving that can be achieved using storage. In reality, storage will generally be operated to maximise economic value, and so electricity tariffs are important in that case. If storage is only exposed to a flat tariff, the effect of storage on reducing peak demand and peak export is very low. An example of another method of incentivising peak shaving with storage is to expose householders to financial penalties associated with high peak flows, particularly if they occur at certain times of day.

4.2. Varying household size

The plots shown so far (and in the rest of this paper, unless specified otherwise) are for mixes of households typical of the UK. The average household size and wealth of an area influence the potential demand reduction from using storage. The lowest possible ADMD is plotted against battery storage capacity per house for various household sizes in Fig. 7, and the lowest possible peak power flows are shown against storage capacity in Fig. 8. Note that in Fig. 8, the curve for 4-person households lies above the curve for 3-person households; this is simply a result of the stochastic nature of the analysis.

In Fig. 7, it can be seen that the reduction in peak demand possible using a given amount of storage increases slightly with larger household sizes. As an example of this, it can be seen that 2 kWh of battery storage per house in an area of 1-person houses could potentially be used to achieve ~ 0.5 kW of peak shaving; in an area of 5-person houses, this increases to ~ 0.7 kW, giving a similar percentage reduction. Also, from Fig. 8 it is clear that in areas with reasonable levels of solar PV, the effect of household size on peak power flow is very low, at all levels of storage capacity. This is because with 3 kW of solar PV per house, the peak power flow is dominated by reverse flows from the PV, rather than by household demand.

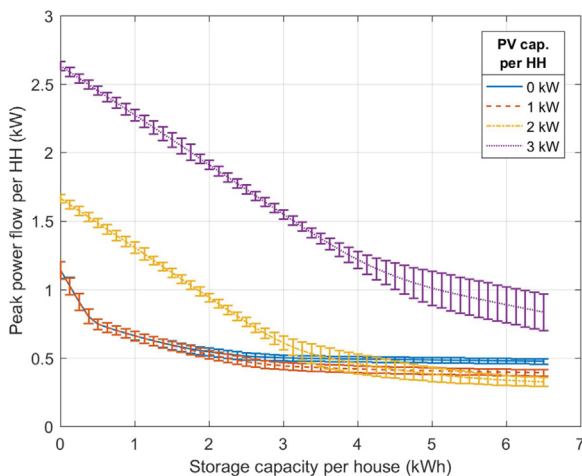


Fig. 6. Lowest possible absolute peak power flows against battery storage capacity per house, on an aggregation of 100 houses with varying penetrations of solar PV. Absolute peak power flow takes into account reverse flows due to export of locally generated solar power, as well as demand. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C. Results averaged over 150 different aggregations. Bars show standard deviations.

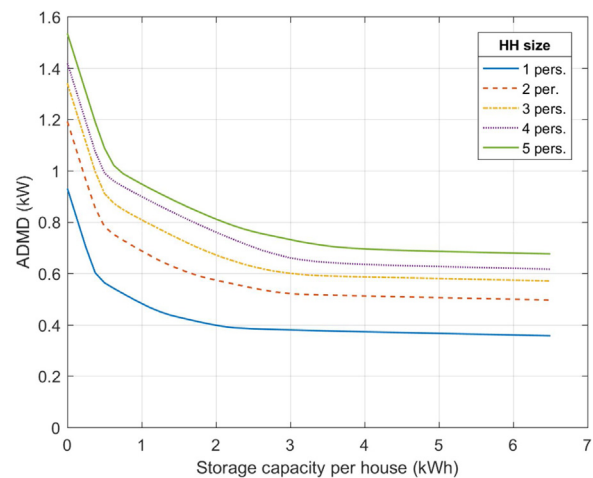


Fig. 7. Lowest possible ADMD against battery storage capacity per house, on an aggregation of 100 houses with no solar PV and varying numbers of occupants. Results averaged over 10 different aggregations for each household size. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C.

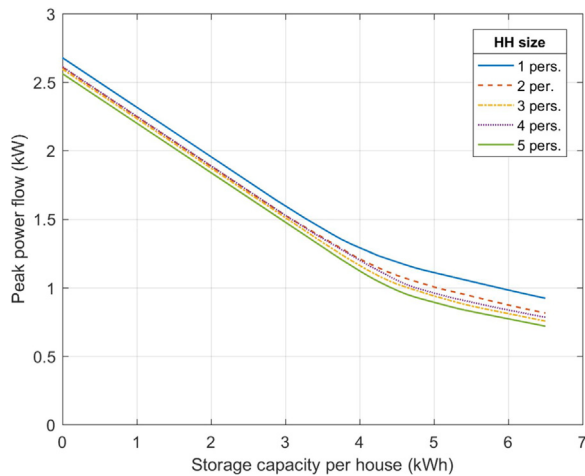


Fig. 8. Lowest possible absolute peak power flows against battery storage capacity per house, on an aggregation of 100 houses with 3 kW solar PV and varying numbers of residents. Absolute peak power flow takes into account reverse flows due to export of locally generated solar power, as well as demand. Results averaged over 10 different aggregations for each household size. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C.

4.3. Varying maximum C rates

A benefit of using the CREST Demand Model to synthesise electricity demand is that it synthesises data at one minute resolution, revealing short-term spikes in aggregate demand which would otherwise be missed when using lower resolution data. This high resolution allows us to understand the importance of the storage's maximum charge and discharge power on peak demand reduction. The power flow to/from an energy storage device is typically represented using C rates. Maximum charging C rate is defined here as the inverse of the minimum time (in hours) taken to completely charge the battery from empty. Similarly, maximum discharging C rate is defined here as the inverse of the minimum time in hours to completely discharge the battery from full.

To understand the importance of storage discharge power, the lowest possible ADMD is shown against maximum discharge C rate in Fig. 9, for an aggregation of 100 households with no solar PV and three different levels of storage capacity. In each case there is clearly a maximum discharge C rate above which there is no further reduction in peak demand, because the storage capacity

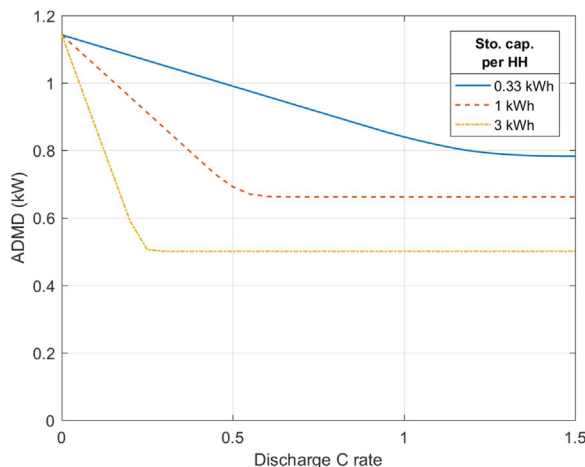


Fig. 9. Lowest possible ADMD against storage discharge C rate, for an aggregation of 100 houses with no solar PV. Maximum charging C rate of 0.33C.

becomes the limiting factor. Evidently with lower levels of storage capacity, higher maximum discharge C rates are required to maximise peak demand reductions.

It is clear that the curves are all flat by $C = 1.5$. This means that higher C rates than 1.5C provide no further increase in the potential peak shaving unless the installed storage capacity is very small. Discharge C rates of at least 1.5C are achievable by many small- and medium-scale electricity storage technologies, including batteries.

Similarly, Fig. 10 shows the lowest possible peak power flow against maximum charge C rate. This shows similar characteristics as Fig. 9. Again, higher C rates are more useful in areas with lower levels of installed storage capacity.

5. The effect of heat pumps

In recent years, considerable progress has been made in reducing the carbon intensity of electricity generation in many parts of the world. To further reduce carbon emissions, efforts are being made to decarbonise heating and transport, predominantly through electrification of both sectors alongside increased low carbon power generation. Great Britain's transmission system operator, National Grid, recently projected that by 2040 there will be somewhere between 1 m and 8 m all-electric heat pumps in Great Britain [35]. In this case, "all-electric heat pumps" means air source and ground source heat pumps, so not including gas heat pumps or hybrid heat pump gas boilers. Projected numbers of all-electric heat pumps out to 2050 in National Grid's four scenarios are shown in Fig. 11. (The four scenarios represent different political and societal approaches to energy issues, and more details can be found in National Grid's Future Energy Scenarios report [35].) Simultaneous operation of millions of heat pumps on cold winter evenings, along with overnight charging of millions of electric vehicles, could have significant impacts on the requirements of electricity distribution networks [36].

In this section we consider the increased residential electricity demand peaks as a result of heat pumps, and the potential to reduce them using distributed electricity storage. While substantial, we will not consider the associated increased demands placed on low carbon power generation.

Heat pumps are not included in the CREST Demand Model, but thermal demands and gas boilers are. The methodology for converting these thermal demands into the electrical demands of heat pumps is given in Subsection 2.3. The effect of heat pumps on ADMD in areas with no storage capacity is shown in Fig. 12, and the

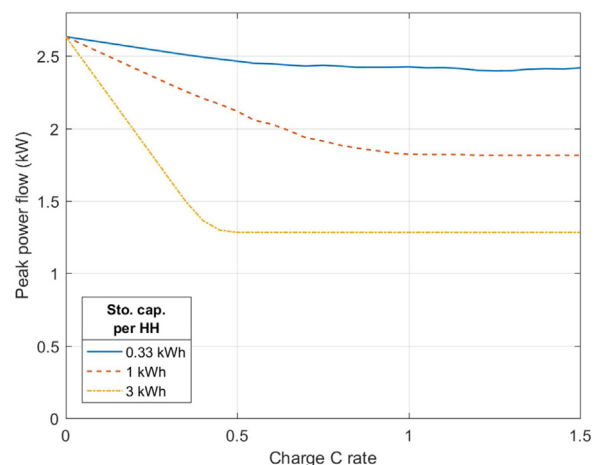


Fig. 10. Lowest possible peak power flow against storage charge C rate, for an aggregation of 100 houses each with 3 kW solar PV. Maximum discharging C rate of 1C.

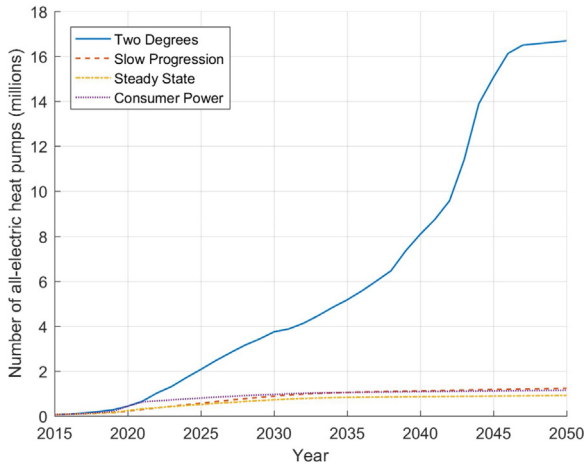


Fig. 11. Projected numbers of all-electric heat pumps in Great Britain according to National Grid’s Future Energy Scenarios 2017 [35]. Gas heat pumps and hybrid heat pump gas boilers are not classed as all-electric.

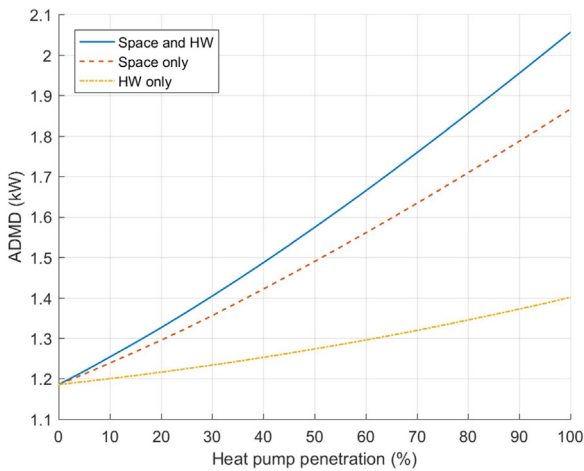


Fig. 12. ADMD against penetration of 10 kW (thermal) heat pumps for space heating and hot water (HW), on an aggregation of 100 households. 3 kW solar PV per household, no storage.

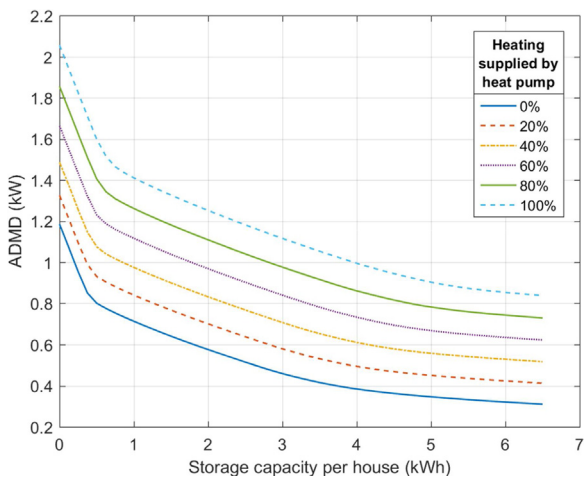


Fig. 13. ADMD against battery storage capacity per house on an aggregation of 100 households, for various penetrations of 10 kW (thermal) heat pumps for space and water heating, 3 kW solar PV per household. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C.

effect of battery storage is shown in Fig. 13. Fig. 14 shows the amount of battery storage required to ensure that the ADMD is not increased above certain limits. From Fig. 12 we can see that with a switch to 100% of space and water heating provided by heat pump, we might expect that ADMD would increase by ~0.85 kW. This lines up well with findings from Northern Powergrid’s Customer-Led Network Revolution project, in which the demands of roughly 331 households with air source heat pumps were monitored from May 2013 to April 2014 [25,37].

Recent analysis of over 400 heat pump installations in the UK has found the ADMD per heat pump to be 1.7 kW, occurring at around 07:30 [38]. ADMD per heat pump is taken to be the per-house ADMD of solely the aggregated heat pump demand, without the rest of the household electricity use. Our work has showed that average weekday winter electricity demand in areas without heat pumps is around 0.5 kW at 07:30 (Fig. 3), thus the effect of heat pumps in our analysis (Fig. 12) matches up well with the results in ref. [38].

From Fig. 13 we can see that for an aggregation of 100 houses, 3 kWh of battery storage per household could potentially be sufficient to ensure that space and water heating could be completely provided using heat pumps without causing an increase in the peak demand of the aggregation above what it is today (i.e. with no battery storage or heat pumps). It has also been found that this drops to 1.8 kWh of battery storage per household if just considering space heating.

Clearly these levels of storage are significant; while 2 kWh and 3 kWh batteries are not particularly large physically, wide-scale adoption is still likely to be some way off. However, it is quite possible that council- or DNO-led schemes could lead to large numbers of storage devices installed in small areas, as recently took place in a town near Barnsley in the United Kingdom [39]. It should be noted that the storage does not necessarily need to be located within individual houses, but could be located on the street-side (as in Scottish and Southern Electricity Networks’ New Thames Valley Vision project [40]) or at the substation. Optimal storage unit size and placement on the feeder are not considered in this work, though they have been considered by others [9].

In terms of validation, it is worth noting the following. In work being conducted at the University of Birmingham within the same project (the C-MADeN project), professional installers of electric heating systems recommended installation of storage heaters with individual output rating of 1.25 kW within a household. The house,

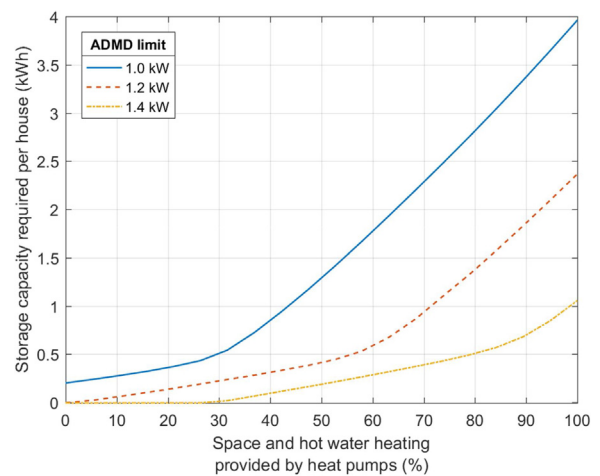


Fig. 14. Storage capacity required to ensure ADMD stays below certain limits with increased penetrations of 10 kW (thermal) heat pumps for space and water heating, 3 kW solar PV per household. Maximum charging C rate of 0.33C, maximum discharging C rate of 1C.

which is a typical terraced house located in Birmingham, contains five radiators, bringing total peak thermal output to 6.25 kW. If this was switched to heat pumps with coefficient of performance of 3, as used in the work presented here, total peak thermal output would reduce to around 2.1 kW. This is very close to the peak battery output power of 1.8 kW that has been found to be needed to maintain ADMD at the level it was before installation of heat pumps for space heating.

6. Discussion and conclusions

This paper has successfully answered the following key research questions that were previously unaddressed:

1. What is the maximum possible peak shaving that is achievable using battery storage in residential areas, both from demand and export of solar PV?
2. Can battery storage in residential areas help to alleviate the impacts of heat pumps?

To accomplish this, we developed a new method of finding the maximum possible peak shaving given perfect foresight of net demand patterns, and this was used within Monte Carlo analysis. Our calculations have demonstrated that small scale electricity storage of the size that is currently being installed within households (e.g. 2 kWh and upwards) has the potential to significantly reduce peak power flows in low voltage networks. By way of example, 2 kWh of battery storage per household could potentially reduce the current peak demand at a low voltage substation in the UK by over 50%. The benefits appear particularly clear in cases where there is significant export from embedded PV, and thus storage could play an important role in the management of future low voltage networks. There remain a number of uncertainties, especially with respect to appropriate coordination and control processes, including forecasting of demand and generation.

We have also demonstrated that small-scale battery storage could contribute to reducing the demand peaks that will arise from the wide-scale deployment of heat pumps. Battery storage of 3 kWh per household proved sufficient to keep peak demands at current levels when 100% of space and domestic hot water heating was provided from heat pumps. Further cost-benefit analysis is required, but we have identified for the first time the potential of household-scale electricity storage systems to ameliorate the impact of heat pump deployment on electrical demand peaks.

If the potential for peak shaving we have identified is to be realised, a key outstanding question is how to encourage consumers to adopt and appropriately operate energy storage technologies. Future work will explore the effects of fixed and variable time-of-use tariffs, demand tariffs, and remote control of storage by aggregators or DNOs (e.g. through a scheme where the DNO pays to take control of home batteries at certain times of day).

A remaining question concerns the materiality of distributed storage for UK electricity objectives. This can be explored by combining our results as shown in Fig. 5, with projections of installed non-transmission connected electricity storage capacity in Great Britain made by the transmission system operator, National Grid, in its Future Energy Scenarios 2017 report [35]. To carry out the analysis, we assume that in areas where storage is installed, it is at a scale of 1 kWh per house (or equivalent, e.g. 3 kWh in every third house), thus each kWh of storage provides up to 0.5 kW peak demand reduction at the secondary substation level, as shown in Fig. 5. Under these conditions, by 2050, non-transmission connected electricity storage operating to bring down peak flows at the secondary substation level has the potential to contribute 3.1 GW of peak demand reduction in Great Britain, if suitably incentivised. This is the best case as realised

under the Consumer Power scenario. With the more conservative Steady State scenario, peak demand reduction might be approximately 1.1 GW, whereas both the Slow Progression and Two Degrees scenarios indicate peak demand reduction of around 2 GW.

Acknowledgments

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