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### Authors

Dutton, Spencer  
Zhang, Hui  
Zhai, Yongchao  
et al.

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## APPLICATION OF A STOCHASTIC WINDOW USE MODEL IN ENERGYPLUS

Spencer Dutton<sup>1</sup>, Hui Zhang<sup>3</sup>, Yongchao Zhai<sup>3</sup>, Ed Arens<sup>3</sup>,  
Youness Bennani Smires<sup>1</sup>, Sam Brunswick<sup>1</sup>, Kyle Konis<sup>2</sup> and Phil Haves<sup>1</sup>

<sup>1</sup>Lawrence Berkeley National Laboratory, Berkeley, California

<sup>2</sup>Portland State University, Portland, Oregon

<sup>3</sup>UC Berkeley, Center for the Built Environment, California

### ABSTRACT

Natural ventilation, used appropriately, has the potential to provide both significant HVAC energy savings, and improvements in occupant satisfaction.

Central to the development of natural ventilation models is the need to accurately represent the behavior of building occupants. The work covered in this paper describes a method of implementing a stochastic window model in EnergyPlus. Simulated window use data from three stochastic window opening models was then compared to measured window opening behavior, collected in a naturally-ventilated office in California. Recommendations regarding the selection of stochastic window use models, and their implementation in EnergyPlus, are presented.

### INTRODUCTION

The California commercial building sector uses a significant portion of the state's primary energy. Of the energy used on-site, 48% is used in heating, cooling and ventilating office buildings (CEUS). In order to meet California's commitment to reduce carbon emissions by 25% by 2020 and 80% by 2050 (AB32), a significant portion of the existing commercial building stock will need to be retrofitted to adopt low-carbon HVAC strategies. During the next 25 years, the potential energy savings from retrofitting existing buildings will greatly exceed the potential savings from optimizing new buildings for energy efficiency (Coffey 2009).

Natural ventilation offers the opportunity to provide energy savings and reductions in greenhouse gas emissions from commercial buildings in both California and the U.S. at large. Consequently, the California Energy Commission is supporting a multi-faceted research project that is intended to address barriers to broader adoption of natural ventilation in California. The principle goal of this project is to conduct a comprehensive study of these issues and provide the knowledge and new tools to the community that will allow owners, designers and policy makers to make

informed decisions on the pros and cons of natural ventilation for cooling and ventilation of commercial buildings in California.

Historically, a significant barrier to realizing these potential savings has been the perceived risk associated with applying unconventional HVAC strategies. Building stakeholders need assurance that natural ventilation will provide comfortable indoor air temperatures and maintain acceptable indoor air quality. Accurate building-simulation-based natural ventilation models can be used to ensure the efficacy of natural ventilation and deliver this assurance. The validity of these models is critical to limiting perceived risks and encouraging the broader adoption of natural ventilation. As a part of this broader research project we plan to assess and build upon the performance of current natural ventilation models.

The work covered in this paper describes a method of implementing stochastic window use models in EnergyPlus. Three variations of an established and previously validated window use model (Rijal 2008) were implemented. Model prediction results were compared to measured window use behavior of occupants in a naturally-ventilated office building in Alameda, California. Using lessons learned from observed behavior in this building case study and other published studies, we explore appropriate methods of implementing occupant behavior models in EnergyPlus. Stochastic window use models offer potential improvements over EnergyPlus's current deterministic window use models. These improved models will be used in future work to estimate the impact on building energy use and IAQ, of retrofitting existing California commercial buildings for natural ventilation.

### **Current stochastic occupant models**

The first window state probability model was derived from three independent surveys in the UK, Pakistan and Europe (Nicol 2001). Since then, a significant number of models describing window use have been developed. A report by Borgeson (2008) provides a summary of developments through 2008. It reports that the



references covered have both areas of general agreement and disagreement.

The key areas where current models generally agree are as follows. Firstly, human behavior is stochastic, not deterministic, but there are clear trends in the measured data. Models based on the probability of a window being used are therefore best suited to represent this behavior. Secondly, occupants tend not to interact with their windows often.

One area where the current models vary significantly is in their approach to implementing these stochastic models of window intervention behavior. Simple models predict whether or not a window is likely to be opened based on environmental conditions, while more complex models use Markov chains or survival analysis to incorporate time varying factors including the current state of the window in their models (Borgeson 2008).

There is currently no consensus as to whether outdoor or indoor temperatures are the dominant factor determining behavior. Recent work by Dutton (2010) goes part way to explaining this uncertainty by proposing that the dominant factor differs depending on whether the interventions are to open or close the windows. During the heating season, the outside temperature was shown to be the dominant factor influencing window closing interventions. By contrast, during periods where the building was free running (no heating), indoor temperatures had the most statistically significant impact on window closing interventions.

Significant differences are noted in the relative importance each author places on temporal aspects of window control, such as initial entry in to the building, as opposed to only considering occupant thermal comfort. Models developed by Haldi et al (2009) and Humphreys (Rijal 2008) are based on the idea that the principle driver of occupant window intervention is occupant discomfort. In contrast, work by Yun-Steemers (2007, 2008), Pfafferott & Herkel (2008) and Dutton (2010) observed that window opening primarily occurred immediately after entry into the room.

## **MODELING BEHAVIOR IN ENERGYPLUS**

Implementing user-defined models using the EnergyPlus building simulation tool is non-trivial. Several options are currently available. Firstly, EnergyPlus is open to collective open source development; users can obtain a copy of the Fortran-based EnergyPlus source code, and implement desired changes in their own development version. Alternatively, building system controls can be modeled in Modelica and then, using the Building Controls Virtual Test Bed, EnergyPlus can be linked with the Modelica development environment (Wetter 2009). This approach holds some significant advantages over

source code development, including rapid development and prototyping, and a free-to-use library of component models. A third option is to use a module within EnergyPlus, the Energy Management System (EMS). The EMS provides a script-based environment where users can simulate system control models. The EMS allows users to gain access to read and override a range of internal simulation variables, some of which are not ordinarily accessible to users. Users read variable values using “sensor” objects and write into “actuator” objects (EnergyPlus 2011). The EMS brings with it its own set of issues. Implementing simple control strategies in EMS can be time-consuming, requiring considerable duplication of script, and increasing occurrences of user error, which is exacerbated by the limited debugging capabilities of the module. The EMS however, is native to EnergyPlus, and allows complete user-defined control of window state based on simulation variables or schedules. For these two reasons, it was selected as the platform to implement our models of occupant window use.

However, as discussed, most recent models of window opening are probabilistic in nature, making them difficult to implement in EnergyPlus. EnergyPlus performs multiple warm-up simulations using design day environmental conditions repeated back to back, prior to performing simulation runs. EnergyPlus expects that by running the same conditions repeatedly, it will eventually reach a stable state. Since the outcome of these stochastic models is likely to change each time the warm-up day is simulated, the models are likely to diverge, resulting in a non-convergence error message in EnergyPlus. Although simulations can complete (i.e. the full annual simulation is performed), the potential impact of this error on EnergyPlus system auto-sizing routines is currently undetermined.

## **Implementation in EMS**

By considering the results of studies monitoring window use, three potential issues related to the application of window opening models in EnergyPlus have been identified. Firstly, a significant proportion of published window models generate a binary outcome where windows are either opened or closed (Borgeson 2008). There is some uncertainty as to whether these binary models are applicable in the case where windows can be opened by varying degrees, such as in our Alameda case study. Secondly, developers of large building models commonly do not implement each individual window in the model. A reduced set of larger windows is often used to represent the glazed portion of the building facade. An example of this is the DOE large office building reference model (NREL 2008). Finally, window-opening models typically do not consider the variable occupancy of open-plan spaces

(Rijal 2008). It is currently uncertain how to apply stochastic models of window use in open-plan spaces, where multiple occupants with varying schedules are impacted.

Methods of addressing these potential issues were explored using three differing implementations of a binary stochastic window opening model in EnergyPlus's EMS module. The original model was selected because it had been previously successfully implemented in building simulation and validated against measured data (Rijal 2008). The first implementation uses Rijal's (2008) model as published (we will call this RM1). A second alternative is proposed for use in simplified building models (we will call this one RM2), and the third (RM3) is identical to RM2, except that windows may be opened when occupants enter the room as long as the space is thermally comfortable.

### Window Opening Model

The RM1 model was implemented in four steps. Firstly, the daily running mean average outdoor temperatures ( $T_{rm}$ ) were calculated (based on the last 20 days), and used to calculate the adaptive comfort temperature ( $T_{comf}$ ).

$$\begin{aligned} \text{for } T_{rm} > 10^\circ\text{C} : T_{comf} &= 0.33T_{rm} + 18.8 \\ \text{for } T_{rm} \leq 10^\circ\text{C} : T_{comf} &= 0.09T_{rm} + 22.6 \end{aligned}$$

*Equation 1*

It should be noted that the result of the RM1 model is acutely sensitive to this adaptive comfort temperature. It is thus recommended that, if the user uses a weather file to calculate the adaptive comfort range, they should ensure that the file is representative of local weather conditions. In addition, a sensitivity analysis should ideally be performed so that a distribution, rather than point estimate of outcomes, can be provided. Then secondly, hourly measurement periods were categorized as either hot, cold or comfortable, determined by whether the indoor operative temperature is more than 2 degrees C above (hot) or below (cold) the comfort temperature. Thirdly, when occupants were either too hot or too cold, an assessment was made of the probability that the window either opened or closed using Equation 2.

The operative indoor temperature ( $T_{op}$ ) and the instantaneous outdoor temperature ( $T_{out}$ ) were obtained using EMS sensor objects and then used in Equation 2.

$$\begin{aligned} \text{logit}(p_w) &= 0.171 T_{op} + 0.166 T_{out} - 6.4 \\ \text{logit}(p_w) &= \log\left(\frac{p_w}{1-p_w}\right) \end{aligned} \quad \text{Equation 2}$$

Where  $p_w$  is the probability of the window opening (when occupants were "hot") and closing (when occupants are "cold").

Finally, whether a window was actually open or closed was determined by comparing  $p_w$  to a randomly-generated number between 0 and 1. If  $p_w$  was greater than the number, then the window was opened, and if  $p_w$  was less than the random number, then the window was closed. This was repeated for all 15 windows and 1 glazed patio door, rolling a new random number each time. Random numbers were obtained in the EMS module using the EMS internal function "@RandomUniform", which returns a uniformly distributed pseudo random number between defined bounds.

The key difference between RM1 and RM2 lies in this final assessment of whether the window is opened or closed. For model RM2, the following simplification was made. In RM1 each window is either fully open or completely closed based on the comparison between  $p_w$  and the outcome of a dice roll. By contrast, in RM2, the window open fraction for all windows in the room is adjusted in accordance with Equation 3. When occupants are either too "hot" or too "cold," the fraction of windows open is adjusted to account for interventions occurring each hour occupants remain uncomfortable. The value of  $p_w$ , and hence the new window open fraction ( $OF_{new}$ ), can be any value between 0 and 1.

If occupants are too hot:

$$OF_{new} = (1 - OF_{previous}) * p_w + OF_{previous}$$

If occupants are too cold:

$$OF_{new} = OF_{previous} * p_w \quad \text{Equation 3}$$

The rationale for this simplification follows: in the limit where the number of windows within each thermal zone is large, the proportion of windows subjected to a change in state (either opening or closing) can be approximated by  $p_w$ . This follows, because the value of  $p_w$  will be identical for each window in a thermal zone with a common operative temperature.

Thus, as the number of windows in the zone approaches infinity, the portion of opened windows as predicted by the RM2 model tends towards an outcome as predicted by RM1.

The RM3 implementation was identical to RM2, except that RM3 accounts for the possibility that occupants may open a window upon entering the office even if they are comfortable. This was implemented as Equation 4:

$$\text{(Upon initial entry only)} \quad OF_{new} = p_w \quad \text{Equation 4}$$

## MEASURED DATA COMPARISON

### Occupant Window Use Monitoring

Installation and collection of window state data was performed by our partners at the UC Berkeley Center for the Built Environment (CBE). The office used in this study occupies the second floor of a two-story building located on Alameda Island, California. The office space is nominally split into two large open-plan areas, with a total floor area of 2,640 ft.<sup>2</sup> The building does not have any mechanical ventilation system, and space heating is provided when necessary using small electrical resistance heaters. Twelve overhead fans with fully variable control are available for use by occupants. Fifteen sash windows located on all four sides of the office provide natural ventilation for fresh air and cooling. Figure 1 shows the locations and identifiers of the windows and the relative positions of the occupants' desks. Windows f1 through to f8 are located in the front office, while windows b1 to b7 are located in the rear. Occupants are free to open any of the functioning windows in the office. However, several of the windows are located above desks and are not easily accessible. The work schedules of the employees are such that people are often away from the office, meeting clients or working remotely.

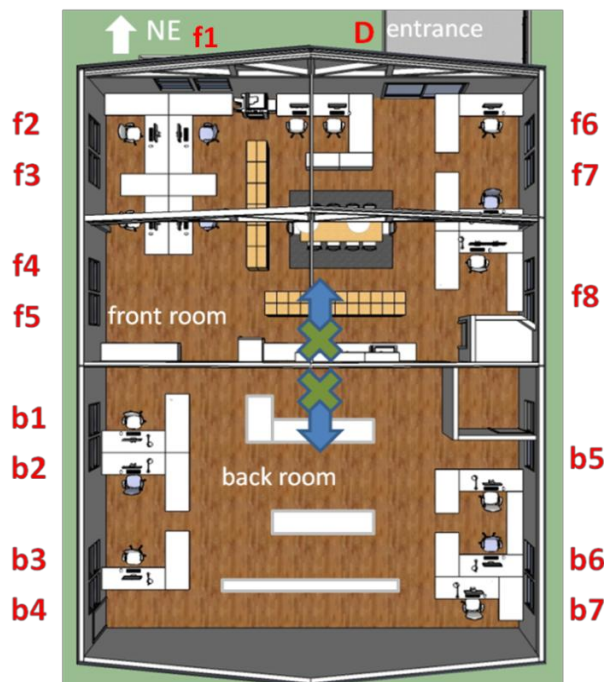


Figure 1 Office layout and camera locations

To measure window position, two digital cameras (Canon PowerShot A570) each with a wide-angle lens converter (Opteka HD 0.20X Professional Super AF fisheye lens, real angle of view = 174 deg.) were

installed on ceiling joists facing the two open-plan offices. Figure 1 shows the locations and directions of the two cameras. The camera's firmware was modified to allow the camera to be controlled automatically using scripting (Konis, 2011). This feature was used to automate the acquisition of JPEG images on regular (5-minute) intervals. Daily batches of JPEGs were then composited into movies and visually examined to determine window position. While it was possible to obtain estimates of the window state for the majority of observed periods, excessive glare caused by low solar altitudes compromised identification for certain periods. Figure 3 shows an example image where window state was mostly indeterminable, Figure 4 was taken during a period with significantly less glare and window states are easily discernable. Methods are now available to produce calibrated High Dynamic Range (HDR) images from bracketed sets of low dynamic range JPEG images (Inanici and Galvin 2004), making it possible to preserve a greater level of scene detail. The use of HDR images would have been useful in recovering the window open fraction and may be used in future studies.

### Measurement of Office Environment

Temperature and humidity were recorded throughout the study period at five-minute intervals using four HOBO loggers. HOBOs were positioned at a height of approximately 1.5 meters, adjacent to occupied desks, and evenly distributed around the office. A weather station was installed on a mast attached to the side of the building to collect outdoor temperature, humidity, wind speed and direction.

### Occupant Comfort and Behavior

Table 1 gives the fraction of occupied time that the given window was open, where occupied time is defined as 6 am to 6 pm, Monday through Friday. The results support observations that certain windows within the space are never used by the occupants.

Table 1 Fraction of occupied window open time

Month	Percent of occupied time open							
	F1	F2	F3	F4	F5	F6	F7	F8
September	19%	19%	29%	27%	0%	49%	31%	54%
October	10%	0%	3%	3%	0%	13%	3%	15%
November	0%	0%	0%	0%	0%	1%	0%	0%
December	1%	0%	0%	0%	0%	0%	0%	0%
	D	B1	B2	B3	B4	B5	B6	B7
September	71%	8%	0%	0%	0%	0%	9%	0%
October	34%	4%	0%	0%	0%	0%	26%	0%
November	16%	0%	0%	0%	0%	0%	3%	0%
December	4%	0%	0%	0%	0%	0%	0%	0%

This may be due in part to a difficulty reaching them, or because, a similarly located, but closer, window was found to provide sufficient ventilation cooling.

Figures 7 through 9 show the number of open windows for each hour for four periods from September through to December. On the same two plots are the coincident indoor temperatures and comfort temperature bands. Table 2 shows the adaptive comfort state of occupants during periods where window opening and closing interventions occurred. More specifically, the metric presented is the number of interventions that occurred when occupants were in a given comfort state, divided by the total number of those interventions.

Figures 7 through 9, and the analysis presented in Table 2 show that the majority of window interventions occurred when the adaptive comfort model predicted that occupants were thermally comfortable, consistent with the 'open when possible' view of behavior.

Table 2 Occupant comfort state during periods with window opening and closing interventions.

	Comfortable	Too hot	Too cold
Window Openings	72%	11%	17%
Window Closings	85%	3%	12%

### Model Comparisons

A comparison was made between measured window use and the outcomes predicted using first the RM1 model, and then the RM2 and RM3 simplifications. A simplified two-zone office model was created in EnergyPlus with 15 windows and one door. A short weather file was then generated that covered the period of study, using the measured outdoor temperature data collected from our station. Indoor environmental conditions in the space were controlled within a narrow range (0.2°C) to an hourly schedule based on measured indoor temperatures. Using the EMS module, the window opening state was then set based on the outcome of an implementation of our three models. The  $T_{out}$  used in Equation 2 was the instantaneous outdoor temperature taken from the bespoke Alameda weather file.

A comparison was then made between the daily average fraction of open windows ( $Fraction_{average}$ ) using the measured and modeled data. For the purpose of this comparison, windows that were never used by occupants were not included in the calculation of the proportion of open windows. Five of the fifteen windows were not used throughout the observed period, and so were assumed to be either inaccessible, inoperable, or superfluous. The daily average fraction of open windows was calculated for both measured and model results using Equation 5.

$$Fraction_{average} = \frac{\sum_{i=0}^{12} \text{Hourly window open fraction}}{\text{Hours in work day}}$$

Equation 5

Where the hourly window open fraction is the number of open windows in a given hour, divided by ten (the total number of used windows.) Figure 2 shows that the comparison between the hourly fraction of open windows over the study period, as measured and predicted by RM1, RM2 and RM3, gave *Pearson product-moment correlation coefficient squared* ( $R^2$ ) values of 0.54, 0.54, and 0.7 respectively.

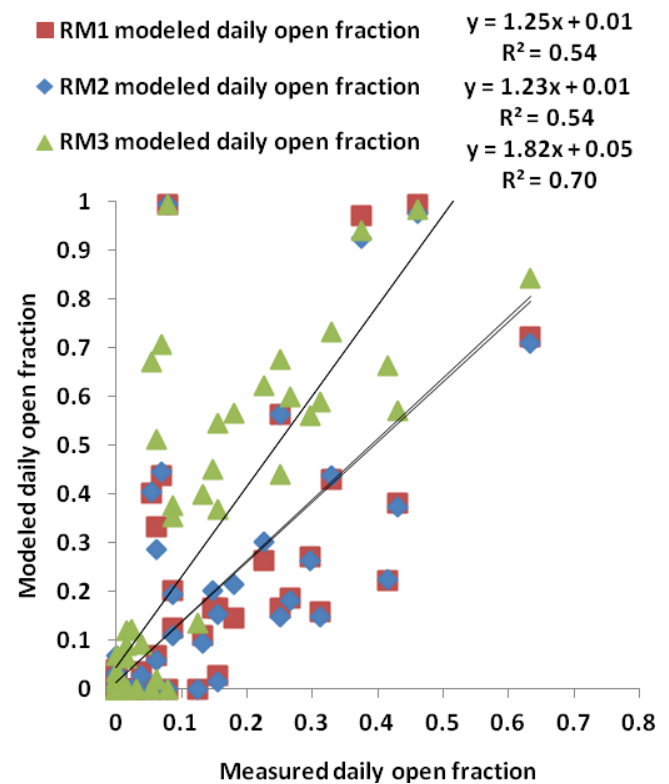


Figure 2 Daily window open fraction

Monthly averages of the daily average fraction of open windows were calculated including only occupied periods during the work week.

Table 3 Monthly average open fraction

Month	Measured	RM1	RM2	RM3
September	0.43	0.51	0.50	0.76
October	0.15	0.27	0.27	0.46
November	0.03	0.02	0.02	0.06
December	0.01	0.01	0.00	0.01

For the total measurement period, predictions of the daily average fraction of open windows given by RM1, RM2 and RM3 were on average 30%, 29% and 60% higher than measured results, respectively.





Results showed that the trend of reduced window use during colder months was well represented by all of the models. However, early morning openings by occupants who either desired fresh air or who anticipated a requirement for cooling later in the day, was found to be reproduced by only RM3. In addition, the models were not aware of specific windows that are rarely or never used, and so overstated the fraction of windows open during hot periods.

## CONCLUSION

The work presented in this paper presents the application of a stochastic window opening model in EnergyPlus. In the cases where multiple windows are known to exist within the thermal zone, two alternative deterministic simplifications of the model were also assessed. Reviews of prior studies of window use together with this case study reveal inherent problems in applying models of window usage. These problems would be confounded without supplemental information on how occupants actually use, or will use, their space.

It is not currently understood how applicable many of the currently published window use models are if applied to office configurations that differ significantly from the office configurations used to derive the models. One possible difference is the type of windows used, whether they are either fully open or fully closed (hopper type), or variable opening (casement or sash). Another potential difference is the office layout, private or open plan.

The window use model applied in this work used a binary indicator of occupant presence as per the original implementation (Rijal 2008). By contrast, in the Alameda case study, occupancy rarely exceeded 80% of full capacity, with a wide variation in arrival times. This disparity likely contributes to the observed differences between modeled and measured behavior. Further work would need to be done to establish whether scaling model predictions by the fraction of occupants present would improve predictions.

It is recommended that EnergyPlus users select occupant models that are derived from data collected under similar office configurations (private office, large open plan, etc.). When possible, engineers should survey occupant building use in an existing or similar building to help inform and guide the selection of occupant models in general.

In our sample case study, several windows were found to be completely unused throughout the measured period over a broad range of internal temperatures. Occupants were often shown to use their windows upon entry to the building, over a range of thermal comfort conditions. This behavior was confirmed by informal

questioning of the occupants. This observation again brings into question the predictive capacity of a window opening model that assumes occupants only intervene to change the state of their windows based solely on their adaptive comfort state. Comparing measured window opening data with modeled data confirmed that models RM1 and RM2 did not capture observed early morning opening, resulting in low  $R^2$  values. Comparisons between the truly stochastic RM1 model and its simplified deterministic derivative, RM2, demonstrated that, for this fifteen-window building model, the difference between the RM1 and RM2 models predicted outcomes were statistically insignificant.

The use of the simplified models presents several advantages. Firstly, because the models are repeatable, EnergyPlus is less likely to give non-convergence errors. Secondly, the effort required to model large numbers of individual windows in a single thermal zone can be significantly reduced, as multiple windows on each facade can be represented by a single window of equivalent effective area. The main focus of this current work was not the validation of a given stochastic model however, but rather to demonstrate the application of stochastic models in EnergyPlus and explore the potential hurdles related to their application.

Future work will assess different window use models from a range of authors. One of these models will be used to make estimates of the energy saving and indoor air quality implications of retrofitting California's commercial buildings to use natural ventilation.

## ACKNOWLEDGEMENTS

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## APPENDIX



*Figure 3 High glare example of "fish eye" image*



*Figure 4 Low glare example of "fish eye" image*



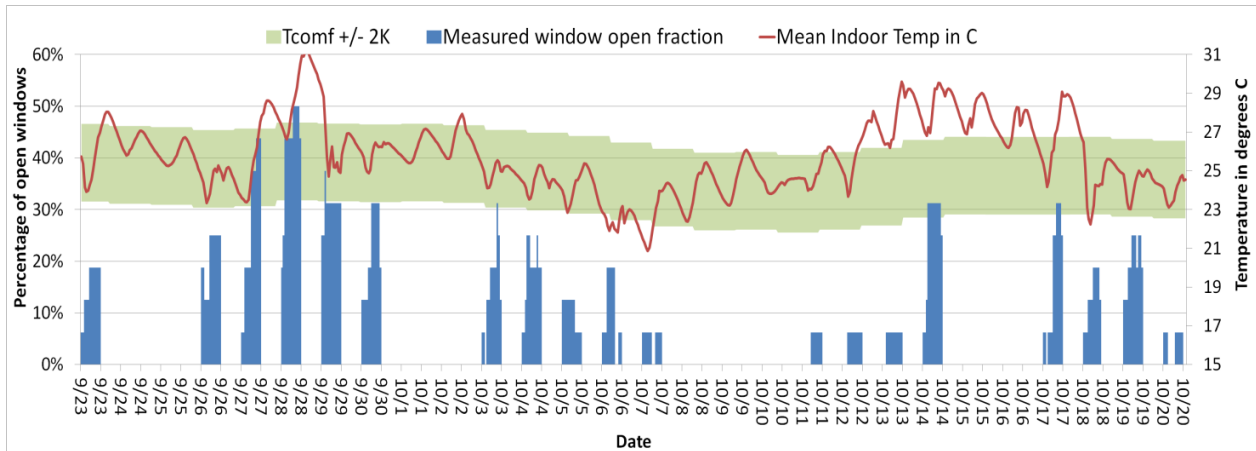


Figure 5 Number of open windows and indoor and comfort temperatures from September to October

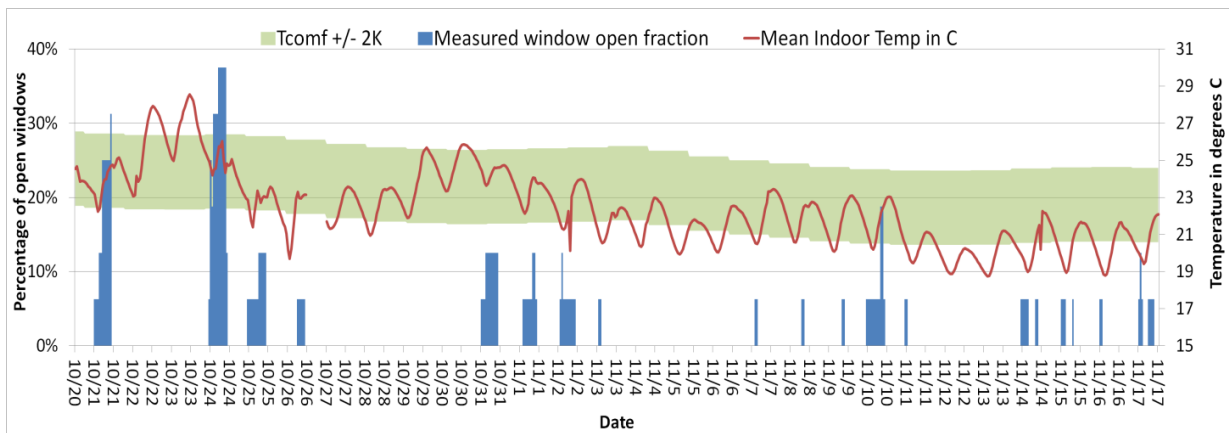


Figure 6 Number of open windows and indoor and comfort temperatures from October to November

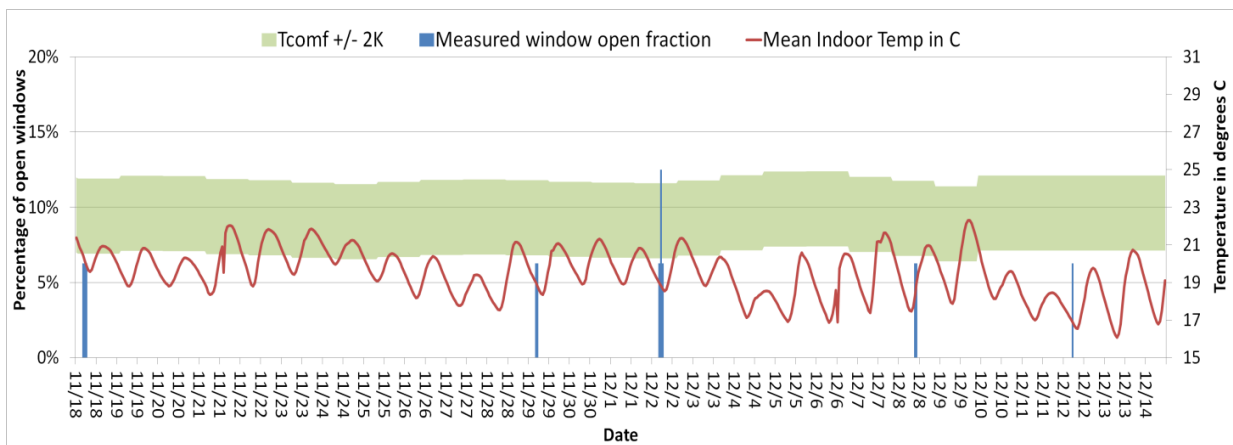


Figure 7 Number of open windows and indoor and comfort temperatures from November to December