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The impact of occupants' behaviour on building energy demand

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Using extensive field survey data acquired over the past 8 years at the Solar Energy and Building Physics Laboratory at EPFL in Switzerland, comprehensive models of occupants' presence, opening and closing of windows and the raising and lowering of blinds have been developed. These new models have been integrated within a new urban energy modelling tool, called CitySim. In this article, we describe briefly the structure of CitySim together with the means for representing occupants' presence and behaviour, both deterministic and stochastic. For a hypothetical scenario, we then go on to present results from simulations of the impact that occupants' behaviour may have on the indoor environment in buildings as well as on buildings' energy demands. From this we conclude that occupants' behaviour has a significant impact (of the order of a factor of two) on buildings' energy demands and that individuals' diversity has a yet greater impact.

Keywords: energy modelling; behavioural modelling; windows; shading devices

1. Introduction

1.1. Context

Although the deterministic features of building simulation programmes are now considered relatively mature, their ability to emulate reality is still undermined by a poor representation of factors relating to occupants' presence and their interactions with environmental controls. Amongst the most noteworthy are occupants' actions on windows, whose associated air flows impact on indoor hygro-thermal conditions and indoor air quality; likewise actions on shading devices, which influence solar heat gains and daylight availability. But how significant are these influences? Do we really need to routinely make use of sophisticated stochastic models of occupants' behaviour and the diversity of these behaviours amongst occupants in building and urban simulation? To shed light on this issue, we have integrated and thoroughly tested comprehensive models of occupants' use of windows and shading devices into the urban energy modelling tool CitySim.

1.2. Previous work

1.2.1. Experimental evidence

Discrepancies between real and assumed deterministic behaviours are such that the energy demands of like buildings may vary by a factor of two (Baker 1994). This has been confirmed by field observations. For example Seligman *et al*. (1977) investigated the energy consumption in 28 identical houses and found that the largest variation was two to one. Considering ventilation, measurements conducted in 25 Danish buildings showed that on average the increase in the mean airflow rate due to the influence of occupancy is more than 100% (Dubrul 1988). Similarly, Iwashita and Akasaka (1997) later measured that 87% of the total air change rate is caused by the occupants' behaviour. More recently, Bahaj and James (2007) observed that the electricity consumption in nine identical low-energy social housing units varied by as much as 600% during certain periods of the year. Amongst other factors, these variations are influenced by occupants' conscious behavioural attitudes, as verified by Gill *et al*. (2010), who observed that a pool of occupants' personal indicators (including behavioural and normative beliefs with perceived behavioural control) accounted for 51, 37 and 11% of the variance in heat, electricity and water consumption between identical low-energy dwellings.

Field observations have also provided evidence that buildings controls empower occupants to adapt their environment and thus to remain comfortable for a wider range of indoor environmental conditions compared with mechanically controlled environments (Baker and Standeven 1996). Quantitatively, Brager *et al*. (2004) observed a 1.5°C difference in the neutral temperature between occupants with high and low

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degrees of control over windows, while the explicit use of windows was found to induce increments of between 0.5°C and 1.1°C (Haldi and Robinson 2008, 2010b). The integration of effective environmental controls has thus a strong positive impact on perceived indoor environment quality and on the energy use of a building. But to determine whether such controls are indeed likely to be effective at the design stage requires some means for simulating occupants' interactions with them and the corresponding energetic and environmental responses – the subject of this paper.

1.2.2. *Applications in building simulation*

According to Hoes *et al.* (2009), the relative influence of users' behaviour increases in passive buildings, which are expected to become more common due to the demand for improved sustainability. They point out that for some buildings detailed behavioural modelling is necessary to ensure that these are robust to the influence of their users' behaviour.

Recently, the impact of different types of occupant behaviour within building simulation tools has also been studied (Bourgeois *et al.* 2006); occupants being typically modelled as 'active' or 'passive', as originally proposed by Reinhart (2004). For instance, according to Schweiker and Shukuya (2010), changes in occupants' behaviour towards the use of air-conditioning are estimated to have a higher impact on energy demand than building envelope improvements. Comparing the impact of ideal and worst case scenarios in simulations, Roetzel *et al.* (2010a) found that the influence of occupants' use of lights and shading devices dominates over an office building's intrinsic design variables on total greenhouse gas emissions and running costs. Parys *et al.* (2010) developed further this type of study by considering four distributions of active and passive users of artificial lights and shading devices. They concluded that heating energy use remains rather robust to variations in occupants' behaviour, in contrast with cooling and lighting energy use.

However, only the case of extreme behaviours expressed as best and worst cases is treated in these preliminary studies. In order to thoroughly evaluate the impact of behavioural diversity on buildings' energy demand, it is necessary to explore the realistic distribution of predicted energy demands on the basis of a representative sample of actually encountered behavioural patterns. This is the purpose of this study.

1.3. *Summary*

Our work on the stochastic modelling of occupants' presence and behaviour is part of a long-term initiative to develop comprehensive tools for the modelling and optimization of urban resource flows (Robinson 2011). The core of this work is the development of CitySim – software for simulating energy demand, storage and supply for urban developments of various scales, from the neighbourhood to the city. It is thus by integrating stochastic models of occupants' use of windows and blinds into CitySim that we examine their impact on buildings' performance.

We begin this article with a brief presentation of CitySim. The models for simulating occupants' use of windows and blinds are then presented, followed by the case study on which our analyses are based. For this case study, we examine occupants' influence on buildings' energy demands and indoor environmental conditions, based both on behavioural models derived from aggregate data and on those derived from individuals' specific behaviours. We do this for different combinations of building design variables, so that the sensitivity of predictions to both (behaviour and design) are considered. We conclude by discussing these results.

2. CitySim: from building simulation to urban simulation

CitySim is software in development that is conceived to support the more sustainable energy planning of urban developments of various scales, from a neighbourhood to a city district and beyond. For these purposes, bespoke models (Figure 1) have been developed to achieve a good compromise between accuracy, computational overheads and data availability. Robinson *et al.* (2009) and Robinson (2011) present a detailed description of the theoretical basis of CitySim; but to place the remainder of this article into context we provide here a brief summary of CitySim's core deterministic models.

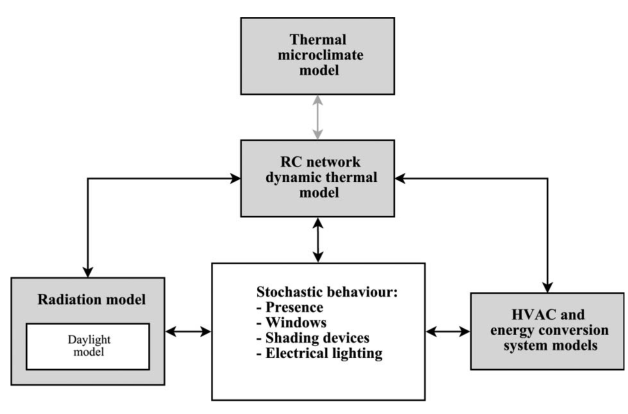

Figure 1. Conceptual structure of CitySim.

2.1. Thermal model

The thermal model is based on a resistor-capacitor network, in which a conducting wall is represented by one or more temperature nodes. The heat flow between a wall and the outside air can be represented by an electric current through a resistor linking the two corresponding nodes and the wall's inertia can be represented by a capacitance linked at that node.

In our model (Kämpf and Robinson 2007), an external air temperature node T_{ext} is connected with an outside surface temperature node T_{os} via an external film conductance K_e, which varies according to wind speed and direction (Figure 2). T_{os}, which also experiences heat fluxes due to shortwave and longwave exchange, is connected to a wall node T_w of capacitance C_w via a conductance defined by the external part of the wall. In fact this node resembles a mirror plane, so that we have similar connections to an internal air node T_a of capacitance C_i via an internal surface node T_{is}. T_{is} may also experience shortwave flux due to transmitted solar radiation and a longwave flux due to radiant heat gains from internal sources (people and appliances) and T_a may experience convective gains due to absorbed shortwave radiation, internal casual gains and heating or cooling systems. Finally, our internal air node may be connected with our external air temperature node via a variable resistance due to infiltration and ventilation (see Section 3.2). Predictions from this simplified model compare well with those of ESP-r for a range of monozone and multizone scenarios.

By default the thermal model is solved using an implicit solution scheme and performs predictions at a one hour time step.

2.2. Radiation model

A simplified radiosity algorithm (SRA) is used to solve for the shortwave and longwave irradiance incident on the surfaces defining our urban scene, see Robinson and Stone (2004, 2005) for a detailed description.

For some set of p sky patches, each of which subtends a solid angle Φ (sr) and has radiance R

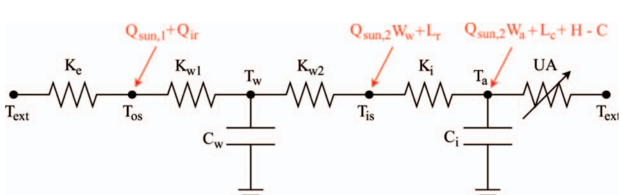

Figure 2. Resistor-capacitor network representation of the thermal model.

($\mathrm{Wm}^{-2}\ \mathrm{sr}^{-1}$) then, given the mean angle of incidence ξ (rad) between the patch and our receiving plane of slope β together with the proportion of the patch that can be seen σ ($0 \le \sigma \le 1$), the direct sky irradiance (Wm^{-2}):

$$I_{d\beta} = \sum_{i=1}^{p} (R\Phi\sigma \cos\,\xi)_i. \tag{1}$$

For this the well-known discretization scheme due to Tregenza and Sharples (1993) is used to divide the sky vault into 145 patches of similar solid angle and the Perez all weather model (Perez *et al.* 1993) is used to calculate the radiance at the centroid of each of these patches. The direct beam irradiance $I_{b\beta}$ is calculated from the beam normal irradiance I_{bn} which is incident at an angle ξ to our surface of which some fraction ψ is visible from the sun, so that:

$$I_{b\beta} = I_{bn}\psi \cos\,\xi. \tag{2}$$

Now the direct sky and beam irradiance contributes to a given surface's radiance R which in turn influences the irradiance incident at other surfaces visible to it, so increasing their radiance and vice versa. To solve for this a similar equation to that used for the sky contribution gives the reflected diffuse irradiance. In this case two discretized vaults are used

$$I_{b\beta} = \sum_{i=1}^{2p} (R^*\Phi\omega \cos\,\xi)_i \tag{3}$$

where ω is the proportion of the patch which is obstructed by urban (reflecting) surfaces and R^* is the radiance of the surface which dominates the obstruction to this patch (in other words, that which contributes the most to ω). As noted earlier, R^* depends on reflected diffuse irradiance as well as on the direct sky and beam irradiances. For this a set of simultaneous equations relating the beam and diffuse sky components to each surface's irradiance, which itself effects the reflected irradiance incident at other surfaces, may be formulated as a matrix and solved either iteratively or by matrix inversion, see Robinson and Stone (2004).

The principal complication in the above algorithm lies in determining the necessary view factors. For obstruction view factors, views encapsulating the hemisphere are rendered from each surface centroid, with every surface having a unique colour. Each pixel is then translated into angular coordinates to identify the corresponding patch as well as the angle of incidence. For sky view factors then, $\Phi\sigma$ cos ξ is treated as a single quantity obtained by numerical integration of $\cos\xi \cdot d\Phi$ across each sky patch. Likewise for $\Phi\omega \cos \xi$, for which the dominant occluding surface is identified as that which provides the greatest contribution. A similar process is repeated for solar visibility fractions for each surface, for which a constant size scene is rendered from the sun position.

In addition to using the above view information to calculate incident shortwave irradiance, this may also be used to calculate longwave irradiance; given the corresponding surface and sky temperatures (see Robinson and Stone 2005). Equations (1)–(3) may also be solved using luminance/illuminance as an input to model the external luminous environment. Additional renderings may then be computed to determine the view information necessary to calculate the direct and reflected contributions to internal illuminance (at known points) as well as the incoming luminous flux for internal reflection calculations (Robinson and Stone 2005, 2006).

2.3. *Plant and equipment models*

This category of model includes both heating, ventilating and cooling (HVAC) systems and energy conversion systems (ECS).

If air is used as the medium for delivering a zone's space conditioning demands, the HVAC model computes the psychrometric state of the air at each stage in its supply (e.g. outside, heat recovered, cooled and dehumidified, re-heated, supply). Given the required mass flow rate (which may be defined by the energy to be delivered or the room fresh air requirement) and the enthalpy change across each stage in the air-conditioning process the total delivered sensible and latent loads for the set of stages is calculated.

The family of ECS models comprises a range of technologies that provide and store heat and/or electricity to buildings. These are, in the main, relatively simple empirical models. If the ECS models have insufficient capacity to satisfy the zone's space conditioning demands, whether or not air-handling (HVAC) plant is integrated, then the supply state is adjusted (in the case of HVAC plant) and the predicted room thermal state is corrected using the thermal model (so that a higher or lower than desired room state may be achieved).

3. Behavioural models and their integration

3.1. *Actions on windows*

For a detailed review of research on the modelling of occupants' use of windows, we refer the reader to Roetzel *et al.* (2010b). In the present context of integration, corresponding models have been integrated into ESP-r (Rijal *et al.* 2007; Yun *et al.* 2009). However, the diversity of behaviours amongst occupants is not considered and the algorithm is based solely on the results from an 'average' occupant arising from the use of aggregated data collected from several people. Furthermore, these algorithms have been shown through cross-validation (Haldi and Robinson 2009) to reproduce reality less satisfactorily than the more comprehensive model described below.

Based on detailed statistical analyses of 8 years' continuous measurements, Haldi and Robinson (2009) developed three models for the prediction of actions on windows performed by office occupants, which also account for occupants' diversity. In each case, explanatory variables were carefully selected on the basis of statistical relevance.

3.1.1. *Bernoulli process based on a single probability*

At each time step, the probability to observe a window open is independently determined by a probability formulated as a logistic model with indoor (θ_{in}) and outdoor (θ_{out}) temperatures as explanatory variables:

$$P_{open}(\theta_{in}, \theta_{out}) = \frac{\exp(a + b_{out}\theta_{out} + b_{in}\theta_{in})}{1 + \exp(a + b_{out}\theta_{out} + b_{in}\theta_{in})}, \quad (4)$$

with calibration parameters $a = 0.794$, $b_{out} = 0.1476$ and $b_{in} = -0.1541$.

3.1.2. *Markov chain*

At each time step, window openings and closings are modelled by action probabilities P_{ij} from state i to state j ($i, j = 0, 1$) also formulated as logistic models:

$$P_{ij}(x_1, \ldots, x_n) = \frac{\exp(a + \sum_{k=1}^{n} b_k x_k))}{1 + \exp(a + \sum_{k=1}^{n} b_k x_k))}. \quad (5)$$

Action probabilities were found to be explained by a set of n predictors x_k depending on occupancy transition. These are indoor (θ_{in}), outdoor (θ_{out}) and daily mean outdoor ($\theta_{out,dm}$) temperature, the occurrence of rain (f_R), occupant presence (T_{pres}) and previous or expected absence durations ($f_{abs,prev}$, $f_{abs,next}$), with associated calibration parameters displayed in Table 1 (top).

3.1.3. *Hybrid model*

The above occupancy-dependent Markov chain is extended to a continuous-time process based on a Weibull distribution for opening durations. Action probabilities P_{ij} are modelled as above, except for

Table 1. Regression parameters for probabilities of actions on windows and shading devices, based on aggregated data from all occupants.

Variables Windows	Opening probability P_{01}	Closing probability P_{10}
Arrival		
a	-13.88 ± 0.37	3.97 ± 0.37
θ_{in}	0.312 ± 0.016	-0.286 ± 0.017
θ_{out}	0.0433 ± 0.0033	-0.0505 ± 0.0045
$f_{\text{abs,prev}}$	1.862 ± 0.044	
f_R	-0.45 ± 0.11	
During presence		
a	-12.23 ± 0.28	-1.64 ± 0.22
θ_{in}	0.281 ± 0.013	-0.0481 ± 0.0098
θ_{out}	0.0271 ± 0.0024	-0.0779 ± 0.0020
T_{pres}	$(-8.78 \pm 0.53) \cdot 10^{-4}$	$(-1.62 \pm 0.06) \cdot 10^{-3}$
f_R	-0.336 ± 0.081	
Departure		
a	-8.75 ± 0.22	-8.54 ± 0.48
θ_{in}		0.213 ± 0.022
$\theta_{\text{out,dm}}$	0.1371 ± 0.0075	-0.0911 ± 0.0061
$f_{\text{abs,next}}$	0.84 ± 0.12	1.614 ± 0.069
f_{GF}	0.83 ± 0.13	-0.923 ± 0.068
Variables Blinds	**Lowering probability, P_{lower}**	**Raising probability, P_{raise}**
Arrival		
a	-7.41 ± 0.16	-1.520 ± 0.051
E_{in}	$(10.35 \pm 0.19) \cdot 10^{-4}$	$(-6.54 \pm 0.46) \cdot 10^{-4}$
B_L	2.17 ± 0.16	-3.139 ± 0.068
During presence		
a	-8.013 ± 0.086	-3.625 ± 0.030
E_{in}	$(8.41 \pm 0.13) \cdot 10^{-4}$	$(-2.76 \pm 0.22) \cdot 10^{-4}$
B_L	1.270 ± 0.086	-2.683 ± 0.040
Full lowering or raising		
a	-0.27 ± 0.14	0.435 ± 0.062
$E_{\text{gl,hor}}$	$(0.91 \pm 1.33) \cdot 10^{-6}$	$(-2.31 \pm 0.11) \cdot 10^{-5}$
B_L	-2.23 ± 0.16	1.95 ± 0.11

closing actions which are predicted by the density of the probability distribution of opening durations:

$$f_{\text{op}}(t) = \lambda\alpha(\lambda t)^{\alpha-1} \exp(-(\lambda t)^{\alpha}), \tag{6}$$

$$\lambda = 1/\exp(a + b\theta_{\text{out}}), \tag{7}$$

with $\alpha = 0.418$, $a = 2.151$ and $b = 0.172$. Based on cross-validation, the predictive accuracy of this latter model has been compared very favourably with other variants and with previously published work.

There is currently no available model to predict the window opening angle chosen by occupants. Therefore, we will assume that the windows are either completely open or closed.

3.2. *Air flow from ventilation*

The time step of 1-h used in this implementation of CitySim being too large for a reliable integration of a behavioural model of window openings, an additional prediction of indoor temperature was implemented, this time using an explicit solution scheme for the thermal model at a time step of 5 min. In parallel, the hourly implicit prediction is used for the prediction of heating and cooling power demands, based on infiltration but not on ventilation. At each 1-h time step, the current explicit prediction is used to update the value for the next prediction with the implicit model.

In the case of single-sided ventilation (CIBSE 1997, p.53), the wind-driven ventilation rate Q_w (m^3/s) is expressed as $Q_w = 0.05AV$, where A is the opening area (m^2) and V the wind speed (m/s) at the opening height. The stack-driven air flow Q_s is given by

$$Q_s = \frac{1}{3} C_d A \sqrt{\frac{gh|T_{\text{in}} - T_{\text{out}}|}{(T_{\text{in}} + T_{\text{out}})/2}} \tag{8}$$

with h (m) being the height of the opening and T_{in}, T_{out} (K) the indoor and outdoor absolute temperatures. The total air flow is then obtained by combining the individual volume flows in quadrature, so that $Q_{\text{tot}} = \sqrt{Q_w^2 + Q_s^2}$, linked with the indoor air by an added variable resistance $\rho Q_{\text{tot}} C_p (T_{\text{in}} - T_{\text{out}})$ to the RC network.

3.3. *Actions on shading devices*

The model for the prediction of actions on shading devices (Haldi and Robinson (2010a)) is also based on a Markov chain, predicting lowering and raising probabilities. The model takes pre-processed occupancy states, outdoor global horizontal illuminance $E_{\text{gl,hor}}$ and indoor illuminance E_{in} as inputs (requiring coupling with a daylight model, see below). The following action probabilities determine lowering and raising actions:

$$P_{\text{act}}(E_{\text{in}}, B_L) = \frac{\exp(a + b_{\text{in}}E_{\text{in}} + b_L B_L)}{1 + \exp(a + b_{\text{in}}E_{\text{in}} + b_L B_L)} \tag{9}$$

where B_L is the current unshaded fraction, with parameters a, b_k displayed in Table 1 (bottom). If an action is predicted, the probabilities of adjusting blinds to their fully (un)shaded position are:

$$P_{\text{full act}}(E_{\text{gl,hor}}, B_L) = \frac{\exp(a + b_{\text{out}}E_{\text{gl,hor}} + b_L B_L)}{1 + \exp(a + b_{\text{out}}E_{\text{gl,hor}} + b_L B_L)} \tag{10}$$

Alternatively, if a partial raising action is predicted, the deduced shaded fraction is drawn from a uniform distribution, or if a partial lowering action is predicted the increase in shading ΔB is drawn from the Weibull distribution:

$$f(\Delta B) = \lambda\alpha(\lambda\Delta B)^{\alpha-1} \exp(-(\lambda\Delta B)^{\alpha}), \tag{11}$$

with $\alpha = 1.708$ and $\lambda = 1/\exp(-2.294 + 1.522 B_{L,init})$. The incident shortwave irradiance is then multiplied by the unshaded fraction to obtain the irradiance actually incident on the glazing (so that we assume in this implementation that our shading devices are external).

3.4. *Internal illuminance prediction*

As noted above, internal illumination is also simulated using the SRA. This method predicts the internal illuminance at two penetration distances. The value closest to the window (that calculated at a distance of half the room height; 1.5 m by default) is retrieved as input E_{in} for the model for actions on blinds. A proportionality constant accounts for the effect of shaded fraction.

3.5. *Individual diversity*

Differences in behaviour (behavioural diversity) between occupants is modelled using calibration parameters similar to those found in Table 1, but derived from the analysis of control actions performed by individuals (rather than from aggregate data). These values are presented in Haldi and Robinson (2009, 2010a).

4. Case study and test variables

4.1. *The case study*

In this study, we focus mainly on the influence of occupants' behavioural diversity on energy demand and indoor conditions. The influence of different building design variables is also examined but less comprehensively. Our aim here is simply to compare their relative influence with respect to occupants' behaviours.

As such we restrict ourselves to a relatively simple 'shoebox' configuration of the hypothetical office building depicted in Figure 3, which has a volume of 44.1 m^3. The climate data of Basel, Switzerland (47° 34′N, 7°36′E, elevation 260 m.) obtained from Meteonorm are used as input for the simulations. The heating system is a boiler of maximum power of 3000 W, which was found in a preliminary study to be the approximate value above which the energy demand remains constant, and the same power is installed for cooling. Real occupancy data monitored from an office building containing single-occupant office spaces (the LESO-PB experimental building at EPFL, see Altherr and Gay 2002) with typical office work schedules including realistic (within day) absences are used. The observed probability of presence is displayed in Figure 4. The sensible casual heat gains induced by the presence of the occupant are assumed to be 90 W.

The composition of the walls is displayed in Table 2. The south façade is 40% glazed, and accommodates double glazed windows with a low emissivity coating ($U = 1.4$ (W/(m^2 K)), $g = 0.54$).

The use of electrical lighting and its associated electricity consumption is not treated in this study, where the focus is rather on the influence of the use of windows and shading devices on heating and cooling demands. However, previously published models (eg. Reinhart 2004) may be integrated in a similar fashion, albeit with a different treatment of behavioural diversity.

4.2. *Parameters studied*

The influence of the following parameters has been evaluated by testing the following variants:

- Openable ratio of the south façade: $O = 0.10$, and alternatively $O = 0.05$, so that respectively 25%, and 12.5% of the glazed surface is comprised of openable (ventilation) windows.

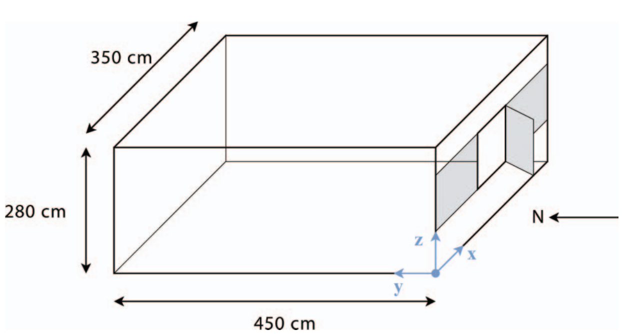

Figure 3. Geometry of our simulated hypothetical building.

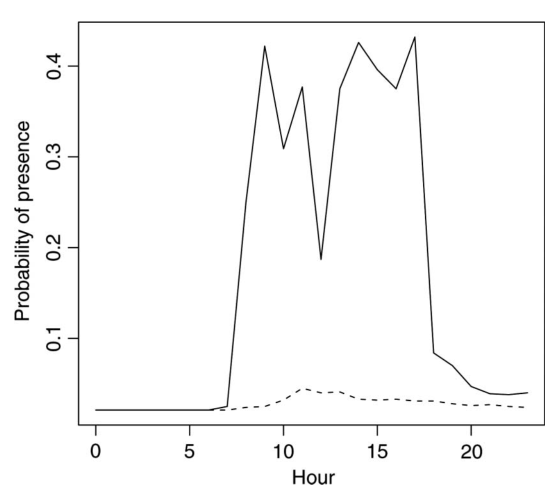

Figure 4. Probability of presence for weekdays (solid line) and weekends (dashed line).

Table 2. Physical properties of construction elements: thickness, thermal conductivity, specific heat capacity, density and U-value.

Wall	Material	d (cm)	λ (W/(mK))	C (J/(kgK))	ρ (kg/m^3)	U (W/(m^2 K))
South wall	Plaster panel	1	0.70	940	1400	0.308
	Insulation	12	0.04	610	200	
	Wood panel	1	0.14	2160	520	
North wall	Concrete bricks	12	1.80	1080	2400	0.435
	Insulation	8	0.04	610	200	
	Concrete bricks	12	1.80	1080	2400	
East and west walls	Concrete bricks	16	1.80	1080	2400	0.427
	Insulation	8	0.04	610	200	
	Concrete bricks	16	1.80	1080	2400	
Floor	Rubber coating	1	0.16	800	1000	0.526
	Screed	6	1.80	1080	2400	
	Insulation	6	0.04	610	200	
	Concrete slab	25	1.80	1080	2400	
Ceiling	Concrete slab	25	1.80	1080	2400	0.229
	Insulation	16	0.04	610	200	
	Concrete and gravel	10	1.80	1080	2400	

- Insulation thickness: The values displayed in Table 2 are used directly ($I = 1$), or are doubled ($I = 2$).
- Setpoint temperatures for heating $\theta_H = 18°C$ and 21°C, and cooling: $\theta_C = 26$°C and 30°C. The values are intended to examine the cases of (i) control systems which keep the indoor conditions close to standard comfort conditions and (ii) control strategies relating to extremes of occupants' tolerance to discomforting stimuli and so almost certainly entailing their intervention. The cases of no heating and no cooling are also investigated.
- Individual behaviours, denoted by P (set to 0, $1, \ldots, 22$, 23, D), linked with corresponding regression parameters; where 0 denotes models based on aggregated data (with the values of Table 1), 1–23 represent occupant-specific regression parameters and D is a deterministic control strategy (window opening if $\theta_{in} > 26$°C, closing if $\theta_{in} < 22$°C, always closing at departure; blind lowering if $E_{in} > 2500$(lx), raising if $E_{in} < 300$ (lx)).

We refer to the above cases through the following notation: the case O0.10-I1-H21-C26-P5 refers to a room with 10% openable ratio on the south façade, insulation thickness as in Table 2, heating and cooling setpoint temperatures of 21°C and 26°C, occupied by an occupant interacting according to our fifth individuals' behavioural characteristics.

The influence of these parameters is studied with respect to:

- Energy use: Total yearly heating and cooling demand per unit gross floor area.
- Thermal comfort: Overheating and underheating are indicated by the proportion of occupied time for which the air temperature is above 28°C and below 18°C.
- Use of controls: average states and number of actions on windows and shading devices.

These parameters are simulated according to a full factorial design (all the possible combinations are tested). The use of stochastic behavioural models suggests the replication of simulations for the assessment of the variability between predictions. In each considered case, annual simulations are repeated 50 times. In this way we are able to study the distribution of results arising from random variations in behaviour, for all the considered design variants, rather than relying on deceptive single values.

5. Results

In this section, we first study the fluctuations in simulation results induced by the use of the stochastic behavioural models, based on aggregated data from several occupants (Section 5.1). The influence of building design on energy demand and its variation is specifically examined in Section 5.2. Occupants' diversity and their impact on the resulting energy demand and the use of controls is studied in Section 5.3, while in Section 5.4 we briefly discuss the impact of behavioural models on simplified indicators of overheating and underheating and how energy and comfort indicators may be used to define a building design confidence space. Finally, the impact of the choice of the modelling algorithm for simulating occupant behaviour is examined (Section 5.5).

5.1. *Stochastic variation induced by behavioural models*

Replicates of simulations with identical design and behavioural inputs display significant variability in their results. This is in agreement with field observations: a given occupant will not behave identically even for similar environmental conditions. Figure 5 illustrates this fact for 50 simulations of the case O0.10 I2 H18 C30 P0, where for instance the heating demand ranges from 83.6 to 161.0 (kWh/m^2/year) for 95% of cases. The degree of the dispersion differs between design variants, as shown in Table 3 and Figure 6. In most cases it can be noticed that heating and cooling demands vary by a factor of two between extreme cases; a range which is in agreement with previous field observations (e. g. Seligman *et al.* 1977 or Gill *et al.* 2010).

5.2. *Influence of design and setpoint temperatures*

Table 3 and Figure 6 present the distributions of simulation results for the above mentioned levels of openable ratio, insulation thickness and setpoint temperature, yielding $2 \times 2 \times 3 \times 3 \times 50 = 1800$ replicates. The simulations show that an increased openable ratio raises heating demand but lowers cooling demand, a direct consequence of the increased air exchanges. We also observe a proportionally greater sensitivity of cooling demand to setpoint temperatures as compared to heating demand.

We also notice in Figure 6 (a) that the design variants with a larger openable ratio experience greater dispersion in heating demand, due to the relatively more significant impact of occupants' random actions on windows. Insulation thickness and setpoint temperatures on the other hand do not induce such a differentiated variability.

5.2.1. *A statistical model*

These findings may in principle be formalized and quantified by expressing the heating Q_H and cooling Q_C demands as multivariate linear models. However it is clear from Figures 6(a) and 6(b) that the variance increases with the magnitude of heating and cooling demands, which indicates that the central underlying assumption that residuals are normally distributed with constant variance is violated. To remedy this type of problem a logarithmic transformation of the dependent variable is the recommended practice, which also ensures that the fitted values of Q_H and Q_C are strictly positive, but precludes the use of data where no heating (or cooling) system is used. The design variables and their first- and second-order interactions are all considered for inclusion in the model. This results in models retaining the following statistically significant explanatory terms:

$$\log(Q_H) = \beta_0 + \beta_H\theta_H + \beta_O O + \beta_I I + \beta_{OI} OI + \varepsilon, \quad (12)$$

$$\log(Q_C) = \beta_0 + \beta_C\theta_C + \beta_O O + \beta_I I + \varepsilon, \quad (13)$$

where the residuals ϵ are assumed to be independently distributed as $\mathcal{N}(0, \sigma^2)$ and the terms β are regression parameters obtained by least squares estimation (Table 4), yielding $R^2 = 0.761$ for heating demand and $R^2 = 0.853$ for cooling demand. The obtained curves are shown in Figure 7. With this logarithmic transformation, the amplitude of the residuals ϵ is, as desired, roughly constant over the studied range of variables. Furthermore, $Q_H \to 0$ as $\theta_H \to -\infty$ and $Q_C \to 0$ as $\theta_C \to +\infty$, which is coherent.

These models allow for a straightforward prediction of heating and cooling demands for given values of the design variables, likewise to examine the impact of every driving variable on the variance of energy demands in this domain of variables. Strictly speaking however, further simulations would be recommended to examine energy demands for other values of the tested design variables, to extend the domain of validity of the models. This may also uncover interactions that were not found significant in the range of values that we have studied.

Such statistical models are also useful in that they allow us to quantify the uncertainty introduced by the stochastic models derived from aggregated data. The fits

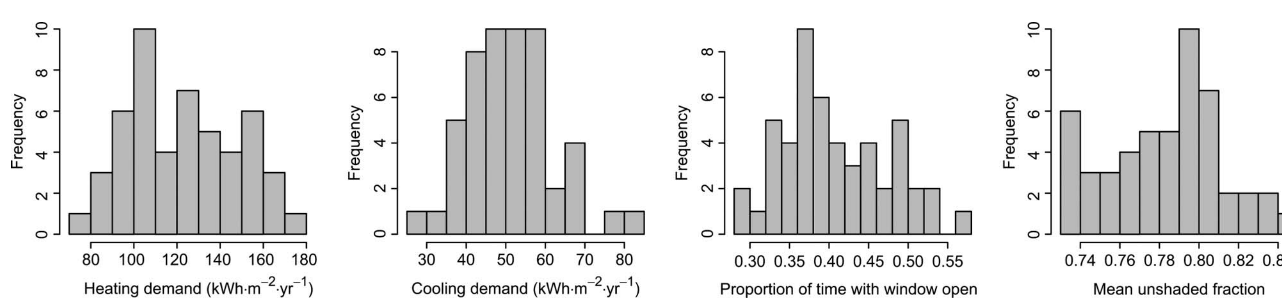

Figure 5. Histograms of simulated heating and cooling demands, the proportion of time with windows open and the mean unshaded fraction for the 50 simulations of the case O0.10 I2 H18 C30 P0.

Table 3. Medians and 2.5% - 97.5% quantiles of simulation results based on 50 repeated simulations per design variant, using the behavioural models based on the aggregated data (P0). From these results we observe a mean unshaded fraction of 0.79 (0.73–0.84) and 65 (52–77) blind lowering actions.

	Energy demand		Thermal comfort			Actions on windows	
Design variant	Heating demand (kWh/m ^{2}/yr)	Cooling demand (kWh/m ^{2}/yr)	Mean temperature (°C)	Fraction above 28°C	Fraction below 18 °C	Ratio open	Opening actions
O0.10 I1 Hno Cno	0 (0–0)	0 (0–0)	16.6 (15.8–17.5)	0.16 (0.14–0.19)	0.52 (0.49–0.55)	0.35 (0.26–0.47)	56 (39–66)
O0.10 I1 Hno C26	0 (0–0)	125.0 (98.1–161.8)	16.2 (15.4–16.9)	0.14 (0.11–0.16)	0.52 (0.49–0.54)	0.33 (0.23–0.44)	44 (33–55)
O0.10 I1 Hno C30	0 (0–0)	59.0 (41.8–84.4)	16.4 (15.6–17.1)	0.16 (0.13–0.19)	0.51 (0.49–0.54)	0.33 (0.25–0.44)	48 (33–59)
O0.10 I1 H18 Cno	139.9 (104.6–196.4)	0 (0–0)	21.3 (20.2–22.1)	0.18 (0.15–0.21)	0.20 (0.16–0.26)	0.41 (0.32–0.53)	63 (46–77)
O0.10 I1 H18 C26	136.1 (96.0–187.0)	133.2 (107.3–174.0)	20.9 (19.9–21.8)	0.15 (0.12–0.17)	0.20 (0.14–0.25)	0.37 (0.26–0.50)	52 (40–65)
O0.10 I1 H18 C30	141.1 (101.6–197.0)	61.7 (43.6–87.7)	21.1 (20.0–21.8)	0.18 (0.14–0.20)	0.19 (0.15–0.25)	0.39 (0.28–0.53)	55 (41–69)
O0.10 I1 H21 Cno	219.0 (172.4–269.0)	0 (0–0)	22.5 (21.4–23.4)	0.19 (0.16–0.22)	0.13 (0.10–0.18)	0.43 (0.34–0.57)	68 (53–82)
O0.10 I1 H21 C26	207.5 (153.9–265.9)	136 (109.8–176.8)	22.2 (21.3–23.0)	0.15 (0.13–0.18)	0.12 (0.06–0.17)	0.41 (0.29–0.53)	57 (42–67)
O0.10 I1 H21 C30	209.3 (160.5–265.7)	64.5 (43.1–89.1)	22.3 (21.3–23.2)	0.19 (0.15–0.22)	0.12 (0.07–0.18)	0.41 (0.30–0.55)	59 (47–71)
O0.10 I2 Hno Cno	0 (0–0)	0 (0–0)	17.2 (16.0–18.2)	0.15 (0.12–0.18)	0.50 (0.46–0.53)	0.36 (0.27–0.48)	54 (40–65)
O0.10 I2 Hno C26	0 (0–0)	100.8 (75.2–128.8)	16.8 (15.8–17.5)	0.12 (0.09–0.14)	0.50 (0.46–0.52)	0.33 (0.25–0.44)	42 (30–54)
O0.10 I2 Hno C30	0 (0–0)	45.9 (29.5–68.2)	16.9 (16.0–17.7)	0.15 (0.12–0.18)	0.50 (0.46–0.52)	0.35 (0.26–0.45)	46 (33–56)
O0.10 I2 H18 Cno	125.0 (94.6–165.0)	0 (0–0)	21.2 (20.0–22.1)	0.17 (0.13–0.20)	0.21 (0.16–0.27)	0.42 (0.33–0.55)	62 (47–75)
O0.10 I2 H18 C26	115.5 (82.3–169.5)	106.9 (84.6–137.2)	20.7 (19.9–21.5)	0.14 (0.11–0.16)	0.18 (0.14–0.24)	0.38 (0.29–0.51)	49 (38–63)
O0.10 I2 H18 C30	120.7 (83.6–161.0)	50.1 (34.4–77.0)	20.9 (20.0–21.8)	0.17 (0.13–0.20)	0.19 (0.15–0.25)	0.39 (0.30–0.52)	53 (41–66)
O0.10 I2 H21 Cno	199.1 (144.9–263.7)	0 (0–0)	22.4 (21.1–23.2)	0.18 (0.15–0.21)	0.16 (0.11–0.21)	0.45 (0.35–0.60)	66 (53–80)
O0.10 I2 H21 C26	189.8 (139.5–245.7)	110.1 (85.9–142.5)	22.0 (20.9–22.7)	0.14 (0.11–0.16)	0.14 (0.09–0.19)	0.40 (0.30–0.54)	54 (42–66)
O0.10 I2 H21 C30	193.5 (130.3–257.7)	52.9 (34.5–79.2)	22.1 (21.1–23.1)	0.18 (0.15–0.21)	0.15 (0.09–0.20)	0.43 (0.31–0.57)	59 (45–69)
O0.05 I1 Hno Cno	0 (0–0)	0 (0–0)	17.6 (17.0–18.4)	0.21 (0.19–0.24)	0.50 (0.48–0.53)	0.30 (0.23–0.40)	78 (63–94)
O0.05 I1 Hno C26	0 (0–0)	154.1 (123.7–178.7)	16.9 (16.2–17.4)	0.17 (0.14–0.19)	0.50 (0.48–0.52)	0.29 (0.20–0.41)	58 (45–69)
O0.05 I1 Hno C30	0 (0–0)	78.6 (58.6–100.4)	17.2 (16.6–17.8)	0.20 (0.18–0.23)	0.50 (0.48–0.51)	0.29 (0.22–0.42)	63 (51–76)
O0.05 I1 H18 Cno	106.2 (86.4–132.6)	0 (0–0)	22.6 (21.5–23.2)	0.24 (0.21–0.26)	0.16 (0.12–0.23)	0.34 (0.26–0.52)	88 (73–108)
O0.05 I1 H18 C26	100.5 (85.2–130.0)	165.1 (130.0–192.0)	21.8 (21.0–22.4)	0.19 (0.16–0.21)	0.15 (0.12–0.20)	0.33 (0.23–0.47)	67 (53–79)
O0.05 I1 H18 C30	104.7 (84.2–131.6)	83.8 (59.7–105.2)	22.1 (21.3–22.7)	0.23 (0.20–0.26)	0.16 (0.12–0.21)	0.33 (0.25–0.47)	74 (59–87)
O0.05 I1 H21 Cno	150.6 (126.3–188.4)	0 (0–0)	24.0 (23.1–24.6)	0.25 (0.22–0.28)	0.06 (0.04–0.10)	0.35 (0.27–0.52)	96 (80–114)
O0.05 I1 H21 C26	147.3 (121.2–185.6)	172.2 (142.6–199.8)	23.3 (22.6–23.8)	0.20 (0.17–0.23)	0.05 (0.02–0.09)	0.34 (0.23–0.48)	72 (57–86)
O0.05 I1 H21 C30	150.9 (120.7–184.4)	87.6 (62.5–106.5)	23.5 (22.6–24.1)	0.24 (0.21–0.27)	0.05 (0.02–0.10)	0.35 (0.24–0.51)	79 (62–92)
O0.05 I2 Hno Cno	0 (0–0)	0 (0–0)	18.3 (17.3–19.2)	0.21 (0.17–0.23)	0.47 (0.44–0.50)	0.31 (0.24–0.45)	76 (59–92)
O0.05 I2 Hno C26	0 (0–0)	121.5 (91.9–146.0)	17.3 (16.6–17.9)	0.15 (0.12–0.17)	0.47 (0.44–0.50)	0.30 (0.21–0.41)	54 (41–66)
O0.05 I2 Hno C30	0 (0–0)	60.3 (42.8–82.2)	17.7 (16.9–18.4)	0.20 (0.17–0.22)	0.47 (0.44–0.50)	0.31 (0.23–0.42)	60 (44–71)
O0.05 I2 H18 Cno	84.1 (65.2–109.8)	0 (0–0)	22.4 (21.2–23.2)	0.23 (0.19–0.26)	0.16 (0.12–0.22)	0.35 (0.29–0.51)	89 (71–109)
O0.05 I2 H18 C26	81.1 (60.2–103.1)	131.8 (95.6–161.0)	21.6 (20.8–22.2)	0.17 (0.14–0.20)	0.15 (0.10–0.20)	0.35 (0.24–0.48)	63 (49–75)
O0.05 I2 H18 C30	82.8 (60.9–107.0)	65.4 (42.8–90.1)	21.9 (21.1–22.7)	0.22 (0.19–0.25)	0.15 (0.11–0.21)	0.36 (0.25–0.50)	69 (54–84)
O0.05 I2 H21 Cno	128.0 (99.4–174.7)	0 (0–0)	23.8 (22.6–24.6)	0.25 (0.21–0.27)	0.08 (0.04–0.12)	0.39 (0.28–0.55)	94 (77–115)
O0.05 I2 H21 C26	123.0 (90.6–162.0)	139.4 (100.7–165.4)	22.9 (22.1–23.5)	0.18 (0.15–0.20)	0.06 (0.03–0.11)	0.36 (0.24–0.52)	69 (55–81)
O0.05 I2 H21 C30	122.4 (91.6–174.9)	69.5 (44.5–91.3)	23.3 (22.3–23.9)	0.24 (0.20–0.27)	0.07 (0.03–0.11)	0.37 (0.28–0.55)	76 (60–90)

indicate that 14.7% and 25.9% of the variance is unexplained by the design parameters, and is thus induced by the variability of behavioural actions. However, this degree of variability is below the actual influence of the diversity of behavioural patterns (due to differences between individuals), which is discussed below.

5.3. *Influence of behavioural diversity*

Due to the the large number of required simulations, the impact of different occupants' behaviours was investigated only for the four cases involving O0.10-O0.05 and I1-I2, and exclusively for the relatively distant setpoint temperatures $\theta_H = 18°C$ and $\theta_C = 30°C$. This part of the study is thus based on $2 \times 2 \times 24 \times 50 = 4800$ simulations.

Figure 8 shows the distributions of heating and cooling demands with respect to the simulated individual behaviours. Compared to the model P0 of an 'average occupant', the dispersion of the results is strongly reduced for a majority of individuals' behaviours, which is a consequence of higher slopes

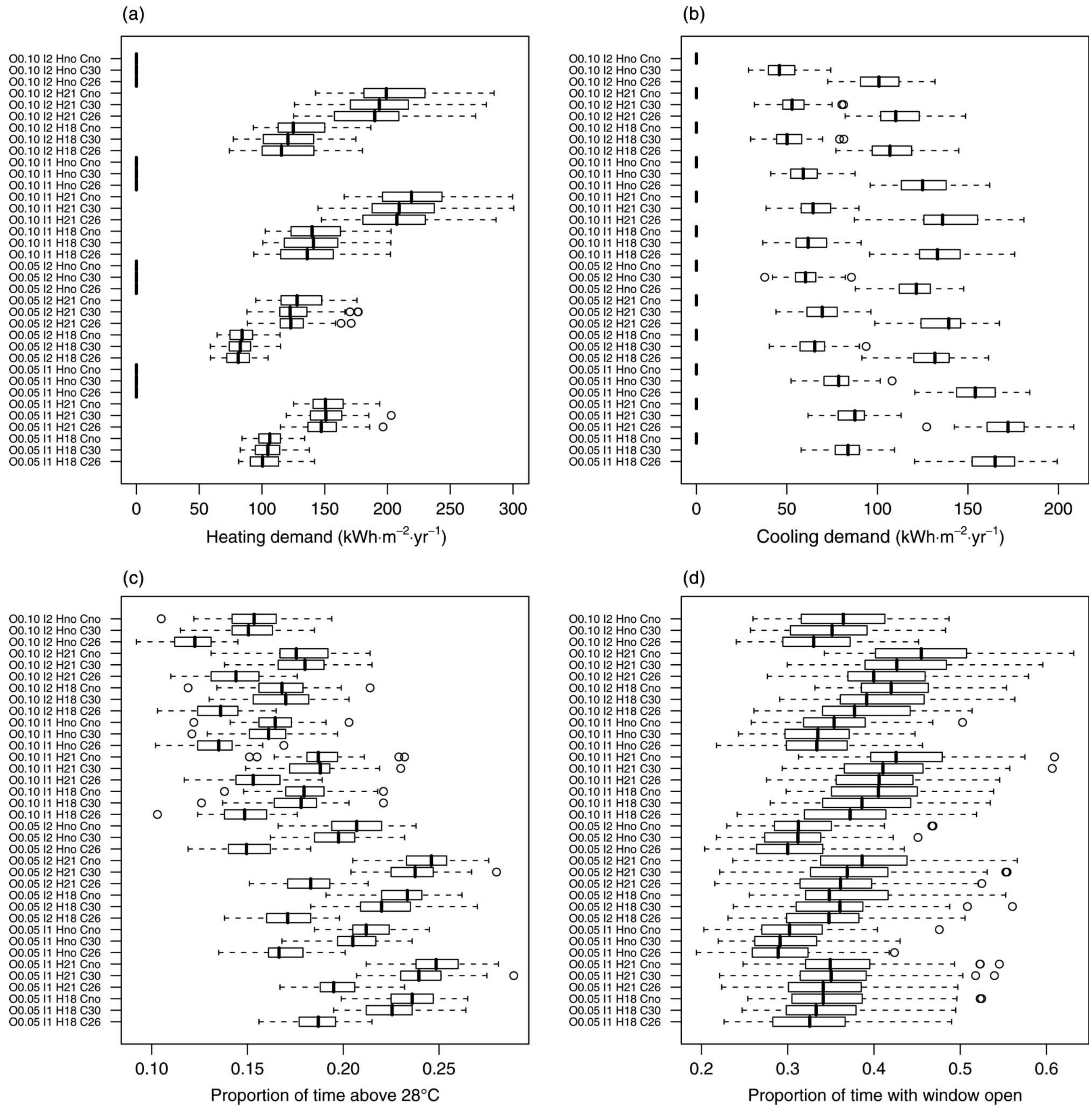

Figure 6. Distributions of results for 36 design variants based on the behaviour of an average occupant (P0).

in the regression parameters (and thus higher determination).

On the other hand, the overall spread of results between occupants outweighs by far the spread that is apparent for the case of the aggregated behavioural model. It would appear that the explicit simulation of behavioural diversity improves the realism with which we are able to simulate the distribution of outcomes in building simulation. Indeed the two sources of variation can be isolated: inter-individual and within-individual.

The determinant impact of the use of building controls – and hence of behavioural diversity – on heating and cooling energy demands is clear in Figure 9. Whilst marginally affected by the use of shading with this configuration (Figure 9(c), bottom left), the heating demand increases sharply with the overall proportion of time that windows are open (Figure 9, (a). It may also be noticed that the impact of openable ratio outweighs thermal insulation when the proportion of time with the window open increases above 50%.

Table 4. Regression parameters and standard deviation of the residuals for the linear models for heating (left) and cooling (right) demands prediction.

Parameter	Heating demand	Cooling demand
β_0 (intercept)	2.105 ± 0.076	10.244 ± 0.069
β_H (heating setpoint)	0.1395 ± 0.0031	
β_C (cooling setpoint)		-0.1802 ± 0.0024
β_O (openable ratio)	4.26 ± 0.59	-4.61 ± 0.19
β_I (insulation width)	-0.304 ± 0.029	-0.229 ± 0.009
β_{OI} (interaction OI)	1.92 ± 0.37	
σ (Residuals sd.)	0.161	0.164

Note: For all parameters, $p < 0.001$. The results are based on 1800 simulations.

As expected, the cooling demand decreases as the proportion of time that windows are open increases (due to increased air exchanges) and as insulation thickness increases. However, in this case the relative influence of shading dominates that of window openings, although when windows are only marginally shaded (unshaded fractions are between 0.8 and 1) the relative prevalence of the use of window openings would appear to lead to considerable variation in cooling demand; likewise for heating demand[1] (Figure 9(d). Finally, the cooling demands obtained for designs with low insulation thickness are very large when windows are seldom used.

These differences are directly induced by behavioural specificities; they are directly linked with the characteristic temperatures for action $\theta_{50,act}$ (higher values imply lower heating demands and higher cooling demands) – a realistic proxy for the 'behavioural activity' of occupants – and the slopes of the probabilistic logistic models (higher slopes induce smaller variability). The exact relationship is however complex, as parameters associated with actions on arrival, during presence and at departure are implied.

When all the simulations are considered, personal specificities alone account for the largest part of the variance in heating ($R^2 = 0.601$) and cooling ($R^2 = 0.661$) demands. As for Section 5.2, a predictive statistical model may be developed using our simulation results. However, the effect of individuals' diversity requires a particular treatment, as this latter is associated with the characteristics of individuals that are drawn at random from a population; unlike the design characteristics such as setpoint temperatures, which are fixed levels of experimental conditions. The former type of variable is treated as a random effect, while these latter are fixed effects. Considering together these factors, a mixed-effects model may be used (see

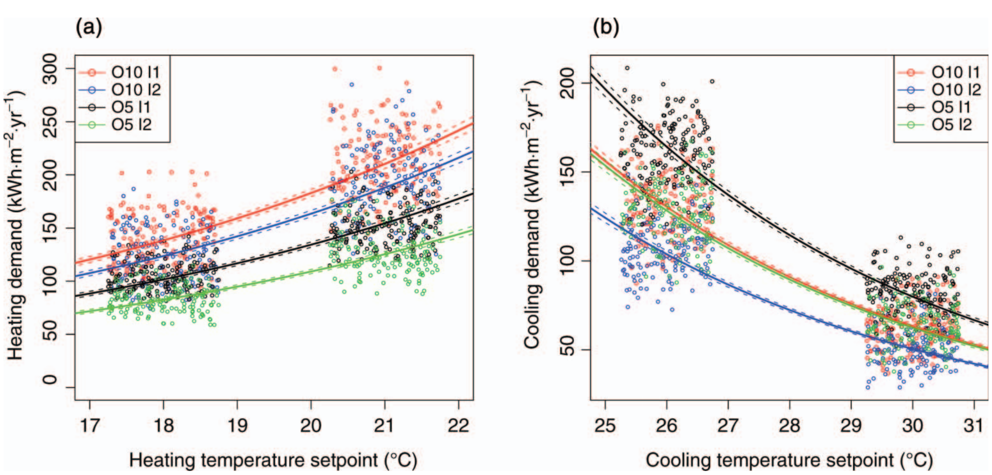

Figure 7. Simulated and fitted heating (a) and cooling (b) demands with respect to heating/cooling setpoint temperatures, openable ratio and insulation width. Heating and cooling setpoint temperatures are jittered for readability.

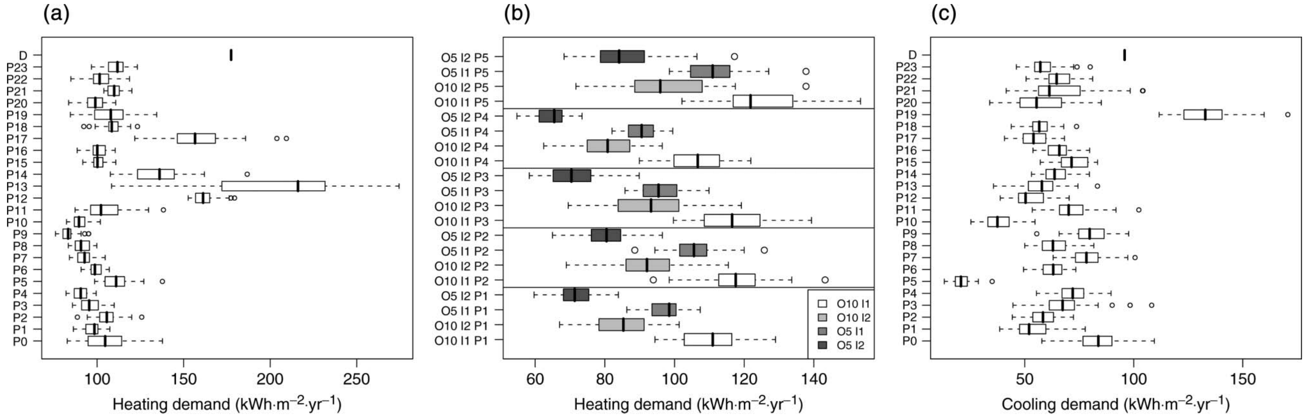

Figure 8. Distribution of heating and cooling demands with respect to behavioural diversity. (a) Left and (c) right: all individual profiles for the case O0.05 I1 H18 C30. (b) Centre: a selection of five individual profiles for all tested design variants.

McCulloch *et al.* (2008) and Pinheiro and Bates (1995) for detailed discussions of these types of model), whereby:

$$\log(Q_H) = \beta_0 + b_i + \beta_H\theta_H + \beta_O O + \beta_I I + \beta_{OI} OI + \varepsilon, \tag{14}$$

$$\log(Q_C) = \beta_0 + b_i + \beta_C\theta_C + \beta_O O + \beta_I I + \varepsilon, \tag{15}$$

where b_i denotes a random variable representing the deviation from the population mean of the mean log-heating or cooling demands for the ith individual. With this convention, b_i is assumed to be distributed as $\mathcal{N}(0, \sigma_b^2)$ where σ_b is the inter-individual variability and ϵ is distributed as $\mathcal{N}(0, \sigma^2)$ where σ is the within-individual variability. These parameters are displayed in Table 5. Fixed-effects parameters are, as expected, little affected by this procedure (compared with Table 4). It can also be observed that the inter-individual variability σ_b largely exceeds σ, which justifies the inclusion of b_i. The model is fitted according to the restricted maximum likelihood (REML) method.

The obtained estimates of σ_b can be used in Equations (14)–(15) to estimate the variability of the final energy demand, by repeatedly sampling b_i from the distribution $\mathcal{N}(0, \sigma_b^2)$, resulting in a behavioural diversity induced variability in Q_H and Q_C.

Finally, the considered deterministic rule for modelling occupants' behaviour yields less comprehensive results: not only are the effects of stochastic variations and occupants' diversity ignored but also the fixed result would appear to be wholly unrepresentative of occupants' observed behaviours based on the rule employed (Figure 8). This indicates that benchmarking applications of building simulation tools – although potentially correctly ranking design variants – would be usefully complemented with explicit consideration of occupants' behaviour to uncover the range and to better predict the magnitude of the performance indicator of interest.

Table 5. Regression parameters of the mixed-effects models for heating (left) and cooling (right) demands prediction and estimations of the variance components.

Parameter	Heating demand	Cooling demand
β_0 (intercept)	2.039 ± 0.084	9.95 ± 0.11
β_H (heating setpoint)	0.1552 ± 0.0028	
β_C (cooling setpoint)		−0.1802 ± 0.0027
β_O (openable ratio)	2.88 ± 0.24	−4.272 ± 0.097
β_I (insulation width)	−0.325 ± 0.012	−0.2153 ± 0.0049
β_{OI} (interaction OI)	1.25 ± 0.15	
σ_b (random eff. sd.)	0.314	0.359
σ (residuals sd.)	0.146	0.185

Note: For all parameters, $p < 0.001$. Results based on 5800 simulations.

5.4. Assessment of thermal comfort and overheating

Thermal comfort standards generally prescribe that a certain value of the indoor temperature (or alternatively PMV) is not exceeded over a given period of time. To this end we may check with the results of Table 3 whether some threshold of temperature is exceeded for a prescribed period of time, and with which level of confidence.

Figure 10 shows charts of heating and cooling demands versus the proportion of time below or above some temperature, where the intrinsic trade-off between both of these values is clear (see for instance the work of Daum and Morel 2010 for further discussion). In this situation, replicates of simulations allow for a definition of a two-dimensional confidence zone (deduced from a chosen probability level) for the performance of a building. Again these zones are wider in cases with a large openable ratio. Thus we are able

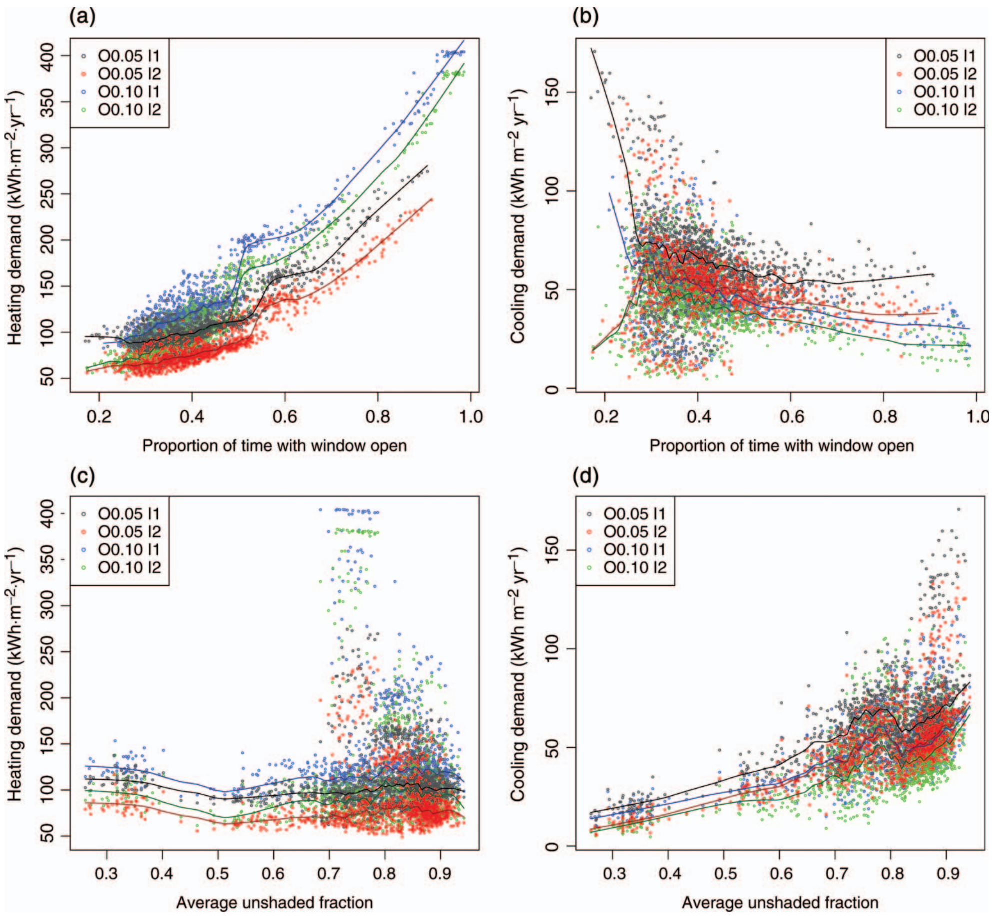

Figure 9. Simulated heating (a,c) and cooling (b,d) demands versus overall proportion of time with windows open (a,b) and average unshaded fraction (c,d), with non-parametric estimates of their variation using locally weighted polynomial regression. Simulations based on deterministic rules are not included.

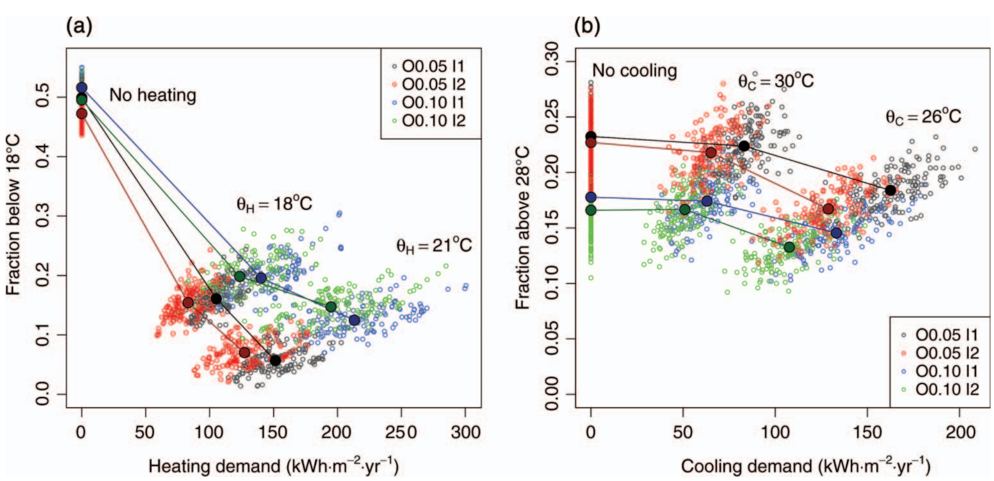

Figure 10. Simulated heating demand versus occupied fraction of time below 18 °*C* (a) and simulated cooling demand versus occupied fraction of time above 28 °C (b), based on the aggregated behavioural profile (P0). Small points represent simulation replicates and large solid points the mean values for a given design choice.

to more reliably estimate the level of risk that a building does not meet some given energy-comfort requirement.

We should concede however that the range and magnitude of fractions of time spent above and below 18°C and 28°C is exaggerated by the fact that the

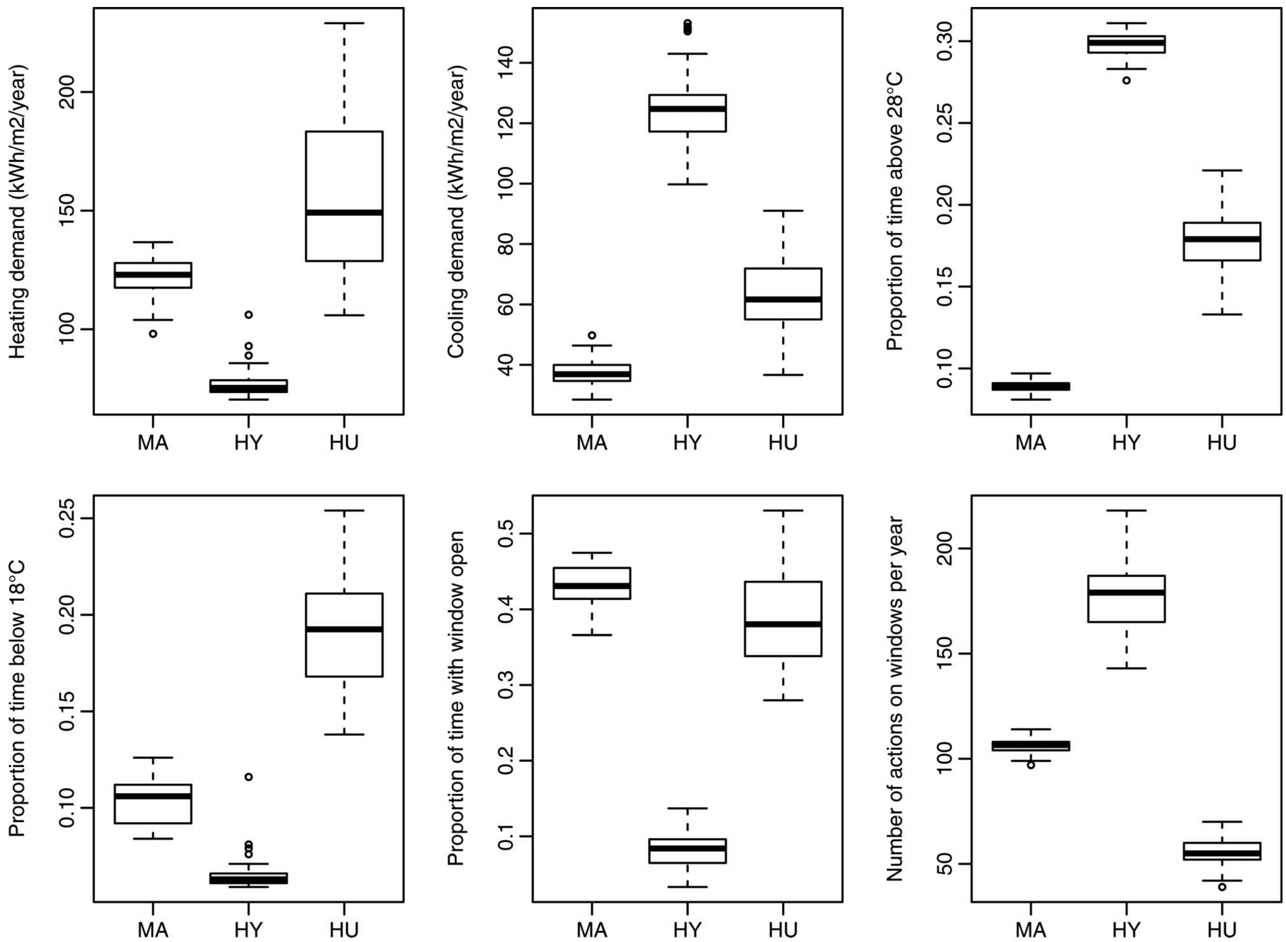

Figure 11. Simulation results for the design variant O0.10 I1 H18 C30 based on three different algorithms: Markov process (MA), hybrid model (HY) and Humphreys algorithm (HU).

heating/cooling prediction is performed at a 1-h time step (and temperature every 5 min) and because we have not allowed for feedback from window openings to heating/cooling systems (causing them to switch off when windows are opened).

5.5. *Influence of modelling algorithm*

Finally, in order to check for the relative impact of alternative window modelling algorithms (we are unable to do likewise for shading devices due to a lack of published model variants), simulations using the three modelling algorithms for windows presented in Section 3.1, as well as for the Humphreys algorithm (described in Rijal *et al*. 2007) were performed, but only for the case O0.10 I1 H18 C30.

The results are graphically summarized in Figure 11. From this it is clearly apparent that the various algorithms result in very different fractions of the time for which windows are open, with corresponding impacts on predicted heating and cooling demands. For instance the hybrid model predicts that windows are open for a relatively small proportion of time, which results in lower heating and higher cooling demands compared with the Markov model. It is also worth noticing that the Humphreys algorithm leads to predictions with larger fluctuations between simulation replicates. The choice of a reliable modelling method is thus crucial for obtaining coherent estimations of energy demands.

6. Conclusion

We have attempted to study, using rigorous methods, the impact on building performance of state of the art models of occupants' adaptations to the building envelope to restore their comfort; in particular with respect to window openings and shading devices for an hypothetical office.

The purpose of this study is to better understand how the range and magnitude of energy demands vary depending on the degree of sophistication with which occupants' behaviour is modelled and how this variance compares with that arising from changes to buildings' intrinsic design characteristics. In this way we hope to place the relative importance of the modelling of human behaviour into context.

To this end we have studied the impacts of the behaviour of an 'average' occupant (using a model calibrated from aggregate data) and of occupants' behavioural diversity (using models calibrated from different individuals' observed behaviours) for different combinations of building variables. This has enabled us to rigorously estimate the magnitudes of both inter-individual and within-individual variabilities and to compare these with the variabilities in performance due to a building's intrinsic design parameters.

From these results we conclude that:

- The explicit consideration of occupants' adaptive actions with buildings allows to predict both the range and a more realistic magnitude for the key performance variables of interest (energy demand, thermal comfort).
- The impact of inter-individual variability on heating and cooling energy demands is shown to exceed that of that arising from important changes to building design variables (such as doubled window openable ratio and insulation thickness), based on relatively distant setpoint temperatures.
- Intra-individual variability is estimated to lead to a dispersion in energy demand which is roughly half of that due to inter-individual variability, again based on relatively distant setpoint temperatures.

Furthermore, based on the methodology employed in this article we also suggest that:

- Repeated simulations of occupants' stochastic behaviour allow for more realistic estimates of energy demand, and a more informative presentation of building simulation results. Indeed deceptive single values (no indication of range) can be replaced by results such that 'in 95% of cases the heating demand will lie in a given range', information of interest for the dimensioning of building services plant and for testing the robustness of passive design strategies, provided that all the relevant sources of variability are considered.
- Similarly, this approach allows designers to ascertain the confidence that their target energy demand or thermal comfort requirements will be met. For instance, repeated simulations enable one to calculate the probability that a buildings' energy demand or over/under-heating requirement will be beyond the limits imposed by a given construction standard.

However, this work would usefully be complemented in the future by extended parametric studies, examining interactions between a greater number of building and urban design parameters (such as building orientation, glazing ratio, etc.) and occupants' behaviour. Some of the modelling assumptions could also be further refined, for example by including a model for occupants' choices of window opening angles.

It should also be stressed that we have examined the stochastic variation of a single class of parameters (behavioural specificities) and that the other sources of variability (e.g. meteorological conditions) and an explicit treatment of uncertainties associated with buildings' intrinsic design features should be jointly considered (see Lomas and Eppel (1992) and Macdonald and Strachan (2001) for further discussion) for a full evaluation of energy demand distribution.

Note

1. With the assumption of completely open windows, we simulate in fact the maximum possible impact of operable ventilation openings, corresponding thus to the maximum heating demand and the minimum cooling demand.

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