PREFERENCE-BASED MODELLING AND PREDICTION OF OCCUPANTS' WINDOW BEHAVIOUR IN NON-AIR-CONDITIONED OFFICE BUILDINGS

by

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CERTIFICATE OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this thesis, that the original work is my own except as specified in acknowledgments or in footnotes, and that neither the thesis nor the original work contained therein has been submitted to this or any other institution for a degree.

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ABSTRACT

In naturally ventilated buildings, occupants play a key role in the performance and energy efficiency of the building operation, mainly through the opening and closing of windows. To include the effects of building occupants within building performance simulation, several useful models describing building occupants and their window opening/closing behaviour have been generated in the past 20 years. However, in these models, the occupants are classified based on the whole population or on sub-groups within a building, whilst the behavioural difference between individuals is commonly ignored. This research project addresses this latter issue by evaluating the importance of the modelling and prediction of occupants' window behaviour individually, rather than putting them into a larger population group.

The analysis is based on field-measured data collected from a case study building containing a number of single-occupied cellular offices. The study focuses on the final position of windows at the end of the working day. In the survey, 36 offices and their occupants were monitored, with respect to the occupants' presence and window use behaviour, in three main periods of a year: summer, winter and transitional.

From the behaviour analysis, several non-environmental factors, namely, season, floor level, gender and personal preference, are identified to have a statistically significant effect on the end-of-day window position in the building examined. Using these factors, occupants' window behaviour is modelled by three different classification methods of building occupants, namely, whole population, sub-groups and personal preference. The preference-based model is found to perform much better predictive ability on window state when compared with those developed based on whole population and sub-groups. When used in a realistic building simulation problem, the preference-based prediction of window behaviour can reflect well the different energy performance among individual rooms, caused by different window use patterns. This cannot be demonstrated by the other two models.

The findings from this research project will help both building designers and building managers to obtain a more accurate prediction of building performance and a better understanding of what is happening in actual buildings. Additionally, if the habits and behavioural preferences of occupants are well understood, this knowledge can be potentially used to increase the efficiency of building operation, by either relocating occupants within the building or by educating them to be more energy efficient.

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LIST OF ACRONYMS

BST – **B**ritish **S**ummer**t**ime

CO_2 – Carbon Dioxide

ESP-r – **E**nvironmental **S**ystem **P**erformance **r**esearch

GMT – **G**reenwich **M**ean **T**ime

IES VE – **I**ntegrated **E**nvironmental **S**olutions **V**irtual **E**nvironment

kWh – **k**ilo **W**att **h**our

MATLAB - **Mat**rix **Lab**oratory

MLE – **M**aximum **L**ikelihood **E**stimation

PMV – **P**redictive **M**ean **V**ote

SCATs – **S**mart **C**ontrols **a**nd **T**hermal Comfort

S.E. – **S**tandard **E**rror

% of EMDs – **% of E**xact **M**atched **D**ay**s**

NOMENCLATURE

Symbols	Description	Units
a	coefficient	$[-]$
A_{open}	flow area through the opening	$[m^2]$
A	intercept of a logistic regression model	$[-]$
b	constant	$[-]$
B	coefficient	$[-]$
B_1 to B_k	regression coefficients in a logistic regression model	$[-]$
c_l	cutpoint in logistic regression	[%]
c	constant	$[-]$
C_a	specific heat capacity of air	$[kJ/(kg \cdot K)]$
C_d	discharge coefficient of the opening	$[-]$
EL_{50}	median effective level	$[-]$
g	gravitational acceleration	$[m/s^2]$
h	total height of the opening	$[m]$
H_c	estimated daily cooling energy extracted by the night ventilation	$[kWh]$
H	height of an opening	$[m]$
I_c	total length of the crack	$[m]$
k_l	flow coefficient per unit length of the crack	$[L/(s \cdot m \cdot Pa^{-n})]$
m	mass transfer of air through the building by natural ventilation	$[kg/s]$
n	total number of observation days in the survey	$[-]$
n_c	number of correct predicted days;	$[-]$
n_w	total number of observation days for the winter period	$[-]$

Symbols	Description	Units
n_s	total number of observation days for the summer period	$[-]$
n_e	flow exponent	$[-]$
n_{tr}	total number of observation days for the transitional (swing) period	$[-]$
n'	total number of sample-days in the survey	$[-]$
n'_w	total number of sample-days for the winter period	$[-]$
n'_s	total number of sample-days for the summer period	$[-]$
n'_{tr}	total number of sample-days for the transitional (swing) period	$[-]$
n'_{open}	total number of sample-days where windows were left open on departure	$[-]$
n_t	total number of samples	$[-]$
n_i	number of interested samples	$[-]$
n_{in}	number of incorrect predicted days;	$[-]$
n_1	total number of output with value 1 in logistic regression	$[-]$
n_{LO}	number of Leave openers	$[-]$
n_A	number of Adjusters	$[-]$
n_{HC}	number of Habitual closers	$[-]$
p	air pressure	$[Pa]$
$\hat{p}$	estimated population proportion	[%]
p_{open}	probability of a window left open on departure	[%]
p_{random}	randomly generated number between 0 and 1	[%]
p_i	estimated probabilities defined by logistic regression model	[%]

Symbols	Description	Units
p_w	probability of window opening	[%]
Δp	pressure difference due to temperature difference across the opening	[Pa]
q_{vc}	volumetric flow rate through the crack	[L/s]
Q	air rate through the opening	[m^3/s]
R	specific air constant	[$-$]
R^2	Nagelkerke R^2 statistic	[$-$]
s	outcome state of each time step in a Bernoulli process	[$-$]
S_{ws}	window state	[$binary$]
t	time point	[$-$]
$time$	number of hours during the unoccupied night-time	[$-$]
dt	average temperature difference between indoors and outdoors over the night	[K]
dt_{max}	maximum temperature difference of indoors and outdoors during the night	[K]
dt_{min}	minimum temperature difference of indoors and outdoors during the night	[K]
T	Air temperature	[℃]
T_{op}	operative temperature	[℃]
T_c	indoor comfort temperature	[℃]
T_{ai}	indoor air temperature	[℃]
T_{in}	indoor air temperature on departure	[℃]
T_{ao}	outdoor air temperature	[℃]
T_{out}	outdoor air temperature on departure	[℃]
T_g	globe temperature	[℃]

Symbols	Description	Units
$\bar{T}$	mean temperature of indoors and outdoors	[℃]
$\bar{T}_{out}$	mean outdoor air temperature	[℃]
ΔT	temperature difference between indoors and outdoors	[℃]
v	relative air velocity	[m/s]
v_{max}	maximum air velocity	[m/s]
$\bar{v}$	mean air velocity	[m/s]
w	width of the opening	[m]
WD	temperature 'deadband' regarding to the window behaviour	[℃]
$Wald$	Wald statistic	[$-$]
x_1 to x_k	predictors in the logistic regression model	[$-$]
$\bar{x}$	mean value of the predictor in logistic regression analysis	[$-$]
X_t	Bernoulli variable	[$-$]
$\bar{y}$	proportion of samples with output=1 in the whole data in logistic regression analysis	[%]
z	height to a reference level	[m]
$z_{\alpha/2}$	coefficient for confidence interval calculation, corresponding to the confidence levels	[$-$]
ρ_o	density of air at $0°C$	[kg/m^3]
ρ_{in}	density of air indoors	[kg/m^3]
ρ_{out}	density of air outdoors	[kg/m^3]
$\Delta\rho$	density different of air indoors and outdoors	[kg/m^3]
$\emptyset$	proportion of windows left open on departure	[%]
θ_{50}	median effective level of outdoor air temperature	[℃]
θ	classification threshold	[%]

Symbols	Description	Units
ψ	proportion of window users	[%]
ψ^{LO}	proportion of Leave openers	[%]
ψ^{A}	proportion of Adjusters	[%]
ψ^{HC}	proportion of Habitual closers	[%]

1. INTRODUCTION

Over the past half century, global warming has become a principal issue in the world. The continuous increase of the average temperature near the earth's surface leads to a number of problems such as coral reef bleaching, flooding and increased rainfall. As one important component of greenhouse gas, carbon dioxide (CO_2) is the second largest contributor to the global warming (only after water vapour) (Kiehl and Trenberth, 1997). Substantial quantities of the gas are generated from various human activities, particularly the combustion of fossil fuels (USGCRP, 2009). In EU countries, buildings account for nearly 40% of final energy consumption, and 36% of greenhouse gas emissions (EC, 2013). Therefore, reduction in the energy consumed by buildings has the potential to make a significant impact on the current levels of society's energy consumption and greenhouse gas emissions.

In commercial buildings, heating, ventilation and air-conditioning account for about 43% of the total energy consumption and about 39% of the total carbon emissions (EIA, 2013). In the UK, natural ventilation is commonly used when designing commercial buildings (CIBSE, 2004), aiming to save energy that is used to provide comfortable indoor thermal environment in summer, by increasing the air change rate between indoors and outdoors (Wallace et al., 2002, Kvisgaard et al., 1985). In winter, however, the use of natural ventilation will increase the load on the heating system for heating the cold air from outdoors. The control of natural ventilation is more challenging than for mechanical systems since they rely on wind driven and buoyancy effects, which are intermittent in nature. Some buildings are designed with automated controls that control the movement of air under a range of conditions. Manually controlled windows are, however, by far the most common means of connecting the indoor and outdoor spaces. The performance of buildings, both in terms of cooling in hot summer months and for controlling heat loss in winter, is directly related to the operation of windows. Where these are controlled manually, the occupants of the building have a key role to play in the performance and energy efficiency of the building operation (Haldi and Robinson, 2008b, Rijal et al., 2007).

Understanding people and their interaction with buildings is a widely researched topic (Gunay et al., 2013), and window operation and comfort in buildings has received significant attention in the literature (Fabi et al., 2012b, Roetzel et al., 2010). A key aspiration in the field of the modelling and simulation of building performance is to be able to use simulation to better predict the performance characteristics of a building, such as energy, thermal, lighting and acoustic. Where the building has windows operated manually, effective models are essential that describe not only the effects of the open window on the ventilation in the space, but also the occupants' responses to stimuli that cause them to operate windows. In current building performance simulation, the prediction of window opening is generally based on deterministic processes, such as following a fixed schedule or using typical control rules (Borgeson and Brager, 2008). Over the past two decades, 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 behaviour models based on the observed behaviour of occupants in actual buildings, with regard to their operation of windows. These models 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 behaviour models for occupants working on the ground floor and working on non-ground floors.

The work presented here extends existing studies by investigating how people's window behaviour can be understood and modelled in greater detail. The work is inspired by Friedrich A. von Hayek, a famous Austrian and British economist and philosopher, who wrote,

> *"from the fact that people are very different it follows that, if we treat them equally, the result must be inequality in their actual position, and that the only way to place in an equal position would be to treat them differently"* (Hayek, 1960).

His words reflect the importance of considering the differences between people in the real life. In the field of planning, behavioural differences between individuals have been addressed by allocating them with different behavioural preferences (Son and

Pontelli, 2004). However, in current building performance simulation, these individual preferences are not considered, rather the individual is allocated to some larger groups who are all expected to behave in a similar manner. Building on this, the work presented here considers whether modelling occupants' behaviour in buildings, such as window behaviour, based on some notion of individuality, or preference, has benefit over the more common approaches that are based on groups or sub-groups of a whole building population.

Most existing studies focus on linking occupants' window operation within environmental factors, such as indoor or outdoor air temperatures. In this study, however, the focus is changed to evaluating the importance of non-environmental factors on occupants' window behaviour. There are three possible ways of viewing the non-environmental factors that can affect behaviour as attention extends from the whole building population to the individual:

- factors affecting the whole building population;
- factors classified by occupant sub-groups; and,
- personal preference.

The first defines the non-environmental factors that are common to all occupants within a building, such as time of day, room occupancy and season. In this thesis, the factors belonging to this level are named as 'whole-population factors'. The second classification 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 property of either the building itself, for instance, floor level, façade orientation, or the occupants within the building, taking into consideration of factors such as occupant gender and age. Consideration of the sub-group factors reflects the fact that occupants' window behaviour may well be different between sub-groups of the whole building population. Personal preference might be expected to influence people's behaviour, beyond the influence from other non-environmental factors, namely, whole-population factors and sub-group factors. This thesis presents an investigation to assess this.

To achieve this this work is based on a longitudinal study monitoring occupants' window use in a non-air-conditioned office building. The influence of non-environmental factors on the end-of-day window position is analysed, using a systematic approach. This is to minimise the influences of confounding factors on the factor being analysed. Then window behaviour models are developed using different occupant classification methods, namely, based on whole building population, based on sub-groups or based on personal preference. This window behaviour modelling is achieved by the logistic regression analysis, which is a popular statistical approach used in this research area. The three window behaviour models are then applied in a stochastic process to predict the observed end-of-day window position, based on which the models are validated and their predictive performances are compared. To demonstrate the impact of predicting window use by different occupant classification methods on the building performance prediction, a two-storey example building is developed and the three developed models are separately used to predict the end-of-day window position for a whole summer month. Then the energy performance of the building with respect to night cooling is predicted by a steady-state ventilation model using the predicted end-of-day window positions by the three models, and the prediction results are compared.

1.1 Research Aim and Objectives

The research aims to establish whether a preference-based approach to the modelling and prediction of occupants' window behaviour, in non-air-conditioned office buildings, has advantages over approaches based on whole-population or sub-group classification, in terms of more accurately predicting the end-of-day position of windows.

The research questions of this project include:

- Do non-environmental factors have a significant impact on occupants' choice of the end-of-day window position?

- Does personal preference play an important role on the end-of-day window position, beyond other influencing factors?

- Does modelling window behaviour based on personal preference have a better predictive performance of occupants' window behaviour than more conventional whole population and sub-group approaches? and,

- Does predicting window behaviour based on personal preference have an impact on the building energy simulation, when compared with prediction based on whole population or sub-groups?

The above research aim and research questions will be achieved and answered by the following objectives:

- Execute a thorough review of relevant literature with respect to factors affecting occupants' window behaviour in non-air-conditioned buildings, and the modelling and prediction of window behaviour for building performance simulation;

- Design a field experiment to collect data from a non-air-conditioned office building, to evaluate the influence of potential non-environmental factors on occupants' window operation, and to demonstrate the influence of personal preference on occupants' choice of the window position;

- Develop and validate two window behaviour models based on whole-population and sub-group classification approaches, from which to compare the performance of the new preference-based approach;

- Develop and validate a new window behaviour model based on personal preference, and compare its performance on predicting the state of windows with the models developed by the traditional modelling approaches; and,

- Develop a window state prediction approach, which implements the preference-based window behaviour model in a realistic building simulation application, and compare its simulation result with those by the whole-population and sub-group models, in terms of energy consumption.

1.2 Structure of the Thesis

Chapter 2 provides a thorough review of relevant literature with respect to factors that influence occupants' window operation in buildings, so as to identify the factors that need to be evaluated in this study, preventing influence of confounding factors in the analysis of window behaviour. The work then continues with a review of how occupants' window behaviour is typically modelled for use in building performance simulation. In Chapter 3, a longitudinal monitoring programme is described to observe occupants' use of windows in a case study building. This data focuses on the final position of the window at the end of the working day, and it provides the basis for the behaviour analysis in the thesis. Chapter 4 analyses the data in order to evaluate the influence of potential non-environmental factors on occupants' choice of the end-of-day window position, using a systematic approach to minimise influence of confounding factors that might otherwise cloud the findings. In addition, the characteristics of the monitored building are validated against other published work in this area.

In Chapter 5, two window behaviour models are developed using traditional modelling approaches that are identified in the review section, one based on whole building population and the other one based on sub-groups. In addition, their predictive performances on window behaviour are validated using a new dataset collected from the case study building, in the following year. In Chapter 6, a new model based on the findings from the analysis in Chapter 4 is developed, validated, and its predictive performance is compared with the two models developed in Chapter 5. In Chapter 7, these models are applied to a realistic building modelling/simulation problem in order to evaluate the potential impact of model selection on the analysis of night-time ventilation.

Finally, in Chapter 8 conclusions from this research project are drawn and further work is outlined.

2. LITERATURE REVIEW

In non-air-conditioned buildings, the windows are often under the control of the occupants. Therefore, identifying the characteristics of this is important in the field of building simulation, for more accurately predicting building energy consumption and performance. Understanding window use behaviour has been the focus of research for some years and this chapter provides a thorough review of the relevant literature.

Firstly, the potential factors that can influence occupants' window behaviour in buildings are reviewed, and this is then concluded with a discussion comparing the influencing factors identified for office buildings and residential buildings (Section 2.1). The existing modelling and prediction approaches that have been developed and used to model and predict occupants' window behaviour in office buildings are then reviewed (Section 2.2). The chapter concludes with a summary of some of the gaps in the current research area (Section 2.3).

2.1 Factors Influencing Window Behaviour

In non-air-conditioned buildings, opening and closing windows is one of the most important adaptive actions, enabling occupants to adjust their indoor environment (Rijal et al., 2007). Occupants' window behaviour has significant impact not only on the performance of buildings (Wallace et al., 2002), but also on the occupants' expectations of thermal comfort within the building (Brager and De Dear, 2004). Work has been carried out in both office and residential buildings and so both are reviewed here.

2.1.1 Office buildings

Influence of outdoor climate: Many studies have identified that outdoor climate has a significant influence on occupants' use of windows in a building, especially outdoor air temperature. Warren and Parkins (1984) carried out a longitudinal field measurement of window use in five British office buildings in the 1980s, and they found that the window state in office buildings was affected strongly by the outdoor air temperature, solar gain and wind speed (in order of decreasing importance). In their survey, the states of windows were recorded twice a day by the photographic method over a three-month period (26th February to 25th May).

The significant influence of outdoor air temperature on window use has also been identified by Nicol and Humphreys (2004), who carried out a series of studies on occupants' window behaviour in a wide range of countries in the world. Their first survey was conducted in five cities in five climatic regions in Pakistan (Nicol et al., 1999), and the survey result reflected that the opening of a window was highly correlated with outdoor air temperature. In this survey, the occupants' window operation was recorded in a transverse survey that was carried out between April 1995 and July 1996, by asking participants to fill out questionnaires during the day. Their second survey was carried out in two cities in the UK (Oxford and Aberdeen) between March 1996 and September 1997, and was introduced by Raja et al. (2001). This survey was conducted in 15 office buildings, containing both naturally-ventilated and air-conditioned buildings. In this survey, occupants' window operation was recorded manually by the participants in both a longitudinal and a transverse sub-surveys, and high correlations between occupants' window behaviour and outdoor air temperature were observed in both sub-surveys. Meanwhile, they also observed a high correlation between indoor air temperature and concurrent outdoor air temperature in the non-air-conditioned buildings investigated. The third survey that was carried out by Nicol and Humphreys was in a European project, named SCATs (**S**mart **C**ontrols **a**nd **T**hermal Comfort). This survey was performed in 25 buildings in five different European countries, namely, the UK, France, Sweden, Greece and Portugal, as introduced by McCartney and Nicol (2002). In this study, 11 buildings were naturally ventilated, and the occupants in these buildings were also asked to manually record their window operation during the survey period. The collected data also reflected a high correlation between occupants' window use and outdoor air temperature, the same as that had been observed in the first two surveys.

Zhang and Barrett (2012) monitored one naturally ventilated office building located in Sheffield, UK, over a period of 16 months (from January 2005 to April 2006). In this study, the same methodology used by Warren and Parkins (1984) and Raja et al. (2001) was adopted. It was found that outdoor air temperature had the strongest correlation with the proportion of open windows, compared with other outdoor stimuli, such as wind speed, rainfall, sunshine hours, solar radiation and relative humidity. In addition, the effect of indoor air temperature was found to be insignificant in the winter period, as users "*will not open window even it is hot inside when the outdoor temp. is low*" (Zhang and Barrett, 2012).

In Germany, Herkel et al. (2008) performed a longitudinal field study from July 2002 to July 2003, monitoring occupants' use of different types of windows in 21 south-facing offices, using particular measurement devices. Again, outdoor air temperature was found to have the highest correlation with the state of office windows, when compared with other factors such as indoor air temperature.

In Switzerland, Fritsch et al. (1990) carried out an analysis of occupants' window operation in one office building located in the Swiss Federal Institute of Technology in Lausanne, aimed at predicting the airflow rate in buildings. The field data was collected over two heating seasons in the early 1980s. In the survey, the opening angles of windows in 4 south-facing offices were recorded every half an hour with concurrent measurements of environmental factors, such as indoor air temperature, outdoor air temperature, wind speed and south vertical solar radiation. In this survey, the outdoor air temperature was also found to be the most effective in influencing occupants' operation of windows. Additionally, they suggested that in the heating season this behaviour was weakly influenced by the wind speed and the south vertical solar radiation.

Following the above study performed by Fritsch et al., Haldi and Robinson (2009b) carried out a window behaviour study in the same experimental building between 2001 and 2008. In this study, 14 south-facing cellular offices were monitored automatically over a period of seven years, with respect to their occupants' behaviour indoors, namely, the use of windows, blinds, doors and lighting. The monitored offices were located on three floors of the experimental building. Some of them were single occupancy, whilst others were double. Other parameters, such as indoor air temperature, occupancy and outdoor environmental data, were also measured concurrently. In this survey, the significant influence of outdoor air temperature on window operation was identified, as in the studies introduced above. Additionally, rainfall was found to influence the state of windows, although the influence was not as significant as the outdoor air temperature.

Influence of indoor climate: Warren and Parkins (1984) have suggested that there are two modes of window use: one mode is to "*maintain adequate indoor air quality*" and the other is to "*control indoor air temperature*". Therefore, the influence of indoor climate, such as indoor air temperature, humidity, CO_2 concentration, on occupants' window behaviour has also been evaluated in several studies, and indoor air temperature was found to be the dominant influencing factor indoors, especially in the summertime.

In many window behaviour surveys, indoor and outdoor air temperatures were monitored and analysed concurrently. Therefore, in some surveys expressed above, the influence of indoor air temperature on occupants' window behaviour has been confirmed, such as those carried by Nicol et al. (1999), Raja et al. (2001), McCartney and Nicol (2002) and Haldi and Robinson (2009b).

Yun and Steemers (2008) also carried out a longitudinal study monitoring occupants' window behaviour in office buildings in the summer periods of 2006 and 2007, in Cambridge, UK. In this study, indoor air temperature was used solely to predict the operation of windows rather than outdoor air temperature, as "*indoor air temperature varies with a range of factors, such as window orientation, the design of an envelope, the thermal mass of the building structure, internal heat gains, etc.*", and these variations could not be explained when outdoor stimuli were used. Based on a statistical analysis of their monitored data, they identified a high correlation between occupants' window behaviour and indoor air temperature. Their survey was carried out in 6 offices with different orientation and type of windows, number of occupants and night ventilation strategy. In the survey, indoor air temperature, outdoor air temperature and the state of windows were measured and recorded automatically by particular measurement devices. The occupancy of the monitored offices during the survey period was deduced by assuming the occupants remained in their offices during working hours, according to a one-week observation.

Besides the above introduced field study, Yun and Steemers (2010) undertook a concurrent survey in the same city, analysing occupants' window behaviour in night-time naturally-ventilated offices. During this survey, the use of windows from three offices was monitored by state data loggers. Indoor air temperature, outdoor air temperature and the state of office doors were also measured and recorded by particular measurement devices. This time, the occupancy of these offices was deduced by the first door opening (regarded as the first arrival of the day) and the last door closing (regarded as the last departure of the day) for all working days. From this survey, they also found that indoor air temperature could be used as a good predictor of occupants' window behaviour in office buildings.

Yun did another study on occupants' window behaviour in Korea from February 2010 to January 2011, and the result of this study was expressed by Yun et al. (2012). In this study, four offices with a varying number of occupants, from three to seven, were monitored. Various measurement devices were used to measure and record parameters, such as indoor air temperature, indoor humidity, indoor carbon dioxide (CO_2), outdoor air temperature, outdoor humidity, the state of doors and the state of windows. From the study statistical relationships between occupants' use of windows and indoor environmental parameters, namely, indoor air temperature, indoor humidity and indoor CO_2 concentrations, were established.

In the summer of 2006 (13th June to 27th September), Haldi and Robinson (2008b) carried out another window behaviour survey in 8 office buildings in Switzerland. In this survey, 60 participants were recruited and were asked to manually record their window operation up to a maximum of 4 times a day during the working hours, by filling out electronic questionnaires. During the survey period, indoor air temperature was measured closely to participants' workstations, and the outdoor climatic data was obtained from a local weather station. From the survey a high correlation was identified between occupants' window behaviour and indoor air temperature.

Influence of non-environmental factors: Besides the above environmental factors, non-environmental factors further influence occupants' window behaviour in office buildings. These include season, time of day, occupant presence, previous state of windows, type of windows, orientation of windows, floor level and shared offices.

Season has been found in many studies to be an important influencing factor on window behaviour. Herkel et al. (2008) suggested that occupants' window behaviour *"on a cold summer day differs from a warm winter day",* based on their survey carried out in the Germany. Additionally, they defined that the change from summer behaviour to winter behaviour occurred on the date when the daily mean outdoor air temperature dropped below 10.0°C for the first time, and the change from winter behaviour to summer behaviour was the first day when the daily mean outdoor air temperature exceeded 15.0°C. Similar conclusions were also obtained from studies performed by other researchers, such as Yun et al. (2012), Zhang and Barrett (2012) and Wallace et al. (2002).

The time of day has been shown to affect window operation. The observed behaviour between arrival, intermediate and departure periods of the day is different significantly (Yun et al., 2012, Yun and Steemers, 2010, Haldi and Robinson, 2009b, Yun et al., 2008, Herkel et al., 2008, Warren and Parkins, 1984). These studies show that for a normal working day more window opening actions will be done by the building occupants when they firstly arrive at their offices, whilst more window closing actions will be done when they finally leave the offices. This is linked directly with the presence of an occupant, as described by Haldi and Robinson (2009a) and Herkel et al. (2005).

Window position and action is state dependent and consequently the previous state of windows also plays an important role on window behaviour. Generally, once a window has been opened, occupants tend to prefer to leave it at that state for some time, until discomfort is reached (Rijal et al., 2007). Additionally, the factors driving occupants to open or close windows could be different as well, as suggested by Haldi and Robinson (2009b). The influence from the previous state of windows on occupants' window behaviour has been confirmed by many researchers, such as

Yun et al. (2012), Haldi and Robinson (2009b), Yun and Steemers (2010), Yun et al. (2008), Herkel et al. (2008), Rijal et al. (2007) and Fritsch et al. (1990).

In the study carried out by Herkel et al. (2008), it was also found that small openings were opened less frequently, compared with large openings. If opened, however, it remained open for a longer period of time. This reflects that window behaviour may also be dependent on the type of windows.

In their seven-year survey of window behaviour, Haldi and Robinson (2009b) identified that floor level had an influence on occupants' behaviour on departure. They observed that occupants working on the ground floor preferred to close more windows when finally leaving their offices on working days, compared with those working on upper floors.

The orientation of windows was suggested to have an influence on window operation in non-air-conditioned office buildings, by Zhang and Barrett (2012), and this may be because of solar radiation and the prevailing wind direction.

Cohen et al. suggested that manual controls, such as for windows, blinds and lights, in open-plan offices tended to "*lapse into default states that minimize conflict and inconvenience but are not optimal*", and this was referenced in the paper written by Fabi et al. (2012b). However, a totally different conclusion was proposed by Haldi and Robinson (2009b), as they found that "*no obvious difference in behaviour related to total opening duration is distinguishable between offices with one or two occupants*". One possible explanation for the conflicting conclusions from these two studies could be that in the survey carried out by Haldi and Robinson, each occupant had a private window to control, so the sense of sharing offices may had been reduced.

Variability between individuals: Some researchers have demonstrated that occupants' window behaviour differed between individuals, such as Haldi and Robinson (2009b), Yun et al. (2009) and Rijal et al. (2007). In their studies some occupants used windows very actively, whilst some did very passively. To reflect this difference occupants have been classified into either two levels (active and passive users) or three levels (active, medium and passive users). Haldi and Robinson (2009b) have considered it as 'Variability between occupants', but there are still no factors that have been defined to explain this variability. While it is clear that many factors influence observed behaviour, a possible criticism of these studies was that the grouping of the data did not account for possible variations due to other classifications, such as occupant age and gender. Hence it is not clear from these studies the extent to which they are just describing a variation in the data, or whether they have eliminated all other conceivable effects. An observation of a sample of 'the same type' of people is needed, into which differences in observations can be more confidently attributed to differences in behaviour between individuals.

2.1.2 Residential buildings

Although the target type of buildings for this study is office buildings, window behaviour in residential buildings is also reviewed, for two reasons:

- To further evaluate the conclusions for office buildings. For example, if an influencing factor discussed in the previous section for office buildings is also confirmed to be an influencing factor for residential buildings, it strengthens confidence in those findings; and,

- To identify any missing factors in studies of window behaviour in office buildings. For example, if a factor is confirmed to be influential in residential buildings but has not yet been evaluated for office buildings, this factor needs to be considered suitably in this study.

Influence of outdoor climate: As in office buildings, outdoor climate, especially outdoor air temperature, also influences occupants' window behaviour in residential buildings, and many previous studies have confirmed this influence. In 1951, Dick and Thomas (1951) reported that 70% of the observed variance of open vents and casements could be accounted for by the outdoor air temperature, based on field measurements carried out in 15 houses during 26 winter weeks. Additionally, they suggested that another 10% of the observed variance was contributed by the wind speed. In their study, the wind speed and direction, the inside and outside air temperatures were measured and recorded automatically using particular devices, and the state of windows was recorded manually.

The IEA Annex VIII project (Dubrul, 1988) includes a series of field studies that were carried out in five different countries: Belgium, Germany, Switzerland, the Netherlands and the United Kingdom. In these studies several measurement techniques were applied to capture occupants' window behaviour in residential buildings, including: questionnaires, interviews, direct measurements, use of independent observers, photography, micro-switches and the use of diaries/log books. Generally, a linear correlation between window opening and outdoor air temperature was observed when the outdoor air temperature was between -10°C to +25°C. In the study carried out in Duisburg, Germany, an inverse linear correlation between window opening and wind speed was observed and the correlation appeared to be independent of the type of the room. Additionally, when the wind speed was over 8m/s, almost all windows were found to be closed. In the investigations undertaken in Belgium and the Netherlands, it was found that windows were opened more often and for a longer period of time when it was sunny outdoors, reflecting the influence from solar radiation on occupants' use of windows. In these studies the level of precipitation was also observed to be a significant variable for window opening, especially for the bedroom and the living room.

Brundrett (1977) carried out a survey in a number of houses in two estates to better understand the window-opening behaviour of families in residential buildings. In the survey the outdoor weather data was recorded by a weather station, six miles away from the survey site, and the state of windows was recorded every weekday over a period of a year (from October 1974 to September 1975). From the study it was found that the mean daily outdoor air temperature was the main factor affecting occupants' window behaviour, especially in the summertime. In addition, other factors also contributed to this behaviour, such as daily outdoor air temperature swing, outdoor humidity, wind speed and solar radiation.

Erhorn (1986) carried out a study on occupants' window behaviour in a demonstration building that was raised in 1983. The building was a row-house and it was composed of 3 blocks. In the study 24 apartments were monitored from the beginning to the end of 1984, and occupants' window operation was monitored by contact sensors and recorded by central data loggers every 30 minutes. Additionally, relevant outdoor weather data (outdoor air temperature, wind speed, global irradiation) and indoor parameters (indoor air temperature, indoor humidity and energy consumptions for heating and appliances) were measured and recorded concurrently by particular devices. Based on the monitored data Erhorn established a correlation between the window opening time and outdoor air temperature. Besides this, he defined 12°C as the outdoor air temperature, at which occupants would change their ventilation behaviour for particular rooms in the house, namely, living rooms and children's rooms. Furthermore, the window opening time was also shown to have a linear correlation with wind speed. To simplify the model, Erhorn introduced a temperature-based correction term to overcome the influence of wind speed, and the term is based on an average wind speed of 3m/s. In this study, the influence of global irradiation was found to be relatively weak when compared with the influence of outdoor air temperature.

Weihl and Gladhart (1990) reported some results from a project named the Family Energy Project, which was carried out in the USA between 1983 and 1987. In this project microprocessor technologies were applied to monitor occupants' thermostat settings of heating, ventilation and hot water automatically, and also to measure and record indoor and outdoor air temperatures and the energy consumption of the furnace and the water heater. In the first phase of this project, which was conducted between 1983 and 1985, seven houses with varying properties, such as house size, family size, occupant age and family income, were monitored. In the second phase, which started in 1986 and ended in 1987, ten houses with low-income occupants were observed. From this project, it was found that outdoor air temperature had a significant influence on both window and door uses in residential buildings in summer.

Johnson and Long (2005) undertook a pilot study monitoring occupants' opening and closing windows in residential buildings in North Carolina, USA, between March 2003 and October 2011. In the study the state of windows was recorded by the experimenters through observations, while other parameters such as outdoor air temperature, outdoor relative humidity, wind direction, wind speed, cloud cover and precipitation were measured by particular devices. From this study, they suggested that outdoor air temperature, outdoor relative humidity, wind speed and cloud cover could significantly influence the state of windows. The precipitation, however, was found to have no influence on occupants' window behaviour in residential buildings.

Nakaya et al. (2008) reported some data collected from 31 detached houses in Takarazuka City and 31 apartments in Takatsuki City, in Japan. The survey was carried out over a two-month period from August to September, in 2003. In the survey thermal measurements and questionnaires were conducted in each individual house by the experimenters. Through statistical analysis, correlations between occupants' window behaviour and outdoor air temperature were established for the houses observed in both cities.

In Denmark, Andersen et al. (2009) carried out questionnaire surveys in 4948 Danish residential buildings in the late summer of 2006, and again in the winter of 2007. These were conducted in order to identify the most important factors that can influence occupants' interaction with building control systems, such as occupants' window opening behaviour, use of heating, solar shading and electrical lighting. During the survey meteorological data was obtained from 25 measuring stations in Denmark, and the data measured by the closest station for each monitored house were used for that house in the data analysis. From the survey a considerable impact of outdoor air temperature on occupants' window opening behaviour was identified. In addition, solar radiation was also found to influence the proportion of open windows. However, in this study, wind speed was found to have no influence on occupants' window behaviour, which is not consistent with some findings from other studies. Andersen et al. explained that this could possibly be because the wind speed used in their study was not measured locally, and thus did not truly reflect the local wind conditions.

Following the work undertaken by Andersen et al. (2009), Fabi et al. (2012a) carried out a web-based questionnaire survey in 15 residential buildings in Denmark. In this study statistical approaches were applied for the analysis of window behaviour, from which outdoor air temperature was found to be one of the most important factors determining the probability of opening/closing windows. Another important outdoor environmental parameter, which was found to influence window behaviour in this study, was solar radiation. This confirmed the relationship between window opening and sunny weather. In weekdays, the wind speed appeared to influence occupants' window opening behaviour, as Andersen et al. (2011) observed that higher wind speed led to less actions of opening windows. However, this influence was found to be very weak at the weekends. For the window closing behaviour, wind speed was identified as a positive factor.

To model occupants' window behaviour in residential buildings, Antretter et al. (2011) undertook a survey in 17 residential buildings, lasting for two years. In this study outdoor and indoor environmental conditions and the duration of open windows were measured hourly. Again, window opening was found to correlate highly with outdoor air temperature. In addition, outdoor air humidity was also found to have an influence on the state of windows, and wind speed was observed to impact the duration of window opening only.

The last study with investigations into the influence of outdoor climate on occupants' window behaviour in residential buildings was performed by Schweiker et al. (2012), based on field measured data in both Switzerland and Japan. In this study the monitoring of occupants' window behaviour was carried out in two residential buildings in Switzerland and one student dormitory in Japan, for at least six months. From the study outdoor air temperature was found to be an influencing factor on occupants' window behaviour, but the precipitation was identified as having no influence.

Influence of indoor climate: Some researchers have suggested that indoor air temperature also has an influence on occupants' window operation in residential buildings, such as Nakaya et al.(2008), Antretter et al. (2011), Schweiker et al. (2012) and Fabi et al. (2012a). In addition, indoor CO_2 concentration, which was generally used as a surrogate indicator of indoor air quality, was also suggested by Fabi et al. (2012a) to be a possible factor.

Influence of non-environmental factors: As in office buildings, non-environmental factors also play an important role in residential window operation, and their influence in residential buildings is potentially more complex. Possible influencing factors investigated in previous studies include season, time of day, occupant presence, type of dwellings/buildings, type of the room, orientation of windows, type of windows, floor level, type of the heating system, occupant age, occupant gender, ownership of the property and smoking.

Brundrett (1977) has observed a strong seasonal pattern of window operation in his study with "*windows progressively closing with the approach of winter and then re-opening with the warmer weather*". In addition, he also suggested that the factors influencing occupants' window behaviour in residential buildings were also different for summer and winter times. This conclusion was supported by other researchers, such as Erhorn (1986), Weihl and Gladhart (1990) and Fabi et al. (2012a). In the study carried out by Johnson and Long (2005), it was found that more windows were open in April, May or June, when compared with other months of the year.

Occupants prefer to use their windows differently at different times of day in residential buildings. Erhorn (1986) suggested that night ventilation happened less, compared with daytime ventilation, and this is supported by Encinas Pino and de Herde (2011), who modelled occupants' ventilation behaviour for daytime and night-time separately. In the IEA Annex VIII project (Dubrul, 1988), it was also observed that the number of open windows was maximum in the morning, and this number gradually decreased during the afternoon. Later, at about 17:00, another peak occurred, because at this time most occupants had returned from their daily work. After 17:00, the number would decrease again during the evening and remain at a fairly constant value during the night when people were sleeping. Fabi et al. (2012a) also reported that the maximum probability of opening windows happened in the morning, between 06:00 and 09:00, when people woke up. Considering the influence from this factor, that is, time of day, Johnson and Long (2005) developed different transitional probabilities of the state of windows for different times of day, and this method was also applied later by Antretter et al. (2011).

In the 1950s, Dick and Thomas (1951) suggested that in similar houses, "*the increase due to occupancy of one air change per hour during the heating season may be taken as generally applicable*". This reflects the influence of occupant presence/occupancy on the ventilation of residential buildings. In later studies, Brundrett (1977) found that for the houses with women in full-time employment, the opening time of windows was only half of those houses in which women generally stayed at home. In the Belgian study of the IEA Annex VIII project (Dubrul, 1988), it was also observed that the number of open windows was directly proportional to the length of occupation time of the dwellings, and this relationship was also observed in the study carried out by Johnson and Long (2005). Nakaya et al. (2008) concluded that passive behaviour, such as opening/closing windows and using fans, was strongly affected by occupants' entering/leaving rooms. Van Raaij and Verhallen (1983) established five behavioural patterns for the occupants in residential buildings, namely, 'Conservers'; 'Spenders'; 'Cool'; 'Warm' and 'Average', based on their monitored data from 145 households in the Netherlands, from November 1976 through November 1977. Within these categories, the 'Spenders' who maintained high ventilation levels in their homes were found to be more often at home.

The influence of the previous state of windows on its current state was confirmed by Schweiker et al. (2012), and this factor was used popularly to predict occupants' window behaviour based on Markov chains.

The type of dwellings/buildings, whether a house or an apartment, influenced window opening time (Dubrul, 1988). However, this influence was dependent on the type of the room being considered. It was observed that the windows in living rooms and kitchens would be open for shorter periods in houses, when compared with those in apartments, whereas the windows in bedrooms were left open for longer periods. Fabi et al. (2012a) also suggested that apartments with a single family had a higher average frequency of opening windows than houses.

Occupants' window behaviour in residential buildings is also affected by the type of the room. Newman and Day (1975) reported that people preferred to open the windows in bedrooms on winter nights in order to increase the ventilation to get a comfortable sleep. In the IEA Annex VIII project (Dubrul, 1988), different window use patterns were observed between the windows in living rooms and those in bedrooms. Erhorn (1986) made a ranking based on the popularity of windows being opened for different types of the room, and the windows in bedrooms were defined as the mostly opened ones, followed by the ones in children's rooms and living rooms. This ranking is supported by many other researchers such as Brundrett (1977), Guerra-Santin and Itard (2010), Antretter et al. (2011) and Fabi et al. (2012a). Additionally, Brundrett (1977) also suggested that the opening of kitchen windows was not influenced significantly by the outdoor climate, unlike the windows in other rooms.

The influence of the orientation of windows on residential window operation has been investigated and identified by Dubrul (1988) and Schweiker et al. (2012), but this influence seems to be caused mainly by the available solar gains obtained by the windows with different orientations.

Occupants use various types of windows differently in residential buildings. Erhorn (1986) reported that in living rooms, bottom-hung windows were used predominantly for ventilation. In addition, for children's rooms, the side-hung position was preferred in the first 6 months of the year, while the bottom-hung position was more often to be used in the last 6 months of the year. In the IEA Annex VIII project (Dubrul, 1988), it was also found that how the window was hung in its frame, and the direction of travel of the opening part, had an influence on occupants' window opening behaviour. In the Belgian study, the bottom-hung windows that open inwards were used more frequently than other types of windows, and this was more obvious in living rooms and kitchens. In the Dutch study, it was found that fanlight windows were opened twice as frequently as side hung casement windows, and the ventilation grilles were observed to be left open nearly always. Guerra-Santin and Itard (2010) also suggested that grilles were kept open much often in residential buildings. Dubrul (1988) explained the influence of the type of windows on occupants' window operation, as different window designs provided different areas of opening and so they were used generally for different purposes in actual buildings.

Schweiker et al. (2012) analysed the influence of floor level on residential window operation and suggested that it was another influencing factor.

The influence from the type of the heating system has been evaluated in some previous studies. In the Belgian study of the IEA Annex VIII project (Dubrul, 1988), researchers found that windows in centrally heated houses were likely to be open for shorter periods, when compared with those in non-centrally heated houses, especially in bedrooms. The Dutch team reported that the windows in houses with warm-air central heating were open less than those in houses with radiator systems. Guerra-Santin and Itard (2010) also suggested that households using programmable thermostats preferred to open windows more in bathrooms, when compared with those using manual thermostats.

The influence of the occupant age on residential window operation has been investigated by van Raaij and Verhallen (1983), who suggested that houses with elderly people performed a low ventilation level. This phenomenon was also observed in the studies carried out by Dubrul (1988), and, Guerra-Santin and Itard (2010). In addition, Guerra-Santin and Itard (2010) also reported that if there were children in the house the windows in living rooms were more likely to be closed.

Studies also found that males and females had different patterns of window operation in residential buildings (Andersen et al., 2009, Schweiker et al., 2012), so occupant gender is another influencing factor. Furthermore, the ownership of the property can also influence occupants' use of windows (Andersen et al., 2009, Fabi et al., 2012a). If the occupants smoked, a higher airing and ventilation of the living room was observed in the IEA Annex VIII project (Dubrul, 1988).

Variability between individuals: In some studies carried out in residential buildings, such as those by Dick and Thomas (1951), Iwashita and Akasaka (1997), Dubrul (1988), Weihl and Gladhart (1990), Papakostas and Sotiropoulos (1997) and Andersen et al. (2011), individual differences were commented on as well. However, as for office buildings, these studies did not separate the influence of personal behavioural preference and from those of sub-group factors.

2.1.3 Factor discussion

Work relating to both office and residential buildings has been reviewed for evidence about which factors affect window operation. The evidence is summarised in Table 2.1, where the numbers refer to the number of reports in the literature that support the influence of the specified factor, for office buildings and residential buildings respectively.

Table 2.1: Factors affecting window operation comparison of reports in evidence between office buildings and residential buildings.

Factors	Office buildings	Residential buildings
Outdoor climate (dominated by outdoor air temperature)	8	11
Indoor climate (dominated by indoor air temperature)	8	4
Season	4	5
Time of day	6	6
Previous state of windows	7	1
Occupant presence	2	6
Type of windows	1	3
Orientation of windows	1	2
Floor level	1	1
Shared offices	1	N/A
Type of dwellings/buildings	N/A	2
Type of the room	N/A	9
Type of the heating system	N/A	2
Occupant age	N/A	3
Occupant gender	N/A	2
Ownership of the property	N/A	2
Smoking	N/A	1

The above review provides guidance on selecting influencing factors for investigation in future window behaviour studies. Outside air temperature has the strongest influence in both office buildings and residential buildings. Meanwhile, there are also some factors, namely, indoor air temperature, season, time of day and previous state of windows, that should be considered. This is because enough evidence has been provided by existing studies (these factors have been identified to influence window operation in both types of buildings, and the number of available studies for office buildings is at least three). For critical analysis, the influences of the remaining factors also need to be considered, as there is not enough evidence to suggest that these factors are irrelevant to window operation. For office buildings, however, the issue of property ownership and smoking can be generally ignored, because firstly, the occupants of an office building are commonly working in the building but are not the owners of the building; and secondly, smoking is commonly prohibited in office buildings.

What is also important is that in the studies in both types of buildings, although observations of individual behaviour have been made, there are, potentially, multiple factors that could confound the results. Hence a study that treats the isolation of such effects more rigorously could be of use in understanding the effects of the individual on window operation.

2.2 Predicting Window Behaviour in Office Buildings

In building performance simulation and modelling, if occupants' window operation is to be considered, the state of windows, either open or closed, must be defined for each timestep within the simulation. This task is achieved commonly by predicting window behaviour either deterministically or stochastically. A review of both techniques is given here.

2.2.1 Deterministic prediction

In building performance simulation tools, such as Energyplus (EERE, 2013), ESP-r (**E**nvironmental **S**ystem **P**erformance **r**esearch) (ESRU, 2012), IES VE (**I**ntegrated **E**nvironmental **S**olution **V**irtual **E**nvironment) (IES, 2012) and DesignBuilder (2013), the common way to model occupants' window behaviour is using a deterministic approach (Brotas, 2004). Here a pre-determined pattern of window states is allocated to each window involved in the simulation. In this approach, the state of a window is defined as a binary variable, generally 1 for open and 0 for closed, for each simulation timestep. The value of this variable at each simulation timestep is determined either by allocating a particular value based on the tool users' experience/preference or by calculating it, based on a conditional statement (IF-THEN), dependent upon a particular variable or some particular variables, such as indoor air temperature and/or outdoor air temperature.

	Time	Value
1	00:00	0.00
2	09:00	0.00
3	09:00	1.00
4	17:00	1.00
5	17:00	0.00
6	24:00	0.00

a) Daily profile_01

	Time	Value
1	00:00	0.00
2	09:00	0.00
3	09:00	(ta>23)
4	17:00	(ta>23)
5	17:00	0.00
6	24:00	0.00

b) Daily profile_02

	Daily Profile:
Monday	Profile_weekdays [DAY_0003]
Tuesday	Profile_weekdays [DAY_0003]
Wednesday	Profile_weekdays [DAY_0003]
Thursday	Profile_weekdays [DAY_0003]
Friday	Profile_weekdays [DAY_0003]
Saturday	Profile_weekends [DAY_0004]
Sunday	Profile_weekends [DAY_0004]
Holiday	Profile_weekends [DAY_0004]

c) Weekly profile

No:	Weekly Profile:	End month:	End day:
1	Profile_winter [WEEK0003]	Mar	31
2	Profile_summer [WEEK0004]	Oct	31
3	Profile_winter [WEEK0003]	Dec	31

d) Annual profile

Figure 2.1: Deterministic profiles for window operation.

The basic unit of a deterministic pattern of window states is a daily profile defined from 00:00 to 24:00, as shown in Figure 2.1a and 2.1b, which come from a commercial building performance simulation tool, IES VE (IES, 2012). In Figure 2.1a, the state of windows at each simulation timestep is defined directly by the tool users (the window is only open during the working hours, which are from 09:00 to 17:00). In Figure 2.1b, the state of windows during the working hours is further determined according to the instant indoor air temperature of each simulation timestep (if the indoor air temperature is higher than 23°C, then the window is open, or it is closed); during the non-working hours the window is always closed. Various daily profiles could then be combined to establish a weekly profile from Monday to Sunday, as shown in Figure 2.1c. The weekly profiles can then be used to develop annual profiles, as shown in Figure 2.1d, in which different patterns of window use are allocated for the heating and cooling periods, respectively.

2.2.2 Stochastic prediction

The prediction of window behaviour by such deterministic approach has been criticised by many researchers because:

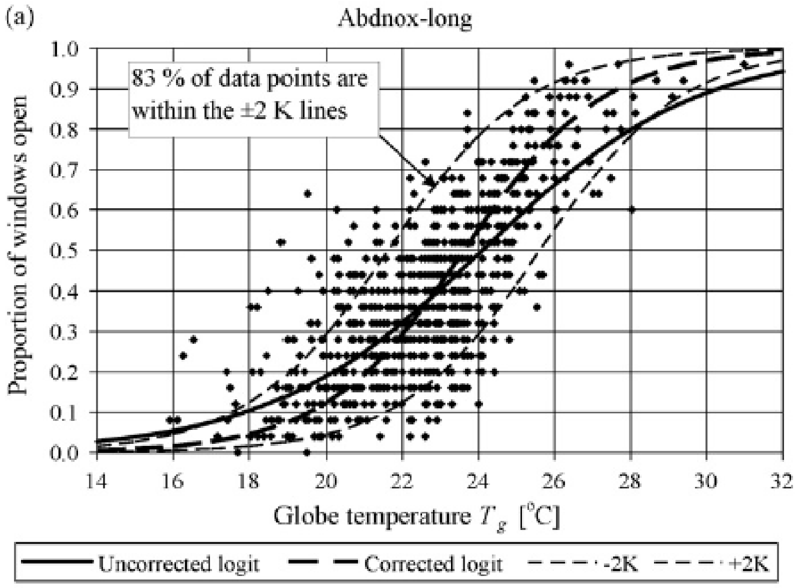
- occupants' window behaviour is complex and it cannot be determined by a limited number of parameters; and,

- the occupants themselves are subject to many immeasurable influences that might affect their actions, some physiological and some psychological.

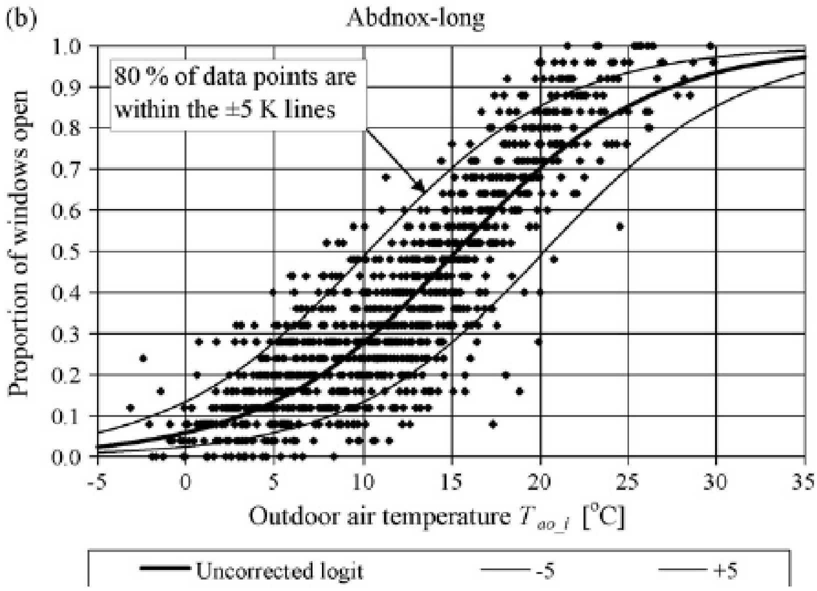
Therefore, many researchers have suggested that this behaviour should be presented as *"an algorithm for the likelihood of a control being used rather than a simple on/off condition"* (Nicol and Humphreys, 2004).

Fritsch et al. (1990) used Markov chains to stochastically predict the opening angles of windows in office buildings, during the winter period. The data used for the model development was collected from four south-facing naturally ventilated offices occupied by either one or two persons. In their study outdoor air temperature was chosen to model the probability of moving the window from one angle to another angle. However, the interest in studying window behaviour began to grow 10 years later.

One of the most important studies in this area was carried out by Nicol and Humphreys (2004). Their window behaviour model was developed by logistic regression analysis (Hosmer and Lemesbow, 2000). At the beginning, Nicol (2001) established a series of probability distributions (logistic regression models) that could be used to predict the state of windows. In this stage, indoor globe temperature and outdoor air temperature were used separately to build these window behaviour models and, in most cases, similar correlations were observed. Therefore, he suggested using outdoor air temperature, rather than indoor globe temperature, when predicting the state of windows, because outdoor air temperature was an input for any simulation, while indoor globe temperature was an output. However, in a later paper, Nicol and Humphreys (2004) reported that indoor globe temperature seemed to be a more consistent predictor of window operation, when compared with outdoor air temperature. In a later study, Rijal et al. (2007) developed two window behaviour models using indoor global temperature (Figure 2.2a) and outdoor air temperature (Figure 2.2b) separately, based on data collected from 10 naturally ventilated office buildings in the UK. Finally, they concluded that combining both indoor globe temperature and outdoor air temperature in one logistic window behaviour model can provide the best modelling of occupants' window behaviour.



a) Window behaviour model based on indoor globe temperature



b) Window behaviour model based on outdoor air temperature

Figure 2.2: Window behaviour models developed by Rijal et al.

(Source: (Rijal et al., 2007))

Using both indoor globe temperature and outdoor air temperature, Rijal et al. (2007) developed a comfort driven window state prediction approach, which is named as the *'Humphreys adaptive algorithm'*. This approach mainly consists of two steps:

- the indoor comfort temperature is firstly calculated by the adaptive thermal comfort model, which has been introduced in detail by Humphreys and Nicol in a previous paper (Humphreys and Nicol, 1998); and then,

- occupants' window behaviour is predicted using the calculated indoor comfort temperature and a 'deadband', which is defined as temperatures within ±2.0°C from the calculated comfort temperature.

The algorithm used here for the window behaviour calculation is that if the indoor globe temperature is within the 'deadband', the current state of the window will remain its previous state. If it is outside the range the window state will be recalculated, using a randomly-generated probability and the probability of window opening, which is calculated by the logistic window behaviour model using the instant indoor globe temperature and outdoor air temperature. Based on the data collected in Pakistan, Rijal et al. (2008) updated the *'Humphreys adaptive algorithm'* by implementing the 'deadband' in the logistic window behaviour model, as defined in Equation 2.1,

$$Logit(p_w) = 0.525 \times [T_{op} - T_c + (S_{WS} - 0.5) \times WD], \qquad (2.1)$$

where,

p_w	probability of window opening, in percentages (%);
WD	is the temperature 'deadband' regarding to the window operation, in degrees Celsius (°C);
$\mathrm{S_{WS}}$	is the state of windows (1 for open, 0 for closed) ($-$);
T_{op}	is the operative temperature, in degrees Celsius (°C);
T_c	is the adaptive comfort temperature, in degrees Celsius (°C).

Herkel et al. (2008) used data collected in 21 south-facing and naturally ventilated offices in Germany to build their model. The influencing factors considered in their prediction algorithm included outdoor air temperature, time of day, occupant presence, season, previous state of windows and type of windows. Herkel et al. chose to use quadratic equations (as shown in Equation 2.2), rather than logistic equations, to develop their probabilistic models that were used to predict the state of windows,

$$p_w = a \times T_{out}^2 + b \times T_{out} + c \ , \tag{2.2}$$

where a, b and c are constants that are obtained by statistical methods, and $\mathrm{T_{out}}$ is outdoor air temperature.

The flow chart of their prediction algorithm for the determination of the state of windows at each simulation timestep is shown in Figure 2.3, combining the influences of many factors that have been discussed in Section 2.1.3.

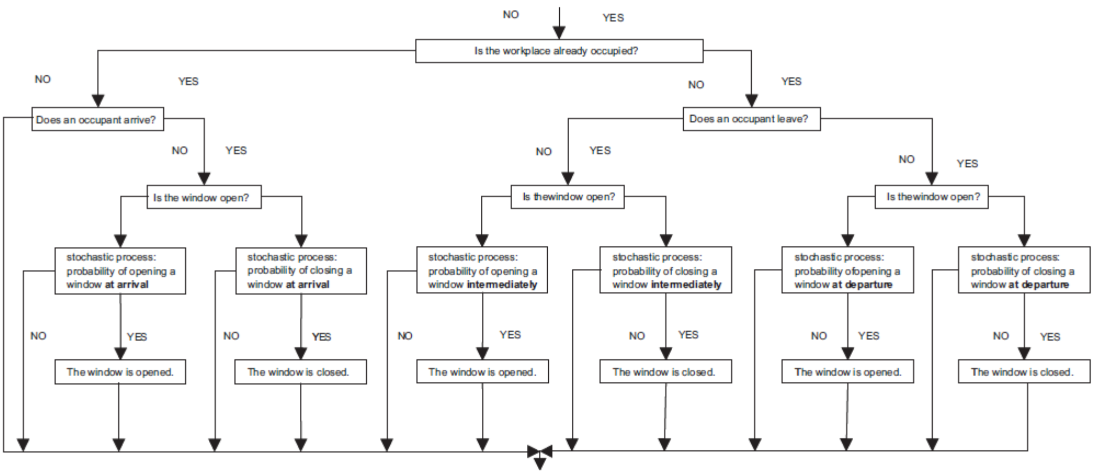


Figure 2.3: The flow chart of Herkel et al.'s algorithm.

(Source: (Herkel et al., 2008))

Yun et al. (2009) also developed a *'Yun algorithm'* for building performance simulation, containing a probabilistic occupant behaviour model and a deterministic heat and mass balance model. Data used for the model development was collected from six offices in two different naturally ventilated buildings, one with night cooling strategy and one without. Besides this, the six offices are also varying with respect to the window orientation, window type and number of occupants. To include the influence of the previous state of windows in the determination of the current window state, Markov chains were chosen for the algorithm. Corresponding transition probabilities from close to open, or from open to close, were developed using the logistic regression method, and indoor air temperature was used to define these transition probabilities. The '*Yun algorithm*' is shown in Figure 2.4, reflecting how the probabilistic behaviour model is combined with a deterministic heat and mass balance model in building performance simulation.

To reflect occupants' various use of windows during the arrival period, which was explained by Yun et al. (2008) to be linked with the design of the building façade, Yun et al. (2009) classified the occupants of a building into 'active', 'medium' and 'passive' window users, for the arrival period only. However, they tried to use the behaviour models developed for these three classes of window users in one example room to demonstrate the influence of different window operation on the predicted performance of buildings. This model implementation is criticised in this study as their behavioural data were collected from offices with differing properties, such as different type and orientation of windows, different number of occupants and different night ventilation strategy. Therefore, these models were not suitable to be used for simulating the performance of one room without changing those properties.

A combined behaviour algorithm

Stage 1: Initialisation

i. Set initial window state: $\theta^{(1)} = \lambda = 0$

Stage 2: Trial State

i. Choose a new trial state: ϕ where $\phi \in S = \{Closed, Open\} = \{0,1\}$

Stage 3: Transition Probability

i. Calculate the probability of the state changing to ϕ : $P^{(i)}(\phi)$

Stage 4: Evaluation

i. Generate random variable: $U \sim U[0,1]$

ii. Compare $P^{(i)}(\phi)$ with U

- if $P^{(i)}(\phi) \geq U$ then, accept the trial state ϕ
- if $P^{(i)}(\phi) < U$ then, reject the trial state ϕ

iii. Set the state of Markov chain at simulation time step i: $\theta^{(i)}$

- if the change is accepted, set $\theta^{(i)} \leftarrow \phi$
- if the change is rejected, set $\theta^{(i)} \leftarrow \theta^{(i-1)}$

Stage 5: Computation

i. Solve thermal and mass balance equations

Stage 6: Internal Repetition

i. Repeat from Stages 2 to 5 until it reaches the last simulation time step

Stage 7: Iteration

i. Repeat Stage 6 until it satisfies the predefined Monte Carlo iteration number

Figure 2.4: The behaviour algorithm of the 'Yun algorithm'.

(Source: (Yun et al., 2009))

Until now, the most comprehensive study on window behaviour in office buildings was performed by Haldi and Robinson (2009b), using the data collected from their experimental building in the Swiss Federal Institute of Technology in Lausanne, Switzerland. The experimental building is naturally ventilated and their monitoring work was undertaken in 14 south-facing cellular offices (occupied by either one or two occupants), lasting for 7 years.

Using this dataset, Haldi and Robinson (2008a) applied three different statistical approaches to model and predict occupants' window behaviour:

- modelling and predicting based on logit distributions (used by Nicol and Humphreys (2004) as well);
- modelling and predicting based on a discrete-time Markov process (used by Herkel et al. (2008) and Yun et al. (2009) as well); and,
- modelling and predicting based on a continuous-time random process (not used previously by other researchers).

In the first approach the occupants' window behaviour was modelled as logit distributions (Figure 2.5), which were generated by the logistic regression method. In the simulation occupants' operation of windows was represented as a Bernoulli process, in which the state of a window at each simulation timestep was affected by the current condition of that timestep only, not considering the previous state of the window. Environmental factors, which were demonstrated to affect occupant' window behaviour in this approach, included indoor air temperature, outdoor air temperature, outdoor relative humidity, rainfall, wind speed level and wind orientation domain. Finally, outdoor air temperature was found to be the best predictor of the state of windows for a whole year period. In addition, they have used a polynomial logit to predict the observed decrease of proportions at high outdoor air temperatures, as shown in Figure 2.5. When outdoor air temperature was used as the basic environmental factor affecting the state of windows, an inclusion of indoor air temperature could help to increase the model performance significantly.

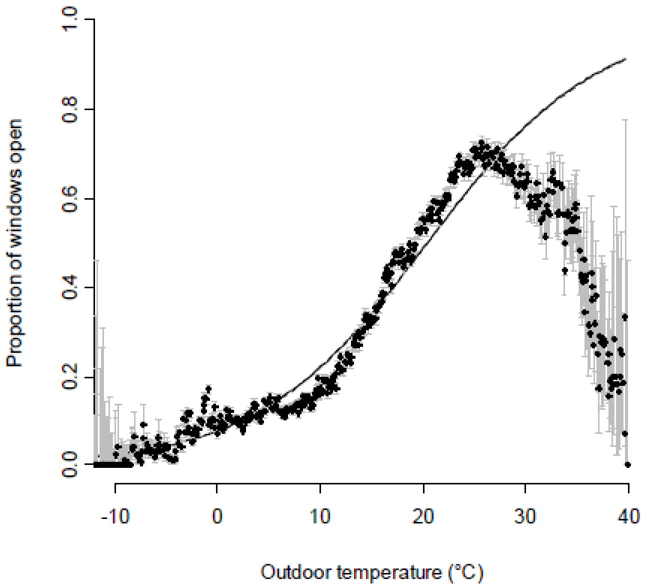


Figure 2.5: Haldi and Robinson's window behaviour model based on logit distributions. (Source: (Haldi and Robinson, 2009a))

The above approach focuses on modelling and predicting the state of a window, whether a window is open or closed, at each simulation timestep, rather than modelling on occupants' window operation, whether a window is to be opened or to be closed. Haldi and Robinson (2008a) pointed out that *"it ignores the real dynamic processes leading occupants to perform actions"*. Thus, in the second approach, Markov processes were applied in predicting occupants' window behaviour, and this approach considered the effect of the previous state of windows in the determination of the current window state. The daily occupancy pattern was also applied in this approach, enabling the influences of the time of day and the occupant presence to be considered. Figure 2.6 shows the basic structure of this approach, with various transition probabilities defined for particular window operation events such as opening a window or closing a window, for different times of day (arrival, during presence and departure).

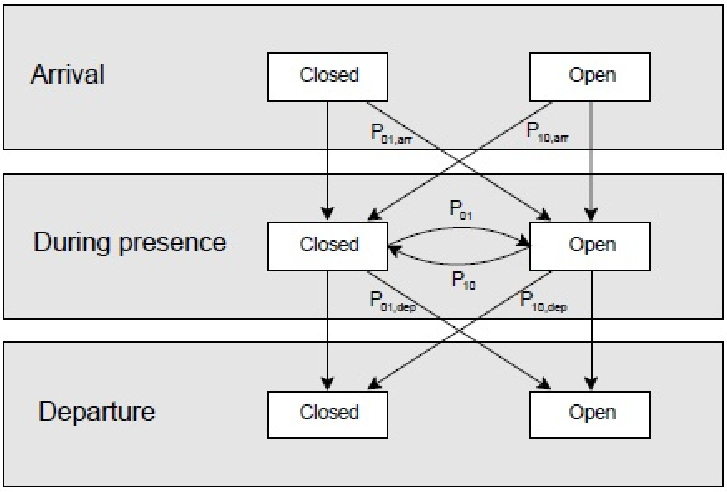


Figure 2.6: The definition of transition probabilities from Haldi and Robinson.

(Source: (Haldi and Robinson, 2009b))

Table 2.2: Influencing factors for transition probabilities modelling window behaviour.

Time of Day	Opening to Closing	Closing to Opening
Arrival	1. indoor temperature 2. outdoor temperature	1. preceding absence > 8 hours 2. indoor temperature 3. outdoor temperature 4. rainfall
During presence	1. outdoor temperature 2. indoor temperature	1. on-going presence duration 2. indoor temperature 3. outdoor temperature 4. rainfall
Departure	1. following absence > 8 hours 2. daily mean outdoor temperature 3. window higher than ground floor 4. indoor air temperature	1. daily mean outdoor temperature 2. following absence > 8 hours 3. window higher than ground floor

The factors that possibly influence the transition probabilities defined in Figure 2.6 were evaluated, including indoor air temperature, outdoor air temperature, daily mean outdoor air temperature, rainfall, wind speed level, wind orientation domain, window higher than ground floor, on-going presence duration, preceding absence longer than 8 hours, and the following absence longer than 8 hours. Statistical analysis revealed that the influencing factors for each transition probability were different, as presented in Table 2.2.

The last approach applied by Haldi and Robinson was based on a continuous-time random process, in which the duration of the window opening was treated, instead of the change of the state of windows. In this approach the duration of a window kept open was found to be correlated mainly with outdoor air temperature, while the duration of a window kept closed was influenced by both indoor and outdoor air temperatures. In their study, these correlations were defined by specific Weibull distributions for both window open and closed durations.

Three statistical approaches were applied by Haldi and Robinson (2008a), to model and predict occupants' window behaviour in office buildings. Based on this, they performed an executed parallel comparison between these approaches, and their conclusion is shown in Figure 2.7. Based on the comparison, they reported that these three approaches were different on both predictive quality and computational cost. The approach based on logit distributions was the simplest, but its prediction accuracy was also worse than the other two approaches. The approach based on a continuous-time random process had the best prediction accuracy, but it was the most complicated one. Therefore, they suggested that the choice of which approach to use should be dependent on both the required accuracy of the project, as well as the available computational resources.

At the last stage of their study Haldi and Robinson (2009a) developed a hybrid approach, in which a discrete-time Markov model was used for the prediction of window openings and a Weibull distribution model was used to determine the duration of the window to be kept open. Finally, they found that this hybrid approach provided a better prediction result than using the three approaches individually.

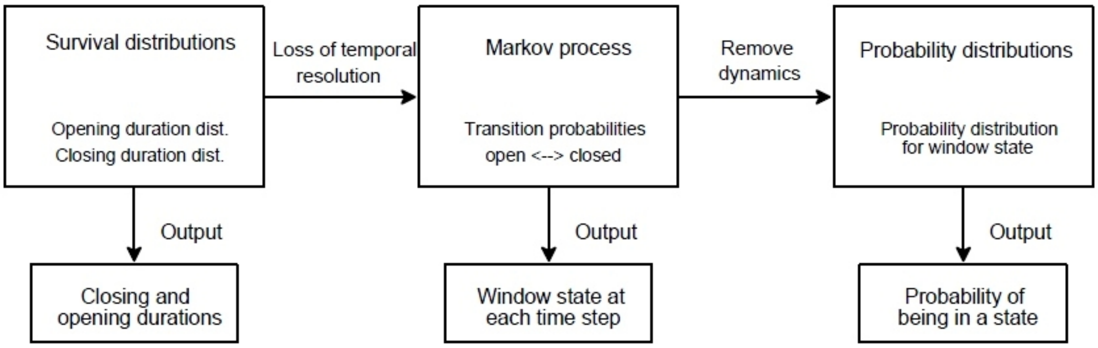


Figure 2.7: Relationship of different window behaviour modelling approaches.

(Source: (Haldi and Robinson, 2008a))

2.3 Summary

This chapter has provided a thorough review of existing studies on occupants' window behaviour in buildings. In Section 2.1, potential factors that can influence occupants' window behaviour in both office buildings and residential buildings are reviewed, providing a list of factors that need to be considered in the later measurement and factor analysis. Section 2.2 introduces the currently available approaches that can be used to model and predict occupants' window behaviour in office buildings. From the review, the following gaps in this research area can be identified:

- previous studies focus on the arrival and intermediate periods in the day, whereas the window use behaviour at the end of day is less understood: *"the behaviour of the occupants' towards night ventilation is generally poorly understood" (Fabi et al., 2012b)*;

- currently, the influence of personal preference on window behaviour has not been examined in such a way as to remove the presence of confounding factors;

- current modelling approaches of occupants' window behaviour focus on whole-population or sub-group approaches, but modelling behaviour based on personal preference has not been investigated; and,

- a suitable approach to allocate individual behaviour models in building performance simulation is needs to be developed, especially for simulation of buildings with multiple rooms.

The rest of this thesis will explore these issues by using a case study building, focusing on the end-of-day window position. Careful monitoring will enable the effects of personal preference of a subset of the building population to be identified through analysis, while also identifying other non-environmental parameters that have statistically significant effects. The data will then be used to develop and validate a preference-based model that can be tested alongside traditional whole-population and sub-group modelling approaches. Finally, the effects of predicting occupants' window behaviour based on personal preference in a realistic simulation environment will be tested and discussed.

3. METHODOLOGY

This chapter introduces the main methods that are used in this study to achieve the aims and objectives defined in Section 1.1. Section 3.1 provides a detailed introduction of the field study designed to monitor occupants' window behaviour in a non-air-conditioned office building, focusing on the end-of-day window position. Section 3.2, 3.3 and 3.4 introduce separately the methods that are used to analyse the influence of potential factors, to develop and validate window behaviour models, and to demonstrate the impact of different occupant classification methods on the predicted energy performance of buildings, but not in detail. Detailed information about these methods is provided at the beginning of each particular chapter in the remaining part of the thesis.

3.1 Design of the Field Study

The previous review chapter of occupants' window behaviour identified that in order to be able to explore the influence of personal preference on window opening behaviour, confounding factors need to be carefully considered in the analysis, and to this end a longitudinal study observing people's window operation is designed in this chapter. The study focuses on a non-air-conditioned office building that has a number of floors, offices on different façades, and a mix of male and female occupants. The building has individually-occupied cellular offices each containing one window, and so eliminates issues surrounding the negotiation of window use, where there is more than one occupant in the office. In addition, all offices are very similar in size, shape and layout. The study focuses on the end-of-day window position since this has been identified to be an under-researched area in Chapter 2. In addition, it is also a pivotal moment in the day where the position of the window has no immediate effect on the occupant (since they are not present), but can have a significant impact on night-time ventilation. This in turn affects office comfort the following day in summer, or excessive heat loss overnight from the office during the winter.

3.1.1 The case study building

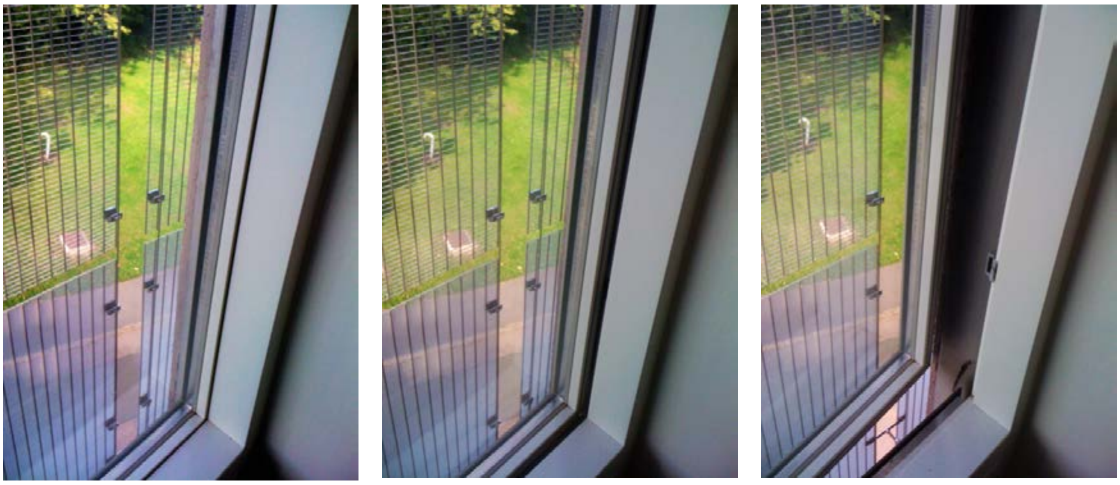
The study was carried out in the building that houses the School of Civil and Building Engineering at Loughborough University, UK (52°45’54’’N, 1°14’15’’W, alt.70m). Figure 3.1 depicts the Southwest façade of the building and shows a typical office. The building is an ‘L’ shape with single-occupied cellular offices around the perimeter (as shown in Figure 3.2), all of which have nominally the same floor area (10.2m^2). Each window shown in Figure 3.1 belongs to an individual office. The windows in each office are typically fully closed, fully open or slightly open (as shown in Figure 3.3). When the window is slightly open, the lever that pulls the frame onto the seal is open and the window 'opening' appears to be about 10mm. However, the actual opening due to the seal is only approx. 5mm, and only over one side of the side hung frame. In addition, the windows sit in a recess, that is tight to the width of the window and hence there is very little air flow when the window is in this position, the only exception being on very windy days. For this reason, the windows when in the slightly open position have been considered to be closed – i.e. providing little cooling during the night time period. Although the outside of the building is curved, there are essentially only two facades, 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 office has a door opposite the window, and the door opens onto communal spaces on each of the three floors, with all floors connected via a full height atrium.

(a) Case study building

(b) A typical single-cell office

Figure 3.1: The case study building (left) and a typical single-cell office (right).

Figure 3.2: Floor plan of the case study building.



a) Fully closed b) Slightly open c) Fully open

Figure 3.3: Positions of the window in the surveyed building.

Typical office occupation is nominally 09:00 to 17:00, with each office being occupied by the same person hence promoting a sense of 'ownership' of each office by its occupant. Room occupancy varies significantly between individuals throughout the year, due to several factors that include teaching, research meetings and off-site visits. Often, absence from, and presence in, the office are not routine and at particular times of the year the building occupancy decreases, most notably in August, which is when most staff have less commitments and hence is a popular period to take a summer holiday. Over the winter holiday break in December/early January, the building closes for about 10 days.

Each occupant has sole control over the environmental conditions in his/her office and typical adaptive opportunities are: window and door position, a window blind position and temperature control for a dedicated radiator (operative during the heating season). The building is mixed mode, supplying additional ventilation in the summer through swirl vents mounted in the floor of each office. Heating during winter is provided by a hydronic heating system, serving each office, and is switched on typically during the first week in October and switched off at the end of April, with some variation due to ambient temperature and work scheduling of the estates staff. The heating switch-on period usually coincides with the end of the daylight saving period in the summer months – **B**ritish **S**ummer**t**ime (BST) (Note BST = GMT+1hr, here GMT = **G**reenwich **M**ean **T**ime).

3.1.2 Data collection

Longitudinal surveying (Singer and Willett, 2003) of window opening is required so that the appropriate characteristic dependencies can be observed, recorded and hence modelled, evidenced by (Rijal et al., 2007, Herkel et al., 2008, Haldi and Robinson, 2009b, Yun et al., 2008). For buildings this is typically over one year to capture the heating season, summertime effects and the transitional seasons that include a shift between GMT and BST.

In this study, a total of 36 offices and their associated office occupants were monitored in three observation periods that were classified by season as summer, transitional (or swing) and winter. Table 3.1 gives the precise dates for the data collection together with other key dates in the operational cycle of the case study building. It should be noted that the actual sequence of the observation periods was summer – winter – transitional, taking place over two years.

Table 3.1: Observation periods and key dates.

Observation Periods		**Key Dates**	
Summer	20/06/2010 to 30/09/2010	Heating switch on	03/10/2010 and 04/10/2011
Winter	01/11/2010 to 26/03/2011	Daylight saving ends	31/10/2010 and 30/10/2011
Transitional	10/10/2011 to 20/11/2011	Winter building closure	24/12/2010 to 04/01/2011

Figure 3.4 depicts how the seasonal observations recorded in 2010 and 2011 would have fitted into a 12 month period. There is an overlap between the winter and transitional periods. This is because the winter period is defined here as the period when the heating system is on and the national time is set to GMT. The summer period is defined as the period when the heating system is off and the national clocks are set to daylight saving. One month either side of the daylight changing was considered to be the transitional period, and the data for this period was collected purposefully either side of this point.

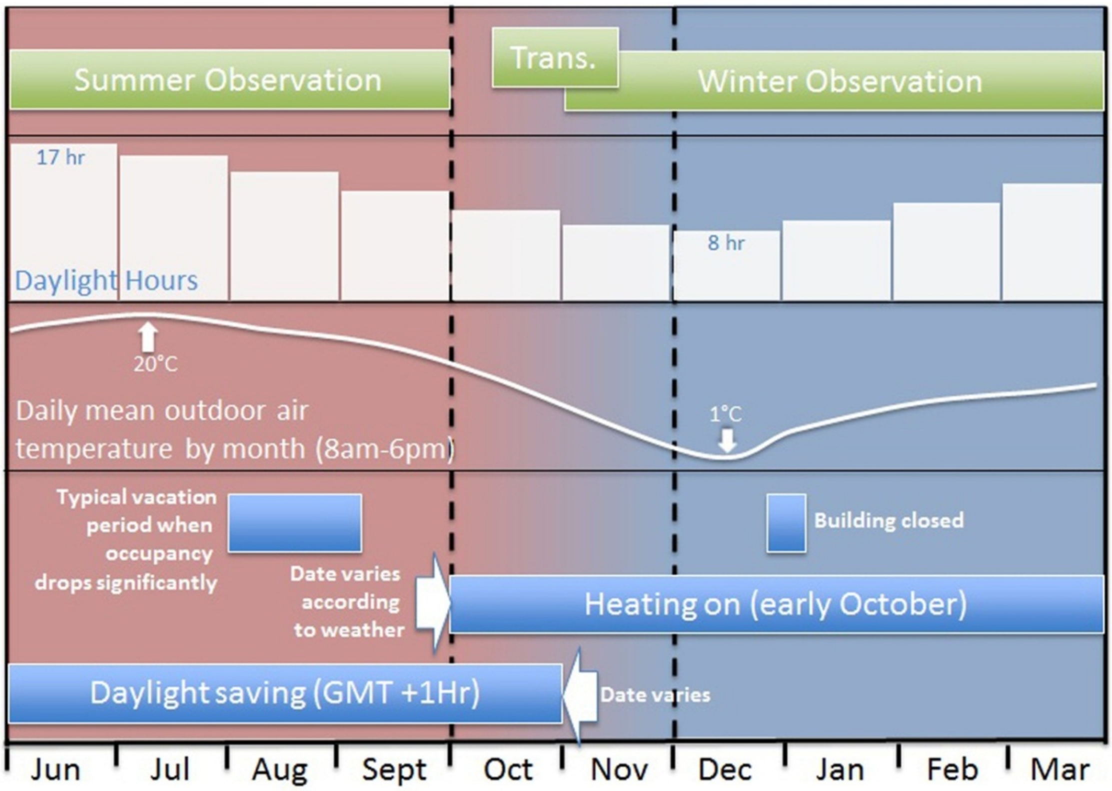


Figure 3.4: The building characterised by environmental and building operational factors.

The parameters that were monitored in the survey are listed in Table 3.2, measured using a combination of automated measurement and human observations.

Table 3.2: Measured key parameters in the survey.

	Measuring Method	**Measuring Periods**
Indoor air temperature	automated	in all 3 periods
Outdoor air temperature	automated	in all 3 periods
Indoor globe temperature	automated	in the transitional observation period only
Occupants’ daily presence	human observations	in all 3 periods
End-of-day window position	human observations	in all 3 periods

Indoor air temperature (T_{ai}): The indoor air temperature was measured by a HOBO UA-001 temperature sensor (Figure 3.5a), located under the occupant's desk at about the abdomen level, avoiding direct sunlight. This temperature measurement at one height, instead of at three different heights (ISO, 2001), was considered to be adequate, since thermal comfort was not the primary focus of the work. Detailed specifications of this sensor are listed in Table 3.3. Before the field measurement all temperature sensors were calibrated at 20°C by the equipment supplier. In addition, every six months, all the sensors were re-collected and their measurement consistency was checked to confirm that there were no sensors damaged during the observation period. In the consistency checking procedure the bias between the recorded value from each temperature sensor, and the mean value of all sensors, should be within ±0.2°C for each time point. In the transitional observation period another measurement of indoor air temperature was carried out by a calibrated Hobo U12-012 data logger attached to a shelf in the office, about 600mm above desk level, 0.5-1.0 meters away from the occupant, so as to avoid the effects from the heat generated from people's bodies and breathing. This measurement enabled a comparison between the air temperature and the globe temperature for the monitored offices. Detailed specifications of the HOBO U12-012 data logger are listed in Table 3.3.

Indoor globe temperature (T_g): The indoor globe temperature was measured in the transitional observation period by a HOBO TMC1-HD temperature sensor surrounded by a blackened, 40mm table-tennis ball, and the measured data was recorded by a HOBO U12-012 data logger (Figure 3.5b). This method has been recommended by Professor Michael Humphreys (Humphreys, 1977) for assessing the warmth of a room with low air movement, due to the rapid response and convenient size of a table-tennis ball. In this study the globe temperature sensor was located closely to the Hobo U12-012 data logger. Detailed specifications of the HOBO TMC1-HD temperature sensor are listed in Table 3.3. Before being used for field measurement, all HOBO TMC1-HD probes had been calibrated at 20°C by the equipment supplier. In addition, the globe temperature sensors thus created were calibrated against a manufactured 40mm globe temperature sensor (of accuracy ±0.2°C) by the Grant Instruments, and were shown to give measurements within 0.2°C.

Outdoor air temperature (T_{ao}): The outdoor air temperature was measured by a DELTA-T WS-GP1 weather station located on the roof of the case study building, as shown in Figure 3.5c. To minimise the effect from the heat extracted from the building on the temperature measurement, the weather station was mounted 3 metres higher than the roof level. Detailed specifications of this weather station are provided in Table 3.3. Prior to the field measurement the temperature sensor had been calibrated by the equipment manufacturer. Furthermore, its temperature measurement was compared annually with one calibrated DELTA-T WS-GP1 weather station, and 100% measurement variations were within ±0.2°C.

In the case study building most departures from the work place occurred between 15:00 and 18:00, hence the outdoor air temperatures at these times were recorded. Averaging these values (the difference of temperatures at these two time points was found to be typically less than 2°C based on the field measured data) gave a good estimate of the external air temperature at the time when occupants would have left their offices for the day.

(a) (b) (c)

Figure 3.5: Measurement devices in the study.

Occupants' daily presence: Due to the flexible working hours, in order to determine occupants' daily presence, the approach adopted in this study was personal observation by the experimenter. The observations were carried out at three times every day, namely, 10:00, 11:30 and 15:00, which maximised the chance of capturing presence. If occupancy was observed at any of these times, then occupant presence for that working day was recorded.

End-of-day window position: The end-of-day window position (or window position on departure) of each office was noted by a further observation at 20:00, when most occupants had vacated the building (on a typical day).

Table 3.3: Specifications of measurement devices.

Product	Measurement Range	Measurement Accuracy	Response time
HOBO UA-001 Temperature Data Logger	-20°C to 70°C	±0.5°C	10 minutes
Hobo U12-012 Data Logger (T_{in})	-20°C to 70°C	±0.4°C	6 minutes
HOBO TMC-HD Temperature Sensor	-40°C to 100°C	±0.3°C	2 minutes
DELTA-T WS-GP1 Weather Station (T_{out})	-30°C to 70°C	±0.3°C	N/A

3.1.3 Ethics risk and data protection

As the monitored subjects in this study are human participants, ethical implications of the research need to be considered. In the ethical review process, generally, there are two main tasks that need to be justified (KCL, 2008). Firstly, balance the benefit of the research to society and the risks involved to participants. Secondly, treat the monitored data confidentially, during and after the research study. To meet this requirement an ethical approval was undertaken prior to commencing this study, and approval was given both by the school, in which the researchers were working, and the Ethics Committee of Loughborough University. The ethical approval application carried out for this study has answered questions in the following aspects:

- researchers' scientific quality on doing the study;
- basic information about the studied subjects, for example, participants' age and pregnancy condition;
- general questions about the methodology and the procedure of the study, such as how participants will be investigated or observed, how the measurement will be carried out;
- consent and deception of the study to the participants;
- how the data will be used and stored confidentially during and after the study; and,
- will participants be provided with any incentives for the study.

When doing the ethical approval, in order not to influence occupants' window behaviour during the data collection period, occupants were only told that some of their behaviours indoors would be monitored for a period of time. However, if they wanted to know some detailed information about the study or the results of the study, it can be provided to them after the study finished.

As mentioned in the Data Collection section (Section 3.2), some measuring devices were used in the study for automated monitoring of important parameters. To ensure participants' safety during the measurement, a risk assessment of these devices was also completed, which resulted in a 'Low' risk. This assessment has considered mainly the mechanical and electrical hazards; potential hazard of the workplace (both physical and environmental); potential hazard from substances; potential hazard of participants' work activity during the experiment; potential hazard of radiation. In addition, before being allocated into the monitored offices, all the measurement devices had been tested carefully by professional electricity technicians in the School of Civil and Building Engineering, Loughborough University, making sure that they were in good working conditions.

3.2 Factor Analysis

Before modelling occupant window behaviour, influencing factors should be identified. In this study, the influence of potential factors on the monitored end-of-day window position in the case study building is analysed using a systematic approach, which addresses carefully the influence of confounding factors. The potential factors analysed are collected from the literature review carried out in Section 2.1, as listed in Table 2.1. The analysis is based on a notion of a 'sample-day', which is fully explained in Section 4.1. For the case study building, non-environmental factors analysed include season, change to daylight saving time, occupant absence in subsequent days, orientation of windows, floor level, occupant gender and personal preference. The influence of each factor is examined from its correlation with the proportion of windows left open on departure, on the basis of the outdoor air temperature, which has been identified in existing studies as the most important environmental factor on window use. Suitable statistical tests, namely, the Wald statistic test and the Likelihood ratio test, are carried out to identify the influence of each analysed factor from a statistical viewpoint. Detailed information about the methods that are used to analyse factors is provided in Section 4.1.

3.3 Model Development and Validation

3.3.1 Model development

An important objective of this research project is to explore whether modelling occupants' window behaviour in non-air-conditioned buildings based on their personal preference has advantages over traditional approaches, namely, based on either the whole building population or based on sub-groups. Therefore, window behaviour models based on the three different occupant classification methods should be established, using the data collected from the field study with a consideration of influencing factors identified in the factor analysis. For the model development, logistic regression analysis, a widely used statistical approach in this research area (Rijal et al., 2007, Yun and Steemers, 2008, Haldi and Robinson, 2009b), is adopted. Logistic regression models are used to model the probability of specific event happening, such as whether the window is open or closed, with a consideration of potential influencing factors that could be either numerical or categorical. In logistic regression analysis, several tests and properties are used to interpret the regression result, including the Score test, the Wald statistic test, the Likelihood ratio test, the Nagelkerke R^2, the Classification table, and the Median effective level. Detailed description about the methods used to develop window behaviour models can be found in Section 5.1.

3.3.2 Model validation

Window behaviour models need to be validated before being used to predict the state of windows in building performance simulation. The main purpose of validating the models is to make sure that the models developed in this study have captured the underlying nature of occupants' behaviour on the end-of-day window position, so can be used to predict window state. For the model validation, occupants' use of windows in the case study building is monitored in a following year, and the validation is carried out by comparing the models' predictive performance for the observed end-of-day window positions in this year and the performance for the ones used to develop the models. The window state prediction is achieved by a stochastic prediction process based on the Bernoulli process (Bertsekas and Tsitsiklis, 2002) and the inverse function method (Fritsch et al., 1990). If the model has consistent prediction results for the two datasets, it is judged as having captured the underlying nature of occupants' behaviour on the end-of-day window position, and hence can be used in the following model implementation chapter.

3.4 Model Implementation

Window behaviour models are developed based on different occupant classification methods, and the next step is to evaluate its impact on the simulated energy performance of buildings. To do this, a two-storey example building with 20 identical cellular offices is established and the developed window behaviour models are used to predict the end-of-day window positions of all offices. As the models developed in this study are only usable for predicting the end-of-day window position, the model implementation cannot be carried out in a traditional dynamic simulation application, which needs the state of windows at the arrival and intermediate periods as well. Under this condition, a steady-state ventilation model is developed, and is used to predict the energy performance of the example building during the unoccupied night-time period only. To evaluate the impact of different occupant classification methods on the predicted energy performance of the example building, the three window behaviour models are used to stochastically predict the end-of-day window position for a hottest month in an available weather data in IES VE (IES, 2012), a commercial building performance simulation package. Then the predicted end-of-day window positions by the three models are separately applied in the steady-state ventilation model and the predicted energy performances of the example building are compared.

3.5 Summary

This chapter has presented the methods that are used in this study to achieve the aims and objectives of the research project. The case study building and the methods that are used to monitor occupants' window behaviour are introduced in detail, and this is to provide a dataset for analysing and modelling occupants' window behaviour in office buildings. The methods that are applied to analyse the influence of factors, to develop and validate window behaviour models, and to demonstrate the impact of different occupant classification methods on the predicted building energy performance are briefly introduce. Detailed description about these methods is provided at the beginning of each particular chapter in the remaining part of the thesis.

4. END-OF-DAY WINDOW POSITION

This chapter evaluates the factors that influence the state of office windows at the end of working days, based on three seasons of data collected from the case study building. The statistical analysis applied is based on the notion of a 'sample day', which is described fully in Section 4.1. A systematic approach, which addresses carefully the influence of confounding factors, is then adopted for the factor analysis carried out in the following sections. In Section 4.2, the influence of outdoor air temperature, which has been identified in many previous studies to be a significant environmental factor of window states, is investigated, using the data collected from all monitored offices. Then in Section 4.3, the degree of influence of many non-environmental factors, such as occupant gender and façade location, is investigated, beyond that of outdoor air temperature. Finally, in Section 4.4, the influence of personal preference on the end-of-day window position is analysed using the data obtained from a particular sub-group of the whole population. In the last section, Section 4.5, a summary and discussion on the implications for modelling is given.

4.1 Analysis Method

The analysis throughout has been based on the notion of a 'sample-day'. Each seasonal observation period was made over a number of days, n. The sub-scripts, $\mathrm{n_s}$, $\mathrm{n_w}$ and $\mathrm{n_{tr}}$ denote the total number of days of observation in each of the summer, winter and transitional (swing) seasons, respectively. A sample-day is defined as a day during which the office must be occupied at some points to provide actuation of the window. Therefore, if an office is occupied for 3 days out of 5, the sample-day count for that period would be 3. In this study there is no distinction made between one office being occupied for 2 days and 2 offices being occupied for only one day; both would yield a sample-day count ($\mathrm{n'}$) of 2. The sample-day count has been used to calculate a value for $\emptyset$, defined as the proportion of windows left open on departure, using,

$$\emptyset = n'_{open}/n' , \qquad (4.1)$$

where,

n'_{open} is the total number of sample-days where windows were left open on departure ($-$);

n' is the total number of sample-days in the survey ($-$).

A total of 36 people (in 36 offices) were observed over 72, 30 and 81 working days in summer, transitional and winter observation periods, respectively, namely, $n_s = 72$, $n_{tr} = 30$ and $n_w = 81$. The total number of sample-days for each period was $n'_s = 1360$, $n'_{tr} = 292$ and $n'_w = 1842$.

The outdoor air temperature, T_{out}, has been demonstrated to be a strong indicator of window operation in a number of existing studies (Warren and Parkins, 1984, Fritsch et al., 1990, Herkel et al., 2008, Zhang and Barrett, 2012, Rijal et al., 2007, Haldi and Robinson, 2009b), for both summer and winter times, and so has been adopted here as the driving variable against which $\emptyset$ is plotted in all cases.

The analysis of the individual factors presented in this study uses sub-sets of the total seasonal sample-day dataset, extracted based on the factors of interest such as occupant gender, or location of the office within the building. In order to estimate confidence in the results, the sample-day data was classified by binning the data in discrete 2K intervals of T_{out}, as used by other researchers (Nicol and Humphreys, 2004). This interval was considered to be an appropriate trade-off between capturing useful characteristics in the data and minimising the uncertainty in the analysis. In addition, each temperature bin contained at least 30 sample-days and at least 80% of the people in the study were represented in each bin. Figure 4.1 depicts the binned daily mean T_{out} values from 08:00 to 18:00, and thus gives an overview of the ambient conditions that were presented over the three observation periods used in this study. The summer and winter periods have distinctly separate mean values and as expected the transitional period overlaps both. The overlapping of summer and winter data allows seasonal differences to be evaluated.

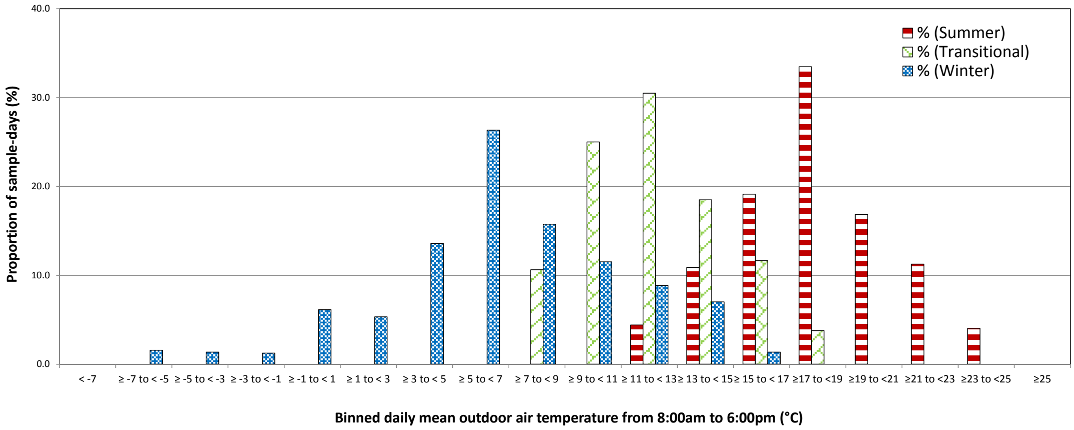


Figure 4.1: The binned daily mean values for T_{out} for each observation period.

The Wald statistic test of the logistic regression analysis is applied here (Hosmer and Lemesbow, 2000). This statistical method is reviewed fully in Section 5.1 of Chapter 5. In the Wald statistic test, the significance of a parameter, or a predictor variable, is evaluated by applying the test and determining the P-value. A value of less than 0.05 at the 95% confidence level implies that the predictor has a significant impact on the binary output of the model. Sometimes, the Wald statistic test may fail to reject the null hypothesis for specific predictors, especially when the sample size is small, resulting in the importance of a particular factor to be underestimated. Therefore, the result from another statistical test provided by the logistic regression analysis, that is, the Likelihood ratio test, is also provided in parts of the analyses, to strengthen the result of the Wald statistic test. The Likelihood ratio test is represented by two important statistical values, namely, the Change in -2Loglikelihood and the corresponding P-value. Detailed description about these two values can also be found in Section 5.1 of Chapter 5. As in Wald statistic test, a P-value less than 0.05 from the Likelihood ratio test represents the factor's influence is statistically significant.

4.2 Temperature Dependent Behaviour

It is important to benchmark the results from this study against the published results of others, in order to determine whether the window opening behaviour in this building is significantly different from other buildings that have been observed, when treated as a whole. The data points in the left hand plot of Figure 4.2 show the relationship between the observed proportion of windows left open on departure and the outdoor air temperature on departure, $\emptyset = f(T_{out})$, in the summer observation period; the mean bin value for T_{out} is used and the 95% confidence intervals are calculated by the Adjusted Wald Method (Sauro and Lewis, 2005), which is described in Appendix A. The 95% confidence interval used here represents the uncertainty that is caused by the number of samples used to calculate the proportion of each temperature bin.

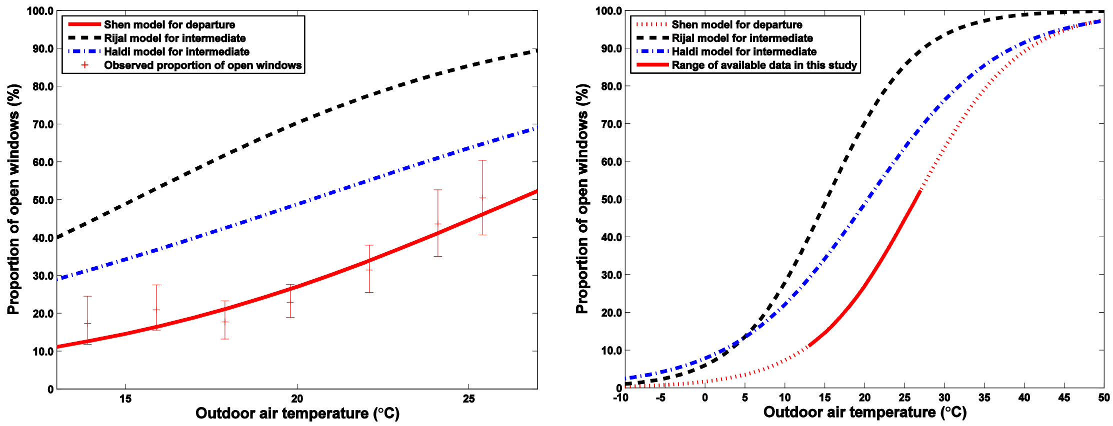


Figure 4.2: Proportion of open windows as a function of outdoor air temperature in summer, with comparisons of the data gathered in this study and the work of others.

The data demonstrates that the proportion of windows left open on departure is generally proportional to the outdoor air temperature (the Wald statistic for T_{out} is 65.593, and the corresponding P-value is 0.000), as expected. The solid line overlaid on these data points is the output from an S-shape logistic regression model generated from the summer data ($R^2 = 0.074$), given by,

$$\emptyset_{model} = \frac{e^{A+B\times T_{out}}}{1+e^{A+B\times T_{out}}}, \tag{4.2}$$

A and B in Equation 4.2 are coefficients of the logistic regression model. This model type has also been used by Haldi and Robinson (2009a) and Rijal et al. (2007) to model their data, and both are reproduced in Figure 4.2 as well, shown by the dashed line and the dot-dashed line, respectively. The model coefficients for all three models are given in Table 4.1.

Table 4.1: Coefficients for the logistic regression model.

Model	***A***	***B***
Rijal et al.	-2.76	0.181
Haldi and Robinson	-2.47	0.120
Shen et al. (Summer)	-4.09	0.155

In the right hand plot of Figure 4.2, all three models shown in the left hand plot of Figure 4.2 are presented over a wider range of outdoor air temperature, showing the S-shape characteristic of logistic regression models. It should be noted that the characteristics generated by the model presented in this thesis have been extrapolated in the right hand plot of Figure 4.2, indicated by the dotted line, and the region of the model where data was available is highlighted by the solid section of the curve. It is also worth noting that in the Midlands in the UK, temperatures above 30.0°C are rare in summer. The data in Figure 4.1 is quite typical for the region.

Comparisons in Figure 4.2 show that the observed behaviours from all three sets of observations are broadly similar in terms of their relationship with $\mathrm{T_{out}}$. This provides some evidence that the building under observation in this study is not significantly different from other buildings. One important difference, however, is that both Rijal et al. and Haldi and Robinson published observations based on window operation during normal working hours, as opposed to the end-of-day when people are departing the work place, as is the case in this study. It might be expected, therefore, that a higher probability of windows being closed at the end of the day would be observed.

Figure 4.3 shows the observed proportion of windows left open at the end of working days during the winter observation period, correlated with T_{out} using the same method as for the summer data. It can be observed that in the wintertime the proportion of windows left open on departure is not strongly affected by T_{out}, supported by the Wald statistic test (the Wald statistic for T_{out} is 2.411, and the corresponding P-value is 0.121). Other factors that have potential influences on this window behaviour will be discussed in following sections.

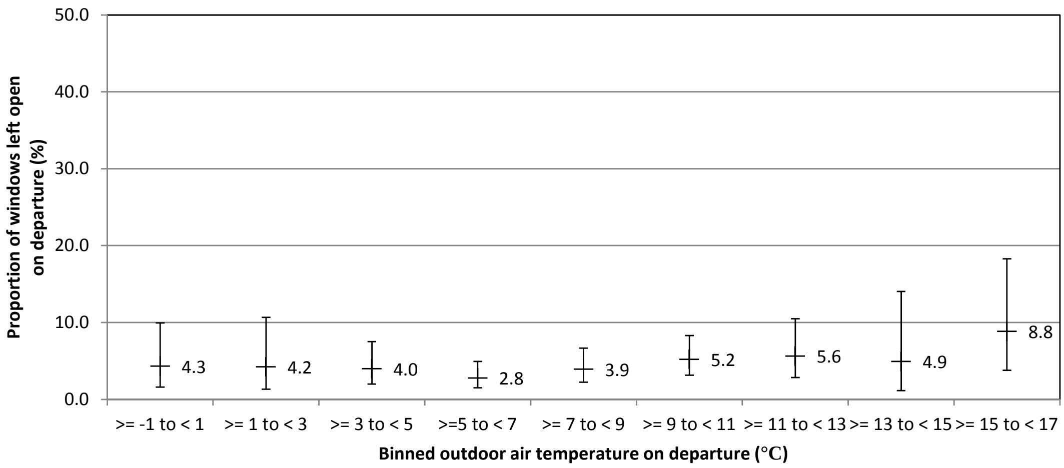


Figure 4.3: $\emptyset = f(T_{out})$ ***in the wintertime for the whole building.***

4.3 Influence of Non-environmental Factors

Table 4.2 lists 13 non-environmental factors that should be considered in studies of window behaviour in office buildings, coming from the review result introduced in Section 2.1 of Chapter 2. Some factors, such as time of day, type of windows, type of dwellings/buildings, type of the room, type of the heating system, occupant presence and shared offices, can be ignored in this study, as these properties are identical for all monitored offices. In addition, the influence of the previous state of windows can be also omitted, as the focus of this study is the state of windows at the end of the day, not occupants' window operation, i.e. whether closing or opening the window, when finally leaving offices (refer to the first modelling approach that was introduced by Haldi and Robinson (2009b), see Section 2.2.2 of Chapter 2). Furthermore, since the age range of the monitored occupants is mainly between 35 and 55 years, the influence of the occupant age has also been ignored. This is because in previous studies, people's window operation behaviour in this age range has been considered to be similar. This leaves season, the orientation of windows, floor level and occupant gender to consider. As additions to these factors, the influence of the change to daylight saving time, and occupant absence in subsequent days, has been explored. The influencing factors, both environmental and non-environmental, evaluated are placed into five classifications and are presented in Table 4.3. The classification is introduced here to provide a framework, within which window use behaviour can be investigated.

Table 4.2: Non-environmental factors having the potential to affect the end-of-day window position in office buildings.

Season	Time of day	Previous state of windows
Presence	Type of windows	Orientation of windows
Floor level	Shared offices	Type of dwellings/buildings
Type of the room	Type of the heating system	Occupant age
Occupant gender		

Table 4.3: Classification of factors having the potential to affect the end-of-day window position in this study.

Classification	Factor	Classification	Factor
Environmental	Outdoor air temperature	**Building**	Orientation of windows
	Indoor air temperature		Floor level
Seasonal, 'cultural', policy	Seasonal change	**Individual**	Occupant gender
	Change to daylight saving time		Personal preference
Operational	Absence in subsequent days		

Table 4.4: Data subsets and their use in the analysis.

Data Subsets:	**Observation Period**			**Building Feature**					**People**	
Factors (from Table 4.3)	Summer	Transitional	Winter	Ground Floor	First Floor	Second Floor	Northwest Façade	Southwest Façade	Male	Female
Seasonal change										
Change to daylight saving time										
Absence in subsequent days										
Orientation of windows										
Floor level										
Occupant gender										
Personal preference										

Eliminating the confounding factors in this type of investigation is difficult. As demonstrated in the previous section, the strong dependency of window operation on T_{out} is ever-present. Accordingly, each factor considered in this study is plotted as a function of T_{out}. Where certain factors have demonstrated a significant influence on $\emptyset$, then the indoor air temperature (on departure), T_{in}, is brought into the analysis to identify whether this could be an influencing factor on the result and is discussed where appropriate. Seasonal changes have been investigated by comparing data from the summer and winter observation periods. A more detailed consideration of the possible influence of the change to daylight saving time was also carried out using the data from the transitional observation period. Building and operational factors were explored using sub-sets of the data from the summer and winter observation periods, respectively. Finally, the 'individualistic' factors were considered. Gender and personal preference, however, were examined. For clarity, the results are presented here in a particular sequence, but have been subject to a number of iterations in order to sub-divide the data sets in such a way, so as to minimise unwanted influences from other factors. A summary of the dataset subdivision is presented in Table 4.4.

4.3.1 Seasonal effects

The sample-days count from the male-occupied offices on the first and second floors, and from both façades were utilised to maximise the available data (refer to Table 4.4). Data from summer and winter was used to compare window behaviours in different seasons; the transitional data was not used because of the changes that take place during that period (shown in Figure 3.4) and the overlap in $\mathrm{T_{out}}$ (shown in Figure 4.1). In order to remove the effect of outdoor air temperature, the same temperature bins from each season were compared, and are shown in Figure 4.4.

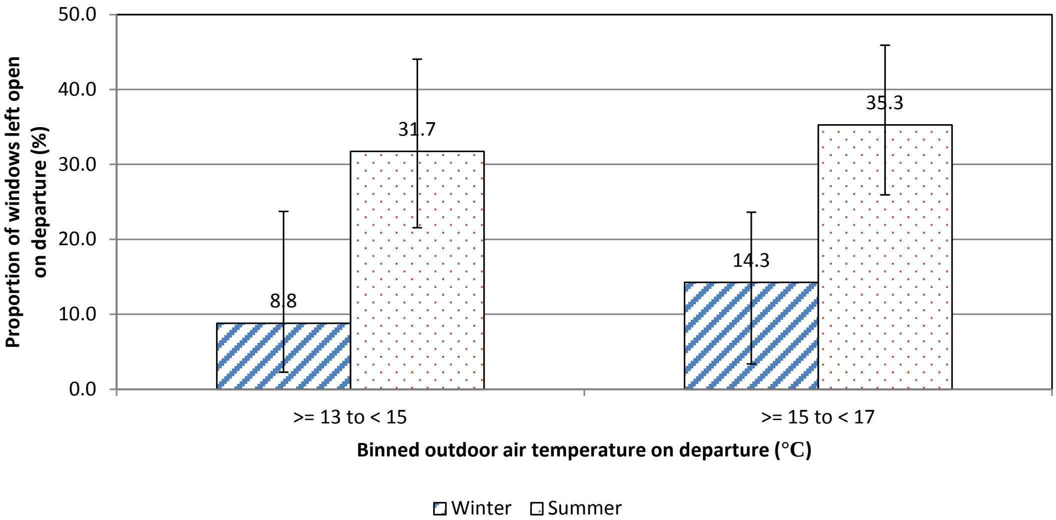


Figure 4.4: $\emptyset = f(T_{out})$***, when the binned outdoor air temperatures in summer and winter times are the same.***

Although the temperature data in Figure 4.1 indicates that there are common values in the temperature ranges $11 \leq \mathrm{T_{out}} < 13$, $13 \leq \mathrm{T_{out}} < 15$ and $15 \leq \mathrm{T_{out}} < 17$ (all values in °C), there were not sufficient *sample-days*, that is, days when the offices were occupied during the daytime, available in the lowest range for the analysis. The number of sample-days in each outdoor air temperature bin in Figure 4.4 is small and hence there is a degree of uncertainty in the data, characterised by 95% level confidence intervals included on the plot. However, the differences between summer and winter, which are greater than 10%, appear significant. Both the Wald statistic test and the Likelihood ratio test confirm this significance from the statistical viewpoint (Wald statistic test: Wald = 13.067, P-value = 0.000; Likelihood ratio test: Change in -2Loglikelihood = 13.380, P-value = 0.000).

Reasons for the behavioural difference between summer and winter times could be that people use windows less in winter than in summer during the working days, which has been observed by Herkel et al. (2008). There may also be influences from the reduction in the number of daylight hours, as during winter in the UK it is often dark when occupants leaving their working place. There could be a degree of energy consciousness amongst the building occupants, giving them a propensity to shut windows. Whilst this discussion is largely conjecture, the important point that has been demonstrated from this comparison is that it is not just the environmental conditions that affect behaviour, other factors influence people and these influences can affect the operation of a building.

4.3.2 Change to daylight saving time

Many countries, including the UK, operate daylight saving time, and so the effect of this change on the end-of-day window position was investigated. The transitional season data was used here, comprised of data recorded three weeks prior to, and three weeks after, the clock change from daylight saving time (GMT + 1h) to GMT. The building heating system was on during the whole transitional observation period. Using the data collected from the transitional observation period (male-occupied offices, first and second floors, northwest façade), the proportions of the end-of-day window position before and after the clock change were compared in Figure 4.5, as given in Figure 4.4, but the differences between the GMT + 1h and the GMT data were less than 10% and these differences had no statistical merit (Wald statistic test: Wald = 0.365, P-value = 0.545; Likelihood ratio test: Change in -2Loglikelihood = 0.366, P-value = 0.545).

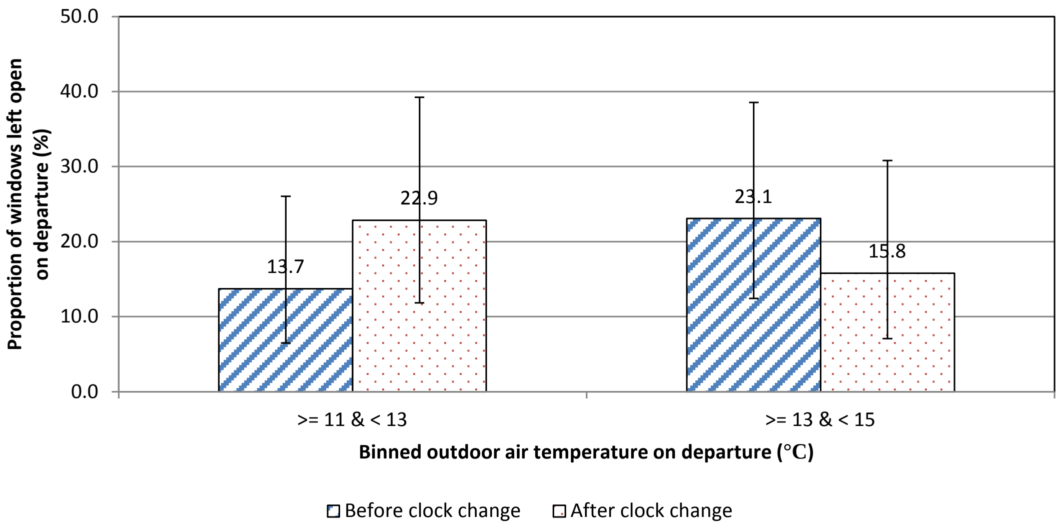


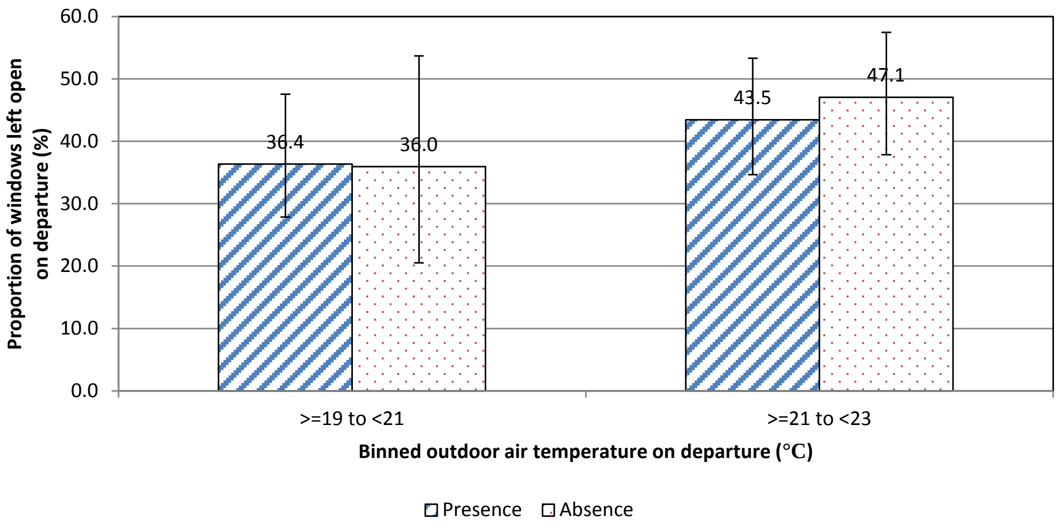
Figure 4.5: $\emptyset = f(T_{out})$***, the same binned outdoor air temperatures before and after the clock change time.***

In addition, the decreased proportion of windows left open on departure at the higher outdoor air temperature bin for the GMT period had been further explored. This is most likely because of a smaller percentage of sample-days collected from the offices whose occupants actively leave windows open overnight in that outdoor air temperature bin, compared with the lower outdoor air temperature bin (31% for the outdoor air temperature bin from 11°C to 13°C, and 24% for the outdoor air temperature bin from 13°C to 15°C), reflecting the influence from occupants' personal behavioural preference on the result. However, this decrease is not big and it does not much affect the comparison result.

To isolate any effects from the potential confounding issue of radiant field, additional measurements of the globe temperature were made in the transitional observation period to identify whether there were any changes to the heat radiation in the working space, due to the 'earlier' onset of darkness affecting glazing surface temperature. The results showed that the difference between the indoor air temperature and the indoor globe temperature was within ±0.3°C for greater than 99% of the samples, confirming observations by Nicol et al. (1999) in a thermal comfort study carried out in Pakistan, where the globe temperature is highly correlated with the air temperature indoors and the mean difference between these two values is about 0.5K. In order to identify the effect of the observed variation between the indoor air temperature and the indoor globe temperature in this study, on occupants' thermal comfort, a sensitivity analysis was carried out using the Fanger's **P**redicted **M**ean **V**ote (PMV) model (Fanger, 1970). The analysis was based on an assumption that the indoor globe temperature was the same as the mean radiant temperature, and this assumption had been validated to be applicable for applications with low air movement, which was the case at the location where the T_g was measured during the transitional observation period. The analysis result revealed that people were not sensitive to this temperature variation. When the clothing insulation level was assumed to be 1.0clo for winter, the change of PMV by this variation was about 0.06 (minimum 0.04 and maximum 0.06), indicating that the change from daylight saving time did not induce an obvious change in thermal comfort conditions in the offices. The above sensitivity analysis covered the range of indoor air temperature from 19°C to 27°C, indoor air velocity from 0.1m/s to 0.3m/s and indoor relative humidity from 40% to 80%, and with the metabolic rate set as 1.2met for sedentary work in offices (ISO, 2005).

4.3.3 Occupant absence in subsequent days

It was postulated that if occupants knew they were going to be absent from the office for one or more days, then that might affect their window closing behaviour at the end of the day, the day before the absence. To avoid any potentially confounding effects of gender and the ground floor, data collected from male occupants on the first and second floors were therefore filtered to create two batches; one where each occupant was present in his/her office the following day, and the second one where each occupant was absent the following day. Again, the data for both summer and winter was tested in a similar manner to the data shown in Figure 4.4, as shown in Figure 4.6, and no significant behavioural difference was identified in this case study building: comparing a 'normal day with presence the following day' to a 'normal day and absence the following day' was less than 5% for a given temperature range for both summer and winter times (Wald statistic test for summer: Wald = 0.243, P-value = 0.622; Likelihood ratio test for summer: Change in -2Loglikelihood = 0.243, P-value = 0.622; Wald statistic test for winter: Wald = 0.541, P-value = 0.462; Likelihood ratio test for winter: Change in -2Loglikelihood = 0.545, P-value = 0.460).



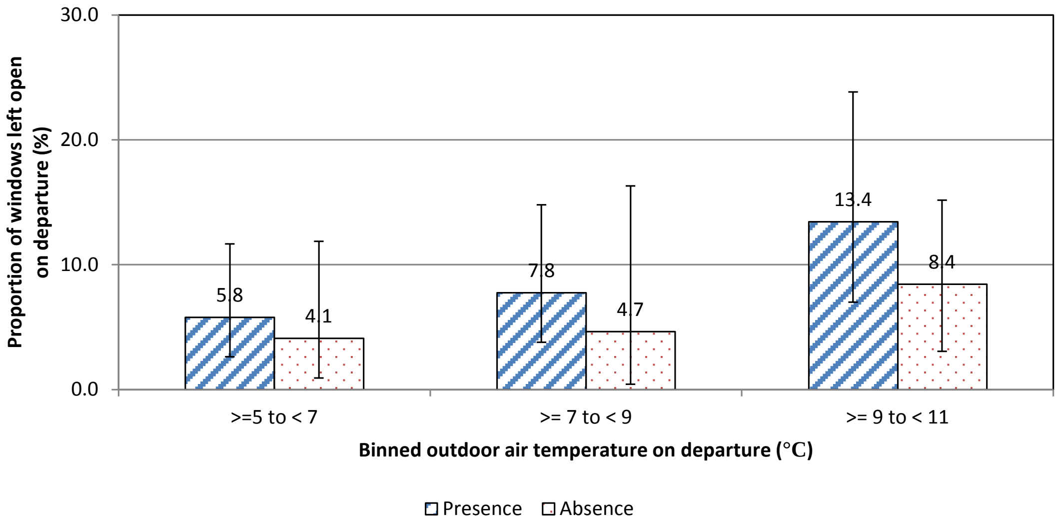


Figure 4.6: $\emptyset = f(T_{out})$***, for the presence and absence the following day for both summer (top) and winter (bottom) times.***

4.3.4 Orientation of windows

Zhang and Barrett (2012) suggested that the orientation of windows was another factor influencing occupants' window behaviour during working hours, due to influences from the solar radiation and prevailing wind direction. Based on the data collected from offices with male occupants on the first and second floors (so as to avoid any potentially confounding effects of gender and the ground floor) in the case study building, however, no evidence was found for any significant behavioural differences due to the orientation of windows, with respect to the end-of-day window position in the summertime (Wald statistic test: Wald = 1.138, P-value = 0.286; Likelihood ratio test: Change in -2Loglikelihood = 1.146, P-value = 0.284). However, for all outdoor air temperature bins, the proportions of windows left open on departure for the windows on the northwest façade were a little bit higher than those on the southwest façade, as shown in Figure 4.7.

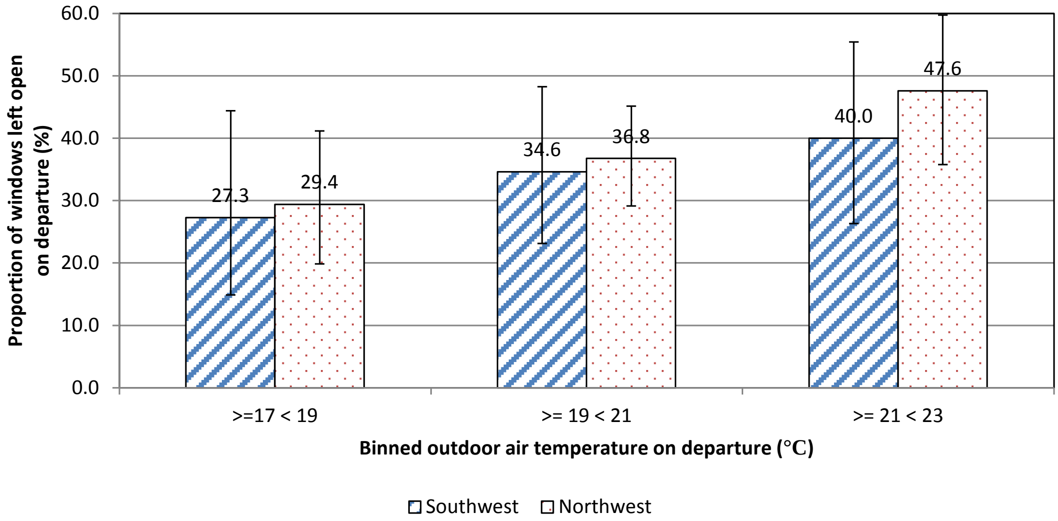


Figure 4.7: $\emptyset = f(T_{out})$***, for southwest and northwest façades for the summertime.***

For the winter period, however, significantly different patterns of the end-of-day window position for the two building façades were observed, based on the data collected from the same offices used for the summer analysis (Wald statistic test: Wald = 21.517, P-value = 0.000; Likelihood ratio test: Change in -2Loglikelihood = 49.513, P-value = 0.000), as shown in Figure 4.8. On the southwest façade, few windows were left open overnight during the winter observation period. However, there were still a number of windows (about 8% – 10%) on the northwest façade observed to be left open at the end of the working day, for all given temperature conditions. Further exploration on the monitored data revealed that more than 95% sample-days with windows left open on departure from the northwest façade were collected from two individual offices, reflecting that the influence of the orientation of windows is not general to most occupants in the building. Therefore, for the case study building, it is difficult to ascertain whether the end-of-day window position is dependent on the orientation of windows in the wintertime, which is contradicted from the conclusion drawn for the summertime. It is assumed that this behavioural difference could be due, possibly, to occupants' personal preferences, which are discussed in Section 4.4. Further work in other buildings, or in the same building with another set of occupants, is needed to strengthen the conclusion that the end-of-day window position is dependent on orientation of windows in winter.

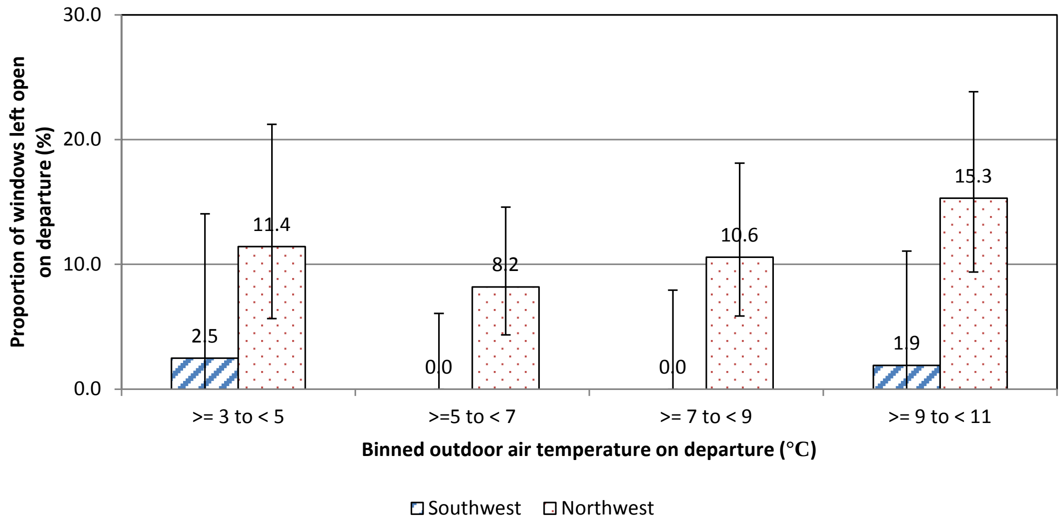


Figure 4.8: $\emptyset = f(T_{out})$***, for southwest and northwest façades for the wintertime.***

4.3.5 Floor level

Haldi and Robinson (2009a) proposed that occupants' window behaviour on departure on the ground floor is significantly different from those on other floors in office buildings. The data from our study supports this finding for both summer and winter times, as shown in Figure 4.9. The data used here was collected from offices with male occupants on the three floors (so as to avoid any potentially confounding effect of gender), and it was identified that people on the ground floor of the case study building closed their windows in the evening more often than those on the upper floors, in both summer and winter times (Wald statistic test for summer: Wald = 55.018, P-value = 0.000; Likelihood ratio test for summer: Change in -2Loglikelihood = 64.581, P-value = 0.000; Wald statistic test for winter: Wald = 13.819, P-value = 0.000; Likelihood ratio test for winter: Change in -2Loglikelihood = 57.037, P-value = 0.000). In the wintertime, few windows were left open on the ground floor after occupants had left their offices at the end of the working day.

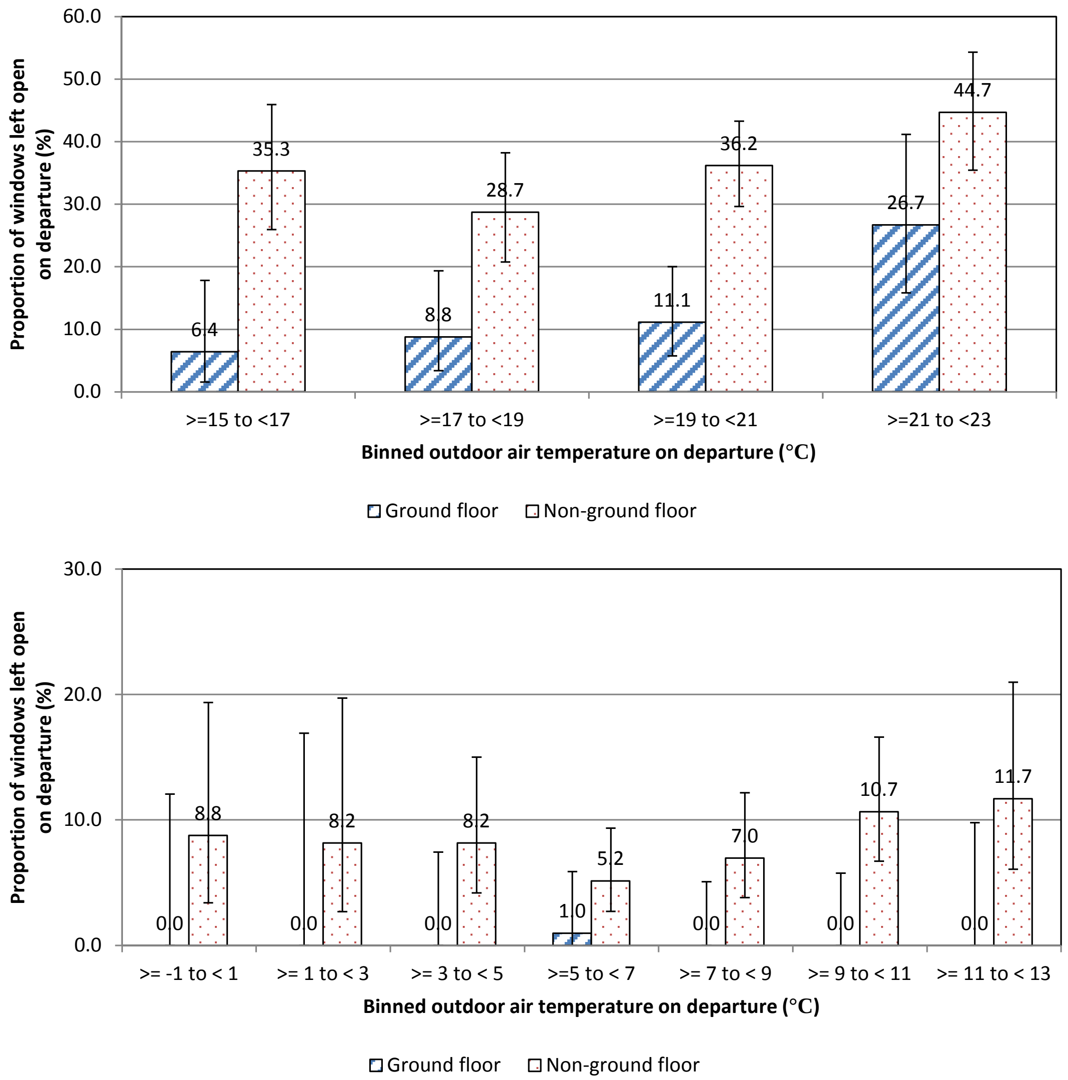


Figure 4.9: $\emptyset = f(T_{out})$***, for the ground floor and non-ground floor (1st and 2nd floors) offices for both summer (top) and winter (bottom) times.***

In this case study building, there is a noticeable difference in indoor temperatures between the offices on the ground floor and those on the upper floors throughout the year, and the first and second floors are similar in temperature (Figure 4.10 plots the internal air temperature on departure as a function of the corresponding outside air temperature, separately, for summer and winter). The difference is most likely due to a combination of a slightly higher floor to ceiling height of 3.5m on the ground floor, as opposed to 3.0m on the first and second floors; greater heat loss through larger windows (2.0m windows on the ground floor verses 1.6m windows on the upper floors), and cooler communal space at the bottom of the atrium onto which each office door opens. Therefore, the cooler indoor environment of ground-floor offices at the same outdoor temperature conditions could be a reason for their occupants choosing to close more windows at the end of the working day, when compared with those on upper floors. However, when the end-of-day window position measured in the summer observation period was binned according to the indoor air temperature on departure, and the same statistical tests between the ground & non-ground-floor offices were carried out, it was found that the difference between $\emptyset = \mathrm{f(floor\ level)}$ was still statistically significant (Wald statistic test: Wald = 13.655, P-value = 0.000; Likelihood ratio test: Change in -2Loglikelihood = 14.452, P-value = 0.000). This indicated that the measured lower indoor air temperature in the ground-floor offices was not the only possible driver of the window closing behaviour.

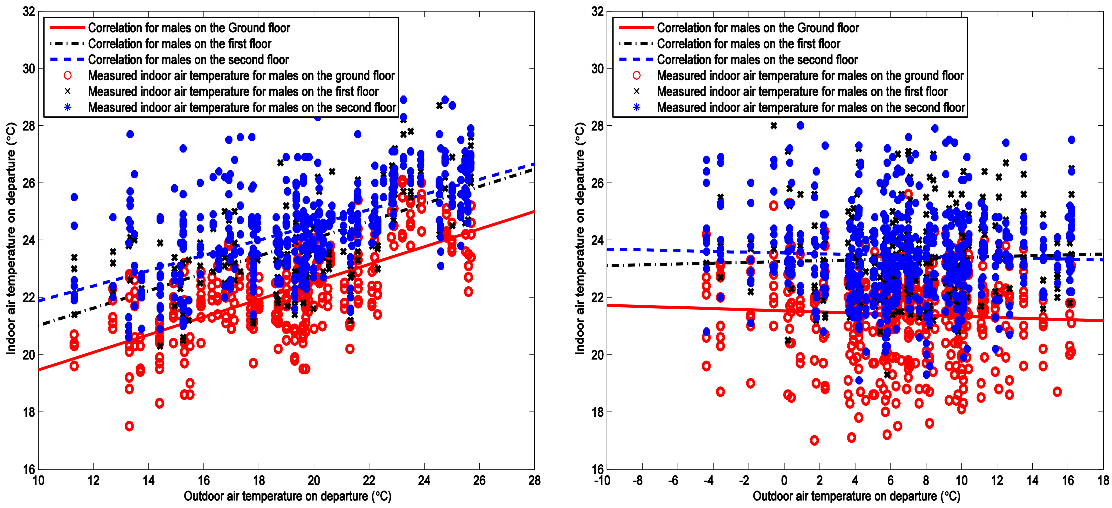


Figure 4.10:** $T_{in} = f(T_{out})$**, for the ground floor and non-ground-floor (1st and 2nd floors) offices for both summer (left) and winter (right) times.

It has been difficult to isolate the effects of these influences and, therefore, the conclusions drawn are that the ground floor in this building does influence window use. This appears to be caused by a combination of the indoor air temperature and a potential feeling of 'security', based on our observations and observations of others (Haldi and Robinson, 2009a).

Another finding from this study is that although the 'security' consideration is a likely reason that causes occupants of ground-floor offices to close their windows when leaving their offices at the end of the working day, there were still a reasonable proportion of windows on the ground floor left open during the night-time at higher temperature conditions. One comment for this is that the 'architectural mesh' (shown in Figure 3.1a in Chapter 3) surrounding the building may offer some perceived reduction in security risk. This comment is supported by the conclusion from Yun et al. that the use of night ventilation is strongly dependent on façade design and security issues (Yun et al., 2008).

4.3.6 Occupant gender

Considering the offices on the first and second floors only (so as to avoid any potentially confounding effect of the ground floor), 8 female and 18 male subjects were available for the study. Although the number of women is small, the possibility of gender as a significant factor was considered worthy of exploration. Figure 4.11 depicts the results. Gender appears to have a significant impact on the window position at the end of the working day for both summer and winter times; differences between female occupants and male occupants are more than 10% for all given temperature conditions in summer, and more than 8% for most given temperature conditions in winter (Wald statistic test for summer: Wald = 69.385, P-value = 0.000; Likelihood ratio test for summer: Change in -2Loglikelihood = 82.919, P-value = 0.000; Wald statistic test for winter: Wald = 17.879, P-value = 0.000; Likelihood ratio test for winter: Change in -2Loglikelihood = 49.961, P-value = 0.000). In addition, in the wintertime, there were nearly no windows left open overnight in the offices occupied by females.

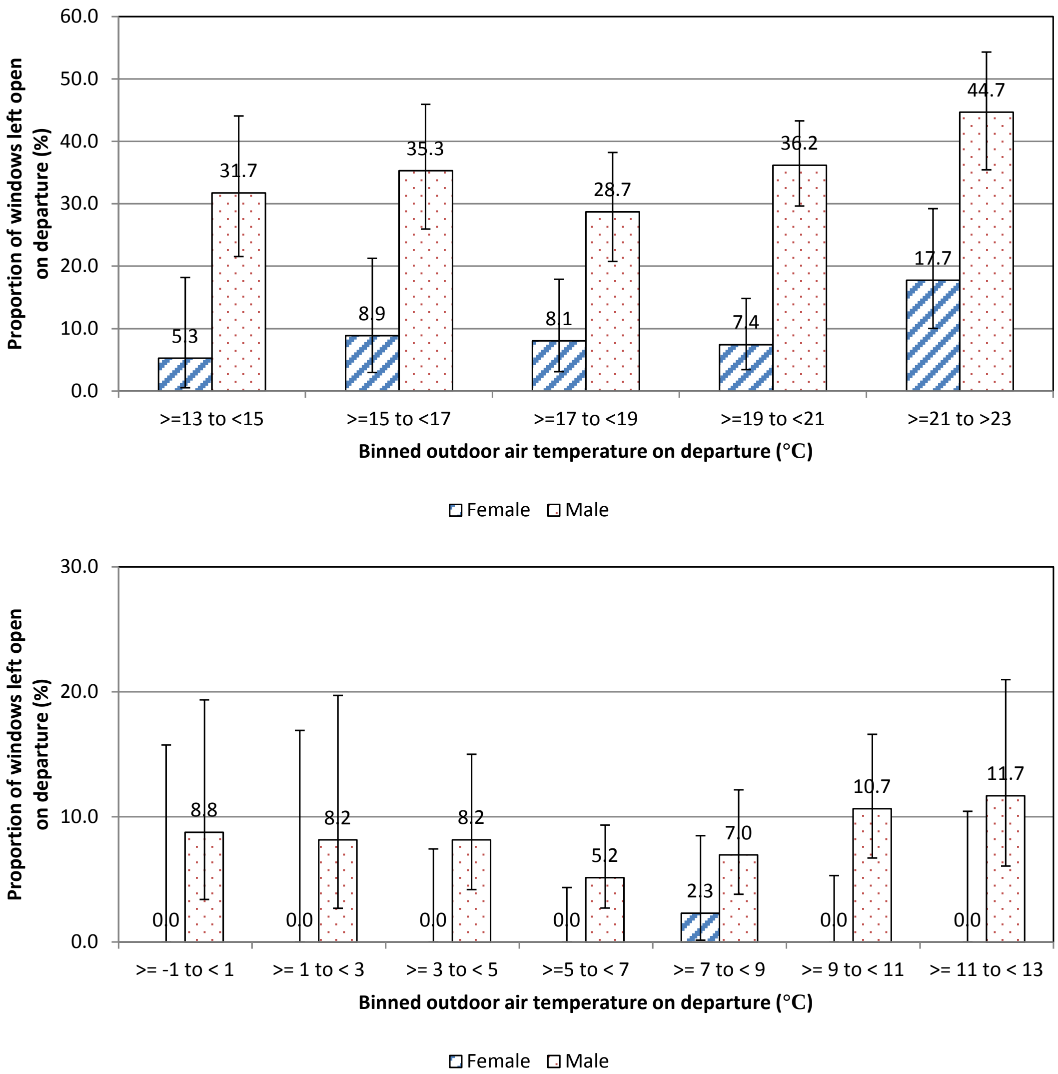


Figure 4.11: $\emptyset = f(T_{out})$***, for differences in gender for both summer (top) and winter (bottom) times.***

Figure 4.12 gives $T_{in} = f(T_{out})$ and there is little difference between the internal air temperatures in the offices occupied by males and females, and hence the internal air temperature can be considered to have no influence on the results from Figure 4.11.

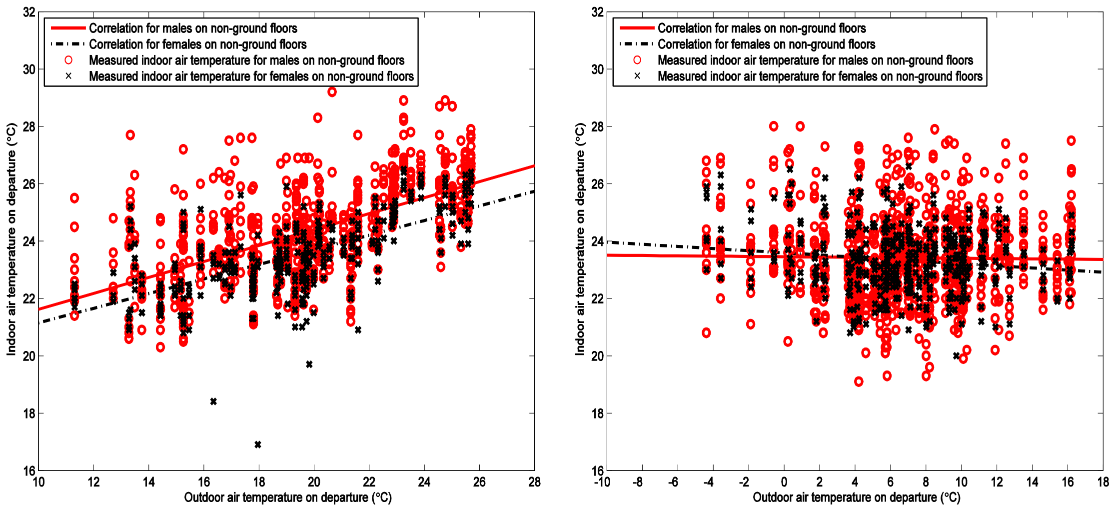


Figure 4.12:** $T_{in} = f(T_{out})$**, for differences in gender for both summer (left) and winter (right) times.

As the research presented here is the first to formally identify gender as a significant factor influencing occupants' window operation in office buildings, some previous studies are provided to support the finding that behaviour can be gender-dependent. Both Schweiker et al. (2012) and Andersen et al. (2009) have suggested that occupants' window behaviour differs between males and females in residential buildings, as already described in the Section 2.1.2 of Chapter 2. In addition, Fishman and Pimbert (1982) reported that, in commercial buildings, females had greater flexibility in choosing their clothing insulation than males. Consequently, they were able to be more tolerant of higher temperatures than men. Karjalainen (2007) carried out a quantitative interview survey to analyse occupants' use of thermostats in homes, offices and in a university. Significant gender difference (females used thermostats less in households than males did) was identified in that study. Parsons (2002) examined how people maintain their thermal comfort by adjusting clothing insulation levels, and found that females tended to make more changes of clothing insulation than the males in his experiment. The preceding discussion would support the suggestion that the gender of occupants of office buildings may have a significant impact on building operation and performance.

4.4 Personal Preference

It was observed that there were apparent differences in window positions during the night-time between individual occupants, in both summer and winter periods. Some windows were rigorously closed at the end of almost every day, whilst others would be left open across a very large range of temperature conditions; particularly apparent during the summer observation period. In this study, this difference is considered to be caused by people's personal preferences, which may be based on a number of factors. The resultant observed window behaviour is then the action that is affected by the occupants' 'personal preference'. Differences such as these have been observed previously by researchers in the summertime operation of windows at the arrival and intermediate periods of the working day (Rijal et al., 2007, Haldi and Robinson, 2009b, Yun et al., 2009). In their studies, window users have been termed 'active', 'medium' and 'passive'. These descriptors suggest that an active user is one who adjusts the window position constantly, whereas this study is more concerned with seeing if individuals leave windows open at the end of the day, or whether they close them habitually regardless of the environmental conditions. Three new descriptors are introduced here that better reflect the findings of this study. Individuals can be classified as those who:

- 'Habitually close' windows (observed to be largely independent of temperature);

- 'Leave open' windows extremely often (some dependency of action on temperature was observed); or,

- 'Adjust' windows depending on the experiencing thermal conditions (more dependent on T_{out}).

Based on the summer data gathered in this study, an attempt has been made to define these classes based on a notion of mean outdoor air temperature and by threshold setting. The approach can be repeated for other studies, so that the observed behaviours can be compared.

The mean outdoor air temperature (end-of-day) during the summer observation period was calculated as $\overline{\mathrm{T}}_{\mathrm{out}} = 19.4℃$. The sample-days with an outdoor air temperature above this were selected to identify to which classification each individual, α, belonged. The challenge is to determine the value of the thresholds used to differentiate between the classes of users. To effect this, symmetrical thresholds, θ, were used and the following rules were applied:

IF α_{i} is found with an open window more than θ% of the time, THEN $\mathrm{n}_{\mathrm{LO}} = \mathrm{n}_{\mathrm{LO}} + 1$

and,

IF α_i is found with a closed window more than θ% of the time, THEN $\mathrm{n}_{\mathrm{HC}} = \mathrm{n}_{\mathrm{HC}} + 1$

where i = 1 to 36 representing the number of rooms in the survey; n_{LO} is the number of users classified as one who 'leaves open' the window, and n_{HC} is the number of users classified as one who 'habitually closes' their windows. These counts are then normalised by the number of users (36 in this case), that is, $\psi^{\mathrm{LO}} = \mathrm{n}_{\mathrm{LO}}/36$, and then the proportion of the group who 'adjust' their windows is given by,

$$\psi^{A} = 1 - (\psi^{LO} + \psi^{HC}) \ , \tag{4.3}$$

applying the rule IF $\psi^{\mathrm{A}} < 0$ THEN $\psi^{\mathrm{A}} = 0$ (that is, IF $\psi^{\mathrm{A}} < 0$, it means individuals have been counted twice). This was done for incremental values of θ and the values are plotted in Figure 4.13. A range of potential thresholds are indicated by the vertical dashed lines that represent what has been observed, in that some individuals leave their windows open, some leave them closed and some vary. For the classification here, the centre of this range has been selected as $\theta = 80\%$.

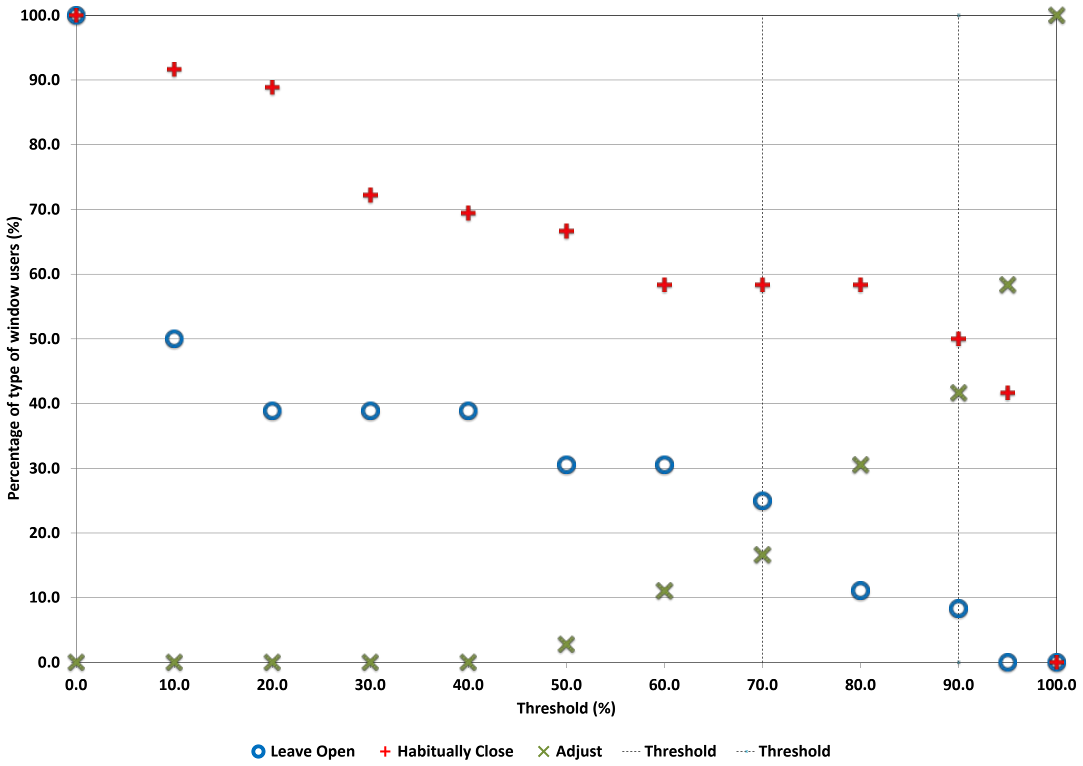


Figure 4.13: Threshold selection criteria.

Figure 4.14 shows the significantly different window use patterns between these types of window users for the summertime (Wald statistic test: Wald = 128.526, P-value = 0.000; Likelihood ratio test: Change in -2Loglikelihood = 369.104, P-value = 0.000). The above classifications were used, based only on the male subjects on the first and second floors of the case study building (so as to avoid any potentially confounding effects of gender and the ground floor). What is interesting is that there are three very different types of window users, and it was found that the temperature difference indoors between offices with different types of window users is very small; the mean difference between 'Leave Open' and 'Habitually Close' groups was 0.2K, with maximum difference of 0.3K. Therefore, this behavioural difference is proposed to be caused by individuals' personal preference, as the influences from confounding factors, namely, occupant gender, floor level and indoor air temperature, have been eliminated in the analysis. However, whether these actions are due to intent, habit or forgetfulness, is difficult to determine, but clearly a bias of one of these groups in a building could have a significant impact on the building thermal and energy performance, particularly for individual offices.

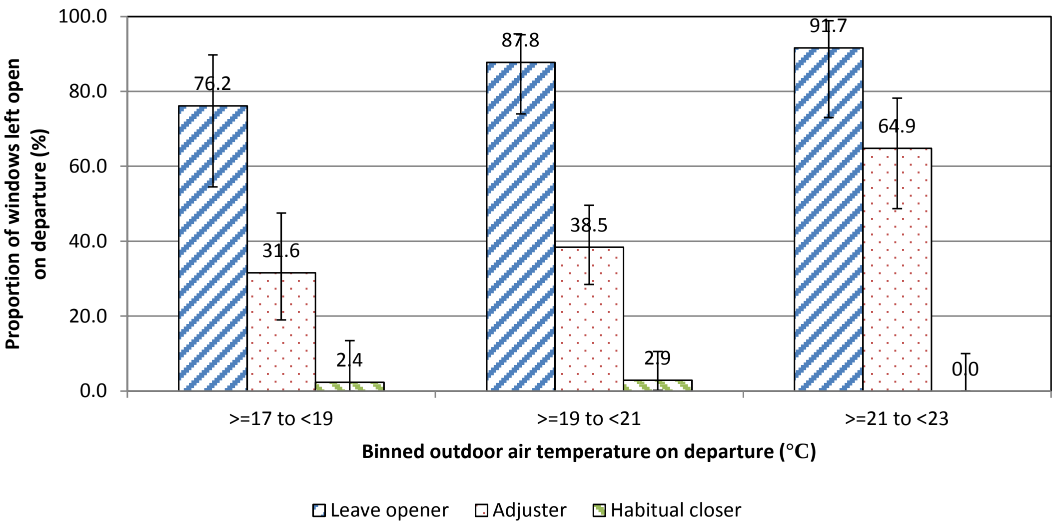


Figure 4.14: $\emptyset = f(T_{out})$***, categorised by window user type for the summertime.***

During the winter observation period, 24 occupants, 66% of the whole monitored population, closed their windows always at the end of the working day. There were 12 rooms whose windows had been found to be left open after departure, in at least one sample-day. For those 12 rooms, the number of sample-days with windows left open on departure was compared with the total number of sample-days collected, for each individual office, as shown in Figure 4.15. It can be observed that the first 10 rooms, Room 01 to Room 10, had an extremely small number of sample-days with windows left open on departure, at most 2 days. This makes an extremely small proportion in the total number of sample-days collected from each room during the winter observation period (the maximum proportion is 5.9% for the Room 06). Therefore, it can be proposed that occupants of those 10 rooms left their windows open after departure in winter unconsciously, possibly because of forgetfulness. Contrary to this, there are two rooms shown in Figure 4.16 (Room 11 and Room 12) showing obviously different window use patterns, compared with the other 34 rooms (24 always closed windows at the end of working days; 10 had been observed to leave windows open at least for one sample-day, but the proportion is extremely small compared with the total number of sample-days during the winter observation period). The windows in these two rooms were found to be left open on departure for more than 50% sample-days during the winter observation period. This suggests that their occupants seemed to intend to leave their windows open overnight in the wintertime.

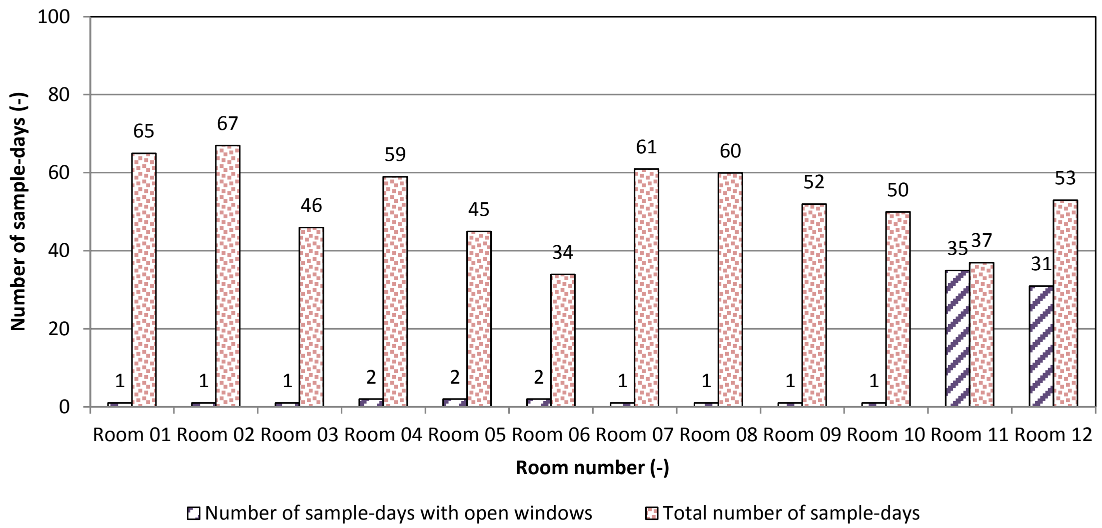


Figure 4.15: Comparisons between the number of days with windows left open on departure and the number of total sample-days for the 12 offices having at least one day with window left open overnight in winter.

In the winter observation period of this study the total number of sample-days gathered from Room 11 and Room 12 was very limited (90 days in total), as indicated in Figure 4.15. Therefore, a correlation between their occupants' window behaviour and the outdoor air temperature was impossible to be built on the basis of 2K intervals of T_{out}. An evaluation, however, of the influence of outdoor air temperature on the occupants' choices of end-of-day window positions was carried out by grouping the sample-days collected from those two rooms at every 20 sample-days, starting from the day with the lowest outdoor air temperature on departure to that with the highest. This grouping method provided a relatively reasonable number of sample-days for each outdoor air temperature bin. The result is shown in Figure 4.16, in which each outdoor air temperature bin is represented by its mean temperature of the 20 samples inside, and the vertical line shows the corresponding proportion of windows left open on departure for that bin. Although the number of sample-days in each group is small, and the temperature bin contains a large range of outdoor temperature conditions, it still reflects, to a certain extent, a trend that the window behaviour of these two occupants is generally proportional to the outdoor air temperature on departure. To strengthen this conclusion more data is needed from future studies.

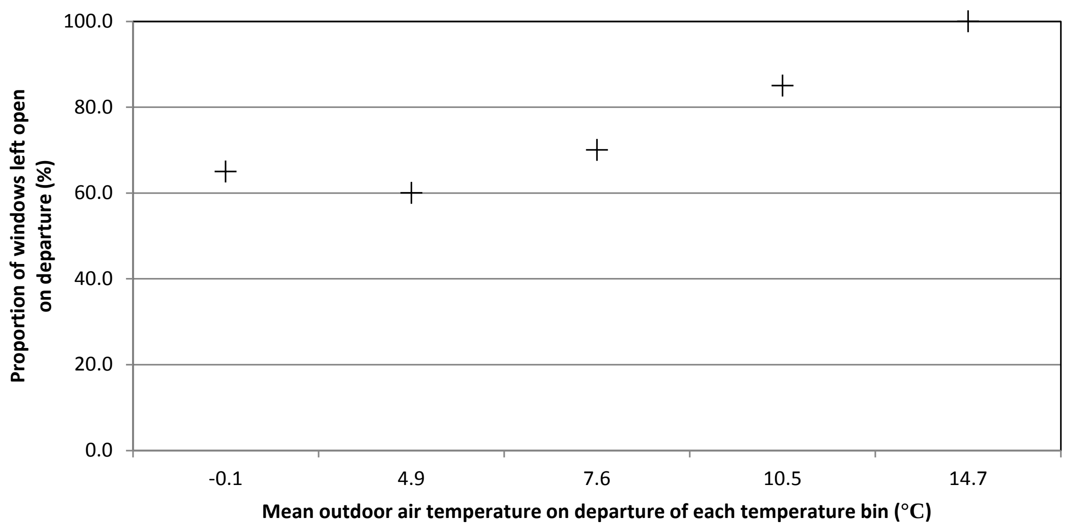


Figure 4.16: $\emptyset = f(T_{out})$***, for two special window users in the wintertime (20 sample-days in each temperature bin).***

Due to the limited number of sample-days collected from occupants who intended to leave windows open overnight, the classification of window users for the wintertime was defined on a two-level basis, namely, 'Habitual closers' and 'Intend openers', instead of three levels as for the summertime. This was to maximise the available data for behaviour analysis. The criterion for this classification is also based on a notion of mean outdoor air temperature ($\overline{\mathrm{T}}_{\mathrm{out}} = 6.9℃$) and by threshold setting (10%). Using this criterion, the occupants of Room 11 and Room 12 shown in Figure 4.15 were classified as 'Intend openers', whose window behaviour seems to be dependent on the outdoor air temperature. All the other occupants were classified as 'Habitual closers', those who close windows after departure every day, or almost every day, in the wintertime. The two rooms occupied by 'Intend openers' were all located on the second floor, and the northwest façade of the case study building, and both rooms were occupied by males. This leads to the overall behavioural differences shown in Figure 4.8, Figure 4.9 and Figure 4.11 in Chapter 4, for the analysis of the orientation of windows, floor level and gender, respectively, for the wintertime.

4.5 Summary

Chapter 4 has analysed the factors that influence the end-of-day window position of the case study building. For this building, the behaviour of the building occupants as a whole is similar to that of other researchers reported in the literature. The dependency of the state of windows on outdoor air temperature was established and then applied in the investigation on the influence of the non-environmental factors. The following factors were found to have a significant effect:

- season, which could be related to comfort, daylight hours, or a prevalence of a more energy-conscious attitude in winter;

- floor level, possibly related to a combination of indoor temperature difference and security issues;

- occupant gender, females appear more likely to close their windows at the end of the working day, when compared with males.; and finally,

- personal preference was found to play a role in the determination of window states, beyond the influence of other factors.

Although further work in a greater number of buildings is still needed to strengthen the findings of this study, the main outcome of this investigation is that there appears to be sufficient evidence to suggest that non-environmental factors may well play a role in determining the end-of-day window position. This merits further investigation. Should this be confirmed, there are important implications for the modelling and predicting of occupant behaviour in building simulations, as well as the possibility of incorporating occupants as ‘unwitting agents’ in the management of building thermal and energy performance.

5. MODEL DEVELOPMENT BASED ON WHOLE POPULATION AND SUB-GROUPS

Statistical models of window behaviour commonly fall into two categories, those that treat building occupants as a whole and those that consider sub-groups of the whole population. The former approach has been adopted by many researchers in previous studies (Herkel et al., 2008, Yun and Steemers, 2010, Rijal et al., 2007). The latter subdivides the whole population into groupings that are likely to have some influence, such as floor level (Haldi and Robinson, 2009b) and orientation of windows (Zhang and Barrett, 2012).

This chapter firstly gives an overview of the appropriate statistical modelling methods (Section 5.1) and then applies these to develop models of the window behaviour observed in the case study building (Section 5.2). The models are characterised using data collected from the observations that have been introduced in Section 3.2 of Chapter 3, and then the predictive performance of these models is tested using a second year's data gathered from the case study building (Section 5.3). Finally, a summary is given in Section 5.4.

5.1 Modelling Methods

Logistic regression analysis (Hosmer and Lemesbow, 2000) is a widely used statistical approach when modelling occupants' window behaviour in office buildings (Rijal et al., 2007, Yun and Steemers, 2008, Haldi and Robinson, 2009b). A logistic regression model defines the probability of specific event happening, such as opening a window, according to various influencing factors, such as air temperature. Therefore, the outcome variable in the logistic regression analysis should be a categorical value, which defines two or more levels, for example, 0 and 1 or 0, 1 and 2. The variables that are used to predict the outcome variable, namely, predictor variables, could be either numerical (such as temperature) or categorical (such as occupant gender), or a combination of them. In logistic regression analysis, there are no restrictions on the distributions for the predictor variables. This makes them particularly suitable for modelling behaviour or actions that result from a combination of environmental and non-environmental factors. A logistic regression model defines the probability of falling into one particular level of the outcome variable for different conditions, defined by one predictor variable (ordinary logistic regression) or a combination of several predictor variables (multiple logistic regression). Equation 5.1 represents a basic logistic equation for a two level outcome variable with several involved predictors (Hosmer and Lemesbow, 2000),

$$Logit(p_i) = ln\left\{\frac{p_i}{1-p_i}\right\} = A + B_{1,i} \times x_{1,i} + \cdots + B_{k,i} \times x_{k,i} \ , \tag{5.1}$$

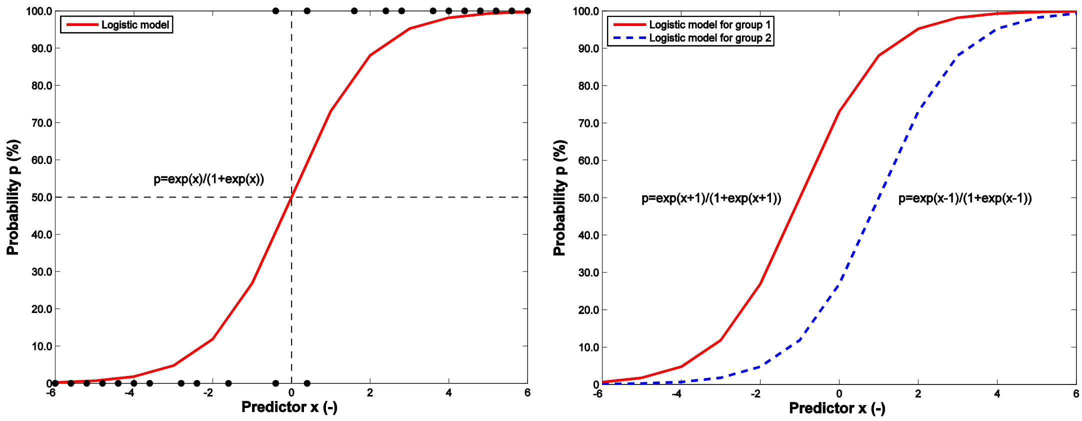
where,

p_i	is the estimated probability falling in one particular level for the i^{th} subject, in percentages (%);
A	is the intercept (a constant) (−);
$x_{1,i}$ to $x_{k,i}$	are the predictors in the logistic regression model for the i^{th} subject (−);
$B_{1,i}$ to $B_{k,i}$	are the regression coefficients for each predictor $x_{k,i}$ (−).

Equation 5.1 builds a linear relationship between the natural log of the odds and involved predictors, in which the odds is defined as the probability of being in one particular level (p_i) divided by the probability of not being in that level ($1 - p_i$). The regression coefficient of each predictor reflects the contribution of the corresponding predictor to the output probability. By solving Equation 5.1, the probability of falling into a particular level is determined by Equation 5.2,

$$p_i = \pi(x_{1,i}, \ldots, x_{k,i}) = e^{A + B_{1,i} \times x_{1,i} + \cdots + B_{k,i} \times x_{k,i}} / (1 + e^{A + B_{1,i} \times x_{1,i} + \cdots + B_{k,i} \times x_{k,i}}) \ , \tag{5.2}$$

Figure 5.1a shows how a logistic regression model fits the hypothetical binary data based on one numerical predictor. The dots in Figure 5.1a represent whether the specific event happens or does not happen (1 means happening, while 0 means not happening).



a) One numerical predictor b) A numerical and a categorical predictors

Figure 5.1: Effects of predictor type to a logistic regression model and how the model fits the hypothetical binary data.

Figure 5.1b shows how a categorical predictor performs in a logistic regression model, based on the model shown in Figure 5.1a. Generally, a categorical variable categorises the data into two or more groups. In Figure 5.1b, Group 1 and Group 2 are categorised by a two-level categorical predictor. Then specific logistic regression models are generated for each group, based on the data of that group.

In linear regression, the classical method used to fit the model to the observed data is called Least Square method. In this method, the coefficients are chosen when they make the sum of the squared deviations of the observed values from the predicted values minimum. However, this method is not applicable for the logistic regression analysis, whose outcome is generally binary. The method that is used in the logistic regression is called **M**aximum **L**ikelihood **E**stimation (MLE), through which the coefficients of predictor variables are chosen when they maximise the probability of obtaining the observed set of data. In this method, a function called the likelihood function is constructed, expressing the probability of the observed data as a function of the coefficients, and is defined in Equation 5.3 (Hosmer and Lemesbow, 2000),

$$l(B) = \prod_{i=1}^{n} \pi(x_{1,i}, \dots, x_{k,i})^{y_i} \times \left[1 - \pi(x_{1,i}, \dots, x_{k,i})\right]^{1-y_i}, \tag{5.3}$$

where B is the vector of parameters: $\mathrm{B} = (\mathrm{A_i}, \mathrm{B_{1,i}}, \dots, \mathrm{B_{k,i}})$. $\pi\,(\mathrm{x_{1,i}}, \dots, \mathrm{x_{k,i}})^{\mathrm{y_i}}$ provides the conditional probability that the model output ($\mathrm{Y} \in \{0,1\}$) equals to 1 ($\mathrm{y_i} = 1$) for given $(\mathrm{x_{1,i}}, \dots, \mathrm{x_{k,i}})$, and $\left[1 - \pi\,(\mathrm{x_{1,i}}, \dots, \mathrm{x_{k,i}})\right]^{1-\mathrm{y_i}}$ provides the conditional probability that the model output equals to 0 ($\mathrm{y_i} = 0$) for given $(\mathrm{x_{1,i}}, \dots, \mathrm{x_{k,i}})$. The log of Equation 5.3, which is called log likelihood, is commonly adopted because it is easier to operate, as defined in Equation 5.4,

$$L(B) = ln[l(B)] = \prod_{i=1}^{n}\{y_i \times ln[\pi(x_{1,i}, \dots, x_{k,i})] + (1 - y_i) \times ln[1 - \pi(x_{1,i}, \dots, x_{k,i})]\}, \tag{5.4}$$

The value of B that maximises $\mathrm{L(B)}$ is denoted as $\hat{\mathrm{B}}$, that is, the maximum likelihood estimate. It is derived by differentiating $\mathrm{L(B)}$ with respect to each parameters and then setting the resulting expressions equal to zero. These equations are called likelihood equations.

In real applications, a logistic regression analysis usually contains four main stages (Peng et al., 2002):

Overall model evaluation: examines whether the involvement of predictor variables provides a better fit to the data, when compared with an intercept-only model, also called a null model. Three statistical tests can be used to achieve this goal; the Likelihood Ratio test, the Score test and the Wald test.

Statistical test of individual predictors: evaluates the significance of the predictor variable to the outcome variable. The Wald chi-square statistic test is an inferential method in real applications. Sometimes, however, the Wald statistic test might fail to reject the null hypothesis for specific predictors, especially when the sample size is small (Bewick et al., 2005). This leads to important predictors being ignored in the logistic regression model. Therefore, it is good to import the result from another test, such as the Likelihood ratio test, to strengthen the result from the Wald statistic test.

Goodness-of-fit statistics: the Goodness-of-fit statistics assess the logistic regression model against actual outcomes. The Cox & Snell R^2 and Nagelkerke R^2 are two descriptive measures of goodness-of-fit of a logistic regression model, and the Nagelkerke R^2 is often preferred in real applications, as it covers the full range from 0 to 1, hence similar to the R^2 value (the multiple correlation coefficient), which is popularly used in the linear regression analysis.

Validations of predicted probabilities: evaluates the degree of the agreement of predicted probabilities against actual outcomes. The Classification table is an appropriate method that can be used in this stage.

These stages involve many useful statistical tests, evaluating both the contribution of individual predictors and the overall performance of the logistic regression model (Bewick et al., 2005). A brief introduction about these tests is provided here.

Score test

The Score test evaluates whether the inclusion of predictors can improve the model's fit to the actual data, compared with an intercept-only model (a model with a constant only). The value of the Score test is obtained by Equation 5.5 (Hosmer and Lemesbow, 2000),

$$ST = \frac{\sum_{i=1}^{n}(x_{1,i},\dots,x_{k,i})\times(y_i-\bar{y})}{\sqrt{\bar{y}\times(1-\bar{y})\times\sum_{i=1}^{n}((x_{1,i},\dots,x_{k,i})-\bar{x})^2}}, \tag{5.5}$$

where $\bar{\mathrm{y}} = \mathrm{n}_1/\mathrm{n}_\mathrm{t}$, in which n_1 is the total number of output with value 1, n_t is the total number of output; $\bar{\mathrm{x}}$ is the mean value of the predictor.

An easy way to interpret the result from the Score test is to use the two tailed P-value based on a chi-square distribution. Its significance is obtained by comparing the P-value with a particular significance level, such as 5% (0.05) for the 95% confidence level. If the P-value is smaller than the selected significance level, it means the Score test provides a significant statistical result, and hence indicates that the logistic regression model with predictors shows a better fitting to the data, when compared with an intercept-only model.

Wald statistic test (Wald chi-square statistic test)

The Wald statistic test is based on the Wald statistic calculated for each predictor variable in the logistic regression model, in order to test the significance of its contribution on the model output. The Wald statistic is defined as the ratio of the square of the maximum likelihood estimate of the coefficient of each predictor and its Standard Error (S.E.), as represented by Equation 5.6 (Hosmer and Lemesbow, 2000),

$$Wald_i = \frac{\hat{B}_i^2}{\widehat{SE}^2(\hat{B}_i)} , \tag{5.6}$$

The Wald statistic also has a chi-square distribution, the same as in the Score test. Therefore, a significant two tailed P-value of a particular predictor reflects that this predictor plays an important role in the logistic regression model. Contrary to this, if the P-value is insignificant, it indicates that the predictor can be deleted from the logistic regression model.

Likelihood ratio test

The Likelihood ratio test examines whether a (set of) predictor(s) improves the model fit to the real data, by comparing the change of -2ln(likelihood ratio) between two logistic regression models, one with the predictor(s) and one without. In the Likelihood ratio test the change of -2ln(likelihood ratio) is denoted as statistic G, which is calculated by Equation 5.7 (Hosmer and Lemesbow, 2000),

$$G = -2ln(likelihood\ without\ the\ variable) - (-2ln(likelihood\ with\ the\ variable)) , \tag{5.7}$$

As in the Score test and the Wald statistic test, the statistic G also follows a chi-square distribution, and a significant P-value represents that the predictor is important for the logistic regression model.

Nagelkerke R^2

The Nagelkerke R^2 is an adjusted version of the Cox & Snell R^2, covering the full range from 0 to 1, just like the multiple correlation coefficient used in the classical regression analysis (Rao, 1973). It measures the proportion of variance 'explained' by the logistic regression model, as defined in Equation 5.8 (Nagelkerke, 1991),

$$R^2 = 1 - exp\left[-\frac{2}{n}\left\{l(\hat{B}) - l(0)\right\}\right] = 1 - \left\{L(0)/L(\hat{B})\right\}^{2/n_t} , \qquad (5.8)$$

where $l(\widehat{B}) = \log L(\widehat{B})$ and $l(0) = \log L(0)$; $L(\widehat{B})$ and $L(0)$ denote the likelihoods of the estimated and the null model, respectively; n_t is the total number of samples.

Classification table

The Classification table is used to validate the predictive performance of the logistic regression model against the observed data (Hosmer and Lemesbow, 2000). This table contains the statistical results from a cross-classifying of the binary outcomes (0 or 1), using a dichotomous variable, whose values are generated based on the estimated logistic probabilities. To get the values for the dichotomous variable, a cutpoint c_l is defined and compared with each estimated probability. Commonly, the default cutpoint is set as 0.5 in the logistic regression analysis. If the estimated probability is higher than c_l, then the value of the dichotomous variable is set as 1; otherwise, it is set as 0. Finally, the estimated outcome is compared with the actual outcome obtained from the field measurement. The evaluation results contain the percentages of correct prediction of each low/high outcome conditions and the percentage of correct prediction of all samples.

Median effective level (EL_{50})

The Median effect level reflects the value of a predictor at which the predicted probability p equals 0.5 (representing 50%), that is, the two possible outcomes are equally likely (Hosmer and Lemesbow, 2000). This value enables a numerical comparison between two logistic regression models. For the logistic regression model shown in Figure 5.1a, the median effect level of predictor x is 0, at which the probability is 0.5. The EL_{50} can be directly calculated by the intercept, A, and the coefficient of the predictor, B, using Equation 5.9,

$$EL_{50} = -A/B, \tag{5.9}$$

5.2 Model Development

In this study, the logistic regression analysis was carried out in the IBM SPSS Statistics V19 (IBM, 2012). Table 5.1 lists some definitions of parameters that were used in the logistic regression analysis.

Table 5.1: Parameter definitions in the logistic regression analysis.

Name	Type	Label	Values
WINDOW_POSITION	Numeric	End-of-day window position	0: Closed 1: Open
TEMP_OUT_DEPARTURE (T_{out} in later equations)	Numeric	Outdoor air temperature on departure	N/A
GENDER	Numeric	Male or Female	0: Female 1: Male
GFLOOR	Numeric	Ground floor or Non-ground floors	0: Non-ground floor 1: Ground floor
USER_TYPE_SUMMER	Numeric	Type of window user in summer	0: Habitual closer 1: Adjuster 2: Leave opener
USER_TYPE_WINTER	Numeric	Type of window user in winter	0: Habitual closer 1: Intended opener

'Name' defines the proposed name of the variable that was considered in the logistic regression analysis; 'Type' defines the type of that variable, for example, numeric, string and date; 'Label' defines an explanation for a particular variable, acting as a reminder of that variable in the analysis procedure; and 'Values' defines the values for a categorical variable, for example, for the variable GENDER, '1' represents males and '0' is for females.

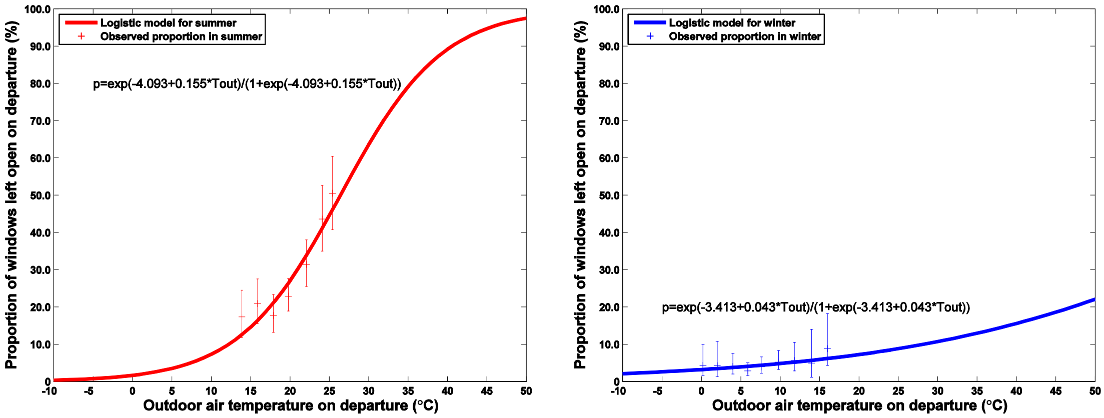
5.2.1 Model development based on whole population

From the factor analysis carried out in Chapter 4, only one whole-population non-environmental factor was identified to influence occupants' choice of end-of-day window positions, that is, Season. Therefore, two whole population models can be developed, one to represent summer behaviour and the other one for winter behaviour. The outdoor air temperature on departure (that is, at the end of the working day) is used as a predictor of the window position. The whole population models for the summer and winter times are defined by Equation 5.10 and 5.11, following the mathematical form defined by Equation 4.2 in Section 4.2 of Chapter 4.

$$p_{whole-pop\_summer} = \frac{e^{-4.093+0.155\times T_{out}}}{1+e^{-4.093+0.155\times T_{out}}}, \tag{5.10}$$

$$p_{whole-pop\_winter} = \frac{e^{-3.413+0.043\times T_{out}}}{1+e^{-3.413+0.043\times T_{out}}}, \tag{5.11}$$

Important statistical properties of these two logistic regression models are listed in Table 5.2. In Figure 5.2, these models are plotted (the summer model is plotted in the left hand image as a red solid line; the winter model is plotted in the right hand image as a blue solid line), with the observed proportions of windows left open on departure against outdoor air temperature on departure. The error bars plotted with the observed proportions in Figure 5.2 were calculated by the Adjusted Wald Method (Sauro and Lewis, 2005), representing the uncertainty due to the number of samples that were used to calculate the probability.



(a) Summer logistic regression model   (b) Winter logistic regression model

Figure 5.2: Logistic behaviour models for the summer and winter times with observed proportions of windows left open on departure for the whole building.

Table 5.2: Statistical properties of the whole population model.

		Whole population model (summer)		**Whole population model (winter)**	
Score test	χ^2	68.754		2.412	
	df	1		1	
	P-value	0.000		0.120	
Nagelkerke R^2 statistic		0.074		0.004	
% of correct prediction		74.0%		95.7%	
Variable		T_{out}	Constant (Intercept A)	T_{out}	Constant (Intercept A)
Independent variable test	**Coefficient**	0.155	-4.093	0.043	-3.413
	S.E.	0.019	0.390	0.028	0.237
	Wald	65.593	110.393	2.411	206.977
	P-value	0.000	0.000	0.121	0.000

The observed proportions of windows left open on departure in Figure 5.2a reflect that the proportion of windows left open on departure in the summertime is affected strongly by the T_{out} (Wald statistic test: Wald = 65.593, P-value = 0.000; Likelihood ratio test: Change in -2Loglikelihood = 70.841, P-value = 0.000), so the available data collected from the summer observation period is concentrated on the middle part of the developed S-shape logistic regression model (summer).

In Figure 5.2b, however, it can be observed that in winter the observed proportions of windows left open on departure are not influenced significantly by the change of the outdoor temperature conditions (Wald statistic test: Wald = 2.411, P-value = 0.121; Likelihood ratio test: Change in -2Loglikelihood = 2.443, P-value = 0.118). Consequently, the available data from the winter observation period is generally spread at the lower part of the developed S-shape logistic regression model (winter). Although the results from both statistical tests, namely, the Wald statistic test and the Likelihood ratio test, reveal that the end-of-day window position in winter is not affected strongly by T_{out} in this model type, this predictor is still kept in the winter model, due to its high importance in the prediction of window use. Section 6.1 of Chapter 6 will show how the T_{out} affects occupants' use of windows in winter.

5.2.2 Model development based on sub-groups

Section 4.3.5 and 4.3.6 of Chapter 4 have provided evidence that occupants' choice of their end-of-day window positions is dependent on both the gender of the occupant and whether they occupy the ground floor. These two sub-group factors can split the occupants in a building into four sub-groups, as presented in Table 5.3.

Table 5.3: Sub-groups of building occupants classified by gender and ground floor occupancy.

Factors	**Males**	**Females**
Ground floor	Males on the ground floor	Females on the ground floor
Non-ground floors	Males on non-ground floors	Females on non-ground floors

When both occupant gender and the ground floor are used as predictors, together with $\mathrm{T_{out}}$, to model occupants' window behaviour, using the dataset obtained in the summer survey and winter survey, two sub-group models for different seasons can be generated using logistic regression analysis, as defined by Equation 5.12 and 5.13,

$$p_{sub-group\_summer} = \frac{e^{-5.085+0.16\times T_{out}+1.49\times GENDER-1.35\times GFLOOR}}{1+e^{-5.085+0.16\times T_{out}+1.49\times GENDER-1.35\times GFLOOR}}, \tag{5.12}$$

$$p_{sub-group\_winter} = \frac{e^{-5.708+0.038\times T_{out}+3.039\times GENDER-3.748\times GFLOOR}}{1+e^{-5.708+0.038\times T_{out}+3.039\times GENDER-3.748\times GFLOOR}}, \tag{5.13}$$

Some important statistics of properties of these two logistic regression models are listed in Table 5.4.

In Equation 5.12 and 5.13, both GENDER and GFLOOR have significant influence on the state of windows, according to the testing results from the Wald statistic test (Wald statistic test for summer: Wald = 69.887 for GENDER, P-value = 0.000; Wald = 55.084 for GFLOOR, P-value = 0.000; Wald statistic test for winter: Wald = 17.880 for GENDER, P-value = 0.000; Wald = 13.820 for GFLOOR, P-value = 0.000).

As defined in Table 5.1, $\mathrm{GENDER} = 1$ is for males and $\mathrm{GENDER} = 0$ is for females; $\mathrm{GFLOOR} = 1$ represents the ground floor and $\mathrm{GFLOOR} = 0$ represents non-ground floors. When these values are substituted into Equation 5.12 and 5.13, particular sub-models can be obtained for the sub-groups that are defined in Table 5.3, for both summer and winter times. These models correlate the end-of-day window position with the outdoor air temperature on departure (following the mathematical form defined by Equation 4.2 in Section 4.2 of Chapter 4). The coefficients of these sub-models are summarised in Table 5.5.

Table 5.4: Statistical properties of the sub-group model.

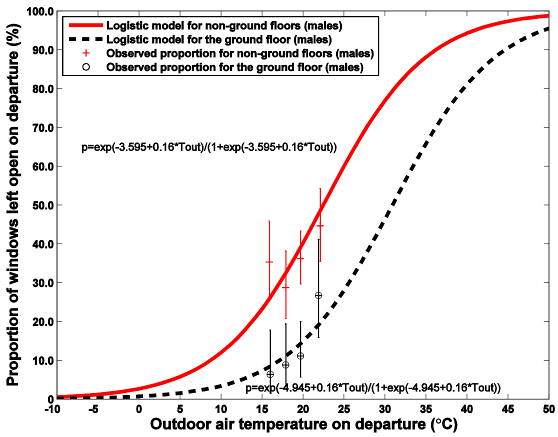
		Sub-group model (summer)		Sub-group model (winter)	
Score test	χ^2	174.727		74.304	
	df	3		3	
	P-value	0.000		0.000	
Nagelkerke R^2 statistic		0.187		0.162	
% of correct prediction		75.9%		95.7%	
Variable		T_{out}	GENDER	T_{out}	GENDER
Independent variable test	**Coefficient**	0.160	1.490	0.038	3.039
	S.E.	0.020	0.178	0.027	0.719
	Wald	63.906	69.887	1.928	17.880
	P-value	0.000	0.000	0.165	0.000
Variable		GFLOOR	Constant (Intercept A)	GFLOOR	Constant (Intercept A)
Independent variable test	**Coefficient**	-1.350	-5.085	-3.748	-5.708
	S.E.	0.182	0.442	1.008	0.738
	Wald	55.084	132.641	13.820	59.899
	P-value	0.000	0.000	0.000	0.000

Table 5.5: Coefficients for the sub-models based on $GENDER$ and $GFLOOR$.

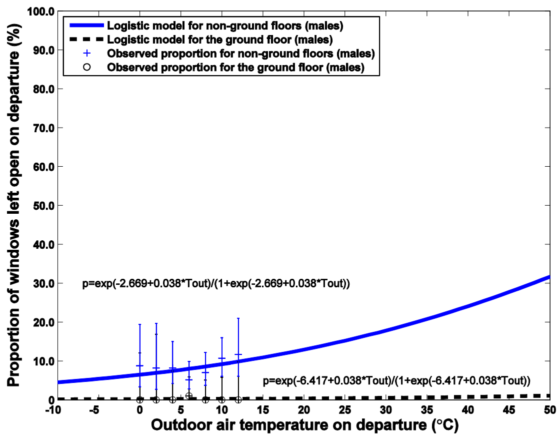
Sub-model	***A***	***B***
Sub-model for males on the ground floor (summer)	-4.945	0.160
Sub-model for females on the ground floor (summer)	-6.435	0.160
Sub-model for males on non-ground floors (summer)	-3.595	0.160
Sub-model for females on non-ground floors (summer)	-5.085	0.160
Sub-model for males on the ground floor (winter)	-6.417	0.038
Sub-model for females on the ground floor (winter)	-9.456	0.038
Sub-model for males on non-ground floors (winter)	-2.669	0.038
Sub-model for females on non-ground floors (winter)	-5.078	0.038

It is worth noting that the sub-models listed in the above table include models for females on the ground floor, for both summer and winter times. However, in the field survey, no females working on the ground floor of the case study building were monitored. Therefore, whether the inclusion of this sub-group population in the behaviour models will influence the predictive performances of Equation 5.12 and 5.13 need to be evaluated. The method used here compares the predictive performances (represented by the $\%\ of\ EMDs$ introduced in the later Section 5.3) of Equation 5.12 and 5.13 with those of the logistic behaviour models developed based on particular subsets of the whole data, namely, data collected purely from males on the ground floor, from males on non-ground floors and from females on non-ground floors. The comparison results reveal that the differences between their predictive performances are extremely small (about 0.1% for both summer and winter times). Consequently, the missing data from females on the ground floor has no obvious influence on the performance of the window behaviour models developed in this section.

Figure 5.3 plots the window behaviour models for males on the ground floor and non-ground floors, using the coefficients listed in Table 5.5, and also with the observed proportions and the corresponding error bars. The plot shows that the model for males on the ground floor is different from the model for males on upper floors, for both summer and winter times. The significance of the difference between two logistic regression models can be identified by looking at two statistical properties from the logistic regression analysis, namely, the P-value of the Wald statistic test and the Mean effective level (see Section 5.1 for detail information). The P-value of the Wald statistic test reflects the significance of the difference between two or more logistic regression models that are classified by a categorical parameter, such as the parameter GFLOOR used in Figure 5.3. The Mean Effective Level is a statistical property representing the value of the predictor, at which the predicted probability equals 0.5 (50% probability). Therefore, the difference of the mean effective levels of two or more logistic regression models can be used to quantify to which degree these models are different. In a logistic regression model with only $\mathrm{T_{out}}$ as predictors of window positions, the mean effective level represents the temperature at which half of the windows are left open on departure, and it is denoted as θ_{50} in this study. It is significant to note that the mean effective level is a property of the logistic regression model, so the θ_{50} calculated in the later analysis could possibly be outside the reasonable range of outdoor air temperatures.



(a) Summer logistic sub-models

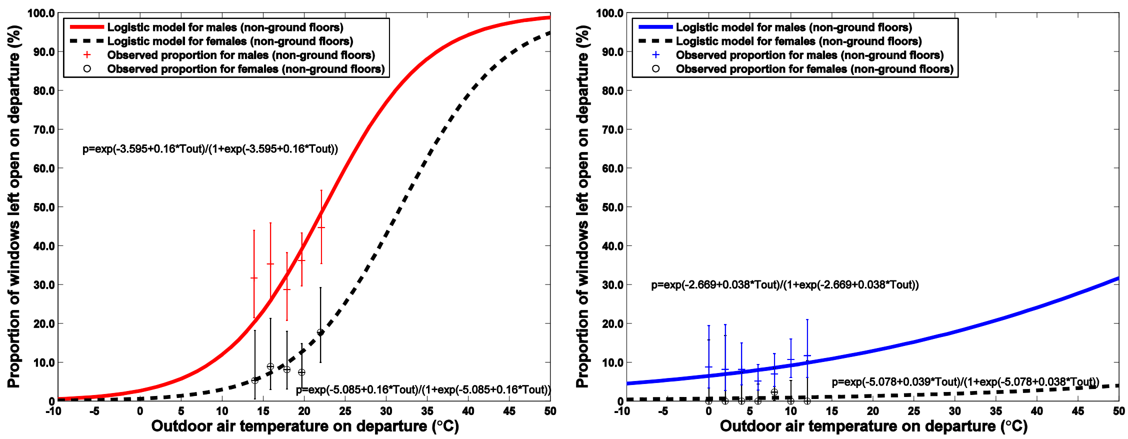


(b) Winter logistic sub-models

Figure 5.3: Logistic behaviour sub-models for male occupants classified by $GFLOOR$ for the summer and winter times, with observed proportions of windows left open on departure.

As shown in Table 5.4, the P-values of the Wald statistic test for the predictor GFLOOR for both summer and winter models are 0.000, representing that the window behaviour of occupants on the ground floor is statistically different from that of occupants on non-ground floors. To quantify the difference between sub-models, the θ_{50} of each sub-model was calculated and compared. For the summertime, the θ_{50} is 30.9°C for males on the ground floor and is 22.5°C for males on non-ground floors, with a difference of 8.4°C. For the wintertime, the θ_{50} is 168.7°C for males on the ground floor and is 70.2°C for males on non-ground floors; the difference has reached 98.5°C.

Figure 5.4 plots the sub-models for males and females on non-ground floors, together with the observed proportions and the corresponding error bars.



(a) Summer logistic sub-models (b) Winter logistic sub-models

Figure 5.4: Logistic behaviour sub-models for occupants on non-ground floors classified by GENDER for the summer and winter times, with observed proportions of windows left open on departure.

From Figure 5.4 an obvious behavioural difference between males and females (on non-ground floors only) can be observed, for both summer and winter times. As for male occupants on different floors, the P-value of the Wald statistic test and the θ_{50} of each sub-model are used here to identify the significance of the behavioural difference between males and females, on non-ground floors. For both summer and winter times, the P-values of the Wald statistic test for the predictor GENDER are 0.000, reflecting that the window behaviours between males and females are significantly different from a statistical view point. For the summertime the sub-model for males on non-ground floors has a θ_{50} of 22.5°C, and this value is 31.8°C for females on non-ground floors, with a difference of nearly 10.0°C. For the wintertime, the θ_{50} is 70.2°C for males and 133.6°C for females, all on non-ground floors, and the difference is higher than 60.0°C.

5.3 Model Validation

In the Section 5.2.1 and 5.2.2 above, whole population models and models based on sub-groups have been presented separately, based on data collected from the case study building (as introduced in Section 3.2 of Chapter 3). Outdoor air temperature has been used as a dependent variable. The data and subsequent models have been classified by season, gender and floor level. The dataset that was used to develop window behaviour models is regarded as a model development dataset.

In order to validate the performance of these window behaviour models, a second survey was carried out in the same case study building, establishing a new dataset for the validation of the models developed in this study, named as the model validation dataset. The model validation dataset contains data that was collected between 20th June and 18th September in the summer of 2011, and between 17th January and 24th March in the winter of 2012. Table 5.6 lists some properties of the model validation dataset and the model development dataset, for both summer and winter times. For the summertime, the model development dataset and the model validation dataset were collected almost at the same period of the year, that is, from the end of June to the end of September. They covered similar ranges of ambient temperature when occupants left their offices at the end of working days. In addition, the temperature range of the model validation dataset is within the range of that of the model development dataset. The wintertime temperatures are also comparable, and the model validation can encompass the conditions when the outdoor air temperature on departure is above 0°C.

Table 5.6: Properties of the model development dataset and the model validation dataset, for both summer and winter times.

	Summertime	
	Model development dataset	**Model validation dataset**
Observation period	20/06/2010 to 30/09/2010	20/06/2011 to 18/09/2011
No. of working days	72	63
No. of sample-days	1360	1130
Range of outdoor air temperature on departure	11.3°C – 26.9°C	13.0°C – 26.2°C
	Wintertime	
	Model development dataset	**Model validation dataset**
Observation period	01/11/2010 to 25/03/2011	17/01/2012 to 24/03/2012
No. of working days	76	46
No. of sample-days	1842	1089
Range of outdoor air temperature on departure	-4.4°C – 16.2°C	0.1°C – 15.9°C

In this study, the predictive performance of the developed window behaviour models was evaluated by a parameter called the percentage of exact matched days, noting as a $\%\ \mathrm{of\ EMDs}$. Table 5.7 lists four possible relationships between the predicted end-of-day window position and the observed end-of-day window position. These four relationships are then categorised into two groups to represent the possible prediction result for each prediction day, that is, either a correct predicted day or an incorrect predicted day. A correct predicted day means that the predicted end-of-day window position is the same as the observed end-of-day window position, that is, both of them are open or both are closed. Conversely, an incorrect predicted day indicates that the predicted end-of-day window position is different from the observed end-of-day window position, namely, the predicted end-of-day window position is open but the observed end-of-day window position is closed, or vice versa.

Table 5.7: Possible combinations of the predicted and the observed end-of-day window positions with the categorised prediction result.

Observed position (1 for open; 0 for closed)	**Predicted position (1 for open; 0 for closed)**	**Prediction result**
1	1	Correct predicted day
0	0	
1	0	Incorrect predicted day
0	1	

Based on the categorised prediction results that are listed in Table 5.7, the $\%\ \mathrm{of\ EMDs}$ for the whole prediction is calculated by Equation 5.14,

$$\%\ of\ EMDs = \frac{n_c}{n_t}, \tag{5.14}$$

and the two values, $\mathrm{n_c}$ and $\mathrm{n_t}$, have the following relationship,

$$n_t = n_c + n_{in}, \tag{5.15}$$

where,

$\mathrm{n_c}$ is the number of Correct predicted days ($-$);
$\mathrm{n_{in}}$ is the number of Incorrect predicted days ($-$);
$\mathrm{n_t}$ is the total number of prediction days ($-$).

5.3.1 Stochastic prediction of window state

In order to validate the window behaviour models, a stochastic approach to reproduce the observed end-of-day window positions is required. The stochastic approach applied here combines the Bernoulli process and the inverse function method.

The Bernoulli process (Bertsekas and Tsitsiklis, 2002) has been adopted widely in previous studies (Haldi and Robinson, 2009a, Rijal et al., 2007), as it is a discrete-time stochastic process dealing with a sequence of binary random variables. This method is considered to be more suitable for this study, rather than the Markov process. This is because the modelling based on Bernoulli processes makes behavioural comparisons between individual occupants easier. For each occupant, the Markov process models his/her window behaviour with a consideration of two behavioural aspects (behaviour on opening a window and behaviour on closing a window), whilst the Bernoulli process only considers one behavioural aspect, that is, the state of windows.

In a Bernoulli process, all Bernoulli variables denoted as $\mathrm{X_t}$, for time points $\mathrm{t} = \{1, \dots, \mathrm{n}\}$, are identical and independent, which means that one specific variable in a Bernoulli process is not influenced by other variables in the process. For each t, $\mathrm{X_t} \in \{0,1\}$, and $\mathrm{P(X_t = 1) = p}$. A mathematical expression of the Bernoulli process is represented by Equation 5.16,

$$P(X_{i+1} = s_{i+1} | X_i = s_i,\ X_{i-1} = s_{i-1}, \dots, X_1 = s_1) = P(X_{i+1} = s_{i+1}) = p\ , \qquad (5.16)$$

where $\mathrm{i} = \{0, \dots, \mathrm{t} - 1\}$, representing each step in the Bernoulli process, and s is the outcome state of each time step. In building performance simulation, the process P can be considered as the dynamic time series of the simulation period.

The independence of all Bernoulli variables implies that the Bernoulli process is memoryless: the next state, $\mathrm{s_{i+1}}$, is only dependent on the condition at that particular state, without any consideration of the current state and past states. This memoryless property is considered to be suitable for this study, as the prediction process considered in this study is not built on a continuous time scale (only treating the state of windows at the end of the day).

The prediction of the end-of-day window position for each time step within the Bernoulli process is achieved by the inverse function method (Fritsch et al., 1990), using the modelled probability distribution functions generated by the logistic regression analysis. In this method a random number generator with a uniform distribution between 0 and 1 ($\mathrm{U}(0,1)$) is needed. For every time step in the prediction, the generated random number, which is between 0 and 1, is compared with the probability distribution functions. If the random number is within the range of the probability of a window to be left open on departure, the end-of-day window position is set as open for that time step; otherwise it is set as closed.

A computational algorithm predicting the end-of-day window position has been implemented in Matlab (**Mat**rix **Lab**oratory) and is described here:

Stage 1: Initialisation

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

Stage 2: Reading inputs

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

Stage 3: Probability calculation and Random number generation

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

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

Stage 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 prediction day is set as open

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

Stage 5: Prediction forward

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

Stage 1 is purely initialisation. Stage 2 reads input variables that are obtained from either building performance simulation (if the algorithm is embedded in the simulation process), or from a predefined file (if the algorithm is working as a third party tool for the simulation process). The latter method is adopted in this study. In Stage 3, two numerical values are generated. The first value is the probability of the window to be left open on departure for the prediction day ($\mathrm{p_{open}}$), calculated by substituting the essential inputs obtained in Stage 2 to the logistic behaviour model. The second value is a random number ($\mathrm{p_{random}}$), which is generated stochastically based on a continuous uniform distribution from 0 to 1 (Park and Bera, 2009). In Stage 4, the end-of-day window position is predicted/determined according to the relationship between $\mathrm{p_{open}}$ and $\mathrm{p_{random}}$, that is, if $\mathrm{p_{random}} \leq \mathrm{p_{open}}$, then the end-of-day window position for this prediction day is set as open; OTHERWISE, it is set as closed. Apparently, a higher $\mathrm{p_{open}}$ provides a higher probability to set the window state as open in the prediction. Finally, in Stage 5, the prediction process checks whether the prediction has reached the end, and, if not, the process will move to the next prediction day.

5.3.2 Validation of summertime models

Figure 5.5 compares the $\%\ \mathrm{of\ EMDs}$, when the whole population model and the sub-group model developed for the summertime are used to reproduce the observed end-of-day window position, in both the model development dataset and the model validation dataset, for the summertime.

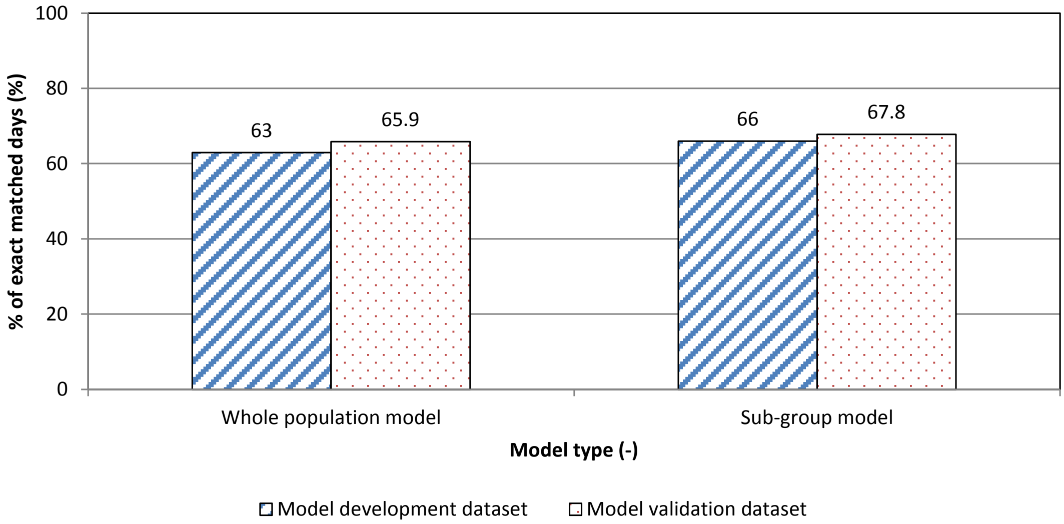


Figure 5.5: Validation results for the whole population model and the sub-group model (summer).

Figure 5.5 shows that the two window behaviour models developed in Section 5.2.1 and 5.2.2 for the summertime provide consistent prediction results using the two different datasets (the variations of the $\%\ \mathrm{of\ EMDs}$ between the two datasets are all less than 3%), when all sample-days from the field studies are considered. This implies that the whole population model, and the sub-group model, for the summertime have captured the underlying nature of occupants' behaviour on the end-of-day window position.

Usually, when validating a model, it would be expected that the prediction result based on the data used to develop the model would be better than the prediction based on the validation dataset. However, this is not the case in this study, as the model appears to represent the validation dataset better. In Table 5.8, it can be seen that for both models, the predictions for Habitual closers are similar for both datasets. The predictions for Adjusters and Leave openers, however, appear to be better for the validation dataset (generally greater than 1%). Figure 5.6 illustrates the whole population model (red-solid line) and the observed proportions of windows left open on departure for both the Adjuster and Leave opener groups. It can be seen that the observed proportions in the model validation dataset (blue stars) are closer to the whole population model, when compared with the observed data used to train the model (black crosses). This causes the reported results to appear to be counter intuitive. This explanation also applies to the sub-group models.

Table 5.8: Predictive performances of the whole population model and the sub-group model for different types of window users for summer.

% of EMDs for Habitual closers

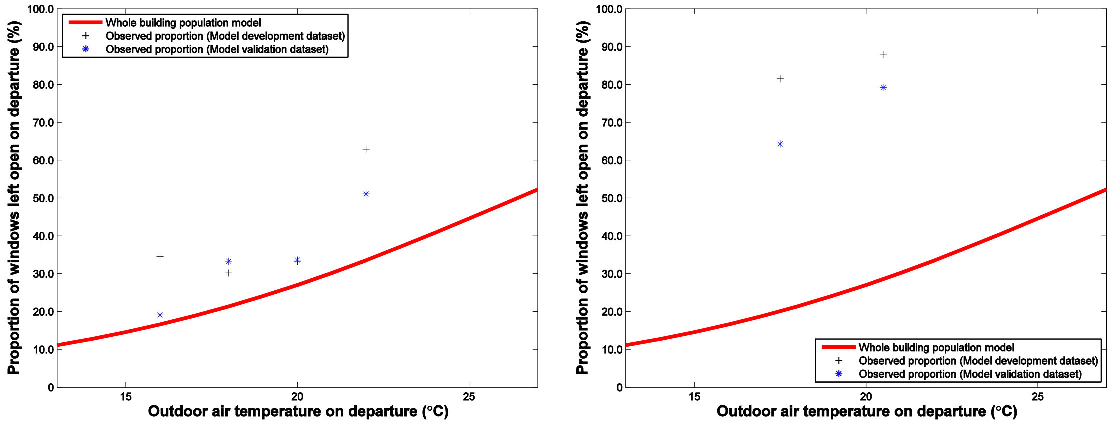
	Whole population model	**Sub-group model**
Model development dataset	73.5%	76.4%
Model validation dataset	73.5%	76.0%

% of EMDs for Adjusters

	Whole population model	**Sub-group model**
Model development dataset	55.1%	56.5%
Model validation dataset	58.7%	58.6%

% of EMDs for Leave openers

	Whole population model	**Sub-group model**
Model development dataset	35.3%	43.4%
Model validation dataset	41.0%	47.9%



(a) Adjusters (b) Leave openers

Figure 5.6: The whole population model with the observed proportions of windows left open on departure in two datasets for different window users in summer.

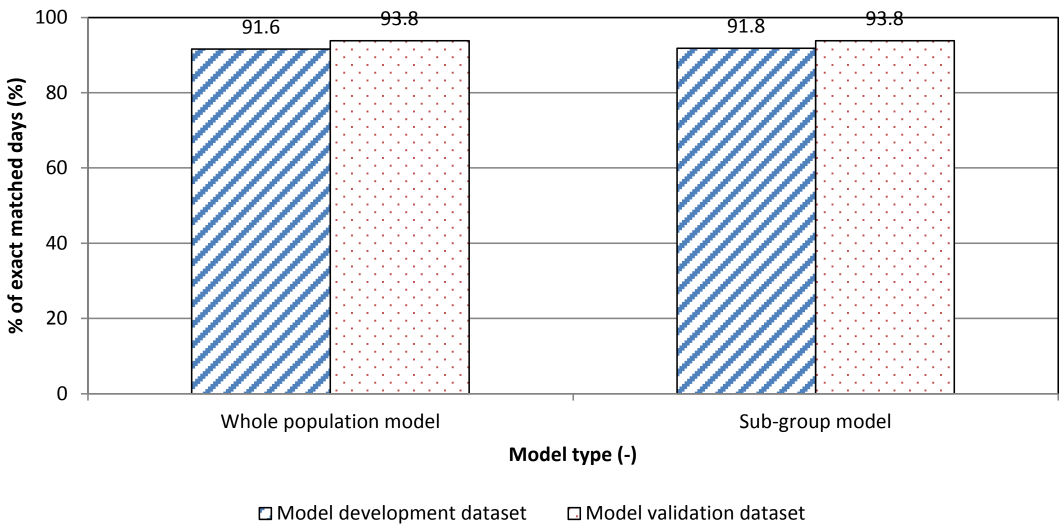


Figure 5.7: Validation results for the whole population model and the sub-group model (winter).

5.3.3 Validation of wintertime models

Figure 5.7 compares the predictive performances of the whole population model and the sub-group model that were developed for the wintertime. The figure shows that the whole population model and the sub-group model for the wintertime also provide almost equivalent prediction results, based on both the model development dataset and the model validation dataset. The variations of the $\%\,\mathrm{of\,EMDs}$ for the two datasets are less than 3%, when all occupants are considered as a whole. Here it is considered that the developed models for the wintertime have captured the underlying nature of occupants' choice of end-of-day window positions.

5.4 Summary

In this chapter two window behaviour models have been generated, one based on whole building population and the other one based on sub-groups within the building. Models were generated for summer and winter times, respectively, using statistical methods. Both models have been validated with a new dataset established by a following-year data collected from the case study building, and have been shown to capture the underlying nature of occupants' behaviour of window operation. These models represent current practice and provide the basis on which to evaluate the preference-based approach described in the following chapter.

6. MODEL DEVELOPMENT BASED ON PERSONAL PREFERENCE

It was shown in Section 4.4 of Chapter 4 that occupants' personal preference relating to window use plays a role in determining the end-of-day window position, beyond the influences of occupant gender and floor level. Also in that section, three types of window users, namely, Habitual closers, Adjusters and Leave openers, were defined for the summertime, and two types of window users, namely, Habitual closers and Intend openers, were defined for the wintertime. These classifications were based on the observed behaviour for each office falling into one of these categories, defined by a temperature threshold and on the probability of an event occurring (either windows being open or closed).

In Chapter 5 two window behaviour models were generated, using the current modelling approaches, that is, based on the whole building population and grouping data from sub-groups for the modelling. As occupants' observed preference has been demonstrated to influence window behaviour, beyond the factors that are used in the current modelling approaches, it is important to evaluate whether grouping the monitored data based on personal preference increases the accuracy of modelling window behaviour. In Section 6.1, therefore, a window behaviour model based on occupants' personal preference and outdoor air temperature is developed, for the summer and winter times, respectively, and validated. Section 6.2 evaluates the performance of the new modelling approach with conventional approaches. Section 6.3 discusses the advantages and limitations of modelling the end-of-day window position using a preference-based approach.

6.1 Model Development and Validation

6.1.1 Model development

Logistic regression models are characterised using the classified data, with outdoor air temperature as a driving variable, and splitting the data into winter and summer subsets. Equations 6.1 and 6.2 define the preference model for the summer and winter times, respectively, using parameters that are defined in Table 5.1 in Section 5.2 of Chapter 5.

$$p_{Preference\_summer} = \frac{e^{-8.582+0.244\times T_{out}+3.632\times USER\_TYPE\_SUMMER(1)+5.946\times USER\_TYPE\_SUMMER(2)}}{1+e^{-8.582+0.244\times T_{out}+3.632\times USER\_TYPE\_SUMMER(1)+5.946\times USER\_TYPE\_SUMMER(2)}}, \quad (6.1)$$

$$p_{Preference\_winter} = \frac{e^{-5.712+0.105\times T_{out}+6.074\times USER\_TYPE\_WINTER}}{1+e^{-5.712+0.105\times T_{out}+6.074\times USER\_TYPE\_WINTER}}, \quad (6.2)$$

According to the definitions in Table 5.1, the variable USER_TYPE_SUMMER defines the three types of window users in the summertime, namely, Habitual closers, Adjusters and Leave openers. To classify these three user types in one logistic model, two dummy variables, USER_TYPE_SUMMER(1) and USER_TYPE_SUMMER(2), are generated in Equation 6.1, following the definitions in Table 6.1.

Table 6.1: Definitions of dummy variables for the $USER\_TYPE\_SUMMER$.

	USER_TYPE_SUMMER(1)	**USER_TYPE_SUMMER(2)**
Habitual closers	0	0
Adjusters	1	0
Leave openers	0	1

Some important statistics of properties of these two logistic regression models are listed in Table 6.2.

Table 6.2: Statistical properties of the Preference model.

		Preference model (summer)		Preference model (winter)	
Score test	χ^2	626.683		1102.046	
	df	3		2	
	P-value	0.000		0.000	
Nagelkerke R^2 statistic		0.600		0.656	
% of correct prediction		87.0%		98.0%	
Variable		T_{out}	Constant (Intercept A)	T_{out}	Constant (Intercept A)
Independent variable test	Coefficient	0.244	-8.582	0.105	-5.712
	S.E.	0.027	0.628	0.041	0.452
	Wald	81.191	186.757	6.520	159.886
	P-value	0.000	0.000	0.011	0.000
Variable		USER_TYPE_SUMMER(1)		USER_TYPE_WINTER	
Independent variable test	Coefficient	3.632		6.074	
	S.E.	0.255		0.390	
	Wald	202.135		242.401	
	P-value	0.000		0.000	
Variable		USER_TYPE_SUMMER(2)		N/A	
Independent variable test	Coefficient	5.946		N/A	
	S.E.	0.362		N/A	
	Wald	269.708		N/A	
	P-value	0.000		N/A	

From the P-values of the Wald statistic test, it can be found that personal preference performs a significant contribution to the binary outcome, that is, end-of-day window position (either open or closed), for both winter and summer times (Wald statistic test for summer: Wald = 202.135 for $\mathrm{USER\_TYPE\_SUMMER(1)}$, P-value = 0.000; Wald = 269.708 for $\mathrm{USER\_TYPE\_SUMMER(2)}$, P-value = 0.000; Wald statistic test for winter: Wald = 242.401 for $\mathrm{USER\_TYPE\_WINTER}$, P-value = 0.000).

According to the definitions in Table 6.1, for the summertime:

- when both $\mathrm{USER\_TYPE\_SUMMER(1)}$ and $\mathrm{USER\_TYPE\_SUMMER(2)}$ are 0, the window behaviour model is for Habitual closers;

- when $\mathrm{USER\_TYPE\_SUMMER(1)} = 1$ and $\mathrm{USER\_TYPE\_SUMMER(2)} = 0$, it is for Adjusters; and,

- when $\mathrm{USER\_TYPE\_SUMMER(1)} = 1$ and $\mathrm{USER\_TYPE\_SUMMER(2)} = 1$, it is for Leave openers.

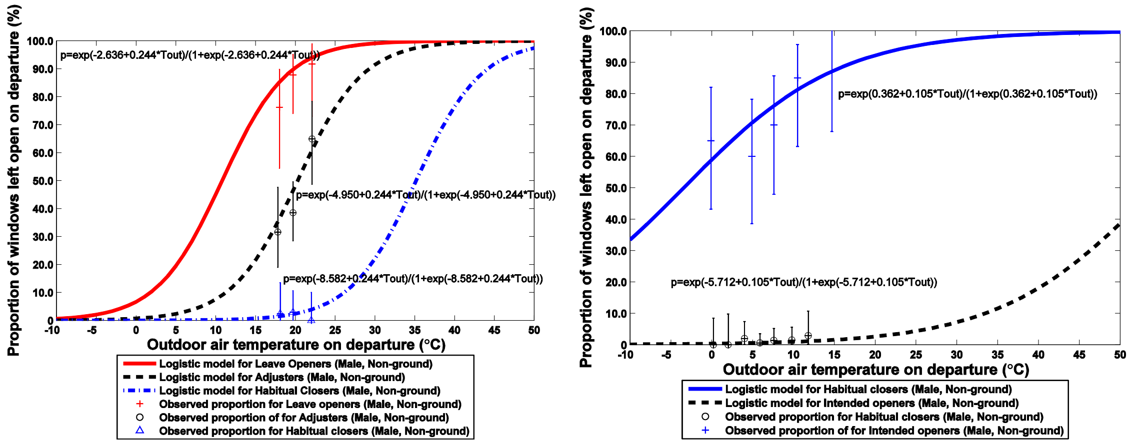
For the wintertime, as defined in Table 5.1 in Section 5.2 of Chapter 5, $\mathrm{USER\_TYPE\_WINTER} = 1$ represents Intend openers and $\mathrm{USER\_TYPE\_WINTER} = 0$ means Habitual closers (according to the definitions in Table 5.1). After substituting these values into Equation 6.1 and 6.2, particular sub-models are obtained for each type of window users, correlating their window behaviour with the outdoor air temperature on departure (following the mathematical form defined by Equation 4.2 in Section 4.2 of Chapter 4). The coefficients of these sub-models are summarised in Table 6.3.

Table 6.3: Coefficients for the sub-models based on window user type.

Sub-group model	***A***	***B***
Sub-model for Habitual closers (summer)	-8.582	0.244
Sub- model for Adjusters (summer)	-4.950	0.244
Sub-model for Leave openers (summer)	-2.636	0.244
Sub-model for Habitual closers (winter)	-5.712	0.105
Sub-model for Intend openers (winter)	0.362	0.105

The development of the above preference model was based on the whole dataset, combining the data from different sub-groups of the whole building population. This combination enables the later comparison among the three developed models as they are developed using the same dataset. However, it ignores the influences of sub-group factors, such as GENDER and GFLOOR, on the modelling accuracy. This data combination was based on an assumption that the window use patterns of the same type of window user were similar, regardless of their gender or their location within the building. For example, Habitual closers of males on non-ground floors have similar window use patterns when compared with those of females on non-ground floors. This assumption had been validated to be reasonable by comparing the behavioural difference of each type of window user in different sub-groups, either males on the ground floor, males on non-ground floors or females on non-ground floors. Logistic regression analysis was used, and the results shown that GENDER and GFLOOR had no statistical merit on the modelling.

Figure 6.1 plots the sub-models for various types of window users in the same diagram (the summer models are plotted in the left hand image; the winter models are plotted in the right hand image), in order to visualise the influence of personal preference on window behaviour; with the observed proportions and the corresponding error bars representing the uncertainty due to the number of samples used for the proportion calculation.



(a) Summer logistic regression models (b) Winter logistic regression models

Figure 6.1: Sub-group models for various types of window users for the summer and winter times with observed proportions of windows left open on departure.

Comparisons between the sub-models shown in the above figure reveal clearly different window use patterns between various types of window users, for both summer and winter times. As for the sub-group model discussed in Section 5.2 of Chapter 5, the P-value of the Wald statistic test and the models' θ_{50} (the Median effective level of the sub-models) are used to identify the significance of the behavioural difference between types of window users. For the summertime, the P-values of the Wald statistic test for both $\mathrm{USER\_TYPE\_SUMMER(1)}$ and $\mathrm{USER\_TYPE\_SUMMER(2)}$ are 0.000, reflecting the window behaviour for the classified types of window users is statistically different. In order to quantify this difference, the θ_{50} of the logistic regression models for Habitual closers, Adjusters and Leave openers were calculated individually, for the summertime. These are 35.2°C, 20.3°C and 10.8°C, with minimum temperature difference of 9.5°C. For the wintertime, the P-value of the Wald statistic test for $\mathrm{USER\_TYPE\_WINTER}$ is 0.000, demonstrating that the window behaviour of Habitual closers is statistically different from that of Intend openers. In addition, the θ_{50} of the logistic regression model for Habitual closers in winter is 54.4°C, whilst it is -3.4°C for Intend openers; indicating significantly large temperature differences.

6.1.2 Model validation

Figure 6.2 and 6.3 compare the $\%\ \mathrm{of\ EMDs}$ when the preference models are used in the statistical approach, introduced in Section 5.3.1 of Chapter 5, to reproduce the observed end-of-day window positions in both the model development dataset and the model validation dataset, for the summer and winter times, respectively.

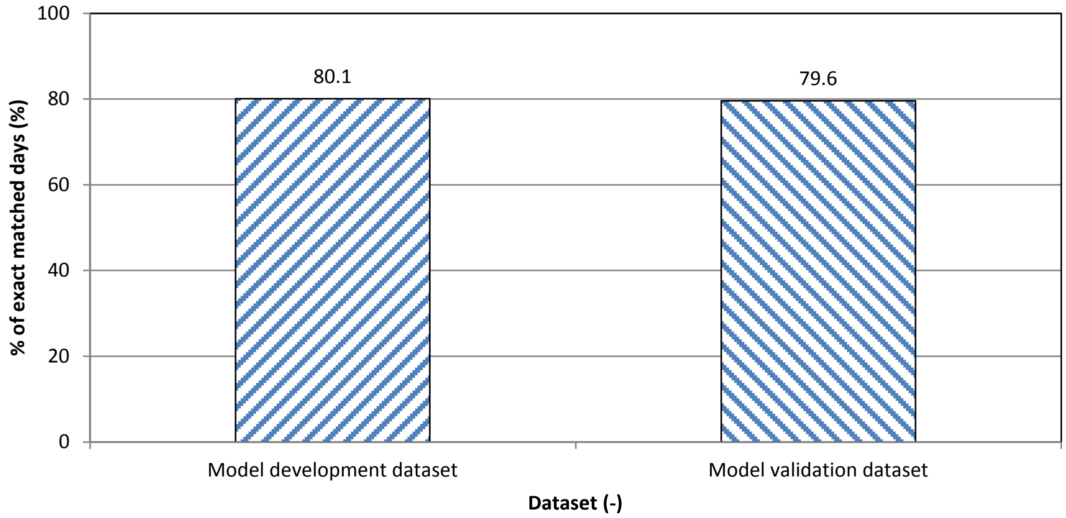


Figure 6.2: Validation result for the preference model (summer).

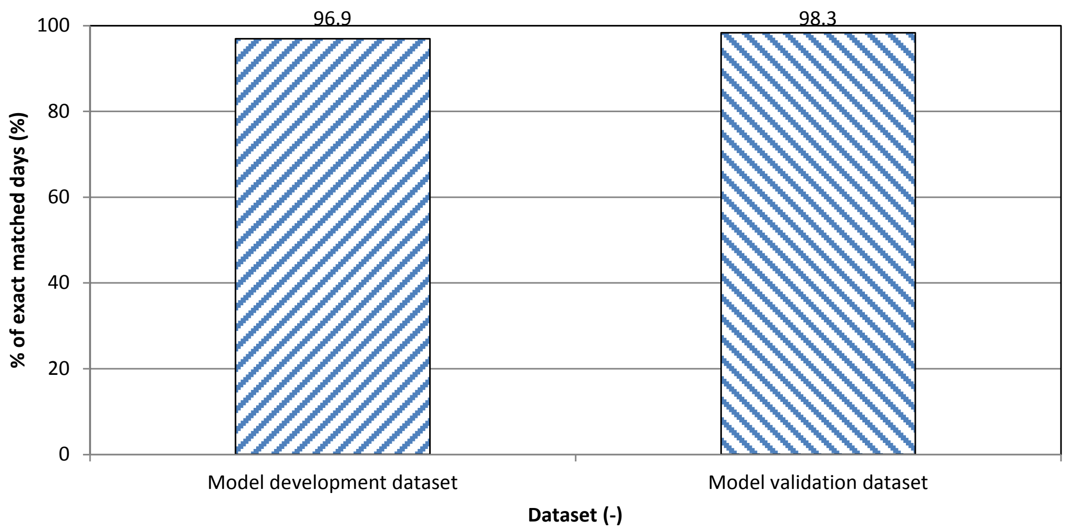


Figure 6.3: Validation results for the preference model (winter).

The above comparisons show that both models provide almost equivalent prediction results using the two different datasets (the variations of the $\%$ of EMDs between the two datasets are all less than 1%), when all sample-days from the field studies are considered. This implies that the preference model developed for both summer and winter times have captured the underlying nature of occupants' behaviour on the end-of-day window position, the same as the two models developed in Chapter 5.

6.2 Comparison of Performance

The importance of this chapter is to evaluate whether grouping the data based on personal preference when modelling window behaviour helps to increase the modelling accuracy, compared with other grouping strategies, that is, considering the building population as a whole or using sub-groups. In this section, therefore, the predictive performance of the preference model developed in this chapter is compared with the predictive performances of the two window behaviour models developed in Chapter 5, for both model development and validation datasets. The comparison for the summertime is shown in Figure 6.4 and the one for the wintertime is shown in Figure 6.5.

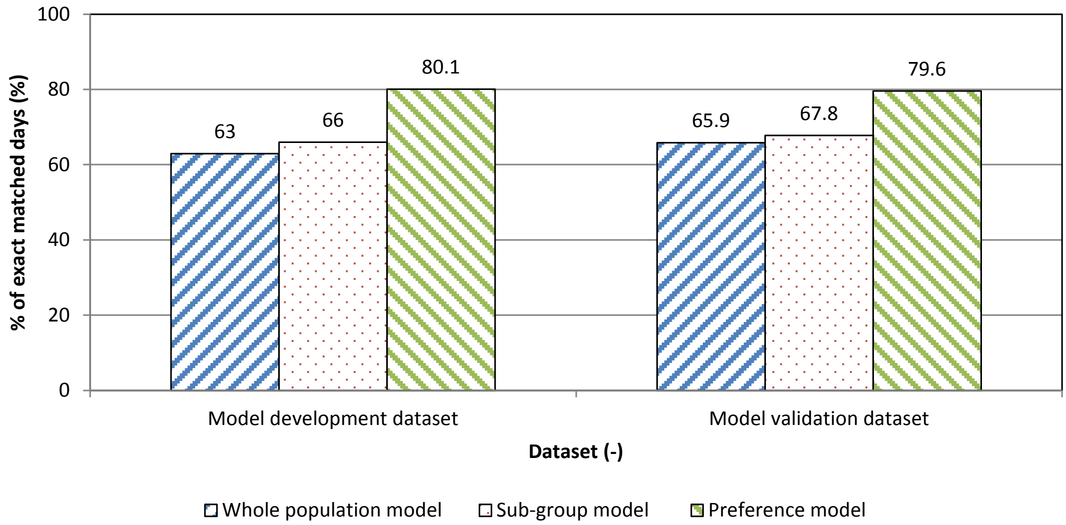


Figure 6.4: Model comparisons for the summertime.

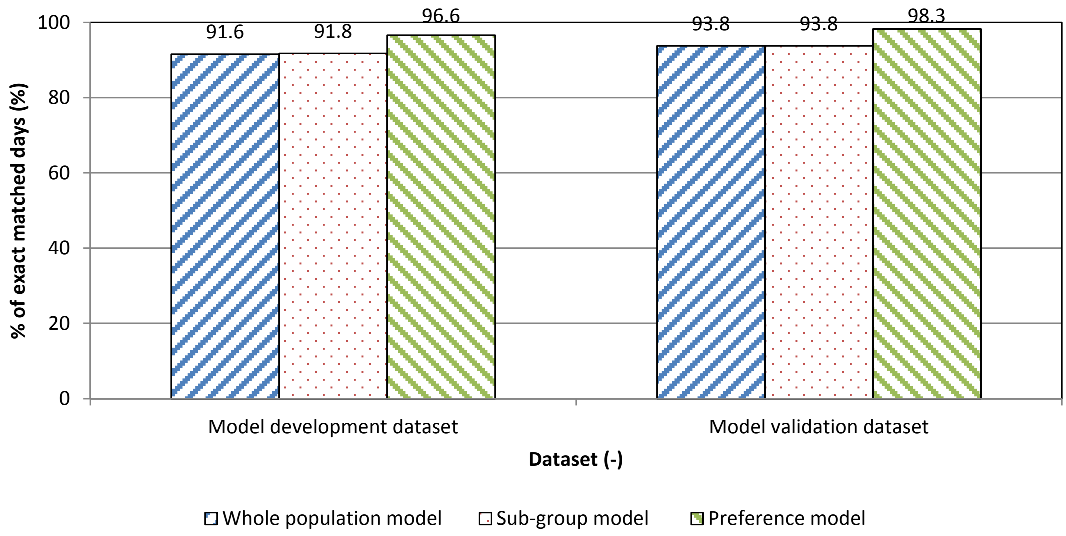


Figure 6.5: Model comparisons for the wintertime.

For the summertime it can be seen that the preference model performs much better than the whole population model and the sub-group model, showing an increase of more than 14% of $\%\ \mathrm{of\ EMDs}$ based on the model development dataset and more than 11% of $\%\ \mathrm{of\ EMDs}$ based on the model validation dataset. It can also be observed that the sub-group model provides a better prediction result when compared with the whole population model, but the improvement seems to be moderate; a 3% improvement on the $\%\ \mathrm{of\ EMDs}$ based on the model development dataset and 1.9% improvement based on the model validation dataset. Similar conclusions can be obtained for the wintertime, as shown in Figure 6.5.

6.3 Summary

In this chapter the preference-based modelling approach was introduced and the models were generated, based on occupants' personal behavioural preference classified in Section 4.4 of Chapter 4. The validation results demonstrated that the preference model had captured the underlying nature of occupants' behaviour on the end-of-day window position, for both summer and winter times.

A model comparison was performed between the preference model and the two window behaviour models developed in Chapter 5. The comparison results revealed that the preference model had a better performance on predicting the observed end-of-day window positions, when compared with the other two behaviour models, for both summer and winter times. Hence, classifying the data in this way better describes the characteristics of the end-of-day window position, than more common approaches employed currently.

In real practice personal preference is not a known aspect of an individual's behaviour, unlike the factors that are used in the other two approaches. Currently, researchers have used various methods to classify building occupants with respect to their frequency of using windows, either deduced by real measured data (Haldi and Robinson, 2009b, Yun et al., 2009) or by occupants' self-statement (Rijal et al., 2007). Thus, the development of a standard method to classify window users in terms of 'personal preference' is still required. In this thesis, whilst the author has provided a method for classifying occupants' window use based on the measured data to determine personal preferences, a practical approval still needs to be devised and validated in future studies.

7. MODEL IMPLEMENTATION

In Chapter 5 and Chapter 6, three window behaviour models, a whole population model, a sub-group model and a preference model, were established, using different grouping strategies of building occupants in the modelling. For both summer and winter periods the preference model can better reproduce the monitored state of windows, when compared with the other two models. In this chapter these three models are applied within a practical building simulation context. This is to demonstrate the impact of using window behaviour models developed by various grouping strategies on the predicted performance of a building.

Section 7.1 introduces the analysis problem, including the example building, whose energy performance is predicted by the three window behaviour models, respectively, for the approach comparison, and the outdoor weather data chosen for the prediction. In this study the energy performance of the example building is predicted using a building ventilation model, which is introduced in Section 7.2. As described at the last part of Chapter 6, personal preference is in practice not generally a commonly known factor about a building occupant. Therefore, in Section 7.3, a preference-based prediction method is developed and introduced, enabling a suitable allocation of behavioural preference to the occupant of each room involved in the prediction. Section 7.4 and 7.5 evaluate the impact of using the models developed by different grouping strategies of building occupants on the prediction result, from two aspects. Firstly, influence on individual rooms, and secondly, influence on rooms occupied by sub-groups. This is utilised when comparing the predicted energy performance of the building using the three developed window behaviour models for different prediction scenarios. A summary is provided in Section 7.6.

7.1 Analysis Problem

7.1.1 Example building

Most existing window behaviour studies used a single room in the simulation to demonstrate the implementation of their models. This is mainly because the researchers in those studies were interested in presenting the algorithm of their window prediction, rather than in comparing the predicted performance of individual rooms. This chapter, however, aims to demonstrate that if the window behaviour model in the simulation procedure is allocated to each particular room based on personal preference, rather than for the whole population or sub-groups within it, what the impact will be on the predicted performance of buildings. Therefore, an example building with 20 single-cell offices is established, as shown in Figure 7.1, similar to the case study building that was used to collect the data for both model development and validation.

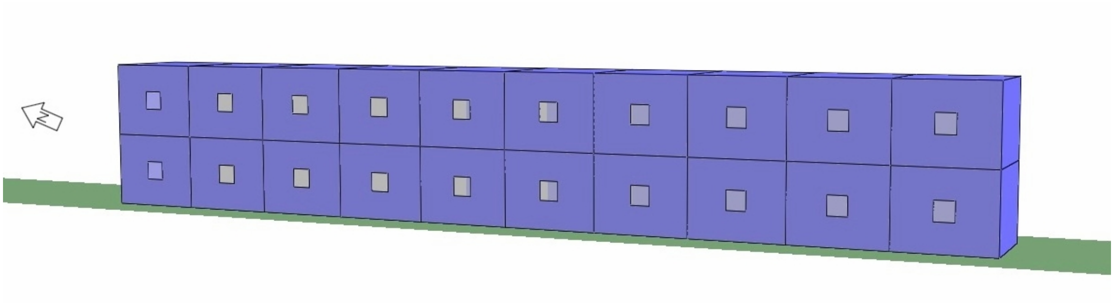


Figure 7.1: An example building for model implementation.

The 20 single-cell offices are spread equally on two floors, with similar construction conditions. In each single office (length: 5m; width: 5m; height: 4m), there is a $1m \times 1m$ side-hung weather strapped casement window located at the middle of the west wall, with a maximum opening angle of 30°.

It is assumed that only one person is working in each office, and his/her working hours are from 08:00 to 18:00 from Monday to Friday.

In the summertime, the building adopts a natural ventilation strategy and the heating system is always off. Night ventilation is available in this building by leaving windows open when departing offices at the end of the working day. There is no mechanical system in this building to control the opening and closing of the office windows. They are controlled manually by the room occupants and hence the window behaviour models developed in Chapter 6 and Chapter 7 can be used to determine the end-of-day position of the windows in the building. The determination of the end-of-day window position follows the rule that, if the room occupant is present during the day time, the state of the window during the night-time is determined by the developed window behaviour models, based on the stochastic approach introduced in Section 5.3.1 of Chapter 5. If the room is unoccupied during the day, the end-of-day window position for that day remains that from the previous day.

7.1.2 Outdoor weather data

Outdoor weather data is a crucial element of dynamic building performance simulation. The outdoor air temperature used here was obtained from available weather data in IES VE, a commercial building performance simulation package (IES, 2012), for London Heathrow, UK (51.48°N, 0.45°W, alt.24m). The model implementation considered a summer month, in order to investigate the influences of different prediction approaches on building performance simulation with night ventilation. As one of the main purposes of applying night ventilation is to reduce the overheating risk during the daily working hours, the month with the highest average outdoor air temperature during the working hours (08:00 to 18:00) was selected for the model implementation, as shown in Figure 7.2.

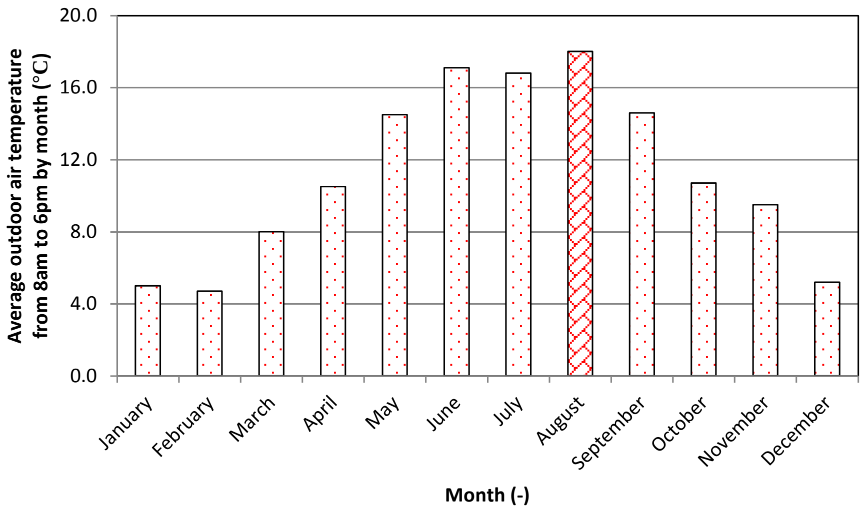


Figure 7.2: Average outdoor air temperatures during the occupied hours by month.

7.2 Steady-state Ventilation Model

A steady-state ventilation model is established here, and is used to predict the energy performance of the example building, based on the predicted state of windows by the three window behaviour models. This model estimates the extracted cooling energy from the outdoor environment when the room is unoccupied during the night-time. Two equations are used to calculate the ventilation through a window. One is for the condition with an open window and the other one is for the condition with a closed window. To simplify the calculation, only the buoyancy-driven air exchange between indoors and outdoors is considered here. Under this condition, the ventilation rate through an open window can be determined by Equation 7.1 (CIBSE, 2006),

$$Q = \frac{A_{open} \times C_d}{3} \sqrt{\frac{g \times h \times \Delta T}{\bar{T}}}\ , \tag{7.1}$$

where,

Q	is the air rate through the opening, in cubic metres per second (m^3/s);
$\mathrm{C_d}$	is the discharge coefficient of the opening ($-$);
$\mathrm{A_{open}}$	is the flow area through the opening, in square metres (m^2);
g	is the gravitational acceleration, in metres per square second ($9.81\mathrm{m}/s^2$);
h	is the total height of the opening, in metres (m);
$\Delta\mathrm{T}$	is the temperature difference between indoors and outdoors, in degrees Celsius (℃);
$\bar{\mathrm{T}}$	is the mean temperature of indoors and outdoors, in degrees Celsius (℃).

The deduction of Equation 7.1 from basic ventilation equations is provided in Appendix B.

When the window is closed, the air exchange between indoors and outdoors is achieved mainly by infiltration through the cracks along the window perimeters. The infiltration rate is calculated by (CIBSE, 2006),

$$q_{vc} = I_c \times k_l \times (\Delta p)^{n_e} \text{ ,} \tag{7.2}$$

where,

q_{vc}	is the volumetric flow rate through the crack, in litres per second (L/s), and $1L/s = 0.001m^3/s$;
I_c	is the total length of the crack, in metres (m);
k_l	is the flow coefficient per unit length of the crack, in litres per second metre pascal ($L/(s \cdot m \cdot Pa^{-n})$);
n_e	is the flow exponent ($-$).

The pressure difference Δp in Equation 7.2 is determined by (CIBSE, 2006),

$$\Delta p = \rho_0 \times g \times 273 \times h \times \left(\frac{1}{T_{ao}+273} - \frac{1}{T_{ai}+273}\right) \text{ ,} \tag{7.3}$$

where,

ρ_0	is the density of air at 0°C, in kilograms per cubic metre ($1.292kg/m^3$);

However, as Equation 7.3 is used for the application with two vertically displaced openings at a certain distance h, driven by stack effect, it is suitable for the flow rate calculation for the upper edge and lower edge of the window. When this equation is applied to the left and right edges, it will overestimate the ventilation rate because the height difference on those two edges is generally smaller than the total height of the window. However, if the left and right edges are not considered in the calculation, the ventilation rate will be underestimated. The method adopted here, to balance this effect on the calculated ventilation rate, is to average the calculation results with and without the left and right edges of the window.

The estimated daily cooling energy extracted by the night ventilation, H_c (kWh), is determined by Equation 7.4 (Moss, 1998),

$$H_c = m \times C_a \times dt \times time \text{ ,} \tag{7.4}$$

where,

m	is the mass transfer of air through the building by natural ventilation, in kilograms per second ($\mathrm{kg/s}$);
$\mathrm{C_a}$	is the specific heat capacity of air, in kilojoules per kilogram Kelvin ($\mathrm{kJ/(kg \cdot K)}$);
dt	is the average temperature difference between indoors and outdoors over the night, in Kelvins (K);
time	is the number of hours during the unoccupied night-time ($-$).

In Equation 7.4, the mass transfer of air through the opening by natural ventilation is calculated by (Moss, 1998),

$$m = Q \times \rho \ , \tag{7.5}$$

where ρ is the density of air in ($\mathrm{kg/m^3}$). The average temperature difference between indoors and outdoors over the night is calculated by the log mean temperature difference, defined by Equation 7.6 (Moss, 1998),

$$dt = LMTD = (dt_{max} - dt_{min})/ln(dt_{max}/dt_{min}) \ , \tag{7.6}$$

where,

$\mathrm{dt_{max}}$	is the maximum temperature difference of indoors and outdoors during the night, in Kelvins (K);
$\mathrm{dt_{min}}$	is the minimum temperature difference of indoors and outdoors during the night, in Kelvins (K).

Equation 7.4 calculates the extracted cooling energy from the outdoor environment through a one-night period. In this study, the total extracted cooling energy, from each room, during the night-time in the simulated summer month was calculated, and used to reflect the contribution of night ventilation to the energy performance of each

individual room in the simulation. The calculations were based on a number of assumptions:

- the design indoor air temperature was assumed to be 25°C and the design outdoor air temperature was chosen to be the average outdoor air temperature during the night-time, that is, between 18:00 and 08:00 + 1 day;

- the lowest indoor air temperature during the night-time was assumed as 21°C when the office window was left open on departure, and as 23°C when the office window was closed during the night-time, and this temperature was proposed to occur at 08:00, which was the end of the night-time period;

- the discharge coefficient of the opening was $\mathrm{C_d} = 0.61$;

- the total length of the crack for infiltration was $\mathrm{I_c} = 4\mathrm{m}$, the perimeter of the window;

- the flow coefficient per unit length of the crack was $\mathrm{k_l} = 0.21\mathrm{L}/(\mathrm{s} \cdot \mathrm{m} \cdot \mathrm{Pa}^{-\mathrm{n}_e})$, where n_e is flow exponent introduced in Equation 7.2; and,

- the number of hours during the unoccupied night-time was $\mathrm{time} = 14\mathrm{hours}$, from 18:00 to 08:00 + 1 day.

7.3 Allocation of Preference Models

An occupant's personal preference with regard to window operation is not generally available in practice, so a key challenge before the simulation is to determine suitably which person has which window behavioural type and in which room they are to be located. To achieve this task, a preference-based prediction approach is developed here, enabling the allocation of one of three window behavioural types, that is, Habitual closers, Adjusters and Leave openers, to each individual room in the example building in the simulation procedure, thus allowing the preference model to be used.

Figure 7.3 proposed a tree structure, showing various populations classified by the non-environmental factors identified in this study, namely, occupant gender, the ground floor and personal preference, for the summertime.

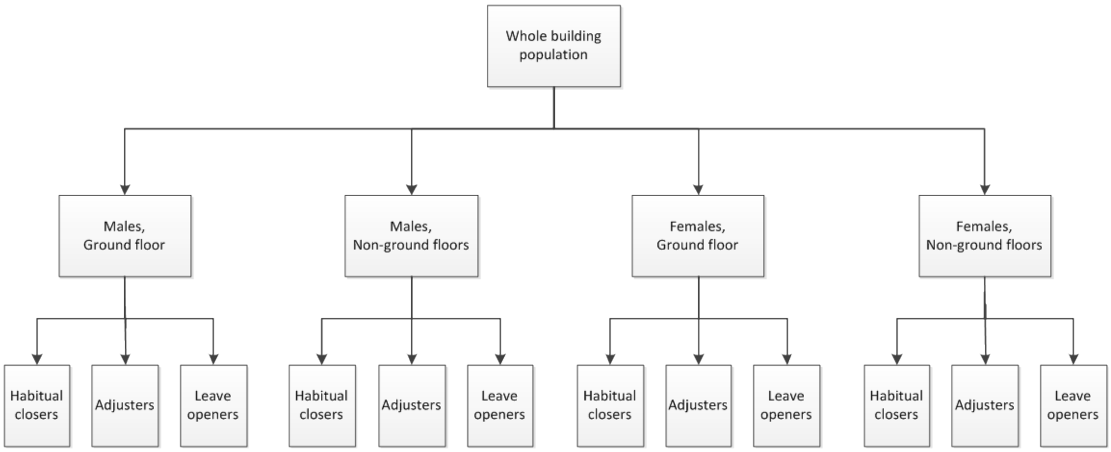


Figure 7.3: A hierarchy of building population classification based on window behaviour.

The effect of sub-group factors, such as occupant gender and the ground floor, is represented by the second tier populations and the effect of personal preference is reflected by the third tier, beyond the effect of whole population and sub-group factors. Therefore, in each sub-group classified by sub-group factors, occupants can be further classified into Habitual closers, Adjusters and Leave openers, based on their personal preference of window use. The field data described in Chapter 3 reflects that the distribution of types of window users is dependent on the sub-group factors identified to influence window behaviour, namely, occupant gender and the ground floor, as shown in Table 7.1. Therefore, in the early stage of the design of a new building, the relative proportions of the user types from the observation of a similar building can be used to link sub-group factors and occupants' personal preference. This enables the allocation of behavioural preferences for each 'occupant' of the simulated rooms.

Table 7.1: User groupings by floor level for male subjects (left) and by gender for non-ground-floor subjects (right).

Floor	Habitual Closer	Adjuster	Leave Opener
Ground	80%	20%	0%
Non-ground	39%	39%	22%

Gender	Habitual Closer	Adjuster	Leave Opener
Female	75%	25%	0%
Male	39%	39%	22%

The individuals and their behavioural preference in each sub-group can be 'hypothetically' placed in offices either randomly or in a more contrived way, in order to explore the potential effects on performance. Once the individuals and their preferences have been allocated to all the rooms in the simulation, the respective window behaviour pattern predicted by the preference model can be applied to each simulated room, and used for the whole simulation process.

The preference-based prediction approach has been developed as a third party tool in Matlab (MathWorks, 2012), and can be used to predict end-of-day window positions for building performance prediction and simulation, as described in Appendix C.

7.4 Influence on Prediction of Individual Rooms

In this section, each of the three behaviour models developed in Chapter 5 and Chapter 6 is applied to two problems:

- the prediction of the end-of-day window position in summer; and

- the impact the prediction has on the simulated airflow rate through the building at night.

The prediction using the whole population model and the sub-group model adopts the same approach as in existing simulation procedures, whist the prediction using the preference model advances current practice by considering the behavioural difference between individuals. In order to avoid the effects of occupant gender and the ground floor, the analysis here was carried out for the first-floor rooms and all rooms were assumed to be occupied by males only. Full occupancy every day was assumed based on a Monday-Friday working week in the summer.

7.4.1 Bias in window state prediction

The predicted positions of windows by the three behaviour models can be found in Appendix D. To compare their prediction results, the corresponding proportion of working days with windows left open on departure to the overall working days within the prediction period was calculated, for each room on the first floor of the example building, occupied by males only. The result is shown in Figure 7.4. A higher percentage indicates that the occupant had more days with his window left open on departure during the summer simulation period.

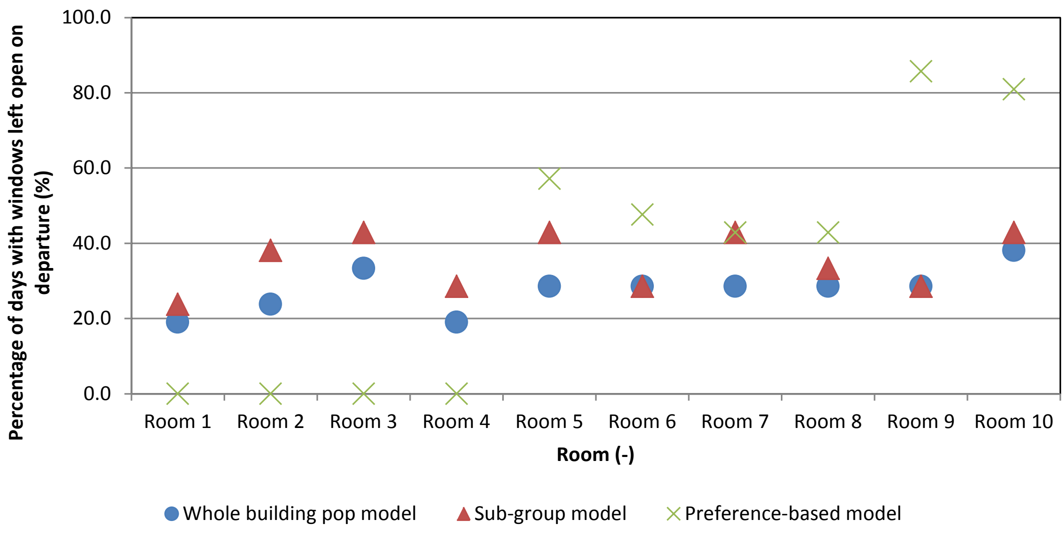


Figure 7.4: Predicted percentages of days with windows left open on departure for each simulated room by the three window behaviour models.

From the prediction, based on either the whole population model or the sub-group model, Figure 7.4 shows that the predicted percentages of days with windows left open on departure are similar between individual rooms. The prediction result from the whole population model reflects that all ‘occupants’ in the example building left their windows open on departure for only a small number of days (varying between 20% – 40% of all working days). The prediction result from the sub-group model gives a slightly higher number of days with windows left open on departure, when compared with the whole population model. However, the ‘occupants’ still perform similar window use patterns (also varying between 20% – 40% of all working days). These prediction results are not consistent with what was observed in the building monitored in this study, where some windows were closed rigorously at the end of almost every day, whilst others were left open across a very large range of temperature conditions (see the discussion in Section 4.4 of Chapter 4). Looking at the prediction result by the preference model, it can be found that it reproduced well the observed behavioural difference between individuals, and much significant than the other two approaches. Some occupants left windows open on departure rarely (Room 1 to Room 4 have almost 0% of days with windows left open on departure), some left windows open frequently on departure (Room 9 and Room 10 have high percentages, with variances between 80% – 100%), and some in the middle (Room 5 to Room 8 have percentages varying between 40% – 60%).

7.4.2 Impact on the estimation of night-time cooling

The above section evaluates the influence of using occupants’ behavioural preference when predicting the position of windows. It reproduced well the observed, significantly different window use patterns. In this section, the impact of this bias on building energy performance is investigated using the steady-state ventilation model described in Section 7.2, for each simulated room, together with the outdoor weather data introduced in Section 7.1.2.

Figure 7.5 shows the estimated total cooling energy extracted from the outdoor environment through night ventilation during the simulation period (the hottest summer month in the weather data), for each room on the first floor of the example building, using the end-of-day window positions predicted by the three window behaviour models for males (see Appendix D).

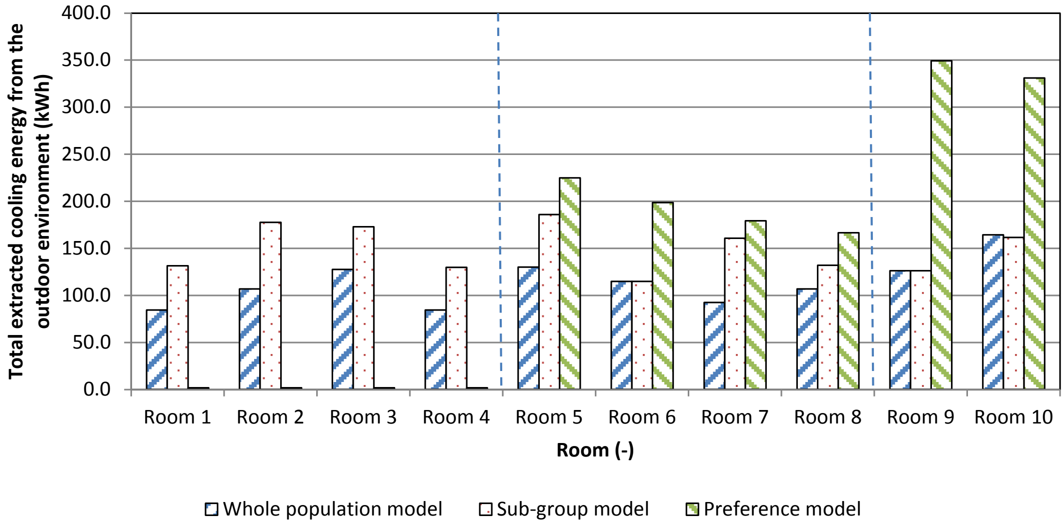


Figure 7.5: Estimated extracted cooling energy during the night for each room in the simulation period based on the window positions predicted by the three window behaviour models.

Figure 7.5 demonstrates that the different window use patterns among occupants (separated by the dashed lines) have an obvious impact on the calculated efficiency of night cooling. According to the prediction result using the predicted state of windows by the preference model, Room 1 to Room 4 had a very little cooling energy from the outdoor environment, as their 'occupants' performed as Habitual closers. Contrary to this, Room 9 and Room 10 received a much larger amount of cooling energy than the other rooms, especially when compared with Room 1 to Room 4, as they were occupied by Leave openers. The highest estimated extracted cooling energy was 349.1kWh for Room 9, which was 347.4kWh higher than the lowest value of 1.7kWh for Room 1 to Room 4. This extra amount of extracted cooling energy could affect the indoor thermal environment in the next working day. Considering the simulation results, using the state of windows predicted by the whole population model and the sub-group model, the magnitude of the difference between individual rooms was much smaller, compared with that by the preference model. The biggest difference between individual rooms was 79.9kWh for the whole population model and was 70.9kWh for the sub-group model.

7.5 Influence on Prediction of Sub-groups

The above prediction scenario demonstrates that when using the preference model, the significantly different window use patterns observed in actual buildings can be reproduced well. This has an impact on the predicted energy performance of buildings, and cannot be achieved by traditional methods. However, sub-group factors, such as occupant gender and the ground floor, can also influence window behaviour in office buildings, as discussed in Section 4.3.5 and 4.3.6 of Chapter 4. Therefore, the prediction using the preference model should also be able to reflect this influence. This characteristic, however, was not demonstrated in the above prediction scenario, in which all occupants were restricted to a particular sub-group, that is, males on the first floor. In this section, all occupants on the first floors are changed to females and the predicted window use patterns are compared with those when all the rooms are occupied by males.

The comparisons of the predicted window use patterns when the first-floor rooms are occupied separately by males and by females are shown in Figure 7.6, for all three window behaviour models developed in this study (the predicted position of windows by the three window behaviour models for the female-occupied scenario can also be found in Appendix D).

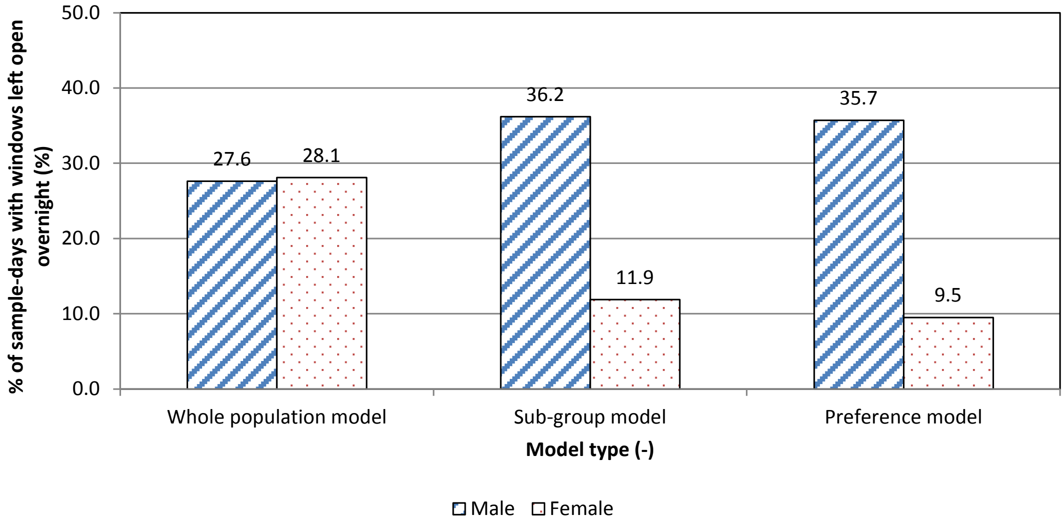


Figure 7.6: Comparison of the predicted percentage of sample-days with windows left open overnight, for male-occupied scenario and female-occupied scenario.

Figure 7.6 demonstrates that both the sub-group model and the preference model reflect effectively the different window behaviour between males and females. The prediction using the whole population model, however, cannot reflect this behavioural difference, as it considered all occupants as a whole. This conclusion also applies to the effect of the ground floor.

7.6 Summary

This chapter demonstrates the implementation of the window behaviour models, which have been generated in the previous chapters, in building performance simulation, and evaluates the impact of considering individuals' preferences of window use on the simulated energy performance of buildings.

As individuals' preference of window use is generally unknown during the early design stage of a new building, a preference-based prediction approach was developed and introduced in this chapter. This approach enabled the preference model to be applied in predicting the position of windows in building performance simulation. Essentially, this assumes that the building occupants behave as found in observations of the case study building examined. Data from a wider group of people can, in future, help to refine this approach. The implementation results revealed that the consideration of individuals' preferences of window use can generate significantly different window use patterns, compared with existing approaches for predicting window behaviour, which are based on either the whole building population or sub-groups within it. Importantly, these different window use patterns were demonstrated to have an obvious impact on the predicted energy performance of buildings.

According to the discussions in Section 7.4 and 7.5, a comparison among using the three modelling approaches to predict occupants' window behaviour is made, as shown in Figure 7.7.

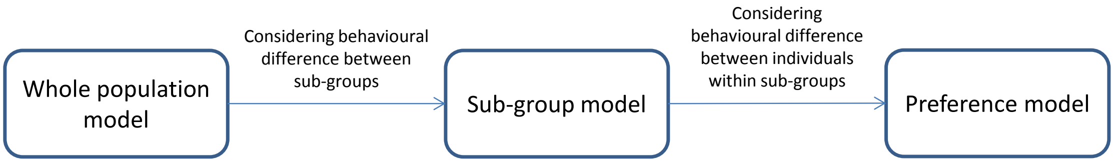


Figure 7.7: Comparison of various models to predict window behaviour.

The sub-group model considers the behavioural difference between sub-groups of occupants, when compared with the whole population model. The preference model imports a further level, as shown in Figure 7.3, in which the behavioural difference between individuals is addressed. The use of the sub-group model, however, requires a good knowledge of the building occupants, such as their gender and location in the building, during the design stage of a building, which is recommended strongly by the BSRIA (2013) in the Soft Landings framework. In addition, to allow use of the preference model, further personal knowledge of occupants is required. For now, the thinking of this study offers a suitable starting point.

Based on the analysis in this chapter, during the design stage of a building the building designers should be aware that the future building occupants may perform various operations on available cooling strategies, such as the use of night ventilation, even between those having similar personal characteristics. This behavioural difference has a direct impact on the energy performance of individual rooms.

Building managers should be aware that if one or more rooms have unacceptable indoor thermal environment when compared with the other rooms, or do not meet the anticipated performance during the design stage of the building, this is possibly because the room occupant(s) do not use the available cooling strategies in the building efficiently. Under this condition, proper interventions need to be taken to help the room occupant(s) control their indoor environment more efficiently, by means of behavioural education or mechanical control of windows.

8. CONCLUSIONS AND FUTURE WORK

8.1 Conclusions

Natural ventilation is used popularly in British buildings to cool down the indoor environment for summer and to provide fresh air in winter, mainly by linking the indoor and outdoor environment through an open window. A great many buildings adopt such a ventilation strategy, having manual control only by the building occupants. The performance of these buildings is more challenging to predict, compared with buildings controlled by mechanical ventilation systems. This is not only because of the variability of the natural driving forces, but also because occupants' behaviour is hard to capture, accurately. In the past two decades, studies based on understanding window opening behaviour in office buildings have generated useful models for use in building simulation. However, these studies classified building occupants either based on the whole population or based on sub-groups within a building, and the behavioural difference between individuals was commonly ignored. This thesis has evaluated whether modelling and predicting window operation based on personal preference has advantages over these traditional classification approaches.

The study focused on the final position of the window at the end of the working day, and the data was collected from a case study building with identical cellular offices occupied by the same person. 36 offices and their occupants were monitored, with respect to their use of windows, through a combination of automated monitoring and human-led observations. Based on the data, several factors that can influence occupants' choice of end-of-day window positions were identified. Three window behaviour models were developed using these factors, classifying the occupants differently when modelling their behaviour, namely, based on whole population, sub-groups and personal preference. The performance of these models for predicting the state of windows was validated using a new dataset that was collected from the same offices that were monitored for developing the models.

To identify the advantage of modelling window behaviour based on personal preference over traditional modelling approaches, the three models were used to reproduce the monitored end-of-day window positions stochastically for both model development and model validation surveys, and their predictive performance was compared. Finally, the influence of this advantage on the predicted building performance was demonstrated in an example building, using a steady state ventilation model that calculated the cooling energy extracted from the outdoor environment during the unoccupied night-time, for the two conditions of windows left open overnight and closed on departure.

The main conclusions from this study are as follows:

(1) **Non-environmental factors do have a significant impact on occupants' choice of the end-of-day window position:** Existing window behaviour models take account more of how the state of windows is affected by environmental factors, such as indoor and outdoor temperatures, when occupants firstly arrive at the offices and during the intermediate working hours. This thesis has demonstrated the importance of non-environmental factors on occupants' window behaviour towards night ventilation.

(2) **Personal preference does play an important role on the end-of-day window position, beyond other influencing factors:** In actual buildings occupants' window behaviour can be significantly different between individuals, and this can be explained by their varying personal preference of window states.

(3) **Modelling window behaviour based on personal preference can have a better predictive performance, when compared with the more conventional whole population and sub-group approaches:** Haldi and Robinson (2008a) have discussed how to use different stochastic approaches to improve the modelling of occupants' window behaviour in office buildings, as introduced in Section 2.2.2 of Chapter 2. This study explored this issue from another angle, that is, grouping building occupants differently (whole

population, sub-groups and personal preference). Modelling window behaviour based on personal preference appeared to be significantly helpful in improving the predictive performance. This finding should not only be applicable for modelling window behaviour, but also for modelling other behaviours in buildings.

(4) **For building performance simulation, predicting the state of windows based on personal preference can have a significant impact on the predicted energy performance of buildings:** The preference-based prediction of window states can reproduce the significantly different window use patterns that have been observed in actual buildings. This has been demonstrated to have a significant impact on the predicted energy performance of buildings.

This study can contribute to existing knowledge for this research area:

(1) Previous studies do not pay much attention to evaluating the role of personal preference in the modelling and prediction of occupants' window behaviour. In this study, personal preference has been formally addressed and its importance for a better understanding of window use has been demonstrated.

(2) Previous window behaviour studies focus on occupants' window behaviour when firstly arrive at the offices and during the intermediate working hours. To date, occupants' window behaviour at the end of the day, and its potential influence regarding night ventilation, has been a poorly-understood research area (Fabi et al., 2012b). This thesis has addressed this gap in knowledge.

(3) Previous window behaviour models take account more of how the state of windows is affected by environmental factors, such as indoor and outdoor air temperatures. In this study, the importance of non-environmental factors has been demonstrated.

(4) An approach allocating personal preference in the simulation of multi-room buildings has been developed, as personal preference is generally unknown during the early design stage of a new building.

A good understanding of occupants' personal preference of window use is helpful for both building designers and building managers to obtain a more accurate prediction of building performance and a better understanding of what is happening in a real building. In addition, there are also some new possibilities that arise as a result of the findings from this research project, which could be used to enhance the energy efficiency of a building. These possibilities are summarised as follows:

(1) **Relocating people with a consideration of their window use preferences and hence offering some degree of control of the whole built environment**: Cross-ventilation could help to increase the air change rate of buildings. Therefore, if the building occupants could be located according to their personal preference of window use (locating two Leave openers at the opposite two sides of a building/room), especially in open offices. It would be helpful for increasing the ventilation, and thus promote the energy efficiency of the building in summer. This approach could easily be extended to, for example, the use of computing equipment, the provision of lighting, and the heating set point preference. By grouping or placing people according to their natural behaviours, it may be possible to impact on productivity, as well as building performance.

(2) **Educating people to change their window use behaviour to enhance the performance of buildings:** It has been demonstrated that occupants' different preference of the end-of-day window position has a potential impact upon the efficiency of the building services systems. Therefore, another way to increase the energy efficiency of buildings is by educating occupants to change their window use from a less energy efficient type to a more energy efficient type, for example, changing from a Habitual closer to an Adjuster or a Leave opener in summer. Similarly, this possibility should be able to be applied to other types of behaviour as well.

8.2 Future Work

This study critically analysed factors that could influence the end-of-day window position in office buildings, and demonstrated the importance of treating occupants individually, for both behaviour model development and building performance simulation. Based on the work carried out in this study, there is still considerable scope for further investigation through future studies as:

(1) This study was carried out in a limited study period, and so more data needs to be collected from the same offices observed in this study to increase the accuracy of the developed behaviour models;

(2) All the data used in this thesis, for both model development and model validation, were collected from the same offices in the same building. For similar types of buildings the behaviour models developed in this study offer a first step for predicting building performance, inclusive of personal preference of window use. More data from other types of buildings, however, is still required to build and extend the application of this approach to the majority of buildings; and

(3) Occupants' window behaviour was predicted using Bernoulli processes in this study, as it is easier for behavioural comparison between individuals. However, as mentioned by Haldi and Robinson (2008a), modelling occupants' window behaviour using Bernoulli processes *"ignores the real dynamic processes leading occupants to perform actions"*. Therefore, modelling window behaviour using Markov chains is a more popular approach (Haldi and Robinson, 2009b, Yun et al., 2008, Herkel et al., 2008), in which occupants' behaviour towards opening and closing windows is treated separately. The modelling using Markov chains, however, is more complex than that using Bernoulli processes. Consequently, how to enable the consideration of personal preference in modelling based on Markov processes needs to be studied further.

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APPENDICES

Appendix A: Adjusted Wald Method

The Adjusted Wald Method is used to estimate the accuracy of an estimated population proportion with respect to the sample size of the survey, and it is quantified by the confidence interval for different confidence levels. It comes from the Wald Confidence Interval, also called Wald Method (Bowerman et al., 2002), as defined by Equation A.1,

$$\left[\hat{p} \pm z_{\alpha/2} \times \sqrt{\frac{\hat{p}\times(1-\hat{p})}{n_t}}\right], \tag{A.1}$$

where,

$\hat{p}$ is the estimated population proportion, in percentages (%);

$z_{\alpha/2}$ is a coefficient corresponding to the confidence levels (–);

n_t is the total number of samples (–).

The population proportion, $\hat{p}$, is determined by Equation A.2 based on the number of interested samples (n_i) and the total number of samples (n_t).

$$\hat{p} = \frac{n_i}{n_t}, \tag{A.2}$$

Definitions of the coefficient $z_{\alpha/2}$ are listed in Table A.1 for different confidence levels:

Table A.1: Specifications of measurement devices.

$\mathbf{z_{\alpha/2}}$	**Confidence level**
1.645	90%
1.96	95%
2.576	99%

However, the Wald Method is generally suitable for applications with large sample sizes ($n_t \geq 150$). For applications with small samples, that is, $n_t < 150$, it was found that the Adjusted Wald Method provides a better coverage (Sauro and Lewis, 2005). In the Adjusted Wald Method, Equation A.1 is also used to calculate the confidence interval, while the difference from the original Wald Method is that the estimated population proportion $\hat{p}$ and the sample size n_t need to be recalculated using Equation A.3 and A.4, before being used in Equation A.1.

$$\hat{p} = \frac{(n_i + z^2_{\alpha/2}/2)}{(n_t + z^2_{\alpha/2})}, \tag{A.3}$$

$$n_t = n_t + z^2_{\alpha/2}, \tag{A.4}$$

Appendix B: The deduction of Equation 7.1

The flow due to buoyancy through a large opening is determined by the pressure difference due to temperature difference across the opening, as defined by Equation B.1:

$$\Delta p(z) = \Delta\rho \times g \times z\ , \tag{B.1}$$

where,

$\Delta\rho$ is the difference of density across the opening, in kilograms per cubic metre ($\mathrm{kg/m^3}$);

z is the height to a reference level, in metres (m);

Also, $\mathrm{v(z)} = \sqrt{2 \times \Delta\mathrm{p(z)}/\rho}$ (v is the air velocity crossing the opening, in metres per second ($\mathrm{m/s}$)). Hence, $\mathrm{v(z)} \propto \mathrm{z}^{1/2}$, and

$$\frac{v(z)}{v_{max}} = \left(\frac{z}{H}\right)^{1/2}\ , \tag{B.2}$$

Therefore, the mean velocity ($\bar{\mathrm{v}}$) through an opening of height (H) is:

$$\bar{v} = \frac{v_{max}}{H^{1/2}} \int z^{1/2} dz = \frac{v_{max}}{H^{1/2}} \times \frac{2}{3} \times H^{3/2} = \frac{2}{3} \times H \times v_{max}\ , \tag{B.3}$$

Then the volume flow rate through the opening (Q) is:

$$Q = C_d \times w \times \bar{v} = \frac{2}{3} \times C_d \times w \times H \times v_{max} = \frac{2}{3} \times C_d \times A_{open} \times v_{max}\ , \tag{B.4}$$

where,

w is the width of the opening, in metres (m).

However, in a buoyancy-driven flow, equal masses of air enter and leave through the same opening. If H is the total height of the opening, then the influx or efflux flow is,

$$Q = \frac{C_d \times A}{3} \times v_{max} \ , \tag{B.5}$$

As $\mathrm{v_{max}}$ is the velocity at the height of $\mathrm{H}/2$ (the flow going in and the flow going out of a large opening are each through only $\mathrm{H}/2$), it is $\mathrm{v(H/2)} = \sqrt{2 \times \Delta\mathrm{p(H/2)}/\rho}$. Substituting Equation B.1 into it, it becomes,

$$v_{max} = v(H/2) = \sqrt{\Delta\rho \times g \times H/\rho} \ , \tag{B.6}$$

Based on the ideal gas low, the density of air is a function of temperature and pressure,

$$\rho = \frac{p}{R \times T} \ , \tag{B.7}$$

where,

T is the air temperature, in Kelvins (K);

p is the air pressure, in Pascals (Pa);

R is the specific air constant, ($-$).

If the pressures for the indoor air and outdoor air are assumed to be the same, then Equation B.8 is established,

$$\rho_{in} \times T_{in} = \rho_{out} \times T_{out} \ , \tag{B.8}$$

where,

ρ_{in}	is the indoor air density, in kilograms per cubic metre ($\mathrm{kg/m^3}$);
T_{in}	is the indoor air temperature, in Kelvins (K);
ρ_{out}	is the outdoor air density, in kilograms per cubic metre ($\mathrm{kg/m^3}$);
T_{out}	is the outdoor air temperature, in Kelvins (K);

Then the indoor air density could be determined by the outdoor air density, outdoor air temperature and indoor air temperature,

$$\rho_{in} = \rho_{out} \times \frac{T_{out}}{T_{in}} , \tag{A.9}$$

Substituting Equation A.9 into Equation A.6, in which ρ is proposed to be the average density of indoor and outdoor air,

$$v_{max} = \sqrt{g \times H \times \frac{(\rho_{out}-\rho_{in})}{\frac{(\rho_{out}+\rho_{in})}{2}}} = \sqrt{g \times H \times \frac{2\times\left(\rho_{out}-\rho_{out}\times\frac{T_{out}}{T_{in}}\right)}{\left(\rho_{out}+\rho_{out}\times\frac{T_{out}}{T_{in}}\right)}}$$

$$= \sqrt{2 \times g \times H \times \frac{\frac{T_{in}-T_{out}}{T_{in}}}{\frac{T_{in}+T_{out}}{T_{in}}}} = \sqrt{g \times H \times \frac{\Delta T}{\bar{T}}} , \tag{A.10}$$

Substituting into Equation A.5, and the flow rate through an orifice opening such as a window, could be determined by,

$$Q = \frac{A\times C_d}{3}\sqrt{\frac{g\times H\times \Delta T}{\bar{T}}} , \tag{0.1}$$

Appendix C: The tool for the Preference-based prediction approach

Figure C.1 shows the user interface of the tool.

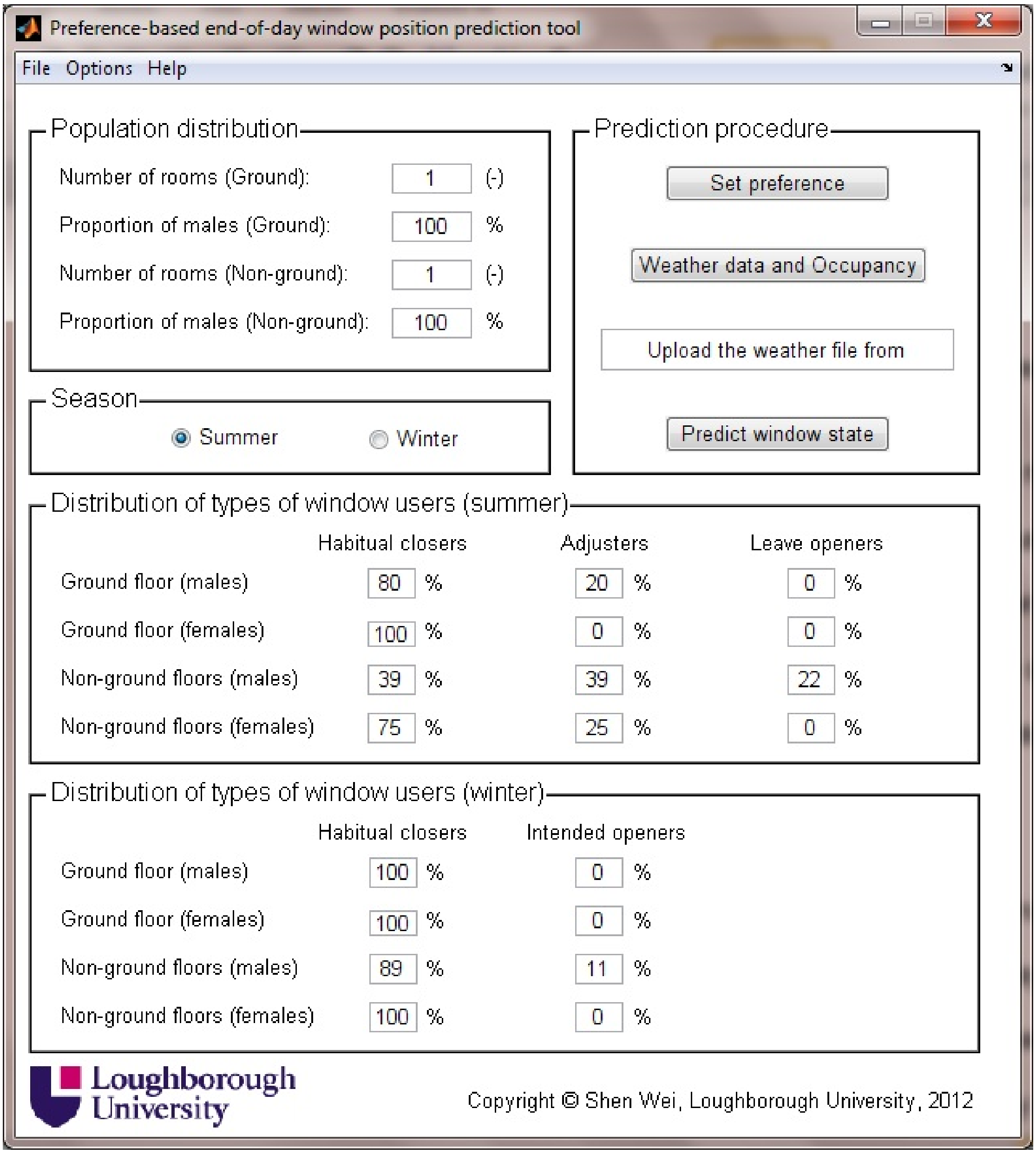


Figure C.1: Preference-based end-of-day window position prediction tool.

The approach splits males/females and ground/non-ground floors, and differentiates between winter and summer. It uses the mean outdoor air temperature between 3pm and 6pm and a binary indicator of whether the room has been occupied during the day time. There is one pair of temperature data per day and this is established from the simulation weather data files. The occupancy indicator is a design decision, or by other occupancy modelling techniques.

Appendix D: The predicted end-of-day window positions

The predicted end-of-day window positions using the three different prediction approaches are listed here for the following conditions:

- end-of-day window positions predicted by the whole building population model (males, 1st floor, summertime);
- end-of-day window positions predicted by the sub-group model (males, 1st floor, summertime);
- end-of-day window positions predicted by the preference model (males, 1st floor, summertime);
- end-of-day window positions predicted by the whole building population model (females, 1st floor, summertime);
- end-of-day window positions predicted by the sub-group model (females, 1st floor, summertime); and,
- end-of-day window positions predicted by the preference model (females, 1st floor, summertime);

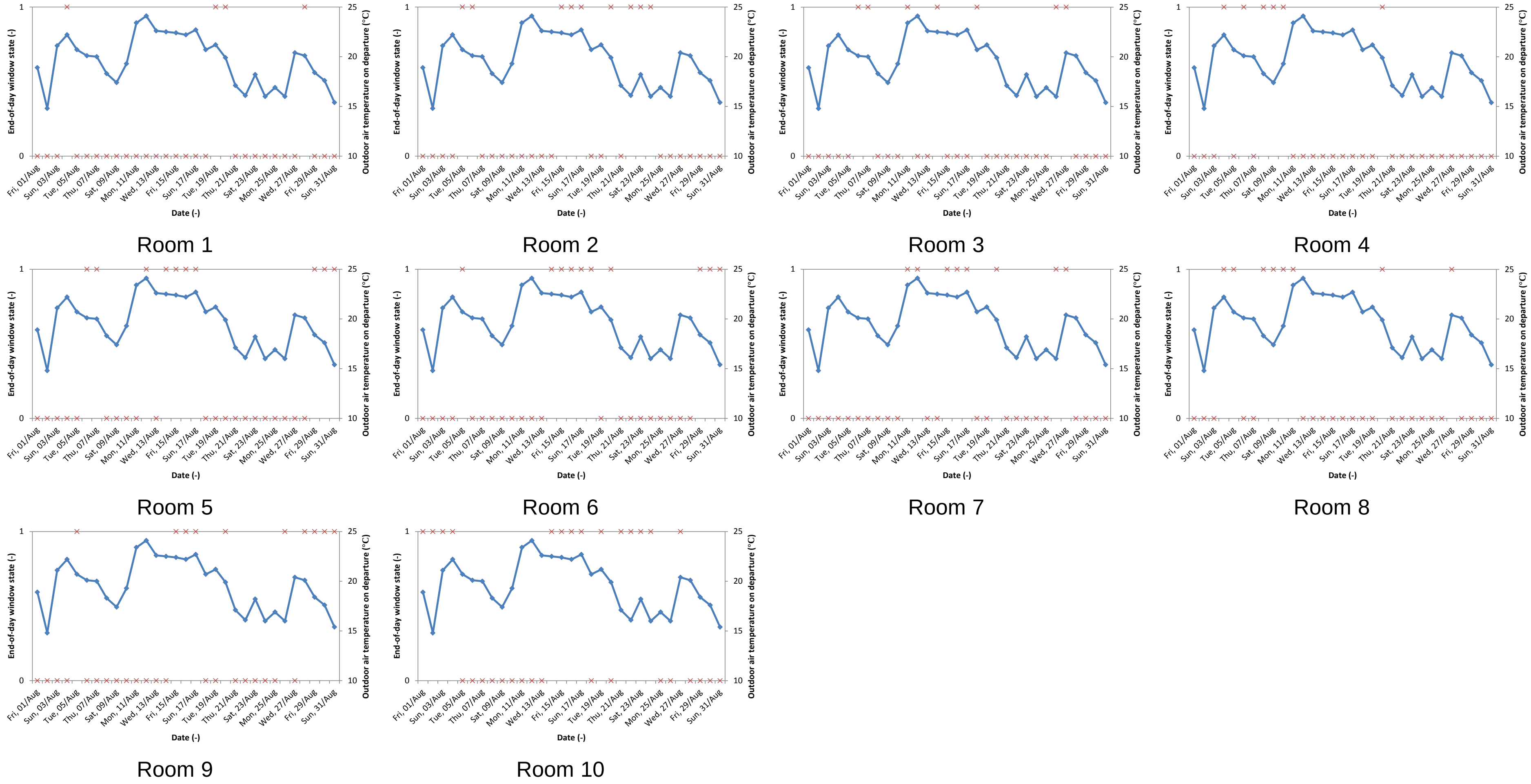


Figure D.1: Predicted end-of-day window positions using the whole population model (males, 1st floor, summertime).

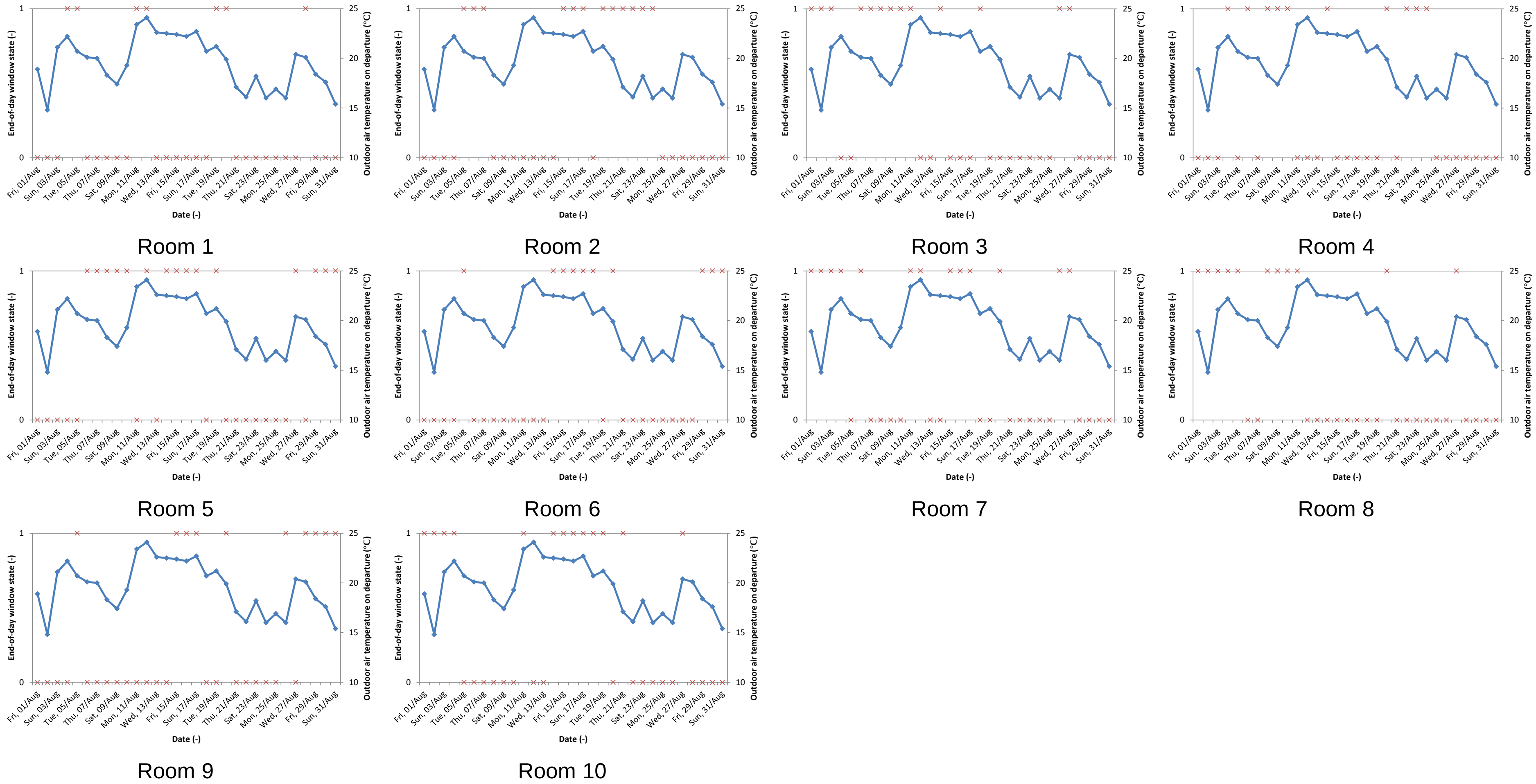


Figure D.2: Predicted end-of-day window positions using the sub-group model (males, 1st floor, summertime).

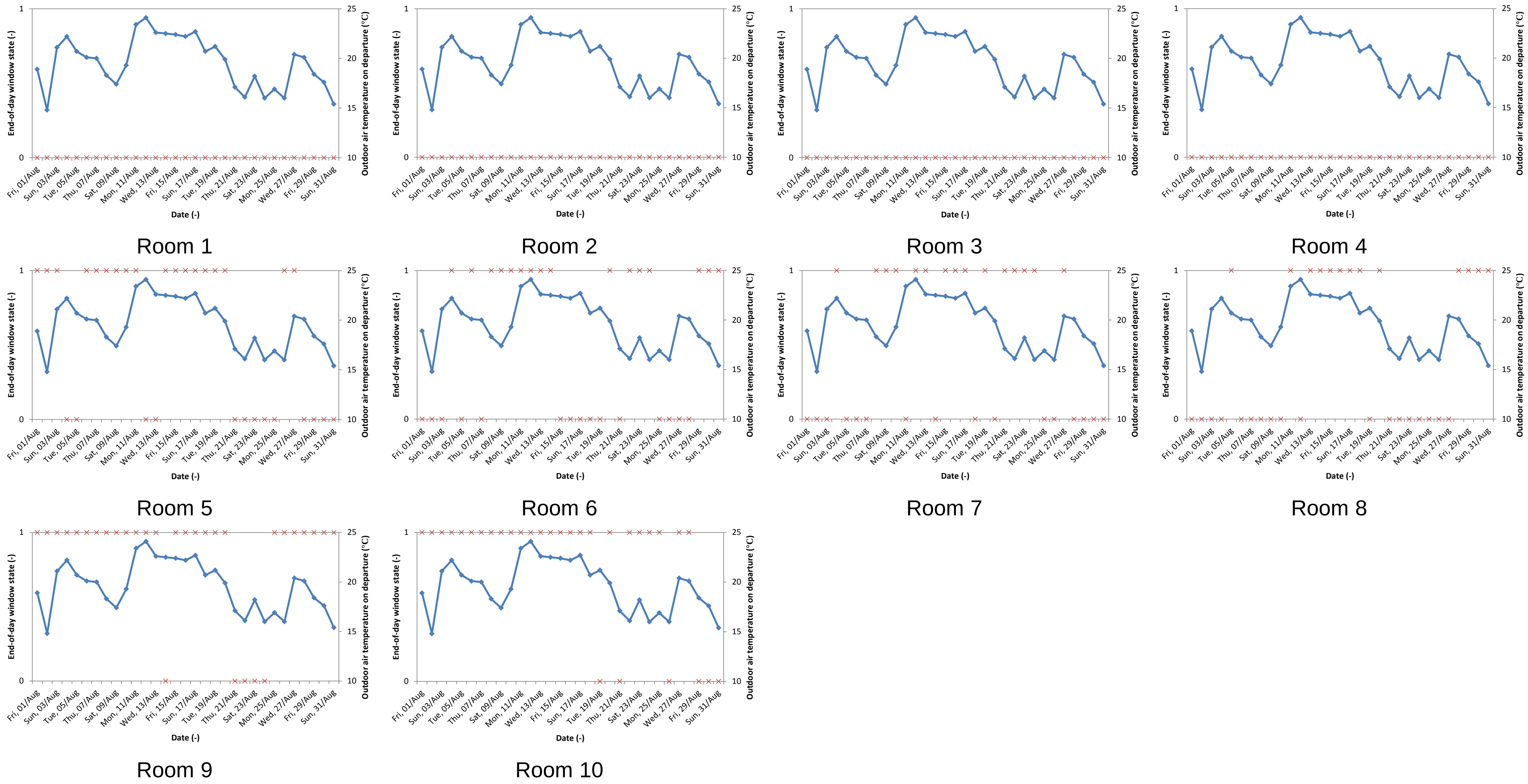
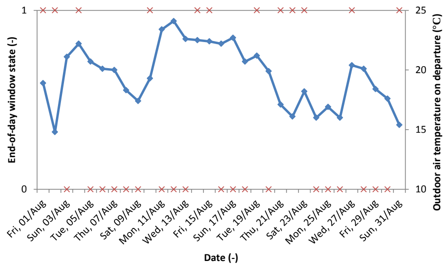
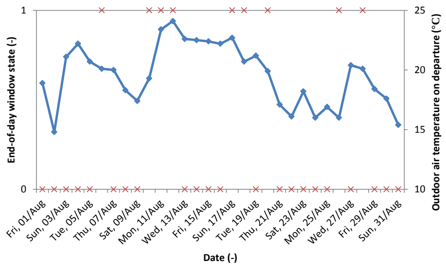


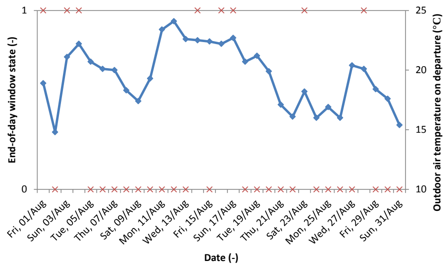
Figure D.3: Predicted end-of-day window positions using the preference model (males, 1st floor, summertime).



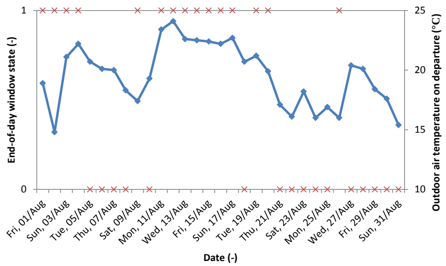
Room F1 (Habitual closer)



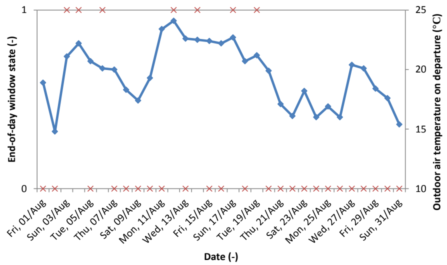
Room F2 (Habitual closer)



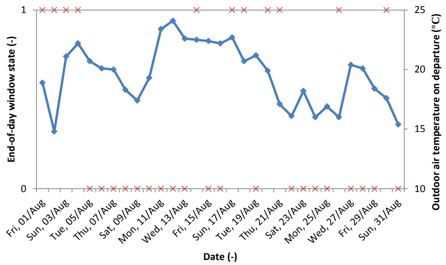
Room F3 (Habitual closer)



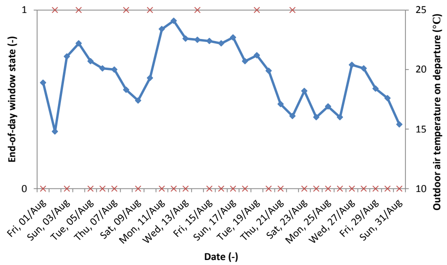
Room F4 (Habitual closer)



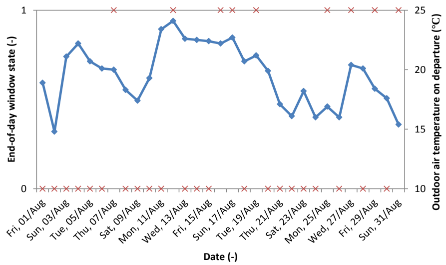
Room F5 (Habitual closer)



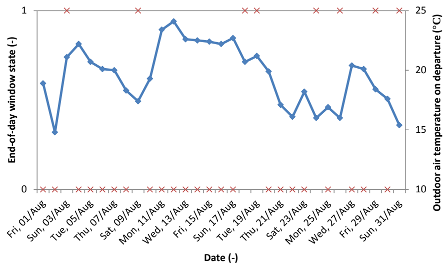
Room F6 (Habitual closer)



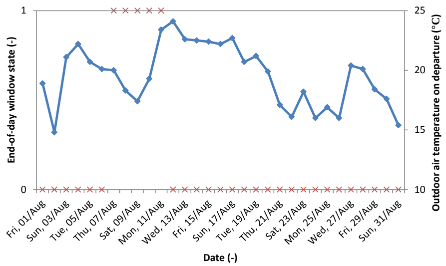
Room F7 (Habitual closer)



Room F8 (Habitual closer)

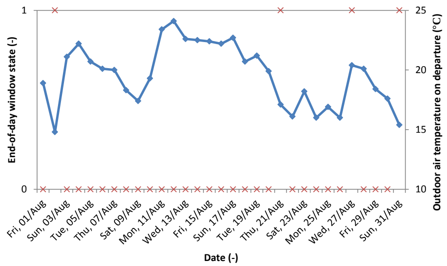


Room F9 (Adjuster)

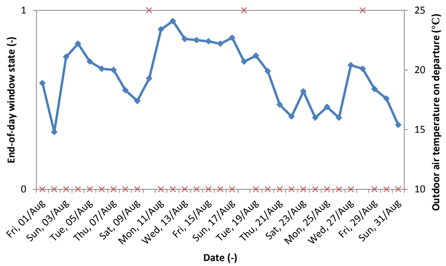


Room F10 (Adjuster)

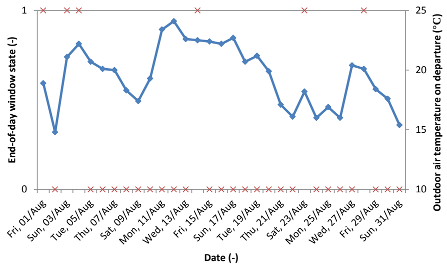
Figure D.4: Predicted end-of-day window positions using the whole population model (females, 1st floor, summertime).



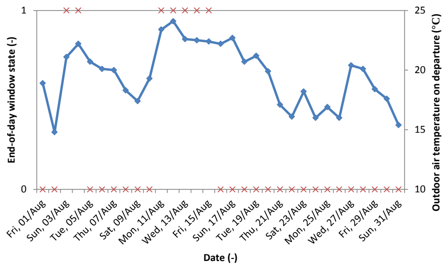
Room F1 (Habitual closer)



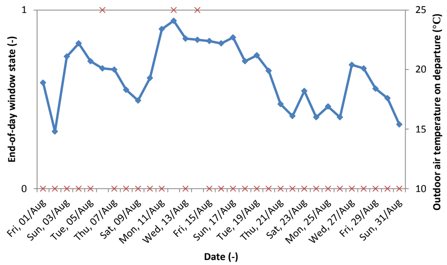
Room F2 (Habitual closer)



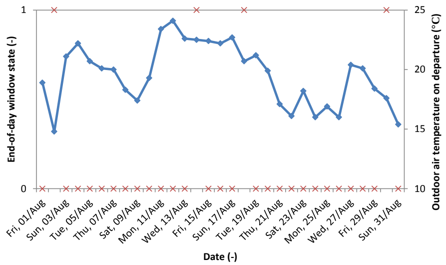
Room F3 (Habitual closer)



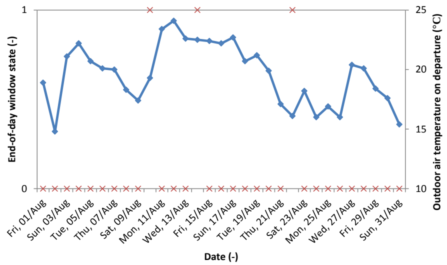
Room F4 (Habitual closer)



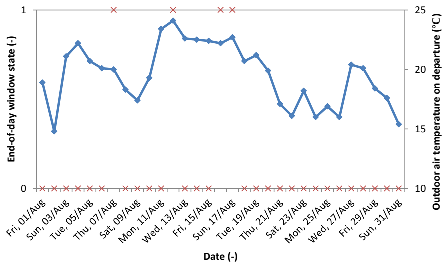
Room F5 (Habitual closer)



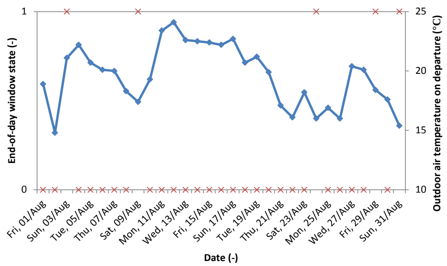
Room F6 (Habitual closer)



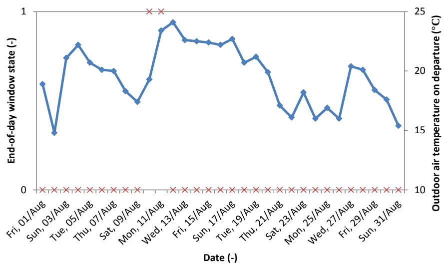
Room F7 (Habitual closer)



Room F8 (Habitual closer)



Room F9 (Adjuster)



Room F10 (Adjuster)

Figure D.5: Predicted end-of-day window positions using the sub-group model (females, 1st floor, summertime).

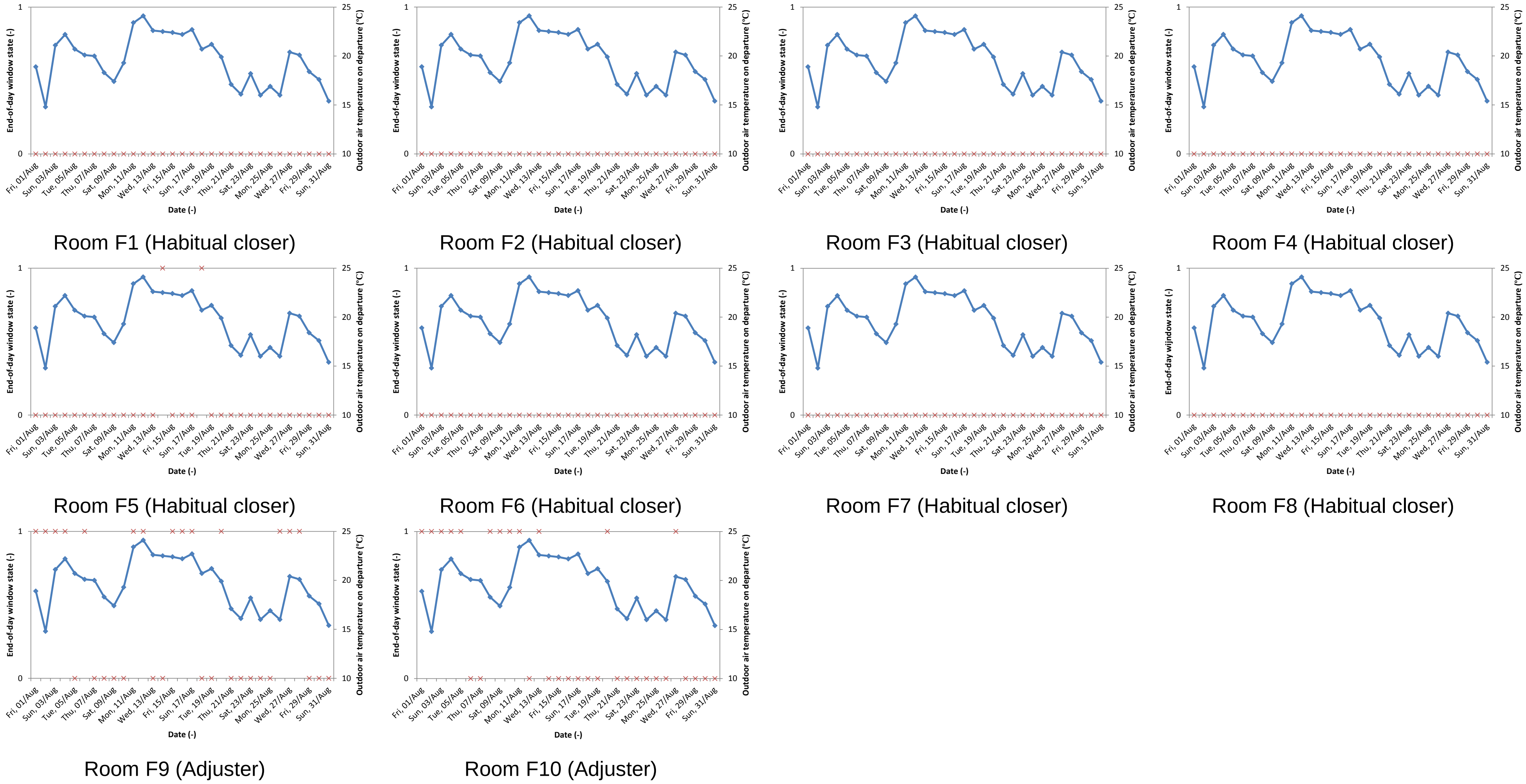


Figure D.6: Predicted end-of-day window positions using the preference model (females, 1st floor, summertime).

PUBLICATIONS

Journal Articles

S. WEI, R. BUSWELL, and D. LOVEDAY. 2013. Factors affecting ‘end-of-day’ window position in a non-air-conditioned office building. *Energy and Buildings*. 62(0): p. 87-96.

Conference Articles

S. WEI, R. BUSWELL, and D. LOVEDAY. 2011. Factors affecting ‘end of day’ window position in non-air-conditioned office buildings. *Proceeding of Building Simulation Conference 2011: Driving better design through simulation*. Sydney, Australia.

S. WEI, R. BUSWELL, and D. LOVEDAY. 2010. Probabilistic modelling of human adaptive behaviour in non-air-conditioned buildings. *Adapting to Change: New Thinking on Comfort.* Cumberland Lodge, Windsor, UK.

S. WEI, R. BUSWELL, and D. LOVEDAY. 2010. Results from an adaptive action preference survey in non-air-conditioned buildings and its application for human behaviour modelling. *Proceeding of CLIMA 2010 Sustainable Energy Use in Buildings*.