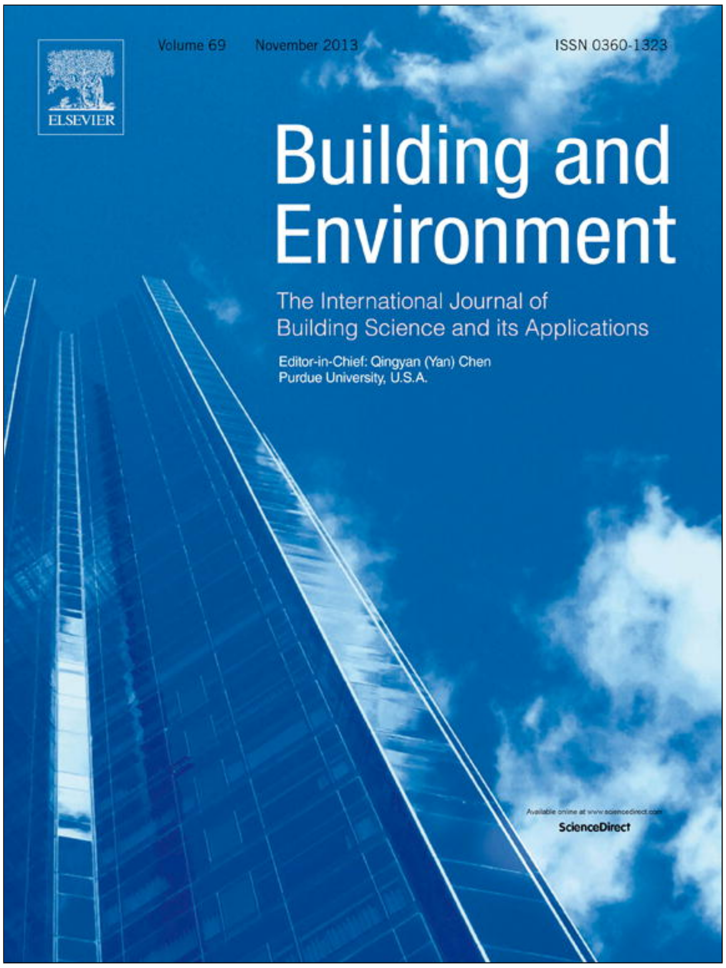
Volume 69
November 2013
ISSN 0360-1323
ELSEVIER
Building and Environment
The International Journal of Building Science and its Applications
Editor-in-Chief: Qingyan (Yan) Chen
Purdue University, U.S.A.
ScienceDirect

Building and Environment 69 (2013) 101–113

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Window opening behaviour modelled from measurements in Danish dwellings

Rune Andersen [a,*], Valentina Fabi [b], Jorn Toftum [a], Stefano P. Corgnati [b], Bjarne W. Olesen [a]

[a] International Centre for Indoor Environment and Energy, Department of Civil Engineering, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark
[b] Department of Energy, Polytechnic of Turin, Italy

ARTICLE INFO

Article history:
Received 8 January 2013
Received in revised form
4 July 2013
Accepted 8 July 2013

Keywords:
Occupant behaviour
Building controls
Adaptation
Window opening
Building energy performance simulation
Air quality

ABSTRACT

A method of defining occupants' window opening behaviour patterns in simulation programs, based on measurements is proposed.

Occupants' window opening behaviour has a strong effect on indoor environment and the energy consumed to sustain it. Only few models of window opening behaviour exist and these are solely based on the thermal indoor/outdoor environment. Consequently, users of simulation software are often left with little or no guidance for the modelling of occupants' window opening behaviour, resulting in potentially large discrepancies between real and simulated energy consumption and indoor environment.

Measurements of occupant's window opening behaviour were conducted in 15 dwellings in Denmark during eight months. Indoor and outdoor environmental conditions were monitored in an effort to relate the behaviour of the occupants to the environmental conditions. The dwellings were categorized in four groups according to ventilation type (natural/mechanical) and ownership (owner-occupied/rented) in order to investigate common patterns of behaviour. Logistic regression was used to infer the probability of opening and closing a window.

The occupants' window opening behaviour was governed by different but distinct habits in each dwelling. However, common patterns were also identified in the analysis: Indoor CO_2 concentration (used as indicator of indoor air quality) and outdoor temperature were the two single most important variables in determining the window opening and closing probability, respectively.

The models could be implemented into most simulation programs, which would enable a better chance of mimicking the behaviour of the occupants in the building and thus simulating the indoor environment and energy consumption correctly.

1. Introduction

Occupants who have the possibility to control their indoor environment have been found to be more satisfied and suffer from fewer building related symptoms than occupants who occupy environments in which they have no control [1–4]. These studies emphasize the significance of providing occupants with rich opportunities of interacting with building controls. In doing so, the control of the building is to some extent left in the hands of the occupants. However, occupant behaviour varies significantly between individuals which results in large variation of the indoor environment and energy consumption of buildings [5–9]. Because of this, it is important to take occupants' interactions with building controls into account when designing buildings.

Most building simulation programs provide possibilities of regulating the simulated environment by adjusting building controls (opening windows, adjusting temperature set-points etc.). However, discrepancies between simulated and actual behaviour can lead to very large offset between simulation results and actual energy use [10,11]. Indeed, Andersen et al. showed that differences in occupant behaviour might lead to differences in energy consumption of over 300% [12]. Thus, there is a need to set up standards or guidelines to enable comparison of simulation results between simulation cases. One method that can provide this is to define typical behaviour patterns that can be implemented in building simulation programs. This would significantly improve the validity of the outcome of the simulations. A definition of such typical behaviours should be based on the quantification of real occupant behaviour.

* Corresponding author. Tel.: +45 4525 4029; fax: +45 4593 2166.
E-mail addresses: rva@byg.dtu.dk, rune.v.andersen@gmail.com (R. Andersen).

0360-1323/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.buildenv.2013.07.005

Table 1
Overview of referenced studies of window opening and ventilation.

Reference	Sample size	Geographical location	Duration of measurement
[13]	One single family house	Virginia, USA	One year
[14]	Two single family houses	California and Virginia, USA	One year
[15]	9 apartments and 19 single family houses	Denmark	One week
[16]	500 dwellings	Denmark	2.5 nights (only nights)
[17]	15 office buildings, Transverse questionnaires from 890 subjects and longitudinal questionnaire and measurements from 219 subjects	UK	Transverse: 1 day each month for one year. Longitudinal: 3 months
[18]	60 subjects from several office buildings	Switzerland	3 months
[19]	One office building (21 offices)	Germany	13 months
[20]	2 office buildings (6 offices)	UK	3 months
[21]	2 office buildings (6 offices)	UK	3 months
[22]	Surveys and spot measurements from 846 people in 33 office buildings	Pakistan	1 questionnaire each month for 16 months
[23]	One office building (14 offices)	Switzerland	7 years
[24]	Three apartments and 39 student dormitory rooms	Switzerland and Japan	Apartments: 1 year. Dormitory: 1 month
[25]	1 office building (4 offices)	Switzerland	One winter
[26]	Repeated questionnaire in 933 (summer) and 636 (winter) dwellings	Denmark	2 questionnaires
[27]	1100 dwelling	North Carolina, USA	72 survey sessions, consisting of 2 observations of 1100 dwellings
[28]	Literature review	–	–
[29]	Literature review	–	–
[34]	24 dwellings	Scotland, UK	Daily visits and spot measurements for 7 months
[35]	Summary report of 22 studies in dwellings. Sample size: from 5 to 3000	Germany, The Netherlands, Switzerland, UK and Belgium	Questionnaires, observations, continuous measurements
[36]	Repeated questionnaire in 933 (summer) and 636 (winter) dwellings	Denmark	2 questionnaires

Two important parameters influencing energy consumption in dwellings are indoor temperature and air change rate. Wallace et al. measured air change rates in a house during one year and found that the opening and closing of windows had the largest effect on the air change rate [13]. Also Howard-Reed et al. found that opening of windows produced the greatest increase in air change rates compared with temperature differences and wind effects [14]. Kvistgaard and Collet [15] measured air change rates in 16 Danish dwellings and noted that there was considerable difference in the total air change between individual dwellings. As the basic air change[1] was similar, it was concluded that the behaviour of the occupants caused these large differences. Also Bekö et al. [16] concluded that the occupants' behaviour had the largest effect on air change rates, in their measurements of air change rates in 500 bedrooms. In Danish dwellings, mechanical cooling is almost never used, which means that the indoor temperature depends on the heating set point in winter and on the air change rate in the summer. As a consequence, window opening behaviour and heating set point behaviour of occupants play an important role in determining the energy consumption and indoor environment of a household.

Recently, the effect of indoor and outdoor temperature on the window opening behaviour in offices has been investigated by means of logistic regression [17–24]. The general trend has been to infer the probability of the window state as a function of indoor and outdoor temperature, while some have investigated the probability of opening a window (change from one state to another) as a function of temperature [20,21,23]. Haldi and Robinson argued that the indoor temperature would be a better predictor than the outdoor temperature because indoor temperature is a driver for opening and closing windows to a much larger extent than outdoor temperature [18]. In a later paper Haldi and Robinson addressed the differentiation between indoor and outdoor stimuli for openings and closings and tested several modelling approaches [23]. Since indoor environmental parameters are influenced by the state of the windows, it is problematic to infer the latter based on indoor parameters e.g. indoor temperature. The problem is that the predictive variable is influenced by the state that it is trying to predict. In a cold climate, the low indoor temperatures would occur when the windows are open and not when they are closed. In such a case the result of the analysis would be that the inferred probability of a window being open increases with decreasing indoor temperature, with the illogical implication that the probability of opening a window would increase with decreasing indoor temperatures.

Another problem with this approach is that the driving forces for opening and closing a window might be different. The window might be opened due to bad air quality or high humidity and closed because of low indoor temperature. We have overcome these problems by inferring the probability of opening and closing windows (change from one state to another) rather than modelling the state of the window itself. When using this approach, the predictive variables are not influenced by the state of the window and the most dominating drivers were inferred separately for each action (opening and closing the window).

Most recent studies have been limited to the investigation of thermal stimuli [17–22,25] although other studies have found that many other stimuli play an important role in determining the window opening behaviour [26–29]. Table 1 provides information on sample size, measuring duration and building type of the referenced studies on window opening and ventilation.

The objective of this study was to quantify the influence of environmental factors on occupants' window opening behaviour in Danish residential buildings.

2. Method

Andersen et al. [26] quantified behaviour of occupants in Danish dwellings by means of a questionnaire survey. A definition of

[1] With all windows and doors closed.

standard behaviour patterns was attempted, but a link to the indoor environment was missing due to the effects of behaviour of the occupants on the indoor environment. As a follow up to the questionnaire survey and to fill this gap, simultaneous measurement of occupant behaviour, and indoor and outdoor environment was carried out in (and outside) 15 dwellings during the period from January to August 2008.

2.1. The dwellings

Measurements were carried out in 10 rented apartments and five privately owned single family houses. Five of the apartments were naturally ventilated (apart from an exhaust hood in the kitchen) while the other five were equipped with constantly running exhaust ventilation from the kitchen and bathroom. Three of the single-family houses were naturally ventilated while the other two were equipped with exhaust ventilation.

With the exception of one (located 60 km from Copenhagen), all dwellings were located less than 25 km from Copenhagen.

Features of the dwellings and residents are described in Table 2.

All dwellings were constructed from brick, used waterborne radiators/convectors and natural gas boilers as a primary means of heating and two of the dwellings (number 10 and 16) had a wood burning stove. None of the dwellings had major overshadow from adjacent buildings.

A survey among 16 690 persons in Denmark, found that outside pollution and noise posed constraints to window opening in very few cases even in the most densely populated areas [30]. Based in this and on observations during the visits to the buildings, we assessed that none of the buildings were located in an environment, where outside pollution and outside noise posed constraints to window opening. In two dwellings (1 and 7) some of the residents smoked inside.

2.2. Measurements

The following variables were measured continuously in all 15 dwellings.

Indoor environment factors measured every 10 min

- Dry bulb temperature (°C)
- Relative humidity (RH) (%)
- Illuminance (Lux)
- CO_2 concentration (ppm)

Outdoor environment acquired from meteorological measuring stations in 10 min intervals [31]

- Air temperature (°C)
- RH (%)
- Wind speed (m/s)
- Global Solar radiation (W/m^2)
- Sunshine hours (daily values) (Number of hours with sunshine (insolation higher than 120 W/m^2))

Behaviour

Window position (open/closed)*

*In three of the dwellings, the actual opening angle of the window was measured.

Fig. 1 depicts some of the monitored windows.

The indoor environment measurements were carried out with Hobo U12-012 data loggers [32]. The CO_2 concentration was measured using a Vaisala GMW22 sensor [33] connected to the Hobo logger as depicted in Fig. 2. Both the CO_2 sensors and the Hobo data loggers were newly calibrated from the factory. The CO_2 sensors were tested against a newly calibrated Innova multigas analyser both before and after the measuring period. The temperature sensors in the hobo data loggers were also tested before the measurements. The outdoor environmental variables were obtained from the Danish meteorological institute [31]. Data from the meteorological station closest to each of the dwellings was used. The closest meteorological stations did not measure precipitation and since local wind direction is very sensitive to local conditions it was decided not to include the direction of the wind.

The window position (open/closed) was measured using a Hobo U9 sensor [32]. Three of the windows were hitched in the top and tilted outwards when opening. In these cases the tilt was measured using an accelerometer (HOBO UA-004-64 Pendant G) [32] attached to the window frame. In this way, the opening angle of the window was measured.

Generally, all measurements were carried out in the (main) living room and the (main) bedroom in each dwelling. The window sensors were installed on windows that inhabitants used most often when ventilating the dwelling. The number of operable windows varied between dwellings from 1 to 4 windows in the bedrooms and 3 to 6 windows in the living rooms.

Table 2
Description of residents and characteristics of the dwellings.

Dwelling index	Number of openings in period	Average age of the residents	Number of residents	Year of construction (and renovation)	Floor area (m^2)	Distance from meteorological station (km)[a]	Floor level	Smokers amongst residents
1	334	65	1	1994	126	8	Ground	Yes
3	82	57	2	1928	145	13	Ground	No
4	235	70	2	1956 (1976)	130	4	Ground	No
5	73	76	2	1981 (2001)	83	11	1st	No
6	337	78	2	1945	86	5	1st	No
7	718	63	1	1981 (2001)	83	11	2nd	Yes
8	258	55	2	1945	109	5	2nd	No
9	25	35	3	1945	87	5	1st	No
10	65	59	2	1901 (1957)	190	8	Ground	No
11	82	71	2	1945	77	5	1st	No
12	1	64	1	1945	109	5	1st	No
13	341	60	3	1981 (2001)	80	11	Ground	No
14	241	28	2	1981 (2001)	85	11	Ground	No
15	166	60	4	1981 (2001)	84	11	1st	No
16	153	26	2	1967	139	9	Ground	No

[a] The distance was measured in a straight line from the address to the geographical location of the weather station.

Fig. 1. Pictures of windows in some of the monitored dwellings. The rest of the monitored windows were of similar type and of similar size.

Fig. 2. Pictures of the instruments used to measure the indoor environmental variables and window opening behaviour. Top left: CO_2 monitor connected to a data-logger with built in temperature, relative humidity and illumination sensors. Top right: Window state sensor (open/closed). Bottom: window state sensor (open/closed) and window position sensor.

2.3. Place of measurement

Our measurements were limited to two rooms in each dwelling. Brundrett [34] found that open windows were most commonly found in the bedroom, particularly the main bedroom, while the sitting room, kitchen and the dining room had the lowest frequency of open windows. This was later supported by Dubrul [35] who found that bedrooms were the main ventilation zone, whereas the majority of windows which were never opened was in the living rooms. Furthermore, the percentage of open windows in kitchens and bathrooms was similar to that of living rooms. Based on these findings we chose to conduct the measurements in the main bedroom and in the main living room in each dwelling. This choice was made in an effort to select the rooms with the highest and lowest window opening frequency.

3. Processing and preparation of data

The indoor environment sensors were placed on internal walls at a height of roughly 1.8 m above the floor with a minimum distance of one metre to the closest radiator/convector. We attempted to place the sensors so they would not be hit by direct sunlight. In eight of the dwellings, this was not always possible due to acceptance of the occupants in the dwellings and other practicalities. In the cases when direct sunlight fell on the sensors, the temperature measurements were corrected for the heating of the sensor. This was done in periods when the measured illuminance was larger than 1000 lux. In these cases the temperature was corrected by linear interpolation between temperature measurements 30 min prior to and one hour after direct sunlight fell on the sensor. In the eight dwellings, between 1% and 2% of the temperature measurements were corrected for direct solar radiation.

The CO_2 concentration was used as an indicator of the occupancy of the rooms where the measurements took place. If the CO_2 concentration was below 420 ppm and the window was closed the room was classified as being unoccupied. Furthermore, if the CO_2 concentration was higher than 420 ppm, but decreased and continued to decrease until reaching values below 420 ppm and the window was closed in the entire period, the room was classified as unoccupied during the period of concentration decay.

The value of 420 ppm was chosen since earlier observations had shown that the outdoor concentrations might reach levels of up to 400 ppm. To ensure that long unoccupied periods were not classified as occupied an uncertainty range of 20 ppm was added to the highest observed outdoor concentration.

The room was classified as occupied if the window was open. This classification was based on a questionnaire survey conducted by Andersen et al. [36] who found that the statement "I had to leave the dwelling" was mentioned amongst the most common reasons for closing windows.

If the bedroom and the living room were both unoccupied, the dwelling was classified as unoccupied. Periods when the dwelling was unoccupied were not taken into consideration in the analysis.

When analysing the window opening data the database was divided depending on the state of the window (open/closed) to infer the probability of opening and closing the window (change from one state to another) separately. The 15 dwellings were divided into four groups based on ownership (owner-occupied or rental) and ventilation type (natural ventilation or mechanical ventilation) (Table 2). This division was based on the findings in Andersen et al. (2009) [26] and an assumed effect of ventilation principle on window opening behaviour. Table 3 shows how the dwellings were divided in the four groups.

Table 3
Description of groups investigated related to the ownership and ventilation type.

Group	Ownership	Ventilation type	Dwelling index
1	Owner-occupied	Natural	3, 4, 16
2	Owner-occupied	Mechanical	1, 10
3	Rental	Natural	6, 8, 9, 11, 12
4	Rental	Mechanical	5, 7, 13, 14, 15

3.1. Statistical analysis

Multivariate logistic regression with interactions between selected variables was used to infer the probability of a window opening and closing event. The method relies on the probability function described in formula (1).

$$\log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n \quad (1)$$

where

p is the probability of an opening/closing event
a is the intercept
b_{1-n} are coefficients
x_{1-n} are explanatory variables such as temperature, CO_2 concentration etc.

However, the probability might depend differently on x_1 at one level of x_2 as compared to another level of x_2 (e.g. an increase in temperature might increase the probability of opening a window in the bedroom, whereas the same increase might result in a lower probability in the living room). An example like the one described above would not be well described by a model based on equation (1). Equation (2) deals with interactions between variables by adding interaction terms to the model.

$$\log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n + c_{12} \cdot x_1 \cdot x_2 + c_{13} \cdot x_1 \cdot x_3 + \cdots \quad (2)$$

Equation (2) was used to infer the probability of windows being opened or closed. The Akaike information criterion (AIC) was used as a basis for forward and backward selection of variables in the regression models [37]. Each individual variable was first fitted to the measured window opening data and then AIC was calculated

Table 4
List of explanatory variables used to infer the models of opening and closing windows.

Variable	Unit
Season	Winter/spring/summer
Room	Bedroom/living room
Time of day	Night/morning/day/afternoon/evening
Week day	Workday/weekend
Outdoor temperature	°C
Wind speed	m/s
Outdoor relative humidity	%
Solar radiation	W/m^2
Solar hours	h
Indoor temperature	°C
Indoor relative humidity	%
Indoor illumination	Lux
Indoor CO_2 concentration	ppm
Indoor Dew point	°C
Dwelling index	–

Table 5
Variable transformations. Log is the natural logarithm.

Variable	Transformed variable
CO_2 concentration [ppm]	Log(CO_2) [Log(ppm)]
Illumination [Lux]	Log(Illumination) [Log(Lux)]
Wind speed [m/s]	Log(Wind speed + 1) [Log(m/s)]
Solar radiation [w/m^2]	Log(Solar radiation + 1) [Log(W/m^2)]

for each fit. The variable with the lowest AIC was selected and the remaining variables were then tested one by one on a bivariate level, to see if any of the bivariate models resulted in a lower AIC. If this was the case, the remaining variables were tested in a model with three variables and so on (forward selection). At each step, the AIC was also calculated for models, where each of the selected variables was removed from the models (backward selection). In this way, the final model included variables and interaction terms that resulted in the lowest AIC. To limit the complexity of the model, only interaction terms between continuous and nominal variables, e.g. indoor temperature and day of week were included in the analyses. Table 4 lists all explanatory variables used in the inference of the window opening and closing models.

In the interpretation of the coefficients, the sign, the size and the scale of the corresponding variable have to be taken into account. For example, a coefficient for solar hours of 0.057 might seem to impact the probability more than an outdoor relative humidity coefficient of 0.029 (group 4, opening model). However, the scales of the two variables (solar hours: 0 to 16.1, outdoor RH: 28%–100%) should be taken into account: Schweiker et al. [39] suggested to multiply the scale of the variable with the coefficient, to get an indication of the magnitude of the impact from each variable. In the example described above the magnitude of the impact was $0.057(16.1-0) = 0.91$ and $0.029(100-28) = 2.08$ for the solar hours and the outdoor relative humidity respectively, revealing that the outdoor RH had a higher impact on the probability than the solar hours.

When using logistic regression, it is required that all variables are independent. Since the data was obtained in 15 dwellings with different physical properties and different inhabitants, all variables could not be assumed a priori to be independent of the dwelling it was obtained from. Variable independency was tested by assigning an index to each of the dwellings, which was used as a factor in the analyses. If an interaction term between a variable and the dwelling index was retained in the model, it was taken as an indication of

Table 6
Descriptive statistics of the monitored variables used to infer the window opening and closing models.

		Indoor temperature	Indoor R.H.	CO_2	Outdoor temperature	Outdoor R.H.	Lux	Wind	Solar radiation	Solar hours
Group 1										
Windows closed	Max	30.3	69	3065	26.9	100	16063	13.2	918	16.1
	Min	17.1	24	355	−6.9	24	4	0.0	0	0.0
	Mean	22.1	46	862	9.6	76	159	2.8	199	8.5
	Median	21.8	45	773	9.3	76	51	2.5	63	8.1
	St. Dev.	2.0	7	369	6.2	18	458	2.1	252	5.0
Windows open	Max	29.2	67	2229	25.5	100	8077	9.1	904	16.1
	Min	17.2	26	328	−1.4	30	4	0.0	0	0.0
	Mean	22.9	38	520	13.5	61	278	3.1	413	10.8
	Median	22.8	38	464	13.6	58	99	3.0	437	13.0
	St. Dev.	1.8	6	175	5.1	18	447	1.7	272	4.7
Group 2										
Windows closed	Max	27.3	49	4453	24.0	100	1494	17.3	904	14.9
	Min	13.5	24	377	−6.0	25	4	0.0	0	0.0
	Mean	22.3	36	722	7.5	75	111	3.3	165	6.9
	Median	22.6	35	648	7.0	78	36	2.7	23	6.1
	St. Dev.	2.0	4	310	5.1	18	183	2.6	234	4.8
Windows open	Max	27.3	53	1959	24.0	100	32280	17.3	883	14.9
	Min	12.0	25	363	−6.0	25	4	0.0	0	0.0
	Mean	18.1	40	516	8.0	74	295	4.3	203	6.7
	Median	17.2	40	468	7.0	78	43	3.7	91	6.3
	St. Dev.	3.2	5	142	5.4	19	1500	2.9	240	4.8
Group 3										
Windows closed	Max	31.2	63	3634	26.3	100	32280	13.0	904	15.3
	Min	14.1	21	338	−5.8	24	4	0.0	0	0.0
	Mean	22.3	37	780	7.4	73	179	3.3	164	6.1
	Median	22.3	37	612	6.8	76	43	2.9	36	5.5
	St. Dev.	2.0	5	462	5.2	18	888	2.2	230	5.0
Windows open	Max	27.7	54	3295	26.3	100	2456	13.0	883	15.2
	Min	11.5	22	333	−5.8	25	4	0.0	0	0.0
	Mean	19.9	38	590	7.9	75	80	3.3	141	6.7
	Median	19.1	38	520	6.3	80	43	2.9	6	5.7
	St. Dev.	3.5	5	232	6.0	19	130	2.2	229	5.4
Group 4										
Windows closed	Max	28.8	73	4636	28.6	100	23442	13.5	918	16.1
	Min	9.8	21	333	−7.7	28	4	0.0	0	0.0
	Mean	20.9	42	702	7.9	80	85	3.0	138	6.6
	Median	20.8	42	628	7.1	84	36	2.5	11	6.2
	St. Dev.	2.2	8	292	5.9	17	206	2.3	208	4.7
Windows open	Max	29.1	69	3530	29.4	100	13935	13.5	918	16.1
	Min	11.9	22	328	−7.2	28	4	0.0	0	0.0
	Mean	22.0	44	492	14.1	71	132	3.1	293	9.2
	Median	22.2	43	437	14.6	71	59	2.7	238	9.4
	St. Dev.	2.4	8	142	5.9	19	229	2.1	276	5.0

Table 7
A list of variables that interacted with the dwelling index indicating that they were not independent of the dwelling in which they were measured. The table states in which models (Open and/or close) the interactions were found. If interactions with the dwelling index occurred, the variable was removed from the window opening and/or closing models.

Model	Indoor temperature	Outdoor temperature	Solar radiation	CO_2 concentration	Time of day	Illumination
Group 1	None	None	None	None	None	None
Group 2	Open and Close	Open	Open	None	None	None
Group 3	None	None	Close	Close	None	None
Group 4	Close	None	None	Close	Open and Close	Close

dependence and the variable was removed from the model. Variables that did not interact with the dwelling index were assumed to be independent of the individual dwelling.

Correlations between explanatory variables may result in inflation of the estimated variance of the inferred coefficient, which in turn will result in too wide confidence intervals. To estimate the size of the inflation due to correlations between all explanatory variables (multicolinearity), generalized variance inflation factors (GVIF) were calculated for coefficients of all continuous explanatory variables. The GVIF estimates the inflation of the variance, due to multicolinearity as compared to no multicolinearity. Since the GVIF is an estimate of the inflation of the variance, the $GVIF^{1/(2 \cdot Df)}$ is an estimate of the factor by which the standard error and confidence interval is inflated due to multicolinearity between explanatory variables.

Prior to the regression analyses, four variables were transformed to obtain a better distribution. Table 5 describes how the variables were transformed.

The statistical analyses were conducted using the statistical software “R” and the models were inferred using the ‘step’ function in R [38].

4. Results

In this section, the main results of the statistical analysis are presented. Table 6 presents descriptive statistics of all measured variables in each of the four groups.

All results from group 1 are presented in this section, while tables with inferred coefficients and results from the VIF analyses from groups 2, 3 and 4 are presented in Appendix 1.

The dwelling index affected the impact of some of the explanatory variables as concerns the probability of opening and closing a window. This indicates different habits in the different dwellings included in the four groups, which were not described by the measured variables. For example, the CO_2 concentration interacted with the dwelling index in the model for closing windows in group 3, indicating that the windows were closed at different (but distinct) concentrations of CO_2 in each dwelling. The variables that interacted with the dwelling index were removed from the models where the interaction occurred. In the further analyses, the dwelling index was not included, since we were not interested in the behaviour in each single dwelling, but in the overall behaviour in all of the surveyed dwellings.

Table 8
Coefficients and magnitudes of the opening and closing models inferred based on data from Group 1. The coefficient refers to the “a” and “b_{1-n}” in formula (2). The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Time/room	Open window				Close window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.5%	97.5%			2.5%	97.5%	
Intercept Spring – Bedroom	Night	−23.83	−27.78	−19.88		−1.93	−3.67	−0.19	
	Morning	−23.04	−27.06	−19.03		−0.84	−2.71	1.03	
	Day	−24.06	−28.10	−20.03		−1.22	−3.09	0.65	
	Afternoon	−24.32	−28.35	−20.29		−1.00	−2.87	0.87	
	Evening	−24.47	−28.49	−20.45		−0.38	−2.25	1.48	
Intercept – Spring – Living room	Night	−10.58	−16.40	−4.76		−5.31	−7.76	−2.87	
	Morning	−9.80	−15.66	−3.93		−4.22	−6.76	−1.69	
	Day	−10.82	−16.69	−4.94		−4.61	−7.15	−2.07	
	Afternoon	−11.08	−16.95	−5.20		−4.39	−6.93	−1.85	
	Evening	−11.22	−17.09	−5.35		−3.77	−6.31	−1.23	
Intercept – Summer – Bedroom	Night	−24.72	−28.69	−20.75		−0.77	−2.59	1.05	
	Morning	−23.94	−27.97	−19.91		0.32	−1.62	2.26	
	Day	−24.96	−29.00	−20.91		−0.06	−2.01	1.88	
	Afternoon	−25.22	−29.26	−21.17		0.16	−1.79	2.10	
	Evening	−25.36	−29.40	−21.33		0.77	−1.17	2.72	
Intercept – Summer – Living room	Night	−11.47	−17.35	−5.60		−4.15	−5.98	−2.32	
	Morning	−10.69	−16.58	−4.80		−3.06	−5.02	−1.11	
	Day	−11.71	−17.60	−5.82		−3.45	−5.40	−1.49	
	Afternoon	−11.97	−17.85	−6.09		−3.23	−5.19	−1.27	
	Evening	−12.12	−17.95	−6.28		−2.61	−4.56	−0.66	
CO_2 concentration [log(ppm)]	Bedroom	1.87	1.37	2.37	4				
	Living room	$0.23 \cdot 10^{-3}$	−0.81	0.81	0.00				
Indoor temperature [°C]		0.163	0.11	0.22	2.15				
Solar radiation [log(W/m^2)]		0.501	0.14	0.86	3.42				
Outdoor temperature [°C]						−0.15	−0.19	−0.12	−4.07
Outdoor relative humidity [%]						−0.02	−0.03	−0.01	−1.21
Indoor relative humidity [%]	Bedroom					0.037	−0.003	0.077	1.56
	Living room					0.104	0.046	0.162	4.34

Table 7 shows a list of variables that were removed from the models due to interactions with the dwelling index.

4.1. Group 1: owner-occupied, naturally ventilated dwellings

As expected, CO_2 concentration, indoor temperature and solar radiation were positively correlated with the probability of opening the window, while Outdoor Temperature was negative correlated with the probability of closing windows. In the bedroom, the CO_2 concentration was the most important variable for the probability of opening windows, while it did not have a significant effect in the living room (the confidence interval for the coefficient contains the number 0). The indoor relative humidity had the biggest effect on the closing probability in the living room, but did not have a significant effect in the bedroom. Both the opening and closing probabilities were influenced by the season and by the time of day. Since no window were opened during the winter time, the seasonal effects only take spring and summer into account. During winter, the inferred probability of opening a window was 0.

The coefficients and intercepts listed in Table 8 constitute the opening and closing model for group 1. The two formulas below are examples of the logistic regression equation for opening probability for a morning in spring in the living room (3) and bedroom (4):

$$\log\left(\frac{p}{1-p}\right) = -9.80 + 0.23\cdot 10^{-3}\cdot\log(CO_2) + 0.163\cdot t_i + 0.501\cdot\log(\text{Rad}+1) \quad (3)$$

$$\log\left(\frac{p}{1-p}\right) = -23.04 + 1.87\cdot\log(CO_2) + 0.163\cdot t_i + 0.501\cdot\log(\text{Rad}+1) \quad (4)$$

Where, p is the probability of opening a window within the next 10 min, CO_2 is the CO_2 concentration in ppm, t_i is the indoor temperature in °C and Rad in the solar radiation in W/m^2.

The results in Table 9 indicate that the confidence intervals of some variables may be inflated due to multicolinearity (the $GVIF^{1/(2\cdot Df)}$ is a measure of inflation due to multicolinearity). Especially the standard error of the categorical variable 'Room' and the interaction terms were inflated due to multicolinearity. This indicates that some variables were biased by the room in which they were measured.

The window opening model for group 1 had three continuous variables (CO_2 concentration, Indoor temperature and Solar radiation). Fig. 3 gives an overview of the effects of these variables on the probability of opening a window. The solar radiation was set to 200 W/m^2 in the figures on the left and in the middle. In the figure on the right, the CO_2 concentration was set to 900 ppm.

Fig. 4 gives an overview of the effect of the three continuous variables (Outdoor temperature, Outdoor relative humidity and indoor relative humidity) on the probability of closing a window. 61% was used as outdoor relative humidity in Fig. 4 left and right and 38% was used as indoor relative humidity in Fig. 4 middle.

4.2. Group 2: owner-occupied, mechanically ventilated dwellings

The models inferred from group 2, 3, and 4 are presented in Tables 1, 3 and 5 in the appendix.

Due to interaction with the dwelling index, indoor and outdoor temperature and solar radiation were removed from the window opening model and indoor temperature was removed from the window closing model (Table 7).

The CO_2 concentration was the most important variable in the determination of the window opening probability, while Outdoor

Table 9
Results of performed VIF analysis for variables of group 1. The $GVIF^{1/(2\cdot Df)}$ describes how inflated the confidence intervals in Table 8 are due to multicolinearity.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{1/(2\cdot Df)}$	GVIF	Df	$GVIF^{1/(2\cdot Df)}$
Time	3.7	4	1.2	1.9	4	1.1
Solar radiation	3.5	1	1.9			
Season	1.1	1	1.0	1.9	1	1.4
Room	353	1	18.8	52	1	7.2
Indoor temperature	1.1	1	1.1			
CO_2 concentration	3.0	1	1.7			
Room: CO_2	338	1	18.4			
Relative humidity				6.4	1	2.5
Outdoor temperature				2.4	1	1.6
Outdoor relative humidity				3.0	1	1.7
RH: Room				60	1	7.7

temperature and illumination turned out to be the most important variables in the window closing model. From the confidence intervals, it is evident that all the variables, except the outdoor temperature for the bedroom and the solar radiation for the living room had a statistically significant impact on the opening/closing probabilities (Table 1 in appendix).

The Variance inflation factors turned out to be small (lower than 5) for all the variables in the models (Table 2 in the appendix).

4.3. Group 3: rented, naturally ventilated dwellings

All of the variables in the window opening model were assumed to be independent from the dwelling they were measured in since none of them interacted with the dwelling index (Table 7). The CO_2 concentration was the only continuous variable having an impact on the window opening behaviour.

The variables Solar Radiation and CO_2 concentration were removed from the model of closing behaviour since they interacted with the dwelling index. Indoor and outdoor temperature were found to be the most important variables driving the closing behaviour. As expected, they had a negative correlation with the exception of the indoor temperature in the bedroom, which was positively correlated with the probability of closing window (Table 3 in the appendix).

The multicolinearity analysis for group 3 (Table 4 in the appendix) revealed highly inflated standard errors of the variables 'time', 'room' and the 'time'–'room' interaction terms. This indicates higher levels of uncertainty in the coefficients. However, the predictive power of the model will only be affected by this if the model is used on data that falls outside the ranges in Table 6 (assuming similar colinearities).

4.4. Group 4: rented, mechanically ventilated dwellings

Both in the window opening and window closing model, the variable 'Time' interacted with the dwelling index and were removed from the model. In the closing model, indoor temperature, CO_2 concentration and illumination depended on the dwelling index and were removed (Table 7).

The results in Table 6 in the appendix show that the confidence interval for many of the coefficients was highly inflated. This might explain the unexpected negative correlation between indoor temperature in the living room and opening probability. Since the interaction between room and indoor temperature was inflated up to 14 times, the impact of the room on the indoor temperature coefficient was not as certain, compared to the case with no multicolinearities.

The impact of outdoor temperature on the closing probability was inflated up to 13 times due to multicolinearity. Consequently,

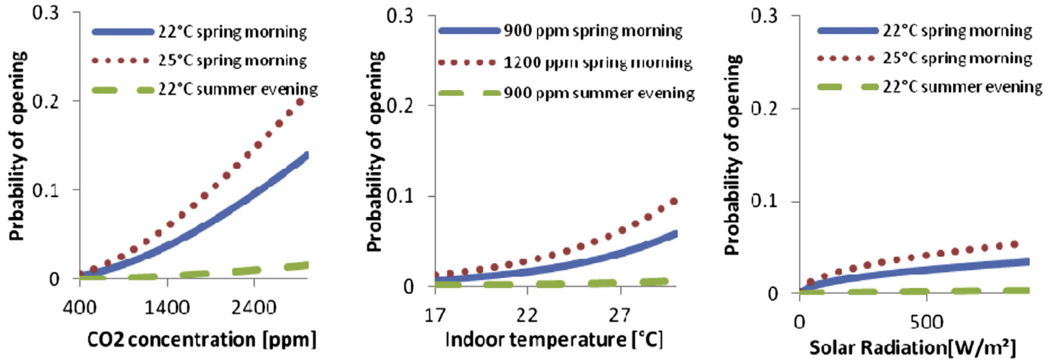

Fig. 3. Graphical representation of the window opening model. The probability of opening a window is depicted for different indoor temperatures as a function of CO_2 concentration (left) for different CO_2 concentrations as a function of indoor temperature (middle) and for different temperatures as a function of solar radiation.

the outdoor temperature coefficients in the closing model may be uncertain. The uncertainties created by the multicolinearities will only affect the model's predictive power if the models are used on data that is outside the ranges listed in Table 4 (assuming similar colinearities).

4.5. Generalized patterns

Generally, the occupants' window opening and closing behaviour was governed by different variables indicating that the occupants had different reasons for opening and closing windows.

From the four opening and closing models, some common patterns of behaviour appeared. The CO_2 concentration had an impact on the window opening probability while the outdoor temperature affected the closing probability.

Interestingly, wind speed did not affect window opening/closing behaviour in any model of the four groups.

5. Discussion

5.1. Behaviour patterns in simulation programs

The results from the analysis provide a possibility of defining window opening behaviour patterns for simulation purposes. Table 8 and Tables 1, 3 and 5 in the appendix provide a method for calculating the probability that the window will be opened or closed during the next 10 min. In the simulation program, a comparison with a random number can determine if the window is opened/closed or not. Since the models predict the probability of an opening/closing event during the next 10 min, the random number should change in 10 min intervals.

When introducing the models and comparisons with random numbers into the simulation software, the results of identical simulations may differ, since the random numbers change between simulations. By running several simulations, it is possible to obtain probability distributions of the performance indicators, rather than a single number. As a consequence, the implementation of the models in simulation software will transform the software from a purely deterministic tool to a simulation tool with capabilities of simulation stochastic behaviour patterns.

Rijal et al. [17] describes three different assumptions (fixed schedules, fixed rules based on indoor and/or outdoor conditions, fixed ventilation/infiltration rates) that designers have made in the past when modelling window opening behaviour. It is clear that these strategies of modelling occupant behaviour will lead to differences in the simulated indoor environment and in the simulated energy consumption of the building. The proposed models are based on measurements in 15 dwellings. While they cannot be assumed representative of the Danish population, an implementation of the models into a simulation program would significantly improve the validity of the simulation results in two ways: It would enable comparability of results from different models, since they would be based on the same behaviour patterns. Secondly, because the behaviour in the models are based on real behaviour it has a better chance of mimicking the behaviour of the occupants in the building and thus predicting the indoor environment and energy consumption correctly. The models are valid for variables that are within the ranges described in Table 6, assuming similar colinearities.

5.2. Occupancy

The occupancy of the dwellings was determined using the monitored CO_2 concentration. This method was better than not

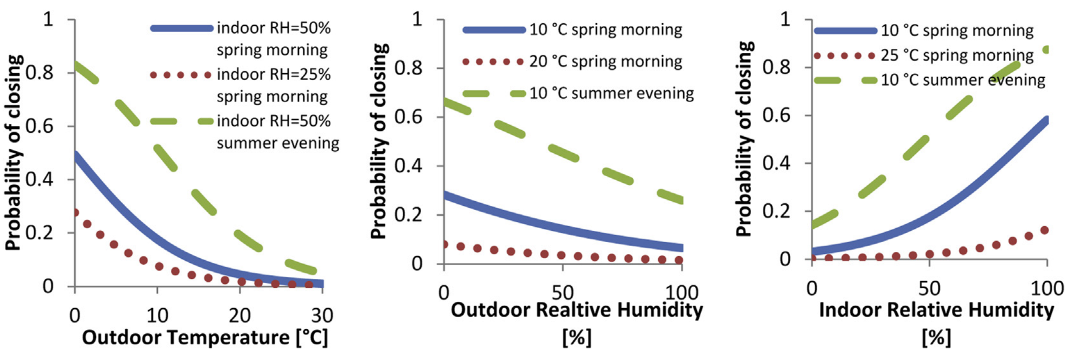

Fig. 4. Graphical representation of the window closing model from group 1. The probability of closing a window is depicted for different levels of indoor relative humidity as a function of outdoor temperature (left), for different outdoor temperatures as a function of outdoor relative humidity (middle) and for different outdoor temperatures as a function of the indoor relative humidity.

considering the occupancy but may have led to uncertainties since short changes in the occupancy may have passed unnoticed and since the dwelling may have been falsely characterized as unoccupied if the occupants stayed in an isolated room that was not monitored. Since most of the periods without occupancy were removed, any correlations between behaviour and CO_2 concentration indicate relationships between air quality and behaviour.

5.3. Statistical approach

We have used logistic regression to infer the probability of a window opening or closing event. In using this method we have assumed that the probability function looks like formula (2). Additionally we have assumed that all observations were independent of each other. This assumption is questionable as the observations were gathered in 15 dwellings. Essentially the assumption would hold true if all inhabitants of the dwellings reacted similarly to the conditions they were subjected to. In any other case the observations in each dwelling will be influenced by the habits of the inhabitants of the individual dwelling and as a result they would not be independent from each other. We have dealt with this problem by using a dwelling index as a factor in the first attempts to infer models. Interactions between variables and dwelling index were taken as signs of dependence and the variables were removed from the final models. In doing so, we may have removed variables that had an influence on the opening/closing probabilities.

We chose to use the Akaike information criterion (AIC) as a basis of variable selection in the inference of the models. Another option would be to use Wald tests to test the significance of each term and use this as a selection criterion. We chose to use the AIC, since selecting variables based on their significance does not take the risk of overfitting into account. This risk increases with the number of observations. The AIC includes a penalty that increases with the number of estimated variables in the model, which discourages overfitting.

5.4. Seasonal variations

The measurements were made during the winter, spring and summer. As a consequence, the results in this paper are only valid for these seasons. There is, however, no evidence that the behaviour of occupants depends differently on the measured variables in the autumn than in spring (or other parts of the year if the model does not include seasonal effects). When implementing the models into simulation programs, the models without seasonal effects (Tables 1 and 3 in the appendix) can be used for the entire year. In models including seasonal effects, the spring season can be used as a representation in autumn.

5.5. Variables for determination of window opening behaviour

Indoor relative humidity influenced the opening/closing probability (Table 8, and Tables 1 and 5 in the appendix), even though it was in the range 30%–70%, where humans are modestly sensitive to relative humidity. On the other hand, the relative humidity does affect both thermal sensation and perceived air quality and this might be why it affected the opening/closing probability.

Johnson and Long [27] conducted a visual survey of residential window and door positions in North Carolina. They found that the window and door opening behaviour was affected by a number of variables including weather, dwelling characteristics and anthropological variables. An AIVC report [35] concluded that there were considerable differences in the ventilations behaviour's weather dependency, which indicates that other variables play a significant role in determining the ventilation behaviour. These results are in accordance with our work and underline the importance of taking more than the temperature into account when investigating the behaviour of occupants.

6. Conclusions

Based on measurement of window opening behaviour and indoor/outdoor conditions in 15 dwellings during winter, spring, and summer it was shown that behaviour differed between dwelling type (rented or owned, mechanical or natural ventilation) and within dwelling type. The indoor CO_2 concentration and the outdoor temperature were the two single most important variables in determining the probability of opening and closing windows respectively.

Based on the measurements, four models of occupants' window opening and closing behaviour patterns in building simulation programs was proposed. When implemented into simulation programs, this definition will significantly increase the validity of the simulation outcome.

Acknowledgement

This study was conducted as part of a project funded by Bjarne Saxhof's Foundation.

Appendix 1. Inferred coefficients and results of the VIF analyses of group 2, 3 and 4.

Group 2:

Table 1
Coefficients and magnitudes of the opening and closing models inferred based on data from Group 2. The coefficient refers to the "*a*" and "b_{1-n}" in formula (2). The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Time/Room	Open window				Close window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.5%	97.5%			2.5%	97.5%	
Intercept	Bedroom	−13.49	−15.64	−11.33	–	−4.75	−5.53	−3.98	–
	Living room	−13.49	−15.64	−11.33	–	4.19	3.03	5.34	–
Illumination [log(Lux)]	–	0.27	0.17	0.37	2	−0.62	−0.67	−0.57	−6
CO_2 concentration [Log(ppm)]	–	1.40	1.10	1.71	3	–			–
Outdoor Relative Humidity [%]	–	−0.02	−0.03	−0.01	−1.5	–			–
Solar hours [h]	–	–			–	−0.06	−0.09	−0.02	−0.86
Outdoor temperature [°C]	Bedroom	–			–	0.03	−0.02	0.08	0.90
	Living room	–			–	−0.26	−0.34	−0.19	−7.85
Solar radiation [Log(W/m^2)]	Bedroom	–			–	0.59	0.45	0.74	4.04
	Living room	–			–	0.04	−0.17	0.26	0.30

Table 2
Results of performed VIF analysis for variables of group 2. The $GVIF^{1/(2\cdot Df)}$ describes how inflated the confidence intervals in Table 1 are due to multicolinearity.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{1/(2\cdot Df)}$	GVIF	Df	$GVIF^{1/(2\cdot Df)}$
Lux	1.4	1	1.2	1.9	1	1.4
CO_2	1.3	1	1.1			
Outdoor RH	1.4	1	1.2			
Solar radiation				6.8	1	2.6
Sun hours				1.7	1	1.3
Room: Outdoor temperature				7.1	1	2.7
Room: Solar radiation				8.9	1	3.0
Room				9.8	1	3.1
Outdoor temperature				3.0	1	1.7

Table 4
Results of performed VIF analysis for variables of group 3. The $GVIF^{1/(2\cdot Df)}$ describes how inflated the confidence intervals in Table 3 are due to multicolinearity.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{1/(2\cdot Df)}$	GVIF	Df	$GVIF^{1/(2\cdot Df)}$
CO_2	1.1	1	1.0			
Time	1.1	4	1.0	7.07E+09	4	17.0
Room				230	1	15.2
Indoor temperature				11.7	1	3.4
Sun hours				2.2	1	1.5
Relative humidity				15.1	1	3.9
Outdoor temperature				22.0	1	4.7
Room: indoor temperature				263	1	16.2
Time: indoor temperature				774.3E+06	4	12.9
Time: relative humidity				110.6E+06	4	10.1
Outdoor temperature: time				18.6E+03	4	3.4
Room: outdoor temperature				7.3	1	2.7

Group 3:

Table 3
Coefficients and magnitudes of the opening and closing models inferred based on data from Group 3. The coefficient refers to the "a" and "b_{1-n}" in formula (2). The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Time/room	Open window				Close window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.5%	97.5%			2.5%	97.5%	
Intercept for bedroom	Night	−17.69	−18.80	−16.59		−2.68	−6.50	1.14	
	Morning	−15.51	−16.63	−14.38		−0.51	−6.37	5.36	
	Day	−17.09	−18.24	−15.94		−7.67	−13.84	−1.50	
	Afternoon	−18.23	−19.40	−17.05		−12.78	−20.94	−4.63	
	Evening	−17.13	−18.26	−15.99		−13.22	−20.81	−5.64	
Intercept for living room	Night	−17.69	−18.80	−16.59		14.68	9.90	19.45	
	Morning	−15.51	−16.63	−14.38		16.85	10.32	23.38	
	Day	−17.09	−18.24	−15.94		9.69	2.88	16.50	
	Afternoon	−18.23	−19.40	−17.05		4.57	−4.07	13.22	
	Evening	−17.13	−18.26	−15.99		4.13	−3.98	12.24	
CO_2 concentration [Log(ppm)]		1.75	1.60	1.90	*4.16*				
Indoor Temperature [°C] Bedroom	Night					0.40	0.29	0.52	*6.55*
	Morning					0.15	0.03	0.27	*2.39*
	Day					0.21	0.08	0.33	*3.38*
	Afternoon					0.70	0.57	0.83	*11.36*
	Evening					0.60	0.48	0.73	*9.79*
Indoor Temperature [°C] Living room	Night					−0.25	−0.37	−0.13	*−4.05*
	Morning					−0.51	−0.69	−0.32	*−8.21*
	Day					−0.45	−0.65	−0.25	*−7.22*
	Afternoon					0.05	−0.23	0.33	*0.75*
	Evening					−0.05	−0.29	0.19	*−0.81*
Outdoor Temperature [°C] Bedroom	Night					0.01	−0.08	0.09	*0.19*
	Morning					0.12	0.03	0.21	*3.85*
	Day					−0.13	−0.23	−0.04	*−4.28*
	Afternoon					−0.07	−0.16	0.03	*−2.10*
	Evening					−0.09	−0.18	0.01	*−2.77*
Outdoor temperature [°C] Living room	Night					−0.13	−0.22	−0.04	*−4.09*
	Morning					−0.01	−0.11	0.08	*−0.43*
	Day					−0.27	−0.36	−0.17	*−8.56*
	Afternoon					−0.20	−0.30	−0.10	*−6.37*
	Evening					−0.22	−0.32	−0.12	*−7.05*
Indoor relative humidity [%]	Night					−0.25	−0.32	−0.17	*−7.75*
	Morning					−0.16	−0.24	−0.08	*−4.93*
	Day					0.06	−0.02	0.14	*1.84*
	Afternoon					−0.15	−0.24	−0.07	*−4.88*
	Evening					−0.07	−0.15	0.02	*−2.14*
Solar hours [h]						−0.08	−0.11	−0.06	*−1.27*

Group 4:

Table 5
Coefficients and magnitudes of the opening and closing models inferred based on data from Group 4. The coefficient refers to the "a" and "b_{1-n}" in formula (2). The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Season/Room	Open window				Close window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.50%	97.50%			2.50%	97.50%	
Intercept – Bedroom	Winter	−18.53	−20.55	−16.51		−4.28	−5.21	−3.35	
	Spring	−18.53	−20.55	−16.51		−2.98	−4.18	−1.78	
	Summer	−18.53	−20.55	−16.51		−4.94	−6.24	−3.63	
Intercept – Living room	Winter	−3.56	−6.82	−0.30		−0.62	−1.72	0.48	
	Spring	−3.56	−6.82	−0.30		0.68	−0.66	2.01	
	Summer	−3.56	−6.82	−0.30		−1.28	−2.71	0.15	
Outdoor temperature – Bedroom	Winter	−0.019	−0.04	0.003	−0.68	−0.038	−0.161	0.084	−1.41
	Spring	−0.019	−0.04	0.003	−0.68	−0.147	−0.321	0.027	−5.38
	Summer	−0.019	−0.04	0.003	−0.68	−0.057	−0.233	0.119	−2.09
Outdoor temperature – Living room	Winter	0.059	0.03	0.09	2.16	−0.17	−0.29	−0.04	−6.06
	Spring	0.059	0.03	0.09	2.16	−0.27	−0.45	−0.10	−10.04
	Summer	0.059	0.03	0.09	2.16	−0.18	−0.36	−0.01	−6.75
Solar radiation	Bedroom	0.18	0.14	0.23	1.24	0.13	0.09	0.16	0.86
	Living room	0.35	0.28	0.42	2.39	0.13	0.09	0.16	0.86
Solar hours		0.057	0.043	0.070	0.91	−0.089	−0.103	−0.075	−1.43
Outdoor relative humidity		0.029	0.024	0.033	2.08	−0.028	−0.033	−0.023	−2.01
Illumination		0.26	0.20	0.33	2.30				
Indoor temperature	Bedroom	0.10	−1.92	2.12	1.93				
	Living room	−0.38	−0.47	−0.29	−7.25				
CO_2 concentration	Bedroom	1.16	0.91	1.40	3.04				
	Living room	0.30	−0.12	0.71	0.78				
Indoor relative humidity	Bedroom					0.063	0.051	0.075	2.99
	Living room					0.036	0.017	0.056	1.72

Table 6
Results of performed VIF analysis for variables of group 4. The $GVIF^{1/(2\cdot Df)}$ describes how inflated the confidence intervals in Table 5 are due to multicolinearity.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{1/(2\cdot Df)}$	GVIF	Df	$GVIF^{1/(2\cdot Df)}$
Solar radiation	4.0	1	2.0	1.7	1	1.3
Outdoor relative humidity	2.0	1	1.4	2.7	1	1.6
Room	530.0	1	23.0	27.0	1	5.2
Sun hours	1.3	1	1.1	1.5	1	1.2
Indoor temperature	3.1	1	1.8			
Lux	1.8	1	1.3			
CO_2 concentration	3.0	1	1.7			
Outdoor temperature	5.5	1	2.3	175.9	1	13.3
Solar radiation: room	8.3	1	2.9			
Room: indoor temperature	203.3	1	14.2			
Room: CO_2 concentration	363.5	1	19.1			
Room: outdoor temperature	9.0	1	3.0	6.8	1	2.6
Indoor relative humidity				3.5	1	1.9
Season				98.3	2	3.1
Outdoor temperature: season				1968.8	2	6.7
Room: indoor relative humidity				34.2	1	5.8

References

[1] Leaman A, Bordass B. Productivity in buildings: the 'killer' variables. Building Research & Information 1999;27(1):4–20.
[2] Paciuk M. The role of personal control of the environment in thermal comfort and satisfaction at the workplace (Ph.D. thesis). University of Wisconsin-Milwaukee; 1989.
[3] Roulet CA, Johner N, Foradini F, Bluyssen P, Cox C, Fernandes EO, et al. Percieved health and comfort in relation to energy use and building characteristics. Building Research and Information 2006;34(5):467–74.
[4] Toftum J. Central automatic control or distributed occupant control for better indoor environment quality in the future, Building and environment. Building and Environment 2010;45:23–8.
[5] Bahaj AS, James PAB. Urban energy generation: the added value of photovoltaics in social housing. Renewable and Sustainable Energy Reviews 2007;11:2121–36.
[6] Rathouse K, Young B. RPDH15: use of domestic heating controls, Defra's Market Transformation Programme.
[7] Seligman, Darly JM, Becker LJ. Behavioral approaches to residential energy conservation. Energy and Buildings 1977/78;1:325–37.
[8] Andersen R. The influence of occupants' behaviour on energy consumption investigated in 290 identical dwellings and in 35 apartments. In: Proceedings of healthy buildings 2012, 8–12 July 2012, Brisbane, Australia 2012.
[9] Offermann F, Brennan S, Hodgson A, Jenkins P. Window usage, ventilation, and formaldehyde concentrations in new California homes. In: Proceedings of the 11th international conference on indoor air quality and climate, indoor air 2008. Copenhagen, Denmark. [Paper ID: 767].
[10] Bishop RC, Frey DJ. Occupant effects on energy performance of monitored houses. In: Proceedings of: the 10th national passive solar conference 1985. p. 395–400.
[11] Kristensen L, Jensen OM, editors. Erfaringsopfølgning på lavenergibyggeri klasse 1 og 2.- med "Fremtidens Parcelhuse" som eksempel, repport for Energiforskningsprogrammet. Det Grønne Hus in cooperation with SBi; 2007 [In Danish].
[12] Andersen RV, Olesen BW, Toftum J. Simulation of the effects of occupant behaviour on indoor climate and energy consumption. In: Proceedings of Clima 2007: 9th REHVA World Congress: WellBeing Indoors, Helsinki, Finland 2007.
[13] Wallace LA, Emmerich SJ, Howard-Reed C. Continuous measurements of air change rates in an occupied house for 1 year: the effect of temperature, wind fans and windows. Journal of Exposure Analysis and Environmental Epidemiology 2002;12:296–306.
[14] Howard-Reed C, Walllace LA, Ott WR. The effect of opening windows on air change rates in two homes. Air and Waste Management Association 2002;52:147–59.
[15] Kvistgaard B, Collet PF. In: Sherman MH, editor. The user's influence on air change, air change rate and air tightness in buildings. Philadelphia: American Society for Testing and Materials; 1990. p. 67–76. ASTM. STP 1067.
[16] Bekö G, Toftum J, Clausen G. Modeling ventilation rates in bedrooms based on building characteristics and occupant behaviour. Building and Environment 2011;46:2230–7.
[17] Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Clarke J. Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. Energy and Buildings 2007;39:823–36.
[18] Haldi F, Robinson D. On the behaviour and adaptation of office occupants. Building and Environment 2008;43:2163–77.

[19] Herkel S, Knapp U, Pfafferott J. Towards a model of user behaviour regarding the manual control of windows in office buildings. Building and Environment 2008;43:588–600.

[20] Yun GY, Steemers K. Time-dependent occupant behaviour models of window control in summer. Building and Environment 2008;43:1471–82.

[21] Yun GY, Tuohy P, Steemers K. Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models. Energy and Buildings 2009;41:489–99.

[22] Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Raja IA, et al. Development of adaptive algorithms for the operation of windows, fans and doors to predict thermal comfort and energy use in Pakistani buildings. ASHRAE Transactions 2008;114(2):555–73.

[23] Haldi F, Robinson D. Interactions with window openings by office occupants. Building and Environment 2009;44(12):2378–95.

[24] Schweiker M, Haldi F, Shukuya M, Robinson D. Verification of stochastic models of window opening behaviour for residential buildings. Journal of Building Performance Simulation 2011. http://dx.doi.org/10.1080/19401493.2011.567422. First published on: 09 June 2011 (iFirst).

[25] Fritsch R, Kohler A, Nygård-Ferguson M, Scartezzini JL. A stochastic model of user behaviour regarding ventilation. Building and Environment 1990;25(2):173–81.

[26] Andersen RV, Toftum J, Andersen KK, Olesen BW. Survey of occupant behaviour and control of indoor environment in Danish dwellings. Energy and Buildings 2009;42(1):11–6.

[27] Johnson T, Long T. Determining the frequency of open windows in residences: a pilot study in Durham, North Carolina during varying temperature conditions. Journal of Exposure Analysis and Environmental Epidemiology 2005;15:329–49.

[28] Fabi V, Andersen RV, Corgnati SP, Olesen BW. Occupants' window opening behaviour: a literature review of factors influencing occupant behaviour and model. Building and Environment 2012;58:188–98.

[29] Roetzel A, Tsangrassoulis A, Dietrich U, Bushing S. A review of occupant control on natural ventilation. Renewable and Sustainable Energy Reviews 2009;14:1001–13.

[30] Keiding L. In: Keiding Lis, editor. Environmental factors of everyday life in Denmark – with specific focus on housing environment. Copenhagen (: Statens Institute for Folkesundhed (SIF); 2003 [in Danish with summary in English].

[31] Danish Meteorological Institute, Lyngbyvej 100, DK-2100 Copenhagen E, Denmark.

[32] http://www.onsetcomp.com/.

[33] http://www.vaisala.com/.

[34] Brundrett GW. Window ventilation and human behaviour. In: Proceedings of the first international indoor climate symposium in Copenhagen: indoor climate, effects on human comfort, performance and health in residential, commercial and light-industry buildings 1978. p. 317–30.

[35] Dubrul C. Technical note AIVC 23, inhabitant behaviour with respect to ventilation – a summary report of IEA Annex VIII; March 1988.

[36] Andersen R, Toftum J, Olesen B. Survey of occupant behaviour and control of indoor environment in Danish dwellings. In: Proceedings of the 10th international conference on air distribution in rooms, Roomvent 2007 June 2007. Helsinki, Finland.

[37] Allison PD. Logistic regression using the SAS system. SAS Institute; 1999.

[38] Documentation of the step function in R: 127.0.0.1:16820/library/stats/html/step.html visited on December 22-2011.

[39] Schweiker M, Schweiker M, Shukuya M. Comparison of theoretical and statistical models of air-conditioning-usage behavior in a residential setting under Japanese climatic conditions. Building and Environment 2009;44:2137–49.