MODELLING RESPONSIVE DEMAND FROM ELECTRIFIED DOMESTIC HEATING AND STORAGE UNDER DIFFERENT OPERATING STRATEGIES

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ABSTRACT

The ability of UK housing with heat-pump-based heating systems to respond to requests for immediate changes to load was assessed using a bottom-up stock modelling approach. Detailed building simulation models of the most common types of UK housing were developed and their ability to respond to signals to drop or pick up load tested under two different operating strategies: on-demand heating and off-peak heating with supporting thermal storage. Both the thermal storage and heat pump capacity were sized prior to undertaking the responsive load simulations. The performance of each building was simulated over a calendar year, with the response to load variation signals constrained by thermal comfort requirements and hot water needs, which took priority. Without thermal storage and following a typical on-demand heating pattern, approximately 20% of heating systems could respond to a drop load or pick up load signal. Switching to an off-peak heating pattern with sized thermal storage resulted, firstly, in the entire operation of the heat pump could be shifted to off peak periods. Secondly, the overall ability to respond to a drop load request was almost unchanged, but typically over 80% of systems could respond to a pick up load signal. The aggregate response figures mask significant seasonal and intra-day variations in response, with the ability to respond being limited during periods of low heating and hot water demand. The addition of thermal storage reduced this variability.

INTRODUCTION

The UK has seen the substantial reduction in the carbon content of its electricity supply over the last decade thanks to a significant increase in renewable generation and a move away from coal as a fuel for power generation (BEIS, 2017a). However, if the UK is to meet its own stringent target of an 80% reduction in greenhouse gas emissions by 2050, then it must also decarbonise other sectors of the economy. One of the most important of these is heat, particularly domestic hot water and space heating, which accounts for 30% of total UK demand (BEIS, 2017b). At present, approximately 80% of domestic heat is supplied by natural gas (Palmer & Cooper, 2013). The most obvious route to decarbonise this sector is to switch from gas boilers to heat pumps, a technology that can capitalise on an increasingly low carbon electricity supply. However, moving such a large demand to the electricity network would significantly increase the use of electricity and peaks in electrical demand: as peak heating demand coincides peak demand for power (Elexion, 2013). Management of electrical heating demands is one means to mitigate some of these impacts and falls into two non-exclusive categories: planned load shifting to off peak periods and unplanned changes in load to a request from an electricity network operator.

Planned shifting of heating-related electrical demands has been employed for decades. For example, in the UK, storage heating has been used to time-shift electrical heating to overnight periods of low-electrical demand, providing a base load for nuclear generation. Planned shifting typically employs thermally-massive storage, allowing a heat demand to be met from the store whilst the electrical heat source is turned off or down. The storage can be charged by the electrical source even when there is no immediate demand for space or water heating.

The use of thermal storage for planned load shifting of heat pumps and peak demand reduction has received much attention in recent years. For example, Arteconi et al. (2013) assessed the opportunities presented by heat pumps and thermal storage to moderate peak electrical demands, though no quantitative analysis was undertaken. Hong et al. (2013) assessed the temporal flexibility offered by heat pumps for two different house types and with different levels of storage. More recently, Baeten et al. (2017) investigated flexible charging of storage using heat pumps using a multi-objective model predictive control strategy to minimise discomfort, cost and emissions; this work involved scaling up results from a single archetype building to a large population of domestic heat pumps.

Unplanned requests for immediate load response could be required to address more acute network needs such as sudden changes in frequency or local voltage levels. Unplanned response from electrical heating technologies is more problematic than planned shifting as typically, priority is given to the provision of heat and maintenance of thermal comfort and so a given heating system may not be in a position to respond to a request to either drop or pick up load. Consequently, a key question that arises is "*what response could be expected from a diverse population of electrified domestic heating systems to a request to pick up or drop load?*"

The ability of domestic electrified heating to provide unplanned load response has received less attention in the literature. Hu et al (2017), look at the ability of air conditioners in Hong Kong to offer demand response through both planned pre-charging and instantaneous set point alteration. Scaling results from a grey-box room model, they indicate electrical demand reductions of over 25% are possible. Alahäivälä et al (2017) use a stock model with 12 different housing archetypes to look at instantaneous and planned demand response. Assuming direct control of heating in housing and a price-based demand response scheme, the authors quantify flexibility on terms of a cost per MWh of response. Using a reduced-order building model, Fischer et al. (2017) simulate the behaviour of a diverse population of German dwellings with heat pumps and subject them to external requests for load response. The authors express response in terms of the power and duration of response to an external 'on' or 'off' signal.

AIM

The aim of the work described here was to assess the ability of UK housing, equipped with domestic heat pump systems to respond to short-duration, external control signals of up to 2-hours to either pick up or drop load. This was tested under two different heating operating strategies: the provision of heat on-demand and where heat is provided by thermal storage, which is pre-charged during off-peak periods. The following work was undertaken:

- a sample of dwelling models that reflect the UK housing stock was developed;
- diverse occupancy and occupant-driven electrical and hot water demand use profiles were developed for each dwelling using a custom statistical tool;
- an air source heat pump heating system plus thermal storage (suitable for off-peak heating operation) was sized for each dwelling;
- the thermal performance of all dwelling models was simulated over a calendar year for four operating scenarios shown in Table 1;
- the results from the simulations were analysed to quantify the ability of domestic electrified heating to respond to requests from the network for load variation.

Table1: scenarios for assessment of instantaneous demand response.

Case	Description
1	no dedicated thermal storage, heating on-demand and no requests for demand response (base case)
2	no dedicated thermal storage, heating on-demand and random requests for short-term demand response
3	dedicated thermal storage, off peak heat pump operation (midnight-7am) and no requests for demand response
4	dedicated thermal storage, off-peak peak heat pump operation (midnight-7am) and random requests for demand response

Contribution

The paper quantifies the ability of UK housing with heat-pump heating systems to respond to short-term load management signals (i.e. pick up or drop load) under different operating scenarios: on-demand and off-peak heating with storage.

METHOD

To obtain an indication of the level of responsive demand that UK housing could provide in a future energy network, an extensive stock modelling exercise has been undertaken. This involved developing a range of housing models complete with an electric (air source heat pump) heating system and dedicated, sized thermal storage. For each model, the ability to respond to calls for demand response was tested by simulating its performance over a calendar year, polling the model with random signals to pick up or drop load and noting whether or not the system could respond when constrained by occupant comfort criteria.

Building Modelling

The modelling software used for the simulations was ESP-r, a long-established building simulation tool that explicitly computes the transient energy and mass transfer processes in a building over a user-defined time interval (e.g. a day, a year, etc.). An ESP-r model comprises a 3-D building geometry, coupled with explicit details of constructions, internal heat gains and hot water draw profiles, and heating control requirements (set points). The tool can model any building type. The technical basis of ESP-r described in detail by Clarke (2001). ESP-r's has been extensively validated and many of these validation efforts are summarised by Strachan et al (2008).

A set of diverse dwelling models have been developed, which were derived from a comprehensive survey of English housing (DCLG, 2013): England accounts for approximately 80% of the UK housing stock. 380 separate house archetypes were generated, which comprise combinations of the different building elements (shown in Table 2)[1]. The archetypes modelled and used in this study represent the vast majority of the dwellings seen in the UK.

Table 2: different building characteristics from the stock survey (DCLG, 2013).

House Type	**Floor Area (m^2)**	**Wall Construction**	**Roof Insulation (mm)**	**Glazing type**
Variants: 6	**Variants: 9**	**Variants: 7**	**Variants: 11**	**Variants: 6**
Semi-Detached	20-40	Filled Cavity	0	Single glazing - wood frame
Mid Terrace	40-60	Cavity	0-25	Single glazing - metal frame
Detached	60-80	Solid Brick	25-50	Single glazing - UPVC frame
End Terrace	80-100	System	50-75	Double glazing - UPVC frame
Flat-purpose built	100-120	Solid Brick - external Insulation	75-100	Double glazing - metal frame
Flat-conversion	120-140	Timber Frame	100-125	Double glazing - wood frame
	140-160	System - external Insulation	125-150	
	160-180		150-175	
	180-200		175-200	
			200-250	
			250-300	

Figure 1 shows typical examples of the modelled house type 3-D geometries. Each building geometry is divided into up to nine thermal zones, each of which represents a defined area of use in the dwelling, e.g. kitchen, living room, bedrooms, etc.

Unique occupancy and occupancy-driven electrical and hot water demand profiles were generated for each of the 380 archetype models, using the approach developed by Flett (2017); this used UK census and time-use-survey data to generate populations of unique occupancy, hot water demand and appliance power demand profiles, which can then be attributed to individual ESP-r models. Figure 3 shows an example of these profiles. Flett (*ibid*) describes the profile generation process in detail.

Infiltration

Each dwelling model was also attributed with unique, randomly generated infiltration rate. This was based on the work reported in Johnstone et al. (2011) and Stephen (2000). It was assumed that variation in infiltration rates in UK housing follows a normal distribution, with a mean of 0.66 air-changes-per-hour (ACH) and a standard deviation of 0.195 ACH.

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[1] Note that not all combinations of building elements are valid and so the number of archetypes is less than the product of the different variants.

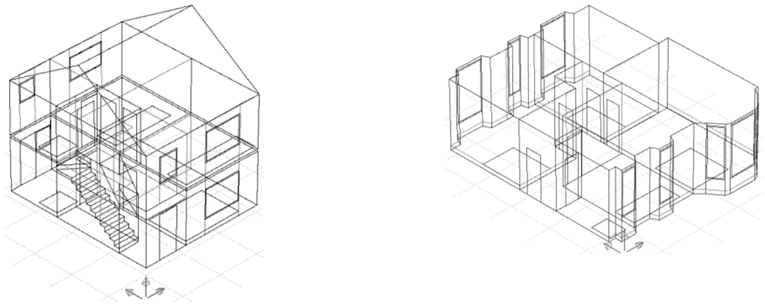


Figure 1: typical ESP-r dwelling model examples.

Heating and Storage

It was assumed that all domestic heating demands (heating and hot water) were electrified and supplied using an air-source heat pump system. Two heating system variants were modelled – with and without thermal storage; this required that storage was sized to meet the heating and hot water demands for each modelled dwelling. An initial, 1-year building performance simulation was run using the UK reference climate data set to determine the heat input required to maintain a heating set point and meet hot water demand. The following three-step equipment sizing process was performed for each case.

1. The dwelling heating demand profile, along with the unique hot water demand profile was combined and scanned to determine the peak heating load and hence the required heat pump capacity. The peak heating load used corresponded to the 3-σ maximum of all daily peaks; this was to eliminate abnormally large outlier heating demands.
2. The same demand data was processed using a thermal storage sizing algorithm developed by Alison *et al*. (2018) to determine the thermal storage capacity required to store the peak daily heat requirement for the dwelling.
3. Finally, the heat pump capacity required to fully charge the thermal store in a 7-hour off peak period (midnight-7am) was calculated and compared to the capacity from step 1 – the larger of the two capacities was used in the performance simulations.

The heat storage model was technology agnostic, with stored heat being modelled as a quantity of energy rather than being explicitly modelled as a volume of storage material at varying temperature. The principal reason for this approach is that it allows the data generated by these simulations to be employed later to investigate different storage options including materials and material locations and builds on earlier work by the authors (Allison *et al.*, 2018).

Heating Control

Two control schemes were used with each housing model, depending upon whether or not there was a thermal store.

- Scheme 1 - without thermal storage heat is supplied 'on-demand' and the heat pump operates whenever space or hot water heating is required during the day. The heating set point was determined stochastically from data from Shipworth et al. (2010), who indicate that heating set points in the UK follow a normal distribution with a mean of 21 ^{o}C and a standard deviation of 2.5 ^{o}C. Heating system start and stop times are also determined stochastically, again using data from Shipworth et al (*ibid*). The mean heating system start time is 06.00 hrs with a standard deviation of 1 hour. The stop time was 23.00 hrs with a standard deviation of approx. 2 hours.
- Scheme 2 - with thermal storage, the heat pump was used to charge the thermal store during periods of low-cost, off-peak electricity; for the purposes of this study, this was assumed to be between 00.00 and 07.00 hrs. If the store depleted during heating, then heat was supplied directly by the heat pump as in Scheme 1.

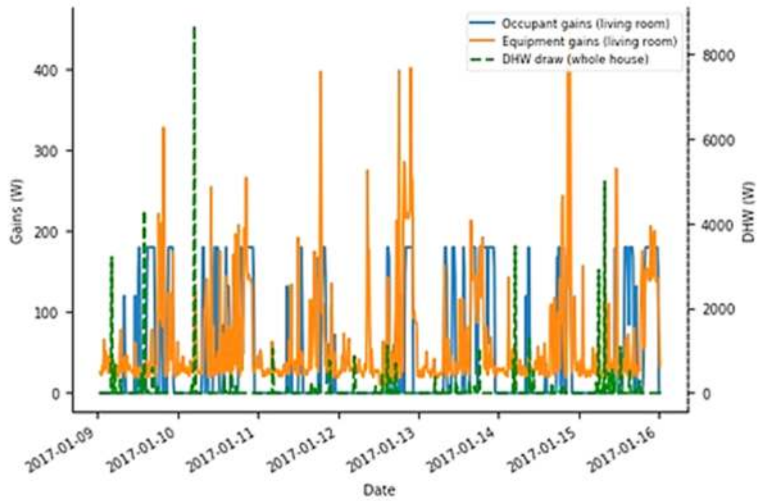


Figure 2: examples of generated occupancy, hot water demand and occupant driven appliance demand profiles.

Grid Signals

In addition to the heating control scheme, a grid signal also affects the operation of the heating system. This is a randomly generated sequence at a 15-minute time resolution, which takes the value of -1 (drop load), 0 (do nothing) or 1 (pick-up load) with each drop or pick up request lasting up to two hours. The sequence was generated based on a uniform 1% probability of a grid signal occurring per time step and a 50/50 probability of the signal being either pick-up or drop load. The duration of the signal was calculated based on a uniform probability distribution of a duration between 15 minutes and 2 hours. An example of the signal is shown in Figure 3.

Local heating control is given priority and a grid signal can *only* be responded too if the space heating and storage conditions described here are met.

Without a thermal store, load can be dropped if there is no hot water draw and if the average space temperature $t > t_{sp} - 2$, where t_{sp} is the set point temperature (21°C). Load can be picked up if $t < t_{sp} + 2$.

With a thermal store then load could be dropped if $t > t_{sp} - 2$, there was no hot water demand and/or the store was not depleted. Load could be picked up if $t < t_{sp} + 2$, there was no load on the system and/or the store was not fully charged.

As the store was modelled in terms of energy content rather than temperature, these conditions were converted to equivalent tests shown in Table 3.

Table 3: criteria for grid signal response from domestic heating.

Grid Signal	Test with no thermal store
drop load	$Q^h_{req-2} < Q^h_{req}$
pick up load	$Q^h_{req+2} > Q^h_{req}$
Grid Signal	**Test with thermal store**
drop load	[$Q^h_{req-2} < Q^h_{req}$ *and* $E_{store} < (Q^w_{req} + Q^h_{req-2}) / n$] *or* [$Q^w_{req} + Q^h_{req-2} = 0$ *and* $E_{store} > E_{min}$ *and* during charging period]
pick up load	[$Q^h_{req+2} > Q^h_{req}$] *or* [$Q^w_{req} + Q^h_{req+2} = 0$ *and* $E_{store} < E_{max}$ *and* not during charging period]

Where Q^h_{req} (kW) is the heating required to meet the set point (°C), Q^h_{req-2} (kW) is the heating required to meet the set point minus 2. Q^h_{req+2} (kW) is the heating required to meet the set point plus 2, and Q^w_{req} (kW) is the required hot water draw; E_{store} (kWh) is the store energy content, and E_{max} (kWh) is the thermal store energy capacity and n is the number of time steps per hour (in all simulations, this was 4). Note that a grid signal may be responded too but have no effect on the load drawn from the grid, if the heating set point being raised or lowered has no effect on the required heating (i.e. $Q_{req-2} = Q_{req}$ or $Q_{req+2} = Q_{req}$); this was not counted as a successful response to a grid signal.

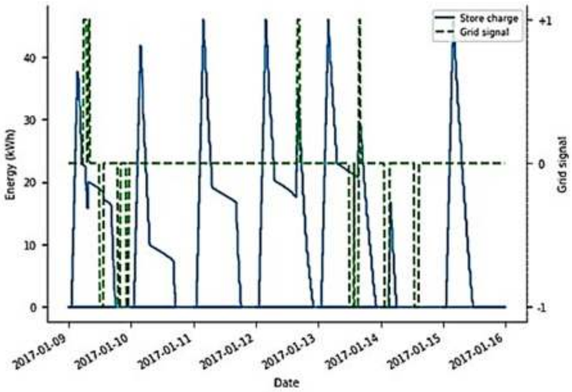


Figure 3: randomly generated grid signals to pick up or drop heating load.

Simulations

The 380 building models provide a diverse test bed for response. Each building simulated was unique, with building geometry, construction types and insulation materials, floor area, occupant numbers and occupancy times, hot water demand, air leakage, heating capacity, heating timing, heating set point and storage size, all varying from model to model.

For each of the four cases shown in Table 1, the performance of each dwelling model was simulated for a calendar year using the UK reference climate data set; this generated 1520 individual results sets. In each simulation, ESP-r calculated the heat required to bring the various zones of the dwelling up to their set point temperature and to meet the hot water demand.

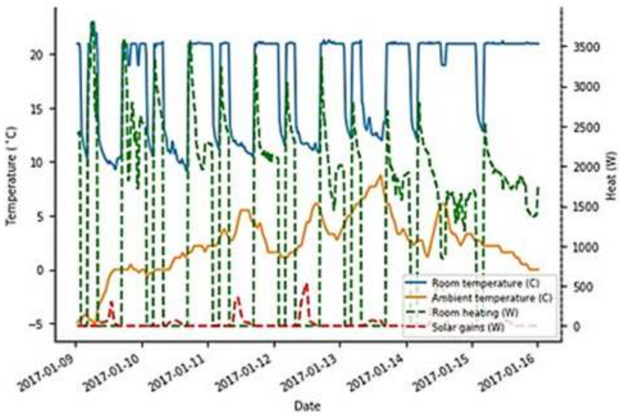
In the case of the heat pump with thermal store, the heat demands were met by the store, so the store energy content was calculated throughout the simulation. The heat pump was operated to charge the thermal store during off-peak electrical demand periods.

Figure 4 shows an example of the data generated, showing the heat pump demand, the thermal store simulated and average dwelling temperature over a one-week period. The results from each simulation were processed to obtain aggregate data such as the percentage of heat pump units from the population of dwellings that could respond to a pick up or drop load signal.

RESULTS AND DISCUSSION

The key question was to determine the ability of a heat pump with and without dedicated thermal storage to respond to an external request to drop or pick up load. Figures 5a and 5b are the box and whisker plots showing the overall response to drop and pick up load requests over all simulations.

Without storage (Case 2), the mean response to a drop load request was just over 20% and approximately 45% for a request to pick up load. When sized storage was added and heating operation altered to off-peak (Case 4), the median response to a drop load request was almost unchanged, but the response to a pick up load request rises to almost 80%. In both cases the variation in response about the median was significantly reduced, due to the off-peak operation constraining the operation of the heat pump.



.Figure 4: typical simulation output.

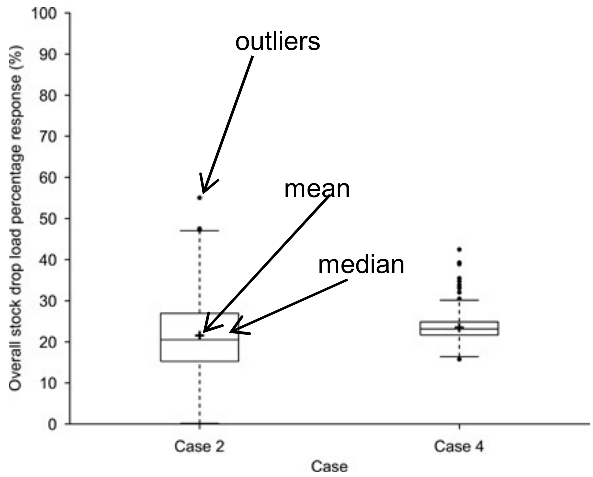


Figure 5a: response to drop load signal.

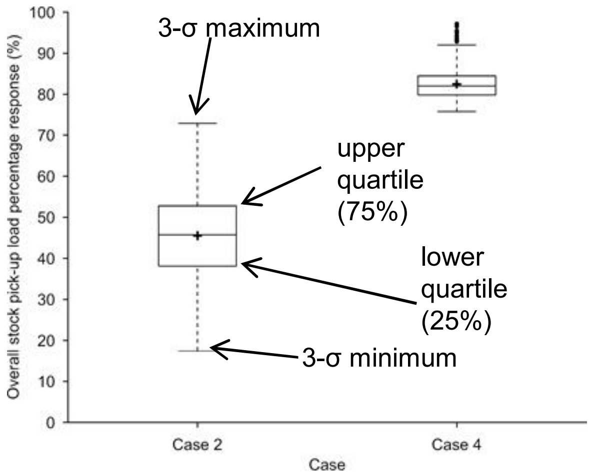


Figure 5b: response to pick up load signal.

Figure 6 shows the range of response (in terms of energy) to a signal to either drop or pick up load. In the case without thermal storage, an average of 100kWh of demand could be dropped per signal across all the houses modelled, up to a 3-σ maximum of about 200kWh. A median of under 200 kWh can be picked up, up to a 3-σ maximum of about 300kWh.

Adding thermal storage and switching operation to off peak increased the median amount of load that can be dropped to around 250 kWh per signal with the 3-σ maximum increasing to up to a maximum of 600kWh. The amount of load that can be picked up increased significantly to a median of c. 750 kWh up to a 3-σ maximum of around 1800kWh.The results demonstrate that thermal storage coupled with off-peak heat pump heating significantly improves the ability of electrified heating to pick up load in response to a signal. However, the ability to drop load is little unchanged.

Both with and without storage, response is significantly less for requests to drop load compared to pick-up load requests.

Further disaggregating the results, Figures 7a and 7b show the variation in load response according to season. The graphs show the median response and corresponding inter quartile range (IQR). Focusing first on response to a drop load request, it is clear from Figure 8a that without storage, response is seasonally dependent, with limited opportunity for dropping load over summer as there is little demand. The addition of storage reduces seasonal variability, with less opportunity to drop load in winter and improved response in warmer months due to the need to charge the store to meet hot water demands.

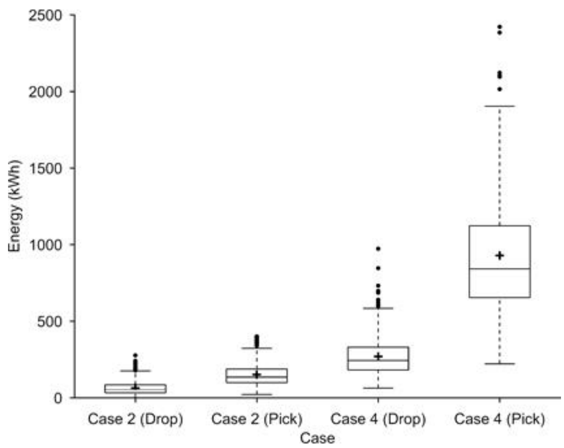
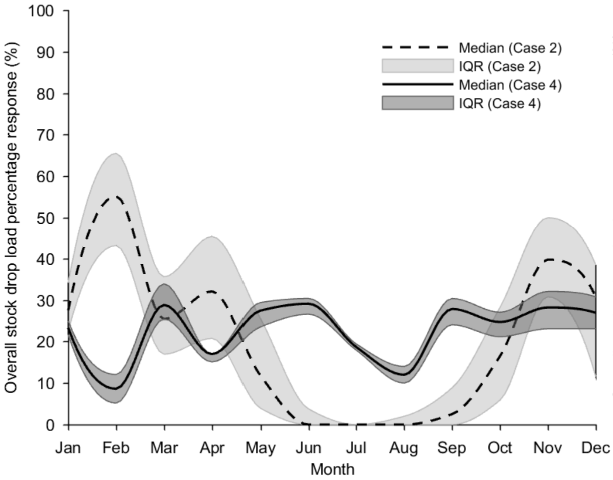


Figure 6 energy response from stock per grid signal.

Turning to the ability to pick up load (Figure 7b), without thermal storage, response is again strongly seasonally dependent, dropping off in summer with reducing heating load. However, with thermal storage and off-peak operation, the ability to pick up load remains consistently high, with the store able to accept heat from the heat pump at any time of year.



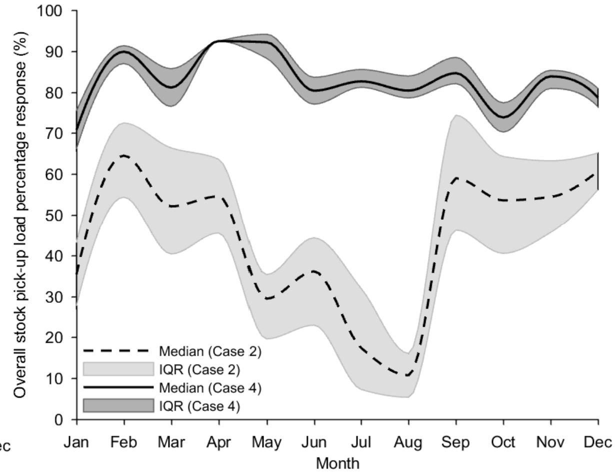


Figure 7a response - drop load by season. *Figure 7b response- pickup load by season.*

Figures 8a and 8b show the variability of the ability to drop or pick up load, respectively, by time of day. The ability to drop load is strongly related to the heat pump operation and thermal storage. Without thermal storage and the heat pump operating on demand, the ability to drop load mirrors heating demand, with morning and evening peaks. With off peak heating, load can only be dropped when the store is being charged. So, although the opportunity to drop load is greater, the hours within which this can occur are far more restricted hence there is little overall change in the aggregate response to load shift signals. The ability to pick up load is also strongly affected by the operation of the heating system and the presence of thermal storage. With no storage and when heating is on demand, the ability to pick up load is dictated by the operating times of the heat pump. However, with storage, and off-peak heating operation, load can be picked up at any time of the day outside the off-peak period of midnight-7am. However, during off-peak hours, the ability to pick up load is limited as it is likely that the heat pump will already be operating at that time to charge the store.

Finally, the ability to load shift to a planned schedule with the thermal store as opposed to responsive load management was analysed. Figure 9 shows the heating energy drawn from the grid during off-peak, low-cost periods. Without thermal storage (Cases 1 and 2), the vast majority of demand is drawn during peak periods, potentially leading to problems with high peak electrical demands. With properly sized thermal storage, the situation is reversed with the vast majority of the energy drawn during off-peak periods. This benefits the end-user in that electricity is less expensive at these times and benefits the network in that planned load shifting such as this can significantly reduce the peak demand that would otherwise occur if heat was supplied on demand.

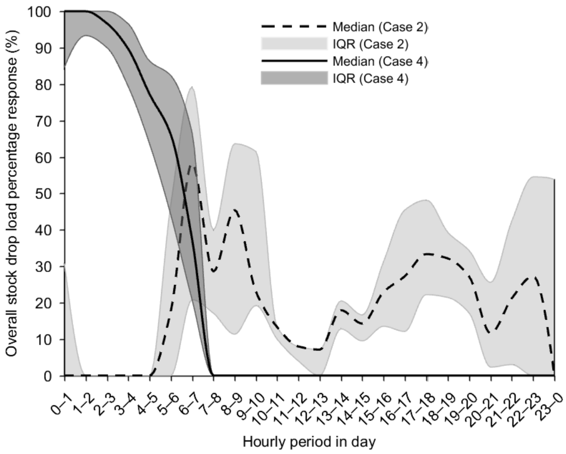


Figure 8a response - drop load by hour.

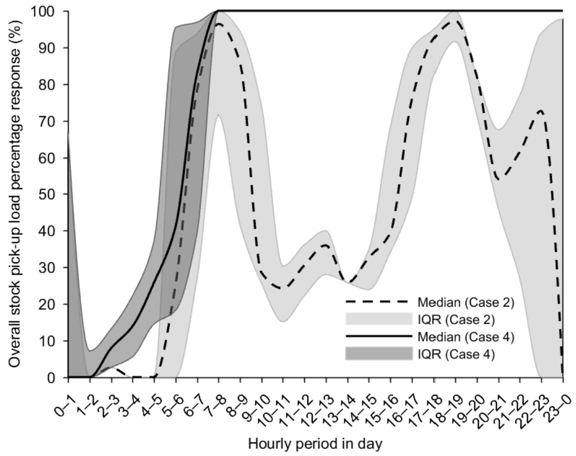


Figure 8b response - pick up load by hour.

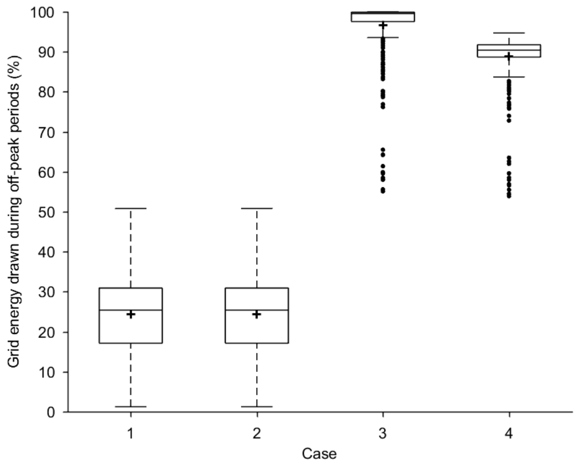


Figure 9: heating energy drawn during peak and off-peak periods.

CONCLUSIONS

Without dedicated thermal storage, and heat pumps servicing thermal load on demand, the median percentage of heat systems able to responding to a signal to drop load was approximately 20% and 45% for pick-up load.

When thermal storage was added and heat pump operation switched to off-peak charging, almost the entire daily heating demand for a dwelling could be shifted to low-cost, off peak electrical tariff periods.

The addition of storage and off-peak operation significantly increased the response to a pick up load signal, with a median, aggregate figure of 85% response. The amount of energy that could be picked also increased significantly. Response to drop load signals increased only marginally but the amount of energy that could be dropped per signal increased.

Response was seen to be highly variable, seasonally and over the course of a day. Seasonal response (to both pick up and drop load signals) was highest in the shoulder months and winter when the heat pump was most active with limited during summer months due to a lack of heat demand. The addition of thermal storage reduced seasonal variability in response.

Response over the course of the day was dictated by the heat pump operating times and by thermal storage. Without storage, the ability to pick up or drop load mirrored heating periods. With thermal storage the ability to drop load was restricted to off-peak hours; conversely, the ability to pick up load was greatest in non-off peak hours, when the thermal store was available to receive heat.

ACKNOWLEDGMENTS

This work was done as part of the Fabric Integrated Thermal Storage in Low Carbon Dwellings (FITS-LCD) research project. The authors gratefully acknowledge the funding provided by EPSRC under grant EP/N021479/1.

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