THE IMPACT OF OCCUPANTS' BEHAVIOUR ON URBAN ENERGY DEMAND

Frédéric Haldi and Darren Robinson
Ecole Polytechnique Fédérale de Lausanne (EPFL), Solar Energy and Building Physics Laboratory (LESO-PB), Lausanne, Switzerland

ABSTRACT

Using extensive field survey data acquired over the past seven years at the Solar Energy and Building Physics Laboratory at EPFL in Switzerland, models of occupants' presence, opening and closing of windows and the raising and lowering of blinds have been developed. These new models, together with existing models of lighting and appliance use, have been integrated within a new urban energy modelling tool, called CitySim.

In this paper 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 simulations of the impact that occupants' behaviour may have on the indoor environment in buildings' as well as on buildings' energy demands at the urban scale.

We close this paper by discussing a more general framework for the more comprehensive representation of occupants and their activities in building and urban simulation tools.

Keywords

Urban energy modelling, Behavioural modelling, Windows, Shading devices

INTRODUCTION

Context

Although the deterministic features of building simulation programs 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. Among the most noteworthy is the influence of buildings' occupants actions on windows, whose associated air flows have an important impact on indoor hygro-thermal conditions and indoor air quality; likewise actions on shading devices, which strongly influence solar heat gains and daylight availability. It is thus of particular relevance to integrate stochastic models of occupants' behaviour into dynamic building simulation tools for a more realistic assessment of energy needs at the design stage.

Previous work

Previous examples of models for occupants' use of windows have been integrated into ESP-r (Rijal et al, 2007; Yun and Steemers, 2008). However, the diversity of behaviours among occupants is not considered and the algorithm is based on the results from an 'average' occupant arising from aggregated data collected from several people. Furthermore, these algorithms have been shown to perform less satisfactorily than the more comprehensive model of Haldi and Robinson (2009).

More recently, interest shifted to the study of the impact of different types of behaviour, typically defined as 'active' or 'passive', as originally proposed by Reinhart (2004). For instance, according to Schweiker and Shukuya (2010), changes in occupant behaviour towards the use of air-conditioning has a higher effect on exergy demand than building envelope improvements. Comparing the impact of ideal and worst case scenarios in simulations, Roetzel et al. (2010) found that the behaviour of occupants regarding control of lighting and shading predominates the influence of building design on total greenhouse gas emissions and running costs in offices. Parys et al. (2010) developed 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 occupant behavior, in contrast with cooling and lighting energy use.

However, only the case of extreme behaviours expressed as best and worse cases are treated. In order to correctly evaluate the impact of behavioural diversity on building energy demand, it is necessary to explore the realistic distribution of predicted energy demands on the basis of a representative sample of encountered behavioural patterns.

Summary

We start this article with a brief presentation of CitySim – a software designed for the prediction of energy demands of urban neighbourhoods – which

was used for this study. The models for simulating occupants' behaviour are then presented, followed by the case study on which our analyses are based. We conclude with a presentation of the results.

CITYSIM: UP TO THE URBAN SCALE

CitySim is a software in development that is conceived to support the more sustainable planning of urban settlements. CitySim simulates energy demand, storage and supply of urban developments ranging from a small neighbourhood to an entire city. For these purposes, specific models were developed to achieve a good compromise between accuracy, computational overheads and data availability. Robinson et al. (2009) provides a description of the modelling methodology.

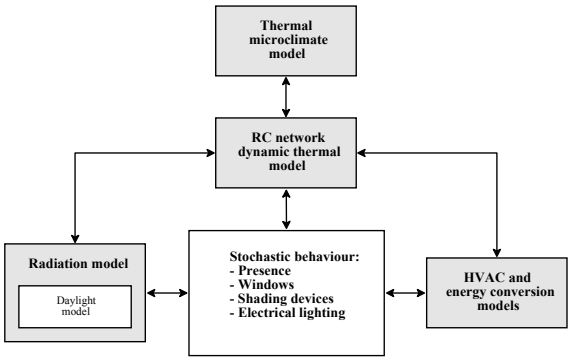

Figure 1 Conceptual structure of CitySim

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.

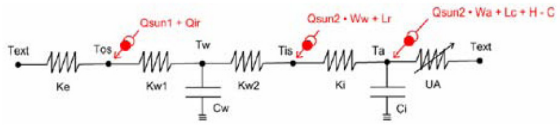

Figure 2 Monozone form of the thermal model

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 next section). Predictions from this simplified model compare well with those of ESP-r for a range of monozone and multizone scenarios. In its current form, the thermal model performs predictions at a one hour time step.

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) for a detailed description.

Plant and equipment models

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

The HVAC model computes the psychrometric state of the air at each stage in its supply (e.g. outside, heat recovered, cooled and de-humidified, 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) the total delivered sensible and latent loads for all stages in the heating and/or cooling of air q is calculated.

The family of ECS models comprise a range of technologies that provide/store heat and/or electricity to buildings. If the ECS models have insufficient capacity to satisfy the HVAC demands then the supply state is adjusted and the predicted room thermal state is corrected using the thermal model.

BEHAVIOURAL MODELS

Actions on windows

The model developed by Haldi and Robinson (2009) is used in this study. It is formulated as an occupancy-dependent Markov chain extended to a continuous-time process based on a Weibull distribution for opening durations. The retained explanatory variables x_i 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 expected absence durations (f_{abs}). Action probabilities P_{ij} from state i to state j are formulated as logistic models:

$$P_{ij}(x_1,\ldots,x_p) = \frac{\exp(a + \sum_{k=1}^{p} b_k x_k)}{1 + \exp(a + \sum_{k=1}^{p} b_k x_k)}$$

with parameters a and b_i as displayed in Table 1 (top). The density of the probability distribution of opening durations is:

$$f_{op}(t) = \lambda\alpha(\lambda t)^{\alpha-1}\exp(-((\lambda t)^{\alpha})) \qquad \lambda = 1/\exp(a + b\theta_{out})$$

Air flow from ventilation

A time step of one hour being too large for a reliable integration of behavioural models, an additional prediction of indoor temperature was implemented using an explicit solution scheme for the thermal model at a time step of 5 minutes. 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 one hour time step, the current explicit prediction is used to update the value for the next prediction with the implicit model.

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

$$Q_s = \frac{1}{3} C_d A \cdot \sqrt{\frac{gh\,|T_{in} - T_{out}|}{(T_{in} - T_{out})/2}},$$

with h the height (m) of the opening and T_{in}, T_{out} the indoor and outdoor absolute temperatures (K). The total air flow is then obtained by $Q_{tot} = (Q_w^2 + Q_s^2)^{1/2}$, linked with the indoor air by an added variable resistance $\rho Q_{tot} C_p (T_{in} - T_{out})$ to the RC network.

Actions on shading devices

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

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

where B_L is the current unshaded fraction, with parameters a, b_i displayed in Table 2 (bottom). If an action is predicted, the probabilities of adjusting blinds to their fully (un)shaded position are:

$$P_{fullact}(E_{in}, B_L) = \frac{\exp(a + b_{out}E_{gl,hor} + b_L B_L)}{1 + \exp(a + b_{out}E_{gl,hor} + b_L B_L)}$$

Finally, if a partial raising action is predicted, the deduced shaded fraction is drawn from a uniform distribution and in the case of partial lowering the increase in shading ΔB is drawn from the Weibull distribution

$$f(\Delta B) = \frac{\alpha}{\lambda}\left(\frac{\Delta B}{\lambda}\right)^{\alpha-1}\exp\left(-\left(\frac{\Delta B}{\lambda}\right)^{\alpha}\right)$$

with $\alpha = 1.708$ and $\lambda = \exp(-2.294 + 1.522 B_{L,init})$.

The incident shortwave irradiance is then multiplied by the unshaded fraction to obtain the transmitted irradiance.

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

WINDOWS: VARIABLES	OPENING PROB. P_{01}	CLOSING PROB. 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
$f_{abs,prev}$	1.862 ± 0.044	
f_R	-0.45 ± 0.11	
During pres.		
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
		0.213 ± 0.022
$\theta_{out,dm}$	0.1371 ± 0.0075	-0.0911 ± 0.0061
$f_{abs,next}$	0.84 ± 0.12	1.614 ± 0.069
f_{GF}	0.83 ± 0.13	-0.923 ± 0.068

BLINDS: VARIABLES	LOWERING PROB. P_{LOWER}	RAISING PROB. 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 pres.		
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
$E_{gl,hor}$	$(0.91 \pm 1.33)\cdot 10^{-6}$	$(-2.31 \pm 0.11)\cdot 10^{-5}$
B_L	-2.23 ± 0.16	1.95 ± 0.11

Internal illuminance prediction

Internal illumination is also simulated using the simplified radiosity algorithm, as described by Robinson and Stone (2006). This method predicts the internal illuminance at two penetration distances. The value closest to the window (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.

Individual diversity

The behavioural diversity between occupants is modelled using regression 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, 2010).

CASE STUDY AND TEST VARIABLES

The case study

In this study we focus more precisely on the influence of occupants' behavioural diversity on energy demand and indoor conditions. The influence of different types of building designs is not specifically examined. Rather we study a simple fixed office configuration as depicted in Figure 3, with a volume of 44.1 m^3. The heating system consists of a boiler of maximum power P = 1000 W. Real occupancy data monitored from an office building are used, totalling a presence of 8.5% of the simulated period.

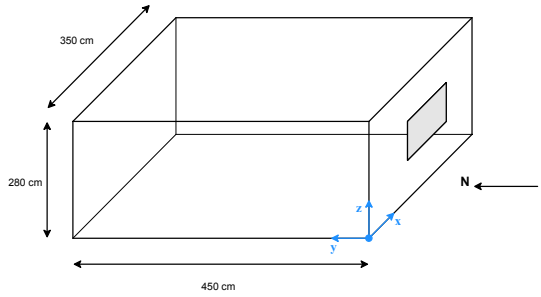

Figure 3 General scheme of the simulated room

Parameters studied

The influence of the following parameters has been evaluated:

- Glazing ratio of the south façade: G = 0.10, and alternatively G = 0.05, which are set equal to the openable ratio of the façade.
- Setpoint temperatures for heating H = 18°C and 21°C, and cooling: C = 26°C and 30°C. The cases of no heating and no cooling are also investigated.
- Individual behaviours, denoted by P (set to 0, 1, …, 22, 23, D), linked with corresponding regression parameters; where 0 denotes the models based on the aggregated data (Table 1) and D a deterministic control strategy (window opening if $\theta_{in} > 26$°C, closing if $\theta_{in} < 20$°C; blind lowering if $E_{in} > 2500$ (lx), raising if $E_{in} < 300$ (lx)).

The influence of these parameters are studied with respect to:

- Thermal comfort: Overheating and underheating are assessed by the proportion of occupied time above 28°C and below 18°C.
- Energy use: Total heating and cooling consumption.
- Use of controls: state of windows and shading devices.

The use of stochastic behavioural models suggests the replication of simulations for the assessment of the variability between predictions. In each considered case, simulations are repeated 50 times, which allows us to study the distribution of results rather than deceptive fixed mean values.

RESULTS

In this section results with respect to stochastic fluctuations, design influence and occupants' diversity are presented.

Pure stochastic variation

Replicates of simulations with identical design and behavioural inputs display significant variability in their results, which is in agreement with observations in reality: a given occupant will not behave identically even for similar environmental conditions. Figure 4 (top) and Table 2 illustrate this fact for 50 simulations of the case G0.10-H21-C26-P0, where for instance the heating load ranges from 2417 to 4496 (kWh/year) for 95% of cases. The degree of this dispersion varies between design variants, as shown in Figure 4 (middle).

Influence of design and setpoint temperatures

Figure 4 (middle) presents the distributions of simulation results for the above mentioned levels of glazing ratio and setpoint temperature, yielding 2×3×3×50 = 900 replicates. The simulations show that an increased glazing ratio raises heating needs but lowers cooling needs, and quantifies this expected effect. We also observe the greater sensitivity of cooling loads to setpoint temperatures compared to heating loads.

Influence of behavioural diversity

Due the the large number of required simulations, the impact of occupants' different behaviours was investigated exclusively in the configuration G0.10-H18-C30; such a setting is characterised by relatively distant setpoint temperatures and a large opening area, which offer together a large degree of adaptation to the occupant.

Figure 4 (bottom) shows the distributions of heating and cooling loads with respect to the simulated individual behaviours. Compared to the model P0 of an "average occupant", the dispersion of the results is strongly reduced, which is a consequence of higher

slopes in the regression parameters (and thus higher determination) in the case of models for individuals.

On the other hand, the overall spread of results between occupants outweighs by far the spread initially noticed in the case of the aggregated behavioural model. The explicit simulation of behavioural diversity brings thus a more realistic estimation of the distribution of outcomes in building simulation.

Nevertheless, no clear trend emerges on the link between energy demand and behavioural specificities. Using $\theta_{50,act}$ – the indoor temperature at which the probability of action is 0.5 – as a realistic proxy for the "behavioural activity" of occupants, no clear correlation can be noticed with heating or cooling loads (Figure 4, bottom right).

Finally, the failure of deterministic rules is clear in the context of modelling occupants' behaviour: not only are the effects of stochastic variations and occupants' diversity ignored, but the fixed result is wholly unrepresentative of reality (Figure 4, bottom left and centre).

CONCLUSION

Repeated simulations of occupants' stochastic behaviour allow for more realistic estimations of energy demand, and a more informative presentation of building simulation results. Indeed fixed deceptive and inexact values can be replaced by results such that *"in 95% of cases the heating needs will lie in a given range"*, information of interest for the dimensioning of building services and for testing the robustness of passive design strategies. However, this work should be further developed with parametric studies, where the interactions between building design and occupant behaviour are studied in greater detail.

Finally, such results must be based on behavioural models which correctly reflect the population which occupies the building. As such further research is essential to enable calibration parameters for stochastic behavioural models to be derived for a sufficiently representative set of building types.

ACKNOWLEDGEMENTS

Financial support received from the European Commission as part of the CONCERTO II Project HOLISTIC is gratefully acknowledged. We are particularly thankful to Jérôme Kämpf for his help in the implementation of the behavioural models.

REFERENCES

CIBSE, 1997. Natural ventilation in non-domestic buildings – CIBSE Applications Manual AM10.

Haldi, F., Robinson, D., 2009. Interactions with window openings by office occupants, Building and Environment, 44(12): 2378-2395.

Haldi, F., Robinson, D., 2010. Adaptive actions on shading devices in response to local visual stimuli, Journal of Building Performance Simulation, 3(2): 135-153.

Kämpf, J., Robinson, D., 2007. A simplified thermal model to support analysis of urban resource flows, Energy and Buildings 39(4): 445-453.

Parys, W., Saelens, D., Hens, H., 2010. Implementing realistic occupant behavior in building energy simulations – the effect on the results of an optimization of office buildings, In Proc. Clima 2010, Antalya, Turkey.

Reinhart, C. F., 2004. Lightswitch-2002: a model for manual and automated control of electric lighting and blinds, Solar Energy 77(1):15–28.

Rijal, H. B., et al., 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(7):823–836.

Robinson, D., Stone, A., 2004. Solar radiation modelling in the urban context, Solar Energy 77(3): 295-309.

Robinson, D., Stone, A., 2006. Internal illumination prediction based on a simplified radiosity algorithm, Solar Energy 80(3): 260-267.

Robinson, D. et al., 2009. CitySim: Comprehensive micro-simulation of resource flows for sustainable urban planning, In Proc. 11th Int. IBPSA Conf: Building Simulation 2009, 1083-1090, Glasgow, United Kingdom.

Roetzel, A., Dietrich, U., Tsangrassoulis, A., Busching, S., 2010. Balancing buildings and occupants, a holistic approach to thermal comfort and greenhouse gas emissions in mixed mode offices, In Proc. Adapting to change: New Thinking in comfort, Windsor, United Kingdom.

Schweiker, M., Shukuya, M., 2010. Comparative effects of building envelope improvements and occupant behavioural changes on the exergy consumption for heating and cooling, Energy Policy 38(6): 2976-2986.

Yun, G.Y., Steemers, K., Baker, N., 2008. Natural ventilation in practice: Linking facade design, thermal performance, occupant perception and control, Building Research and Information 36(6): 608-624.

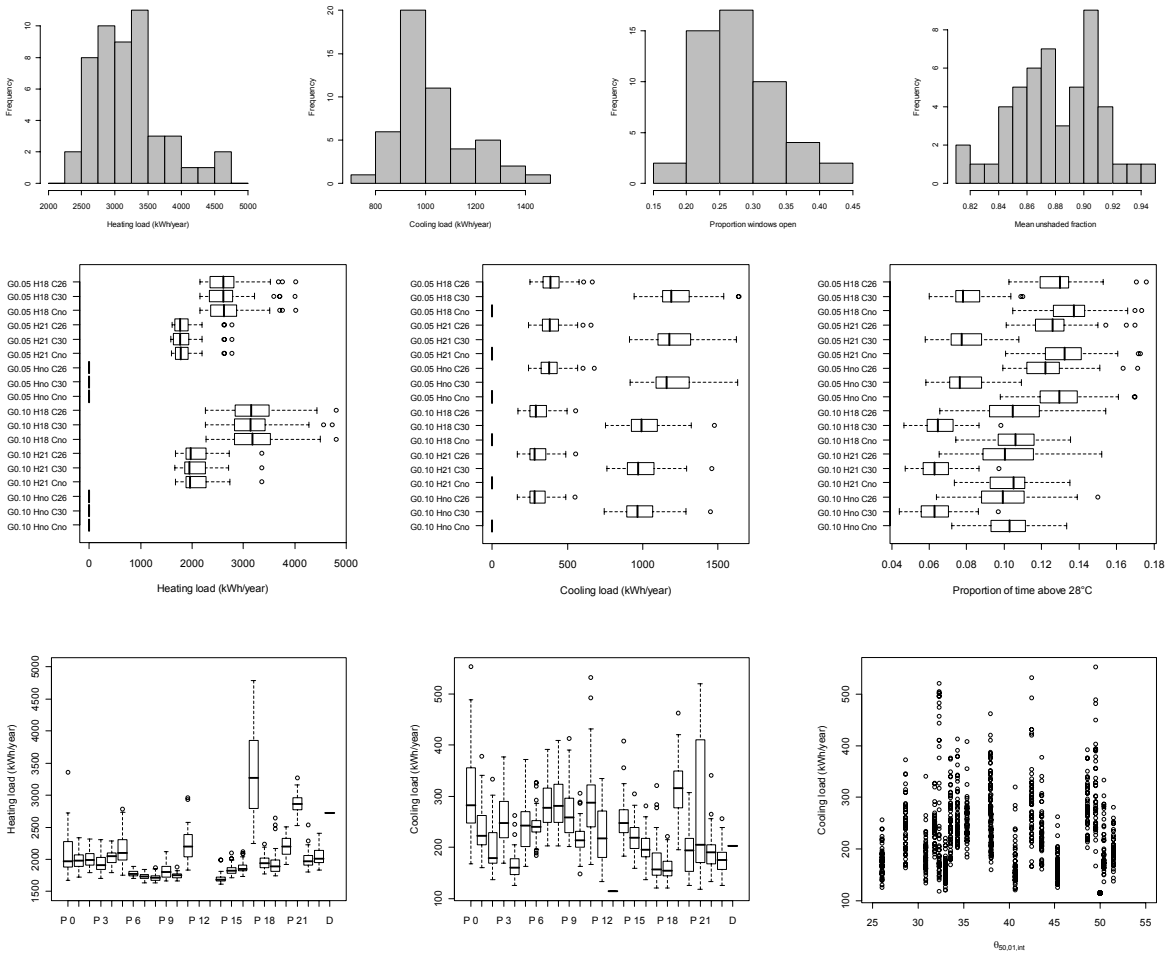

Figure 4 - Top: Distributions of simulation results for the case G0.10-H21-C26-P0 based on 50 iterations. Middle: Distributions of results for 18 design variants based on average occupant behaviour (P0) Bottom: Distribution of heating and cooling loads with respect to behavioural diversity

Table 2
Medians and 2.5% - 97.5% quantiles of a selection of simulation results

	G0.10H21 C26P0	**G0.05H21 C26P0**
Heating load (kWh/year)	3138 (2417 - 4496)	2605 (2185 – 3709)
Cooling load (kWh/year)	991 (809 - 1320)	1189 (973 – 1617)
Mean temp. (°C)	21.9 (21.0 - 22.5)	22.5 (21.8 - 22.9)
Fraction above 28°C	6.5% (5.0 - 8.6)	7.8% (6.2 - 10.8)
Fraction below 18°C	7.5% (2.9 - 15.8)	3.3% (0.9 - 10.8)
Ratio window open (any occ)	27.6% (19.3 - 39.9)	24.4% (14.4 - 38.1)
Opening actions	25 (19 - 32)	27 (20 – 33)
Mean unshaded fraction	87.9% (82.1 - 92.9)	91.0% (83.9 – 94.7)
Lowering act.	39 (28 – 51)	33 (22 – 46)
Raising act.	34 (26 – 42)	28 (19 – 35)