Heating patterns in English homes: Comparing results from a national survey against common model assumptions ☆

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ABSTRACT

Heating patterns and temperatures are among the most important determinants of English home energy use. Consequently, building stock models, widely used for informing UK energy policy, are highly sensitive to the assumptions they make on how occupants heat their homes. This study examined heating patterns in English living rooms and compared them to model assumptions. A time-series of winter spot temperature measurements was translated into statements of the heating system being on or off during weekdays and weekend days, and the heating demand temperature estimated. The analysis showed that weekdays and weekend days are far more similar than commonly assumed. Contrary to model assumptions, homes were frequently heated outside assumed heating hours and not all homes were heated at the same time or followed the same pattern. The estimated demand temperature was about 20.6 °C, and the average temperature during heating periods was about 19.5 °C, both lower than the commonly assumed 21 °C used in models. Significantly, variability between homes in demand temperature and hours of heating was substantial. The results indicate the need to revisit some assumptions made in building stock models, and to take account of variability between homes when aiming at predicting space heating demand for an individual home.

1. Introduction

The Climate Change Act 2008 committed the UK to reducing its greenhouse gas emissions by 80% by 2050 from a 1990 baseline [1]. In order to achieve this, carbon emissions from UK homes will need to be near zero by that time. In order to reach that goal, the UK has set an intermediate goal of reducing emissions from homes by 29% by 2020 based on 2008 levels [2]. Energy use in homes makes up just under a third of total energy use in the UK, and within a home, approximately 57% of energy use is attributable to space heating [3].

Modelling energy consumption is a widely used method of understanding how much energy is used in the UK housing stock, the outputs of which provides a benchmark for making recommendations on energy saving policies and programmes, thereby reducing greenhouse gas emissions. In the UK, a widely used model for predicting home energy consumption is the Building Research Establishment Domestic Energy Model (BREDEM) that is consistent with the BS EN ISO 13790 standard. This is a data-driven building physics model which has a core space heating equation based on gains from heating systems and other elements (i.e. heating water, cooking, lighting, appliances) balanced against heat losses through the building fabric [4]. In BREDEM, space heating calculations are based on heat losses, gains and temperatures inside the dwelling [5]. Internal temperatures are calculated in two zones: the living area and the rest of the dwelling. The default assumption in the model is that the whole dwelling is heated only during specific time periods, and that the living area is heated to a higher temperature (usually of 3 °C) than the rest of a home during these periods [4]:

- Heating demand temperature in the living room: 21 °C
- Heating period weekday: 7:00 to 9:00 and 16:00 to 23:00
- Heating period weekend: 7:00 to 23:00

Outside these specified time periods, the heating system is assumed to be off. It is understood that a single temperature and heating pattern are "idealised" in order to reflect assumed "standard heating regimes" to estimate energy consumption on a monthly (BREDEM 8) or yearly (BREDEM 12) basis ([4], p.7). However, the validity of some of the assumptions of these models is questionable and not sufficiently based on robust data [6,7].

It is important that BREDEM reflects reality as closely as possible as it is a foundation for many other UK building stock models (e.g. BREHOMES, The Cambridge Housing Model, DeCARB, UKDCM and CDEM [7]) and a current simplified BREDEM version (BREDEM 9) forms the basis for the Standard Assessment Procedure (SAP), the UK Government's primary assessment mechanism for determining energy efficiency of homes. The BREDEM family of models serves a variety of purposes. As part of regulatory instruments, like the SAP, they set standards for energy use against which individual dwelling design proposals are evaluated for compliance. In doing this, they serve a normative function representing how the fabric and heating technology in dwellings should perform; they standardize occupant influences in order to assess the building performance independently of occupant effects. When used as the basis for building stock modelling, however, their purpose is to indicate how homes (i.e. occupied houses) actually perform. In this function they should correctly represent occupant influences in order to correctly estimate national energy demand from the nation's homes. There is relatively little evidence from national UK studies comparable to BREDEM default values to assess whether they accurately reflect reality, either on average, or for individual homes.

Kelly demonstrated that estimates of energy demand made using SAP have been shown to be poor predictors of actual energy consumption [8]. Shipworth et al. found that the average maximum internal temperature for three winter months, used as a proxy for thermostat settings, was 21.1 °C, in line with the heating demand temperatures as assumed by BREDEM based models, but finding great variability between homes [9]. The variability echoes the findings of earlier studies: Hunt and Gidman's large UK study in 1978 [10] and Palmborg's small Stockholm study in 1981 [11].

The analysis of Shipworth et al. estimated a heating duration of 8.2 h on weekdays and 8.4 h on weekends, again with large variability between homes. This is substantially different to the BREDEM standard assumption of 16 h of heating for a weekend day but roughly in line weekday assumptions. Even the 1996 English House Condition Survey found regularly heated living rooms were *reportedly* heated for an average of 12.2 h per weekday, 13.5 h per weekend day, each with a standard deviation of 6.4 h [12]. A recent study of 59 homes that had received insulation upgrades found daily heating periods varied from 2 to 20 h [13]. None of these studies explicitly examined whether the temporal pattern of heating over the day coincided with the heating periods as assumed in BREDEM default values. Analysis of the 1996 English House Condition Survey found 36% of households heated their living rooms intermittently and 35% heated them all day during the week, with 45% heating them all day at the weekend [12]. In addition, almost half of households with central heating heated their living rooms intermittently, whereas almost half of households with a retiree heated their living rooms all day.

In a previous paper, internal temperatures were compared against BREDEM default values [14]. The analysis showed that temperatures in the assumed heating periods were significantly lower than the 21 °C assumed by BREDEM. However, the analysis only focused on comparing measured temperatures to the assumed temperature and did not consider the actual heating patterns of living rooms.

The heating patterns that are built into BREDEM indicate assumptions of when heating systems are 'on' or 'off'. In order to test these assumptions, we have developed an algorithm that translates temperature sequences into statements about the heating system being 'on' or 'off' and applied this to temperature data from living rooms in English homes during winter. We compare our findings against the time windows of heating assumed in BREDEM. Further, we estimate the 'heating demand temperature' when the heating is 'on'.

2. Methods

2.1. Survey and temperature measurements

The data analysed in this paper are derived from the Carbon Reduction in Buildings Home Energy Survey (CaRB HES), the first national survey exclusively focused on energy use in English homes, that commenced in early 2007 (for details, see Ref. [9]). Households were selected by stratified random sample drawn from the Postcode Address File. Sampling and face-to-face interviews in 427 homes were carried out by the National Centre for Social Research (NatCen). During the interview, householders answered questions on the building characteristics of their home, heating practices, and socio-demographics. For a subset of homes, temperatures were monitored in the bedroom and living room from mid July 2007 to early February 2008. HOBO UA 001-08 sensors are self-contained data loggers that recorded spot temperature every 45 min, resulting in 32 measurements per day. These sensors have a manufacturer reported accuracy of ±0.47 °C at 25 °C, and were placed in the home by the interviewer and/or the homeowner with instructions on correct placement, i.e. between knee and head height, away from any heat sources or direct sunlight. Calibration measurements were taken of each sensor in a climate chamber at 25 °C before placement in the home and used to correct the readings after the logged data had been extracted. The calibration error from all sensors was found to be minimal with an average error of $M_{error} = 0.19$ °C $(SD = 0.11)$.

2.2. Sample characteristics

Of the 275 dwellings with data on living room temperatures, 11 used night-storage heaters, and 16 used other types of non-central heating technology; they were excluded from the following analysis as BREDEM assumptions differ for those technologies [4]. Of the remaining 248 homes, 93.5% had central heating with gas or LPG, and the other 6.5% had some other sort of central heating. For 119 dwellings, the existence of additional forms of heating for the main living room was reported, 125 did not use other heating in the main living room, and for four homes the data is missing.

A comparison of the CaRB data sample to the English House Condition Survey [15] showed an over-representation of owner-occupied and detached homes and bungalows, and an under-representation of privately rented accommodation and flats. Overall, the CaRB sample is largely similar to national estimates; for a more detailed comparison, see Ref. [14].

2.3. Temperature data and data cleaning

For this paper, the analysis focused on living room data in the winter months. Winter was defined as a 92-day period between November 2007 and January 2008, after which point the temperature loggers were withdrawn. A variable expressing average daily external temperature was created based on minimum and maximum temperature at local weather stations within the respondent's Government Office Regions [16]. For no day or region in the data analyses for this paper did the maximum external temperature exceed 15.5 °C; due to the natural elevation of internal temperatures above external due to incidental gains, above this

temperature, it is assumed that no heating is necessary [17]. Hence, all days considered in this study would be classified as "heating days" using this criteria and constituted valid units of analysis. It should be noted however that for some homes on some days close to 15.5 °C, incidental gains may maintain internal temperatures without the heating system being on leading to false positive results. The recorded internal temperature data was screened for outliers, i.e. for recorded temperatures below 10 °C or above 35 °C, and for changes of more than 10 °C in 45 min (indicating possible placement close to a heating source or in direct exposure to sunlight). Those potentially erroneous data points occurred on less than 0.2% of days and were excluded from further analysis. The dataset was managed and analysed using MS Access, SPSS, STATA, and MatLab.

2.4. Analyzing the data

The basic data used for analysis were a matrix of internal temperatures in 248 homes over 92 days with 32 measurement points per day (i.e., 248 homes × 92 winter days × 32 measurement points). Considering that BREDEM models assume differences in heating demand depending on weekday versus weekend, we separated days into weekdays (66 days) and weekends (26 days).

2.4.1. Probability of the heating system being on or off

Measured temperatures were translated into statements regarding whether the heating system was on or off. This was done by by examining the data for sequences of increasing and decreasing temperatures. If the magnitude of change was at least 0.75 °C, it was considered as a change in the state of the heating system. A change of less than 0.75 °C was considered to reflect hysteresis of the thermostat, i.e. the difference between the temperature at which the thermostat switches off and the temperature at which it switches on again, or mini-fluctuations in the logger. Boait and Rylatt [18] reported 1 °C as the hysteresis value. However, other work reported a value of 0.56 °C [19]. The cut-off value 0.75 °C was chosen as it is approximately in the middle of the other two estimates, and we present a summary of results using two additional cut-off points to test the sensitivity of results to the choice of cut-off point. In detail, the following steps were applied. Table 1 contains examples to illustrate the individual steps.

For each home, one vector of temperature measurement points was created which encompassed 2944 values, i.e. 92 days × 32 measurement points (Table 1, Row 1) and then the difference of the temperature at point t_{n+1} and t_n was calculated resulting in a vector of 2943 difference values (Row 2).

In this vector of differences values, points were identified where a sequence changed from positive to negative (or vice versa) difference values (Row 3), for example, after five negative difference values corresponding to falling temperatures, the sign of the temperature difference changed to positive at the 6th point in the sequence. Then the magnitude of change was calculated for each sequence (Row 4) by summing difference values in Row

2 of positive or negative sequences (e.g. −0.2 + −0.2 + −0.6 + −0.3 + −0.6 = −1.9). The absolute magnitude was then compared against a set criterion of 0.75 °C (Row 5); in the example of Table 1, −1.9 and 1.8 °C were above the criterion and hence kept whereas −0.3, and 0.5 °C did not meet the criterion. If a change was of a lesser magnitude, it was considered as having no change in the heating system and hence, as not causing a change in a sequence. The temperature sequence was translated into a binary variable indicating if the heating system was on or off at any point in time (Row 6). A sequence of decreasing temperatures means the heating system is off, or of increasing temperatures means it is on. For changes that are smaller than the criteria, the previous state is continued. Note that this is done on the level of temperatures not temperature difference, e.g. in the example, the first six temperatures are judged as the heating being off; the 7th point in the temperature sequence (17.8 °C) is when temperatures started to increase as indicated by the 6th value of temperature differences.

The vector was turned back into a matrix of 92 days with 32 columns. A column refers to the state of the heating system between two measurement points, for example, the first column has the state of the heating system between 00:00 and 00:45, the second one from 00:45 to 01:30 etc. For the last day, the last measurement point was excluded as no subsequent measurement point existed with which to calculate the sequence of change.

Days were separated into weekdays and weekend days, resulting in a matrix of (maximally) 65 weekdays or 26 weekend days × 32 binary coded variables for each home (31 values for the last day). Then, for each home, for each of the 32 (time-point) columns, the entries were summed across all days for which we had valid data for that home; this sum was then divided by the number of days for which we had valid data for that home. The resulting value is the probability of the heating system being on - for each home, at each of the 32 time intervals.

For the overall sample, the resulting matrix of 248 (dwellings) × 32 (probability estimates of the heating system being on at each time-point) formed the basis of subsequent analysis. It was a deliberate decision to not exclude days in which the heating was always off, because a model to calculate overall energy demand for heating should take into account that there are days without heating. The impact of excluding those days is shown in the results section (see 3.1.1).

2.4.2. Calculation of average heating duration

The probability values were translated into an estimate of hours of the heating system being on. For each dwelling, the probability estimates were averaged over the course of a day, separately for weekdays and weekends. This value was multiplied by 24 (as there are 24 h in the day) which gives the number of hours the heating system was on.

2.4.3. Calculation of the estimated heating demand temperature

Firstly, in each sequence that was identified as having the heating on, the maximum temperature was located. When the

Table 1
Example for the steps performed to translate temperatures into statements on the state of the heating system.

	Order of operations											
1	Identify Temperature	19.5	19.3	19.1	18.5	18.2	17.6	17.8	18.5	19.5	19.4	19.2	19.7...
2	Temperature_differences ($t_{n+1}-t_n$)		−0.2	−0.2	−0.6	−0.3	−0.6	0.2	0.7	1.0	−0.1	−0.2	0.5
3	Point_sequence (bold = changed from increasing to decreasing, or vice versa)		1	2	3	4	5	**6**	7	8	**9**	10	**11**
4	Magnitude_change						−1.9			1.9		−0.3	0.5
5	Point_sequence_corrected (bold = changed from negative to positive, or vice versa, by 0.75C)		1	2	3	4	5	**6**	7	8	**9**	10	11
6	Binary coding (0 or 1, which means 'off' or 'on')	Off	Off	Off	Off	Off	Off	On	On	On	On	On	On...

Table 2
Examples for temperature sequences during a 'heating-on' period with different implications for the heating demand temperature.

	Temperature sequence (maximum temperature in bold)					
Case 1: Maximum temperature reflects demand temperature.	20.52	20.70	21.31	21.63	**21.70**	21.67
Case 2: Maximum temperature reflects demand temperature.	20.52	20.70	21.31	21.63	21.67	**21.70**
Case 3: Maximum temperature does not reflect demand temperature.	20.52	20.70	21.31	21.63	21.60	**21.91**

maximum temperature was not the last temperature point in the sequence but was followed by other data points (Case 1 in Table 2), i.e. indicating that temperature had reached a plateau, it was assumed that the maximum temperature reflected approximately the heating demand temperature.[5] If the maximum temperature was the last data point in the sequence but differed only by less than 0.1 °C of the previous data point (Case 2 in Table 2), it was also counted as indicating the heating demand temperature. This was done because inspection of all temperature differences had shown that the minimum value of change was 0.0950 °C in all homes (except for one where the value was 0.096 °C) and presumably reflected some noise or jitter in the temperature sensors. If the maximum temperature was the last data point in the sequence and differed by 0.1 °C or more from the previous data point (Case 3 in Table 2), the maximum value could mean two things:

(1) It could reflect the actual demand temperature. Reaching the demand temperature may have coincidentally coincided with the time at which the heating system was turned off (respondent-operated or through the time-clock).
(2) It could be lower than the actual heating demand temperature. The heating system would have been turned off before the heating demand temperature was reached, i.e. before temperatures stabilized around the demand temperature.

It was impossible to decide which option was true; hence, when the maximum temperature was the last data point, this value was not included in estimating the heating demand temperature.

For each dwelling, all estimated heating demand temperatures, i.e. maximum values in an 'on' sequence that were not the last data point, were identified and averaged over all days and sequences, arriving at one value of average heating demand temperature per dwelling.

3. Results

3.1. Probability of the heating system being on over the course of the day

The averaged probability over the course of the day did not differ significantly between homes who reported having additional heating in the main living room and those who had no other forms of heating in the main living room. Therefore, in all following analysis the full dataset is considered.[6] Fig. 1 shows that average

probability (i.e. averaged over the 248 dwellings) for the heating system being on at all of the 32 temperature-difference intervals.

Both for weekdays and weekends, the probability of the heating system being on is about 0.1 from midnight onwards, and then starts to increase at about 4:30, and reaches a morning peak between 6:45 and 7:30 on weekdays and between 7:30 and 8:15 on weekends. For weekdays, the probability then declines by just over 0.1 and then increases again from 11:15 onwards; for weekends, the decline is less pronounced. Probability peaked in the early evening, i.e. about 18:00, both for weekdays and weekends. The maximum probability was $p_{\text{max.weekday}} = 0.74$ and $p_{\text{max.weekend}} = 0.71$ which means that in less than 75% of the homes, the heating system was on. This means there was no period during which the heating was estimated to be on in all homes during days in which the heating system was assumed to be in use. Further, the heating system was judged to be on in a considerable share of homes during those periods in which BREDEM would assume homes not to be heated. This was particularly pronounced for the weekday period between 9:00 and 16:00 where the mean probability was about $p = 0.5$, indicating that the heating was estimated to be 'on' in 50% of homes, as compared to 0% in BREDEM assumptions.

Table 3 summarizes the mean probability for the heating system to be on in the assumed heating periods. For each home, the probability values for the respective heating period were averaged and then the average and standard deviation of these estimates was calculated across homes. A perfect mapping on the times as assumed by BREDEM was not possible as temperatures were taken at 45 min-intervals. As an approximation, the weekday morning time window was defined as ranging from 7:30 to 9:00, and the evening window as 16:30 to 22:30. The weekend time window ranged from 7:30 to again 22:30. These times were slightly shorter than the BREDEM-defined heating periods due to the nature of our data collection (i.e. every 45 min), but they only included times that were part of BREDEM periods. Note that the probability estimates refer to time intervals. For example, for the morning heating, the time period from 7:30 to 9:00 corresponds to the average of the probability estimates 7:30 to 8:15 and 8:15 to 9:00.

To take into account that heating was judged to be on outside assumed heating periods, the probability values were average across the day. The mean probability for weekdays was $p = 0.41$ ($SD = 0.08$) and for weekends $p = 0.42$ ($SD = 0.08$). Kolmogorov–Smirnov tests were used to test if data followed a normal distribution; this was the case in all of the distributions under consideration, allowing statistical tests that rely on the assumption of normally distributed data. A paired sample t-test showed that the difference in the two estimates was not statistically significant. This translates to approximately 10 h of heating on weekdays and weekend days.[7] Using one-sample t-tests, the calculated duration was compared against the values assumed by BREDEM, i.e. 9 h (weekdays) and 16 h (weekends). For weekdays, the mean difference $M_{\text{diff\_weekday}} = 53$ min (95% CI: 39–68 min) was significant, $t(247) = 7.18$, $p < 0.001$, indicating the calculated duration was longer than the BREDEM assumption. For weekends, the mean difference $M_{\text{diff\_weekend}} = -6$ h (95% CI: -6 h, 15 min to -5 h, 45 min) was also significant, $t(247) = -48.56$, $p < 0.001$, indicating shorter estimated durations than assumed under BREDEM.

3.1.1. Effect of days without heating

BREDEM assumes that homes are heated every day. Analysis was conducted on how many days the heating system was judged

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[5] The term 'heating demand temperature' is used here in preference to the term 'thermostat setting'. This is done because the thermal characteristics of individual homes vary. The temperature at the thermostat (frequently located in the hallway) may not reflect the desired temperature of the occupants in the living room where temperatures were recorded.

[6] Excluding the period of Christmas holidays and New Year's, i.e. from the 24th of December to the 1st of January, did not change the average probability over the course of a day so those days were maintained in the subsequent analysis.

[7] Using the exact probability estimates gives an estimate of 9 h and 50 min on weekdays and 10 h and 5 min of heating on weekends, given that the values do not differ significantly, 10 h was used as the value for both estimates.
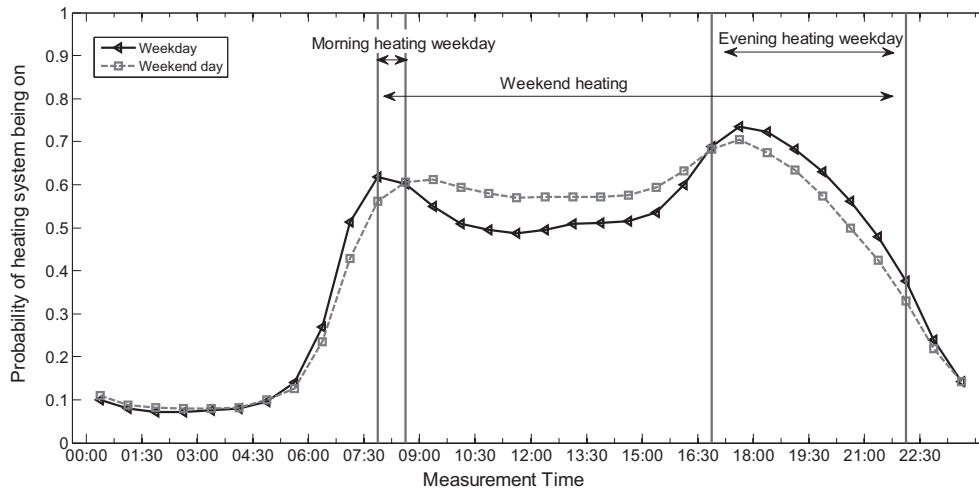
Fig. 1. Average probability for the heating system being on or off for weekdays and weekends. The vertical periods indicate times in which BREDEM would assume heating to be on.

to be off throughout the day. The distribution of the frequency of non-heating days was highly positively skewed: 55% of homes had no days without heating; 20% only had one or two days without heating. Only 16% of homes had five or more days over the 92 day period without heating. The probability estimates were tested to see if they differed when excluding days without heating; the average probability of the heating system declined somewhat (i.e. $M_{weekday} = 0.43$ and $M_{weekend} = 0.44$), however, the effect was only on the order of 20–35 min per day. It was a deliberate decision to not exclude days without heating from analysis because assumptions on heating patterns should take into consideration that there are days when homes are not heated.

3.2. Variability between homes

Fig. 2 shows the histogram of estimated hours of heating for all homes for a weekday (2a) and weekend (2b), with values rounded to the nearest integer.

For weekdays, 13% of homes met the BREDEM assumption of 9 h heating, 53% had longer durations, and 34% shorter durations. For weekends, no home showed a heating duration equivalent to the 16 h as assumed by BREDEM; all homes had shorter durations. The histograms indicate substantial variability between homes in their estimated hours of heating.

3.3. Estimated heating demand temperature

For each home, the average heating demand temperature was calculated. The average demand temperature was based on a

Table 3
Probability estimates for the three heating periods assumed in BREDEM.

	Morning weekday heating	Evening weekday heating	Weekend heating
Probability heating on			
Mean	0.57	0.61	0.58
SD	0.28	0.17	0.12
95% Confidence interval for mean	0.54–0.60	0.59–0.63	0.56–0.59

The probability estimates shown in Table 2 reiterate the finding of Fig. 1: the empirically derived estimates did not correspond to the BREDEM assumption that all homes are heated during the periods as assumed in BREDEM. About 60% of homes were judged to have the heating on in the three heating periods under consideration.

different number of cases per home, depending on the number of heating sequences with a plateau. The mean number of cases was $M = 60$ ($SD = 26$). There was no significant correlation between demand temperature and number of cases it was based on; hence, allowing retention of all estimated demand temperatures irrespective of how many cases they were based on. The mean demand temperature across all homes was $M = 20.47\ °C$ ($SD = 2.47$; 95% CI for the mean: 20.16–20.78), Fig. 3.

Using a boxplot analysis, six values of estimated heating demand temperatures that fell outside the whiskers were excluded and were hence considered outliers.[8] The outlier-omitted calculated demand temperature was determined to be $M = 20.58\ °C$. We compared this to the BREDEM assumed demand temperature of 21 °C using a one-sample t-test. The mean difference $M_{diff} = -0.42\ °C$ (CI: −0.71 to −0.13) was significant, $t(241) = -2.87$, $p = 0.004$, indicating a statistically significant lower estimated demand temperature, albeit of small magnitude.

3.4. Average temperature for heating sequences

In addition to calculating the estimated average heating demand temperature, the average temperature was calculated across all homes during all heating-on periods. This was $M = 19.52\ °C$ ($SD = 2.39$). This was calculated for each sequence of the heating being on for each home and averaged across sequences. BREDEM models assume that the demand temperature is achieved throughout the entire assumed heating periods. This finding challenges that assumption, as even during heating periods temperatures vary considerably, with average temperature approximately 1 °C below estimated demand temperature for our sample. The use of estimated demand temperature for heat loss calculations in models would therefore lead to an overestimation of fabric heat loss.

3.5. Effect of changing the cut-off point

The above analyses are based on a minimum change in temperature sequences of 0.75 °C. The same analysis was run with

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[8] Points are drawn as outliers if they are larger than Q3+W*(Q3−Q1) or smaller than Q1−W*(Q3−Q1), where Q1 and Q3 are the 25th and 75th percentiles, respectively. The default value of $W = 1.5$ corresponds to approximately ±2.7 sigma and 99.3 coverage if the data are normally distributed. The plotted whisker extends to the adjacent value, which is the most extreme data value that is not an outlier.
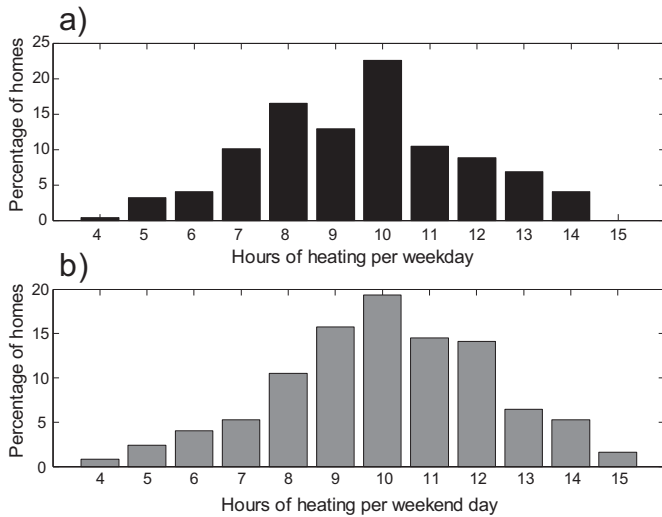
Fig. 2. Histogram of the hours of heating for weekdays (a) and weekends (b).

Table 4
Mean probabilities of the heating system being on using different change criteria.

Change criterion	Mean probability heating on (SD)		
	Morning weekday heating	Evening weekday heating	Weekend heating
0.5 °C	0.61 (0.29)	0.62 (0.17)	0.58 (0.12)
0.75 °C	0.57 (0.28)	0.61 (0.17)	0.58 (0.12)
1 °C	0.60 (0.28)	0.58 (0.18)	0.58 (0.13)

Three repeated measures ANOVA were used to test for differences in the mean probability of the heating being on depending on the chosen cut-off point; one for morning weekday heating, one for evening weekday heating, and one for weekend heating. For morning weekday and evening weekday heating, the ANOVA were significant (all $F > 6.8$, all $p \leq 0.004$). Posthoc comparisons with Bonferroni adjustment showed that for the morning heating period, the chosen cut-off of 0.75 °C led to a significantly lower probability than using 0.5 °C or 1 °C as cut-off point. For evening heating, all pairwise comparisons were significant. For the weekend estimates, no significant differences in probability estimates were found. Despite the statistical significance in two of the comparisons, the differences are of low, if any, practical significance, and do not change the implications of the study. The maximum difference in the estimated probabilities is $p_{maxdiff} = 0.04$ which translates to a difference of 4% in the percentage of homes with the heating on. All other differences depending on cut-off point were even smaller, showing how little results depend on the assumption of the cut-off point.

alternate cut-offs, as per the literature: 0.5 °C and 1.0 °C. Results were virtually identical to using a cut-off of 0.75 °C. The overall daily mean probability using a criterion of 0.5 °C was $p_{weekday} = 0.41$ and $p_{weekend} = 0.42$; for a criterion of 1 °C $p_{weekday} = 0.41$ and $p_{weekend} = 0.42$. The probability of the heating system being on in the three heating periods as assumed under BREDEM was also calculated. Table 4 summarizes the results.

4. Discussion

In this paper, estimated heating patterns and temperatures were compared to commonly used assumptions on those variables. The analysis showed the following:

- An estimated average heating duration of 10 h both for weekdays and weekends
  - In comparison to BREDEM assumptions, this means 1 h more per weekday and 6 h less per weekend day. On an (average) weekly basis, BREDEM overestimates heating duration only by 7 h.
- Homes do not follow the temporal pattern of heating as assumed under BREDEM.
  - In particular for weekdays, the heating is on in a substantial proportion of homes outside the assumed heating periods, i.e. between 09:00 and 16:00.
- Probability never reached a value of 1, meaning at no point in time did all homes have the heating system on as current BREDEM based stock models assume.
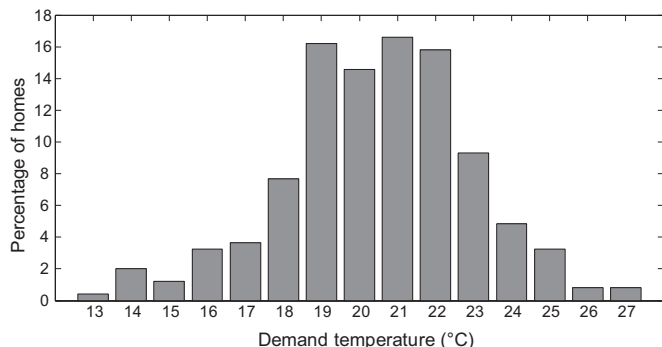

Fig. 3. Heating demand temperature across all buildings.

- Demand temperature is 20.58 °C. This is significantly lower, statistically, than the assumed demand temperature but in real terms is only about 0.4 °C less.
- The average temperature during 'heating-on' periods was 19.52 °C, approximately 1 °C lower than the estimated demand temperature, challenging the assumption used in BREDEM class models that homes achieve the heating demand temperature throughout the heating period.
- Using different assumptions about thermostat cut-off points hardly changed results, indicating insensitivity of findings to this assumption.
- Homes differed substantially in heating durations and demand temperature.

The estimates derived in this paper differ slightly from previous estimates [9]. This is due to using a different method to determine if the heating system is on. We introduced a minimum amount of change necessary to trigger a change in the state of the heating system whereas Shipworth et al. considered every increase in temperature as an indication of the heating system being on [9]. Also, they used the daily maximum temperature as the thermostat setting whereas we used the maximum temperature in a heating sequence in which temperatures reached a plateau to approximate the heating demand temperature. Despite the different approaches, both studies found a large similarity between weekend and weekday heating, and substantial variation between homes.

4.1. Implications for BREDEM based models

Our data imply that the distinction made between heating on weekdays and weekends should be revised, considering the similarity both in duration and temporal pattern. Also, the notion of a rigid pattern which all homes follow should be reconsidered. At no point in time were all homes found to have the heating system on, and in general, the assumed temporal pattern of BREDEM did not match the observed patterns. The analysis showed that in an average week and home, BREDEM would overestimate the heating duration by about 7 h and very slightly overestimate the demand temperature by about 0.4 °C. This 9% overestimate in heating hours could, for example, have a substantial impact when calculating future energy demand as current projections predict an increase in the number of households of about 221,000 per year [20].

In addition, the analysis identified that the average temperature during heating periods of 19.52 °C was approximately 1 °C lower than the estimated demand temperature of 20.58 °C. This both challenges the assumption that homes reach the demand temperature throughout the heating period, and suggests that the assumed internal temperature for heat-loss calculations in BRE-DEM based stock models should be reassessed.

4.2. Implications beyond BREDEM

Assuming a fixed pattern and hence one duration and temperature to calculate overall energy demand of the building stock is not problematic as long as the assumptions on temperature and duration accurately reflect reality. However, the temporal distribution is of importance when considering, for example, peak demand. In particular, given current proposals to increase the electrification of domestic heat supply through use of heat-pumps and electric resistive heating powered through a decarbonised national electricity system, the issue of peak power demand is critical [21,22]. The data here imply that not all homes demand heating at the same time, which would mean a lower peak power demand than if all homes heated at the same time.

4.3. Implications of the variability in heating patterns

The analysis also showed considerable variability between homes in heating duration and demand temperature. Whilst using the average duration and temperature minimizes the prediction error across homes, the error in prediction of energy consumption for an individual home could be high. Gill et al. showed that occupant behaviour accounted for 51% of the variance in heat between dwellings that were nearly identical and designed to high energy-efficiency [23]. Considering variability in heating data is also important in order to avoid negative financial consequences for home occupiers. In the UK, the Government launched the "Green Deal" scheme that gives loans for energy efficiency measures that are paid back through the energy bills [24]. The intention is that savings on energy bills will outweigh the cost of repayments, the so called "Golden Rule". In order for this to work out, predictions at the individual home level need to be as accurate as possible so that households will not be left with much higher bills than expected to repay the loans. Both the sources of inaccuracy, and imprecision in estimates of home energy use highlighted in this paper create risks to schemes such as the UK Green Deal.

4.4. Limitations of the current study

The analysis used temperatures recorded in the living room to conclude whether heating was on or off; however a range of factors beyond the heating being on or off may impact internal temperatures, such as various forms of incidental gains and ventilative heat losses. Whilst certain checks were used to control for these confounding factors in the data by, for example, excluding recordings where temperatures increased or decreased by more than 10° between two measurement points (which might be the result of sensor being in direct sunlight or a window being opened on a cold winter's day), only monitoring of radiator and/or thermostat would

allow ruling out such confounding factors with certainty.[9] Also, whilst the CaRB survey was designed to be a nationally representative survey, comparison of characteristics of sample dwellings to a nationally representative survey showed that the CaRB survey did not match national statistics in all cases. However, even when assuming a certain error margin around our findings to take into account these limitations, data is still very strong in supporting the key findings of the study.

4.5. Outlook for further research

The next natural extension to this analysis would involve linking heating durations and temperatures to socio-demographic and building-demographic explanatory variables, and external temperatures in order to allow more accurate prediction of heating demand temperature or heating duration for an individual home or segment of homes. This could then allow targeting sub-segments of the population for interventions to reduce energy consumption, and allow much more accurate prediction of energy demand for segments of homes. Also, previous research using cluster analysis had shown that internal temperatures followed distinctive patterns [25]. Applying similar clustering methods to heating probabilities could identify the most common heating patterns. Identifying common heating patterns may have important implications for the design of heating technologies and control systems.

Analysis of within-home variability in heating patterns from seasonal to daily timescales could be instructive in the design of heating control systems by highlighting the degree of required flexibility necessary to accommodate such variable heating system demands. Highly irregular heating patterns would reduce the efficiency of low carbon heating technologies such as ground-source heat-pumps, and may indicate that occupants accustomed to such patterns would find it challenging to adapt to the reduced responsiveness of such systems.

Finally, a similar analysis on the rest of the house would be of interest given that BREDEM distinguishes living room and the rest of the house.

4.6. Conclusions

The study challenges common model assumptions on heating patterns, hours, and temperatures. The results clearly show that no deterministic heating pattern exists in English homes, that weekdays and weekends are very similar in their heating pattern, that average temperatures during heating periods are substantially below estimated demand temperatures, and that there is a substantial variability between homes in heating duration and temperature. The findings have important implications for the calculation of overall energy demand, energy demand of an individual property, and of heat loss parameters of a building, and suggest the need to revise current assumptions and applications of models.

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[9] It is unlikely though that in very poorly insulated homes on very cold days the heating system was not able to deliver enough heat to prevent temperatures from declining which would have led to the error of judging the heating system as off even though it was on. In that case, the probability of the heating system being on should have been lower; however, the average probability for the coldest ten days was with an average of $M = 0.44$ higher than the average for all days (i.e. $M = 0.41$).

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