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A COMPREHENSIVE STOCHASTIC MODEL OF WINDOW USAGE: THEORY AND VALIDATION

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ABSTRACT

Based on almost seven years of continuous measurements we have analysed in detail the influence of occupancy patterns, indoor temperature and outdoor climate parameters (temperature, wind speed and direction, relative humidity and rainfall) on window opening and closing behaviour. This paper presents the development and testing of several modelling approaches, including logistic probability distributions, Markov chains and continuous-time random processes. Based on detailed statistical analysis and cross-validation of each variant, we propose a hybrid of these techniques which models stochastic usage behaviour in a comprehensive and efficient way. We conclude by describing an algorithm for implementing this model in dynamic building simulation tools.

INTRODUCTION

A range of studies of occupants' interactions with window openings have been conducted in recent years. To place our work in this topic into context, we therefore present a brief overview of these studies. We refer the reader to Haldi and Robinson (2009) for further details.

Pioneering investigations, such as the one conducted by Warren and Perkins (1984) showed – using stepwise multiple correlation analysis – that external air temperatures accounted for most of the observed variance in window states. Marginal contributions due to sunshine and wind speed were also observed. A mathematical model based on Markov chains to predict the state of windows was later developed by Fritsch et al. (1991) to predict transitions between bins of opening angles, with outdoor temperature as the driving variable.

Based on measurements from three separate surveys, Nicol (2001) proposed the first coherent probability distributions for the prediction of the state of windows, as logit functions (see below) of indoor and outdoor temperature. In most cases, the correlation with indoor temperature is similar to that with outdoor temperature. Nicol recommends the use of outdoor temperature on the basis that it is an input of any simulation program, while indoor temperature is an output. However, Nicol and Humphreys (2004) later reported that indoor temperature was a more coherent predictor for the use of windows than outdoor temperature. This approach may seem more sensible: as Robinson (2006) points out, predicted probabilities of interaction are otherwise independent of the design of the buildings in which occupants are accommodated.

Rijal et al. (2007) subsequently published a refined model, which has become known as the *Humphreys algorithm*, considering both indoor and outdoor temperature. A multiple logit distribution (with two variables) was derived for the probability of a window to be open. A deadband of ±2K for θ_{in} and ±5K for θ_{out} was defined to distinguish the probability of opening from that of closing. This refinement potentially solves the problem of repeated actions that would take place if a single distribution were used.

Based on their summer field survey, Haldi and Robinson (2008) suggest that in summer the strong correlation between indoor and outdoor conditions in naturally-ventilated buildings could dampen the efficiency of multiple logistic regressions. The works of Yun and Steemers (2008) seem to strengthen this hypothesis. Rijal et al. (2008) have subsequently published a refinement of the Humphreys algorithm, including a window opening effectiveness parameter. This modification imposes a window to be closed if $\theta_{out,rm} > 28.1°C$ and $\theta_{out} < \theta_{in} + 5°C$.

Yun and Steemers (2008) developed a model with indoor temperature as driving stimulus, considering that "the prediction as a function of external temperatures cannot be considered as an intrinsic result", in agreement with Robinson's (2006) observation. It was noticed that changes in window states mainly occurred on arrival or at departure. This observation led them to use separate probabilistic sub-models for window opening on arrival, and during occupancy. Retained offices did not enable night ventilation, so actions on departure are not considered (windows are assumed to be closed at departure). The final model retains thus indoor temperature, occupancy transitions and previous window state.

Herkel et al. (2008) also pointed out that most window openings can be associated with the arrival of an occupant, and so proposed separate sub-models for window opening and closing on arrival, at departure and during occupancy. However, these sub-models consider outdoor temperature as the driving stimulus, based on the observation that this variable had a higher correlation with the hourly mean value of opening status of the monitored windows. An additional effect from season was noticed (eg. similar outdoor temperatures do not imply the same action probabilities in spring or autumn).

From these studies it is apparent that:

- No clear consensus has as yet been reached as to whether indoor or outdoor temperature should be used in the simulation of actions on windows.
- The treatment of occupants' behaviour towards night ventilation has not yet been considered.
- Opening angles are mostly ignored, even though these are crucial for reliable air flow prediction.
- Existing models are informed by measurements in office buildings and behaviour in residential environments is not specifically treated.
- Published studies do not provide any common robust cross-validation procedure, which prevents any comparison of quality between published models.
- Finally, the case of offices with several occupants is not specifically treated (authoritarian versus democratic behaviour).

The purpose of this study is to attempt to resolve, at least partly, these issues.

THE FIELD SURVEY

Data used for the development of our models were collected from the Solar Energy and Building Physics Laboratory (LESO-PB) experimental building, located in the suburb of Lausanne, Switzerland (46°31'17"N, 6°34'02"E, alt. 396 m). In every office, occupants have the possibility to tilt or open up to any angle each of the two windows (height 90 cm, width 70 cm). Furthermore, external lower and upper roller blinds are controllable from within each office. Six offices are occupied by two persons, which can both individually access their own window, while eight offices accommodate single occupants able to act on the two windows. It is safe to leave windows open (eg. for night ventilation) during periods of absence, except on the ground floor. A typical office is shown in Figure 1.

All 14 south-facing cellular offices of this building have been equipped with sensors whose real-time measurements are archived by a centralised EIB data acquisition system. For a period covering 19 December 2001 to 15 November 2008 (with the exception of a few short interruptions caused by maintenance and technical reasons), local indoor temperature, occupancy, window openings and closings were continuously measured.

Figure 1 Typical cellular office of the LESO building

Outdoor temperature was measured by a sensor located on the roof from 17 March 2005. In parallel, a weather station located 7.7km away recorded the temperature, mean wind speed and direction, relative humidity and rainfall at 10 minute intervals.

Local outdoor climate data are missing for the first three years of measurements. To rectify this, linear regression between local and meteorological data for the period <u>with</u> local data was used to extrapolate from meteorological measurements for the period <u>without</u> local data.

Measurements of wind speed and direction present the additional problem of the highly local nature of observations, which undermines the relevance of more distant observations. We have thus used a coarse representation of wind speed and direction, by considering four levels of wind intensity defined by the observed quartiles of wind speed at the weather station. These choices allow us to assess whether wind influences window opening behaviour (but not to quantitatively estimate this influence).

RESULTS

We present in this section three models based on different modelling approaches. The statistical software package *R* was used for all data analyses and for programming the different models.

Models based on logit probability distributions

From now on we use the following notation for all the models based on (linear) logit distributions:

$$\text{logit}(p) = \log(p/(1-p)) = a + b_{in}\,\theta_{in} + b_{out}\,\theta_{out} + b_{\phi}\,\phi_{out} + b_R\,f_R + b_{WS}\,f_{WS} + b_{WD}\,f_{WD}, \quad (1)$$

where a and b_i are the regression parameters (see the nomenclature for other definitions). Further details regarding the principles of logistic regression may be found in Hosmer and Lemeshow (2000).

We have first performed separate logistic regressions using each available independent variable, together with some possible transformations of these latter. The model with θ_{out} has the largest likelihood ratio statistic, implying that it best describes the variations of our outcome variable. We present the obtained probability distribution (a = -2.4716 ± 0.0045, b_{out} = 0.12118 ± 0.00027) in Figure 2.

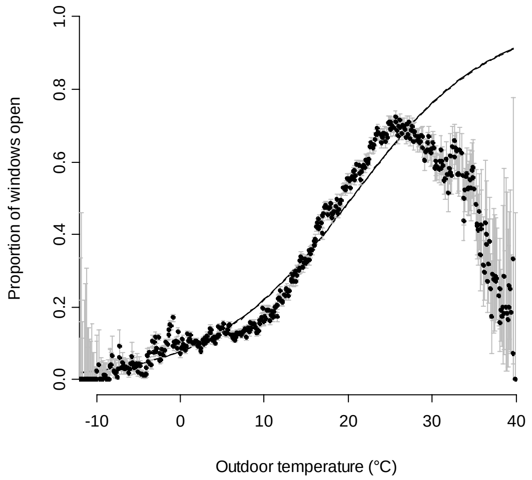

Figure 2 Observed proportion of windows open as a function of outdoor temperature, with 95% level confidence intervals and logistic regression curves

However, statistical significance itself does not necessarily provide clear-cut conclusions concerning the model's capacity to correctly explain our outcome variable. We therefore give in Table 1 a summary of the possible measures of goodness-of-fit for each of these models. According to all these goodness-of-fit criteria, the model with θ_{out} once again offers the best fit among all variables. We thus conclude that θ_{out} should be integrated in a final model, possibly in conjunction with other variables if their contributions are statistically significant and improve the quality of adjustment. The implications of this superiority of θ_{out} as a predictive variable are discussed later.

Table 1
Goodness-of-fit estimators (area under ROC curve, Nagelkerke's R^2, Brier score and Somers' D_{xy}) for logistic models including one or several variables

VARIABLES	AUC	R^2	B	D_{XY}
θ_{out}	0.769	0.247	0.172	0.537
θ_{in}	0.611	0.046	0.204	0.222
ϕ_{out}	0.577	0.022	0.208	0.154
f_{WD}	0.575	0.023	0.208	0.151
f_{WS}	0.564	0.016	0.209	0.128
f_R	0.507	0.001	0.212	0.015
θ_{out}, θ_{in}	0.774	0.260	0.170	0.547
θ_{out}, θ_{in}, ϕ_{out}	0.777	0.268	0.168	0.554

Following from theses univariate models we proceeded to consider models with several variables and assess the increased predictive value of more complex models. We then determined the best model containing two variables, and identified the significance of the added variable and the stability of the primary variable; continuing this procedure to other predictors until no further addition may provide extra significance. This procedure is known as forward selection.

Based on logistic regression for models including together θ_{out} and each other available variable, we observe that the model with θ_{out} and θ_{in} (a = 1.459 ± 0.032, b_{out} = 0.14477 ± 0.00033, b_{in} = -0.1814 ± 0.0015) has the highest statistical significance, according to the likelihood ratio statistic, and the best goodness-of-fit parameters; but the improvement to these indicators is rather modest. A plot of the observed proportions of windows open versus θ_{out} and θ_{in}, with regression surface levels (Figure 3) shows that observed variations are better accounted for, which confirms the existence of an independent contribution of each variable. Finally, the stability of the slope associated with θ_{out} is preserved, as its standard error remains extremely low, which shows that the correlation between θ_{in} and θ_{out} is not problematic for this model.

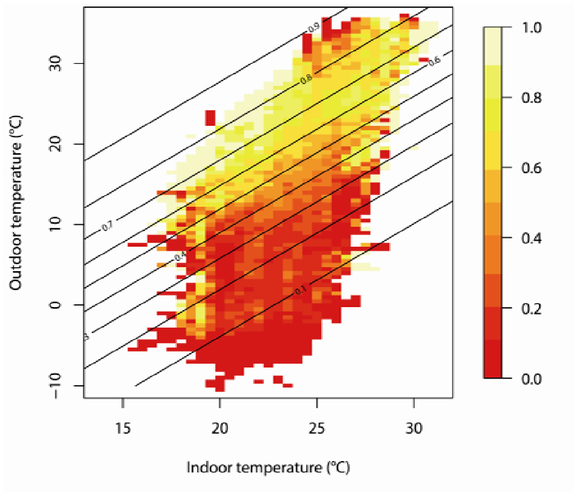

Figure 3 Observed proportion of windows open as a function of indoor and outdoor temperature, with logistic regression surface levels

We checked for the significance of the inclusion of a third parameter. The best model with three variables includes external relative humidity ϕ_{out} and this inclusion is statistically significant (p<0.001). However the goodness-of-fit criteria increase only very slightly (Table 1); which shows that its added predictive accuracy is marginal. Some other parameters in models with four or five variables were also found to be statistically significant, but without any increase in the goodness-of-fit indicators. For the sake of parsimony, it is thus sensible to keep the model with just the two variables θ_{out} and θ_{in}.

Inspired by the results of Herkel (2008), we attempted to include a factor with twelve levels corresponding to each month of the year, in order to check the existence of an additional effect of season on window actions. This factor does not bring any significant improvement; that is we observe almost the same logit distributions based on θ_{out} for every month. We tested other logistic models: one based on polynomial logits and another using the deviation to CEN comfort temperature, without observing better performance.

See Haldi and Robinson (2009) for further details.

Model based on a discrete-time Markov process

As noted earlier, a single probability distribution ignores the real dynamic processes leading occupants to perform actions, as the data used to infer them are aggregated observations of window states, but not actual opening or closing actions. In other words these models do not describe an actual probability of opening or closing, but a probability for a window to be "found" open, provided relevant physical parameters. Furthermore it ignores the particular patterns caused by occupancy events, like arrivals or departures of occupants. We thus present in this section an alternative dynamic modelling approach to account for the real adaptive processes of occupants.

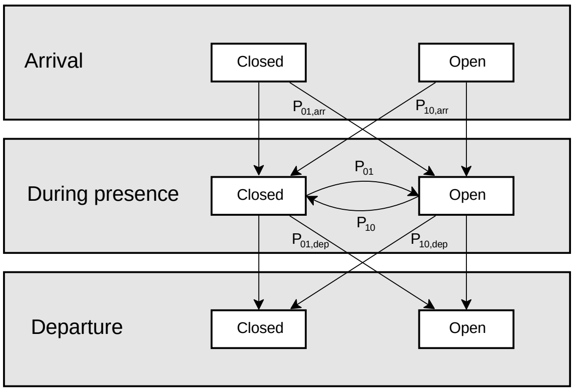

Figure 4 General scheme of the Markov process

Guided by the observation that occupancy events have an influence on actions, we may infer different transition probabilities P_{ij} for these events, so that we have three different sub-models for actions on arrival, at departure and during occupancy, as proposed by Yun and Steemers (2008) and Herkel et al. (2008). Simulation may then be conducted as presented in Figure 4: opening on arrival is predicted by a specific probability $P_{01,arr}$, and closing on arrival by $P_{10,arr}$. Actions after arrival are predicted by another sub-model launched at regular time steps, with transition probabilities $P_{01,int}$ if the window is closed at this time and $P_{10,int}$ if opened. When the occupant leaves his/her office, a third sub-model similarly predicts actions on departure, with transition probabilities $P_{01,dep}$ and $P_{10,dep}$. In each case, P_{00} and P_{11} are deduced: $P_{00} = 1\text{-}P_{01}$ and $P_{11} = 1\text{-}P_{10}$.

For each sub-model, we filter the data to retain observations related to the relevant occupancy status and perform logistic regressions on the most relevant environmental parameters; retaining the optimal set of variables in an adapted version of Equation (1), where we add the terms $b_{dm} \cdot \theta_{out,dm} + b_{GF} \cdot f_{GF} + b_{pres} \cdot T_{pres} + b_{abs,prev} \cdot f_{abs,prev} + b_{abs,next} \cdot f_{abs,next}$ (see nomenclature).

From our statistical analyses, we retain the following driving variables – in order of decreasing importance – for the six sub-models:

- Openings on arrival: $f_{abs,prev}$, θ_{in}, θ_{out}, f_R
- Closings on arrival: θ_{in}, θ_{out},
- Openings during presence: T_{pres}, θ_{in}, θ_{out}, f_R
- Closings during presence: θ_{out}, θ_{in}
- Openings at departure: $\theta_{out,dm}$, $f_{abs,next}$, f_{GF}
- Closings at departure: $f_{abs,next}$, $\theta_{out,dm}$, f_{GF}, θ_{in}

Concerning the sub-model for actions during occupancy, we see that θ_{in} is the main driving variable for $P_{01,int}$, while θ_{out} dominates for $P_{10,int}$. Thus, we see that θ_{in} is the real underlying stimulus for openings, while θ_{out} (linked to the feedback of the opening) determines primarily the probability of closing (eg. to prevent over- or underheating).

Goodness-of-fit criteria show that our sub-models do not offer equal performance. We obtain the highest predictive power for $P_{01,arr}$, followed by the sub-models for actions on departure and $P_{10,arr}$, and the lowest performance for actions during presence, with $P_{10,int}$ being the least satisfactory sub-model. This is in part due to the relatively small dataset relating to interactions during occupancy.

One final observation is that transition probabilities remain in all cases very close to zero, so that the efficiency of using a discrete-time random process is questionable, as consecutive repeated predictions of the same state are very likely to take place. An alternative would be to increase the time step but this would result in neglecting openings of short duration or artificially increasing the duration of other openings. A more appropriate method for intermediate actions is proposed in the next section.

Continuous-time random process

In this case we model the explicit duration of processes rather than transitions in them. Our analyses are based on the concepts developed in survival analysis. The reader is referred to Kleinbaum and Klein (2005) for an introduction to this subject.

With this approach, we infer a distribution for the duration for which people leave their window closed following their arrival and for which the window is left open. Kaplan-Meier estimates of survival curves are shown in Figure 5, in which each curve refers to an interval of observed initial values of θ_{in} or θ_{out}.

Window openings which were interrupted upon departure need special treatment. In this case, the reason for closing (or for leaving open) windows is not linked to discomfort. We thus classify such opening durations as censored data; which correspond to points on curves in Figure 5.

The decay rates are more clearly differentiated by domains of θ_{out}, which implies that opening durations are more strongly associated with this variable.

However, both variables are significant ($p<0.001$) according to the log-rank test.

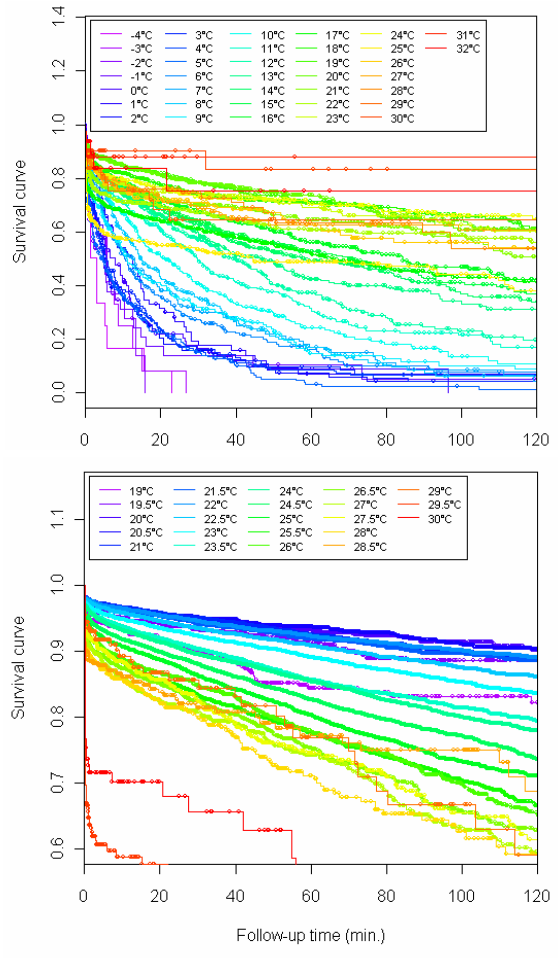

Figure 5 Kaplan-Meier estimators of survival functions of opening duration by domains of θ_{out} (top) and closing duration by domains of θ_{in} (bottom) duration, where points show censored data

Detailed analysis of the distribution of opening times shows that the hazard rate h(t) is clearly non-constant and decreases with t, meaning that closings have an increased risk to occur shortly after openings. Using a Weibull distribution we find that the best model with a single variable uses θ_{out} as its predictor ($p<0.001$, $R^2=0.102$). The variable θ_{in}, if included with this model, is not statistically significant ($p>0.1$), likewise other potential variables. These results are consistent with our sub-model for window closings during occupancy, where θ_{out} is the main driving variable in $P_{10,int}$. The explanation for this result is that our change in thermal sensation is directly influenced by the flow of air at θ_{out}.

The data of closing duration include two types of intervals: delay until opening following occupants' arrival, and delay until opening following a prior closing. We observed that θ_{out} has less influence than θ_{in} on closing duration and therefore on the decay of survival curves which differ less in the range of values of θ_{out}. Conversely, the survival curves vary clearly for different values of θ_{in} (in this case, θ_{in} is our principal thermal sensation stimulus). Furthermore, we can straightforwardly interpret the immediate decays along the ordinates in closing durations as opening probabilities on arrival, that increase strongly with θ_{in} as expected. Intermediate openings are then described by the rest of the curve, with higher proportional decays being observed for higher temperature.

As for openings, we once again use the Weibull distribution to describe closing durations. We include first θ_{in}, and notice that the addition of θ_{out} is significant ($p<0.001$, $R^2=0.033$).

The obtained Weibull distributions confirm that delayed opening of windows is mainly caused by indoor stimuli, while the main driving stimulus for window closings is external (the feedback of the opening).

Related issues

In addition to the above, we have also considered the following factors influencing window opening and closing behaviour:

- Integration of individual behaviours
- Treatment of group actions
- Use of several windows
- Treatment of opening angles

For this, we refer the reader to Haldi and Robinson (2009).

DISCUSSION

We observed that indoor conditions describe opening actions better than do outdoor conditions – this being our interaction stimulus. But closing actions tend to be better described by outdoor conditions, based on perceived draughts or a risk of overheating when $\theta_{out} > \theta_{in}$. Prevailing outdoor conditions also seem to better determine whether windows will be left open overnight for cooling purposes. Therefore if we consider the aggregate dataset it is understandable that for a univariate probability distribution θ_{out} is statistically stronger than θ_{in}, but this does not make it a better model. This is partly because the previously mentioned subtleties are ignored and partly because, as noted earlier, when using θ_{out} only the predicted window states are independent of the design of the building; so that occupants of very different adjacent buildings (eg. with minimal and high façade glazing ratio) would be predicted to interact with their windows with similar probability. For such hypothetical buildings θ_{out} may again be the best predictor for the (aggregate) logit distribution, but with drastically different parameters. Any distribution based on θ_{out} is thus strongly building-dependent and without generality, requiring separate calibration for each building to which it is applied – an impossible task.

The obtained transition probabilities for the discrete-time Markov process solve this problem, as they directly link the probability for an occupant to take action with the direct environmental stimuli (θ_{in}), whilst also accounting for the fact that θ_{out} has a determinant influence on intermediate closing probability (the sole situation where θ_{out} has a direct effect on the occupant). However, a possible lack of generality is that the closing probabilities, which depend on θ_{out}, are likely to depend on window size and opening angle, possibly needing further calibration according to these parameters. The same remarks apply to our continuous-time random process.

In summary then not only do the presented models improve the quality of predictions; they also account for the real stimuli motivating adaptive actions, so improving upon their generality.

VALIDATION

Methodology and results

In this paper we have presented models of occupants' interactions with windows based on three different methods. In order to retain the optimal model, it is necessary to perform a consistent evaluation of their predictive powers.

For this we check: (1) correct reproduction of the list of observed window states, (2) consistent predicted overall fraction of openings throughout the simulation period, (3) consistent predicted delays between actions and (4) coherent total number of predicted open windows.

In particular, we performed 20 repeated simulations using 5 minute time steps for the 14 measured offices, producing 20 x 14 = 280 sets of simulated window states W_{sim} (t), to be compared with 14 sets of observed states W_{obs} (t). This procedure was repeated for each of our models, and the above four indicators were computed and compiled in Table 2.

Table 2
True (TPR) and false (FPR) positive rates, accuracy (ACC), overall opening proportion (POP) and median error on number of windows open (MER)

MODEL	TPR	FPR	ACC	POP	MER
Exact	100%	0%	100%	30.2%	+0.00
Logit	43.0%	25.0%	65.1%	30.4%	+1.38
Markov	30.6%	17.9%	66.4%	21.8%	+0.71
Weibull	33.4%	22.1%	64.2%	25.5%	+2.29
Hybrid	31.4%	12.4%	70.3%	18.1%	+0.29
Random	30.2%	30.2%	58.6%	30.2%	+2.67

In addition to this, we also compare the results from these models with a random guess based on observed overall opening proportion and a hybrid model. This latter model is a modification of the discrete-time Markov process completed by the Weibull distribution for opening times.

The corresponding results indicate that this model reproduces well the temporal variation of window openings. See Figure 7 for the period 27 January 2005 to 14 January 2006, which offers representative climatic conditions and uninterrupted measurements.

From these validation results, we recommend the use of a hybridised model including a discrete-time Markov model for the prediction of openings and a Weibull distribution for their duration. Although this model somewhat underestimates the overall proportion of the year for which windows were open, we observed that it offers the highest accuracy, produces an optimal discrimination between window states, reproduces acceptably the delays between actions and offers the best aggregated predictions at the scale of a whole building. See Haldi and Robinson (2009) for a comprehensive presentation of model validation studies.

Integration into building simulation tools

All the models for the prediction of window openings presented here may be integrated in any dynamic simulation environment. We present in Figure 6 a general scheme for the implementation of our discrete-time Markov process hybridised with a Weibull distribution to predict opening durations. This algorithm assumes that occupancy and climate data are first predicted through a pre-processor for the simulation period. The model's output is window state $W_{sim}(t)$ for time steps of length $\delta t = (t_{i+1} - t_i)$.

CONCLUSION

Based on almost seven years of observations we have developed three different modelling methods for the prediction of actions on windows: a logit probability distribution, a discrete-time Markov process with sub-models for different occupancy statuses and extended this latter to a continuous-time random process. Supported by rigorous cross-validation, we have demonstrated the superiority of a discrete-time Markov process approach and its strong added value compared with existing models. We have furthermore inferred a continuous-time model that could be efficiently used for a fast calculation of opening and closing durations.

We have finally tested possible combinations in these approaches and selected a hybrid model. This hybrid combines the accuracy of the discrete-time Markov process with the efficiency of the continuous-time model for opening durations. For this we also describe a step-by-step process by which the algorithm may be implemented.

Although this is a more accurate model than the alternatives that have been published there remains a range of possible influencing factors that have yet to be taken into account in the prediction of window opening behaviour. In particular, our measurements did not allow us to treat window opening angles (which are crucial for precise predictions of air flows) and are limited to the south façade of a single office building. It would thus be desirable to make use of measurements from other buildings (residential in particular), in which opening angles are also recorded, to have a stronger basis for calibration. Such surveys might also usefully include other variables which may influence actions on windows, such as radiant temperature or indoor relative humidity (particularly for tropical climates). Factors related to indoor air quality (eg. CO_2 or pollutant concentration) should also be treated; however it is plausible that the inclusion of T_{pres} in our intermediate openings model ($P_{01,int}$) could implicitly account for this at least in part.

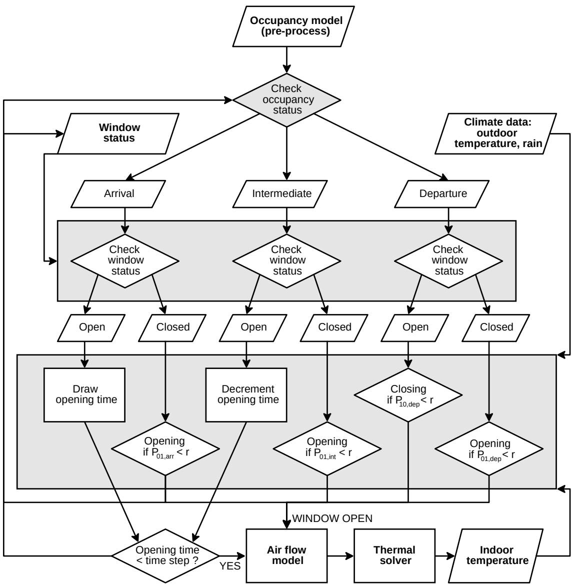

Figure 6 Implementation scheme of the window opening algorithm

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NOMENCLATURE

θ_{in}	Indoor temperature (°C)
θ_{out}	Outdoor temperature (°C)
$\theta_{out,dm}$	Daily mean outdoor temperature (°C)
v_{wind}	Wind speed (m/s)
f_{WS}	Wind speed level (four levels factor)
α_{wind}	Wind direction (°)
f_{WD}	Wind orientation domain (four levels factor)
ϕ_{out}	Outdoor relative humidity (%)
f_R	Rainfall (binary variable)
T_{pres}	Ongoing presence duration (min)
$f_{abs,prev}$	Preceding absence longer than 8 hours (binary)
$f_{abs,next}$	Following absence longer than 8 hours (binary)
f_{GF}	Window higher than ground floor (binary)

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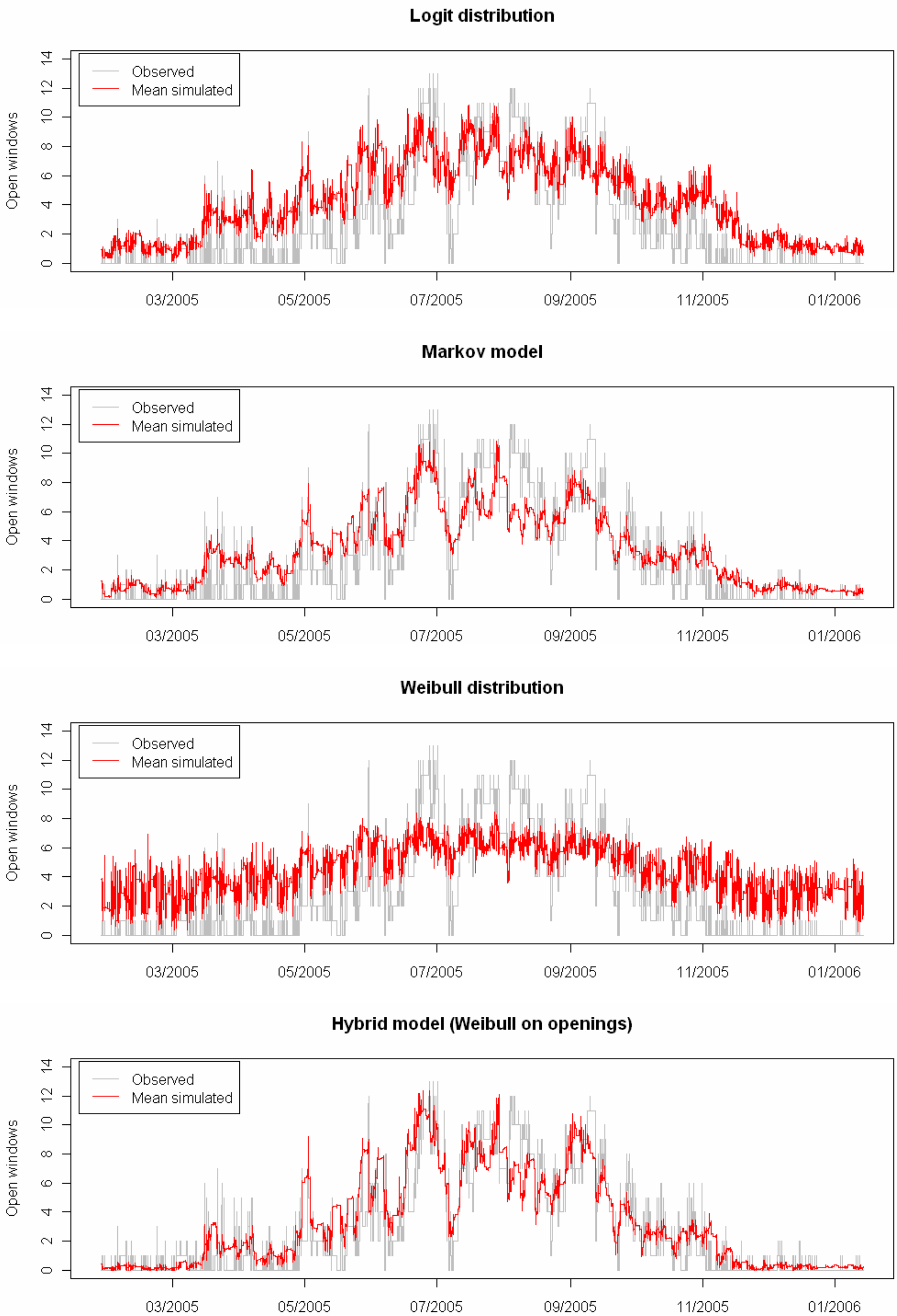

Figure 7 Observed and mean simulated number of windows open on a period of a year, using different models