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Occupant Heating Practices in Dwellings: A Methodology for Identifying Scheduled Heating Periods and Manual Override Events

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Abstract

Heating operation can be automated using a timer/programmer and thermostat, manually controlled by occupants, or both. In ten UK dwellings, both automated and manual override heating events were identified from 30 minute time series data of living room air temperature measurements. Multivariate logistic regression was used to infer a model of occupants' manual override heating events based on indoor and outdoor environmental factors. The results showed that occupants manually override their programmed heating events and indoor temperature is the main factor influencing the override events. This study is the first model of manual override heating events developed for UK dwellings. The results have significant implications for energy modellers as they aim to improve building energy modelling in order to reduce the energy performance gap.

Introduction

The domestic sector accounts for 29% of total final energy consumption in the UK and energy used in space heating in dwellings accounts for the biggest proportion (70%) (BEIS 2017). As the UK has set a stringent, legally binding target to reduce carbon emissions by 80% by 2050 from the 1990 levels (HM Government 2008), space heating energy consumption should be targeted for efficiency and reduction.

Energy demand for space heating is driven by external temperature, dwelling characteristics including the thermal properties of the building, type of heating system and controls, household characteristics and occupant behaviour (Wei et al. 2014). It has been shown that interventions aimed at improving the thermal performance in order to reduce energy consumption in domestic buildings (e.g. thermal upgrades, more energy efficient heating systems and better controls), do not always save as much energy as predicted, due to the rebound effect (Hong et al. 2006; Dowson et al. 2012). One of the reasons for the energy performance gap is the uncertainty about model inputs for occupants' space heating behaviours (Steemers and Yun 2009; Gram-Hanssen 2010). Therefore, to help close the performance gap, it is important to have a better understanding of the way households heat their homes.

Building energy modelling is used to predict the energy performance of new build and retrofitted buildings to influence the building design. Therefore, it is necessary that the input data of the building simulation model is as close as possible to the reality, including occupant heating behaviour patterns. Understanding how and when occupants use their heating systems will be useful for improving the predictions of energy models.

This paper presents a methodology for identifying programmed and manual override heating events from indoor temperature measurements and develops a stochastic model to describe when the state of heating is manually changed from off to on as a departure from the programmed settings.

Previous studies

Previous studies have used different methods to determine occupant heating behaviour (i.e. the thermostat setpoint temperature and duration of heating periods). These methods can be classified into either survey methods, where the occupants self-report their heating patterns and preferences (Belzer and Cort 2002; Pritoni et al. 2015; Shipworth 2011; Guerra-Santin and Silvester 2017; Shipworth et al. 2010; Jones et al. 2016) or measurement methods, where temperature sensors are used to measure the indoor air temperature (Andersen, Olesen, and Toftum 2011; Huebner et al. 2013; Shipworth et al. 2010; Kane, Firth, and Lomas 2015; Martin and Watson 2006). In their literature review, Jones et al. (2016) showed that heating setpoint temperatures used in previous domestic energy modelling studies ranged from 15°C to 26°C. Regarding heating periods used, they summarised that studies defined the heating period according to the dwelling's expected occupation hours and it was based on the assumption that occupants do not heat their homes when they are not at home.

As part of the Energy Follow-Up Survey (EFUS) (BRE 2013) conducted to collect data on domestic energy use in England, households with central heating systems were asked whether they manually switch on their boiler to provide additional heat outside of the programmed hours. An analysis of the data showed that 61% (n=850) of the households involved in the survey reported manually overriding their programmed schedule (Hulme et al. 2013). This finding is corroborated by Kane et al. (2015), in their study of heating practices in UK homes, which concluded that it was impossible to categorise the number of heating periods in a day because of inconsistent heating schedules. This was due to occupants regularly changing or manually overriding their timer settings.

To the authors' knowledge, there has not been a detailed study investigating the distinction between regular programmed heating and manual override events during the heating season and the factors that influence these override events. Using indoor temperature measurements in ten UK homes, this paper presents, a novel method for identifying both the automated and occupant induced manual overide events.

Simulating occupant heating behaviour

The factors that influence building energy consumption have been summarised into six categories: (1) climate, (2) building envelope characteristics, (3) building services and energy systems characteristics, (4) building operation and maintenance, (5) occupant activities and behaviour and (6) indoor environmental quality provided (IEA 2016). Occupant behaviour has been noted to significantly affect a buildings' energy consumption (Hoes et al. 2009). Occupant behaviour varies significantly between individuals which results in large variations in energy consumption. Building performance simulation is used to support energy efficient building designs and predict the operation of buildings, and occupant behaviour is a major contributing factor to the uncertainties in the results obtained. There is therefore a need to define more realistic occupant behaviour patterns that can be implemented in building simulation programs to significantly improve the validity of the outcome of the simulations. Occupant behaviour has been modelled stochastically, as behaviour patterns vary between individuals and can also change with time (e.g. Fabi et al. 2013; Jones et al. 2017). Yan et al. (2015) provides a detailed review of occupant behaviour modelling for simulaton and outline the processes involved: (1) occupant monitoring and data collection, (2) model development, (3) model evaluation and (4) integration into building simulation tools. The methods for occupant behaviour model development is also explained by Haldi and Robinson (2009). From the literature, the stochastic behaviour modelling methods, include, the logistic regression model, the Bernoulli process, the discrete-time Markov chain process and the survival analysis. Using these methods, occupant interation with building controls, such as windows and shading devices, light switches and heating systems, have been found to be influenced by a large number of factors and these are referred to with the general term "drivers" (Fabi et al. 2012). Regarding heating behaviour patterns, Wei et al. (2014) have provided a detailed literature review on the driving factors for occupant-controlled space heating in residential buildings in which they identified 27 factors that have been suggested in previous studies to influence this behaviour. However, in building performance simulation programs, only a few of the 27 drivers have been considered for the definition of heating schedules. The previous literature reviews both suggest that further work is needed to improve the representation of occupant behaviour in building performance simulation.

The current study

The 10 homes in this study had a gas-fired central heating system, which is atypical domestic heating system found in over 91% of UK homes (DCLG 2015). The heating system is made up of a central boiler and a pump and individual radiators. The boiler and pump are most often controlled by a thermostat and a timer or programmer. The thermostat turns the boiler on and off according to a predefined heating demand temperature, and the timer/programmer is used to set the on/off times, hence defining the heating duration. The radiators are controlled by thermostatic radiator valves (TRVs) fitted to individual radiators which turn the radiators off according to a selected setting which corresponds to zonal demand temperatures. The timer installed in the dwellings allowed multiple, regular heating periods to be programmed – i.e. multiple time periods within a day and different time periods for each day of the week (e.g. for weekday/weekend time periods). Most timers also allow occupants to manually control the heating duration. This can be used as the main heating on/off pattern or can be used for departures from the regular heating schedules. Using indoor air temperature data collected in the living rooms of the ten dwellings, programmed and manual override heating events have been identified and a stochastic model of occupant manual heating behaviour has been developed based on indoor and outdoor environmental variables.

Method

Case study dwellings

The case study dwellings were seven purpose built rented flats and three rented end-terrace houses located on a new build housing estate in Torquay, a town in the South West of the UK. A detailed description of the dwellings is provided in Jones et al. (2017). Six of the flats were located in a Code for Sustainable Homes (CSH) Level 4 apartment building. The seventh flat was located in a minimum compliance, 2006 Building Regulation Standards apartment building. Two of the end-terrace houses met CSH Level 5 and the third house, was constructed to the 2006 Building Regulations Standards. All ten dwellings were gas centrally heated and had a full set of heating controls. All the dwellings were given a unique identification number (DW01 – DW10).

Environmental measurements

An automated monitoring system was installed in the dwellings. The variables used in this paper form a subset of data measured continuously from 28 Oct-13 to 02 Nov-14 (370 days). The variables measured were:

- Indoor variables – air temperature (°C) and relative humidity (RH) (%)
- Outdoor variables - air temperature (°C), RH (%) wind speed (m/s), global solar radiation (W/m^2) and rainfall (mm)

All variables were measured at 10 min intervals. The internal loggers were installed in the living room and one bedroom in each dwelling, away from heat sources and

direct sunlight. The outdoor variables were measured using an onsite meteorological station. Specifications of the data loggers are presented in Jones et al. (2017).

Data preparation and processing

The indoor air temperature measured in the living room was processed and analysed in the current study. The dataset was managed and analysed using MS Excel and IBM SPSS Statistics 24. All time steps were converted to half hour intervals. Having data at a half hour resolution was adequate to determine a change in temperature, which corresponded to heating practices.

Statistical method

Logistic regression was used as the modelling method to determine the environmental factors that statistically influence occupants to manually override their scheduled heating periods and to infer the probability of a manual override event occuring due to a change in the influencing variable. The method is explained in detail by Field (2009) and Haldi and Robinson (2009). In the current study, the dependent variable is categorical: '0' for heating being off and '1' for heating turned on and the predictor variables are continuous. The full model consisted of all the environmental variables. The variables were firstly assessed in a univariate model. For a multivariate analysis, the backward selection method was used where the variables that were not significant (i.e. *p*-value ≥ 0.05) were removed from the model. As indoor air temperature is affected by the heating being on, the environmental conditions occurring within the 30 minutes before the heating is turned on were taken as the predictor variables. In the interpretation of the results, the sign of the variable's coefficient determines the direction of the influence of the predictor variable on the outcome, i.e. whether the variable influences directly (positive) or inversely (negative) the probability of the action.

Identifying heating days

Outdoor temperature was used to select the days where the dwellings were most likely to be heated. The meteorological station was located onsite hence it was assumed that throughout the study, all the homes experienced the same external weather conditions as measured. As recommended by Kane et al. (2017), in order to use room temperature methods for the assessment of heating behaviours in dwellings, only days when mean outdoor air temperature is lower than 10°C should be used. A plot of the daily average external temperature (Fig. 1) was used to identify the potential heating days. The days considered as heating days were from 01 Nov-13 to 31 Mar-14 (151 days). The average daily outdoor temperatures ranged from 7.1°C to 9.0°C in these months.

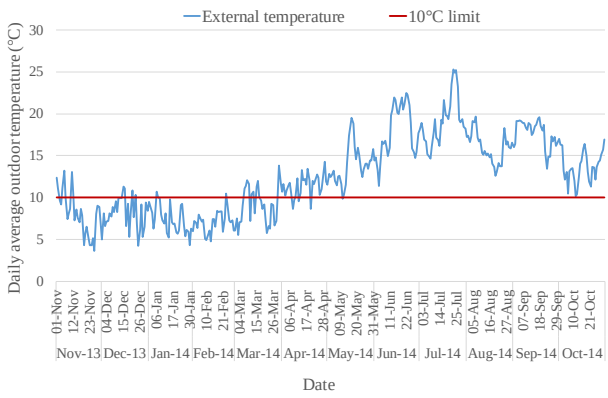

Figure 1 Daily average outdoor air temperatures

Identifying heating periods

Figure 2 presents the indoor air temperature profiles for the weekday and weekend heating days (between Nov-13 and Mar-14) in DW05. A visual inspection of the profiles shows the differences in weekday and weekend heating practices: on the weekdays, the heating is turned on at 06:00 until 07:30, from 09:00 to 13:00 and again from 17:00 to 19:30. On the weekends, the heating comes on from 08:00 to 12:30 and from 16:00 to 20:00. In this dwelling, a single demand temperature cannot be identified as the indoor air temperature in each heating period is different. This could be due to several reasons such as different demand temperatures selected for each programmed heating period or poor thermostatic control.

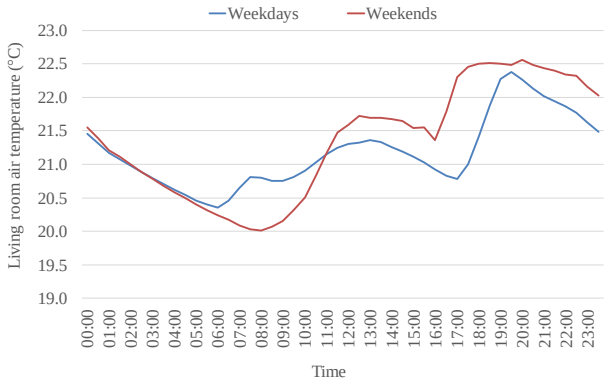

Figure 2 Weekday and weekend living room indoor air temperature profiles in DW05 during the heating season

Methods for the systematic identification of heating periods have been assessed and compared in a study by Kane et al. (2017). Huebner et al.'s (2013) method was adopted for the analysis conducted in this paper. Indoor temperature was measured at 10min intervals and increases by at least 0.3°C within 30min were translated into whether the heating system was turned on. A plot of the temperature differences in DW05 on all the weekday (107 days) and weekend (44 days) heating days are presented in Figures 3 and 4 respectively. The continuous line indicates a 0.3°C temperature increase. Each coloured data point represents one single day, hence at each half hour there is a maximum of 107 data points for weekdays and 44 data points for weekend days. The plots confirm that between 00:00 and 06:00, when occupants are most

likely to be asleep, there is no increase in temperature, indicating that the heating is not turned on. The half hourly temperature difference during this period is always below 0.3°C and the negative differences indicate a decrease in temperature. Temperature starts to increase from 06:30 indicating that the heating is on. However, this increase in temperature does not occur in all the heating days suggesting that, even during the identified heating season, the dwelling is not always heated. One reason could be that the dwelling may not be occupied on these days.

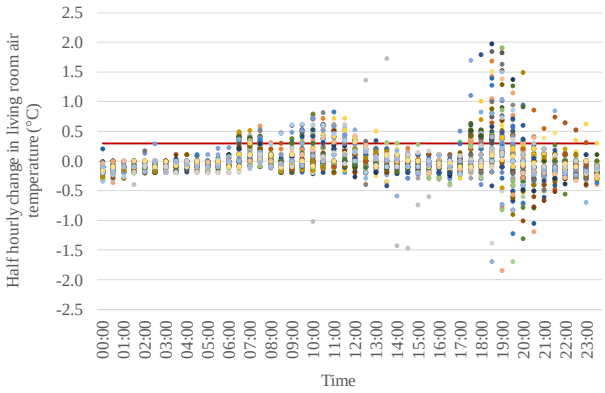

Figure 3 Half hourly indoor air temperature difference on weekdays in DW05

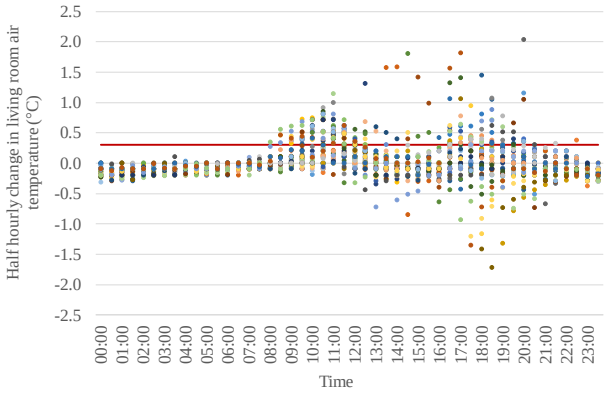

Figure 4 Half hourly indoor air temperature difference onweekends in DW05

Figure 5 shows, on a daily basis, for each half hourly interval, the percentage of heating days when the indoor air temperature difference is at least 0.3°C on weekdays and weekends. It confirms that in DW05, (i) the heating is not turned on when the occupants may be asleep, (ii) not all the days are heated (maximum percentage of days is less than 50%), and (iii) there are multiple heating periods in the day. The profiles also show the differences in heating behaviours between weekdays and weekends. During weekdays, the heating comes on at 06:30 for an hour. This is most likely to occur when occupants wake up for routines such as work/school. At the weekend, the heating is turned on later in the morning as occupants may have longer sleeping times. In this dwelling, there are three clear heating periods during weekdays and two at weekends.

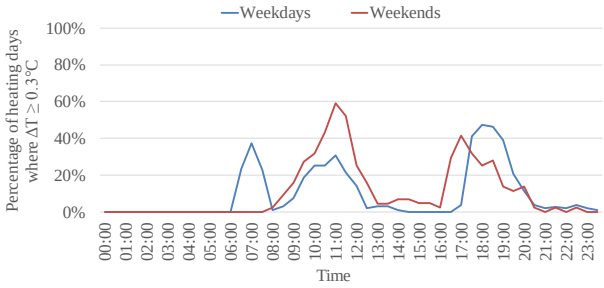

Figure 5 Proportion of heating days for weekdays and weekends during the heating season, where half hourly indoor air temperature increase is at least 0.3°C

Figures 6 and 7 are the daily heating profiles for all the case study dwellings for weekdays and weekends. Again, there are differences between the weekday and weekend profiles. The heating period seems to be more regular on weekdays as the proportion of heating days with at least 0.3°C increase in temperature is higher than at the weekend. Also, there seem to be three distinct heating periods on weekdays, whereas at the weekends this is less obvious.

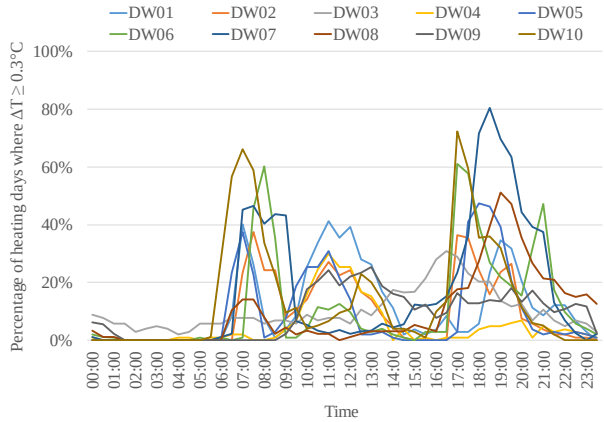

Figure 6 Daily heating profiles on weekday heating days for all case study dwellings

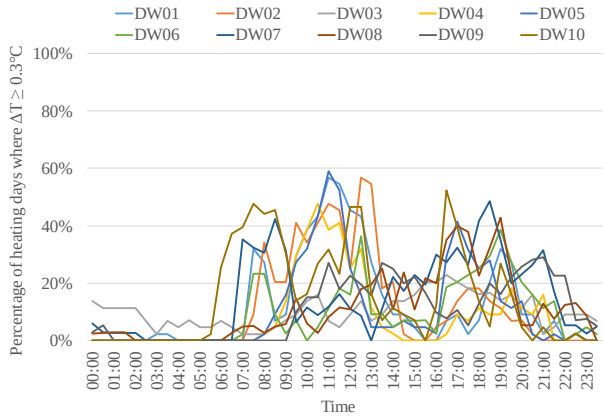

Figure 7 Daily heating profiles on weekend heating days for all case study dwellings

The method to determine regular/programmed heating events and manual override events was based on identifying the proportion of days when an indoor air temperature increase of 0.3°C was recorded. If the percentage of heating days with a 0.3°C increase was

above 10%, it was assumed a regular heating event, and if the proportion was below 10%, it was assumed a manual override event.

Results

Daily heating periods

This study focuses on the manual override events where the heating state is changed from off to on. Table 1 presents the regular heating periods and manual override events on weekdays and weekends for DW05. The average daily heating durations from regular/programmed heating on weekdays and weekends were six hours and seven hours, respectively. Manual override events occurred within the hours shown in Table 1 and the heating was on for a maximum of two additional hours. The number of days where manual override events occurred within the identified hours are shown in the last column. It shows that in this dwelling, during weekdays, manual overrides occurred mainly in the morning after the regular heating period. During the weekends, it was mainly in the afternoons.

Table 1 Identified regular heating periods and manual override events in DW05

Heating periods	Regular events	Manual overrides events	Number of days with manual override events
Weekdays	06:30 – 07:30		
		08:00 – 09:00	9
	09:30 – 12:00		
		12:30 – 14:00	5
		17:00	3
	17:30 – 20:00		
		20:30 – 23:30	6
Weekends		08:00 – 08:30	4
	09:00 – 12:30		
		13:00 – 16:00	6
	16:30 – 20:00		
		21:30, 22:30	2

Manual override events were identified in all the case study dwellings. The analysis of data of all the dwellings suggest that the average weekday and weekend dayregular heating periods were 8.3 hours and 9.1 hours, and the manual override heating periods last on average for 3.4 hours on weekdays and 5.3 hours on weekend days. On average, manual override events occurred on 27 weekdays and 12 weekend days. During the week, manual override events occurred mainly in the afternoons between 14:00 and 16:00 and in the evenings from 21:30. During the weekends, the manual override events took place in the mornings between 05:30 and 07:00 and in the evenings from 21:30.

Logistic regression analysis

Regression models were obtained to describe the probability of manual override heating events for the whole heating season and for weekday and weekend heating days separately, based on the environmental variables measured. Table 2 presents the intercepts and coefficients of the environmental variables assessed in the three cases and also the *p*-values of the variable in predicting a manual override event. Essentially, manual override heating events in all the models were influenced mainly by indoor air temperature. The negative sign of the coefficient for indoor air temperature shows that as indoor air temperature falls, the likelihood of a manual override event occurring increases. The impact of solar radiation was significant and positive for the weekdays, indicating that as solar radiation increases, the probability of a manual override event occurring increases. It is worth noting that the magnitude of the coefficients of the variables are relatively small.

Using the intercept and the coefficient, a probability profile can be plotted for a range of indoor temperatures. The plot in Figure 8 shows that at the same indoor air temperature, the probability of a manual override heating event is slightly higher in the weekends compared to the weekdays.

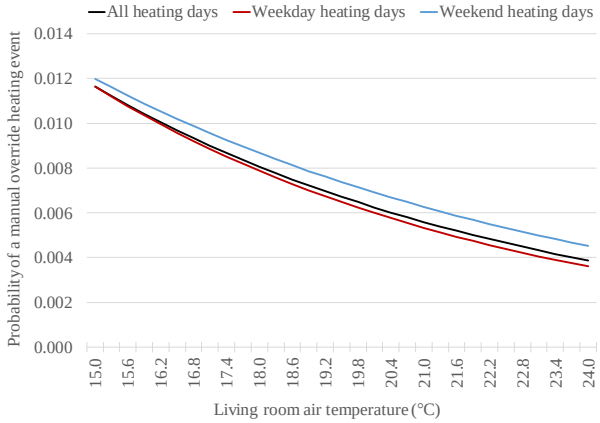

Figure 8 Probability profiles for manual heating override events due to indoor air temperatures

A multivariate model was created, which included the variables indoor air temperature and solar radiation. All remaining variables were not included as they were not significant (i.e. $p > 0.05$). The coefficient for solar radiation in the multivariate model was however very small. The final model obtained is shown in Equation (1):

$$\ln\left(\frac{p}{1-p}\right) = -2.656 - 0.127T_i + 0.002SR \quad (1)$$

Where, p is the probability of a manual override heating event within the next 30 min, T_i is the living room indoor air temperature in °C, and SR is the solar radiation in W/m^2.

Table 2 Regression parameters for the logistic model including a single variable for all the heating days and the weekday and weekend heating days from all dwellings

Manual override events	Variables	Intercept	Coefficient	*p*
All heating days (n=392)	Indoor air temperature (°C)	-2.598	-0.123	< **0.05**
	Indoor RH (%)	-5.508	0.009	0.20
	Outdoor air temperature (°C)	-5.123	0.003	0.86
	Outdoor RH (%)	-4.639	-0.006	0.44
	Wind speed (m/s)	-5.184	0.028	0.15
	Global solar radiation (W/m^2)	-5.216	0.002	< **0.05**
	Rainfall (mm)	-5.131	0.011	0.36
Weekday heating days (n=268)	Indoor air temperature (°C)	-2.478	-0.131	< **0.05**
	Indoor RH (%)	-5.497	0.008	0.35
	Outdoor air temperature (°C)	-4.929	-0.026	0.25
	Outdoor RH (%)	-5.049	-0.001	0.91
	Wind speed (m/s)	-5.19	0.017	0.48
	Solar radiation (W/m^2)	-5.275	0.002	< **0.05**
	Rainfall (mm)	-5.186	0.017	0.22
Weekends heating days (n=124)	Indoor air temperature (°C)	-2.777	-0.109	**0.01**
	Indoor RH (%)	-5.541	0.011	0.37
	Outdoor temperature (°C)	-5.408	0.048	0.09
	Outdoor RH (%)	-4.088	-0.011	0.33
	Wind speed (m/s)	-5.181	0.056	0.12
	Solar radiation (W/m^2)	-5.089	0.001	0.12
	Rainfall (mm)	-5.020	-0.001	0.95

Discussion

Household daily heating patterns

Calculating and plotting the indoor air temperature difference for all the heating days showed some clear heating patterns in the dwellings. In seven out of the ten dwellings, there was no significant temperature increase between 00:00 and 05:30 indicating that the heating is turned off when occupants are assumed to be asleep. There were clear heating periods in the mornings although the start times were different, ranging from 05:30 to 09:00. The daily heating patterns give an indication of occupancy patterns and routines. If it is assumed that the dwelling is only heated when it is occupied, then the patterns suggest that these dwellings are occupied throughout the day as most of them had heating periods in the mornings, afternoons and evenings. During the weekdays, only three out of the ten dwellings had only two heating periods, one in the morning and the second in the afternoon. The remainder had three heating periods in a day. In the dwellings with two heating periods, it can be assumed that the occupants have the heating programmed to come on for a short period in the mornings before they leave the dwelling and again in the evening when they return. During weekends, the heating periods are not as distinct as those during weekdays. In seven out of ten dwellings, the first weekend heating period started later than the first weekday heating period. In general, the first heating period starts around 06:30 on weekdays and stays on until 08:30. During the weekends, the first heating period is from 07:00 until 14:30. The thermostats installed in these dwellings allow multiple heating periods to be programmed within one single day. This can be replicated for the rest of the days of the week or individual daily heating schedules can also be set up. The differences observed between weekday and weekend heating patterns indicate that occupants may have a schedule for the weekday and a different schedule for the weekend. The results therefore show that the occupants in these dwellings are making use of this feature of the thermostat to set different heating schedules to suit their routines.

The average daily heating durations calculated for the regular/programmed heating events were 8 hours and 9 hours on weekdays and weekends respectively. These durations are lower than the BREDEM/BS EN 13790 (Anderson et al. 2002) values which are used in energy modelling (9 hours for weekdays and 16 hours for weekends) and lower than what was self-reported by householders (9.5 hours for weekday and 11.2 hours for weekend) (Jones et al. 2016). However, they fall within the range of durations previously estimated from room air temperature (between 6.7 hours and 11.4 hours per day – they do not distinguish between weekday and weekend) (Kane et al. 2017). The longer heating durations estimated in earlier studies could be because there has not been a separation between regular heating periods and manual override events.

Manual override events

The findings reported in this study suggest that there is considerable variation in household heating practices. Although occupants set regular heating schedules, they also override these schedules for additional heating (i.e. change the heating state from off to on). In all the case study dwellings, there were manual override events and these occurred on average 27 out of the 107 weekday days, and 12 out of the 44 weekend days measured.

Manual overrides as departures from programmed heating schedules could be explained by a change of the outdoor or indoor environmental conditions, a change of the household's regular occupancy patterns or it may be due to household activities. Manual overrides may also occur when occupants require warmer conditions for activities such as drying laundry. In the winter months, clothes take longer to dry due to the low temperatures. Households without dryers may turn the heating on, either regularly or on occasion, to dry clothes. This practice may be done during the regular heating schedule or through a manual override event.

Although manual override events occur on only a few days over the heating season, they increase the daily heating duration significantly. In this study, the daily heating duration was increased by an average of 3.4 hours on weekdays and 5.3 hours at weekends. Even with the increase in weekend heating hours, the calculated heating duration is lower than what is currently specified by BREDEM for energy modelling.

Manual change of heating state

This study also assessed environmental factors that influence a manual override event (i.e. from off to on outside the regular heating periods). Indoor temperature was found to be the best predictor of manual override of heating. The probability of turning the heating on manually increased with decreasing indoor temperature. This could be because occupants respond to the indoor conditions, regardless of what the outside conditions may be. If it is cold outside but indoor thermal conditions are comfortable/acceptable, occupants will not need to take action to change the conditions. Furthermore, solar radiation was found to have a significant, increasing effect on manual heating operation. The possible reason for this result could be because manual override events occurred in the mornings and afternoons, i.e. when the sun is out. No other environmental variables were found to have a significant impact on manual heating operation and the impact of indoor temperature and solar radiation were relatively small. This suggests that other factors may be better predictors of manual overrides of heating. Dwelling characteristics (e.g. type and fabric properties), household characteristics (e.g. size, composition and health status) and motivation, perception and behaviour characteristics (e.g. understanding of household energy use) are all factors known to have an effect on heating behaviours.

Conclusion

Based on measurements of living room temperatures, a method was developed to establish household heating patterns and identify regular/programmed heating periods and manual override events. This was carried out in ten dwellings in the UK. The results show that the dwellings were not heated on all the heating days in the heating season. On days when the dwellings were heated, there is often a regular pattern which suggests that a programmer/timer is being used to set daily heating schedules. Multiple heating periods per day and differences in schedules between weekdays and weekends were observed. Aside from the regular heating schedules, manual override events were evident in all the dwellings, indicating a departure from the programmed schedule. Using logistic regression, the probability of a manual override event (off to on) due to environmental variables were modelled. Indoor temperature and solar radiation were found to be significant predictors of manual override events. The research reported in this paper has implications for occupant behaviour modelling in building performance simulation. This study presents the first model for manual override heating events. The study will benefit from a validation of the method used to identify the heating events in order to confirm that the detected indoor temperature increases are due to the use of central heating systems and not environmental factors such as solar radiation.

Acknowledgement

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