Physical environmental and contextual drivers of occupants' manual space heating override behaviour in UK residential buildings

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Abstract

This paper investigates the physical environmental (indoor and outdoor temperature and relative humidity, wind speed, solar radiation and rainfall) and contextual drivers (time of day) affecting occupants' manual space heating override behaviour during the heating season based on measurements collected in ten UK dwellings. Logistic regression modelling is used to understand the probability of occupants manually overriding their scheduled heating periods. To the authors' knowledge, these are the first stochastic models of manual heating override behaviour developed for residential buildings. The work reported in this paper suggests that occupants' manual overrides are influenced by indoor and outdoor temperature, indoor relative humidity, and solar radiation. In addition, the effects of the physical environmental variables varied in relation to the time of day. At night, none of the physical environmental variables influenced manual overrides. In the morning, afternoon and evening, manual overrides were governed by a mix of indoor air temperature, indoor relative humidity and solar radiation. The models presented can be used in building performance simulation applications to improve the inputs for space heating behaviour in residential buildings and thus the predictions of energy use and indoor environmental conditions.

Keywords:

Domestic space heating, Occupant behaviour, Manual heating overrides, Scheduled heating periods, Stochastic modelling, Residential buildings.

1. Introduction

The housing sector is the second largest energy consuming sector in the UK, accounting for 29% of total final energy consumption [1]. The sector is responsible for about a quarter of the nation's greenhouse gas (GHG) emissions [2]. In UK homes, space heating accounts for over two thirds of a typical household's total energy consumption [1] and results in 11% of the UK's GHG emissions [3]. These figures indicate that reducing domestic energy use, in particular that related to space heating, is imperative if the UK is to achieve its commitment to reduce national carbon emissions by 80% of 1990 levels by 2050 [4].

Occupant behaviour in buildings, which includes interaction with building systems, such as windows, lighting and heating, has been noted as the leading source of uncertainty in accurately predicting the indoor environmental conditions and energy performance of buildings [5–10]. Occupant behaviour in buildings is stochastic, complex, and related to a wide range of factors, both individually and as an interaction [11]. These factors are commonly referred to as "drivers" and are defined as "*the reasons leading to a reaction in the building occupant and suggesting him or her to act (they namely "drive" the occupant to an action)* [12]. The potential drivers have been divided into five groups: physical environmental, contextual, psychological, physiological and social factors.

There has been significant progress in building performance simulation (BPS) in the last decades and it is increasingly used to predict and optimise energy and environmental performance of buildings. However, the stochastic nature of occupant behaviour is often poorly defined in simulation tools [13,14]. Fabi et al. [11] noted that in part the gap between simulated and actual energy consumption of buildings was the result of the unrealistic schedules used to represent occupant behaviour in simulation tools. In relation to occupant space heating behaviours in residential buildings, many simulation tools assume fixed heating settings for all dwellings [15] (e.g. Building Research Establishment Domestic Energy Model (BREDEM) assumes the setpoint temperatures: 21°C in living rooms and 18°C in all other zones and heating durations: nine hours on weekdays and 16 hours on weekends). Whereas, in reality, recent studies have shown that heating settings vary due to environmental factors [11,16–19], building characteristics [20–23] and occupant related factors [21–25]. Jones et al. [23] provide a detailed review of the typical input values for heating setpoint temperatures and periods that have been used in previous domestic energy modelling studies.

Providing modellers with typical occupant behaviour profiles is the key to improving model inputs and the resulting accuracy of the outputs. Constructing models of typical occupant heating behaviour requires the quantification of real life occupant behaviour measured in real buildings, combined with an understanding of the underlying drivers of the behaviour. Accordingly, in 2014, the International Energy Agency launched IEA-EBC Annex 66 – Definition and Simulation of Occupant Behaviour in Buildings [26], which aims to help close the energy performance gap through the modelling and integration of occupants' behaviour in building simulation software. Of particular relevance to the current paper is Subtask B: Occupant action models in residential buildings.

In the last 15 years, probabilistic models have increasingly been developed to capture the stochastic nature of occupant behaviour [27–33]. Detailed reviews of the state-of-the-art in occupant behaviour modelling have been presented by Yan et al. [7] and Delzendeh et al. [14].

Regarding the modelling of space heating behaviour in dwellings, Fabi et al. [34], using logistic regression, inferred the probability of occupants adjusting the setpoint of Thermostatic Radiator Valves based on indoor and outdoor environmental conditions in 13 Danish dwellings. The study found that depending on the type of TRV user (i.e. active, medium or passive), outdoor temperature, indoor relative humidity, time of day and wind speed were influencing factors for increasing, and solar radiation, time of day and wind speed for decreasing TRV settings. Studies by Guerra et al. [18] and Haas et al. [35] have shown that the most influential physical environmental driver of heating setpoint temperatures is indoor temperature. Furthermore, Yang et al. [24] have reported that physiological (e.g. gender) and psychological (e.g. attitudes to energy use and perceived thermal comfort) factors also help to explain heating behaviours.

Specifically for manual overrides of scheduled heating settings, the UK Energy Follow-Up Survey (EFUS) [36] showed that 60% of households with a central heating system controlled by an automatic timer, also manually switched on their heating for additional periods of heating at least once a week and 18% did so every day. Only one previous study has modelled manual heating override behaviour based on data from four office buildings [37]. In three of the office buildings, overrides were executed centrally upon hot and cold complaints and in the fourth, the occupants themselves could adjust the setpoint temperatures. Using multivariate logistic regression, models for predicting the frequency of setpoint changes were developed. The results showed that the frequency of manual overrides was higher when occupants had control, however, the magnitude of change in settings was greater when it was based on complaints. The regression analysis showed that when based on complaints, both indoor and outdoor temperatures were significant predictors of manual overrides. However, only indoor temperature was found to influence manual overrides when the occupants had control.

2. Current study

The aim of this work was to develop stochastic models of occupants' manual overrides of their scheduled heating periods in residential buildings. The study uses multivariate logistic regression to understand the probability of a manual heating override event occurring according to physical environmental drivers (indoor and outdoor temperature and relative humidity, wind speed, global solar radiation and rainfall) and according to contextual drivers (time of day). The study uses indoor air temperatures measured in the living room of the dwellings to determine when the heating system is in scheduled operation or is manually overridden by the dwelling occupants throughout the heating season.

The study benefits from having a small sample where a fine-grained description of the homes can be produced in order to evaluate the complex factors that influence occupant heating behaviour. The paper responds to a number of key gaps identified in the literature. To date, manual override events have only been assessed as part of a questionnaire survey, the EFUS. For UK residential buildings, no other study has attempted to identify these events and to differentiate between them and scheduled heating periods. To the authors' knowledge, for residential buildings, no previous studies have investigated the probability of occupants manually overriding their heating schedules and consequently there are no available models to explain this occupant behaviour.

3. **Data and methods**

3.1 The dwellings

Measurements were undertaken in the living room of ten purpose built rented dwellings - seven flats and three end-terrace houses (Fig. 1) located on a new-build housing estate in Torquay, a town in the South West of the UK. Table 1 provides a summary of the main features of the dwellings and an in-depth description of the structural characteristics of the dwellings has been presented in Appendix A, Table A.1 in Jones et al. [33]. The stated orientation relates to the direction of the façade containing the living room window. The Code for Sustainable Homes (CSH) was a voluntary UK national standard for the sustainable design and construction of new homes [38]. Level 4 of the code relates to a 44% improvement over the Target Emission Rate (TER) as determined by the 2006 Building Regulation Standards (BRS) and Level 5 of the code relates to a 100% improvement over the 2006 BRS [39].

All the dwellings have a gas-fired central heating system, which is the typical domestic heating system found in over 91% of UK homes [40]. The heating system is made up of a central boiler, a pump and individual radiators. A central thermostat and a timer/programmer control the boiler and pump and TRVs control the individual radiators. The thermostat and timer/programmer (Fig. 2) was located in the corridor of the dwellings. It turns the boiler on and off according to a predefined heating setpoint temperature, and the timer/programmer is used to set the on/off times, thus defining the heating duration.

Figure 1 Case study dwellings: CSH Level 4 flats (left) and CSH Level 5 end-terrace houses (right)

Table 1 Dwelling characteristics

Dwelling index	Performance standard	Floor area (m^2)	Orientation	Airtightness ($m^3/hr.m^2$)	Wall U-value (W/m^2K)	Window U-value (W/m^2K)
Flats 1-4	CSH Level 4	80.5	South East	2	0.10	1.20
Flats 5-6	CSH Level 4	80.5	North West	2	0.10	1.20
Flat 7	2006 BRS	80.5	North West	5	0.24	1.80
Houses 1-2	CSH Level 5	140	North West	2	0.10	0.70
House 3	2006 BRS	140	South East	5	0.26	1.80

Figure 2 Thermostat and timer/programmer installed in the dwellings

The programmer allows multiple, scheduled heating periods to be set – 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). The programmer also allows occupants to manually control (i.e. to set the main heating on/off pattern) or override (i.e. to set departures from the scheduled heating periods to either increase or decrease heating requirement) the heating duration and setpoint temperature. However, the programmer installed in the case study homes are not smart thermostats or meters and therefore they do not store the data on heating controls and/or household gas consumption (which will represent energy used in space heating, water heating and cooking). None of the dwellings had mechanical cooling, which is typical for UK dwellings. They were however equipped with either exhaust air ventilation (EAV) or mechanical ventilation with heat recovery (MVHR) systems. The domestic hot water is also provided by the gas central heating system.

3.2 Measurements

An automated monitoring system was installed in all ten dwellings. The monitoring system captured indoor environmental conditions and gas and electricity use. The sensor data was transmitted by radio frequency every 10 minutes to data hubs located in the loft spaces of the dwellings. The data hubs exported the data to a remote server every hour using General Packet Radio Service (GPRS), which was accessed by the researchers on the Internet. The data used in this study were collected as part of a larger Post Occupancy Evaluation (POE) to assess the actual operational performance of the dwellings [33,41,42].

Two indoor environment variables were measured every 10 minutes: Air temperature (°C) and Relative humidity (RH) (%). In addition, five outdoor environment variables were measured using an onsite meteorological station every 10 minutes: Air temperature (°C); RH (%); Wind speed (m/s); Global solar radiation (W/m^2); and Rainfall (mm).

The indoor environment variables were measured using HWM Radio-Tech Ecosense internal loggers. The loggers were installed in the living room of each dwelling and were sited away from heat sources and direct sunlight. The outdoor environmental variables were collected from a meteorological station setup on the housing estate where the dwellings were located. All the indoor and outdoor sensors were newly calibrated by the manufacturer. The measurement range and accuracy of the sensors are shown in Table 2.

Table 2 Details of internal and external sensors

Sensor	Variables	Measurement range	Accuracy
Indoor environment	Air temperature	-20°C – 65 °C	±0.3 °C
	Relative humidity	0% - 100%	±1.8%
Outdoor environment	Air temperature	-40 °C – 75 °C	±0.3 °C
	Relative humidity	0% - 100%	±1.8%
	Wind speed	0 – 76m/s	±1.1m/s
	Global solar radiation	0 – 1800W/m^2	±5% of full scale
	Rainfall	0 – 100mm per hour	±1% at up to 20mm per hour of rainfall

All variables were measured continuously from 28^{th} October 2013 to 2^{nd} November 2014 (370 days). The data used in this paper was a subset of the full measurement time period (i.e. the heating season).

3.3 Preparation and processing of data

For each dwelling, average daily indoor air temperatures were plotted and the profiles were scrutinised by eye to identify and remove outliers. The outliers were temperatures below 10 °C indicating possible sensor placement very close to an open window or vent and temperatures above 35 °C indicating placement very close to a heating source. Temperature changes of more than 7 °C within 30 minutes were also considered errors as this may also indicate proximity of a heating source or the direct incidence of sunlight. These outliers were removed from the dataset before analysis.

All the indoor and outdoor environment variables were considered explanatory variables and were included in the dataset as continuous values. The manual override actions (determined from the indoor air temperature) were binary responses and were introduced into the dataset as 1 or 0, where 1 was assigned to "a manual override - changing the state of the heating system from off to on" and 0 was assigned to "no manual override, i.e. heating system remained off".

In addition to the continuous indoor and outdoor environment variables used in the inference of the stochastic models of manual heating overrides, a time of day variable was also computed based on the data's time series. This was to account for changes in some of the drivers of heating operation according to the time of the day (morning, afternoon, evening, night). The variable was considered as a categorical variable.

The measured gas consumption was used to verify the method for identifying the scheduled heating periods. Gas consumption was measured at 30 minute intervals, in m^3 and was converted to energy in kWh[1] to produce daily profiles of heating energy consumption.

The dataset was managed and analysed using Microsoft Excel and IBM SPSS Statistics 24.

3.4 Identifying heating days

A number of methods for identifying heating days have been discussed in previous studies [20,22,43]. In the current study, 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 weather conditions as measured. As previously suggested by Huebner et al. [43], a maximum outdoor temperature of 15.5 °C was selected as the cut-off criteria below which the heating systems were assumed to be turned on in the dwellings. Based on this criteria, the identified heating season was from 01 November 2013 to 30 April 2014 (181 days). All the days in this period were classified as heating days as the average daily temperatures were below 15.5 °C.

3.5 Identifying scheduled heating periods and manual heating override events

The active heating times on weekdays and weekends were estimated from the measured living room air temperatures. Active heating was defined by Shipworth et al. [20] as times when the heating system is supplying heat to the dwelling. Based on Huebner et al.'s [43] method for identifying heating periods, the measured temperatures were translated into statements regarding whether the heating system was on. If the magnitude of change in a sequence of 30 minute temperatures was 0.3 K or higher, it was considered to be a change in the state of the heating system, from off to on. An example is shown in Fig. 3 where the half-hourly temperature changes in House 2 on weekdays (129 days) and weekends (52 days) give an indication of the heating profile. Each coloured data point represents one single day, hence at each half hour there is a maximum of 129 data points for

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[1] The standard conversion from m^3 of gas consumed to kWh multiplies the volume of gas consumed by a calorific value of gas (39.2, which was estimated from the average values of gas supplied to the South West of England between 2012 and 2015) and by an industry standard conversion factor (1.02264, which accounts for air pressure) and dividing by 3.6 (which is the kWh conversion factor).

weekdays and 52 data points for weekend days. The continuous line is the 0.3 K temperature increase that indicates active heating. In this dwelling, there is no temperature increase of 0.3 K or more between 00:30 and 05:30 on weekdays and between 02:30 and 05:30 on weekends. Hence there was no active heating at these times.

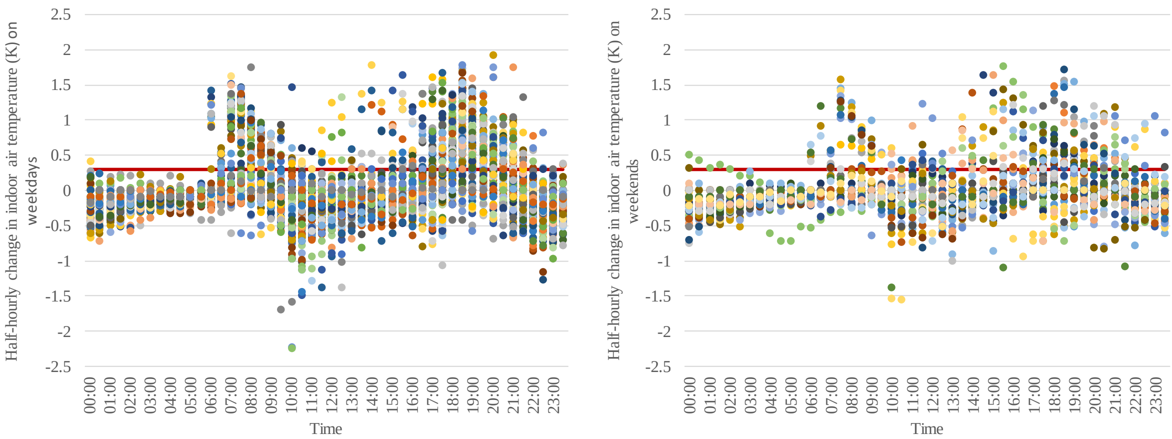

Figure 3 Half-hourly indoor air temperature changes on weekdays (left) and weekend days (right) in House 2

Based on the approach derived by Kane et al. [22], scheduled heating periods and heating times were estimated. A scheduled heating period was defined here as the most common occurring times for heating 'off-on' periods, where a limit of 10% of the total days in the heating season is used. The start of the scheduled heating period was assumed to be the first 30 minute period for which the temperature increase was at least 0.3 K for 10% or more of the total days in the heating season. The end time of the scheduled heating period was determined as the last 30 minute period for which the temperature increase was at least 0.3 K for 10% or more of the heating season days. Using this methodology, average weekday and weekend heating durations for all homes were 8.8 h and 9.8 h respectively.

At times where the heating was on for less than 10% of the heating days, it was assumed to be a manual heating override event, i.e. a departure from the scheduled heating times. All the days in the identified heating season were considered in the analysis. Fig. 4 provides an illustration of the identified scheduled heating periods in one of the dwellings. The dashed lines on the plots indicate the 10% limit used to establish regular heating periods.

As a significant proportion of gas is used for space heating, the 30 minute gas use profile measured in the homes was used to verify the estimated scheduled heating periods. This is indicated by the blue line on the plots in Fig. 4. As expected, the gas consumption profile followed the calculated active heating profile. Across all the case study homes, the daily average space heating energy consumption corresponding to the weekday and weekend heating durations were 10.6kWh and 12.1kWh respectively.

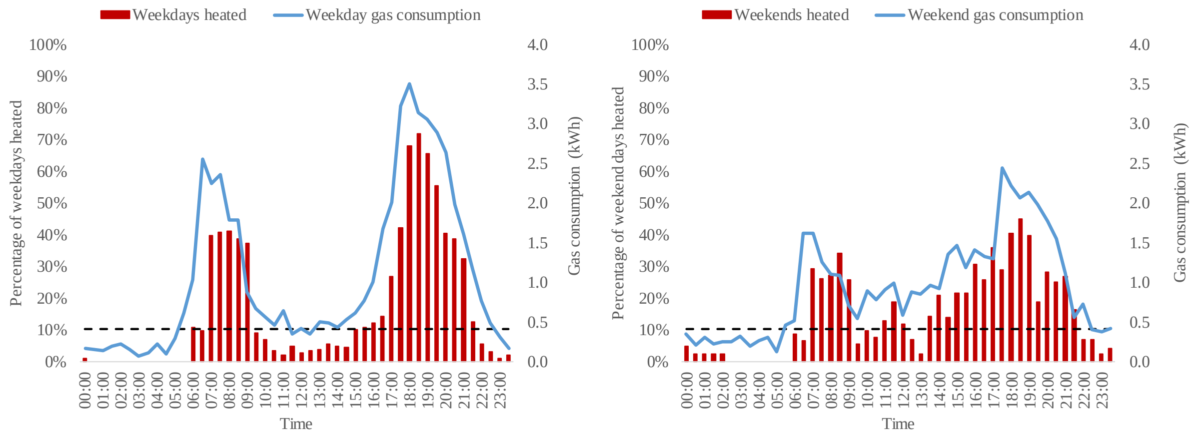

Figure 4 Estimated daily heating and gas consumption profiles on weekdays (left) and weekends (right) in House 2

Manual override events were identified in all ten homes and there were temporal patterns associated with their occurrence. In the full season (181 days), a total of 649 manual override events were recorded across the ten homes. The maximum number of manual override events were recorded in the morning period (06:00 – 11:59 = 232 events) and the least number of events were at night (00:00 – 05:59 = 64 events). The number of manual override events recorded in the afternoon (12:00 – 17:59) and evening (18:00 – 23:59) periods were 194 and 159 respectively. The number of manual overrides identified in individual dwellings ranged from 37 events to 103 events with an average of 65 events during the heating season. On average, manual overrides are estimated to increase weekday and weekend heating duration by 2.4 h and 1.5 h respectively, equating to an increase in space heating energy demand of 2.9kWh (21.5%) on weekdays and 1.9kWh (13.6%) on weekend days.

3.6 Statistical analysis

Logistic regression was used as the modelling method for the manual heating override events. In occupant behaviour modelling, logistic regression is used to describe the probability of an action occurring, which is a categorical variable (i.e. the outcome/dependent variable), based on either single (univariate) or multiple (multivariate) explanatory variables (predictor/independent variables), which can be either categorical or continuous. In this study, the outcome variable is the manual heating override event (i.e. turning the heating on outside the scheduled heating periods) and the predictor variables are the measured indoor and outdoor environment conditions and time of day (Table 3). A log transformation of global solar radiation was computed in order to obtain a better distribution.[2]. The description of the transformation is shown in Table 3.

Table 3 List of continuous and categorical variables used to infer the manual heating override event models

Variable type	Variable	Unit
Continuous	Indoor air temperature (t_i)	°C
	Indoor RH (RH_i)	%
	Outdoor air temperature (t_o)	°C
	Outdoor RH (RH_o)	%
	Wind speed (WS)	m/s
	Log(Global solar radiation+1) (Log(Rad))	Log(W/m^2)
	Rainfall (RF)	mm
Categorical	Night	00:00 – 05:59
	Morning	06:00 – 11:59
	Afternoon	12:00 – 17:59
	Evening	18:00 – 23:59

The relationship between the outcome variable and a single predictor is described in Eq. (1) (a univariate model). The relationship between the outcome variable and multiple predictors is described in Eq. (2) (a multivariate model).

$$P(x) = \frac{1}{1+e^{-(\alpha+\beta x)}} \qquad (1)$$

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_0 x_0 + \beta_1 x_1 + \cdots + \beta_n x_n \qquad (2)$$

Where P is the probability of the outcome (i.e. a manual heating override action occurring in the next 30 minutes); x is the predictor variable (e.g. indoor and outdoor environment conditions); α is the constant; β is a coefficient. The multivariate logistic regression method has been used for modelling occupant behaviour in a range of previous studies, (e.g. [27,28,33,44]).

In the multivariate analysis, the predictors were determined based on a forward and backward selection procedure using Akaike Information Criterion (AIC) [45,46]. The procedure produced a model containing only explanatory variables that had a consistent effect on the probability function. A step by step explanation of the statistical analysis is described in Jones et al. [33].

One assumption of logistic regression is that there should be little or no correlation between the continuous predictor variables. Correlation between the variables is referred to as multicollinearity and it causes inflation of

[2] The original solar radiation data ranged from 0 to 997W/m^2 with an average of 68W/m^2. Solar radiation levels over 200W/m^2 constituted 12% of the data. The solar radiation was transformed using the natural logarithm.

the estimated variance of the inferred coefficients of the model [46]. In each model, generalised variance inflation factors (GVIF) were calculated for the coefficients to estimate the inflation of the variance due to multicollinearity. A GVIF of 1 indicates that a model's predictors are not correlated, between 1 and 5, the predictors are moderately correlated and over 5 means they are highly correlated. The $GVIF^{1/(2.Df)}$ was calculated to assess the inflation of the variance as a result of multicollearity, compared to a model with no multicollinearity. Table 4 presents the results of the multicollinearity analysis conducted to assess the correlation between the environment variables. All the GVIF values were less than 5 indicating that the inflation of the estimated variance of the inferred coefficients were acceptable.

Table 4 Results of the VIF and GVIF analyses for the variables in the manual heating override event models

Variable	VIF	Df	$GVIF^{1/(2.Df)}$
Indoor air temperature (°C)	1.4	1	1.2
Indoor RH (%)	1.6	1	1.3
Outdoor air temperature (°C)	1.6	1	1.3
Outdoor RH (%)	1.5	1	1.2
Wind speed (m/s)	1.1	1	1.0
Global solar radiation (W/m^2)	1.0	1	1.0
Rainfall (mm)	1.2	1	1.1

To interpret the regression parameters, the sign and the size of the coefficient and the range of the corresponding predictor have to be taken into account. The sign of the coefficient gives the direction of the effect of the predictor on the probability. A positive coefficient means that the predictor directly influences the probability of the action, therefore, an increase in the predictor causes an increase in the probability. A negative coefficient has the inverse effect; an increase in the predictor will cause a decrease in the probability of the action. The product of the size of the coefficient and the range of the predictor gives an indication of the effect of a predictor. This is known as the magnitude of the predictor.

Appendix A Table A.1 presents the descriptive statistics of all the measured indoor and outdoor environment variables in the models.

4. Results

4.1 Modelling of manual heating override events

The manual heating override events are classed as irregular departures from the scheduled heating periods and hence are stochastic behaviours of the occupants. Manual override events were identified in all ten dwellings. In the full heating season, a total of 649 manual override events were identified from all the dwellings. The highest number of events occurred in the morning period (06:00-11:59 = 232 events), followed by the afternoon (12:00-17:59 = 194) and the evening (18:00-23:59 = 159). The least number of events was recorded at night (00:00-05:59 = 64 events).

This section presents the results of the logistic regression analysis to describe the probability of a manual override event occurring due to the prevailing indoor and outdoor environment variables occurring at the time of the event as well as the time of day.

4.1.1 Univariate logistic regression models

Table 5 presents the constants, coefficients and magnitudes for each predictor obtained from the univariate logistic regression analysis. For the full heating season, according to the magnitudes of each environmental predictor variable, the most influential factor driving manual override events is indoor air temperature. The negative coefficient indicates that as indoor air temperature decreases, the probability of a manual override event (turning the heating on) increases. Regarding the contextual drivers (i.e. day of the week and time of day), there were no significant differences between the probability of a manual override event on a weekday or weekend ($p = 0.606$). Furthermore, using the night-time period as a reference, there were significant differences between events occurring in the other time periods ($p < 0.05$).

Table 5 Coefficients and magnitudes of the univariate logistic regression models for manual heating override events

	Variable	Constant	Coefficient	Magnitude
All season	Indoor air temperature (°C)	-3.306	-0.079	1.70
	Outdoor air temperature (°C)	-5.079	0.023	0.51
	Log(Solar + 1) (Log(W/m^2)	-4.714	-0.164	0.47
	Rainfall (mm)	-4.912	0.010	0.28
	Indoor RH (%)	-5.014	0.003	0.21
	Wind speed (m/s)	-4.913	0.009	0.20
	Outdoor RH (%)	-4.777	-0.001	0.05
	Weekend (reference)*	-4.921		
	Weekday		0.045 ($p = 0.606$)	
	00:00 - 05:50 (reference)*	-5.824		
	06:00 - 11:50		1.295 ($p < 0.05$)	
	12:00 - 17:50		1.115 ($p < 0.05$)	
	18:00 - 23:50		0.914 ($p < 0.05$)	
Night	Indoor air temperature (°C)	-4.315	-0.073	1.51
	Indoor RH (%)	-5.13	-0.013	0.79
	Wind speed (m/s)	-5.763	-0.026	0.41
	Outdoor air temperature (°C)	-5.983	0.023	0.29
	Log(Solar + 1) (Log(W/m^2)	-6.002	0.177	0.19
	External RH (%)	-6.186	0.004	0.11
	Rainfall (mm)	-5.822	0.009	0.09
Morning	Indoor air temperature (°C)	-2.13	-0.121	2.48
	Wind speed (m/s)	-4.425	-0.041	0.91
	Indoor RH (%)	-4.964	0.009	0.63
	Rainfall (mm)	-4.514	-0.011	0.28
	Log(Solar + 1) (Log(W/m^2)	-4.439	-0.077	0.22
	Outdoor RH (%)	-4.846	0.004	0.18
	Outdoor temperature (°C)	-4.513	-0.001	0.02
Afternoon	Log(Solar + 1) (Log(W/m^2)	-4.203	-0.535	1.51
	Rainfall (mm)	-4.753	0.016	0.44
	Outdoor RH (%)	-5.284	0.008	0.42
	Indoor air temperature (°C)	-4.268	-0.02	0.39
	Wind speed (mm)	-4.767	0.017	0.36
	Indoor RH (%)	-4.852	0.004	0.25
	Outdoor air temperature (°C)	-4.788	0.008	0.14
Evening	Indoor air temperature (°C)	-3.2	-0.079	1.63
	Indoor RH (%)	-4.451	-0.009	0.57
	Outdoor air temperature (°C)	-4.664	-0.028	0.49
	Outdoor RH (%)	-5.728	0.01	0.47
	Rainfall (mm)	-4.858	-0.015	0.42
	Log(Solar + 1) (Log(W/m^2)	-4.817	-0.076	0.15
	Wind speed (mm)	4.858	0.007	0.10

* For the models with categorical factors, the constants are provided on the row of the selected reference factor

4.1.2 Multivariate logistic regression models

Following on from the univariate models, the impact of multiple variables on the predictive value of the models were assessed. Eq. (3) describes the multivariate logistic regression model for manual heating overrides for the full heating season. Eqs. (4)-(6) describe the morning, afternoon and evening models respectively. Weekday and weekend models are not presented as no statistical difference was identified. For the full heating season model, indoor air temperature, indoor relative humidity, outdoor air temperature and global solar radiation were the significant factors retained in the model. In the morning model, only indoor air temperature was an influencing factor. In the afternoon, the model indicates that solar radiation was the only environmental parameter influencing manual overrides. In the evening, indoor air temperature and indoor relative humidity were the key driving factors. It should be noted that none of the indoor or outdoor environment variables were found to influence manual heating overrides during the night and thus a model is not described.

Full heating season: $\ln\left(\frac{p}{1-p}\right) = -2.107 - 0.107t_i - 0.015RH_i + 0.038t_o - 0.155Log(Rad) \quad (3)$

Morning: $\ln\left(\frac{p}{1-p}\right) = -2.072 - 0.123t_i \quad (4)$

Afternoon: $\ln\left(\frac{p}{1-p}\right) = -4.170 - 0.531Log(Rad) \quad (5)$

Evening: $\ln\left(\frac{p}{1-p}\right) = -0.835 - 0.123t_i - 0.029RH_i \quad (6)$

5. Discussion

5.1 Models describing manual heating override events

The analysis undertaken in this study provides a method for calculating the probability that a manual heating override event will occur in the next 30 minutes. Manual overrides could be explained by a change in environmental conditions and the time of day.

The state of the heating system (i.e. on or off) will have an impact on the physical indoor environment conditions. For example, when the heating is on, the indoor air temperature will rise. Hence to analyse the factors that influence a manual override event, it makes sense to use environmental conditions occurring just before the action (in this case turning on from an off state). Indoor and outdoor environment conditions measured 30 minutes prior to the heating system being turned on were therefore assigned as the potential factors influencing the manual override events. Models for different times of the day were produced as time influences the prevailing environment conditions as well as occupant activities. As recommended by O'Brien and Gunay [47], contextual factors should be reported and accounted for in occupant models so potential users of models can judge their suitability for their own modelling purposes. Thereby ensuring a more accurate application and results. In this context, the models reported in this study may be most useful for predicting occupants' interactions with gas central heating systems in UK residential buildings during the heating season (when the outdoor temperature is 15.5°C or below).

From the analysis, there was no evidence that manual override behaviour differs depending on the day of the week (i.e. weekday or weekend). Huebner et al. [48] previously found statistical differences between weekday and weekend heating profiles, but the absolute size of the differences were very small. The models developed in this study (Eqs. 4 – 6) can therefore be implemented for any day of the week.

This study identified the drivers of heating override behaviour for the full heating season as well as for different times of day. Indoor air temperature, indoor RH and solar radiation were the physical environmental variables that influenced manual override events at different time periods.

The analysis revealed that there was no impact of physical environmental factors at night, implying that other factors drive manual override behaviour at this time. Note, living room conditions were used to generate the models, but at night, it is expected that occupants will be sleeping in the bedroom and therefore the environmental conditions in these two rooms may be different. There is limited research on thermal environments and thermal comfort in bedrooms. Previous studies have shown that occupants prefer cooler conditions in bedrooms compared to living rooms (e.g. [15, 22, 49]). Lan et al. [50] undertook a detailed review of thermal environment and sleep quality and describe a bed microenvironment as a space where occupants use sleepwear and bedding, such as a mattress, sheets and duvet, to create thermal comfort conditions which are different to the air temperature at night. Lan et al. [50] discussed that thermal neutral temperature is often higher at night when occupants are sleeping. Therefore, even though the measured temperature in the room may be low, occupants may be feeling thermally comfortable in their warmer microenvironment and do not need to turn the heating on. When thermally uncomfortable, occupants have the capacity to adapt themselves [51]. This is also applicable when sleeping – adaptation does not only have to be a conscious act. At night if occupants should get cold whilst they are sleeping, they are able to move a duvet or blanket to cover up and fine tune throughout the night. This adaptation will be quicker and cause less disruption to their sleep than to get out of bed to turn the heating on as an adaptive measure.

Furthermore, if the heating is turned on, it will have to be turned off when it gets uncomfortably hot and unless the occupant sets the timer during the manual override event, they will have to get out of bed again to turn the system off. This may be inconvenient and cause further disruption to sleep and could explain why there are so few manual overrides at night. Lan et al. [50] recognised that there are few studies that have evaluated thermal responses during sleep and thus causal relationships between thermal physiology and sleep cannot be developed yet. The current study suggests that factors other than environmental variables, e.g. household characteristics and occupancy patterns, may need to be assessed in future studies to explain manual heating override events at night.

In the morning and evening, indoor temperature influenced manual override probabilities. Temperature is usually considered "*the most important environmental variable affecting thermal comfort*" [52]; therefore changes to temperature are likely to trigger adaptive actions. In relation to manual heating override events, the work presented in this paper supports this statement, as in both the mornings and evenings, as indoor air temperature decreased, the probability of manually overriding the heating system to turn it on increased.

The study identified solar radiation to influence manual override events, but this variable was only significant in the afternoon and not in the evening when solar radiation is at its minimum during the heating season. The results showed that an increase in solar radiation resulted in a decrease in the probability of a manual override event. This observation could be because of the relationship between solar radiation and time of day, whereby occupants may attempt to increase the indoor thermal conditions towards the end of the day as there is less perceived solar thermal gain to increase indoor temperatures. Solar radiation was the only influencing environmental factor in the afternoon, despite being the period with the second largest number of override events. This suggests that manual overrides in the afternoon may also be due to factors other than environmental variables, for example household activities such as drying laundry. Again, more information on household routines and activities will have to be recorded and assessed in future studies to provide further insight into manual override behaviour.

This study also identified that indoor relative humidity had an inverse relationship with occupants' manual override behaviour. The measured RH in the evening ranged from 19.8% to 82.9% with an average of 49.5%. The range of RH, 40% - 70%, which is recommended for comfort [52] made up 94.5% of the measurements. RH affects thermal sensation and has an impact on thermal comfort, and is one of the variables included in Fanger's Predicted Mean Vote (PMV) model [53] and may explain why it affects the probability of manual override behaviour. In the evenings, household activities such as cooking will increase temperature and RH. The dwellings in the current study are made up of seven flats which are identical in layout. The flats comprise an open-plan kitchen-living room, hence the measured conditions in the living room will be affected by the activities carried out in the kitchen area. It may be hypothesised that in the absence of activities such as cooking, thermal conditions may be too cool and uncomfortable for the occupant, thus prompting a manual heating override event.

5.2 Applications for the research

A key finding from this research is that all of the households manually override their scheduled heating periods to demand additional heat. This is an important finding for energy modellers who often use fixed heating schedules for modelling the energy and indoor environmental performance of buildings. The prevalence of manual override events are unlikely to be reflected in the fixed heating profiles and will result in limitations in capturing the diversity of heating behaviours observed throughout a day. Manual overrides will increase household gas energy consumption. In these case study households, manual overrides, on average, increased weekday and weekend space heating energy consumptions by 21.5% and 13.6% respectively. A better understanding of occupant heating behaviours will enable improvements in the prediction of heating energy demand in energy models and consequently reduce the energy performance gap between design and actual consumption.

The findings obtained in this work can also be used by government policy makers to target demand side energy efficiency response interventions. Interventions can be aimed at improving the understanding of heating behaviours at home and their impact on heating energy demand. Future demand side interventions will require flexible heating behaviours and the first step to investigating the flexibility of heating behaviours is to explore and understand how households are currently heating their homes.

Furthermore, to meet the 2050 carbon reduction target, it has been recognised that heating needs to move rapidly away from natural gas to low carbon sources and this will mainly result in the electrification of heating [54]. The results provided in this paper will be valuable for energy supply companies and energy distribution operators who need to understand the profiles and temporality of heating energy demand. It could be useful for informing decisions about transitions to future energy systems with a high proportion of low carbon heat sources. For example, regarding improvements or changes to electricity networks, until battery storage becomes common place, electricity generation from renewable sources has to match demand. With manual override events, the electricity network must be designed to match these short-term demand peaks.

5.3 Limitations and Future work

The results obtained in this study are based on an indirect method using indoor air temperature measurements. The use of an indirect method to estimate heating periods does however have a limitation as from the temperature data alone it is unclear whether increases in indoor air temperature are due to the heating system being turned on or other heat sources, such as secondary heating or internal heat gains from occupancy and household activities like cooking. To address this issue, the current study also used 30 minute gas consumption measurements to verify the calculated heating periods. The 30-minute gas consumption profiles were found to provide a good indication of the start and end times of the heating periods, which were consistent with those identified using the indoor temperature measurements. In between the scheduled heating periods, gas consumption decreased significantly but was not zero, as there was still some heating due to the manual overrides. Gas demand was lower at night, where there were no scheduled heating periods. This validation method provided assurance that the increases in indoor temperature were due to the heating system and no other sources of heat.

Direct methods such as those implemented by Andersen et al. [19], Hanmer et al. [55] and Huchuk et al. [56] could also be used to overcome this limitation. For example, Andersen et al. [19] used custom made TRVs to record zonal setpoint temperatures selected by householders. The TRVs were equipped with a variable electronic resistance so that the electrical resistance varied with the TRV setpoint. The electrical resistance was measured and stored using a data logger. In addition, heat flow meters installed in the dwellings could also potentially be used to directly monitor heating operation.

The authors believe that the advent of smart, internet-connected heating programmers and their inherent centralised data collection will provide future studies with an easier means for direct measurements of heating behaviours and their potential drivers. Smart programmers will provide a new stream of data, including real time data on heating settings, i.e. on/off times indicating regular scheduled heating periods and manual overrides, gas consumption and even physical environmental measurements, where they are connected to environmental sensors. Smart programmers have been used by Hanmer et al. [55] and Huchuk et al. [56]. Hanmer et al. [55] obtained a dataset of heating settings collected by smart thermostats installed in 337 UK homes. Data included records of temperature setpoints selected by the householders. By analysing the households' direct interaction with the controller the study identified how patterns of heating operation in individual homes contributed to daily patterns of space heating energy consumption. On a much larger scale, Huchuk et al. [56] used a dataset of more than 10,000 smart thermostats installed across North America spanning multiple years. In this case, the thermostats were also connected to remote environmental sensors as well as the home's heating, ventilation and air conditioning unit. The study assessed how a thermostat user's behaviour changes as a function of seasonal variation, climatic regions and energy pricing. As noted by Huchuk et al. [56] findings from data obtained from smart thermostats are however restricted to that subset of the population, which represent a distinct, often early technology adopter demographic and are unlikely to be representative of the wider UK housing stock. Therefore, early findings obtained from such studies will be difficult to extrapolate to other households.

6. Conclusions

This paper presents the development of stochastic models of manual heating override behaviour based on physical environmental and contextual drivers. The data was collected in ten UK dwellings over a period of a year.

The study used multivariate logistic regression to understand the probability of occupants manually overriding their scheduled heating periods (i.e. changing the state of the heating system from off to on) based on a range of indoor and outdoor environment factors (physical environmental drivers) and according to the time of the day (contextual drivers). To the authors' knowledge, these are the first stochastic models of manual heating override events developed for UK residential buildings.

The results reported in this paper support the recommendations of others that when analysing and modelling occupant behaviours in buildings, factors other than environmental drivers should also be taken into account. The results suggest that the drivers of manual heating override behaviour vary depending on the time of day, indicating the importance of capturing contextual drivers. However, the study found that the drivers of override behaviour did not change between weekdays and weekends.

At night, none of the physical environmental factors were found to effect manual heating override behaviour, implying that factors other than indoor and outdoor environmental conditions influence the behaviour at that time. In general, only a small number of manual override events were recorded at night and this supports findings by others that when occupants are sleeping, they perhaps choose to improve their bed microclimate, for example by putting on a jumper or getting an extra blanket, instead of increasing the room air temperature with their heating system.

In the other time periods, indoor temperature, indoor relative humidity and solar radiation were identified as the drivers influencing occupants to manually override their heating settings.

The multivariate logistic regression models provided in this work can be used to calculate the probability that a manual heating override action will happen in the next 30 minutes. These models could be used in building performance simulation applications to improve the predictions of the energy use and indoor environmental conditions of residential buildings. It should be noted that the models proposed in this paper are however obtained from a study of ten UK dwellings and are therefore not representative of the wider housing stock. A larger national scale study of manual heating override behaviour, representative of the UK housing stock (i.e. dwelling and household characteristics) would be a valuable extension to the current work.

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Appendix A. Descriptive statistics of the monitored variables

Table A.1 Descriptive statistics of the monitored variables used to infer the models

		Indoor air temperature (°C)	Indoor RH (%)	Outdoor air temperature (°C)	Outdoor RH (%)	Wind speed (m/s)	Global solar radiation (W/m^2)	Rain (mm)
All heating season	Min	11.5	18.1	-0.1	40.1	0.0	0.4	0.0
	Max	33.0	88.6	21.9	94.1	22.3	997.4	28.2
	Median	20.4	49.1	8.3	83.1	2.0	2.0	0.2
	Mean	20.4	50.0	8.5	81.5	2.6	67.7	2.1
	SD	2.12	7.07	3.15	8.02	2.37	137.9	3.97
Night (00:00-05:59)	Min	11.8	18.9	0.4	67.1	0.0	0.5	0.0
	Max	32.4	79.5	13.1	94.1	15.8	29.3	10.4
	Median	20.3	48.9	7.4	84.8	1.6	1.9	0.0
	Mean	20.1	49.8	7.2	84.4	2.1	2.0	0.4
	SD	1.85	6.90	2.53	4.51	2.16	1.05	1.19
Morning (06:00-11:59)	Min	11.5	18.1	-0.1	48.7	0.0	0.4	0.0
	Max	32.0	88.6	17.7	94.1	22.3	997.4	25.8
	Median	19.8	49.5	7.9	84.8	2.1	41.8	0.2
	Mean	19.8	50.5	8.0	83.5	2.7	115.8	1.4
	SD	1.99	7.12	2.92	6.49	2.57	163.6	3.0
Afternoon (12:00-17:59)	Min	12.9	18.9	4.1	40.1	0.0	0.5	0.0
	Max	32.3	81.9	21.9	93.0	21.1	987.4	27.4
	Median	20.4	49.2	9.9	77.2	2.7	81.8	0.6
	Mean	20.4	50.1	10.5	76.1	3.2	149.9	2.5
	SD	2.19	7.23	3.39	10.35	2.39	178.17	4.24
Evening (18:00-23:59)	Min	12.4	19.8	1.5	46.2	0	0.5	0
	Max	33.0	82.9	18.9	93.6	14.6	155.9	28.2
	Median	21.4	48.9	8.3	82.8	1.7	1.9	1.4
	Mean	21.2	49.5	8.3	81.9	2.3	3.3	3.8
	SD	2.2	7.0	2.7	6.8	2.2	9.2	5.3

References

[1] Department for Business Energy & Industrial Strategy (BEIS), Energy Consumption in the UK: Tables - 2017 Update, (2017). https://www.gov.uk/government/collections/energy-consumption-in-the-uk (accessed January 15, 2018).

[2] Department for Energy and Climate Change (DECC), United Kingdom housing energy fact file, Publ. URN 13D/276. (2013). https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/345141/uk_housing_fact_file_2013.pdf (accessed February 20, 2018).

[3] Department for Energy and Climate Change (DECC), Emissions from Heat: Statistical Summary, (2012) 1–12. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/140095/4093-emissions-heat-statistical-summary.pdf (accessed March 19, 2018).

[4] HM Government, Climate Change Act 2008, London, 2008. http://www.legislation.gov.uk/ukpga/2008/27/pdfs/ukpga_20080027_en.pdf.

[5] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy Build. 41 (2009) 295–302.

[6] T. Hong, D. Yan, S. D'Oca, C. fei Chen, Ten questions concerning occupant behavior in buildings: The big picture, Build. Environ. 114 (2017) 518–530. http://dx.doi.org/10.1016/j.buildenv.2016.12.006.

[7] D. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and future challenges, Energy Build. 107 (2015) 264–278. http://dx.doi.org/10.1016/j.enbuild.2015.08.032.

[8] H.X. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renew. Sustain. Energy Rev. 16 (2012) 3586–3592. http://dx.doi.org/10.1016/j.rser.2012.02.049.

[9] T. Hong, S.C. Taylor-Lange, S. D'Oca, D. Yan, S.P. Corgnati, Advances in research and applications of energy-related occupant behavior in buildings, Energy Build. 116 (2016) 694–702. http://dx.doi.org/10.1016/j.enbuild.2015.11.052.

[10] V. Oikonomou, F. Becchis, L. Steg, D. Russolillo, Energy saving and energy efficiency concepts for

policy making, Energy Policy. 37 (2009) 4787–4796. doi:10.1016/j.enpol.2009.06.035.

[11] V. Fabi, R.V. Andersen, S.P. Corgnati, B.W. Olesen, A methodology for modelling energy-related human behaviour: application to window opening behaviour in residential buildings, Build. Simul. 6 (2013) 415–427.

[12] V. Fabi, R. Vinther, S. Corgnati, B.W. Olesen, Occupants ' window opening behaviour : A literature review of factors in fl uencing occupant behaviour and models, Build. Environ. 58 (2012) 188–198. http://dx.doi.org/10.1016/j.buildenv.2012.07.009.

[13] A. Mahdavi, People in building performance simulation, in: J.L.M. Hensen, R. Lamberts (Eds.), Build. Perform. Simul. Des. Oper., Spon Press, London and New York, 2011: pp. 56–83.

[14] E. Delzendeh, S. Wu, A. Lee, Y. Zhou, The impact of occupants' behaviours on building energy analysis: A research review, Renew. Sustain. Energy Rev. 80 (2017) 1061–1071. http://dx.doi.org/10.1016/j.rser.2017.05.264.

[15] B.R. Anderson, P.F. Chapman, N.G. Cutland, C.M. Dickson, S.M. Doran, G. Henderson, J.H. Henderson, P.J. Iles, L. Kosmina, L.D. Shorrock, BREDEM-8 Model Description: 2001 Update, Building Research Establishment (BRE), Garston, and Department for Environment, Food and Rural Affairs (DEFRA), London, 2002.

[16] L.J. French, M.J. Camilleri, N.P. Isaacs, A.R. Pollard, Temperatures and heating energy in New Zealand houses from a nationally representative study-HEEP, Energy Build. 39 (2007) 770–782.

[17] R.V. Andersen, J. Toftum, K.K. Andersen, B.W. Olesen, Survey of occupant behaviour and control of indoor environment in Danish dwellings, Energy Build. 41 (2009) 11–16.

[18] O. Guerra Santin, L. Itard, H. Visscher, The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock, Energy Build. 41 (2009) 1223–1232.

[19] R.V. Andersen, B.W. Olesen, J. Toftum, Modelling occupants' heating set-point preferences, 12th Conf. Int. Build. Perform. Simul. Assoc. Sydney, 14-16 Novemb. (2011) 151–156.

[20] M. Shipworth, S.K. Firth, M.I. Gentry, A.J. Wright, D.T. Shipworth, K.J. Lomas, Central heating thermostat settings and timing: Building demographics, Build. Res. Inf. 38 (2010) 50–69.

[21] O. Guerra-Santin, L. Itard, Occupants' behaviour: Determinants and effects on residential heating

consumption, Build. Res. Inf. 38 (2010) 318–338.

[22] T. Kane, S.K. Firth, K.J. Lomas, How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling, Energy Build. 86 (2015) 817–832.

[23] R. V. Jones, A. Fuertes, C. Boomsma, S. Pahl, Space heating preferences in UK social housing: A socio-technical household survey combined with building audits, Energy Build. 127 (2016) 382–398.

[24] S. Yang, M. Shipworth, G. Huebner, His, hers or both’s? The role of male and female’s attitudes in explaining their home energy use behaviours, Energy Build. 96 (2015) 140–148.

[25] E. Sardianou, Estimating space heating determinants: An analysis of Greek households, Energy Build. 40 (2008) 1084–1093.

[26] Energy in Buildings and Communities Programme, IEA-EBC Annex 66 - Definition and Simulation of Occupant Behavior in Buildings, (2014). https://www.annex66.org/ (accessed June 8, 2018).

[27] F. Haldi, D. Robinson, Interactions with window openings by office occupants, Build. Environ. 44 (2009) 2378–2395. http://dx.doi.org/10.1016/j.buildenv.2009.03.025.

[28] R. Andersen, V. Fabi, J. Toftum, S.P. Corgnati, B.W. Olesen, Window opening behaviour modelled from measurements in Danish dwellings, Build. Environ. 69 (2013) 101–113. http://dx.doi.org/10.1016/j.buildenv.2013.07.005.

[29] S. Wei, R. Buswell, D. Loveday, Factors affecting “end-of-day” window position in a non-air-conditioned office building, Energy Build. 62 (2013) 87–96. doi:10.1016/j.enbuild.2013.02.060.

[30] F. Haldi, D. Robinson, A Comprehensive stochastic model of window usage: Theory and validation, in: Build. Simul. Conf., Glasgow, Scotland, 2009: pp. 545–552.

[31] C.F. Reinhart, Lightswitch-2002: A model for manual and automated control of electric lighting and blinds, Sol. Energy. 77 (2004) 15–28. doi:10.1016/j.solener.2004.04.003.

[32] X. Zhou, D. Yan, T. Hong, X. Ren, Data analysis and stochastic modeling of lighting energy use in large office buildings in China, Energy Build. 86 (2015) 275–287. doi:10.1016/j.enbuild.2014.09.071.

[33] R. V. Jones, A. Fuertes, E. Gregori, A. Giretti, Stochastic behavioural models of occupants’ main bedroom window operation for UK residential buildings, Build. Environ. 118 (2017) 144–158.

[34] V. Fabi, R.V. Andersen, S.P. Corgnati, Influence of occupant's heating set-point preferences on indoor environmental quality and heating demand in residential buildings, HVAC R Res. 19 (2013) 635–645.

[35] R. Haas, H. Auer, P. Biermayr, The impact of consumer behavior on residential energy demand for space heating, Energy Build. 27 (1998) 195–205.

[36] Building Research Establishment (BRE), Energy Follow-up Survey 2011 Report 4 : Main heating systems, 2013.

[37] H.B. Gunay, W. Shen, G. Newsham, A. Ashouri, Modelling and analysis of unsolicited temperature setpoint change requests in office buildings, Build. Environ. 133 (2018) 203–212. doi:10.1016/j.buildenv.2018.02.025.

[38] Department for Communities and Local Government (DCLG), Code for Sustainable Homes: Technical Guide, (2010). http://www.planningportal.gov.uk/uploads/code_for_sustainable_homes_techguide.pdf (accessed March 13, 2018).

[39] H.M. Government, The Building Regulations 2010: Conservation of Fuel and Power (New Dwellings), (2010). http://webarchive.nationalarchives.gov.uk/20150601190348/http://www.planningportal.gov.uk/uploads/br/BR_PDF_AD_L1A_2010_V2.pdf (accessed March 13, 2018).

[40] Department for Communities and Local Government (DCLG), English Housing Survey: Headline Report 2013-14, (2015) 1–73. https://www.gov.uk/government/statistics/english-housing-survey-2013-to-2014-headline-report (accessed December 27, 2017).

[41] R. V. Jones, S. Goodhew, P. De Wilde, Measured indoor temperatures, thermal comfort and overheating risk: Post-occupancy evaluation of low energy houses in the UK, Energy Procedia. 88 (2016) 714–720. http://dx.doi.org/10.1016/j.egypro.2016.06.049.

[42] R. V. Jones, A. Fuertes, P. De Wilde, The gap between simulated and measured energy performance: A case study across six identical New-Build flats in the UK, 14th Int. Conf. IBPSA - Build. Simul. 2015, BS 2015, Conf. Proc. (2015) 2248–2255. http://www.scopus.com/inward/record.url?eid=2-s2.0-84976402519&partnerID=tZOtx3y1.

[43] G.M. Huebner, M. McMichael, D. Shipworth, M. Shipworth, M. Durand-Daubin, A. Summerfield,

Heating patterns in English homes: Comparing results from a national survey against common model assumptions, Build. Environ. 70 (2013) 298–305.

[44] S. Shi, B. Zhao, Occupants' interactions with windows in 8 residential apartments in Beijing and Nanjing, China, Build. Simul. 9 (2016) 221–231.

[45] M. Schweiker, M. Shukuya, Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions, Build. Environ. 44 (2009) 2137–2149. doi:10.1016/j.buildenv.2009.03.004.

[46] A. Field, Discovering Statistics Using SPSS, 3rd ed., SAGE Publications, London, 2009.

[47] W. O'Brien, H.B. Gunay, The contextual factors contributing to occupants' adaptive comfort behaviors in offices - A review and proposed modeling framework, Build. Environ. 77 (2014) 77–88. doi:10.1016/j.buildenv.2014.03.024.

[48] G. Huebner, D. Shipworth, M. Shipworth, A. Summerfield, M. McMichael, M. Durand-Daubin, Daily temperature profiles, household size, and ageing: the shape of things (to come), in: ECEEE 2013 Summer Study Oon Energy Effic. Eur. Counc. an Energy Effic. Econ., 2013: pp. 2355–2366.

[49] A. Bruce-Konuah, R. V. Jones, A. Fuertes, L. Messi, A. Giretti, The role of thermostatic radiator valves for the control of space heating in UK social-rented households, Energy Build. 173 (2018) 206–220. doi:10.1016/j.enbuild.2018.05.023.

[50] L. Lan, K. Tsuzuki, Y.F. Liu, Z.W. Lian, Thermal environment and sleep quality: A review, Energy Build. 149 (2017) 101–113. doi:10.1016/j.enbuild.2017.05.043.

[51] F. Nicol, M. Humphreys, S. Roaf, Adaptive thermal comfort: Principles and practice, Routledge, Abiingdon, 2012.

[52] Chartered Institution of Building Services Engineers (CIBSE), Environmental Design CIBSE Guide A, Eighth ed., London, 2017.

[53] P.O. Fanger, Thermal comfort: Analysis and applications in environmental engineering, Danish Technical Press, Copenhagen, 1970.

[54] National Grid, Future Energy Scenarios, 2017.

[55] C. Hanmer, M. Shipworth, D. Shipworth, E. Carter, How household thermal routines shape UK home heating demand patterns, Energy Effic. (2018) 1–13.

[56] B. Huchuk, W. O'Brien, S. Sanner, A longitudinal study of thermostat behaviors based on climate, seasonal, and energy price considerations using connected thermostat data, Build. Environ. 139 (2018) 199–210. doi:10.1016/j.buildenv.2018.05.003.