ASSESSING THE IMPACTS OF ADVANCED CONTROL FOR STORAGE HEATING IN UK SOCIAL HOUSING

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ABSTRACT

In this paper, building simulation was used to assess the impact of smart electric heating control on heating performance and costs in UK social housing. A smart storage heating controller model was developed, comprising two elements: 1) day-ahead heating load prediction, based on outside air temperature and solar radiation; and 2) load shifting of the predicted heating charge to the lowest cost periods of a flexible tariff. A pre-simulation was used to generate a regression equation for heating charge as a function of day-ahead mean air temperature and solar insolation; this mimicked a controller learning process. The controller was applied to a case study of 1960's UK high rise housing. The simulation results showed that, compared to conventional storage heating control, the smart controller resulted in energy savings of 18-24%, and cost savings of 20-50%. There were some negative effects on indoor air temperatures, but comfort in the principal occupied spaces was maintained. Much of the cost saving was attributable to switching from an off-peak tariff to the time-varying tariff, and to reduced energy use due to better charge estimation. Moving demand to low-cost periods had a more marginal impact on heating costs.

INTRODUCTION AND REVIEW

Storage heating is direct electric heating with added thermal mass in the form of an encapsulated, high-density thermal block. A typical storage heater is illustrated in Figure 1. There are around 1.7 million households in the UK with electric storage heating, with over 25% of flats in the UK, electrically heated (Darby, 2018).

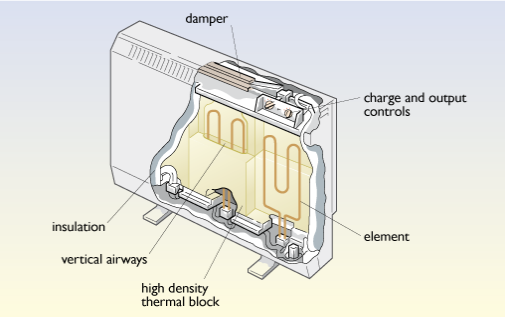

Figure 1. domestic storage heater (image: Open University).

The mode of operation is that the storage heater charges overnight, using low-cost electricity, with the core reaching temperatures between 200-600 °C (Romero, 2013). The heat then discharges during the day, providing heat for the dwelling. Storage heating emerged in the 60's to provide overnight demand for an electricity network with surplus night-time thermal generation. However, the technology has a poor reputation, often providing inadequate levels of thermal comfort for end users, due to the following (Boait *et al*., 2017).

- Limited controllability, with the electrical charge and heat discharge controlled manually, using poorly understood controls.
- Inadequate heater insulation, resulting in an inability to hold heat between the time of charging, and when the heat was required, later in the day.
- And high running costs compared to gas central heating.

Despite its historical shortcomings, interest in the performance of storage heating is rekindling (e.g. Clarke et al., 2013, 2015; Arteconi *et al*. 2016; Edrah *et al*., 2017; Darby, 2016, 2018, Centrica, 2022), as new heater designs are emerging (e.g. Dimplex, 2022), and the technology offers flexibility in demand timing: a feature becoming increasingly useful in an electricity system with ever growing volumes of wind turbines and solar PV. Further, heat pumps are seen as the most appropriate means to decarbonise domestic heating in the UK, however not all properties may be able to accommodate them (EUA, 2021), and storage heating may be an alternative option, where space constraints exclude heat pumps.

Modelling can provide insight into the means to improve the performance of storage heating and its potential for flexibility. In an early paper, Wright (1997) outlined how storage heating could be simulated using building simulation and how to mimic manual control of the input charge. Clarke *et al*. (2015), modelled next generation, domestic smart storage heating technologies participating in a smart grid. Koponen *et al.* (2019), reviewed the application of price-based and forecast-based control of storage heating in Finland, though do not provide any indication of the performance. Boait *et al*. (2017) applied advanced control to storage heating in a small number of houses, which learned and varied the heating charge required over different climatic conditions and offered users limited flexibility in the delivery of the heating charge. The results indicated cost savings of up to 25% were achievable.

This paper builds on previous modelling work (Allison *et al*., 2017), developing a smart controller that "learns" the amount of charge to input into storage heaters and varies the input time to minimise costs against a flexible heating tariff (Octopus Energy, 2022).

AIM

The goal of the work reported in this paper, was to assess the impact that more intelligent control of electric storage heating could have on the heating energy use, cost, and indoor conditions in UK social housing.

METHODOLOGY

A model of a UK high rise development was created for the ESP-r building simulation tool (ESRU, 2022) to test the impact of the smart storage heating control. The model was initially configured with baseline manual storage heating controls, reflecting those commonly employed in UK housing (Boait *et al*., 2017) and then augmented with a more advanced "smart" controller.

Building Model

The high-rise development simulated for this paper is an example of late 1960's UK social housing, which houses over 200 flats on 31 floors. These are a mixture of social housing and privately-owned properties.

The structure is relatively unchanged from the late 60's with a concrete façade, timber-framed glazing, and open balconies. The flats are a mix of 1-, 2- and 3-bedroom properties along with, maisonettes (split level properties with internal stairs). All are heated using electrical storage heating (Historic England, 2021; RBKC 2013).

A partial simulation model of the block was developed (Figure 3), that captures the 5 key flat types: 1- and 2-bedroom flats, maisonettes, a split-level 2-bedroom flat and a 3-bedroom gable-end 2-bedroom flat. The geometry and construction materials were derived from publicly available architectural reports and drawings (RKBC, *ibid*).

Figure 2. 60's high rise block (image: Footprints of London).

The model is shown in Figure 3. Individual flats are modelled using a group of thermal 'zones', each of which describe a characteristic space, such as the kitchen, living room or a hallway. The model geometry also extends to exterior balconies, as these impact on the solar radiation received by sunward-facing glazing.

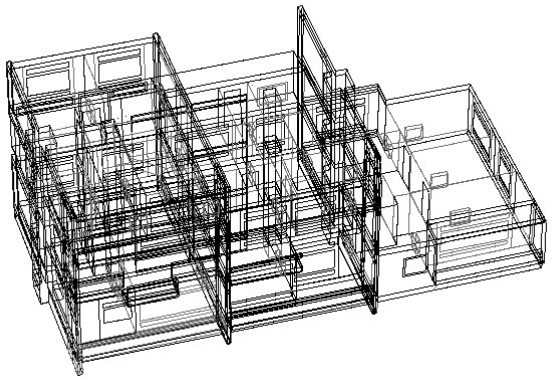

Figure 3. ESP-r partial model of a section of the tower block.

The basic geometrical details of each flat type are as follows.

Table 1. Details of the different flat types included in the model.

Flat Type	Volume (m^3)	Wall Area (m^2)	Windows (m^2)	Floor (m^2)
Maisonette	261	330.4	23.9	105
Split Level Flat	167.4	218	15.9	65
2 Bedroom Flat	163.7	207	14.2	67.3
1 Bedroom Flat	114.5	153.4	7.4	48.2
Gable End (3 bed)	192.2	236.6	15.9	79.1
Total	898.8	1145.4	77.3	364.6

Representative occupancy profiles from previous London flat studies were used (Dowson, 2016). Resident numbers were set by the size of the flat, e.g., the 1-bedroom flat had single person occupancy, the Maisonette – 4 people. Occupancy followed a working day profile (Figure 4), with the main activity in the morning 7-9 am and 6 pm to midnight.

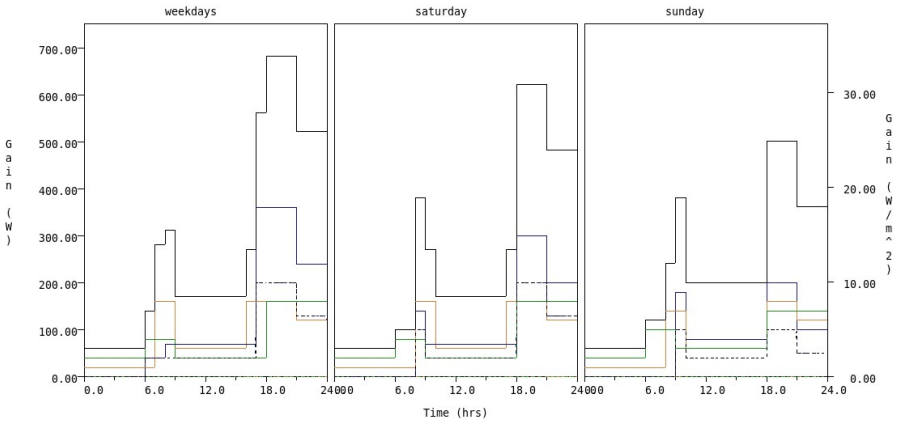

Figure 4. Example gains profiles from the Maisonette living room.

Infiltration was assumed to be typical of that found in older dwellings (Johnston *et al.*, 2004), and a value of 0.5 air-changes per hour was applied in each flat.

The flats modelled, feature different sized storage heaters of 0.5, 0.7, 1.0 and 1.25 kW capacity, with the smaller heaters serving bedrooms and hallways, and the larger heaters serving living rooms. Each heater was modelled in detail and included the heater casing, storage blocks and vents.

Baseline Heater Control

During a simulation, electrical power was injected into the heater storage blocks, according to the power rating of the heater. Charging followed an "Economy 10" heating schedule, which allowed the heating to charge between the hours of midnight and 0700, 1200-1400 and 1900-2100. The amount of charge delivered varied with the indoor and external temperatures. During the charging periods, the heating system used low-cost, off-peak electricity (Table 2).

Table 2: Economy 10 costs used in baseline simulation[1].

	Off-peak cost (p/kWh)	Peak cost (p/kWh)	Standing Charge (p/day)
Economy 10	11.8	19.3	23.8

Calibration and Verification

Prior to running the simulations, the predictions of the model were checked against a limited data set collected from various flats in the block over a winter month; this included air temperature data, heater operating times and external air temperatures, but did not include information on occupancy, solar data or storage heater internal set points. Occupancy data was assumed based on the work of Dowson (*ibid*). To rectify the lack of solar information, alternate data was taken from ESP-r's existing London climate data set, and the model was run over a winter period when solar effects would not be too significant.

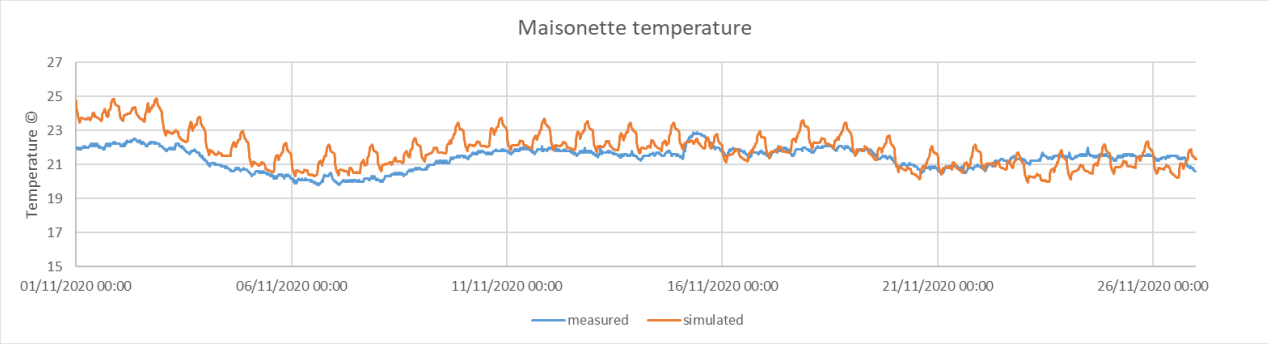

Figure 5. Simulated and modelled temperatures in the maisonette flat model.

Figure 5 shows the predicted temperatures from the model compared to the measured temperature in the maisonette living room. The best fit with the measured data was achieved by charging the average core temperature of the storage heaters to 150°C. This is less than the 200°C-600°C temperatures reported by Romero (2013), however, these were spot temperatures measured close to the storage heater heating element, and the average block temperature will be lower.

The average discrepancy between the measured and modelled temperatures was within 1°C of the measured data. The model also followed the longer-term temperature seen in the actual data but was more sensitive to indoor heat gains due to occupancy and solar gains; this may be due to the placement of the temperature sensor, e.g. if located close to a massive wall, temperature response would be damped. However, given the limited nature of the verification data set, the differences are relatively minor, and the model provides a reasonable proxy for the actual flats.

Modelling Smart Heater Control

The main complaints regarding existing storage heating controls, relate to poor comfort levels and high energy costs. Both problems are related. The poor comfort is due to the heating charge being delivered well in advance of when the heat is required, and the leakage of heat from the storage heaters. This can lead to overheating during nighttime charging and underheating in the evening, as

[1] Prices from https://economy10.com/prices/ historical data for 2020. The modelling for this paper was undertaken prior to the steep energy price rises experienced after the invasion of Ukraine, consequently the prices used reflect costs in early 2022.

the available charge has dissipated, especially if the controls are poorly set (Boait et al., 2017; Ofgem, 2015). Crude control of storage heaters can exacerbate high costs and poor comfort: users are required to set the heating charge level based on likely weather conditions, but settings are typically only changed if users experience over or underheating (Wright, 1997). Finally, the cost of electricity, per unit of heat delivered is approximately 4-times that of natural gas[2], so inefficient space heating inevitably leads to high heating costs.

To assess the impact of improved control, a new heating controller was developed for ESP-r, building on the example outlined by Allison et al. (2017). This had two specific features to reduce energy use and costs.

1. *"Intelligent" charge estimation* – the controller used day-ahead climate data from the model's climate data file to estimate the amount of heat needed to bring the heated space up to its setpoint temperature. This approach mimics a smart controller, "learning" the heating requirements of a property over time.

A calendar-year simulation was undertaken, where the model was simulated against a CIBSE London climate data set, using the baseline heating controller; this injected heat during Economy 10 periods 0200-0700, 1400-1600, and 1900-2100 hrs[3], aiming to maintain a set point temperature of 21°C. The results from this simulation were then fed into a regression analysis to generate a relationship between the daily heating requirement for each flat (kWh) against the mean ambient temperature (°C) and daily solar insolation (kWh). Figure 6 shows the outcomes of this process, the red points are simulated results for each day, the blue surface is the resulting best-fit surface from the regression. The regression functions generated from this process all had R^2 values of more than 0.9.

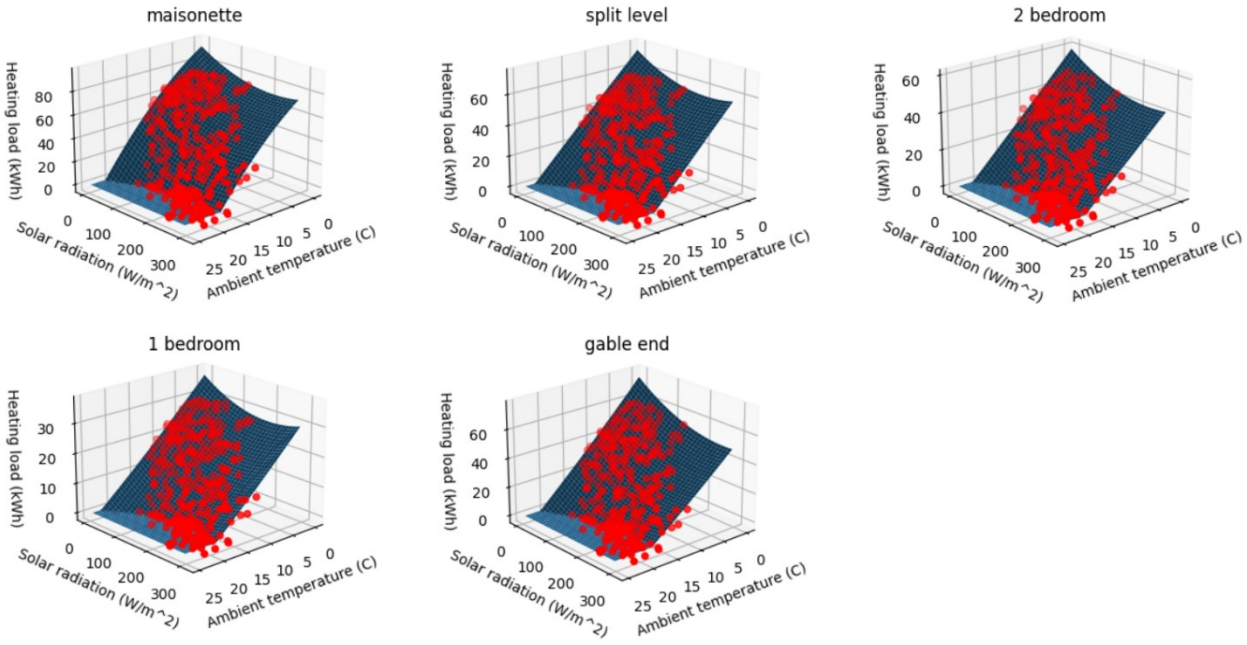

Figure 6. Regression analysis showing daily charge against mean air temperature and solar.

The regression equations were integrated into a modified version of ESP-r's heating control algorithm, to set the day-ahead charge input for each flat. This was attributed to individual heaters according to their capacity.

2. *Flexible charging* - the modified heating algorithm also "flexed" the times when the storage heating was charged, to take advantage of a variable electricity pricing tariff; at the start of each simulated day, the algorithm scanned the day-ahead hour electricity prices (e.g. Figure 7, derived from a historical dataset [Octopus, 2022)]) to identify the cheapest period or periods of the day in which to deliver the electrical charge to the storage heater. The controller iteratively moved a user-defined portion to identify the minimum heating cost.

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[2] https://www.britishgas.co.uk/energy/guides/average-bill.html

[3] Charging times were verified by analysis of measured energy data from the flats.

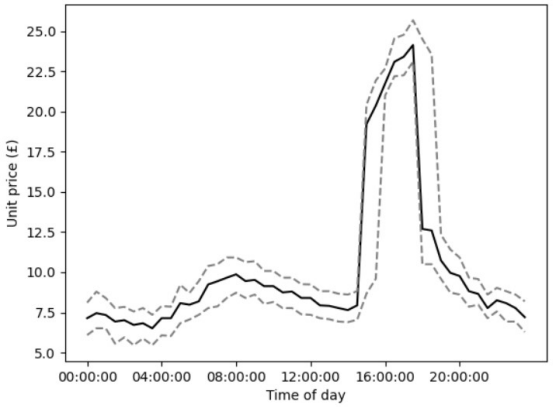

Figure 7. Typical variation of half-hourly 'agile' tariff rate over a day (solid line is the median, dashed lines are the bounds of the upper and lower quartiles).

SIMULATIONS

Recall, the purpose of the simulation exercise was to assess the impact of more intelligent "smart" control on the performance of the storage heating system. To this end, annual simulations were undertaken for five different cases using the CIBSE London climate dataset:

- Case 0: a "baseline" simulation - using the manual heating control, where the charge fed into the heater and charging periods and costs were fixed by the Economy 10 tariff (Table 2).
- Case 1-3: "smart control" - where the day-ahead heating charge was determined using the regression surfaces shown in Figure 6. The impact of increasing the temporal flexibility in the delivery of the heating charge was explored by increasing the portion of charge shifted to low-cost periods and extending the time windows over which charge could be delivered compared to the base case (Table 3).

Table 3. Details of scenarios covered in the simulations.

Modelled case	Charge	Heating Times and % of Charge Delivered	Flexibility
Baseline-0	Fixed charging of heater mass to 150°C.	0200-0700 – 50%; 1400-1600 – 25%; 1900-2100 -25%	None - charge delivered during Economy 10 time periods
Smart-1	Charge determined by regression surface and day-ahead weather for each flat.	0200-0700 50%; 1400-1600 – 20%; 1900-2100 – 20%	10% of charge attributed to cheapest tariff period
Smart-2		0000-1200 50%; 1200-1800 – 20%; 1800-2100 – 20%	10% of charge delivered over wider time periods
Smart-3		0000-1200 30%; 1200-1800 – 10%; 1800-2100 – 10%	50% of charge attributed to cheapest tariff period, wider periods

RESULTS

Figure 8 shows a sample of the results output from ESP-r, these include the time-varying temperatures in the living space of one of the flats, the mean storage heater temperature and the electrical power input to the storage heater. The simulation data was processed to produce the summary results shown in Table 4, which highlight the impact of day-ahead charge estimation against the base case of heating the core of the storage heater to a fixed set point.

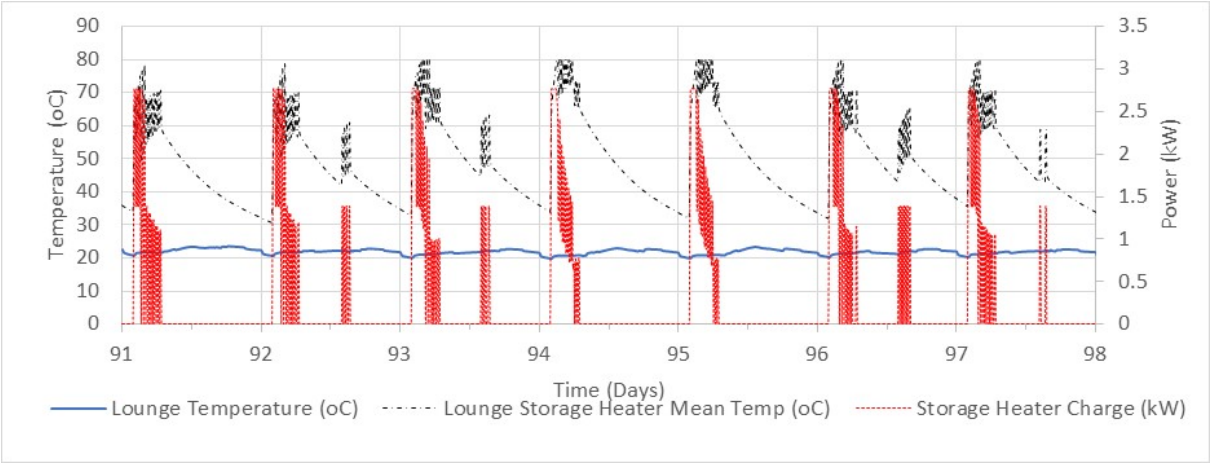

Figure 8. Example results from ESP-r simulation.

Table 4 shows the space heating primary energy use (electrical energy used to charge the storage heating), along with the occurrence of over or underheating for each flat. Overheating being temperatures above 27°C and underheating being temperatures less than 18°C. Note that the energy use for all the "smart" cases stays the same, as the same algorithm to calculate the heating charge was used in each case, the only difference between the cases was in the time when the charge was delivered.

The change to the predictive charge control from manual control, reduced the annual space heating energy use in the flats by 18-24%. However, this change had implications for indoor conditions, as the underheating metric was significantly affected, with a large increase in underheating hours for all the smart charging cases. The under/overheating values are the summation of the under/overheating hours in every zone of each flat over the simulated year.

Table 4. Summary results from annual simulation on flat models using London climate data.

Flat Type	Metric	Baseline	Smart 1	Smart 2	Smart 3
1 Bedroom	Overheat (hrs)	61.32	52.6	52.6	52.6
	Underheat (hrs)	297.84	6771.5	6929.2	6736.4
	Energy kWh/yr	4205.2	3185.8	3185.8	3185.8
Split Level	Overheat	376.68	359.2	359.2	359.2
	Underheat	3863.16	13034.9	13411.6	13026.1
	Energy kWh/yr	8529.7	7006.7	7006.7	7006.7
2 Bedroom	Overheat	254.04	245.3	236.5	245.3
	Underheat	3030.96	10319.3	10021.4	10258.0
	Energy kWh/yr	6610.8	5140.3	5140.3	5140.3
Gable end	Overheat	1340.28	1217.6	1173.8	1191.4
	Underheat	1576.8	8488.4	8339.5	8567.3
	Energy kWh/yr	8052	6195.5	6195.5	6195.5
Maisonette	Overheat	429.24	403.0	394.2	403.0
	Underheat	5930.52	15128.5	15435.1	15102.2
	Energy kWh/yr.	12643.5	10317.5	10317.5	10317.5

Further investigation (e.g. Table 5 which shows simulation results for the smart-3 controller applied to the maisonette) indicated that the increase in underheating occurred primarily in intermittently occupied bathrooms and the kitchens, which had no storage heater. Mean temperatures during

heated hours in these spaces were near or slightly below 18°C. Temperatures in spaces with heaters such as living rooms and bedrooms were maintained at comfort conditions. So, although the effect of smart control on underheating appears dramatic, the actual impact on occupant comfort was marginal.

Table 5. Simulation output from Smart 3 controller in Maisonette.

Zone	Lounge	Bed 1	Bed 2	Bed 3	Kitchen	Bath/WC	WC	Hall
Overheating hrs	131.5	20	46.25	56.25	198.5	0	7	6.5
Underheating hrs	171.5	142.8	497.5	299.5	1535.5	2314.3	2832.3	110.3
Mean Temp.	20.2	20.3	19.7	20.0	18.7	18.2	17.8	20.0

The hours of overheating change very slightly, but generally overheating is only evident on warm summer days when, typically, no heating charge was required.

Table 4 also indicates that flexing of the heating charge, i.e., changing when charge is delivered to lowest cost periods with a flexible tariff, has far less impact on conditions than changing the amount of charge delivered.

Table 6. Space heating costs (£).

Flat Type	Baseline - Economy 10	Baseline - Agile	Smart 1	Smart 2	Smart 3
1 Bedroom	582.2	463.0	365.2	360.6	353.8
Split Level	1104.3	866.8	704.4	689.7	678.4
2 Bedroom	875.5	684.0	533.7	531.3	518.8
Gable end	1044.7	810.8	624.9	622.7	606.7
Maisonette	1578.8	1135.8	816.5	810.8	789.2

The calculated heating costs associated with the different modelled cases are shown in Table 6. Two sets of costs were calculated for the baseline analysis: using the Economy 10 and Agile tariffs. This was to isolate the effect on cost of changing between tariffs, from the effects due to predictive heating charging and flexible charge delivery.

The impact of swapping tariffs was substantial, with the Agile tariff 20-28% cheaper than the Economy 10 option; this is with no reduction in energy use or change on timing of that energy use. Both the Agile and Economy 10 tariffs used in this analysis date from 2020, and both sets of costs include standing or daily charges.

Use of the Smart-1 controller, where the input charge to the storage heating was calculated based on day-ahead temperature and solar data, and 10% of the input charge was allocated to the lowest cost charging period (the charging periods were the same as the Economy 10 tariff), resulted in a reduction in costs of 37-48% compared to the Baseline Economy 10 case, and 21-28% cost reductions were achieved when comparing the Smart-1 costs to the baseline energy costs calculated using the Agile Tariff.

Using the Smart-2 controller, which featured increased flexible charging periods as shown in Table 3, resulted in a small further reduction in costs, with a reduction of between 38-49% compared to the Baseline - Economy 10, and 22-29% compared to the baseline Agile Tariff. Broadening the window of flexibility therefore had only a limited effect.

Finally, increasing the width of the flexible time periods and allowing up to 50% of the heating charge to be allocated to the lowest cost period (Smart-3) resulted in the lowest space heating costs. These were 39-50% less than the Economy10 baseline and and 24-31% less than the Agile baseline. However, again, the effect of increasing the amount of load shifted was marginal compared to the Smart-1 controller.

CONCLUSIONS

This paper has assessed the impact of applying smarter heating control to storage heating in UK social housing, using the case study of a 1960's-style high rise block in London.

The “smart” control comprised two elements – intelligent charge estimation based on day-ahead climate conditions and shifting of heating charge to low-cost periods using a flexible tariff.

Applying the intelligent charge estimation, reduced heating energy use by between 18 and 24%.

The reduced heating charge resulted in increases in underheating in intermittently occupied spaces, but comfort in the main spaces such as living rooms and bedrooms was maintained.

Applying smart control and switching to a flexible tariff, resulted in heating energy cost savings of between 20 and 50%. However, simply switching tariffs between Economy 10 and the Agile Tariff was the cause of over half of these cost savings. The day-ahead estimation of the heating charge accounted for the bulk of the rest of the savings.

Flexing the heating charge to low-cost periods resulted in only marginal cost savings.

FUTURE WORK

There are several areas for future investigation. For example:

- The outcomes of the work need to be extrapolated to the larger scale.
- The storage heaters modelled in these simulations were the existing models installed in the flats in the 80’s. The impact of design improvements to insulation and venting remains to be investigated.
- The work used a limited range of occupancy profiles; a more diverse range of occupancy should be assessed.
- Charging flexibility was constrained in these simulations, the impact of fully flexible charging on indoor conditions remains to be simulated.
- The flats modelled in this paper are a relatively heavyweight construction, with significant internal thermal mass. This is likely to be beneficial when flexing the heating charge and further modelling needs to be undertaken to assess the impact of flexible charging with more modern, lightweight constructions.
- An assessment of the impact of differing degrees of temporal load shift on comfort.

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