Stochastic behavioural models of occupants' main bedroom window operation for UK residential buildings

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Abstract

This paper presents the development of stochastic models of occupants' main bedroom window operation based on measurements collected in ten UK dwellings over a period of a year. The study uses multivariate logistic regression to understand the probability of opening and closing windows based on indoor and outdoor environment factors (physical environmental drivers) and according to the time of the day and season (contextual drivers). To the authors' knowledge, these are the first models of window opening and closing behaviour developed for UK residential buildings. The work reported in this paper suggests that occupants' main bedroom window operation is influenced by a range of physical environmental (i.e. indoor and outdoor air temperature and relative humidity, wind speed, solar radiation and rainfall) and contextual variables (i.e. time of day and season). In addition, the effects of the physical environmental variables were observed to vary in relation to the contextual factors. The models provided in this work can be used to calculate the probability that the main bedroom window will be opened or closed in the next 10 minutes. These models could be used in building performance simulation applications to improve the inputs for occupants' window opening and closing behaviour and thus the predictions of energy use and indoor environmental conditions of residential buildings.

Keywords: Window opening behaviour, Occupant behaviour, Behavioural modelling, Residential buildings, Statistical modelling, Building energy performance simulation

1. Introduction

In UK residential buildings, space heating accounts for around two thirds of energy consumption [1]. The energy required for space heating in buildings is dependent on the balance between six heat flows: heat from the heating system; heat transmission through the building's façade; external and internal heat gains; heat stored in or released from thermal mass; and heat from ventilation and infiltration [2]. As dwellings typically have a higher degree of direct control by the occupants than non-domestic buildings, the latter heat flow from ventilation is greatly influenced by the occupants' window opening and closing behaviour [3,4]. Consequently, any attempt to predict the space heating demand and indoor environmental conditions of residential buildings using dynamic building energy performance simulation (BEPS) programs requires realistic models of the occupants' window operation [5-7].

The sophistication of BEPS has made significant progress during the last decades and is increasingly used to predict and optimise the energy and environmental performance of buildings. However, the stochastic aspects of occupant behaviour (e.g. window and shading operation, adjusting temperature setpoints, etc.) are often poorly defined in simulation tools [8]. In addition to a wide number of other contributing factors throughout the building lifecycle, from planning and design to operation, discrepancies between simulated and actual behaviour can lead to significant differences between the predictions of building energy use at the design stage and actual use in operation. This is referred to as the "energy performance gap" [9,10]. For a detailed review of all the root causes of the energy performance gap, see de Wilde [9]. Improving the model inputs for the representation of occupants and their behaviour has only recently been identified and researched [11-15]. Accordingly, in 2014, the International Energy Agency launched IEA-EBC Annex 66 – Definition and Simulation of Occupant Behavior in Buildings [16], 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.

As a result, the modelling of occupant's behaviour in buildings has steadily increased in the last few years, however, as early as 1990, Fritsch et al. [17] using a Markov Chains process modelled window opening angles in office buildings for four different outdoor temperature ranges. In 2009, Haldi and Robinson [18] set a milestone in the modelling of window operation in office buildings using data collected over a period of seven years. They modelled window position (open or closed) using several modelling approaches including, Bernoulli process, discrete time random (Markov) process and continuous random process and hybrid combinations of those techniques. In 2013, Andersen et al. [19] using multivariate logistic regression proposed the first window opening (closed to open) and closing (open to closed) models for domestic buildings based on observations from 15 dwellings located in Denmark.

Providing modellers with typical occupant behaviour patterns is one method to improve model inputs and thus the accuracy of simulation outputs. Constructing models of typical occupant behaviour requires the quantification of real occupant behaviour measured in real buildings, combined with an understanding of the underlying "drivers" of the behavioural action. Fabi et al. [20] define drivers as *"the reasons leading to a reaction in the building occupant and suggesting him or her to act (they namely "drive" the occupant to action)"*.

Previous studies have identified the key factors that influence occupants' window opening behaviour in buildings (e.g. [17-19,21-34]). A detailed international review and discussion of these factors is provided by Fabi et al. [20]. In their review, the "drivers" of window opening behaviour in residential buildings were categorised as: (1) physiological drivers (age and gender); (2) psychological drivers (perceived illumination and preference in terms of temperature); (3) social drivers (smoking behaviour and presence at home); (4) physical environmental drivers (outdoor and indoor temperature, solar radiation, wind speed and CO_2 concentration) and (5) contextual drivers (dwelling type, room type, room orientation, ventilation type, heating system, season and time of day).

The review concluded that: (1) window operation has a strong impact on the energy use and indoor environmental conditions of buildings; (2) there remains a lack of consensus as to which drivers actually influence occupants' window operation; (3) the majority of previous studies analyse window state (open or closed) rather than change of state (open to closed; closed to open) and (4) significant further effort is required to understand the dynamics of the relationship between indoor environment, occupant behaviour and energy consumption, as well as the development of more accurate, reliable and realistic occupant behaviour models.

Furthermore, as Fabi et al. [20] reviewed window interaction studies in both domestic and non-domestic buildings, it was evident that most previous analyses have focused on office buildings (e.g.

[17,18,35-41]) and there is a lack of studies related to residential buildings. Stochastic models of occupants' window interactions developed based on measurements in office buildings can provide useful inputs for modelling large buildings or clusters of buildings (city scale) with many occupants. In addition, Schweiker et al. [27] have shown that window operation models developed from data collected in office environments can also be used to reliably predict window usage in the residential context and vice-versa.

This paper presents stochastic models of occupants' main bedroom window operation behaviour based on measurements collected in ten UK dwellings over a period of a year. The study uses multivariate logistic regression to understand the probability of opening and closing windows (change from one state to another) based on a range of indoor and outdoor environment factors (physical environmental drivers) and according to the time of the day and season (contextual drivers). This work is a pilot study of window operation behaviour for UK domestic buildings, replicating the methodology previously used in the studies by Andersen et al. [19] and Fabi et al. [24].

This study specifically targets an understanding of the drivers of main bedroom window operation behaviour, as it is the room most often used for ventilation in domestic buildings. Previously, Brundett [42] found that open windows were most commonly found in bedrooms, in particular the main bedroom, and Dubrul [32] identified that bedrooms were the main ventilation zones in dwellings. In addition, the living rooms of the ten dwellings investigated had French doors, instead of windows, onto either an exterior patio or balcony and were therefore excluded from the analysis.

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 [43,44], rather than a specific study of occupant's window behaviour, therefore the range of indoor and outdoor environment factors used for modelling (i.e. indoor air temperature and relative humidity; outdoor air temperature and relative humidity; wind speed; global solar radiation; and rainfall) were those available to the researchers. Similarly, the monitoring system installed only allowed data to be collected about the window state rather than the position. It should be noted that there are other possible drivers of window interactions that were not captured in this study and further research on these for the UK domestic sector would be beneficial (e.g. removal of odours from smoking or pets, presence at home, CO_2 concentration, metabolic activity, clothing insulation, etc.). The analysis undertaken does however partition the data to account for variations in window opening according to the time of day and season.

The dwellings investigated in this study are new-build properties and should therefore achieve current standards for airtightness as set by the building regulations. This means that the models developed in this work may better capture occupant's window operation behaviour in new homes or those which have undergone refurbishment (i.e. the future housing stock), as it could be imagined that window opening behaviour studies undertaken in older dwellings may well be affected by the higher air leakage rates.

To the authors' knowledge, these are the first stochastic models of window opening and closing developed for UK residential buildings. Previously, Rijal and Stevenson [45] proposed a window state model (open or closed) for autumn only, based on data collected in a single UK dwelling and for one potential driver: outdoor temperature. Window state models are problematic as the predictive indoor environment variables are affected by the window state itself. By modelling the change of window state (open to closed; closed to open) rather than the window state, this work overcomes this limitation and also allows the important drivers of window opening and closing to be inferred separately.

The development of national models of occupant behaviour is important as occupants' living patterns and behavioural practices vary internationally [46-48]. Nicol [49], albeit for offices, previously identified differences in window opening behaviour between occupants of buildings in the UK, other European countries and Pakistan. The research identified that the proportion of open windows in European offices was generally lower than in the UK at any given temperature. In addition, Pakistani office workers were observed to use windows less than their counterparts in Europe and the UK. This behaviour was attributed to the hot dry conditions in Pakistan, whereby opening windows has little advantage and may even increase indoor temperatures.

The objective of this work was to develop stochastic models of window opening and closing behaviour for UK residential buildings, based on a range of indoor and outdoor environment factors for different seasons and times of the day.

2. Data and methods

2.1. The dwellings

Measurements were undertaken in the main bedroom of 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. Table 1 provides a summary of the main features of the dwellings. The seven flats were all identical in layout, but varied in orientation and construction standard. The same applied for the three houses. Six of the flats were located on the third floor of a Code for Sustainable Homes (CSH) Level 4 apartment building, four facing South East and two North West (Fig. 1 Left). The CSH was a voluntary UK national standard for the sustainable design and construction of new homes [50]. CSH Level 4 relates to a 44% improvement over the Target Emission Rate (TER) as determined by the 2006 Building Regulation Standards (BRS) [51]. The seventh flat was located on the third floor of a minimum compliance, 2006 Building Regulation Standards apartment building, facing North West. Two of the end-terrace houses were CSH Level 5, oriented North West, which relates to a 100% improvement over the 2006 Building Regulation Standards (Fig. 1 Right). The third house was constructed to the 2006 Building Regulations Standards and faced South East. The main bedroom of the houses was located on the first floor. The main bedroom was identified by the dwelling occupants and is defined as the room which was used for sleeping by the person or persons who head the household. The stated orientation relates to the direction of the façade containing the main bedroom window. The housing development is built on an elevated side surrounded by undeveloped sites and green spaces. It consists of one main street with dwellings on each side, accessible through public front gardens (mainly grass and bushes), creating a sense of space and reducing the risk of overshadowing the front façade of the neighbouring buildings. Due to its location surrounded mainly by undeveloped sites, and the fact that it is a gated community with one single entry, the development is perceived to be safe and quiet. Therefore, potential constraints to window opening for the dwellings in the study, such as outdoor air pollution, noise, or security concerns are not considered significant.

The flats comprised of an open plan kitchen-living room, two bedrooms, a main and ensuite bathroom and a corridor. The houses consisted of a living room, bathroom and corridor on the ground floor; an open plan kitchen-dining room, living room and corridor on the first floor; and three bedrooms, a bathroom and a corridor on the second floor. The flats and houses were gas centrally heated (GCH), which is the typical heating system installed in 91% of the UK housing stock [1]. In such heating systems, a gas-fired boiler located inside each dwelling, heats water, which is then pumped to radiators (RAD) in each room. The heating pattern is controlled by a timer/programmer (PROG) and the heating demand temperature by a central thermostat (TSTAT) located in the corridor as well as thermostatic radiator valves (TRVs) in individual rooms. None of the dwellings had mechanical cooling, which is typical for UK dwellings, as a result the indoor temperature depends on the heating setpoint in winter and on the air change rate in the summer. Occupants' window operation therefore has a significant effect on the energy use and indoor environmental conditions of UK residential buildings. The domestic hot water (DHW) was also provided by the gas central heating system. The dwellings were equipped with either exhaust air ventilation (EAV) or mechanical ventilation with heat recovery (MVHR) systems. Details of the construction materials and specifications of the main construction elements used in the flats and houses are presented in the Appendix A Table A.1.

Table 1. Dwelling characteristics.

Dwelling index	Performance standard	Floor area (m^2)	Wall U-value (W/m^2K)	Window U-value (W/m^2K)	HVAC	Heating control	DHW	Airtightness ($m^3/hr.m^2$)
Flats 1-6	CSH Level 4	80.5	0.10	1.20	GCH, MVHR, RAD	PROG, TSTAT, TRVs	GCH	2
Flat 7	2006 BRS	80.5	0.24	1.80	GCH, EAV, RAD	PROG, TSTAT, TRVs	GCH	5
Houses 1-2	CSH Level 5	140	0.10	0.70	GCH, MVHR, RAD	PROG, TSTAT, TRVs	GCH	2
House 3	2006 BRS	140	0.26	1.80	GCH, EAV, RAD	PROG, TSTAT, TRVs	GCH	5

Fig. 1. Case study apartment building (CSH Level 4) and houses (CSH Level 5).

2.2. Measurements

An automated monitoring system was installed in each of the 10 dwellings. The sensor data were 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 [43,44]. The variables used in this paper were measured continuously for all dwellings from 28th October 2013 to 2nd November 2014 (370 days).

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

The indoor environment variables were measured using HWM Radio-Tech Ecosense internal loggers. The internal sensors were newly calibrated by the manufacturer and found to be accurate to ±0.3°C for air temperature (measurement range: -20°C – 65°C) and ±1.8% for relative humidity (0% – 100%). The internal loggers were installed in the main bedroom of each dwelling and were sited away from heat sources and direct sunlight. The outdoor environment variables were collected from a meteorological station setup on the housing estate where the dwellings were located. The outdoor environment sensors were newly calibrated by the supplier and found to be accurate to ±0.3°C for air temperature (measurement range: -40°C – 75°C); ±1.8% for relative humidity (0% – 100%); ±1.1m/s for wind speed (0 – 76m/s); ±5% of full scale for global solar radiation (0 – 1800W/m^2); and ±1% at up to 20mm per hour for rainfall (0 – 100mm per hour).

The window state (open/closed) was monitored using a HWM Radio-Tech open/close sensor (Fig. 2 a). The open/close sensor comprised two magnetic contacts, one part mounted to the window frame and the other to the window's moveable panel. The main bedroom of all the dwellings had a single side hung casement window, with only one fully openable section, which opened to the outside (Fig. 2 b-c). The main bedroom windows were 1500 mm in height and 1000 mm wide (Fig. 2 d). The ease of opening and closing the main bedroom windows was checked during the installation of the open/close sensors: all the windows easily opened and closed.

Occupancy is a requirement for occupants' actions in buildings. However, as discussed by Yan et al. [13] in their review of methods and procedures for occupant monitoring and data collection, *"accurate occupancy detection remains a challenge"*. In this work, passive infrared (PIR) motion detectors were installed in the living rooms and corridors of the dwellings to provide an indication of when they were occupied. Whilst motion detectors are the most commonly used sensor for capturing occupancy [52], they are unable to detect near motionless occupants and therefore record significant proportions of false negatives (i.e. record unoccupied when occupied). As bedroom activities are primarily sedentary or sleeping, data captured from PIR motion sensors are poor for developing occupancy patterns. Coupled with issues of privacy, it was decided that motion detectors should not be installed in the bedrooms. Due to the high uncertainty of developing occupancy patterns for the bedrooms based on the measurements taken in the living rooms and corridors, in this paper the modelling was undertaken for the full monitoring period, without distinction for occupied and unoccupied periods. Future researchers could attempt to overcome this limitation by measuring occupancy using Radio Frequency Identification (RFID) tags or by deducing occupancy from CO_2 concentration. Yan et al. [13] have however also noted further limitations with these alternative occupancy monitoring approaches in their review of previous research, including using hybrid techniques, such as coupling motion detection with CO_2 concentration.

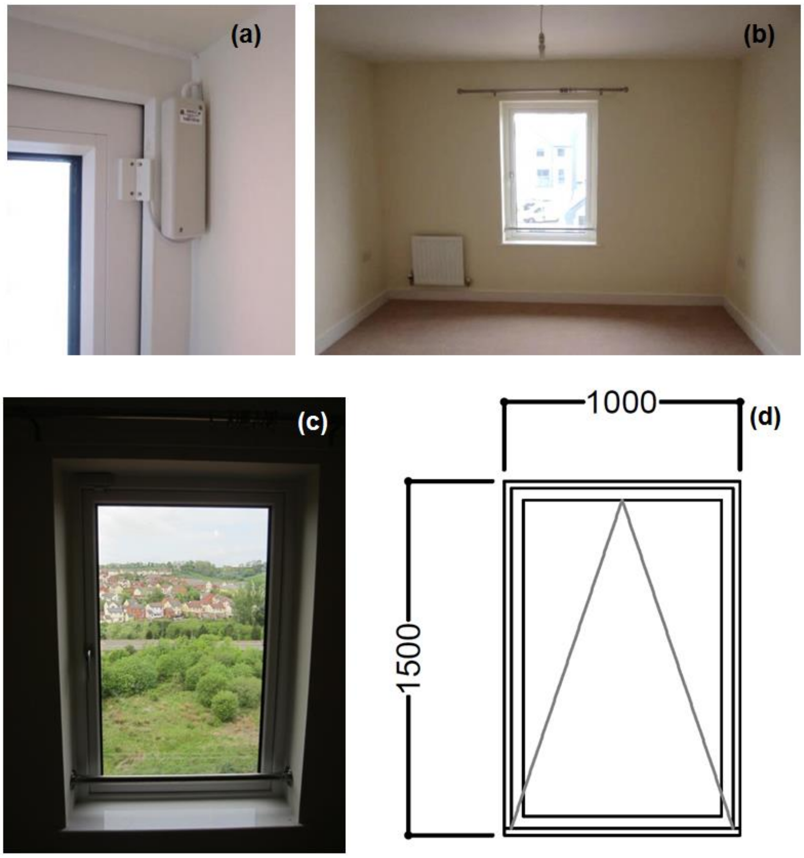

Fig. 2. a) HWM Radio-Tech open/close sensor installed on a bedroom window; b) and c) examples of the main bedroom window from two dwellings in the study; and d) drawing with dimensions of a main bedroom window.

2.3. Processing and preparation of data

Measured data for the indoor and outdoor environment variables were assigned to the window state variable (open/closed) according to time, obtaining an array of data for every 10 minutes.

Indoor and outdoor environment variables were considered explanatory variables and were included in the dataset as continuous values. The window state was a binary response variable and was introduced into the dataset as 1 or 0, where 1 was assigned to "window open" and 0 to "window closed". From the window state, the window opening and closing actions were identified. The opening signal was defined as 1 if an opening action (closed to open) occurred and 0 otherwise. Similarly, the closing signal was assigned the value 1 if a closing event (open to closed) occurred and 0 otherwise.

As recommended by Andersen et al. [19], window opening and closing models were developed in this work instead of a window state model. Window state models are problematic as the indoor environment variables used to predict the window state are influenced by the window state it is trying to predict. For example, low indoor temperatures occur when the window is open; therefore a state model illogically infers that the probability of a window being open increases with decreasing indoor temperature. In addition, it is suggested that the drivers of window opening and closing may be different (e.g. opened due to high relative humidity and closed due to low indoor temperature). Modelling window opening and closing rather than window state overcomes these limitations.

Table 2 shows the list of continuous indoor and outdoor environment variables used in the inference of the stochastic models of window opening and closing behaviour. In addition, two categorical variables, time of the day and season were also computed based on the data's time series, to account for differences in the frequency and drivers of window operation behaviour according to the time of the day (morning, afternoon, evening and night) and the season (spring, summer, autumn, and winter). These temporal categorical variables were necessary as variations in main bedroom window opening activity were observed according to the time of day and season, as shown in Fig. 3 and Fig. 4.

Table 2. List of continuous and categorical variables used to infer the window opening and closing models.

Continuous variables	Unit
Indoor air temperature (t_i)	˚C
Indoor relative humidity (RH_i)	%
Outdoor air temperature (t_o)	˚C
Outdoor relative humidity (RH_o)	%
Wind speed (WS)	m/s
Global solar radiation (Rad)	W/m^2
Rainfall (RF)	mm
Categorical variables	
Spring	March - May
Summer	June - August
Autumn	September - November
Winter	December - February
Morning	00:00 – 05:59
Afternoon	06:00 – 11:59
Evening	12:00 – 17:59
Night	18:00 – 23:59

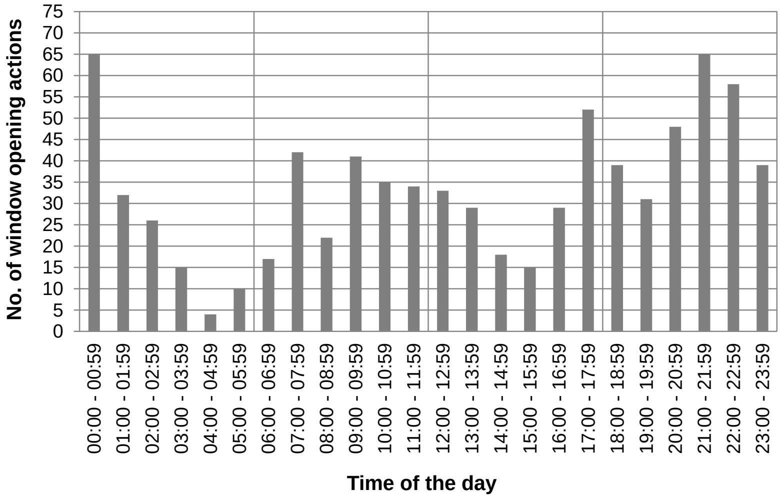

Fig. 3. Observed main bedroom window opening actions according to the time of day.

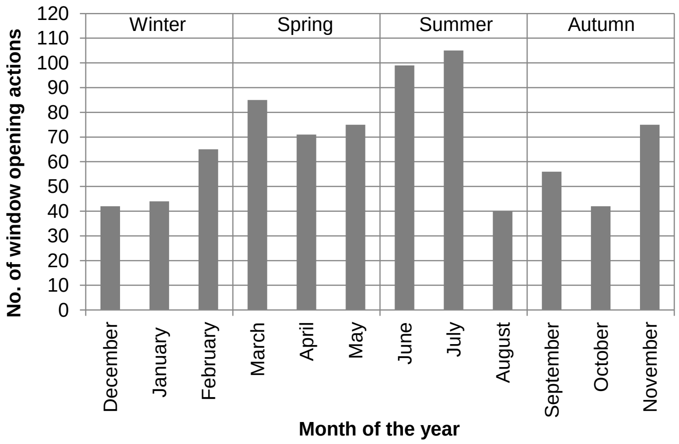

Fig. 4. Observed main bedroom window opening actions according to the month of the year.

2.4. Statistical analysis

Logistic regression was used as the analysis and modelling method. Logistic regression is an established statistical method for analysing and modelling binary dependent variables and has been used extensively in previous studies to describe the probability of a window being open or closed (window state (e.g. [18,22,45])) or changes in window state (closed to open or open to closed (e.g. [19,21])) based on a range of explanatory variables. The relationship between the probability of a binary response and the individual explanatory variables can be expressed by univariate linear logistic regression according to Eq. (1).

$$P(x) = \frac{1}{1+e^{-(\alpha+\beta x)}} \qquad P(x) \; \varepsilon \; [0,1] \; \forall \; x \quad (1)$$

Where *P(x)* (or simply *p*) is the probability of the binary response; *α* is the intercept; *β* is a coefficient; and *x* is the explanatory variable, such as indoor air temperature, wind speed, etc.

For the purpose of this paper, multivariate logistic regression was used to establish the probability of opening or closing the main bedroom window, based on multiple indoor and outdoor environment variables. This statistical method has recently been used by Cali et al. [21] for modelling window opening and closing in German households, Shi and Zhao [22] for Chinese households, and Andersen et al. [19] for Danish households. For multivariate regression, the probability function can be expressed as in Eq. (2). The statistical software package IBM SPSS Statistics 22 was used for the logistic regression modelling [53].

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

The explanatory variables contained in each multivariate logistic regression model were determined based on a forward and backwards selection procedure using the Akaike information criterion (AIC) [54]. This procedure produced a model containing only explanatory variables that had a consistent effect on the probability function. In practice, the following steps were undertaken:

1. The AIC of each univariate logistic regression model was calculated, the single variable model with the lowest AIC was selected;
2. Bivariate models were then fitted by adding the remaining variables one by one to the univariate model. The bivariate model with the lowest AIC was selected and its AIC compared to the univariate model;
    a. If the bivariate model had a lower AIC than the univariate model, a three variables model was fitted (forward selection);
    b. If the bivariate model had a higher AIC, the univariate model was chosen;
3. In addition to fitting a three variables model, three bivariate models were fitted, obtained by removing each of the selected variables (backward selection);
    a. If neither the three variables model or any of the three bivariate models had a lower AIC than the bivariate model fitted in step 2a., the bivariate model from step 2a. was chosen;
    b. Otherwise, the process continued with the same criteria, up to *n* variables models.

To compare the effect of the different explanatory variables within one multivariate linear logistic model, the sign and magnitude of the variables have to be taken into account. The sign of the coefficient β indicates whether the variables influence directly (positive) or inversely (negative) the probability of the action. Therefore, a positive coefficient means that an increase in the explanatory variable causes an increase in the probability of the opening/closing action. A negative coefficient means that an increase in the explanatory variable causes a decrease in the probability of the opening/closing action. To get an indication of the magnitude of the effect of the variables on the probability of the event, Schweiker and Shukuya [54] suggest multiplying the scale of the variable with the coefficient according to Eq. (3):

$$Magnitude = |\beta\ (x_{max} - x_{min})| \quad (3)$$

Where β is the coefficient, x_{max} is the maximum value of the explanatory variable recorded, and x_{min} is the minimum value of the explanatory variable recorded.

Furthermore, possible inflation of the estimated variance of the inferred coefficients of the window opening and closing models due to correlations between the explanatory variables (i.e. multicollinearity) was assessed for all of the continuous variables in each model using generalized variance inflation factors (GVIF). The $GVIF^{1/(2 \cdot Df)}$ assesses the inflation of the variance as a result of multicollinearity, compared to a condition in which no multicollinearity existed between the explanatory variables. GVIF was used to assess all the window opening and closing models for the whole year, by time of day and season. The GVIF analyses for the all year window opening and closing models are shown in Table 3.

A GVIF of 1 indicates that a model's explanatory variables are not correlated. A GVIF between 1 and 5 indicates that the explanatory variables are moderately correlated, and over 5 highly correlated. For example, a GVIF of 5 implies that the standard errors are larger by a factor of 5 than would otherwise be the case, if there was no multicollinearity between the explanatory variable of interest and the remaining explanatory variables included in the analysis. Various recommendations for acceptable levels of GVIF can be found in the literature, most commonly, a value of 10 has been recommended as the maximum acceptable level [55,56], however, more recently, maximum GVIF values of 5 [57] and 4 [58] have been suggested. The GVIF values calculated for all the explanatory variables included in the window opening and closing models presented in Tables 5 and 6 were all less than 4 and therefore the inflation of the estimated variance of the inferred coefficients was considered acceptable. It should be noted that the predictive power of the individual models would only be affected if the model is used on data that falls outside the ranges in Appendix B Table B.1.

Table 3. Results of the VIF and GVIF analyses for the variables in the all year window opening and closing models.

Variable	Window opening (All year)			Window closing (All year)		
	VIF	Df	$GVIF^{1/(2 \cdot Df)}$	VIF	Df	$GVIF^{1/(2 \cdot Df)}$
Indoor air temperature (◦C)	1.9	1	1.4	1.7	1	1.3
Indoor RH (%)	1.9	1	1.4	1.4	1	1.2
Outdoor air temperature (◦C)	3.8	1	1.9	1.9	1	1.4
Outdoor RH (%)	2.3	1	1.5			
Wind speed (m/s)	1.1	1	1.0	1.1	1	1.0
Global solar radiation (W/m^2)						
Rainfall (mm)	1.1	1	1.0	1.1	1	1.0

3. Results

This section presents the results of the logistic regression analysis for the window opening and closing models (all year, by time of the day and season). Appendix B Table B.1 presents descriptive statistics of all measured variables in the models. Table 5 and Table 6 present the coefficients (Coef.) and magnitudes (Mag.) of the explanatory variables included in the window opening and closing models, respectively.

For the full year, two multivariate window operation behaviour models were obtained. Eq. (4) describes the window opening model, and Eq. (5) presents the window closing model:

$$\ln\left(\frac{p}{1-p}\right) = -9.275 + 0.233t_i + 0.038RH_i - 0.105t_o - 0.042RH_o + 0.057WS + 0.034RF \quad (4)$$

$$\ln\left(\frac{p}{1-p}\right) = -2.984 - 0.178t_i - 0.017RH_i + 0.062t_o + 0.063WS + 0.032RF \quad (5)$$

Where, *p* is the probability of opening or closing the main bedroom window within the next 10 minutes, t_i is the indoor air temperature in $^{\circ}$C, RH_i is the indoor relative humidity in %, t_o is the outdoor air temperature in $^{\circ}$C, RH_o is the outdoor relative humidity in %, WS is the wind speed in m/s and RF is the rainfall in mm.

According to the magnitudes of each explanatory variable, the most influential factors driving annual window operation behaviour in the main bedroom are indoor air temperature, outdoor air temperature and wind speed. Although with smaller magnitudes, other parameters were also identified as drivers of occupants' window operation behaviour: outdoor relative humidity, indoor relative humidity, and rainfall. Global solar radiation did not present any effect on window opening behaviour. Outdoor relative humidity and also global solar radiation were not identified as drivers of window closing behaviour. Table 4 summarises the major parameters found in the literature driving occupant's window operation split into five categories of influential factors for residential and office buildings [20], and compares these drivers to the driving and non-driving factors identified in the all year window operation models developed in the current study.

Table 4. Summary of the major parameters found in the literature driving occupant's window operation [20] compared to the results obtained in this study.

		Residential buildings	Office buildings	Results of current study: All year window opening model	Results of current study: All year window closing model
Physiological	Age	x		●	●
	Gender	x		●	●
Psychological	Perceived illumination	x		●	●
	Preference in terms of temperature	x		●	●
Social	Smoking behaviour	x		●	●
	Presence at home	x		●	●
	Shared offices	x	x	●	●
Physical environmental	Outdoor temperature	x	x	■	■
	Indoor temperature	x	x	■	■
	Outdoor relative humidity			■	▲
	Indoor relative humidity			■	■
	Solar radiation	x	x	▲	▲
	Wind speed	x	x	■	■
	CO_2 concentrations	x		●	●
	Rain		x	●	●
Contextual	Dwelling type	x		●	●
	Room type	x		●	●
	Room orientation	x		●	●
	Window type		x	●	●
	Ventilation type	x		●	●

Heating system	x		●	●
Season	x	x	■	■
Time of day	x	x	■	■

Note: X Factor found to be a driver in previous studies. ● Factor not investigated in the current study. ▲Factor found not to drive window operation behaviour in the current study. ■ Factor found to be a driver for window operation behaviour in the current study.

Different relationships were found between variables and the probability of opening or closing the main bedroom window. For example, the probability of opening the main bedroom window had a positive relationship with indoor air temperature, indoor relative humidity, wind speed and rainfall. However, the outdoor air temperature and relative humidity negatively influenced the opening of windows. However, the probability of closing the bedroom window had a negative relationship with indoor temperature and relative humidity. Whereby, increasing indoor temperature or relative humidity leads to a decrease in the probability of closing the window. A positive correlation was identified between the outdoor air temperature, wind speed and rainfall.

In addition to the all year models, thirty-two different sub-models were also obtained to represent the changes in window operation behaviour (opening and closing) according to the times of the day and seasons.

Indoor air temperature was the most common explanatory variable of bedroom window opening and closing behaviours. The influence of indoor temperature on window opening was particularly strong in the morning, as well as at most times of the day during autumn and winter. In general, the seasonal models suggest that an increase in indoor temperature leads to an increase in window opening. Consequently, a decrease in indoor temperature leads to an increase in the probability of closing the window. The main exception to this pattern was observed during spring and summer nights, when the probability of window opening decreased with increasing indoor temperatures.

Outdoor air temperature was found to have a strong relationship with both bedroom window opening and closing. This variable clearly explains opening behaviour in the morning (except in winter) and during the evening in autumn and winter. With the exception of the summer night model, outdoor air temperature consistently had a negative relationship with the window opening action. A different effect was observed in the closing model, were the direction of the relationship primarily varied according to the time of the day, with direct relationships evident during the evening and night and inverse relationships during the morning.

Whilst an increase in indoor relative humidity was in general found to result in increased window opening, this variable presented mixed relationships across the window closing seasonal models. In addition, no relationship was identified between this variable and window closing behaviour in spring, and window opening behaviour in the summer. Outdoor relative humidity, on the other hand, was generally negatively associated with window opening, apart from the summer season, when no relationship was found. Although outdoor relative humidity was not present in the all year closing window behaviour model, the sub-models suggest that its effect on window closing can vary directly and inversely depending on the time of the day and season.

Wind speed was present in the majority of evening and night models and was found to have a positive relationship with window opening. Wind speed however had no influence on window opening during the morning in any season and was not an important driver during spring. Increasing wind speed leads to increased window closing regardless of time of day or season.

Rainfall was positively related with the probability of both window opening and closing actions. Focusing on the window opening behaviour, this variable was mostly present in the spring and summer morning models, and the autumn and winter evening models. The comparatively small magnitude values for rainfall however, indicate that its influence on window opening is weak.

Although global solar radiation was not identified as a driver of window opening and closing behaviour in the all year model, the sub-models suggest that there is a relationship and its effect can vary depending on the time of the day and season. For example, global solar radiation positively influences the probability of opening a window in the summer-night, autumn-morning, and winter morning and afternoon. However, a negative relationship was observed in the spring afternoon and evening models.

Table 5. Coefficients and magnitudes of the logistic regression models for window opening behaviour.

Variable		All year		Spring		Summer		Autumn		Winter	
		Coef.	Mag.	Coef.	Mag.	Coef.	Mag.	Coef.	Mag.	Coef.	Mag.
Intercept (α)	Morning			-10.126		-7.529		-18.147		-6.845	
	Afternoon			-3.837		-3.358		-17.252		-14.406	
	Evening			-6.392		-8.980		-6.914		-3.653	
	Night			-2.747		-8.580		-34.202		-18.420	
	All year	-9.275									
Indoor air temperature (°C)	Morning			0.413	5.00	0.174	2.02	0.498	6.32	-	-
	Afternoon			-	-	-0.155	1.71	0.602	7.04	0.363	4.54
	Evening			0.062	0.69	0.110	1.17	-	-	-0.117	1.60
	Night			-0.043	0.48	-0.148	1.67	0.617	7.03	0.709	9.78
	All year	0.233	3.80								
Indoor RH (%)	Morning			0.053	2.78	-	-	0.064	2.99	-0.008	0.39
	Afternoon			-0.002	0.09	-	-	0.087	3.94	-	-
	Evening			-	-	-	-	0.024	1.07	-	-
	Night			-	-	-	-	-	-	0.107	4.89
	All year	0.038	2.11								
Outdoor air temperature (°C)	Morning			-0.137	3.38	-0.151	3.40	-0.215	5.31	-	-
	Afternoon			-	-	-	-	-0.250	5.87	-	-
	Evening			-	-	-	-	-0.097	2.20	-0.285	3.02
	Night			-	-	0.269	3.90	-	-	-	-
	All year	-0.105	3.62								
Outdoor RH (%)	Morning			-0.077	3.93	-	-	-	-	-	-
	Afternoon			-0.037	0.85	-	-	-0.051	2.42	-	-
	Evening			-0.007	0.37	-	-	-	-	-	-
	Night			-0.053	1.62	-	-	0.160	4.03	-0.107	2.73
	All year	-0.042	2.45								
Wind speed (m/s)	Morning			-	-	-	-	-	-	-	-
	Afternoon			-	-	-	-	0.127	1.59	-	-
	Evening			-	-	0.164	1.67	-	-	0.191	3.74
	Night			-	-	0.301	3.34	0.149	2.22	0.054	0.88
	All year	0.057	1.27								
Global solar radiation (W/m^2)	Morning			-	-	-	-	0.002	1.72	0.003	2.08
	Afternoon			-0.001	1.14	-	-	-	-	0.004	2.77
	Evening			-0.009	1.91	-	-	-	-	-	-
	Night			-	-	0.017	3.26	-	-	-	-
	All year	-	-								
Rainfall (mm)	Morning			0.039	0.63	0.013	0.26	-	-	-	-
	Afternoon			-	-	0.058	1.21	-	-	-	-
	Evening			-	-	-	-	-0.093	1.99	0.051	1.44
	Night			-	-	-	-	-	-	-	-
	All year	0.034	0.96								

Table 6. Coefficients and magnitudes of the logistic regression models for window closing behaviour.

Variable		All year		Spring		Summer		Autumn		Winter	
		Coef.	Mag.	Coef.	Mag.	Coef.	Mag.	Coef.	Mag.	Coef.	Mag.
Intercept (α)	Morning			-3.727		-8.215		-4.017		5.563	
	Afternoon			1.226		-5.032		-11.306		-14.617	
	Evening			-4.300		-9.306		-3.049		-5.852	
	Night			-1.995		-14.165		3.132		43.857	
	All year	-2.984									
Indoor air temperature (°C)	Morning			-0.102	1.23	-	-	-0.161	2.04	-0.454	5.81
	Afternoon			-0.128	1.47	-0.263	2.89	0.268	3.14	0.337	4.21
	Evening			-0.276	3.09	-	-	-0.060	0.72	-	-
	Night			-0.244	2.71	-	-	-0.667	7.60	-0.299	4.13
	All year	-0.178	2.90								
Indoor RH (%)	Morning			-	-	0.053	2.44	-	-	-0.089	4.33
	Afternoon			-	-	-	-	0.036	1.63	0.052	2.47
	Evening			-	-	0.039	1.62	-0.054	2.40	-0.038	1.84
	Night			-	-	0.055	2.10	-	-	-	-
	All year	-0.017	0.94								
Outdoor air temperature (°C)	Morning			-	-	-0.038	0.85	0.099	2.44	0.145	1.74
	Afternoon			-0.115	2.63	-	-	-0.201	4.72	-0.189	1.78
	Evening			0.239	4.90	-	-	0.124	2.81	-	-
	Night			-	-	0.216	3.13	0.204	3.81	-0.841	9.84
	All year	0.062	2.14								
Outdoor RH (%)	Morning			-	-	-	-	-	-	-	-
	Afternoon			-0.060	3.26	0.050	2.61	-	-	-	-
	Evening			-	-	-	-	-	-	-	-
	Night			-	-	-	-	-	-	-0.508	12.95
	All year	-	-								
Wind speed (m/s)	Morning			-	-	-	-	-	-	-	-
	Afternoon			0.184	2.67	-	-	0.146	1.82	0.095	2.00
	Evening			-	-	0.247	2.52	-	-	0.199	3.90
	Night			-	-	-	-	-	-	-0.449	7.32
	All year	0.063	1.40								
Global solar radiation (W/m^2)	Morning			-	-	-0.001	1.12	-0.003	2.58	-	-
	Afternoon			-	-	0.002	2.25	-	-	-	-
	Evening			0.003	0.81	-	-	-0.392	19.60	-	-
	Night			-	-	0.019	3.65	-	-	-	-
	All year	-	-								
Rainfall (mm)	Morning			-	-	-	-	-	-	0.067	1.74
	Afternoon			-	-	0.035	0.73	-	-	0.042	1.15
	Evening			-	-	-	-	-	-	-	-
	Night			0.182	1.93	-	-	-	-	-	-
	All year	0.032	0.90								

4. Discussion

The findings reported in this paper suggest that occupants' main bedroom window operation in UK residential buildings is influenced by a range of physical environmental (i.e. indoor and outdoor air temperature and relative humidity, wind speed, solar radiation and rainfall) and contextual variables (i.e. time of day and season). In addition, the magnitudes of the effects of the physical environmental variables on window opening and closing behaviour were found to vary in relation to the contextual factors. For example, outdoor relative humidity was found to be a driver of window opening in spring but not in summer and outdoor relative humidity had a much stronger influence on window opening during a spring morning than a spring evening. The results of this study support the recommendations of others (e.g. [19,21,22]) that when investigating occupant behaviour in buildings, other drivers than just indoor and outdoor temperature should be taken into account.

Accordingly, this paper has developed window opening and closing models using both physical environmental and contextual factors for the full year, as well as for different seasons and time of day. The contextual factors, time of day and season, have been explicitly included in the models, whilst other known contextual factors influencing occupant window operation (e.g. room type, ventilation type, heating system and window type) have been methodologically controlled for by monitoring identical dwellings in these respects. As recommended by O'Brien and Gunay [59] as the role of contextual factors is often underestimated, they should therefore be reported and accounted for in occupant behaviour models. By doing so, potential users of the models can judge their suitability for their own modelling purposes. In this context, the models reported in this study may be most useful for predicting occupants' interactions with single side hung casement windows in the main bedroom of UK residential buildings with gas central heating and mechanical ventilation.

The analysis undertaken in this paper provides a method for calculating the probability that the main bedroom window will be opened or closed in the next 10 minutes (Tables 5 and 6). This method could be used in building performance simulation applications to improve predictions of the energy use and indoor environmental conditions of residential buildings by reducing the discrepancies between assumed and actual window operation.

Some salient observations and discussions stemming from the analysis undertaken follow.

In general, the relationships between the physical environmental and contextual variables, and the probability of opening or closing windows identified in this study are similar to those reported by others (e.g. [17-19,21-34,45]). The authors refer readers to the comprehensive review papers by Fabi et al. [20] and Roetzel et al. [4] who provide useful, in depth discussions of the known factors that influence occupants' window operation behaviour.

The work conveyed in this paper is theoretically underpinned by the so –called "adaptive approach to thermal comfort" [60,61], which proposes that occupants of buildings will adapt to the thermal conditions to which they have recently been exposed by making adjustments to their clothing, activity and posture, and surroundings (e.g. controlling ventilation by opening or closing windows). Temperature is usually considered *"the most important environmental variable affecting thermal comfort"* [62]; therefore changes to temperature in buildings are likely to trigger adaptive actions. In relation to window adaptions, this work supports this statement, as indoor and outdoor temperatures were identified as the most important drivers of window opening and closing in the full year models and also appear in each of the seasonal models. This result is also consistent with the findings of many previous window interaction studies undertaken in residential buildings (e.g. [19,21-23,26,32-34]).

This study also identified that indoor and outdoor relative humidity affected occupants' window operation behaviour. This is perhaps unexpected, as humans do not directly perceive humidity due to there being no sensors in the body that respond to it. Discomfort from humidity is only expected as a result of sweating prompted by high temperatures or humidities outside of the 40-70% range. This could offer an explanation for the current findings, as some of the dwellings investigated in this study have previously been shown to exceed recommended indoor temperatures and be at risk of overheating in summer [43]. In addition, the descriptive statistics reported in this paper show that in some instances, the humidities were also outside the acceptable range: 32-88% (indoor) and 36-99% (outdoor). Andersen et al. [19] in their study of Danish dwellings also found that indoor relative humidity influenced the probability of opening or closing windows, despite being in the 30-70% range. Relative humidity is also known to affect occupant's thermal sensation and perceived air quality, which would influence occupants need to open or close windows. It should also be noted that indoor relative humidity often appeared in the morning window opening models. It could be hypothesised that as the main bedrooms investigated in this study have ensuite bathrooms, the window opening behaviour may be triggered by the occupants' desire to ventilate steam from showering or bathing. The need to ventilate the main bedroom may in fact be prompted visually rather than thermally, as a result of condensation forming on the windows.

Furthermore, wind speed was found to have an effect on occupants' window opening and closing behaviour. Air movement in buildings, which is the result of a combination of indoor and outdoor ventilation, has a cooling effect on humans and therefore can either positively or negatively affect occupants' thermal comfort, depending on the prevailing indoor environmental conditions. Occupants are therefore likely to regulate ventilation by opening or closing windows depending on their thermal comfort. Several previous studies have also recognised a relationship between wind speed and window operation [32,33].

The current work also found that rainfall influenced window operation. This has not previously been reported in the literature. The effect of rainfall on occupants' window interactions has been excluded from the majority of previous studies investigating residential buildings. The analysis showed that as rainfall increased, so too does the probability of occupants closing windows. This is perhaps unsurprising as occupants are likely to act to prevent rain penetration and potential water damage to their home[i].

Seasonality influenced both the frequency (Fig. 4) and drivers of window operation in bedrooms (Tables 5 and 6). This apparent seasonal effect suggests that models of occupants' window interactions require data from a full year of monitoring. This study monitored window interaction for a full annual period, which is longer than the majority of previous studies. Whilst the effect of seasonality on window operation is generally consistent with studies undertaken in residential buildings in other countries; there were also evident variations in both the frequency and drivers of window interactions between the spring and autumn seasons. This result questions Andersen et al.'s [19] assertion that when implementing window operation models in simulation programs with seasonal effects: *"the spring season can be used as a representation in autumn"*. Further work is required to determine whether occupant behaviour varies from year-to-year and whether multi-year studies are in fact necessary.

5. Limitations and future research

The window operation behaviour models obtained in this study are based on a small sample of 10 UK dwellings and are therefore not representative of the wider housing stock. Despite this limitation, to the authors' knowledge, these are the first models of window opening and closing behaviour proposed for UK residential buildings and therefore the work presented constitutes a significant pilot study for the UK. The study also measured window interactions longitudinally (1 year), incorporating seasonal effects, which is a longer duration than the majority of previous studies internationally. A larger national-scale study of window operation behaviour for a much larger sample, representative of the UK housing stock as well as household groups, would of course be a valuable extension to the current work and could be used to validate the findings of the current study.

Undertaking research in homes occupied by the general public over a prolonged period of time (minimum of 1 year), invariably results in compromises between research ideals and what can actually be achieved in practice. This study focused on developing window opening and closing models based on indoor and outdoor environment factors (physical environmental drivers) for different times of day and seasons (contextual drivers), but it is acknowledged, that there are other possible drivers of window interactions that were not captured in this study and further research on these for the UK domestic sector would be useful (e.g. removal of odours from smoking or pets, presence at home, CO_2 concentration, metabolic activity, clothing insulation, etc.). Follow-up surveys with dwelling occupants could be used in future studies to gather information about some of these potential drivers, such as whether the dwelling has household members that smoke. This method alone however would not elicit the temporal and spatial data required for stochastic modelling. New technologies such as wearable sensors (e.g. smart watch, activity trackers) could allow future researchers to understand the relationship between metabolic activity and window operation. In addition, pioneering monitoring techniques using wearable cameras [63], may also prove useful for understanding the effects of clothing insulation levels. Collecting such data with wearable sensor technology over a longitudinal monitoring period is however likely to be challenging. Future researchers could also employ qualitative methods (i.e. interviews) to gather further information on the unmeasurable drivers of window operation behaviour (e.g. opening the window to ask children to come in from the garden, watering flowers in a window box, etc.).

Although, this study has attempted to account for the majority of physical environmental and contextual factors previously reported as drivers of window opening in residential buildings, there are other factors (e.g. physiological, psychological and social drivers), *"many of which are immeasurable and unanticipated"* [13] which are excluded. Therefore, whilst the method for occupant behaviour modelling used in this paper has moved beyond the common method of treating all occupants the same, without any consideration of contextual factors, it is acknowledged that due to these other unaccounted factors, predicting the window operation behaviour of a specific occupant, living in a specific dwelling, may not be possible. Future research should seek to collect larger datasets of window operation behaviour from similar population groups capturing a wider range of possible drivers. This would enable models to be developed for specific population groups using a similar modelling strategy to that employed in the current work. Mixed effects models could also be considered where a longitudinal study of a specific population cluster has been undertaken and missing values for potential drivers still exist.

This paper investigated the drivers of window interactions in the main bedroom (defined as the room which was used for sleeping by the person or persons who head the household). Previously, Dubrul [32] identified that bedrooms were the main ventilation zones in a dwelling, and Brundett [42] found that open windows were most commonly found in bedrooms, in particular the main bedroom. This work has therefore developed window opening and closing models for the room which is most often used for ventilation in homes. Consequently, application of the models to other bedroom windows or windows in other zones (e.g. living rooms, dining rooms, kitchens, etc.) may not be appropriate and could lead to an overestimation of ventilation. Further research is required to verify whether the models obtained in this research can be applied to predict window interactions in other bedrooms or zones.

5. Conclusions

This paper presented the development of stochastic models of occupants' main bedroom window operation based on measurements collected in ten UK dwellings over a period of a year. The paper has presented the development of window opening and closing models for a full year, as well as for seasons and time of day. The study used multivariate logistic regression to understand the probability of opening and closing windows (change from one state to another) based on a range of indoor and outdoor environment factors (physical environmental drivers) and according to the time of the day and season (contextual drivers). To the authors' knowledge, these are the first stochastic models of window opening and closing behaviour developed for UK residential buildings.

By modelling the change of window state (open to closed; closed to open) rather than the state of the window (open or closed), this work overcomes a major limitation inherent in window state models that the indoor environment variables used to predict the window state are affected by the window state itself. Also by modelling window opening and closing, this paper has understood the significant drivers of these actions separately, this is important as the factors driving each action can vary.

The work reported in this paper suggests that occupants' main bedroom window operation is influenced by a range of physical environmental (i.e. indoor and outdoor air temperature and relative humidity, wind speed, solar radiation and rainfall) and contextual variables (i.e. time of day and season). In addition, the effects of the physical environmental variables were observed to vary in relation to the contextual factors. The results of this study support the recommendations of others that when analysing and modelling occupant behaviours in buildings, other drivers than just indoor and outdoor temperature should be taken into account.

The multivariate logistic regression models provided in this work can be used to calculate the probability that the main bedroom window will be opened or closed in the next 10 minutes. These models could be used in building performance simulation applications to improve predictions of the energy use and indoor environmental conditions of residential buildings. It should be noted that the window operation models proposed in this paper are obtained from a pilot study of 10 UK dwellings and are therefore not representative of the wider housing stock. A larger national-scale study of window operation behaviour for a much larger sample, representative of the UK housing stock and household groups, would therefore be a valuable extension to the current work and could be used to validate the findings of the current study.

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Appendix A. Construction materials and specifications of the main construction elements used in the flats and houses

Table A.1. Construction materials and specifications of the main construction elements used in the flats and houses.

Construction element	Dwelling type	Construction materials and main properties
Roof	CSH Level 4 Flats 1-6 CSH Level 5 Houses 1-2	U-value at 0.10 W/m^2K 370 mm total of Knauf Loft roll 44 (Thermal conductivity 0.044 W/mK) or similar approved. 100 mm between and 270 mm over ceiling ties (170 mm + 100 mm). Air barrier fixed to the underside of truss. 30 mm PIR extruded insulation batt with thermal conductivity of 0.022 W/mk. Counter bat with 50 mm and 12.5 mm plasterboard screwed to underside. Joints taped and sealed to form first floor ceilings.
	2006 BRS Flat 7 2006 BRS House 3	U-value at 0.14 W/m^2K 300 mm total of Knauf Loft roll 44 (Thermal conductivity 0.040 W/mK) or similar approved. Between and over ceiling ties. 12.5 mm plasterboard screw fixed to underside of ceiling ties (joints taped and sealed) to form first floor ceilings. To sloping sections of ceiling, 150 mm Celotex or similar foil faced PIR rigid insulation (thermal conductivity value of 0.022 W/mK) between rafters with 30 mm T10 reflective foil insulation fixed to rafters. 25mm ventilation provided either side of foil. Plasterboard fixed to sloping sections of roof onto void battens.
External wall	CSH Level 4 Flats 1-6	U-value at 0.10 W/m^2K (Timber frame) Silicone coat render system (Wetherby 1.5 silicone 'k' finish or similar) resin bonded fibre mesh applied as per manufactures recommendations onto 90 mm ridged insulation board thermal conductivity of 0.020w/k (KOOLTHERM K5 EWB or similar approved with render system). Insulation fixed back to 15 mm stainless steel rails at 600 mm vertical spaces to create drainage channel (25 mm cavity above 2 storey's). Channel fixed back through 12 mm OSB on 140 mm timber frame in alignment with stud works.140 mm timber studwork panels filled with 120 mm of ridged insulation board with thermal conductivity of 0.022 w/k (Kingspan Thermawall TW55 or similar). The 9 mm OSB board is covered with a breather membrane stapled to the boarding with SS staples. Internal face of timber frame stud to vapour permeability membrane under a 38 mm batten to provide air gap and service void. The surface finish to the Inner face is 2x12.5 mm plasterboard (10 kg/m^2) dry lining with 3 mm plaster skim finish. Weep holes are required at the top and bottom of insulation drainage channel with proprietary movement joints as per manufactures recommendations. Intumescent fire protection at floor levels within drainage channel.
	CSH Level 5 Houses 1-2	U-value at 0.10 W/m^2K (Block Work) Silicone coat render system (Wetherby 1.5 silicone 'k' finish or similar) resin bonded fibre mesh applied as per manufactures recommendations onto 200 mm ridged insulation board thermal conductivity of 0.020 w/k (KOOLTHERM K5 EWB or similar approved with render system), insulation fixed back to single leaf minimum 215 mm 7N/sq mm Aircrete concrete blocks with thermal conductivity of 0.19 w/mk or lower with manufactures recommended fixings. The surface finish to the inner face is 1x12.5 mm plasterboard (10 kg/m^2) dry lining with 3 mm skim finish on dot & dabs on 13 mm scratch coat.
	2006 BRS Flat 7	U-value at 0.24 W/m^2K (Timber frame) 20 mm two coat render on rendalath mesh panel (or similar) on 25 mm counter batten fixed 140 mm timber studwork panels filled with 140 m mineral wool with thermal conductivity of 0.035w/k (Knauf flex or similar). The panels are clad in 9 mm OSB board with a tf200 breather membrane stable to the boarding with SS staples. The surface finish to the Inner face is 2x12.5 mm plasterboard (10 kg/m^2) dry lining finish with all joints sealed on top of 25 mm counter batten fixed back to timber stud over Glidevale VC foil air barrier. The decoration is to be of emulsion paint to the clients' requirements on 3 mm skim coat. Weep holes are required at the foot of each cavity wall at cavity tray

		positions and above any horizontal line where the cavity is bridged by fire barriers (i.e. first floor level in flats) at a maximum of 1200 mm centers. Weep hole sleeves incorporate insect resistant grilles.
	2006 BRS House 3	U-value at 0.26 W/m^{2}K (Block Work) 20 mm two coat render on 100 mm outer leaf minimum 7 N/sq mm medium dense concrete blocks with thermal conductivity of 0.5 w/mk or lower. 125 mm full fill cavity insulation board with thermal conductivity of 0.035 w/k (DriTherm Cavity Slabs or similar approved), 100 mm inner leaf medium dense concrete blocks 7 N/sq mm with thermal conductivity of 0.5 w/mk or lower, 12.5 mm plasterboard dry lining on adhesive dabs with 3 mm skim coat. The decoration is to be of emulsion paint to the clients' requirements
Ground Floor	CSH Level 4 Flats 1-6	U-value at 0.13 W/m^{2}K (Timber frame) 22 mm T&G moisture resistant flooring grade chipboard laid on 150 mm Celotex or similar flooring grade foil faced PIR rigid insulation (thermal conductivity value of 0.023W/mK) on 1200 gauge monoflex gas barrier dpm turned up around edges to top of insulation level and taken across the cavity to lap with perimeter cavity tray. 10 mm gap to perimeter of floor insulation boards to allow for product expansion. Structural floor to consist of pre-stressed block and beam to manufacture details.
	CSH Level 5 Houses 1-2	U-value at 0.13 W/m^{2}K (Block Work) 40mm water based screed on slip membrane on 125 mm or similar flooring grade foil faced PIR rigid insulation (thermal conductivity value of 0.020 W/mK) on 1200 gauge monoflex gas barrier dpm turned up around edges to top of insulation level and taken across the cavity to lap with perimeter cavity tray. 10 mm gap to perimeter of floor insulation boards to allow for product expansion. Structural floor to consist of pre-stressed block and beam to manufacture details.
	2006 BRS Flat 7	U-value at 0.18 W/m^{2}K (Timber frame) 22mm T&G moisture resistant flooring grade chipboard laid on 150 mm Flooring grade foil faced PIR rigid insulation (thermal conductivity value of 0.036 W/mK, Jabfloor 100 of similar) on 1200 gauge monoflex gas barrier dpm turned up around edges to top of insulation level and taken across the cavity to lap with perimeter cavity tray. 10 mm gap to perimeter of floor insulation boards to allow for product expansion. Structural floor to consist of pre-stressed block and beam to manufacture details.
	2006 BRS House 3	U-value at 0.19 W/m^{2}K (Block Work) 40mm water based screed on slip membrane on 125 mm Flooring grade foil faced PIR rigid insulation (thermal conductivity value of 0.036 W/mK, Jabfloor 100 of similar) on 1200 gauge monoflex gas barrier dpm turned up around edges to top of insulation level and taken across the cavity to lap with perimeter cavity tray. 10 mm gap to perimeter of floor insulation boards to allow for product expansion. Structural floor to consist of pre-stressed block and beam to manufacture details.
Party walls (separating flats walls or house walls)	CSH Level 4 Flats 1-6	75 mm thick Rocksilk RS100 or similar installed on timber stud partitions. Batts between 89 mm studs in wall on both skins of party walls. 89 mm studs to have minimum 240 mm between inner face of studs. 500g Visqueen vapour barrier stapled to timber studs of the wall and taped to ceiling vapour barrier to provide air tight seal to both skins of party wall. 1x layers 19 mm (14.5 kg) plasterboard plank and 1x layer of 13 mm (8.5 kg) plasterboard, sheets staggered over joints. Counter batten with 25 mm and 1x layer of 13 mm (8.5kg) plasterboard and 3 mm skim coat. This provides an 8db improvement over existing Part E acoustic regulations.
	CSH Level 5 Houses 1-2	Twin leaf 100 mm solid dense blocks (1350-1600 kg/m^3) with 100 mm min. cavity filled with isover RD party wall roll or similar, Type A wall ties, 13 mm scratch coat each side gypsum-based board (9.8 kg/m^2) on dabs with 3 mm skim and paint. This provides an 8db improvement over existing Part E acoustic regulations.
	2006 BRS Flat 7	75mm thick Rocksilk RS30 or similar installed on timber stud partitions. Batts between 89mm studs in wall on both skins of party walls. 89 mm studs to have minimum 240 mm between inner face of studs. 500g Visqueen vapour barrier stapled to wall and taped to ceiling vapour barrier to provide air tight seal to both skins of party wall. Counter battern timber frame with 25 mm, to form stud work and prevent penetration through air permeable barrier. 2x layers 19 mm plasterboard plank fixed to counter batten, plasterboard sheets staggered at joints over, 3 mm skim coat.
	2006 BRS House 3	Twin leaf 100 mm solid aircrete blocks (600-800 kg/m^3), with 100 mm min. cavity including proprietary foil faced glass wool acoustic batts Isover RD35 or similar, Type A wall ties, gypsum-based board (9.8 kg/m^2) on dabs with 3 mm skim and paint.
Compartment floor	CSH Level 4 Flats 1-6 2006 BRS Flat 7	18mm T&G Board (3 mm ply over where vinyl floor installed), 2x19 mm 13.5 Kg plasterboard on 45 mm composite acoustic battens. 25 mm mineral wool

	(10-36 kg/m^3) between batten on top of cassette floor board, thickness specified by manufacture. Within floor joist area, 150mm thick Rocksilk RS45 or similar. Batts between 241 mm engineered joists. To underside of joists, 500 g Visqueen vapour barrier stapled to joist and taped to wall vapour barrier to provide air tight seal. 16 mm resilient bar attached to underside of joists and hang 19.5 mm 13.5 Kg board and overlap with 12.5 mm 12 kg knauf sound shield board or similar. Metal Frame suspended ceiling fixed to the underside of double plasterboard layer giving a 150 mm ceiling void. 1 layer 15 mm 13.8 kg Knauf Soundshield or similar plasterboard sheets. This provides an 8db improvement over existing Part E acoustic regulations.

Appendix B. Descriptive statistics of the monitored variables

Table B.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)	Rainfall (mm)
All year	All year	Mean	20.6	55.9	12.4	77.6	2.4	105.3	1.8
		Median	20.7	55.0	11.9	80.3	1.9	2.1	0.0
		SD	2.1	8.3	5.4	10.4	2.1	185.1	3.8
		Min	11.4	32.3	-0.1	35.9	0.0	0.3	0.0
		Max	27.7	87.9	34.4	94.2	22.3	1171.4	28.2
Spring	Morning	Mean	19.9	54.0	10.9	79.0	2.4	278.9	1.1
		Median	20.0	52.8	10.9	80.9	2.1	216.3	0.0
		SD	1.9	8.0	3.5	8.8	1.8	242.0	2.5
		Min	13.7	33.3	2.0	41.5	0.0	0.4	0.0
		Max	25.8	85.8	26.7	92.5	12.4	1171.4	16.2
	Afternoon	Mean	20.1	52.5	14.7	67.4	3.1	311.1	1.8
		Median	20.2	51.5	14.3	68.1	2.8	258.6	0.0
		SD	1.8	7.8	4.3	12.3	1.8	233.6	3.2
		Min	14.2	32.3	5.7	37.8	0.0	2.1	0.0
		Max	25.7	78.2	28.6	92.1	14.5	1143.6	16.4
	Evening	Mean	20.5	52.6	11.0	76.6	2.0	9.4	2.6
		Median	20.7	51.8	10.9	77.8	1.6	1.9	0.2
		SD	1.8	7.1	3.2	8.3	1.6	25.5	4.2
		Min	14.4	33.2	3.7	39.7	0.0	0.3	0.0
		Max	25.6	87.2	24.2	92.2	12.2	270.7	18.2
	Night	Mean	20.0	53.6	9.0	82.3	1.7	4.7	0.4
		Median	20.2	52.0	9.1	83.2	1.3	1.9	0.0
		SD	1.8	8.1	2.6	5.2	1.5	15.1	1.3
		Min	13.9	35.9	2.5	61.9	0.0	0.4	0.0
		Max	25.0	78.5	17.1	92.5	11.6	212.3	10.6
Summer	Morning	Mean	21.9	58.8	17.3	73.3	2.1	337.0	1.4
		Median	22.0	58.5	16.8	74.7	1.9	278.4	0.0
		SD	1.7	5.9	3.4	9.5	1.5	244.6	3.7
		Min	16.1	41.8	8.7	41.2	0.0	2.8	0.0
		Max	27.7	87.9	31.2	88.3	9.1	1125.2	19.8
	Afternoon	Mean	22.3	57.3	21.2	60.8	3.0	390.6	2.1
		Median	22.3	57.0	20.1	60.0	2.9	344.2	0.0
		SD	1.8	6.1	4.6	11.5	1.4	241.3	4.6
		Min	16.7	40.6	9.9	35.9	0.0	9.5	0.0
		Max	27.7	81.5	34.4	88.1	10.6	1137.1	20.8
	Evening	Mean	22.5	56.8	17.4	71.1	1.9	23.6	2.6
		Median	22.6	56.6	16.8	72.5	1.7	1.9	0.0
		SD	1.8	6.2	3.6	10.2	1.4	53.5	5.3
		Min	17.0	37.3	9.2	36.0	0.0	0.3	0.0

		Max	27.6	78.8	30.8	88.6	10.2	518.9	21.4
	Night	Mean	22.2	58.0	14.7	79.3	1.3	6.7	0.6
		Median	22.2	57.7	14.8	80.8	1.0	1.9	0.0
		SD	1.8	6.1	2.5	5.8	1.3	18.3	2.4
		Min	16.1	39.9	8.1	59.3	0.0	0.4	0.0
		Max	27.4	78.0	22.6	89.0	11.1	192.3	19.6
Autumn	Morning	Mean	20.3	61.5	12.5	81.8	2.1	141.2	1.0
		Median	20.5	61.4	13.3	83.0	1.7	83.5	0.0
		SD	1.9	8.3	4.5	6.6	1.9	156.4	2.7
		Min	12.9	41.2	-0.1	51.9	0.0	0.3	0.0
		Max	25.6	88.0	24.6	94.1	15.1	858.8	19.0
	Afternoon	Mean	20.3	60.6	15.4	73.1	2.6	143.3	1.3
		Median	20.5	61.2	14.9	74.1	2.3	95.7	0.0
		SD	2.1	8.3	5.4	10.2	1.8	149.0	3.2
		Min	13.5	40.7	4.3	44.8	0.0	0.4	0.0
		Max	25.2	86.0	27.8	92.3	12.5	804.3	21.4
	Evening	Mean	20.6	60.6	12.8	79.6	1.8	2.2	1.8
		Median	20.9	61.3	12.9	80.9	1.3	1.8	0.2
		SD	1.9	8.1	4.5	7.1	1.9	2.9	3.9
		Min	13.5	39.2	1.2	54.0	0.0	0.3	0.0
		Max	25.5	83.7	23.9	93.6	13.6	50.3	21.4
	Night	Mean	20.5	61.4	11.6	83.2	1.6	1.9	0.4
		Median	20.7	61.4	12.4	83.5	1.1	1.9	0.0
		SD	2.0	8.4	4.0	4.8	1.9	0.4	1.5
		Min	13.5	41.7	0.3	69.0	0.0	0.5	0.0
		Max	24.9	87.4	19.0	94.2	14.9	12.8	13.6
Winter	Morning	Mean	19.3	54.0	7.2	84.7	3.3	61.8	2.0
		Median	19.7	51.9	7.2	85.8	2.6	15.8	0.4
		SD	2.0	8.8	2.3	5.1	3.0	98.0	3.6
		Min	11.4	35.8	0.9	67.3	0.0	0.5	0.0
		Max	24.2	84.5	12.9	93.4	22.3	693.8	26.0
	Afternoon	Mean	19.3	52.8	8.7	80.5	3.6	80.4	3.6
		Median	19.7	51.1	8.7	80.4	3.0	35.6	1.4
		SD	1.9	8.2	1.9	6.8	2.7	105.8	5.1
		Min	12.9	37.4	3.4	60.2	0.0	0.4	0.0
		Max	25.4	84.9	12.8	93.0	21.1	692.0	27.4
	Evening	Mean	20.1	52.8	7.3	84.3	2.9	1.9	5.2
		Median	20.6	51.1	7.4	84.6	2.1	1.9	3.4
		SD	2.1	8.0	2.4	4.9	2.7	0.1	5.9
		Min	12.3	37.1	2.3	64.7	0.0	0.7	0.0
		Max	26.0	85.6	12.9	92.7	19.6	4.3	28.2
	Night	Mean	19.7	53.9	6.7	85.1	2.7	1.9	0.6
		Median	20.0	51.9	6.9	85.3	2.0	1.9	0.0
		SD	2.0	9.0	2.5	4.0	2.5	0.1	1.3
		Min	11.6	37.9	1.2	67.1	0.0	1.6	0.0
		Max	25.4	83.6	12.9	92.6	16.3	2.2	10.0

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[i] It is somewhat ironic that in a country for which rain is something of a national obsession, that it would affect occupants' window interactions, whereas solar radiation (sunny weather) was in general found to have little or no effect.