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# A comparison of alternative occupant classification approaches for the modelling of window opening behaviour in office buildings

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## Abstract

In the past 20 years, better representation of occupants' window operation in building performance simulation has received great attention, and several useful window opening behaviour models have been developed. Beyond these, this paper describes the development of window opening behaviour models based on alternative occupant classification approaches, namely, modelling occupants' window operation actions as a whole; modelling actions based on sub-groups (i.e. gender, floor level, etc.); and modelling window actions of groups based on the observed propensity to operate windows (tendency to leave open, closed, etc.). The paper examines the benefits of more specifically modelling occupants' action versus modelling actions more generally, in terms of predication accuracy. A comparison between predictive performances reveals that modelling occupants' behaviour based on their observed personal preference helps improve the accuracy of the model predictions, when compared with traditional approaches, but requires a greater degree of knowledge about personal preferences of a building's occupants.

Key words: Building performance simulation, window opening behaviour, behaviour modelling, personal preference.

## 1. Introduction

Natural ventilation and mixed-mode ventilation are becoming common place when designing commercial buildings in the UK (CIBSE, 2004), aiming to save energy used to provide comfortable indoor thermal environments in summer. In these types of buildings, ventilation is directly related to the room occupants' operation of windows, unless the windows are controlled by mechanical systems. Therefore, the occupants of these buildings have a key role to play in the performance and energy efficiency of the building operation (Fabi et al., 2012). Due to this, better representation of building occupants' window operation in building simulation has gained much attention since 1990s (Roetzel et al., 2010).

The traditional way of predicting occupants' window opening behaviour in building performance simulation is by deterministic processes, either following a fixed schedule or using typical control rules (Borgeson and Brager, 2008). However, several studies have shown that the interaction of people with window operation is much more complex and should be better predicted by stochastic processes (Nicol and Humphreys, 2004). These studies have developed useful window opening behaviour models based on the observed behaviour of occupants in actual buildings, with regard to their operation of windows (Zhang and Barrett, 2012, Yun and Steemers, 2010, Haldi and Robinson, 2009, Haldi and Robinson, 2008, Yun et al., 2008, Herkel et al., 2008, Rijal et al., 2007). These models, however, have been based on either modelling the occupants of a building as a whole, or by modelling sub-groups of the whole population, for example, developing different window opening behaviour models for those occupants working on the ground floor and for those working on non-ground floors. However, these modelling approaches neglect the behavioural difference between individual occupants. Therefore, this study imports personal behavioural preference into the modelling of window opening behaviour and discusses whether a preference-based modelling approach has advantages over approaches based on whole-population or sub-group classification, in terms of accuracy, for the case of the end-of-day position of windows in non-air-conditioned office buildings.

The paper starts with an introduction of various occupant classification approaches used for modelling occupant window opening behaviour in office buildings. Then the methodology that has been used in the study is described, including data collection, model development, model validation and model comparison. Subsequent to this, the results of this study are expressed, followed by a discussion about the limitations of using the preference-based modelling approach in building performance simulation. Conclusions of this study are provided at the end of the paper.

## 2. Occupant classifications

Table 1 lists several factors that can influence occupant window operation in non-air-conditioned office buildings, based on an extensive review of literature (Wei, 2014).

Table 1. Factors having influence on window operation in non-air-conditioned office buildings.

| **Environmental factors** | **Non-environmental factors** | | |
|---|---|---|---|
| Outdoor climate (dominated by outdoor air temperature) | Season | Time of day | Previous window state |
| | Presence | Window type | Windows orientation |
| | Floor level | Shared offices | Building type |
| Indoor climate (dominated by indoor air temperature) | Room type | Heating system type | Occupant age |
| | Occupant gender | Personal preference | |

Generally, there are three ‘tiers’ of viewing the above factors as attention extends from the whole building population to the individual:

1. factors affecting the whole building population, including outdoor climate, indoor climate, season, time of day, previous window state and presence;

2. factors classified by occupant sub-groups, including window type, window orientation, floor level, shared offices, building type, room type, heating system type, occupant age and occupant gender; and,

3. personal preference.

The first tier defines the factors that are common to all building occupants, so the factors belonging to this level are named as ‘whole-population factors’. The second tier includes the factors that can further classify the building occupants into several sub-groups, beyond the influence from the whole-population factors. Therefore, these factors are named as ‘sub-group factors’. These factors are often related to the properties either of the building itself, for instance, floor level and window orientation, or of the occupants within the building, taking into consideration such factors as occupant gender and age. Consideration of sub-group factors reflects the fact that occupants’ window opening behaviour may well differ between sub-groups of the whole building population, mostly influenced by the design of the building or the characteristics of the building occupants. Personal preference can influence people’s behaviour, beyond the influence of other factors. This means that even when all other factors are identical, occupants may also perform different window operations. This paper aims to evaluate the advantages of modelling occupant window opening behaviour with a deeper consideration of the third-tier factors, comparing to more common approaches that are based on the first two tiers of factors.

## 3. Methodology

This section expresses the methods that have been used to achieve the aim of this study, including the data collection, model development, model validation and model comparison.

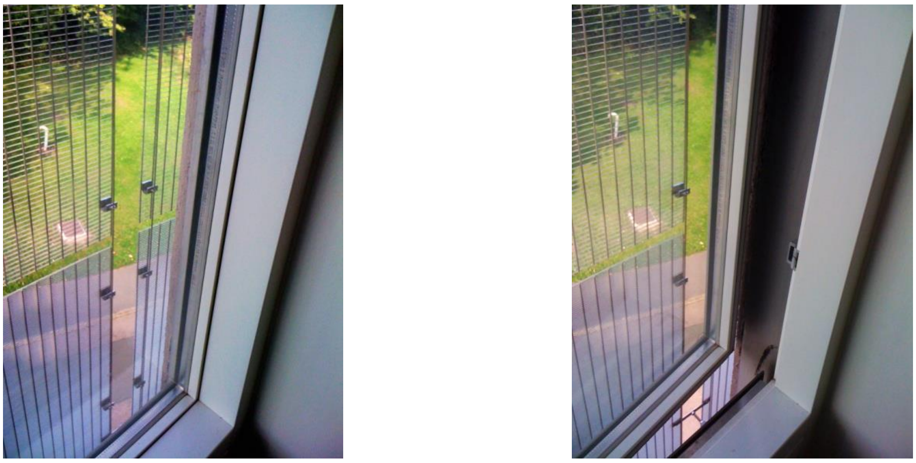
### 3.1 Data collection

The study was carried out in the building that houses the School of Civil and Building Engineering at Loughborough University, UK (52°45’54’’N, 1°14’15’’W, alt.70m). Figure 1 depicts the Southwest façade of the building and shows a typical office. The building is an ‘L’ shape with single-occupied cellular offices around the perimeter, all of which have nominally the same floor area (10.2m$^2$). Each window shown in Figure 1 belongs to an individual office. The office window in each monitored office can be set normally to one of two positions, either closed or open to a limited position (Figure 2). Although the outside of the building is curved, there are essentially only two façades, one facing Southwest and the other Northwest. The exterior of the building is covered by a mesh, which is designed to both shade the façade and provide a degree of security on the ground floor, allowing windows to be left open with reduced risk of theft. Each occupant in the building has sole control over the environmental conditions in his/her office and typical adaptive opportunities are: window and door positions, a window blind position and temperature control for a dedicated radiator (operative during the heating season).

To capture occupants’ window behaviour determining the end-of-day window positions, a longitudinal survey was carried out between 20 June and 30 September 2010 (72 working days in total). In the survey, the state of windows of 36 single-cell offices was monitored and these offices were located on two façades and three floors of the case study building. Indoor air temperature and outdoor air temperature were measured automatically every 10 minutes by sensors (Figure 3). Occupants’ daily presence (whether working in their offices on a particular day, which impacts upon the possibility of making decisions on the end-of-day window positions for that working day) was determined by three observations during the day time, i.e. 10:00am, 11:30am and 3:00pm. If occupancy was observed at any of these times, then occupant presence for that working day was recorded. The end-of-day window position (or window position on departure) of each office was noted by a further observation at 8:00pm when most occupants had vacated the building (on a typical day).

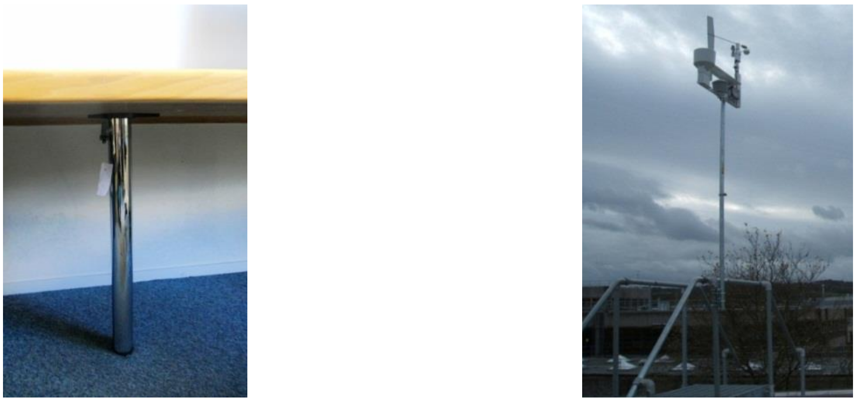
(a) Case study building (b) A typical single-cell office

Figure 1. The case study building (left) and a typical single-cell office (right).



a) Closed b) Open

Figure 2. Positions of the window in the monitored office.



(a) Hobo UA-001 temperature sensor (b) Delta-T WS-GP1 weather station

Figure 3. Automated measurement in the study.

### 3.2 Model development

In the study, logistic regression analysis (Hosmer and Lemesbow, 2000) was used as the basic statistical approach for the development of window opening behaviour models. A logistic regression model defines the probability of a specific event happening, such as opening a window, according to various influencing factors, which can be both numerical (e.g. temperature) and categorical (e.g. floor level). Equation 1 presents the basic form of a logistic model,

$$p = e^{A+B_1\times x_1+\cdots+B_k\times x_k}/(1+e^{A+B_1\times x_1+\cdots+B_k\times x_k}), \quad (1)$$

where $p$ is the estimated probability of a specific event happening; $A$ is a constant (intercept); $x_1$ to $x_k$ are model predictors and $B_1$ to $B_k$ are regression coefficients of each predictor.

In the later analysis, the *Nagelkerke $R^2$ statistic* from the logistic regression analysis is used to evaluate the goodness-of-fit of the developed model to the real measured data. It covers the full range from 0 to 1, just like the multiple correlation coefficient used in the classical regression analysis (Rao, 1973), and measures the proportion of variance 'explained' by the logistic regression model.

### 3.3 Model validation

Prior to being used for predicting window states, window opening behaviour models developed in this study should be validated to make sure that they have captured the underlying nature of occupants' behaviour on the end-of-day window position. To do this, a new set of data was collected from the same offices between 20 June and 18 September 2011 (63 working days in total). In the validation process, all models developed in the study were used separately to predict the monitored end-of-day window states in this new dataset, and their predictive performance on this dataset was compared with the one on the dataset that has been used to develop the models. If the model has consistent predictive performances for the two datasets, then it is judged as having captured the underlying nature of occupants' behaviour on the end-of-day window position, and hence can be used to predict the state of windows. In this study, the model's predictive performance was represented by a parameter named as the 'percentage of exact matched days', noting as a % of EMDs. It was calculated as the percentage of days with correctly predicted window states (both predicted window state and observed window state are open or both are closed) in the total number of prediction days.

The window state prediction was carried out by a stochastic process containing five steps:

**Step 1: Initialisation**

Set the initial end-of-day window position for the current prediction day: State = 0 (1: window open and 0: window closed)

**Step 2: Reading inputs**

Read essential inputs requested by the logistic behaviour model for the current prediction day

**Step 3: Probability calculation and random number generation**

i. Calculate the probability of windows being left open on departure by substituting the essential inputs obtained in Step 2 into the logistic behaviour model ($\mathrm{p_{open}}$)

ii. Generate a random number following $\mathrm{p_{random}} \sim \mathrm{U}[0,1]$ ($\mathrm{p_{random}}$)

**Step 4: Evaluation**

Determine the end-of-day window position based on the following criteria

a. IF $\mathrm{p_{random}} \leq \mathrm{p_{open}}$, THEN the end-of-day window position for the current prediction day is set as open

b. OTHERWISE, the end-of-day window position for the current prediction day is set as closed

**Step 5: Prediction forward**

Repeat Steps 1 to 4 for the next prediction day until it reaches the end of the prediction process

The above process has been used in previous studies to stochastically predict window states, by Rijal et al. (2007), Fritsch et al. (1990) and Yun and Steemers (2010).

### 3.4 Model comparison

The advantages of the preference-based modelling of window opening behaviour were investigated by comparing its predictive performance on the window state with those of the two models developed by more common occupant classification approaches, using the same dataset. The prediction of window states was achieved by the stochastic process described above. In the comparison, a higher % of EMDs value meant that the model can better reproduce the monitored end-of-day position of windows, hence the occupant classification approach used to develop the model can better capture occupant window opening behaviour in real buildings.

## 4. Results

In a paper published already (Wei et al., 2013), the authors have evaluated the influences of potential factors on the occupants' choice of the end-of-day window position in the case study building, using a systematic approach in an attempt to isolate dependencies. The factors investigated included season (summer or winter), change to daylight saving time (before or after), occupant absence in subsequent days (present or absent), window orientation (southwest or northwest), floor level (ground floor or non-ground floors), gender (males or females) and personal preference[1]('habitual closers', 'adjusters' or 'leave openers'). After this process the factors that demonstrate the great influence were outdoor temperature on departure, season, gender, floor level and personal preference. The data used in this paper was collected for the summer months only, so the influence of season was neglected. This paper has used the remaining influencing factors to model the monitored end-of-day

[1] Habitual closers are occupants who almost always close windows at the end of the day; Leave openers are people who leave windows open on departure for most working days; Adjusters are someone between Habitual closers and Leave openers, who seem to adjust the end-of-day window position depending on thermal conditions.

window position in the case study building, based on various occupant classification approaches, to explore the advantages of modelling occupant window opening behaviour based on observed personal preference versus modelling this action more generally. Figure 4 presents a hierarchy of building population classification with respect to occupant window opening behaviour on the end-of-day window position in the case study building.

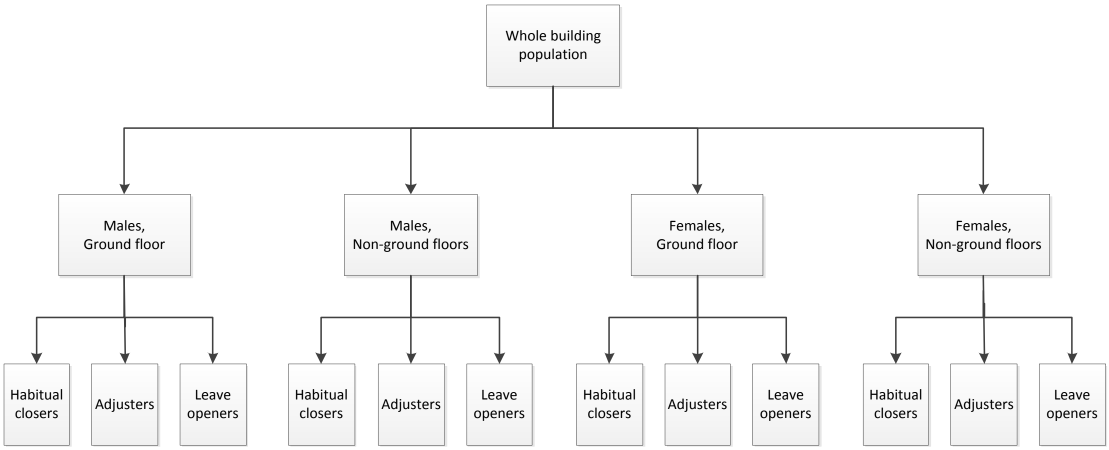



Figure 4. A hierarchy of building population classification with respect to window opening behaviour.

The development of window opening behaviour models was carried out in the IBM SPSS Statistics V19 (IBM, 2012), using the logistic regression analysis function. Based on the various occupant classification approaches introduced in Section 2, three logistic models were generated: a whole-population model (Equation 2), a sub-group model (Equation 3) and a (personal) preference model (Equation 4). The whole-population model only considers the influence of outdoor temperature on occupants' window operation so $T_{out}$ (outdoor air temperature on departure) is the only predictor in the model. The sub-group model imports the various behavioural responses of different sub-groups to the outdoor air temperature so factors *GENDER* (either males or females) and *GFLOOR* (either ground floor or non-ground floors) are added to the modelling. The preference model considers the occupants' personal preference of opening windows regarding to outdoor air temperature, so $T_{out}$ and *USER_TYPE* (either habitual closers, adjusters or leave openers) are used as predictors.

$$p_{whole-pop} = \frac{e^{-4.093+0.155\times T_{out}}}{1+e^{-4.093+0.155\times T_{out}}}, \tag{2}$$

$$p_{sub-group} = \frac{e^{-5.085+0.16\times T_{out}+1.49\times GENDER-1.35\times GFLOOR}}{1+e^{-5.085+0.16\times T_{out}+1.49\times GENDER-1.35\times GFLOOR}}, \tag{3}$$

$$p_{preference} = \frac{e^{-8.582+0.244\times T_{out}+3.632\times USER\_TYPE(1)+5.946\times USER\_TYPE(2)}}{1+e^{-8.582+0.244\times T_{out}+3.632\times USER\_TYPE(1)+5.946\times USER\_TYPE(2)}}, \tag{4}$$

where *USER_TYPE(1)* and *USER_TYPE(2)* are two dummy variables that are used to define the three types of window users with respect to the end-of-day window position (Habitual closers: *USER_TYPE(1)*=*USER_TYPE(2)*=0; Adjusters: *USER_TYPE(1)*=1 & *USER_TYPE(2)*=0; Leave openers: *USER_TYPE(1)*=0 & *USER_TYPE(2)*=1).

Table 2 lists the *Nagelkerke* $R^2$ *statistic* of the three logistic models. These values suggest that, from a statistical viewpoint, the sub-group model has a better fit to the actual data than the whole-population model, and the preference model has the best goodness-of-fit amongst the three models. Their predictive performances on the window state will be compared in the later part of the paper.

Table 2. Statistical properties of the logistic models.

| | Whole-population model | Sub-group model | Preference model |
|---|---|---|---|
| *Nagelkerke* $R^2$ *statistic* | 0.074 | 0.187 | 0.600 |

Figure 5 shows the validation results of the three models developed above. It shows that the three window opening behaviour models have consistent predictive performances on both datasets, hence they are considered to have captured the underlying nature of occupants' behaviour on the end-of-day window position.

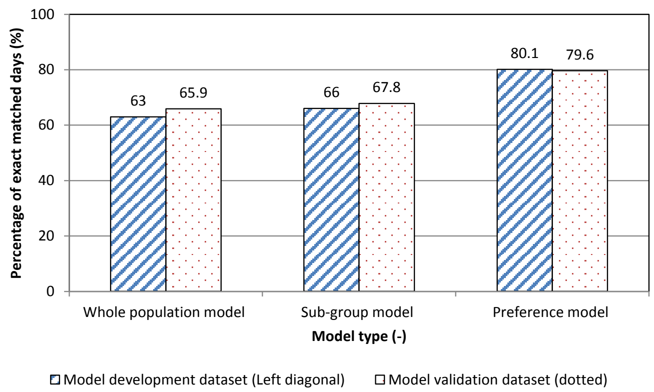



Figure 5. Validation of the three window opening behaviour models.

The main purpose of this paper is to evaluate whether modelling occupant window opening behaviour based on personal preference has advantages over approaches based on whole population or sub-groups, in terms of better-predicting window states. This is achieved by comparing the predictive performances of the three models on a single dataset, either the dataset used for developing the models or the new dataset collected for validating the models. The comparison results are shown in Figure 6, from which it can be seen that the preference model has a much better predictive performance, comparing to the whole-population model and the sub-group model, for both datasets. Meanwhile, the sub-group model has a slightly better predictive performance than the whole-population model.

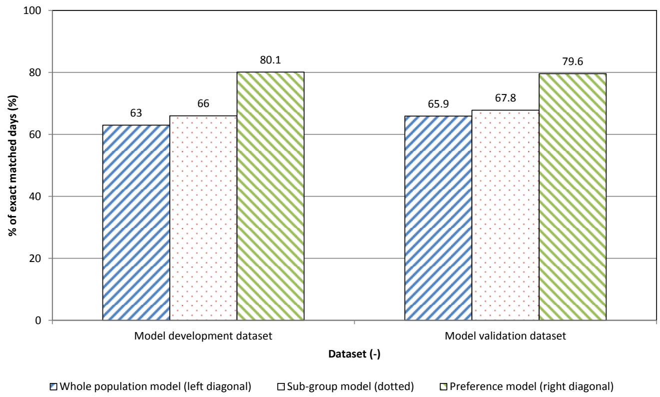



Figure 6. Model comparisons for the summertime.

## 5. Discussions

Occupants' window opening behaviour can be significantly different between individuals (Wei et al., 2013, Yun et al., 2009), and the preference-based approach of modelling window opening behaviour considers this difference. Modelling based on observed behavioural preference can improve model prediction accuracy. However, in practical simulation work, this observed characteristic of building occupants is not a known aspect of an individual, unlike the factors that are used in the other two approaches. Therefore, further explorations on how to assign personal preference in building performance simulation is still needed in future studies, especially for buildings with more than one office.

Another question is how to identify occupants' personal preference of window use in real buildings. Existing studies have used two methods, that is either based on real measured data (Yun et al., 2009, Haldi and Robinson, 2009) or based on occupants' self-statement (Rijal et al., 2007), and currently there is still no standard method that can be used to classify occupants based on personal preference. The three types of window users used in this study (habitual closers, adjusters and leave openers) were defined for occupants' behaviour determining the end-of-day window position in office buildings, and were based on a notion of mean outdoor air temperature and by threshold setting, using real measured data (Wei et al., 2013). It is suggested that the approach is repeated for other studies, so that the observed behaviours can be compared.

## Conclusions

This paper has investigated the advantages of modelling occupant window opening behaviour based on personal preference over more common approaches that are based on either the whole building population or sub-groups within the building. The data used for the model development was collected from a non-air-conditioned office building located in the East Midlands of the UK. Based on the data, three window opening behaviour models, referring to occupants' choice of the end-of-day window position, have been developed, using three different occupant classification approaches, namely: whole population approach, sub-group approach and preference-based approach. All models have been validated as having captured the underlying nature of occupants' behaviour on the end-of-day window position, and hence can be used to predict the end-of-day window position for building performance simulation. Comparisons between their predictive performances on the window state have demonstrated that the preference-based modelling of occupant window opening behaviour has a significant contribution to increasing the modelling accuracy, when compared with the other two approaches. However, as occupants' personal behavioural preference is generally not a known aspect of an individual when performing the simulation, the preference-based model requires a greater degree of knowledge about personal preferences of a building's occupants to implement.

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