Journal of Building Performance Simulation
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tbps20

Verification of stochastic models of window opening behaviour for residential buildings

Marcel Schweiker [a], Frédéric Haldi [b], Masanori Shukuya [c] & Darren Robinson [b]

[a] Karlsruhe Institute of Technology (KIT), Building Science Group (fbta), Englerstrasse 7, D-76131, Karlsruhe, Germany

[b] Ecole Polytechnique Fédérale de Lausanne (EPFL), Solar Energy and Building Physics Laboratory (LESO-PB), Station 18, CH-1015 Lausanne, Switzerland

[c] Tokyo City University (TCU), Laboratory of Building Environment, Ushikubo-Nishi 3-3-1, 224-8551, Yokohama, Japan

Available online: 09 Jun 2011

To cite this article: Marcel Schweiker, Frédéric Haldi, Masanori Shukuya & Darren Robinson (2012): Verification of stochastic models of window opening behaviour for residential buildings, Journal of Building Performance Simulation, 5:1, 55-74

To link to this article: http://dx.doi.org/10.1080/19401493.2011.567422

Journal of Building Performance Simulation
Vol. 5, No. 1, January 2012, 55–74

Taylor & Francis
Taylor & Francis Group

Verification of stochastic models of window opening behaviour for residential buildings

Marcel Schweiker[a]*, Frédéric Haldi[b], Masanori Shukuya[c] and Darren Robinson[b]

[a]*Karlsruhe Institute of Technology (KIT), Building Science Group (fbta), Englerstrasse 7, D-76131 Karlsruhe, Germany;* [b]*Ecole Polytechnique Fédérale de Lausanne (EPFL), Solar Energy and Building Physics Laboratory (LESO-PB), Station 18, CH-1015 Lausanne, Switzerland;* [c]*Tokyo City University (TCU), Laboratory of Building Environment, Ushikubo-Nishi 3-3-1, 224-8551, Yokohama, Japan*

(*Received 16 August 2010; final version received 27 February 2011*)

Based on the analyses of data from two distinct measurement campaigns conducted in residential indoor environments in Japan and Switzerland, we identify the specificities of occupants' behaviour with respect to their interactions with windows, including the choice of opening angles for axial openings. As a first step, each dataset is analysed to develop separate predictive models which account for the specificities of window usage in the residential context. The predictive accuracy of these models is then challenged by validation on external data: using models inferred from data obtained from one survey, actions on windows are simulated for the other survey and the predictions are compared with observations. Dynamic models developed using data from office buildings as well as previously published models are also compared using this verification procedure. In the case of the Swiss dataset, these analyses demonstrate the ability of carefully formulated behavioural models developed from office environment data to reliably predict window usage in a residential context and vice-versa. However, we observe that the same models perform less satisfactorily in the prediction of window usage in Japan. From these results it seems that such models require specific calibration in the case of buildings equipped with an air-conditioning unit as was the case for the hot and humid summer climate of Japan.

Keywords: behavioural modelling; windows; validation

1. Introduction

1.1. *Impact of occupants' behaviour on buildings' energy demand*

Building simulation programs are now relatively mature in their modelling of deterministic features influencing buildings' energy balances, with the most fully developed integrated solvers supporting simultaneous solutions of building thermal, plant, fluid, electrical power and computational fluid dynamics (CFD) equation sets (Clarke 2001). But their ability to faithfully represent reality is undermined by a poor representation of non-deterministic variables, particularly relating to occupants' presence and their interactions with environmental controls. Indeed several field studies have identified that the behaviour of buildings' occupants is one of the major factors influencing the amount of energy used within the built environment (see for instance Socolow 1978; Levermore 1985; Andersen *et al*. 2007; Bahaj and James 2007; Schweiker and Shukuya 2010).

Furthermore, according to Hoes *et al*. (2009) the relative influence of occupants' behaviour increases in passive buildings, which are becoming more commonplace as building performance standards improve. They point out that detailed behavioural modelling may be necessary to design buildings that are robust to the influence of occupants' behaviour. It is thus important to integrate models of occupants' use of building controls such as windows, shading devices and HVAC systems into dynamic building simulation programs to support more realistic energy use and thermal comfort evaluation at the design stage.

Occupants' actions on windows – whose associated air flows have a particularly significant impact on the hygro-thermal conditions and indoor air quality in naturally ventilated buildings – are a key source of uncertainty for the prediction of buildings' energy demand. For instance, measurements conducted by Dubrul (1988) in 25 Danish buildings revealed that on average the increase in the mean airflow rate due to the influence of occupancy is more than 100%. These findings are consistent with the observations of Iwashita and Akasaka (1997), who later observed that 87% of the total air change rate is caused by the behaviour of the occupants.

*Corresponding author. Email: marcel.schweiker@kit.edu

ISSN 1940-1493 print/ISSN 1940-1507 online

http://dx.doi.org/10.1080/19401493.2011.567422
http://www.tandfonline.com

As summarized by Roetzel *et al.* (2010), window opening behaviour has been investigated by several researchers (see for instance Nicol 2001; Haldi and Robinson 2008; Andersen *et al.* 2009). This has led to the derivation of a variety of logistic models expressing the probability with which actions will be performed on windows, as a function of indoor temperature (Yun and Steemers 2008), outdoor temperature (Herkel *et al.* 2008) or both (Rijal *et al.* 2007). Haldi and Robinson (2009) have subsequently developed three detailed modelling approaches (presented in Section 3.1) in which the impact of each variable and the diversity among occupants are studied, based on long-term observations in an office building; ultimately recommending the use of a hybrid of two of the models developed.

1.2. *Validation of behavioural models*

In general, the previously developed models of window opening behaviour have not been rigorously validated, with the notable exception of that of Haldi and Robinson (2009). This model has been tested by cross-validation based on a re-sampling of their data and by comparison with independently collected data (Haldi *et al.* 2010). But in common with all of the previously developed models, this model formulation has not been calibrated and validated for residential environments.

To this end, we first develop and calibrate two independent models for application to the residential context, using locally collected field survey data, from Switzerland and Japan; more specifically using a long-term survey conducted in three apartments of two buildings (CO and CT) in Neuchâtel (Switzerland) and two short-term surveys in a dormitory building located in Tokyo (Japan). We then test the ability of these models to predict the window opening behaviour of their counterpart, so that the model calibrated to Japanese data is used to predict the window opening behaviour of Swiss residents and vice versa.

Indeed this exercise is conducted in a double-blind way, as predictions and verifications are carried out independently, without prior knowledge of the true result. As a further challenge we have differences in the measured context and the measured parameters; for example occupants' presence, recorded as occupancy profiles. Furthermore, the previously published model of Haldi and Robinson (2009) based on office data as well as the modelling approach proposed by Rijal *et al.* (2007) are also validated in order to compare their ability to predict occupants' interactions with respect to windows.

2. The field surveys

In this section, the general characteristics of the surveyed buildings and of their occupants are presented, along with a general account of the experimental design and a statistical summary of the measurements undertaken.

2.1. *Measurements in Swiss residential buildings*

Two residential buildings were selected for the long-term monitoring of indoor conditions and actions on windows in the centre of the city of Neuchâtel, Switzerland (46° 60′N 6° 56′E, altitude 430 m, population 34,000). In both of these cases, selection was based on the desire to obtain members of two typical generations of buildings (new and relatively old) prevailing in the city centre, none of them being equipped with air-conditioning. Measurements took place for periods of at least six months of representative climatic conditions. Figure 1 presents external photographs of these buildings while Table 1 summarize the specificities of the surveys.

2.1.1. *Description of the surveyed buildings*

2.1.1.1. CO residential building. This four-storey building (Figure 1(a)) was built in the 1920s. Two identical apartments of the second and third floors, both accommodating 6 rooms, were surveyed for a period of six months. The observed windows are double-glazed, PVC-framed and fully openable. They include both left and right axial openings. The glazed surface area is 1.52 m^2 and the total area (glazing plus frame) is 2.7 m^2. Shading is provided by external shutters. Internal cloth curtains provide another element of privacy.

In both cases, the occupants rent their apartments and have been living there for more than a decade. The first family (CO-DEV) groups a professional, a housewife and two students; while there are two professionals and one student in the second family (CO-VIA).

2.1.1.2. CT residential building. This modern residential building (Figure 1(b)) – whose construction was completed in 2000 – offers high standard accommodation with modern furniture. One apartment housing a couple who have been renting the apartment for the last 5 years was selected for a measurement campaign of 6 months. One occupant works full time while the other is unemployed. The windows have a glazed surface area of 3.2 m^2 and a total surface area (glazing plus frame) of 4.14 m^2. No shading is available, but the large balcony of the upper

Figure 1. General views of the residential buildings surveyed in Neuchâtel, Switzerland. (a) Residential building CO, east façade. (b) Residential building CT, north façade.

apartment provides effective solar protection to the south façade during the summer.

2.1.2. *Experimental design and measurements*

Every chosen apartment was surveyed for a period of at least 6 months covering summer, mid-season and winter periods, in order to observe behavioural specificities in each case. All measurements were recorded in the living room, where the occupants spend the majority of their time whilst present and awake.

During these periods, indoor temperature (θ_{in}) was measured with Pt-100 resistance thermometers and the positions of the windows with a potentiometer whose electrical resistance varies with the opening angle (α). The calibration of these devices was performed before and after each measurement campaign, resulting in estimated uncertainties of 0.2 $^\circ C$ for θ_{in} and 5 $^\circ$ for α. A data logger recorded the observed values at 1-min intervals; instantaneous values are systematically used in our analyses.

After the measurements were completed, the occupants of the surveyed apartment were asked to provide an estimation of their presence profile as a probability of being at home for every day of the week at time intervals of 1 h, likewise any noteworthy periods of long absence (weekends and holidays). Furthermore, several general questions were asked to identify possible specificities in their behaviour regarding their use of building controls (see Table 1).

In parallel, a weather station located in close proximity to the surveyed buildings (maximum 1.2 km) recorded every 10 min measurements of dry bulb air temperature (θ_{out}), mean wind speed (v_{wind}) and direction (α_{wind}), relative humidity (ϕ_{out}), rainfall (D_{prec}) and reduced atmospherical pressure ($p_{atm,red}$). A statistical summary of these variables is presented in Table 1.

2.2. *Measurements in a Japanese dormitory building*

2.2.1. *Surveyed building*

The second investigation was conducted within a student dormitory (Figure 2) (TKY) opened in 1989 in Tokyo (Japan). This is a five-storied building with 320 identical single rooms. It is constructed of concrete and has little thermal insulation and single glazed windows (Schweiker and Shukuya 2009). During 2007, the decay rate of CO_2 was measured for a range of outdoor wind speeds, from which the infiltration rates were deduced. Based on these measurements it is estimated that the average air infiltration rate is around 0.7 h^{-1}, indicating the poor quality of the building envelope.

The single rooms of 15 m^2 each, including a bathroom, are oriented east, south or west. Each room has one door opening into the corridor and one sliding window on the opposite side, and is equipped with an air-conditioning unit. In contrast to the rooms observed within the Swiss survey, these rooms are used as sleeping, living and study rooms. However, it should be mentioned that many students are commuting to university during daytime of weekdays and and they are therefore in their room only during the evening and night hours. The kitchens as well as the shower rooms are shared spaces, also accessed via the

Table 1. Characteristics of buildings and occupants of the survey in Switzerland, with statistical summary of measured environmental variables.

Building	CO	CO	CT
Survey	CO-DEV	CO-VIA	CT
Start date	01.09.2008	01.09.2008	06.08.2009
End date	05.04.2009	05.04.2009	08.02.2010
Duration (days)	216	216	186
Buildings			
Thermal characteristics	Thick stone walls without insulation		Insulated envelope according to recent norms $U_{max} \leq 0.3\text{W}/(\text{m}^2\text{K})$
Observed space	Living room ($23.2\ m^2$)	Living room ($23.2\ m^2$)	Living room ($25.7\ m^2$)
Year of construction	1920s	1920s	2000
Floor	2	3	1
Windows, orient.	3 (E, SE, S)	3 (E, SE, S)	3 (S)
Window opening	Axial	Axial	Axial and tilted
Shading devices	Shutters	Shutters	External blinds
Sources of heat gains	1 TFT TV	2 halogen lamps	1 TFT TV 1 halogen lamp
Occupants			
Number of occupants	4	3	2
Activity, sex and age of occupants, proportion of time present according to estimation by occupants	Professional (M, 50, 67.3%) Housewife (F, 50, 81.4%) Student (F, 20, 85.3%) Student (F, 20, 77.2%)	Professional (M, 50, 75.2%) Professional (F, 50, 71.4%) Student (M, 20, 73.1%)	Professional (M, 40, 63.4%) Housewife (F, 40, 88.1%)
Origin of occupants	Switzerland	Switzerland	East Europe
Smoking in the room	Never	Sometimes	Never
Environmental variables measured			
Proportion open (%)	7.48	5.15	17.32
Indoor temperature			
Min	20.0	18.0	16.0
Mean	24.1	22.1	25.2
Max	28.4	26.0	29.8
Outdoor temperature			
Min	−7.8		−10.0
Mean	5.4		9.0
Max	26.4		33.6
Outdoor humidity			
Min	14.1		21.9
Mean	79.7		76.5
Max	100		100
Wind speed			
Min	0		0
Mean	2.6		2.4
Max	14.9		12.4

corridors. Further facilities within the dormitory building include common rooms, such as a cafeteria and study room, where the students go to meet one another, which further decreases occupancy in the rooms. The key parameters of this survey are presented in Table 2.

The residents were free to use electrical fans to keep their rooms as comfortable as possible in addition to or instead of the air-conditioning unit. All of the residents are foreign students originating from countries other than Japan. The students who agreed to participate in the measurement campaign came from 27 countries from all continents, the majority being from Europe and Asia.

2.2.2. *Experimental design*

One measurement period was conducted during the summer of 2007 (TKY-SUM) and the winter of 2007/2008 (TKY-WIN) each. Two wireless sensors were provided to each of the students who agreed to participate in this survey (39 students in winter and 34 students in summer): a TandD RTR-53 sensor, which records air temperature and humidity and a TandD

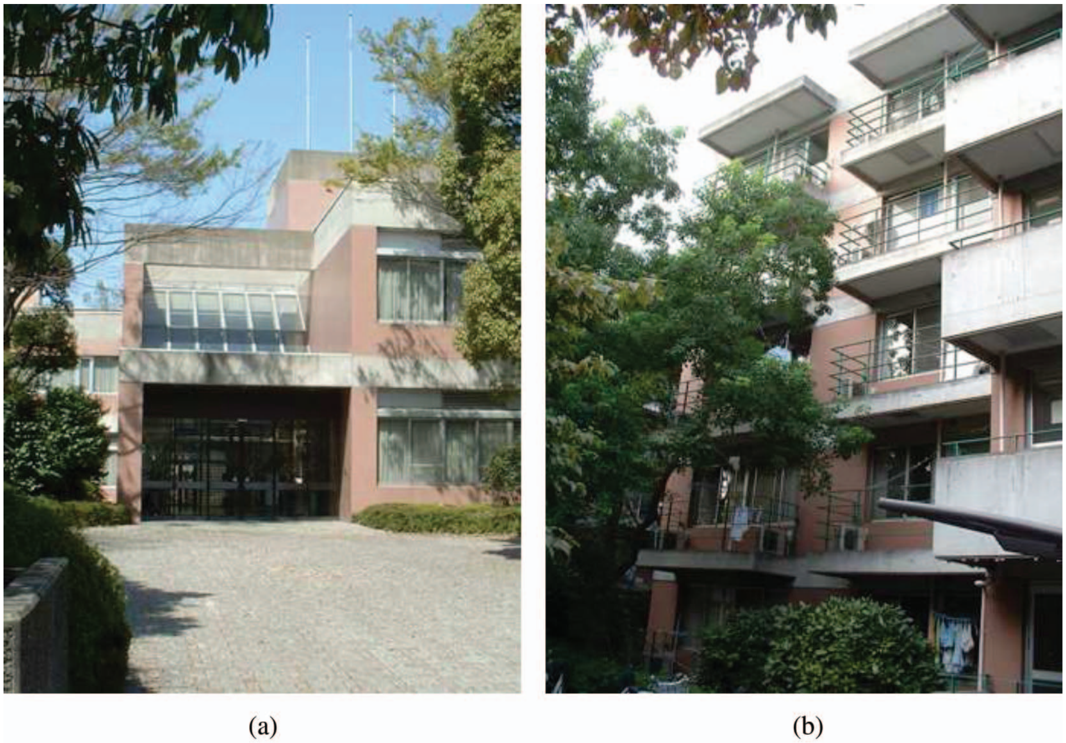

Figure 2. Dormitory building surveyed in Tokyo, Japan. (a) Entrance wing. (b) Residential wing.

RTR-52 voltage recorder. These latter were provided in combination with two switches to 24 students during the winter survey and with a potentiometer to 19 students for the summer survey, to record window opening and closing times. The measurement uncertainty using the TandD RTR-53 sensor is estimated to be $\pm$ 0.3° C and $\pm$ 5% RH.

To avoid invading the students' privacy, they were asked to install these sensors themselves. Prior to doing so they were also asked to complete a questionnaire survey, with 35 questions written in English, regarding their typical behaviour with regard to window opening and AC-unit usage, their preferences and their strategies for keeping the room cool in summer or warm in winter.

Measurements of the students' rooms' air temperature and relative humidity were collected from the end of June until mid-August and from mid-January until mid-February, respectively. Instantaneous values were logged every minute. During these periods, the outdoor temperature (θ_{out}), humidity (ϕ_{out}) and mean wind speed (v_{wind}) were also measured.

3. Model formulation and evaluation procedure

The first part of this section presents the different types of behavioural models developed in this study (Section 3.1), followed by a detailed description of the successive validation procedures designed to evaluate their predictive accuracy (Section 3.2).

3.1. *Model formulation*

In their previous study of office occupants' use of windows, Haldi and Robinson (2009) developed three different model formulations (Bernoulli process, Markov chain and hybrid model), each of them including a set of variables retained on the basis of forward selection. Schweiker and Shukuya (2009) on the other hand have previously developed a single type of model (Bernoulli process) for the prediction of the use of air-conditioning, focusing particularly on the optimal choice of variables – including occupants' personal background – in order to obtain an effective yet parsimonious model. A similar approach is applied here with respect to window openings.

The combination of these distinct approaches results in nine different types of model for the prediction of actions on windows. However, the lack of exact occupancy data precludes the inference of hybrid models, which leaves six actual possibilities, summarized in Table 3. Validation of all these variants allows us to check for the relative superiority in predictive accuracy of a given type of model as well as for the optimal set of included variables.

Table 2. Characteristics of the dormitory buildings (TKY) and occupants of two surveys (summer: TKY-SUM and winter: TKY-WIN) in Japan, with statistical summary of measured environmental variables.

	Dormitory building	
Building	TKY	TKY
Survey	TKY-SUM	TKY-WIN
Start date	29.06.2007	11.01.2008
End date	13.08.2007	11.02.2008
Duration (days)	46	32
Buildings		
Thermal characteristics	Low level of insulation and single-glazing windows with aluminium frame	
Type of observed spaces	Single-room apartment	
Year of construction	1989	
Floor	1–5	
Windows, orientation	One window each (either E, S, W)	
Window opening	sliding	
Shading devices	Fixed overhang	
Sources of heat gains	Fridge, computer, lights	
Occupants		
Number of observed spaces	39	34
Number of observed spaces with window sensors	19	24
Activity, sex and age of occupants	Students (M or F, 20–35)	
Estimated proportion of time present	39.5%	
Origin of occupants	27 different countries from 5 continents	
Smoking in the room	depending on occupant	
Measured environmental variables		
Indoor temperature		
Min	14.45	8.00
Mean	28.32	17.84
Max	38.30	31.80
Indoor humidity		
Min	23	14
Mean	60	38
Mean	98	80
Proportion windows[a] open (%)	51.0	10.9
Proportion open at the same time step[a]		
Min	5.2	0
Mean	43.6	11.6
Max	84.2	41.7
Outdoor temperature		
Min	17.80	−2.35
Mean	24.33	3.66
Max	33.40	12.10
Outdoor humidity		
Min	46	27
Mean	83	51
Max	99	99

Note: [a]The proportion of windows open gives the overall percentage the windows were opened during the measurement period, i.e. the sum for all windows of the periods each window was open divided by the product of measurement period and number of windows observed. The proportion at the same time step gives the percentage of windows out of those observed open at the same time.

3.1.1. *Types of algorithms*

The different rows of Table 3 represent the three approaches of Haldi and Robinson (2009) who analysed their datasets using three different statistical methods in order to retain the formulation offering the highest predictive accuracy. These are presented in brief here. Note that the Humphreys algorithm, described in detail by Rijal (2007), is also considered in the evaluation procedure.

3.1.1.1. Bernoulli process based on a single probability (first row). At each time step, the probability of observing a window to be open is independently determined by a logistic model including p explanatory variables $x_1, \ldots, x_p$:

$$P_{\text{open}}(x_1, \ldots, x_p) = \frac{\exp\left(a + \sum_{k=1}^{p} b_k x_k\right)}{1 + \exp\left(a + \sum_{k=1}^{p} b_k x_k\right).} \quad (1)$$

In their previous study, Haldi and Robinson (2009) retained the indoor (θ_{in}) and outdoor (θ_{out}) air temperature as predictors x_i.

3.1.1.2. Markov chain (second row). At each time step, window openings and closings are modelled by transition probabilities P_{ij} from state i to state j (i, $j = 0, 1$) also formulated as logistic models (Equation (1)), with P_{01} being the probability of a transition from closed to open, and vice-versa for P_{10}. Haldi and Robinson (2009) found that state transition probabilities depend on different variables x_i depending on the occupancy transition (differentiating between arrival, continued presence and departure), including 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 duration (f_{abs}) as driving variables.

For these modelling variants, window states are predicted at a 5-min time step using Monte-Carlo simulation. We refer the reader to Haldi and Robinson (2009) for a detailed description of the implementation of these algorithms. The hybrid model developed by Haldi and Robinson (2009) is not considered here as its calibration requires exact occupancy measurements.

3.1.2. *Set of predictors*

The columns of Table 3 represent possible choices for the set of driving variables. Although originally only applied by Schweiker and Shukuya (2009) to a Bernoulli process, the use of personal characteristics is here extended to the case of a Markov chain.

3.1.2.1. Models based on thermal variables (first column)

For each type of model, parameters are derived by statistical analysis including indoor (θ_{in}) and outdoor (θ_{out}) temperature as explanatory variables, i.e. the parameters x_i in Equation (1) refer to θ_{in} and θ_{out}.

3.1.2.2. Models based on thermal variables and personal characteristics (second column). In addition to indoor and outdoor temperature, explanatory variables are carefully selected on the basis of their statistical relevance for every dataset and model. The differences in Nagelkerke's R^2 index (Nagelkerke 1991) and the AIC-value (Akaike 1974) were used to judge whether a variable is included or not in the model of Schweiker and Shukuya (2009). For this article we evaluated only those variables which were known for both datasets, so that the following factors were evaluated:

- Indoor air temperature (θ_{in}) and its polynomials up to the fifth degree,
- Outdoor air temperature (θ_{out}) and its polynomials up to the fifth degree,
- Exponentially weighted running mean outdoor air temperature ($\theta_{out,rm}$),
- The climatic origin of the individual grouped on the basis of the climate map of Koeppen (Kottek *et al.* 2006) (hot and humid, hot and dry, moderate, cold climate),
- The geographic background of the individual (Central-Asia, East-Asia, Europe, South-America, none of them),
- The gender (male, female),
- The position of the room/apartment within the building (ground, middle, top floor),
- The orientation of the window (East, South, West/North).

3.1.2.3. Models based on thermal variables, personal characteristics and timesteps (third column). Following the absence of exact occupancy measurements, a further approach is to account for specific behavioural patterns for each hour, and separately for weekdays as well as weekends and bank holidays. This led to the definition of eight time-intervals for each type of day with some similarities between them as summarized in Table 4.

Table 3. Features of the six types of model with their abbreviations.

	Thermal variables	Personal characteristics	Personal characteristic and timesteps
Bernoulli	BeTeTi	BePers	BePersTime
Markov	MaTeTi	MaPers	MaPersTime

3.2. Validation procedure

3.2.1. A blind methodology

Four cases of comparisons between measurements and predictions were conducted. In order to perform an unbiased validation, separate calibration parameters are derived for each dataset. First, a subset of the data from one building (say A) was taken to predict the remaining data from that same building (A), and then all data from that building (A) was taken to perform predictions on the other one (say B):

(1) The experimenters agree on a preliminary schedule and validation criteria.
(2) Having measured the dataset A, the experimenter develops the model variants including the selection of statistically significant predictors. The predictive accuracy of internal data is studied on the basis of k-fold cross-validation: using a part of the dataset as a training set for model calibration and the remaining part as a validation set. The process is repeated k times for each data point to be selected once in the validation set and k - 1 times in the training set.
(3) In parallel, the other experimenter performs a similar procedure with his own measured dataset B.
(4) The experimenter B provides the experimenter A with the set of potential explanatory variables of the dataset B. Based on the model calibrated with the dataset A, the experimenter A runs simulations of the window states of dataset B, which are sent to experimenter B.
(5) Meanwhile, the experimenter B completes similar simulations, based on the model from dataset B and predictors from dataset A.
(6) The experimenter B assesses the predictive accuracy of the simulations performed by experimenter A, and vice-versa, using the methods introduced in Section 3.2.2.
(7) Finally, they exchange their full datasets (including measured window states) to double-check these results.

Note that in each case our simulations, which are performed using a 5-min time step, simply involve

Table 4. Specific time-intervals to account for variations in occupancy rate.

Period	Weekday	Weekend	Description
01:00–07:59	WD1	WE1	Sleeping phase
08:00–09:59	WD2	WE2	Wake up/ breakfast/ morning routine[a]
10:00–11:59	WD3	WE3	Morning study/work phase
12:00–12:59	WD4	WE4	Lunch time
13:00–16:59	WD5	WE5	Afternoon study/work phase
17:00–20:59	WD6	WE6	Return from work/increasing occupancy rate
21:00–23:59	WD7	WE7	Evening in room/return from work
00:00–00:59	WD8	WE8	Especially in winter last ventilation before going to sleep

Note: [a]The shower was placed on the corridor, so that there is no relation to be expected due to higher humidity.

using measured explanatory variables to predict the corresponding behavioural response, but without considering the feedback of this response. This approach allows for comprehensive internal validation complemented with an effective blinded independent external verification and avoids dataset-specific bias, as calibration parameters are separately derived and the experimenters are initially unaware of their results.

3.2.2. *Criteria for predictive accuracy*

The criteria used by Haldi and Robinson (2009) are used in this study and defined below.

3.2.2.1. Discrimination. Discrimination criteria are deduced by comparison between observed and simulated outcomes. Simulation results may be classified in four groups: a predicted positive outcome (window open, P) is (i) truly positive (TP), (ii) falsely positive (FP); a predicted negative outcome (window closed, N) is (iii) truly negative (TN), (iv) falsely negative (FN). We may then aggregate these results to define:

- The *true positive rate* (proportion of actual positives which are correctly predicted positive): $TPR = TP/(TP + FN)$,
- The *false positive rate* (proportion of actual negatives which are wrongly predicted negative): $FPR = FP/(FP + TN)$,
- The *accuracy* (proportion of correct classifications): $ACC = (TP + TN)/(P + N)$.

These criteria allow for a good understanding of the ability of a model to correctly discriminate between periods where windows are open and closed. It is however not possible to faithfully summarize this ability in a single figure, so that these indicators should be considered in combination.

3.2.2.2. Overall proportion open. Based on the total survey duration $T_{meas,tot}$ and the total window opening time $T_{open,tot}$, we define for each office the overall window opening ratio as $r_{open} = T_{open,tot}/T_{meas,tot}$. This criterion allows us to check for the general coherence of the total predicted opening duration.

3.2.2.3. Number of actions. In order to check for the coherence and the dynamics of occupants' actions, the observed number of actions $N_{act,obs}$ per day is compared with these simulated $N_{act,sim}$.

3.2.2.4. Median opening and closing durations. The delays between actions, or alternatively the durations for which windows are left open and closed, is another indicator which is related to the dynamics of occupants' behaviour. In order to reduce the influence of extreme values, the medians of these durations are considered for evaluation, rather than the means.

4. Results of model development

We present in this section the models separately derived from each database, which forms the basis for simulations and validations presented in Section 5. All data analyses were performed using the statistical software R (R Development Core Team 2008).

4.1. *Treatment of occupancy*

As noted earlier occupants' presence was not explicitly measured for either of our two datasets. One solution would be to simulate occupants' presence using a known occupancy profile (see Figure 3 for two examples), for instance based on the algorithm developed by Page *et al.* (2008). But this would also require a mobility parameter, which has not previously been deduced for residential environments. We choose thus to represent occupancy in the following simplified ways:

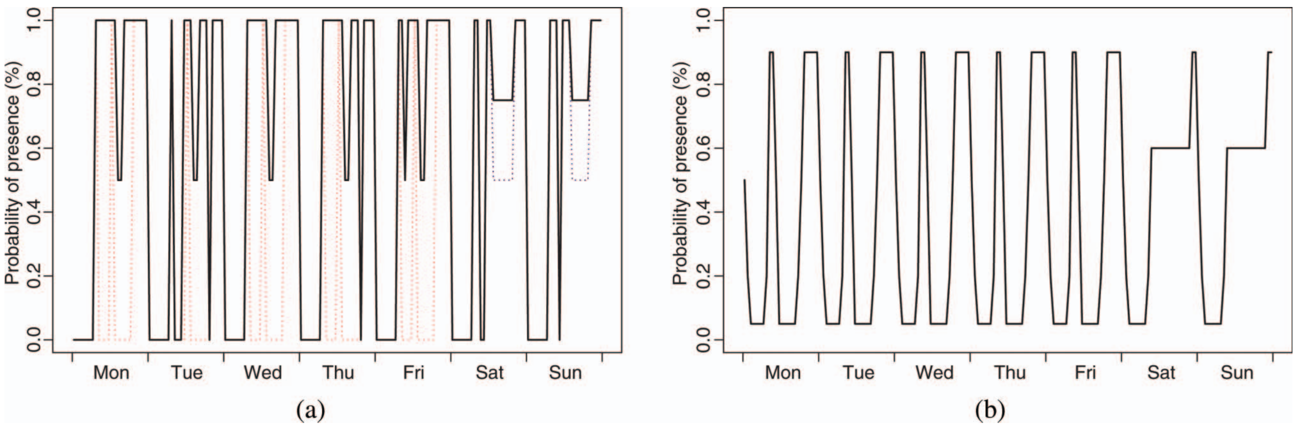

Figure 3. Examples of presence profiles of individuals living in the household (dashed lines) and the resulting overall probability of presence (solid line) from Equation (2) for the CT building (a) and the Tokyo building (b).

- The room is assumed to be occupied all the time (OccAll).
- The room is assumed to be occupied when the probability of presence (Equation (2)) exceeds 0.5 (Occ50).
- For each period of the day as presented in Table 4, a separate model is developed to represent changing probabilities of occupancy and behavioural patterns simultaneously (BePersTime and MaPersTime).

For the Swiss apartments which are occupied by several persons, all the N_{occ} occupants of the surveyed building provided an average individual presence profile $P_{pres,i}$ for each day of the week, which is shown in Figure 3(a). From this we deduce the probability of finding at least one occupant $P_{pres}(t)$ as follows:

$$P_{pres}(t) = 1 - \prod_{i=1}^{N_{occ}} P_{abs,i}(t) = 1 - \prod_{i=1}^{N_{occ}} (1 - P_{pres,i}(t)), \quad (2)$$

assuming independence between occupants. Figure 3(b) shows an assumed occupancy profile for Japanese data set. In all cases, we simulate the window states for 24 h, except for those marked in Table 9 as 'day' for which we have assumed that occupants are inactive between 12 pm and 7 am.

However, we do not attempt to infer specific submodels for actions on arrival or at departure, due to the impossibility of defining accurate occupancy transitions.

4.2. *Probability of observing windows open – Bernoulli process*

Based on observed window states, logistic models (as defined in Equation (1)) are developed first with outdoor and indoor air temperature as predictors, followed by the addition of personal specificities in the case of the Japanese data. The obtained regression parameters are displayed in Table 5 and Figure 4.

4.2.1. *Swiss data*

The forward selection procedure retains outdoor temperature as the most influential variable, followed by the addition of indoor temperature. No other variable from among those measured (see Section 2.1.2) was found to significantly improve the goodness-of-fit. It can be seen in Figure 4(b), that the dashed lines representing the different apartments are closely grouped, as very similar regression parameters are obtained. These findings are in agreement with parameters previously published by Haldi and Robinson (2009) for different offices of an academic office building (Table 5, right). It should be noted that the Swiss and Japanese experiments were not designed in common, so that the Swiss dataset does not permit an analysis of the significance of personal specificities.

4.2.2. *Japanese data*

Using a similar procedure outdoor and indoor temperature were both found to be significant – tested individually as well as in a combined model. Concerning the latter, outdoor temperature was found to contribute most to the variation in the chosen window state due to the higher χ^2, which is 4441 for θ_{out} and 4117 for θ_{in}, even though the influence of both variables is nearly the same. The R^2 values given in Table 5 and Figure 4(d-f) show that the observed and fitted data are not congruent and that, especially with regard to outdoor temperature a polynomial model would better represent the data. The conceptual

Table 5. Regression parameters of the retained models with standard errors and Nagelkerke's R^2 , the parameters obtained by Haldi and Robinson (2009) are displayed in the right column for comparison (actions during presence).

Models and variables	Neuchâtel (residential)	Tokyo (residential)	LESO (office)
Bernoulli	$R_N{}^2$=0.530	$R_N{}^2$=0.230	$R_N{}^2$=0.283
a	0.711 ± 0.094	-3.737 ± 0.025	0.794 ± 0.03
θ_{out}	0.3813 ± 0.0014	0.0497 ± 0.00074	0.1476 ± 0.0003
θ_{in}	-0.3077 ± 0.0044	0.0886 ± 0.0014	-0.1541 ± 0.0013
Markov			
P_{01}	$R_N{}^2$=0.057	$R_N{}^2$=0.008	$R_N{}^2$=0.040
a	-1.51 ± 0.89	-6.528 ± 0.112	-11.78 ± 0.30
θ_{out}	0.1389 ± 0.0076		0.0394 ± 0.0036
θ_{in}	-0.245 ± 0.037	0.0549 ± 0.0046	0.263 ± 0.014
T_{pres}			$(-\ 9.00 \pm 0.57) \cdot 10^{-4}$
f_R			-0.336 ± 0.088
P_{10}	$R_N{}^2$=0.158	$R_N{}^2$=0.054	$R_N{}^2$=0.024
a	-0.15 ± 0.32	-2.367 ± 0.17	-4.14 ± 0.24
θ_{out}	-0.1725 ± 0.0046	-0.0543 ± 0.0066	-0.0625 ± 0.0024
θ_{in}	-0.071 ± 0.015	-0.0474 ± 0.011	0.026 ± 0.011

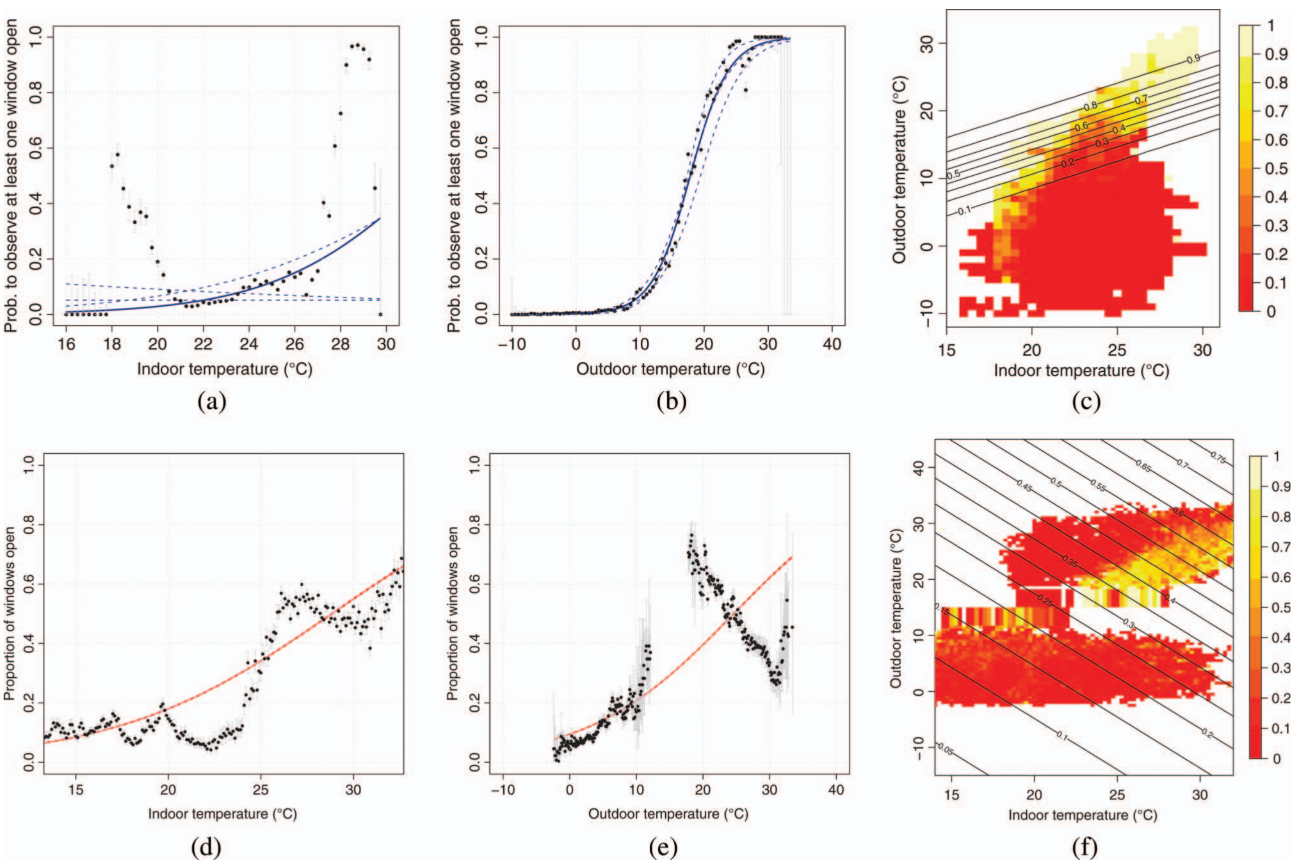

Figure 4. Observed (points/coloured squares) and fitted (solid lines) probabilities to observe at least a window open in Swiss (a–c) and Japanese (d–f) residential buildings, using θ_{in} (a,d) θ_{out} (b,e) and both (c,f) as predictors. Results from individual Swiss apartments are displayed as dashed lines (a, b). In the case of two predictors (c,f), observed transition probabilities are given as bins of observed indoor and outdoor temperature, with contour lines of equal fitted probabilities.

implications of including polynomial terms are discussed in Section 6.

The parameters for the models including personal characteristics are given in the Table 6. They can be separated into six groups; the environmental variables, the climatic origin, the geographic origin, the gender, the position within the building and the orientation of the window. Except for the environmental variables, each of the discrete variables includes one reference level, for which the coefficient was set to be 0. Therefore, the regression coefficients of the other levels measure the shift in probability (more precisely the log-odds) compared to the reference group. For instance, those living at the ground floor (where the coefficient is negative in the case of the Bernoulli model) are less likely to open their window than those living in the middle floor (the reference variable), while those living in the top floor are more likely to open their window (positive coefficient).

Figure 5 is based on individual models for each group of students separated by their climatic background and are therefore distinct from the model presented in Table 6. This figure indicates the effects of the climatic origin of the subject with respect to the window opening probability in relation to indoor and outdoor temperature. For both variables, those originating from a cold climate open their windows with a higher probability, and those from a moderate climate tend to open their windows slightly more often at lower outdoor temperature compared to those from hot and humid or hot and dry climates. Between these latter, no significant differences were found.

4.3. *Probability of action – Markov chain*

As noted earlier the absence of direct occupancy measurements precludes any reliable examination of the specific patterns of window usage upon arrival, during presence or at departure. Therefore, models are developed for the probabilities of action that refer to any interval of five minutes without regard to occupancy transitions, based on time intervals where the probability of presence exceeds 0.5. Figure 6 shows observed and fitted transition probabilities for Swiss and Japanese datasets.

4.3.1. *Swiss data*

Indoor and outdoor temperatures are significant variables for both opening and closing probabilities.

Table 6. Regression parameters of the retained models for the Tokyo dataset with standard errors and Nagelkerke's R^2 for the multivariate models.

	Bernoulli	Markov	
Models	BePers	MaPers open	MaPers closing
R_N^2	0.396	0.034	0.121
Variables			
a	9.4635 ± 0.3088	-9.1839 ± 2.0270	-8.7570 ± 2.1330
θ_{out}	0.2483 ± 0.0062	0.1618 ± 0.0324	-0.0501 ± 0.0349 (0.12)
θ_{out}^2	0.0063 ± 0.0005	0.0003 ± 0.0031 (0.73)[a]	-0.0072 ± 0.0034 (0.02)
θ_{out}^3	$-4.04 \times 10^{-4} \pm 0.0000$	$-1.50 \times 10^{-4} \pm 0.0002$ (0.01)	$2.96 \times 10^{-4} \pm 0.0002$
θ_{in}	-1.0720 ± 0.0439	0.4725 ± 0.2883 (0.14)	0.3892 ± 0.3089 (0.31)
θ_{in}^2	0.0399 ± 0.0020	-0.0176 ± 0.0132 (0.20)	-0.0097 ± 0.0146 (0.81)
θ_{in}^3	$-3.99 \times 10^{-4} \pm 0.0000$	$2.51 \times 10^{-4} \pm 0.0001$ (0.19)	$-6.00 \times 10^{-6} \pm 0.0001$ (0.57)
θ_{rm}[b]	-0.0678 ± 0.0023	-0.0655 ± 0.0155	-0.0243 ± 0.0167 (0.04)
Originating from hot and humid climate	-1.1165 ± 0.0158	0.0418 ± 0.1448 (0.90)	0.4090 ± 0.1223
Originating from hot and dry climate	-2.6918 ± 0.0216	-0.6174 ± 0.1549	2.0310 ± 0.1583
Originating from moderate climate	-1.3388 ± 0.0160	-0.2177 ± 0.1108 (0.02)	0.7321 ± 0.1116
Originating from cold climate	0	0	0
Originating from Central-Asian country	-0.3927 ± 0.0293	-0.3445 ± 0.2202 (0.02)	-0.2547 ± 0.2179 (0.74)
Originating from East-Asian country	-1.9255 ± 0.0219	-0.6648 ± 0.1574	1.1140 ± 0.1782
Originating from European country	-1.6018 ± 0.0214	0.2509 ± 0.1605 (0.42)	1.4880 ± 0.1551
Originating from South American country	-0.9927 ± 0.0227	0.0150 ± 0.1686 (0.60)	0.5989 ± 0.1667
Originating from other country	0	0	0
Being male	0.4255 ± 0.0138	-0.0451 ± 0.0894 (0.36)	-0.0174 ± 0.0888 (0.43)
Being female	0	0	0
Living in ground floor	-1.1762 ± 0.0144	0.2037 ± 0.0704	1.3301 ± 0.0721
Living in middle floor	0	0	0
Living in top floor	0.5642 ± 0.0173	0.6221 ± 0.1233	0.2481 ± 0.1209 (0.04)
East-orientated window	-1.3893 ± 0.0183	-0.9369 ± 0.1266	0.7788 ± 0.1308
South-orientated window	-0.3000 ± 0.0124	-0.2674 ± 0.0680	0.0913 ± 0.0764 (0.15)
West- or North-orientated window	0	0	0

Note: [a]Numbers in brackets show the significance level if not less than 0.001. [b]weighted running mean of the five foregoing days.

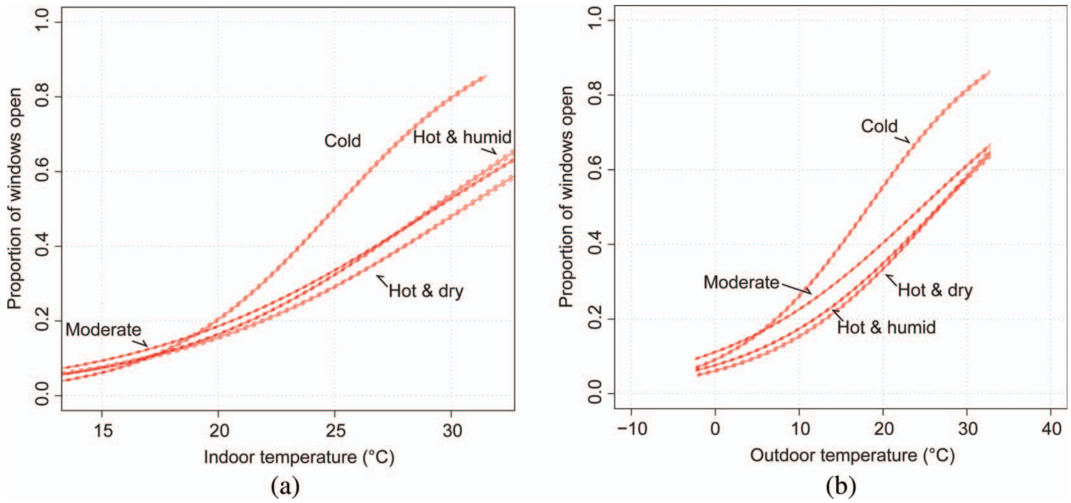

Figure 5. Fitted probabilities to observe an opened window for occupants with different climatic background in relation to indoor air temperature (a) and outdoor temperature (b).

As was the case in the study of Haldi and Robinson (2009), the effect of θ_{out} largely dominates for closing probability, but no significant effect of precipitation was noticeable. Due to the lack of occupancy data, the influence of presence and absence durations could not be studied.

4.3.2. *Japanese data*

Tested individually, indoor and outdoor temperature are significant variables for both opening and closing probabilities. However, when developing a multivariate logistic model outdoor temperature was not found to be significant for opening probabilities. As indicated by the number in brackets, some of the variables in the Markov chain models are not significant according to the Wald test (Table 6). However, based on AIC and Nagelkerkes-R^2 index, their inclusion does lead to better Bernoulli models so that they were retained for simulation purposes. This property of the Wald test to dismiss some significant predictors, known as the Hauck–Donner effect, is well documented (Hauck and Donner 1977).

4.4. *Results on the choice of opening angle*

In this section, we present our observations on the choice of opening angles and propose two possibilities to model it. These models will not be validated against external data as no other record of angles is available to us from other surveys.

Following the approaches retained in the preceding sections, we present two possibilities which were previously applied to the modelling of actions on shading devices and the choice of (un)shaded fraction (Haldi and Robinson 2010). With the first variant, the probability to observe a window open (a dichotomous event) is extended to produce an ordinal logistic model, resulting in a probability of observing a window to be open at a given angle. The second variant is meant to extend the Markov chain approach, in which we add a probability distribution for the choice of opening angle when an opening is predicted. In this, we neglect actions where occupants modify the angle of an already open window, which our observations suggest are in any case relatively rare.

4.4.1. *Probability distribution of observed opening angles*

Ordinal logistic regression generalizes logistic regression to non-binary outcomes such as an opening angle, which can take any value between 0° and 90°[1]. For this the proportional odds model gives a probability for the opening angle α to be at least α_j as the function:

$$p(\alpha \geq \alpha_j | x_1, \ldots, x_n) = \frac{\exp\left(a_j + \sum_{i=1}^{n} b_i x_i\right)}{1 + \exp\left(a_j + \sum_{i=1}^{n} b_i x_i\right)} \qquad (3)$$

where α is discretized into say 19 bins: $\alpha = 0^\circ, 5^\circ, \ldots, 90^\circ$. With this convention, we have a regression parameter b_i per predictor x_i and an intercept a_j per threshold angle. Observed and fitted distributions for the opening angles are displayed in Figure 7(a), which extends Figure 4 (b) by including the degree of opening.

We have carried out this procedure with respect to each of the available variables, from which we observe that the most influential variable is θ_{out}, resulting in $R_N^2 = 0.229$. The corresponding regression parameters are displayed in Table 7. No further

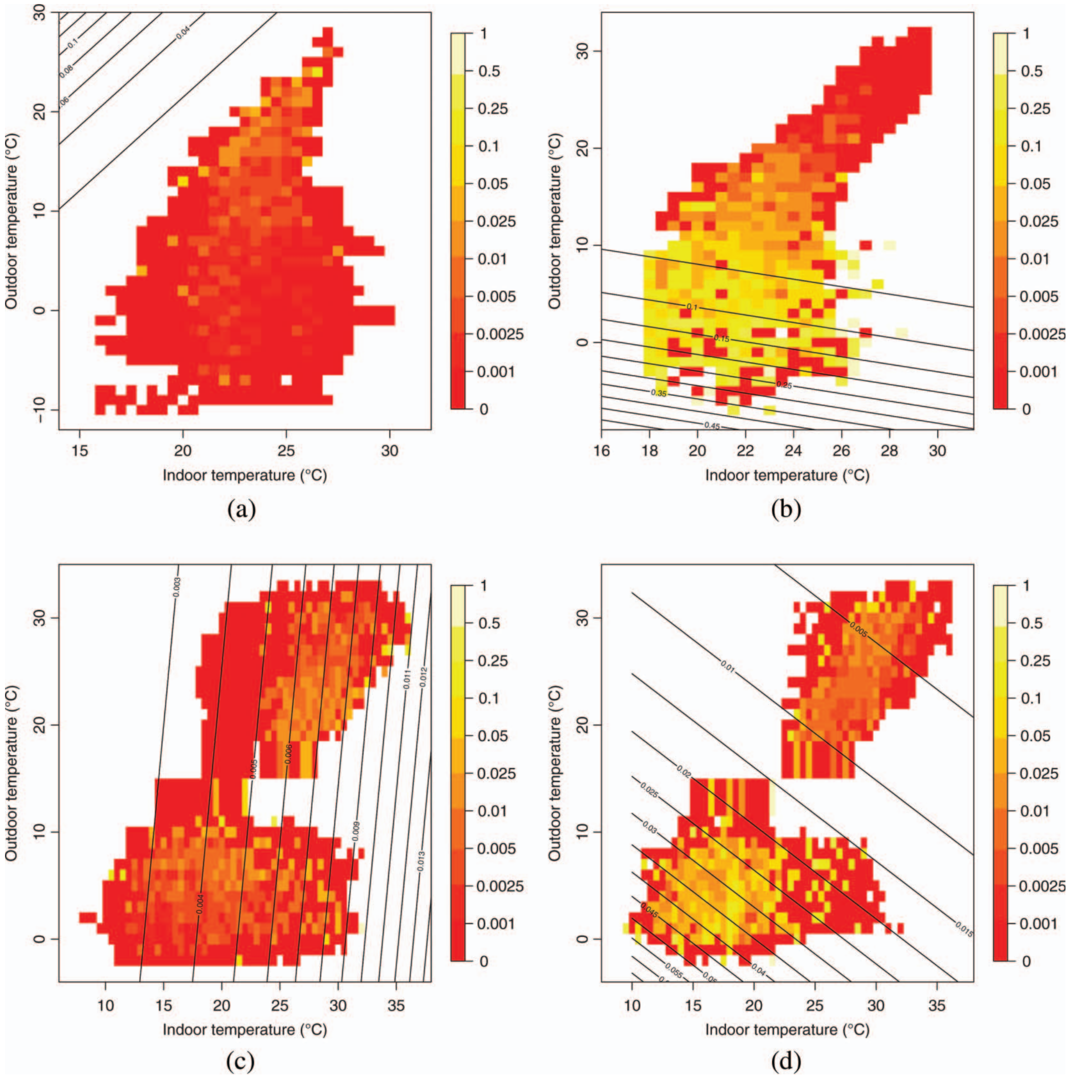

Figure 6. Observed (coloured squares) and fitted (solid lines) transition probabilities – from closed to open (a,c), from open to closed (b,d) in Swiss (a,b) and Japanese (c,d) residential buildings are given on a quasi-logarithmic scale in form of bins of indoor and outdoor temperature and contour lines of equal fitted probabilities.

variable tested was found to significantly improve upon this fit. Based on Equation (3), window opening angles may be simulated by sampling from a multinomial distribution.

4.4.2. *Probability distribution for the choice of opening angle*

As mentioned above, another approach for modelling opening angles is to add a sub-model for the choice of the opening angle when an opening action is predicted by the Markov process. In this case, we observe that θ_{in} is the only significant variable ($R_N^2 = 0.139$). We also obtain the counter-intuitive result that the probability to choose large angles decreases with θ_{in}. We may interpret this as meaning that when θ_{in} is low (typically in winter), occupants choose to open their window rarely but widely, and the opposite in summer; although the small amount of recorded opening events in winter precludes a statistically significant effect of θ_{out}. The obtained distributions of the opening angle choice are displayed in Figure 7(b).

In conclusion, the first approach shows a dominating effect of θ_{out}, like its binary counterpart (the Bernoulli process), while the second approach which predicts the actions themselves isolates the determinant effect of local thermal stimuli (as does the Markov process for opening and closing actions).

5. Results of model validation

5.1. *Methodology*

Informed by the regression parameters derived in Section 4, simulations have been performed using all

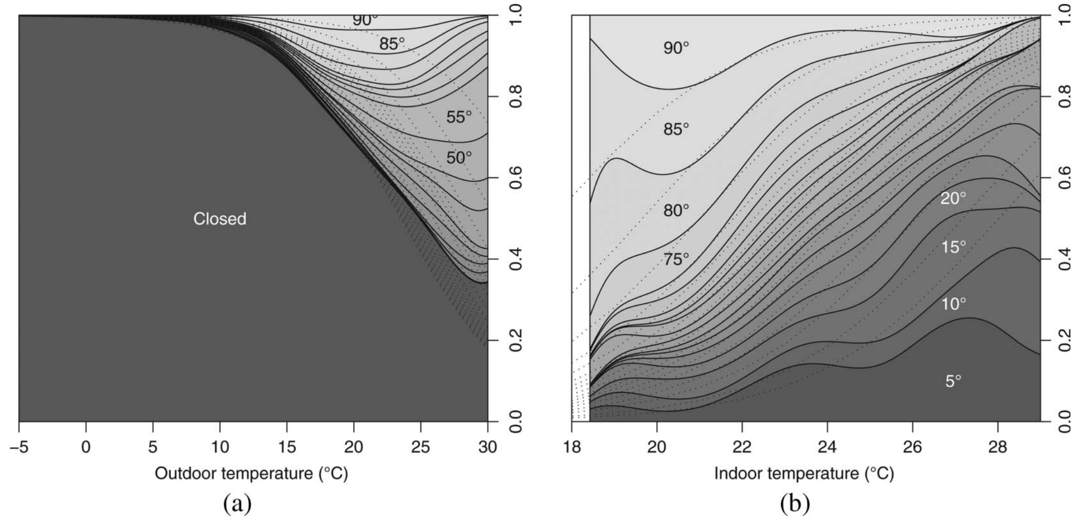

Figure 7. Choice of the opening angle. (a) Observed distribution of the opening angles of the windows (grey surfaces) with fitted ordinal logistic probabilities (dashed lines). (b) Observed distribution of the choice of opening angles when an opening action was performed.

Table 7. Regression parameters for the ordinal logistic models for window opening angles for the probability of observing opening angles (left) and the distribution for the choice of opening angle (right).

Static probability				Choice of angle			
α_j	Estimate	α_j	Estimate	α_j	Estimate	α_j	Estimate
5°	-5.528 ± 0.010	55°	-6.098 ± 0.011	10°	13.13 ± 0.79	55°	10.90 ± 0.77
10°	-5.556 ± 0.010	60°	-6.257 ± 0.011	15°	12.73 ± 0.78	60°	10.78 ± 0.77
15°	-5.584 ± 0.010	65°	-6.347 ± 0.011	20°	12.22 ± 0.78	65°	10.64 ± 0.77
20°	-5.628 ± 0.010	70°	-6.432 ± 0.011	25°	11.94 ± 0.78	70°	10.43 ± 0.77
25°	-5.675 ± 0.010	75°	-6.526 ± 0.011	30°	11.69 ± 0.78	75°	10.21 ± 0.76
30°	-5.723 ± 0.010	80°	-6.752 ± 0.012	35°	11.51 ± 0.77	80°	9.84 ± 0.76
35°	-5.782 ± 0.010	85°	-7.191 ± 0.012	40°	11.35 ± 0.77	85°	9.21 ± 0.75
40°	-5.845 ± 0.010	90°	-8.077 ± 0.015	45°	11.22 ± 0.77	90°	8.22 ± 0.75
45°	-5.923 ± 0.010	θ_{out}	0.2352 ± 0.0006	50°	11.07 ± 0.77	θ_{in}	-0.468 ± 0.033
50°	-5.970 ± 0.010						

the presented model variants, first by cross-validation based on internal data, and then using measured environmental variables from other datasets, as outlined in Section 3.2. For each of the 35 retained cases presented in Tables 8 and 9, 10 repeated simulations were completed.

These results were then analysed to compute the indicators introduced in Section 3.2.2, which are presented for each simulated model in Table 9 (prediction of Japanese dataset) and Table 8 (prediction of Swiss dataset).

For the discrimination criteria, we may also draw the corresponding points in the receiver-operating space (Figure 8), in which our ideal model would be located at minimum x and maximum y. Each small point corresponds to a single simulation of an apartment, while parameters referring to the aggregated results of a model are plotted as larger solid points. In such a representation, a point located at (0, 1) corresponds to exact predictions, (1, 0) to exactly opposite predictions and points on the $x = y$ line to random predictions. A point at (0,0) would indicate a model predicting windows always closed and (1, 1) to windows always open. Models with a strong predictive value are characterized by true positive rates significantly larger than false positive rates.

5.2. *Performance*

The obtained results differ strongly between the two considered validation datasets. It appears from the indicators of Table 8 that the window states recorded in the Swiss buildings can be reproduced with reasonable accuracy, as TPR is significantly higher than FPR for all the tested model variants except for those including personal characteristics (BePers, BePersTime, MaPers, and MaPersTime) and those using the Humphreys algorithm. The opposite is the

Table 8. Validation parameters for the Swiss data set: true positive rate, false positive rate, accuracy, total proportion of simulated time steps with window open, average number of opening actions per day and median duration (min.) of openings and closings.

Model	Base[a]	Occupancy profile	TPR [%]	FPR [%]	ACC [%]	Proportion of openings [%]	Actions [-]	Duration of openings [min]	Duration of closings [min]
Exact			100.0	0.0	100.0	10.2	3.9	83.2	691.4
Bernoulli process									
-BeTeTi	TKY	AllOcc	32.2	20.1	75.4	21.6	480	1.2	4.8
-BePers	TKY	AllOcc	11.7	33.0	88.8	4.58	130	1.2	4.6
-BePersTime	TKY	AllOcc	7.8	2.7	88.7	3.46	961	1.1	5.6
-BeTeTi	LESO	AllOcc	39.3	12.8	78.3	16.8	175	5.0	15.0
-BeTeTi	LESO	Occ50	33.9	13.4	74.7	17.7	79	5.0	15.0
-BeTeTi	NE	AllOcc	44.9	5.3	85.9	10.6	78	5.0	15.0
-BeTeTi	NE	Occ50	35.0	6.2	81.2	12.1	56	5.0	10.0
Markov chains									
-MaTeTi	TKY	AllOcc	31.9	20.3	75.2	21.7	12.7	50.4	176.2
-MaPers	TKY	AllOcc	12.0	38.2	88.3	5.03	14.4	9.4	235.9
-MaPersTime	TKY	AllOcc	11.7	42.0	87.5	5.11	14.3	11.8	252.2
-MaTeTi	LESO	Occ50	27.9	12.5	76.5	10.5	1.9	135	1405
-MaTeTi	NE	Occ50	32.6	7.5	79.9	12.9	1.9	155	1320
Humphreys algorithm									
-BeTeTi	RIJ[b]	AllOcc	29.6	54.5	44.2	51.6	0.37	16107	8602
-BeTeTi	TKY	AllOcc	28.6	54.4	44.3	51.4	0.38	17090	8780
-BePers	TKY	AllOcc	26.5	50.6	47.6	47.9	0.31	20586	25012
-BePersTime	TKY	AllOcc	25.7	49.5	48.7	46.7	0.32	23830	23264
-BeTeTi	LESO	AllOcc	28.2	53.4	45.1	50.5	0.34	17293	11432

Note: [a]Dataset from which the coefficients were derived; [b]as in Rijal *et al.* (2007).

case when the dataset recorded in Japan is used as the validation dataset: TPR is in all cases almost equal to FPR, with the exception of the models BePersTime and MaPersTime, which include individual characteristics and timesteps (Table 9). This difference can be clearly observed in Figure 8, where the charts referring to the Japanese validation datasets display points close to the diagonal line, indicating random predictions.

For Swiss and to a lesser extent Japanese data, noticeable differences in predictive accuracy are observed between internal and external validation runs. Understandably internal cross-validation yields the best results, whereas the use of external calibration data leads to a TPR that approaches the FPR, and the points of the ROC charts lie closer to the diagonal (Figures 8(c)–(f)). The Swiss residential data are of particular interest, the models' ability to reproduce it is significant in all cases. This is in part due to the size of the dataset and in part because the Swiss dataset fortuitously corresponds to a range of climatic conditions in which air-conditioning tends not to be used in Tokyo; this helping with computability. Nevertheless for this dataset, models calibrated from previous Swiss office data (Haldi and Robinson 2009) result in higher accuracy than based on Japanese residential data, graphically speaking the simulation results of Figure 8(e) all lie beyond the convex hull defined by the results of Figure 8(c). Furthermore the observed decrease in predictive accuracy is moderate (Table 8), indicating a clear applicability of these models based on Swiss office to this instance of a residential environment. It would appear that models derived from one type of building used may be robust enough to be applied to another type of building use under a comparable climatic context.

6. Discussion

6.1. *Use of temperature polynomials*

The significance of polynomial terms, when added to some of the models, shows clear deviations from the expected linear logistic link between thermal stimuli and adaptive actions on windows. These additional regression parameters do not as such enhance physical interpretation (we might as well describe this trend using non-parametric estimators). Rather their presence shows that the link between temperature and window use is perturbed by other factors, such as hot outside air or the presence of air-conditioning, that are not explicitly modelled. For example, people like to have their windows open *up to a certain temperature*, but this preference may change at very high outdoor temperatures, to reduce the ingress of relatively hot outside air.

6.2. *The special case of the residential environment*

The modelling approach of Haldi and Robinson (2009) allows for a direct comparison of behaviours arising from

Table 9. Validation parameters for the Japanese data set: true positive rate, false positive rate, accuracy, total proportion of simulated time steps with window open, average number of opening actions per room and measured period and median duration (min.) of openings and closings.

Model	Base[a]	Occupancy profile	Period	TPR (%)	FPR (%)	ACC (%)	Proportion of openings (%)	Actions (−)	Duration of openings (min)	Duration of closings (min)
Exact				100.0	0.0	100.0	28.4	66.4	406.4	853.7
Bernoulli process										
BeTeTi	TKY	AllOcc	24 h	28.5	29.1	66.2	28.7	3442	3.82	13.7
BePers	TKY	AllOcc	24 h	34.4	30.0	71.0	31.4	2917	4.70	29.1
BePers	SCH[b]	AllOcc	24 h	46.5	44.8	53.8	42.4	406	152.1	173.4
BePersTime	TKY	AllOcc	24 h	33.7	25.5	72.7	28.7	2701	4.62	31.6
BeTeTi	LESO	AllOcc	Day	29.0	26.9	68.1	26.9 (17.0)[c]	3713 (66.9)	4.07 (314.5)	9.80 (1026.5)
BeTeTi	LESO	Occ50	Day	29.8	29.3	66.3	28.8 (21.1)[c]	1674 (66.9)	4.07 (314.5)	9.72 (1026.5)
BeTeTi	NE	AllOcc	Day	21.3	20.1	75.9	19.8 (17.0)[c]	2025 (66.9)	6.17 (314.5)	34.0 (1026.5)
BeTeTi	NE	Occ50	Day	24.9	24.7	74.6	24.1 (21.1)[c]	889 (66.9)	6.24 (314.5)	34.8 (1026.5)
Markov chains										
MaTeTi	TKY	AllOcc	24 h	28.4	29.0	66.8	28.6	67.3	211	524
MaPers	TKY	AllOcc	24 h	29.9	26.6	71.2	27.8	65.9	246	641
MaPersTime	TKY	AllOcc	24 h	29.4	22.0	72.8	24.5	66.7	238	763
MaTeTi	LESO	Occ50	Day	21.7	21.8	76.7	21.8 (21.1)[c]	27.6 (66.9)	123 (314.5)	2074 (1026.5)
MaTeTi	NE	Occ50	Day	25.4	25.6	74.2	24.8 (21.1)[c]	45.9 (66.9)	390 (314.5)	408 (1026.5)
Humphreys alg.										
BeTeTi	RIJ[d]	AllOcc	24 h	37.4	33.9	72.6	35.6	25.2	10397	2192
BeTeTi	TKY	AllOcc	24 h	35.8	31.1	73.1	33.8	27.2	9171	2283
BePers	TKY	AllOcc	24 h	35.5	30.6	73.7	33.5	24.1	9152	2458
BePersTime	TKY	AllOcc	24 h	35.4	30.3	73.9	33.2	22.9	9134	3313
BeTeTi	LESO	AllOcc	24 h	35.3	30.8	73.7	33.3	17.7	10320	3068

Note: [a]Dataset from which the coefficients were derived. [b]As in Schweiker and Shukuya (2009). [c]Number in brackets shows exact number of proportion open for evaluated sub-datasets - the data of some of the occupants had to be neglected due to missing values, which the algorithm was not able to deal with. [d]As in Rijal et al. (2007)

both office and residential environments. As with office environments, θ_{out} is found to be the most influential predictor for a single logistic model predicting the probability to observe a window open, whereas both θ_{in} and θ_{out} are to be included in action probabilities.

Although the obtained regression parameters differ from previous office-based observations (Table 5), those based on Swiss residential buildings remain within the measured range of variability that occurs between office occupants. But these findings refer to the behaviour of occupants in a living room, which is not necessarily representative of window opening behaviour in other residential spaces (e.g. kitchens and bathrooms in which window usage may be related to a higher degree to the desire to reject water vapour and gaseous pollutants). Indicators of air quality such as CO_2, which were mentioned as important drivers of window opening behaviour (see e.g. Warren and Parkins 2007 for office buildings and Andersen *et al.* 2009 for residential buildings), could not be evaluated here due to missing data. Further investigations including such indicators and those for occupancy transition would be an important addition to be done in future studies. The regression parameters derived from the Japanese dataset differ significantly from those of the Swiss dataset, as discussed below.

6.3. *Differences between the two datasets*

The most noteworthy difference between models inferred from Swiss and Japanese data lies in the much smaller values of R_N^2 and the regression parameters for the latter case (which lower action probabilities). Indeed these findings lead to the conclusion that the difference in behaviour between these residential buildings is higher than is the case between Swiss office and residential buildings.

One explanation might relate to the effectiveness of windows in enhancing occupants' thermal comfort as compared with the use of air-conditioning (in Japan). Indeed in the hot and humid climate of Japan in summer window usage decreases significantly as θ_{out} rises[2] (see Figure 4). In such a situation, air-conditioning use is privileged by occupants, while it appears that windows are used for moderate outdoor conditions. Other likely reasons for this discrepancy relate to the differences in the buildings' thermal performance; in particular the relatively poor insulation of the Japanese building may influence the indoor radiant environment, which was not assessed within these studies. The particular window usage patterns of a one-room apartment used for living, sleeping and in some cases studying has to be mentioned as well as the differences in the way the windows are operated (tilted and axial openings in the Swiss survey, in comparison to sliding openings in the Japanese survey). Which of these influences contributes most to the observed differences should perhaps be clarified in a future study, ideally based on a larger database and including the assessment of occupancy transition as well as more complete environmental measurements than these here (in particular operative temperature).

In consequence, the models calibrated from Swiss data provide poor predictions of window use in Japan. On the contrary, linear logistic models fitted from Japanese data result in poorly adjusted increasing functions of θ_{out} which nevertheless provide acceptable predictions of window use in Switzerland, for which less elevated temperatures are experienced.

6.4. *Impact of unknown occupancy*

The comparison of simulation results between presence modelling strategies shows that uncertainty with respect to occupancy decreases the congruence significantly, leading to a lower accuracy than that observed by Haldi and Robinson (2009) and Haldi *et al.* (2010). Surprisingly, in all cases assuming permanent occupancy (AllOcc) the quality of predictions is better than when presence is deduced from an occupancy profile (Occ50). Having two randomly generated numbers compared with certain threshold levels seems to cause more error than the expected benefit of such a modelling approach.

6.5. *Applicability of stochastic behavioural models*

We have observed a good agreement between calibration parameters from Swiss office and residential data, resulting in an accuracy similar to that obtained in internal cross-validation. However, the predictions from both these datasets for a Japanese residential setting did not perform significantly better than a random guess (Figure 8).

Our observations suggest that the climate, quality of the built environment, type of usage and the existence of an air-conditioning unit has a determinant influence on occupants' behaviour, so that appropriate models need to consider the most important of these factors (especially conflicting behaviours such as use of windows and air-conditioning).

6.6. *Impact of including individual factors*

The factors most relevant to describe differences in occupants' behaviour according to Schweiker and Shukuya (2009) could not be tested in the Swiss context due to unknown personal characteristics in the Swiss dataset. The results of internal compared to external validation show the strengths and weaknesses

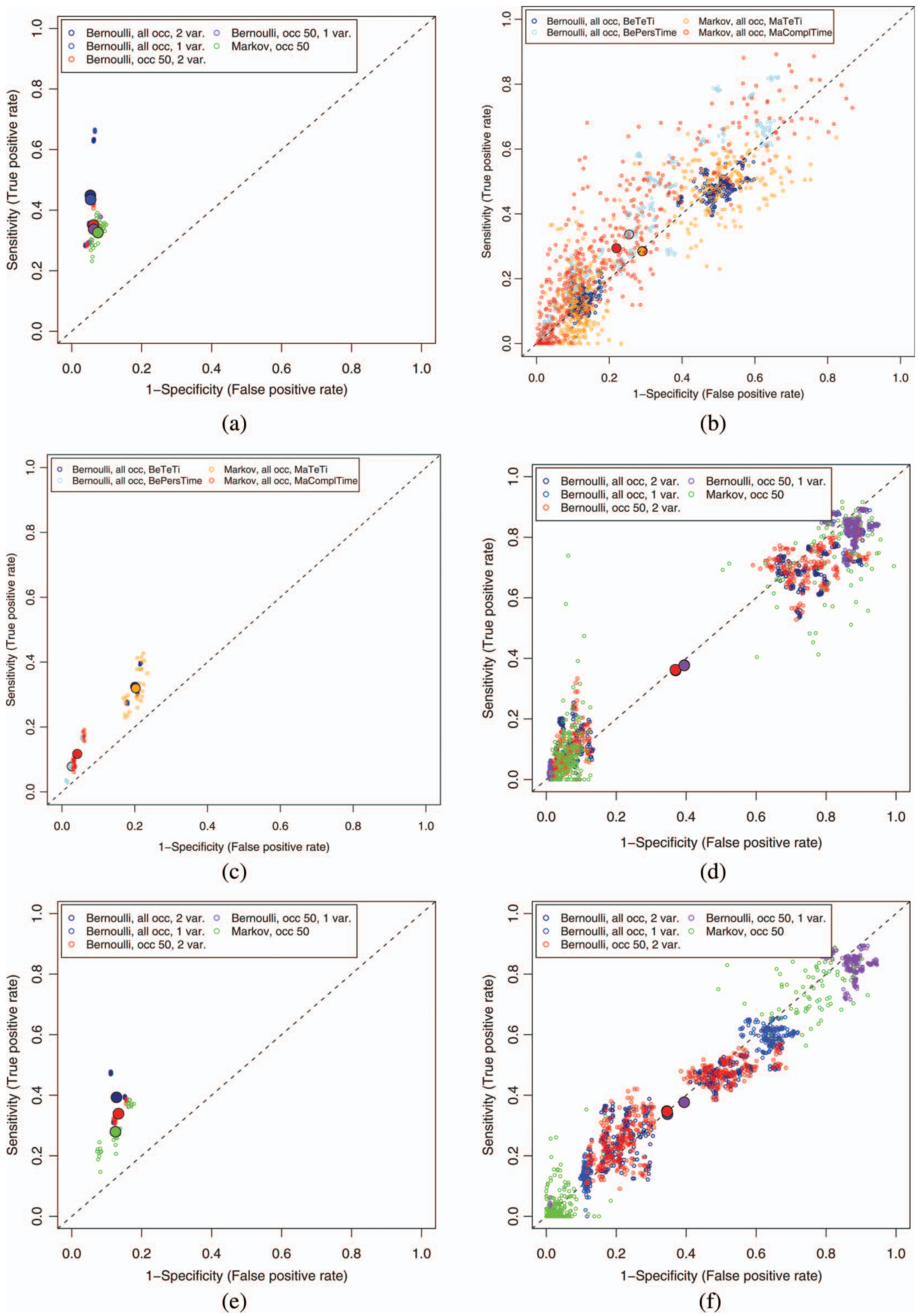

Figure 8. Discrimination criteria displayed in the receiver-operating space. (a) Calibration and validation: Neuchâtel dataset. (b) Calibration and validation: Tokyo dataset. (c) Calibration: Tokyo dataset, validation: Neuchâtel dataset. (d) Calibration: Neuchâtel dataset, validation: Tokyo dataset. (e) Calibration: LESO dataset, validation: Neuchâtel dataset. (f) Calibration: LESO dataset, validation: Tokyo dataset. Note: Small points represent single simulations of individual apartments and larger solid points show aggregated results for a simulation approach as of Tables 8 and 9.

of this approach. For internal validation, the models including personal characteristics certainly do give added value by improving the simulation results. However, when applied to the Swiss dataset – the external validation part – they lead to worse results than the models including indoor and outdoor temperature alone. This might be caused either by over-fitting of the models or due to other differences between the cases surveyed, such as the quality of the building envelope or the existence of air-conditioning units which were not considered in the Swiss case.

6.7. Impact of modelling approach

As expected, the models based on Bernoulli random variables do not predict coherent delays between actions (Tables 8 and 9), as they do not explicitly model behavioural dynamics. The Markov models estimate rather reliably these durations, accounting well for the dynamics of occupants' behaviour. In contrast to the Markov model, the Humphreys algorithm (Rijal *et al*. 2008) predicts durations that are too long, which may be caused by too large a deadband (indeed a significant proportion of actions occurs at moderate temperatures).

6.8. Validity of results

The analysis presented above is based on a relatively small number of buildings, i.e. two buildings in Switzerland and one building in Japan. One might reasonably assume therefore, that the results might not be applicable to buildings or climatic contexts which are significantly different. It is encouraging then that the coefficients derived from a residential environment in Switzerland match well those derived from an office environment in the same country Haldi and Robinson (2009): behaviours in different building types but in a similar climate appear to be similar.

It is interesting that our simulation results suggest that the Humphreys algorithm performs relatively poor: the median duration open and closed is very long compared to the other models. This appears to be because once a window opening / closing action has been performed, the extent of this action (and any other performed actions) is such that the indoor environment has been maintained within the algorithm's deadband: further actions are only predicted to take place when the temperature signal has exceeded this deadband. To further investigate this, it would be useful in the future to perform a further comparison of models in which the explanatory variable is the predicted environmental state following from occupants' adaptive actions (i.e. the feedback from window opening / closing) rather than only the measured state.

7. Conclusion

For the first time, models for the prediction of window usage in the residential environment calibrated for a specific dataset were validated externally on a second very distinctive dataset and vice versa. The double-blind method used was conducted for several modelling approaches of varying complexity with respect to the number of variables included in the models. Based on comparisons of the predictive accuracy of these models, we conclude the following:

- In the case of the investigation in Switzerland, both the formulation of the tested models appear to be robust, being applicable to both residential and office environments. Furthermore, for a similar context (similar temperate climate, absence of air-conditioning device, no particular source of pollutants), regression parameters derived from one type of building reproduce well the behaviour of occupants of another type of building. In other words, the regression parameters are also rather robust.
- Japanese data are not well reproduced by any of the considered models. This results from a low utilization of windows in the summer period, which may be caused by the hot and humid outdoor conditions, the presence of air-conditioning, the absence of many students during daytime in order to go to university, or the concomitant influence of these factors. This indicates that conflicting adaptive actions need to be explicitly considered. Nevertheless, models based on these data offer acceptable predictions for the Swiss context, because the fitted trend for increased window use at moderate temperatures (prior to switching on air-conditioning) matches the observed behaviour in Switzerland.
- The Japanese survey on heterogeneous populations suggests that cultural background and associated comfort expectations influence occupants' behaviour. The associated model specificities could however not be tested on Swiss data, which do not present these cultural specificities.

Although this article describes a reasonably comprehensive analysis of the predictive accuracy of models of occupants' use of windows in the residential building context, and indeed of the robustness of models and their regression coefficients between building types, there remains considerable scope for further work. Of immediate relevance to this article a more comprehensive study of the relationships between behaviour and activity (e. g. reading, bathing, cooking) supplemented by additional environmental measurements would be helpful; as would analysis of the effect of the type of building envelope and systems on behaviour, based on a broader sample of buildings.

In the meantime the robustness of the models reported in this article are encouraging – suggesting that they may be used with a fair degree of confidence. For this their implementation into standard building simulation programs should be relatively straightforward.

Acknowledgement

Financial support received from the European Commission as part of the *CONCERTO II Project HOLISTIC* is gratefully acknowledged.

Notes

1. Depending on window configurations, opening angles up to 135°C were recorded.We are however not interested in modeling angles higher than 90° as they have a marginal impact on the resultant air flow.
2. It was also observed that opening probability decreases in temperate climates under hot conditions, but such a situation did not occur in Neuchâtel during this survey.

References

Akaike, H., 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19 (6), 716–723.

Andersen, R.V., Olesen, B., and Toftum, J., 2007. Simulation of the effects of occupant behaviour on indoor climate and energy consumption. *In:* O. Seppänen & J. Säteri, eds. *Proceedings of REHVA world congress Clima 2007 – wellBeing indoors, FINVAC ry*, Helsinki, Finland, Session C03, paper no. 1577.

Andersen, R.V., *et al.*, 2009. Survey of occupant behaviour and control of indoor environment in Danish dwellings. *Energy and Buildings*, 41, 11–16.

Bahaj, A.S. and James, P.A.B., 2007. Urban energy generation: the added value of photovoltaics in social housing. *Renewable and Sustainable Energy Reviews*, 11, 2121–2136.

Clarke, J.A., 2001. *Energy simulation in building design*. 2nd ed. Oxford, UK: Butterworth-Heinemann.

Dubrul, C., 1988. Inhabitant behaviour with respect to ventilation – a summary report of IEA Annex VIII. Technical report. Paris: International Energy Agency.

Haldi, F. and Robinson, D., 2008. On the behaviour and adaptation of office occupants. *Building and Environment*, 43, 2163–2177.

Haldi, F. and Robinson, D., 2009. Interactions with window openings by office occupants. *Building and Environment*, 44, 2378–2395.

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

Haldi, F., *et al.*, 2010. A partial double blind evaluation of a comprehensive window opening model. *In: BauSIM 2010 Conference*, Vienna, Austria.

Hauck, W.W.J. and Donner, A., 1977. Wald's test as applied to hypotheses in Logit analysis. *Journal of the American Statistical Association*, 72 (360), 851–853.

Herkel, S., Knapp, U., and Pfafferott, J., 2008. Towards a model of user behaviour regarding the manual control of windows in office buildings. *Building and Environment*, 43 (4), 588–600.

Hoes, P., *et al.*, 2009. User behaviour in whole building simulation. *Energy and Buildings*, 41, 295–302.

Iwashita, G. and Akasaka, H., 1997. The effects of human behavior on natural ventilation rate and indoor air environment in summer – a field study in southern Japan. *Energy and Buildings*, 25 (3), 195–205.

Kottek, M., *et al.*, 2006. World map of the Koeppen-Geiger climate classification updated. *Meteorologische Zeitung*, 15, 259–263.

Levermore, G.J., 1985. Monitoring and targeting: motivation and training. *In*: A.F.C. Sherratt, ed. *Energy management experience conference*. Cambridge, UK: CICC, 21–30.

Nagelkerke, N.J.D., 1991. A note on a general definition of the coefficient of determination. *Biometrika*, 78 (3), 691–692.

Nicol, J.F., 2001. Characterising occupant behaviour in buildings: towards a stochastic model of occupant use of windows, lights, blinds heaters and fans. *In*: Proceedings of the seventh international IBPSA conference, Rio, 1073–1078.

Page, J., *et al.*, 2008. A generalised stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40 (2), 83–98.

R Development Core Team, 2008. *R: A language and environment for statistical computing*. Vienna, Austria. Electronic edition. ISBN 3–900051–07–0.

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.

Rijal, H.B., *et al.*, 2008. Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings. *Journal of Building Performance Simulation*, 1 (1), 17–30.

Roetzel, A., *et al.*, 2010. A review of occupant control on natural ventilation. *Renewable and Sustainable Energy Reviews*, 14 (3), 1001–1013.

Schweiker, M. and Shukuya, M., 2009. Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions. *Building and Environment*, 44, 2137–2149.

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

Socolow, R.H., 1978. *Saving energy in the home: Princeton's experiments at twin rivers*. Cambridge, MA: Ballinger Press.

Warren, P.R. and Parkins, L.M., 2007. Window-opening behaviour in office buildings. *Building Services Engineering Research and Technology*, 5, 89–101.

Yun, G.Y. and Steemers, K., 2008. Time-dependent occupant behaviour models of window control in summer. *Building and Environment*, 43 (9), 1471–1482.