Effect of thermostat and window opening occupant behavior models on energy use in homes

Article *in* Journal of Building Performance Simulation · July 2014

Impact Factor: 1.62 · DOI: 10.1007/s12273-014-0191-6

4 authors:


Simona D'Oca
Politecnico di Torino


Valentina Fabi
Politecnico di Torino


Stefano Paolo Corgnati
Politecnico di Torino


Rune Korsholm Andersen
Technical University of Denmark

Build Simul (2014) 7: 683–694
DOI 10.1007/s12273-014-0191-6

Effect of thermostat and window opening occupant behavior models on energy use in homes

Simona D'Oca[1], Valentina Fabi[1], Stefano P. Corgnati[1] (✉), Rune Korsholm Andersen[2]

1. TEBE Research Group, Department of Energetics, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy
2. ICIEE, Department of Civil Engineering, Technical University of Denmark, Nils Koppels Allé Building 402, 2800 Kgs. Lyngby, Denmark

Research Article

Abstract

Existing dynamic energy simulation tools exceed the static dimension of the simplified methods through a better and more accurate prediction of energy use; however, their ability to predict real energy consumption is undermined by a weak representation of human interactions with the control of the indoor environment. The traditional approach to building dynamic simulation considers energy consumption as fully deterministic, taking into account standardized input parameters and using fixed and unrealistic schedules (lighting level, occupancy, ventilation rate, thermostat set-point). In contrast, in everyday practice occupants interact with the building plant system and building envelope in order to achieve desired indoor environmental conditions. In this study, occupant behavior in residential building was modelled accordingly to a probabilistic approach. A new methodology was developed to combine probabilistic user profiles for both window opening and thermostat set-point adjustments into one building energy model implemented in the dynamic simulation tool IDA Ice. The aim of the study was to compare mean values of the probabilistic distribution of the obtained results with a singular heating energy consumption value obtained by means of standard deterministic simulations. Major findings of this research demonstrated the weakness of standardized occupant behavior profile in energy simulation tools and the strengths of energy models based on measurements in fields and probabilistic modelling providing scenarios of occupant behavior in buildings.

Keywords

occupant behavior,
residential buildings,
building energy modelling,
window opening,
thermostat set-point

Article History

Received: 13 February 2014
Revised: 16 June 2014
Accepted: 17 June 2014

1 Introduction

Being able to assess the energy consumption to a certain level of accuracy is a key factor in the aim of sustainability and efficiency in buildings.

Moreover, reducing the energy use for space heating is a challenging task not only related to the technical performance of a building, but also strongly related to occupant behavior. In fact, de Dear and Brager (2001) and Baker and Standeven (1996) claim that occupants adaptive behavior has potential to reduce heating and cooling energy consumption by allowing greater variations in indoor thermal conditions when personal environmental control is made available. However, such reductions require that the occupants are allowed to affect building performance, by manipulating control devices such as windows, radiator valves, shades and devices to bring about desired indoor environment conditions.

Apart from simplification and numerical assumption of actual energy simulation tools, this active participation of users to building performance has been suggested (Andersen et al. 2007; Fabi et al. 2013) as being one of the paramount aspects affecting the discrepancy between simulated and measured energy uses in buildings.

Several investigations (Marchio and Rabl 1991; Andersen 2012; Emery and Kippenhan 2006) show significant uncertainties in the estimation of energy consumption in dwellings, highlighting a gap between calculated and actual energy consumption that may exceed 300% in extreme cases. Occupants having the possibility to control their living or working indoor environment have been found to be generally more satisfied than users exposed to environments of which

Architecture and Human Behavior

E-mail: stefano.corgnati@polito.it

they have no control (Leaman and Bordass 1998; Paciuk 1989; Toftum et al. 2009). Giving occupants the possibility to interact with the building control system results in a better perceived indoor environmental quality and higher occupant's satisfaction. But occupant behavior could vary enormously between individuals and groups, resulting in large variations in building energy consumption. Due to natural uncertainties in human behavior, developing a single deterministic description of occupant behavior is neither possible nor accurate; instead, probabilistic modelling is required (Nicol 2001). In the last decade a broad use of probabilistic approach in modelling human adaptive behavior is emerging in the field of building energy efficiency, ventilation and thermal comfort in indoor environments.

Different actions have been modelled for different cases such as window opening, thermostat adjustments, blind and lighting use (Nicol 2001; Clevenger and Haymaker 2006; Bourgeois 2005; Rijal et al. 2007; Borgeson and Brager 2008; Page et al. 2008; Andersen et al. 2007; Hoes et al. 2011; Wei et al. 2010; Haldi 2013; Korjenic and Bednar 2011; Wang et al. 2011; Fabi et al. 2013; Schweiker et al. 2011). In this paper, we propose a new methodology to quantity both the effect of thermostat and window opening occupant behavior on energy use in homes. To do this, we applied a probabilistic methodology in modelling occupant behavior in building energy models.

2 Method

The presented research was an extension of a previous probabilistic modelling approach (Andersen et al. 2011; Fabi et al. 2012a, b) taking into account separately windows control and heating set-point adjustments in residential buildings. A new methodology was developed to combine these two probabilistic inputs into a single building energy model by using the dynamic simulation software IDA Ice.

2.1 Probabilistic modelling approach

The probabilistic modelling approach we used can be simplified in five main steps (Fig. 1):

1. Collecting real data from field measurements (environmental and behavioral).
2. Data analysis and definition of the most influencing parameters (inference of behavior models from data) on occupant energy related behavior in residential buildings.
3. Implementation of probabilistic models of occupant behavior as inputs in the dynamic energy simulation program.
4. Run of a set (10) of simulations.
5. Consideration of a probabilistic distribution of the outputs.

2.1.1 *Data collection and analysis*

A field monitoring campaign of indoor and outdoor climate conditions and occupants control actions was performed in fifteen naturally ventilated dwellings located 10 to 25 km from Copenhagen in the period from January to August 2008 (Andersen et al. 2011). Ten minutes step indoor condition data were recorded both in living room and bedroom in each dwelling regarding indoor temperature [℃], indoor relative humidity [%], CO_2 concentration [ppm] and luminance [lx]. Outdoor condition data were gathered

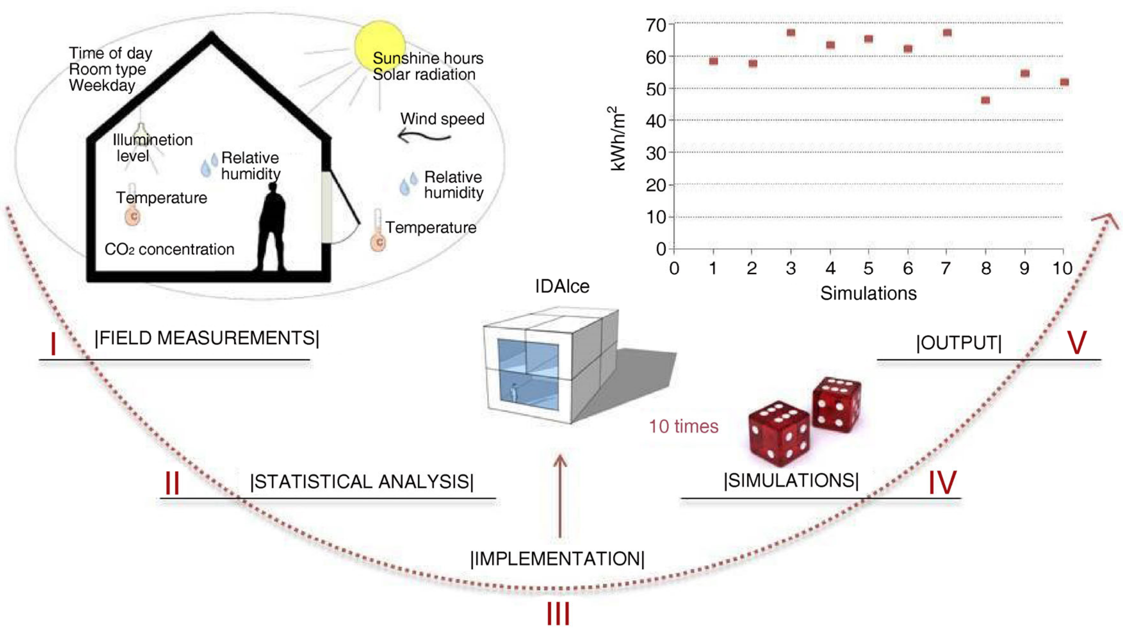

Fig. 1 Approach to the statistical modeling of occupant behavior

from the closest weather station regarding outdoor temperature [℃], outdoor relative humidity [%], global solar radiation [W/m^2], wind speed [m/s] and number of solar hours per day. Moreover, interactions of occupant with regard to window position [open/close] and heating set-point on thermostatic radiator valves [℃] were recorded. Window sensors were installed on windows that inhabitants declared to use more often when ventilating the dwellings. Large variety between individual behaviors was recorded and the dwellings were eventually grouped after the number of interactions with window and thermostat occurred during the monitoring period. As shown in Table 1, the total number of window openings varies from dwelling number 1 (334) to number 12, in which window has been opened only one time during the whole period of monitoring survey. Similar patterns occurred for thermostat adjustment monitoring. As a result, three users' type representing Active, Medium and Passive users were settled and the probability of opening window and adjusting the thermostat was inferred for three different statistical models.

2.1.2 Statistical analysis

Data collected during measurements were statistically treated by means of the statistical software R in order to determine which variables had an influence on opening and closing a window or turning up or down the thermostat in a previous correlated study (Andersen et al. 2013). A multiple logistic regression formula was used to infer the probability of opening windows and adjusting the thermostat for each of the Active, Medium and Passive user type.

Table 1 Windows opening frequency for monitored dwellings, considering bedroom and living room variation

Dwelling number	Total number of window openings	Number of window openings in bedroom	Number of window openings in living room
1	**334**	202	132
3	82	63	19
4	235	109	126
5	73	55	18
6	337	137	200
7	718	559	159
8	258	131	127
9	25	7	18
10	65	61	4
11	82	80	2
12	**1**	1	0
13	341	263	78
14	241	82	159
15	166	55	111
16	153	93	60

2.1.3 Implementation

To replicate probabilistic control actions of window opening and thermostat set-point, two logistic regression formulas were implemented in the dynamic building simulation software IDA Ice. These formulas describe a relationship between the change in window or thermostat state and a set of independent predictors used when the outcome is binary, that is when there are only two possible accounts (0 or 1) in the case:

- open/not open windows – turn up/not turn up thermostats;
- close/not close windows – turn down/not turn down thermostats.

The outcomes of the models were probabilities of an action occurring (windows open/close heating set-point increase/decrease) within the next 10 minutes (since the independent variables were measured in 10-minute intervals). To determine the state of the windows and heating set-point, the probabilities were compared to a random number that was generated with 10-minute intervals. An action occurred in the simulation if the calculated probability was higher than the random number. The window would stay open or the thermostat would stay turned up until the probability of closing the window or turning down the thermostat was higher than the matching random number.

Window sensor recorded a binary state of window being open or closed, no information about window tilting angle was available. For this reason, the opening signal in the simulation model was multiplied with a fixed degree of opening of 20%.

2.1.4 Simulations

The logistic regression formulas were implemented in IDA Ice for both system controls by using a two-room model consisting of living room and bedroom, for which a suitable room is provided by the European Standard 15265:2005 "*Thermal performance of buildings—Calculation of energy use for space heating and cooling—General criteria and validation procedures*". Thermo physical properties of the transparent and opaque components are summarized in Tables 2 and 3.

Table 2 Thermo physical properties of the transparent components

Type of component	Double pane 4.12.4 glass
Size and orientation of component	2 windows (1.2 m × 1.2 m), west
U_w value	2.9 W/(m^2·K)
Solar transmittance	T = 0.7
Solar heat gain coefficient	g = 0.76

Table 3 Thermo physical properties of the opaque components

	Material	Thermal conductivity (W/(m·K))	Density (kg/m^3)	Specific heat (J/(kg·K))	*U*-value (W/(m^2·K))	Thickness (cm)
External wall	Internal plastering	70	1.400	85	49	365
	Masonry	79	1.600	85		
	Insulation layer	4	30	85		
	Outer layer	99	1.800	85		
Internal wall	Gypsum plaster	21	900	85	36	125
	Mineral wool	4	30	85		
	Gypsum plaster	21	900	85		
Floor covering	Acoustic board	6	400	84	241	40
	Mineral wool	4	50	85		
	Concrete	210	2.400	85		
	Mineral wool	4	50	85		
	Concrete	140	2.000	85		
	Floor covering	23	1.500	15		
Roof	Rain protection	23	1.500	13	438	284
	Insulation layer	0.04	50	0.85		
	Concrete	2.10	2400	0.85		
External floor	Concrete	2.10	2400	0.85	76	284
	Mineral wool	0.04	50	0.85		
	Concrete	140	2.000	85		
	Plastic floor covering	23	1.500	15		

Both bedroom and living room were naturally ventilated and heated by waterborne radiator from September to June, working with a dead band of 2℃ and a maximum power of 2500 W placed under the windows in the two rooms. Cracks were added to the two rooms, inducing an average infiltration rate of respectively 0.4 h^{-1} in the living room and 0.2 h^{-1} in the bedroom. Both living room and bedroom had only one wall facing the exterior environment in the west orientation, only one operable window and external shading (Fig. 2).

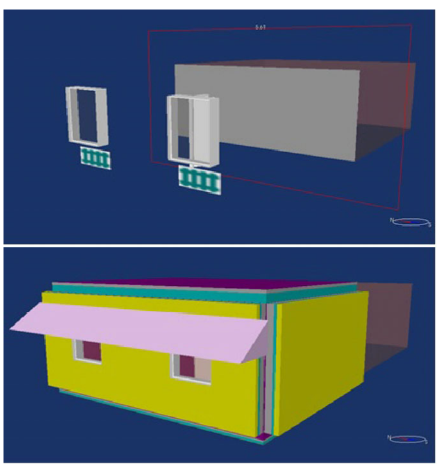

Fig. 2 Visualization of the two-room model in IDA Ice

As internal source, a house living schedule for weekday from Monday to Friday has been fixed. In both bedroom and living room one person was considered present from 17:00 to 8:00 and half occupation has been taken into account from 15:00 to 17:00 at an activity level of 70 W/m^2 and a metabolic activity of 1.2 met. The lighting schedule followed 100% the presence of people. Moreover, lights in the room with an emitted heat per unit equal to 50 W automatically switched on if the minimum work plane illuminance was lower than 100 lx; on the contrary, light switched off automatically at an illuminance level of 500 lx.

The electrical equipment consumed 50 W from 18:00 to 22:00 from Monday to Friday, and from 15:00 to 22:00 on weekends. In the standard schedule, windows opened if the indoor temperature exceeded a certain value (25℃±2℃) and the outdoor temperature was lower than the indoor temperature. Windows opened with a fixed degree of opening corresponding to a tilting angle of 20% of the total opening. Moreover, windows would stay close whenever the room is unoccupied.

2.1.5 Outputs

Each model was run 10 times. Since window openings and heating set-points were modelled stochastically, the 10 simulations did not have identical results. The mean value of a probabilistic distribution of results (fluctuation of 10 simulations) instead of single deterministic value was considered as more representative of actual energy consumption. In the simulation phase, for every model we simulated a set of 10, 20 and 30 runs, in order to highlight the oscillation among results distribution. No evident benefits emerged in running each model more than 10 times since (a) small variation (from 10% to 12%) among results distribution was found between the sets of 10, 20 or 30 runs and (b) one IDA Ice yearly simulation implementing probabilistic inputs for window and thermostat operation lasted up to 2 hours.

2.2 Methodology

The presented study developed a new methodology to combine probabilistic window openings and thermostat set-point schedules in building energy models. The methodology of the research is synthesized in Fig. 3 and explained hereafter.

In order to highlight the magnitude of occupant behavior leverage on energy consumption, simulations were performed for three different climate locations: Mediterranean (Athens), Continental (Frankfurt) and Nordic (Stockholm) climate. Additionally, with the aim to investigate the influence of thermal comfort and air quality perception on occupant behavior, simulations were performed for the three comfort category conditions (Categories I, II, III) as defined in Standard EN 15251:2006 (Table 4), both for heating set-point acceptability (21°, 20°, 18°) and for ventilation rate values (0.49 L/(s·m^2), 0.42 L/(s·m^2), 0.35 L/(s·m^2)).

Table 4 Standard EN 15251:2006. Recommended internal temperature ranges in residential buildings

Type of building/space	Category	Operative temperature for heating (winter season) ~1 clo (℃)	Air change rate (L/(s·m^2))
Residential building: living spaces (bedrooms, drawing room, kitchen, etc.)	I	21–25	0.49
	II	20–25	0.42
	III	18–25	0.35

Firstly, we treated dwelling energy performance as normally performed in the design stage of energy consumption simulation. Secondly, a model considering probabilistic of the interaction between users and window opening and closing was built, with heating set-point considered in a deterministic way as a fixed input value and being dependent on the comfort category. Finally, both window opening and closing and heating set-point adjustments were described through probabilistic models as logistic functions by combining the so called "hybrid models". Specifically three kinds of hybrid models were implemented into IDA Ice, and five scenarios of the research were defined.

2.2.1 *Scenario zero: Deterministic model*

- Window opening: deterministic
- Heating set-point adjustments: deterministic

In order to get an indication of the performance of the four probabilistic models developed and their ability to reproduce occupant behavior interactions with building envelope and system control, a first *reference deterministic*

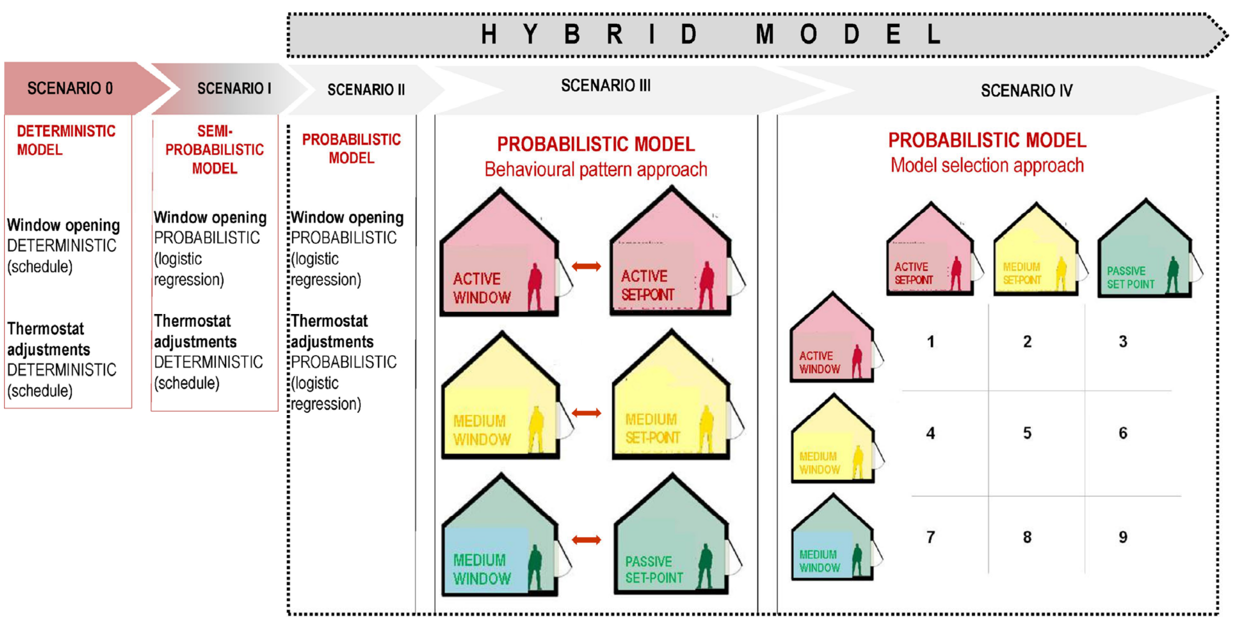

Fig. 3 Graph explaining the methodology of the research

model was implemented. This simulation model considered standard window and thermostat controls, by using deterministic inputs for both variables. Results of this fully deterministic model were considered as singular, since no probabilistic distribution of the output was needed, and subsequently compared with probabilistic model results.

2.2.2 Scenario I: Semi-probabilistic model

- Window opening: probabilistic
- Heating set-point adjustments: deterministic

The probability of opening and closing windows was inferred for a behavioral model, regarding naturally ventilated dwellings. Scenario I model was implemented by using variables and coefficients statistically treated (Table 5) as published by Fabi et al. (2012a). In this scenario, heating set-point was treated as a deterministic input.

2.2.3 Scenario II: Hybrid probabilistic model

- Window opening: probabilistic
- Heating set-point adjustments: probabilistic

We integrated a probabilistic simulation model considering both the influence of occupant behavior on window opening and closing and heating set-point adjustments. A probabilistic control of thermostats was added to the previous model whereby variables and coefficients statistically treated have been used (Andersen et al. 2011).

The probability of turning up/down the thermostat was inferred for three separated behavioral models based on the number of interactions with system controls and named as active, passive and medium user type (Table 6) as published by Fabi et al. (2012b). Window opening was modelled as in Scenario I.

2.2.4 Scenario III: Hybrid probabilistic model—Behavioral pattern approach

In the attempt to model probabilistic both the users interaction with windows and thermostats as related to users' level of interaction, a model of window opening for active, medium and passive users was implemented (Bakkær Sørensen 2012). As described in Table 7, the probability of opening and closing windows is affected by diverse variables and coefficients for different levels of users' interactions.

Table 5 Variables and coefficients for window opening/closing probability

		Open window		Close window	
Variable	Time	Coefficient	Magnitude	Coefficient	Magnitude
Intercept in spring – bedroom		−23.83		−1.93	
	Night	−23.04		−0.84	
	Morning day	−24.06		−1.22	
	Afternoon	−24.32		−1.00	
	Evening	−24.47		−0.38	
Intercept in spring – living room		−10.58		−5.31	
	Night	−9.80		−4.22	
	Morning day	−10.82		−4.61	
	Afternoon	−11.08		−4.39	
	Evening	−11.22		−3.77	
Intercept in summer – bedroom		−24.72		−0.77	
	Night	−23.94		0.32	
	Morning day	−24.96		−0.06	
	Afternoon	−25.22		0.16	
	Evening	−25.36		0.77	
Intercept in summer – living room		−11.47		−4.15	
	Night	−10.69		−3.06	
	Morning day	−11.71		−3.45	
	Afternoon	−11.97		−3.23	
	Evening	−12.12		−2.61	
CO_2 concentration	Bedroom	1.87	5.07		
	Living room	0.00023	0.62		
Indoor temperature		16	215		
Solar radiation		50	342		
Outdoor temperature				−0.15	−4.07
Outdoor relative humidity				−0.02	−0.04
Indoor relative humidity	Bedroom			0.04	1.56
	Living room			0.10	4.34

Table 6 Variables and coefficients for Active, Medium, Passive users thermostat turning up/down probability

Variable		Coefficient	Max–Min	Magnitude
ACTIVE USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−4.29	—	—
Time of the day	Morning	3.66	1.00	3.66
	Noon	3.45	1.00	3.45
	Afternoon	3.42	**1.00**	3.42
	Evening	2.14	1.00	2.14
Indoor relative humidity		−0.09	50.12	4.27
Outdoor temperature		−0.14	36.30	5.23
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−3.51	—	—
Solar radiation		−0.02	849.00	16.52
MEDIUM USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−7.64	—	—
Outdoor temperature		−0.23	36.30	8.29
Wind speed		0.37	10.70	3.96
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−22.84	—	—
Time of the day	Morning	17.68	1.00	17.68
	Noon	16.74	1.00	16.74
	Afternoon	16.26	**1.00**	16.26
	Evening	16.18	1.00	16.18
PASSIVE USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−9.72	—	—
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−14.28	—	—
Solar radiation		−1.01	10.70	10.78

A new probabilistic simulation model was run, representing different users' frequency of interaction within the same dwelling.

Thus, three models were indicative of active, medium and passive users behavior both for window control and for heating set-point adjustment (active-active, medium-medium, and passive-passive models).

2.2.5 *Scenario IV: Hybrid probabilistic model—Model selection approach*

Starting from the assumption that users' willingness in reaching a certain level of comfort could be different regarding window openings and heating set-point adjustment, each of three behavioral models of window control previously developed was matched in a macro with the three concerning thermostat adjustments. Accordingly, nine models were implemented, covering all possible combinations between them.

3 Results

By switching from a deterministic to a probabilistic approach in dynamic simulation software, high variation in energy consumption predictions was found. Results of the research focused on differences in delivered heat energy consumption between singular values of deterministic simulations and mean values of probabilistic simulations.

3.1 Window openings

In the probabilistic models windows opened accordingly to a probability which was strictly correlated to indoor and outdoor parameters. In living room (Fig. 4), the window opening probability had a bell-shaped curve distribution and presented a peak between June and September in Athens. The maximum value was observed between March and May in Stockholm's simulations. In Frankfurt, the tendency was in between the Mediterranean and Nordic climates, with maximum values ranging from May to September.

Since no fixed air change rate but variable indoor and outdoor parameters drove the probability of opening windows, great variation in ventilation losses between the deterministic and the probabilistic scenarios was found in every climate location. Among other factors, such as transparent building components' air tightness and cracks in opaque building envelope, ventilation rate operated by users was the paramount driver for variation in heat energy consumption in residential buildings.

Figure 5 displays a comparison among results of infiltration and natural ventilation for deterministic simulations (Scenario 0, deterministic input) and for the distribution of a set of 10 simulations (Scenario IV, probabilistic inputs), both for living room and bedroom. Representative results are shown for the Category of Comfort II. In Athens, ventilation losses simulated by using fixed value of ventilation rate was 38 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 28 kWh/(m^2·year) to 56 kWh/(m^2·year), with a maximum variation of 47%. In Frankfurt, ventilation losses simulated by using fixed value of ventilation rate was 72 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 48 kWh/(m^2·year) to 102 kWh/(m^2·year), with a maximum

Table 7 Variables and coefficients for Active, Medium, Passive users window opening/closing probability

		ACTIVE		MEDIUM		PASSIVE	
		Open	Close	Open	Close	Open	Close
Intercept (hour 0)	Bedroom	−11.9	3.43	−28.75	−18.27	−16.10	−21.19
	Living room	−11.9	3.26	−28.75	−16.16	−16.50	−18.56
Indoor *T*		0.10	−0.08	0.15		0.14	
Indoor RH	Bedroom	0.02	−0.07	−0.10	−0.19	0.07	
	Living room	0.02	−0.15	−0.10	−0.13	0.07	
CO_2 concentration				1.40	2.24	1.01	1.62
Illuminance		0.28	−0.48	−0.34			
Outdoor *T*	Bedroom	0.10		0.16	−0.01	−0.04	−0.13
	Living room	−0.09		0.16	−0.09	0.07	−0.13
Wind	Bedroom	0.34	−0.29	0.34	0.47	−0.14	
	Living room	0.34	−0.29	0.34	0.47	0.91	
Outdoor RH		0.01	0.02	0.02	0.01		
Solar radiation						0.19	
Sunshine hours		−0.08		−0.09		−0.08	
Hour 1		−0.02		11.73	−12.06	−13.05	
Hour 2		−0.72		11.07	−0.41	−13.02	
Hour 3		−0.43		11.10	−1.10	−13.00	
Hour 4		0.97		15.21	−0.49	−12.98	
Hour 5		2.48		15.32	1.86	2.02	
Hour 6		**3.0**		15.85	2.80	3.28	
Hour 7		2.81		**16.07**	2.89	**4.62**	
Hour 8		2.49		15.99	3.47	4.11	
Hour 9		2.12		15.57	3.21	3.22	
Hour 10		1.69		15.03	3.45	3.06	
Hour 11		1.85		14.37	**3.68**	3.23	
Hour 12		1.67		14.64	3.21	2.71	
Hour 13		1.46		14.90	3.30	2.36	
Hour 14		1.51		14.98	3.01	2.40	
Hour 15		1.59		14.74	3.20	2.90	
Hour 16		1.93		14.84	3.43	2.67	
Hour 17		1.90		14.20	3.17	2.79	
Hour 18		1.38		14.15	3.02	1.69	
Hour 19		1.0		14.48	2.89	1.92	
Hour 20		1.2		14.42	3.11	1.91	
Hour 21		1.8		14.58	2.70	2.03	
Hour 22		2.15		13.50	2.30	1.62	
Hour 23		1.84		12.12	2.05	−13.06	

variation of 42%. In Stockholm, ventilation losses simulated by using fixed value of ventilation rate was 89 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 53 kWh/(m^2·year) to −133 kWh/(m^2·year), with a maximum variation of 49%.

3.2 Heating set-point adjustments

Simulated thermostat set-points during heating season (from 15 September to 15 June) in living room and bedroom were analysed for each scenario.

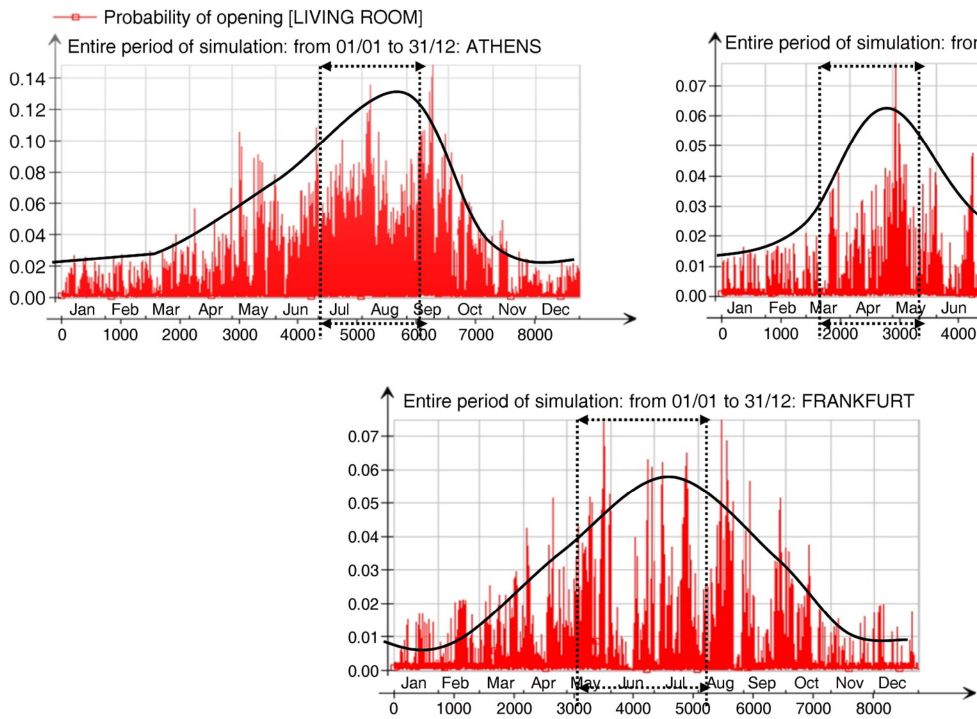

Fig. 4 Probability of window opening in living room. Results for Athens, Frankfurt, Stockholm

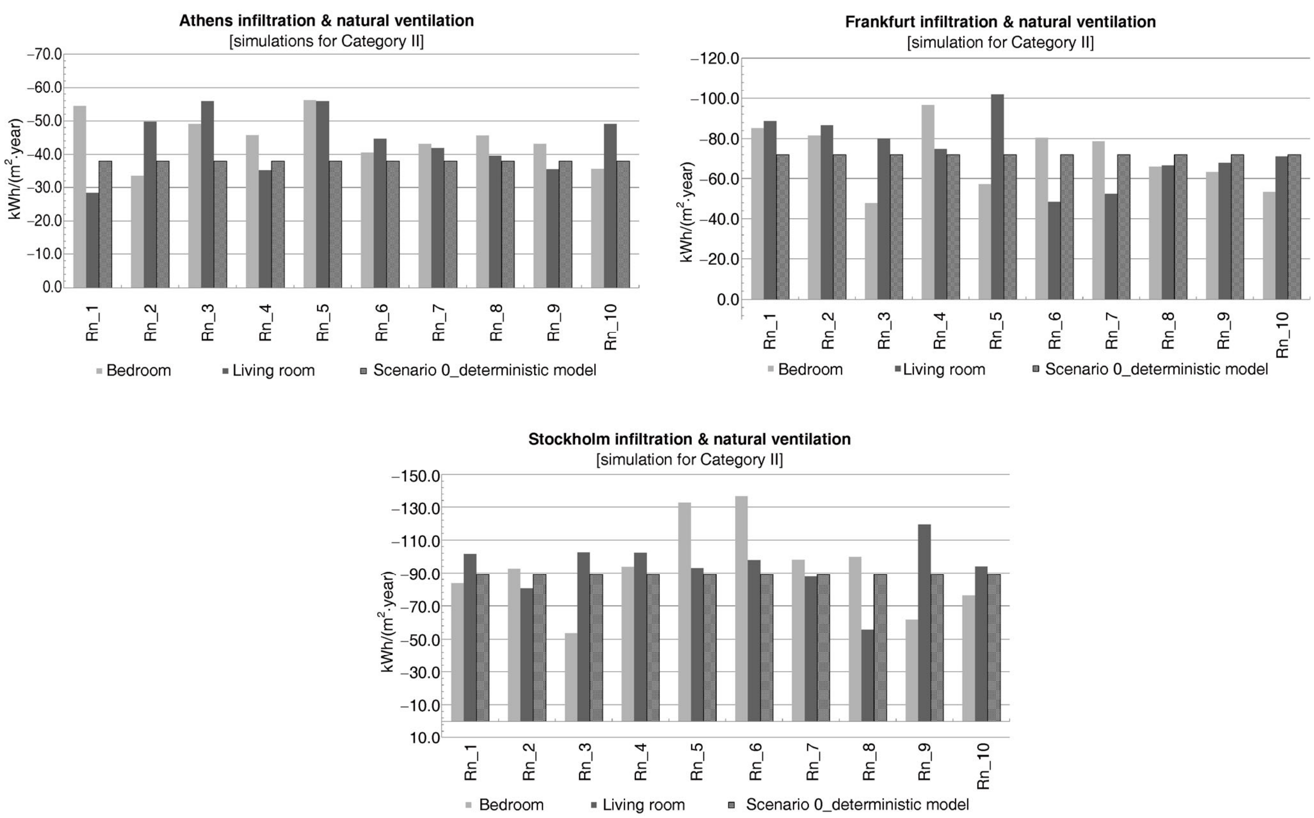

Fig. 5 Simulated infiltration and natural ventilation for deterministic simulations (singular value) and for the distribution of a set of 10 simulations (probabilistic inputs)

In scenario 0, a heating set-point of 18℃ was considered acceptable for the comfort category III, according to the deterministic approach of European standard EN 15251:2007. However, from the simulated occupant behavior (inferred from field measurements) it was evident that if occupants have the opportunity to choose the heating set-point, they tend to prefer temperatures above 21℃ (Category I), both in living room and bedroom. As a consequence, simulations based on category III in EN 15251, resulted as the greater underestimation in heating consumption, when compared to probabilistic results (Fig. 6).

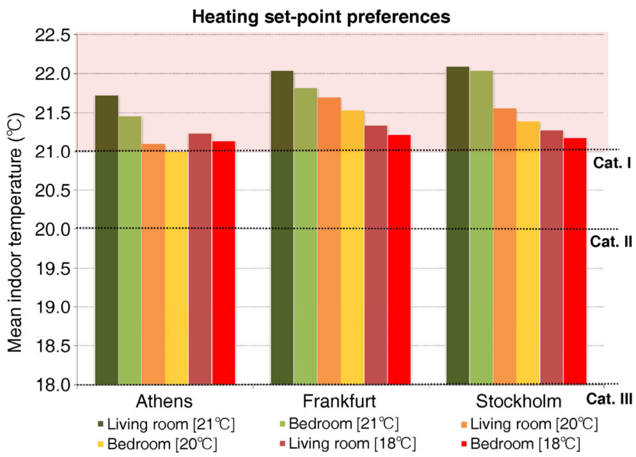

Fig. 6 Heating set-point preferences. Mean value for living room and bedroom

3.3 From deterministic to probabilistic approach in modelling

Figure 7 displays a comparison among results of heating delivered energy for deterministic simulations (Scenario 0, deterministic input) and for the distribution of three sets of 10 simulations (Scenario IV, probabilistic inputs). Representative results are shown for Category of Comfort II. In Athens, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 47 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 46 kWh/(m^2·year) to 68 kWh/(m^2·year), with a maximum variation of 45%. In Frankfurt, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 153 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 160 kWh/(m^2·year) to 206 kWh/(m^2·year), with a maximum variation of 36%. In Stockholm, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 212 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 212 kWh/(m^2·year) to 267 kWh/(m^2·year), with a maximum variation of 26%.

Figure 8 shows how the deterministic approach (Scenario 0) generally underestimated the heating consumption, when compared to probabilistic predictions taking occupant behavior into account (Scenario IV). The largest impact in delivered energy variation from deterministic to probabilistic simulations was simulated for category III in Athens (61%), Frankfurt (47%) and Stockholm (35%). Maximum variation resulted in Mediterranean climate (Athens) for Category I (24%), Category II (47%) and Category III (61%).

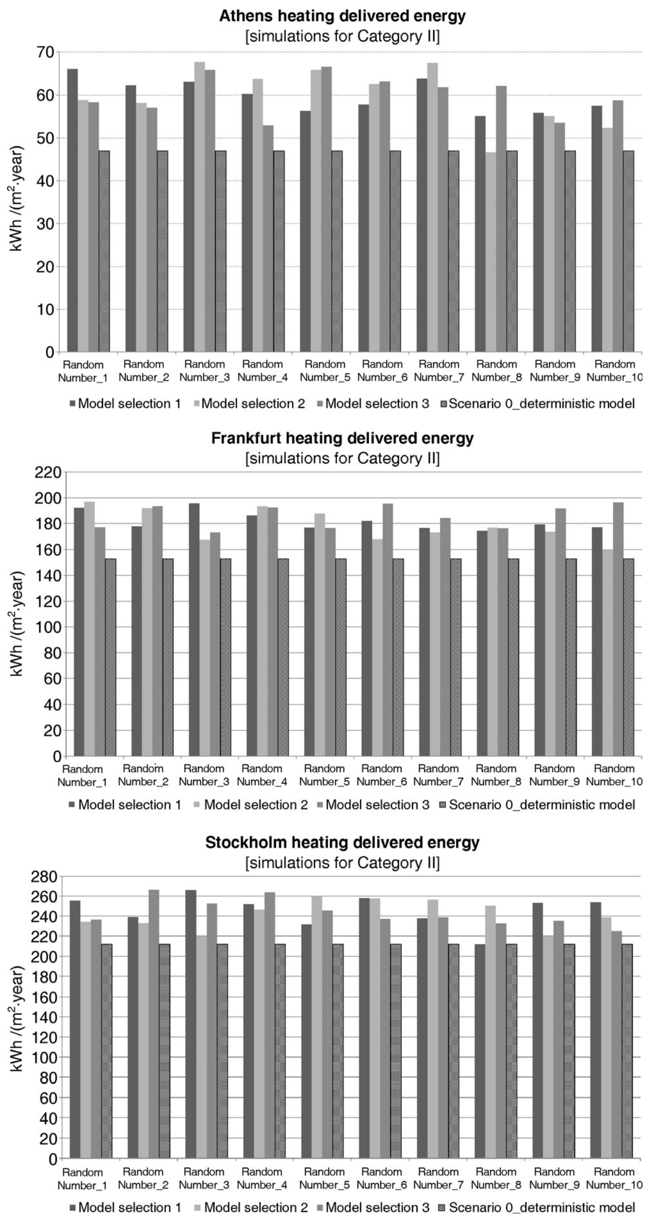

Fig. 7 Simulated heating delivered energy for deterministic simulations (singular value) and for the distribution of 3 sets of 10 simulations (probabilistic inputs)

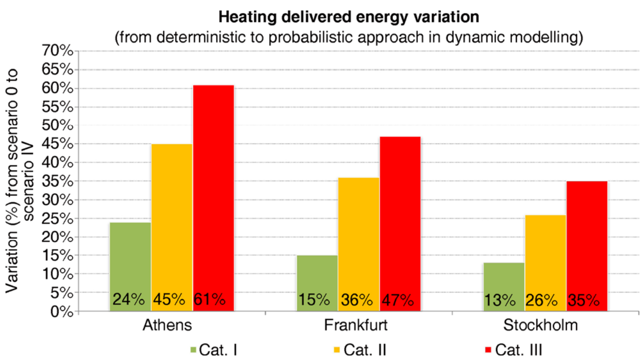

Fig. 8 Heating delivered energy augmentation from deterministic to probabilistic approach in modelling

4 Discussion

Results of this research gave confirmation to the hypothesis that occupants behavior in buildings is to be regarded one of the key reasons of discrepancies between predicted and actual energy consumption in dwellings. Some building occupants are very much aware of their energy bills (heating and electricity) and tend to act in ways to reduce their bill rather than to maintain a high level of comfort. In contrast, energy-unconscious occupants liberally interact with control system in order to improve comfort conditions in their homes.

Findings of this research underlined that occupants interactions within building envelope and control systems are strictly interrelated to the pursuit of personal comfort, the perceived indoor environmental quality and therefore global energy performance of the buildings.

The research presented in this paper cannot be regarded as concluded. On the contrary, analysis methods, developed models and results should rather be taken as starting points for future research aiming at a further understanding of the occupant behavior leverage on thermal comfort and energy consumption in buildings. Specifically, validating these models with new data set coming from different geographical areas is highly advisable in order to strengthen the applicability of human based models to cultural and climatic differences. Moreover, implementing more statistical variability of user control over indoor environmental conditions, such as blind adjustment, electric systems and domestic hot water usage, is strongly appealed in the aim of a better prediction of total energy use in buildings.

In this paper, we have investigated the influence of nine different probabilistic behaviour patterns (combinations of active, medium and passive operation of windows and thermostats). Haldi (2013) discussed how different occupants could be assigned different model coefficients, to model the fact that different occupants will have different behavior patterns. In that sense, the nine behavior patterns could be regarded as models of nine specific persons. However, since the models were inferred from data from 15 different dwellings including more than 40 residents, the models could also be regarded as a representation of nine standard behavior patterns, covering the variation observed in the 15 dwellings.

5 Conclusions

The energy consumption of dwellings in which occupants control (window opening and heating set-point adjustments) was simulated by probabilistic functions, was up to 61% higher than when the control system was simulated in a deterministic way by fixed schedules. The maximum variation in heating performance prediction, due to a switch from deterministic to a probabilistic modelling approach was recorded for Athens. This discrepancy could be attribuited to users interaction specifically within windows opening. In the Mediterranean climate naturally ventilated buildings tend to get over heating during warmer periods and consequently users tend to open windows more often. This interaction necessarely leads to an increase of ventilation losses.

Maximum impact in the step from a deterministic to a probabilistic approach in simulation was found for the comfort category III. Significantly, the probabilistic models of occupants behavior (infered from field measurements) led heating set-points and ventilation rate to the highest comfort condition, often close to category I. This confirms that a gap between deterministically predicted and actual heating consumption in dwelling is partly due to occupants interaction with control systems, performed in order to restore a comfort condition in indoor environments.

The presented paper applies an innovative "best practice" approaches and develops new models on human energy behaviors. The positive effects of major innovations of this paper can benefit building energy performance during the whole-building life cycle:

- Design phase: predicting actual building energy use more realistically. The improved simulation model implemented in IDA Ice with new behavioral modules will support decision making in the early design stage.
- Operation phase: using predictive models and algorithms of occupant behavior embedded in users device and control technologies to supply advice to users through "smart" communication.
- Building retrofit: evaluating the impact of occupant behavior on different building technology solutions.
- Building management: allowing building energy flows, control systems, appliances usage and comfort level mapping.
- Building codes and policy: advancing building standards development by quantifying variation of energy savings of technologies related to occupant behavior.

References

Andersen RV, Olesen BW, Toftum J (2007). Simulation of the effect of occupant behavior on indoor climate and energy consumption. In: Proceedings of Clima 2007: 9th Rehva World Congress: Wellbeing Indoors, Helsinki, Finland.

Andersen RV, Olesen BW, Toftum J (2011). Modelling heating set-point references. In: Proceeding of IBPSA International Conference, Sydney, Australia.

Andersen R (2012). The influence of occupants' behavior on energy consumption investigated in 290 identical dwellings and in 35 apartments. In: Proceedings of Healthy Buildings 2012, Brisbane, Australia.

Andersen RV, Fabi V, Toftum J, Corgnati SP, Olesen BW (2013). Window opening behavior modelled from measurements in Danish dwellings. *Building and Environment*, 69: 101–113.

Korjenic A, Bednar T (2011). Impact of lifestyle on energy demand of a single family house. *Building Simulation*, 4: 89–95.

Baker N, Standeven M (1996). Thermal comfort for free-running buildings. *Energy and Buildings*, 23: 175–182.

Bakkær Sørensen J (2012). Impact of alternating window opening behavior on different building envelope designs. Master Thesis, Department of Civil Engineering, Danish Technical University, Denmark.

Borgeson S, Brager G (2008). Occupant control of windows: Accounting for human behavior in building simulation. Centre for the Built Environment, Internal Report.

Bourgeois D (2005). Detailed occupancy prediction, occupancy-sensing control and advanced behavioral modeling within whole-building energy simulation. PhD Thesis, Faculté des Études Supérieures Université Laval Québec, Canada.

Leaman A, Bordass W (1998). Productivity: The killer variables. *Building Services Journal*, June: 41–43.

de Dear R, Brager GS (2001). The adaptive model of thermal comfort and energy conservation in the built environment. *International Journal of Biometeorol*, 45: 100–108.

Clevenger CM, Haymaker J (2006). The impact of the building occupation on energy modeling simulations. Presented at the Joint International Conference on Computing and Decision Making in Civil and Building Engineering, Montreal, Canada.

Wang C, Ya D, Jiang Y (2011). A novel approach for building occupancy simulation. *Building Simulation*, 4: 149–167.

Emery AF, Kippenhan CJ (2006). A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards. *Energy*, 31: 677–693.

Fabi V, Andersen RV, Corgnati SP, Olesen BW (2013). A methodology for modelling energy-related human behavior: Application to window opening behavior in residential buildings. *Building Simulation*, 6: 415–427.

Fabi V, Andersen RV, Corgnati SP (2012a). Window opening behavior in residential buildings using models based on field survey. In: Proceedings of 7th Windsor Conference: The Changing Context of Comfort in an Unpredictable World, Longon, UK.

Fabi V, Andersen RV, Corgnati SP, Venezia F (2012b). Influence of user behavior on indoor environmental quality and heating energy consumption in Danish dwellings. In: Proceedings of 2nd International Conference on Building Energy and Environment, Boulder, USA.

Haldi F (2013). A probabilistic model to predict building occupants' diversity towards their interactions with the building envelope. In: Proceedings of IBPSA International Conference, Chambéry, France.

Hoes P, Trcka M, Hensen JML, Hoekstra BB (2011). Optimizing building design using a robustness indicator with respect to user behavior. In: Proceedings of IBPSA International Conference, Sydney, Australia.

Marchio D, Rabl A (1991). Energy-efficient gas heated housing in France: Predicted and observed performance. *Energy and Buildings*, 17: 131–139.

Nicol JF (2001). Characterising occupant behavior in buildings: Towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans. In: Proceedings of 7th IBPSA International Conference, Rio de Janeiro, Brazil.

Paciuk M (1989). The role of personal control of the environment in thermal comfort and satisfaction at the workplace. PhD Thesis, University of Wisconsin, USA.

Page J, Robinson D, Morel N, Scartezzini JL (2008). A generalized stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40: 83–98.

Rijal HB, Tuohy P, Humphreys MA, Nicol JF (2007). Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings*, 39: 823–836.

Schweiker M, Haldi F, Shukuya M, Robinson D (2011). Verification of stochastic models of windows opening behavior for residential buildings. *Journal of Building Performances Simulation,* 5: 55–74.

Toftum J, Andersen RV, Jensen KL (2009). Occupant performance and building energy consumption with different philosophies of determining acceptable thermal conditions. *Building and Environment*, 44: 2009–2016.

Wei S, Buswell R, Loveday D (2010). Probabilistic modelling of human adaptive behavior in non-air conditioned buildings. In: Proceedings of 6th Windsor Conference: Adapting to Change: New Thinking on Comfort, London, UK.