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Time-dependent occupant behaviour models of window control in summer

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Abstract

This study aims to extend the understanding of the window-opening control by occupants in private and two-person offices in summer. A field study was carried out from 13 June to 15 September 2006 in offices with and without night ventilation, located in Cambridge, UK. The monitoring data give evidence that there is a statistically significant relationship between window-opening behaviour patterns and indoor stimulus (i.e., indoor air temperature) in summer. The activity of window control in offices both with and without night ventilation was mostly constrained to the start of period of occupation. Once a window state had been set up on the arrival it mainly stayed the same until departure. The percentages of total window change events in offices without night ventilation during the intermittent period from open to closed and closed to open were 3% and 2%, respectively. A window in an office that featured a night cooling strategy was always open upon the departure whenever the room temperature was over 23.6 °C. Finally, the stochastic models to predict window-opening behaviour patterns as a function of indoor temperature, time of day and the previous window state were developed.

Keywords: Occupant behaviour; Window-opening patterns; Natural ventilation

1. Introduction

Occupants of buildings consciously interact with the environmental system to satisfy their specific needs for comfort. Occupant involvement in operating the environment system includes opening windows, adjusting blinds, switching lights, controlling the heating, cooling, ventilating equipment, and so forth. Indeed field investigations have indicated that the variation in energy consumptions of identical buildings were mainly due to the behaviour of the occupants [1]. According to Baker and Steemers [2], occupants can change the energy use of similar buildings by a factor of 2. Therefore, the understanding of the occupant interaction with environmental control systems is of significance.

Previous research on occupant behaviour regarding ventilation mainly focused on the heating conditions. One of the reasons is that opening windows in winter can result in a heating energy penalty. Warren and Parkins [3] found that the window-opening events in offices during the heating season were closely correlated with outdoor air temperature. Fritsch et al. [4] developed a stochastic model of window opening in the winter period. Their model, which applies Markov chains to linking the current window angle with the outdoor temperature and previous window angle, were used to generate a time series of window-opening angle.

More recently, Nicol [5] presented a stochastic model, relating the use of windows to outdoor temperature. It was derived from extensive field studies in five European countries with a probit analysis. Herkel et al. [6] also proposed the stochastic model to associate a window state with the corresponding occupancy and outdoor temperature.

The previous studies have given an insight into the interaction between occupants and environmental controls. However, it seems that they have limited implications on free-running buildings in summer or mid-seasons because

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indoor stimulus is not considered. Indoor thermal stimulus within the same building would vary considerably according to different orientations, façade designs or effects of neighbouring buildings under identical outdoor thermal stimulus. In reality, it is not outdoor but indoor stimulus that occupants can perceive. Therefore, as stated by Robinson [12] coupling indoor stimulus with occupant interaction would be more appropriate.

Based on the previous studies with regard to the window-opening behaviours, a field study was carried out in order to expand the understanding of the occupant interaction with a window control in summer. The specific aims of this study are:

- to analyse the interrelationship between window-opening behaviours and indoor stimulus,
- to clarify the effects of both the time of day and the previous window state on the subsequent window state,
- and finally to develop the stochastic model to be used for the statistical thermal simulations of the building performance.

2. Field study

2.1. Case study offices

Two naturally ventilated office buildings, located in the Sidgwick site at Cambridge, UK, were selected for a field study. Each building houses mainly offices for one or two people, but also contains a small number of rooms for various purposes. In one of buildings (building A), ventilation is provided by a central pivot window. Another building (building B) employs a night ventilation strategy for cooling. A carefully designed tilt and turn window enables occupants to open windows in two ways. A bottom pivoted window is used for small opening; a side hung option for large opening. There are an insect screen and tilted external louver in front of an openable window, and therefore, offices are free from security problems and protected from heavy rain.

Six monitored offices are identified as 1–6. Only office 6 was situated in a building with night ventilation. Office 5 is occupied by two people while the others are private offices. Details of offices are explained in Table 1.

2.2. Data acquisition

The measurements were carried out from 13 June to 15 September 2006. Occupants were observed for the first week of the measurement. This observation revealed that they typically stayed in the office during normal working hours.

Indoor temperatures and the state of the window were collected from data loggers installed in each office. External temperatures recorded at 30 min intervals were obtained from the nearest weather station, available on an online database [7]. Indoor temperatures in each office were monitored by two stand-alone data loggers that recorded the temperature at 10 min intervals. One logger was installed on the workstation and another was set on the book shelves, away from a window. State data loggers were mounted on the window frame for continuous monitoring of the window state. The logger checks whether a window is closed or open at every half second and records the time and state whenever the state of window changes. During the whole monitoring period, the monitoring data were downloaded at three times on 30 June, 14 August and 15 September. When downloading, the questionnaire survey was also conducted in order to identify the unoccupied period and occupant's overall evaluation of indoor environmental conditions.

For the analysis of the field measurement, indoor and outdoor temperatures were averaged over a 1 h interval when there was no change in a window state over the period. In case when the change of a window state occurred within a 1 h interval, the temperature recorded at the point just before the change of a window state was used for the data analysis. It should be mentioned that as soon as the window state changes from open to closed or from closed to open, indoor temperature goes up or drops. Therefore, it seems reasonable to choose the indoor temperature immediately preceding the interaction with window controls for the analysis. This was used to better represent thermal stimulus that stimulates occupants to interact with the window.

3. Thermal stimulus: indoor and outdoor temperatures

Previous research [3–6] explains the occupant interaction with window controls as a function of external temperature. The main reason for this is the practicality of using

Table 1
Descriptions of the monitored offices

	Building	Night ventilation	Orientation	Window type	Number of occupant
Office 1	Building A	No	West	Central pivot	1
Office 2	Building A	No	East	Central pivot	1
Office 3	Building A	No	East	Central pivot	1
Office 4	Building A	No	East	Central pivot	1
Office 5	Building A	No	South	Central pivot	2
Office 6	Building B	Yes	East	Tilt and turn	1

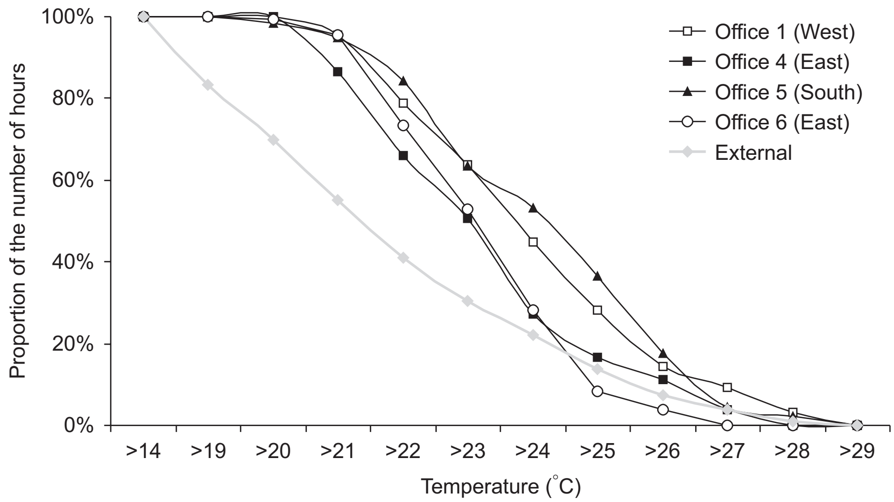

Fig. 1. Comparison of the number of hours of indoor and outdoor temperatures over a certain temperature.

outdoor temperature instead of indoor temperature. The outdoor temperature is an independent variable while the indoor temperature is a dependent variable and relatively hard to obtain [3,5]. Another difficulty of using indoor thermal stimulus was due to the fact that room temperatures are relatively invariable in the heating season. So, no statistically significant relationship was found between indoor temperatures and window positions in winter [4].

However, Fig. 1 suggests that indoor thermal stimulus, (i.e., the indoor temperature) has a potential to account for occupant behaviour patterns of opening a window in summer. Fig. 1 shows the proportions of the number of hours in which a certain temperature was exceeded from 08:30 to 18:30 h for the monitoring period. Only workdays when all the offices (in this case offices 1, 4, 5 and 6) were occupied were analysed for an accurate comparison. This eliminated weekends and day-offs. There were wide variations in occupied dates of each occupant due to different vacation schedules during the monitoring period. Thus, office 4 was selected among east facing offices without night ventilation in order to maximise the period of analysis.

The inside temperatures showed a wide variation according to orientation, while the outdoor temperatures remained the same. Internal temperatures over 25° were most frequent (37%) in a south-facing office (office 5) and the highest number of hours (17 h out of 180 h) of temperature over 27° was observed in the west-facing office (office 1). The east-facing offices (offices 4 and 6) maintained more comfortable conditions in summer, compared to other offices. Only 14% (office 4) and 8% (office 6) of the analysis period exceeded the indoor temperature of 25°. In particular, the positive effect of night ventilation on the indoor temperature distributions in office 6 was obvious. The number of temperatures over 25° of the office with night ventilation was the lowest (8%) and even lower than that (14%) of the outside temperatures.

As partially shown in Fig. 1, the indoor temperature varies with a range of factors, such as orientation, the design of an envelope, the thermal mass of the building structure, internal heat gains, etc. However, the existing occupant model, in which occupant behaviour is explained by outdoor stimulus, would result in the identical prediction of behavioural patterns even if the indoor thermal stimuli are different. Thus, the prediction as a function of external temperatures cannot be considered as an intrinsic result [3]. It seems more reasonable to link the indoor temperature with window-opening behaviour patterns in summer.

4. Occupant behaviour patterns

4.1. Offices without night ventilation

The time of day is a crucial factor in characterising the interaction of an occupant with a window. It was observed that the pattern of occupant interactions with a window varied considerably with the time of day. Figs. 2 and 3 reveal that there was a clear distinction of window-opening behaviours between on arrival and during the intermittent hours in the offices without night ventilation. In this paper, the *intermittent* hours represents the occupied hours except the arrival at and departure from an office.

The change of a window state mainly occurred on the arrival at or departure from offices. All windows of the monitored offices in building A were closed as a security measure, when leaving the offices. So, the state of the window at the previous time step of the arrival was *closed*. The average frequency of a window state from closed to open at the first arrival was 61%. There was a variation in the occupant interaction with a window on the arrival among investigated offices. In particular, the occupant in office 1 opened the window just 29% of total arrival times while other offices showed that the window was opened more than 60%.

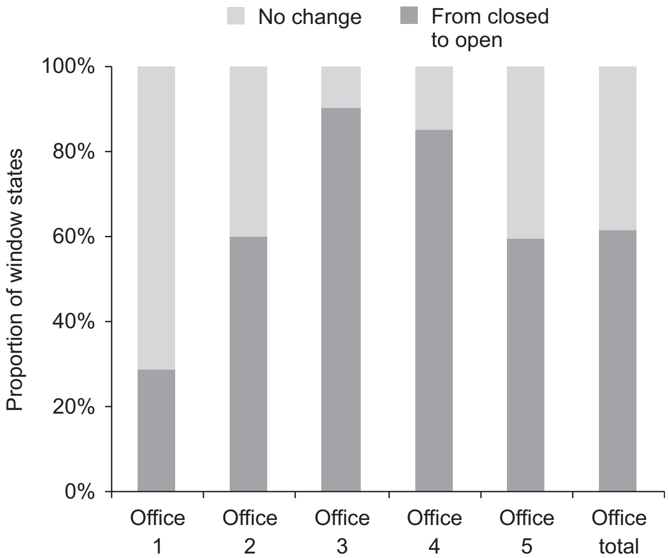

Fig. 2. The proportion of the events of changing a window state on arrival in offices without night ventilation.

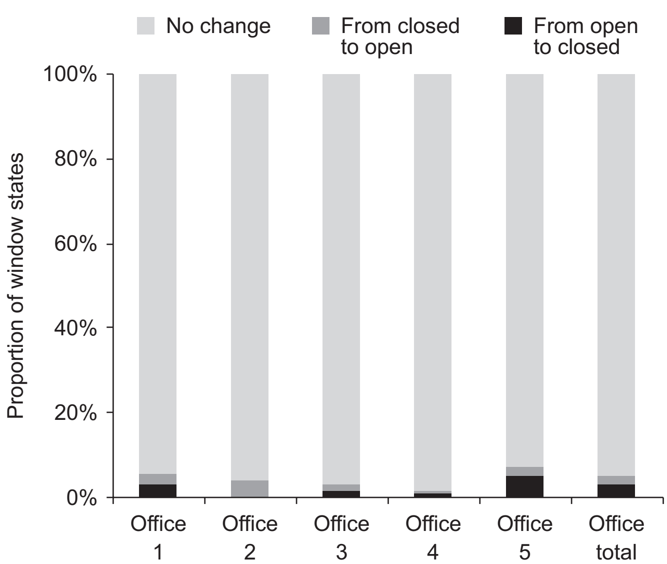

Fig. 3. The proportion of the events of changing a window state during the intermittent hours in offices without night ventilation.

In contrast, the state of window remained almost unchanged during the majority of the intermittent hours. The percentages of window change events from open to closed and closed to open were 3% and 2%, respectively.

4.2. *Office with night ventilation*

This study found that the activity of window controls in an office with night ventilation predominantly occurred at the beginning of the working day (Fig. 4). When the window on the departure had been widely open, the frequency of a window state change on arrival was 34%

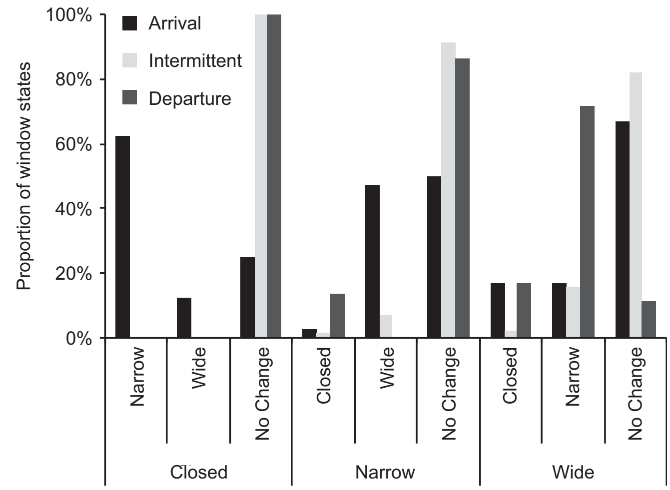

Fig. 4. The proportion of the events of changing a window state at arrival, intermittent period and departure in an office with night ventilation.

and it rose to 75% when the previous state of a window was closed.

Also, the analysis of the monitoring data showed that a window was slightly opened in most cases, when vacating the office. Consequently, the behaviour patterns on the arrival with the previous window state of slight open were of interest. On the arrival, the window state from slightly open to closed hardly occurred. Instead, the window usually remained unchanged or switched to widely open.

Once a window state had been set up on the arrival it generally stayed the same during the intermittent period until the departure. For instance, when the window was slightly open, the percentage of a window state change to close was 2%; to widely open, 7%; and no change, 91%.

On departure, a relatively small proportion of changes of a window state were found in the office with night ventilation. This was because of a strong tendency for an occupant to position a window to slightly open on the departure from the office. Eighty-six percent of a slightly open window remained unchanged whereas 72% of a widely open window changed to slightly open.

5. Time-dependent occupant behaviour model

As identified above, the occupant behaviour patterns are time dependant. For that reason, we divided an occupied day into the three periods of arrival, intermittent hours and departure, when analysing the relationship between indoor stimulus and window-opening controls.

5.1. *Thresholds of changing window states*

Investigations were conducted to find out whether there are specific temperatures in which occupants change a window state from open to closed or closed to open.

On arrival, the analysis confirmed a general trend of window-opening patterns, such that the higher the indoor temperatures were, the more frequent the window-opening

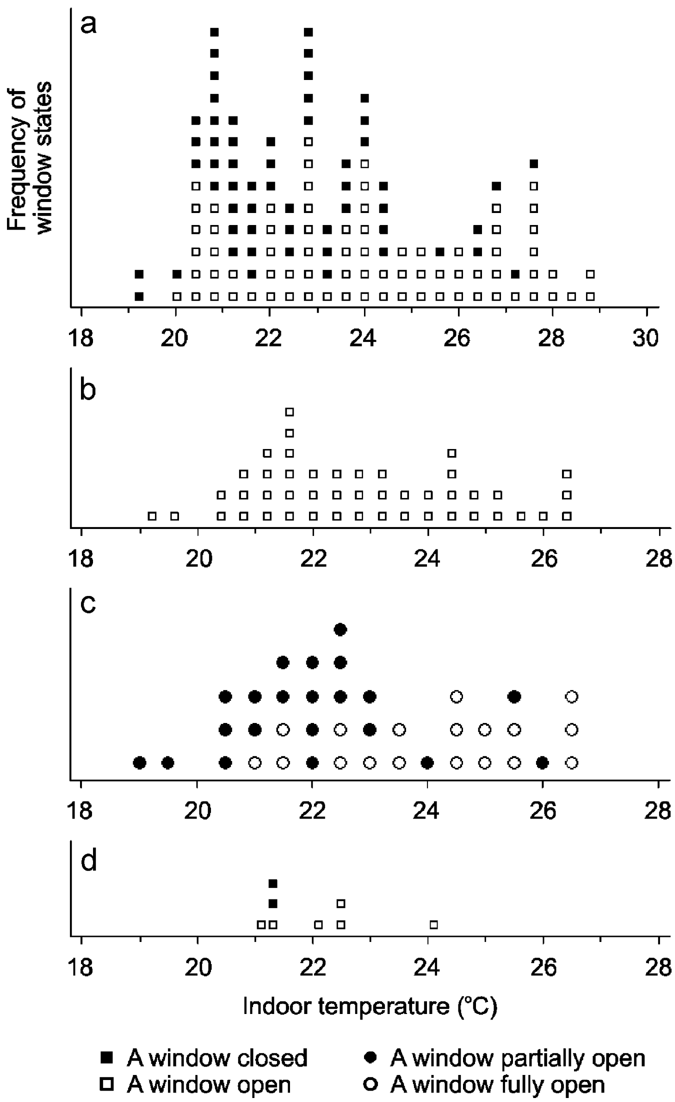

Fig. 5. The frequency distributions of a window state with corresponding indoor temperature on the arrival. (a) Total offices without night ventilation with a previous window state being closed. (b) A night ventilated office with a previous window state being open. (c) A detailed analysis of a night ventilated office with a previous window state being open. (d) A night ventilated office with a previous window state being closed.

events were (Fig. 5(a)). In cases without night ventilation, the frequency of a window open was considerably increased when the temperatures were over 22 °C.

The trend was less clear in an office with night ventilation where in most cases the window had been set to open for night cooling on the departure (Fig. 5(b)–(d)). On arrival, no monitoring data of a shift of a window from open to closed were recorded. However, as can be seen in Fig. 5(c), as the temperature goes up, the number of shifts from slightly to widely open increased. In cases when a widow had been closed on departure (Fig. 5(d)), the occupant opened a window whenever the corresponding temperatures were over 22 °C.

Fig. 6 again confirms that occupants were inclined to keep the window state unchanged during the intermittent

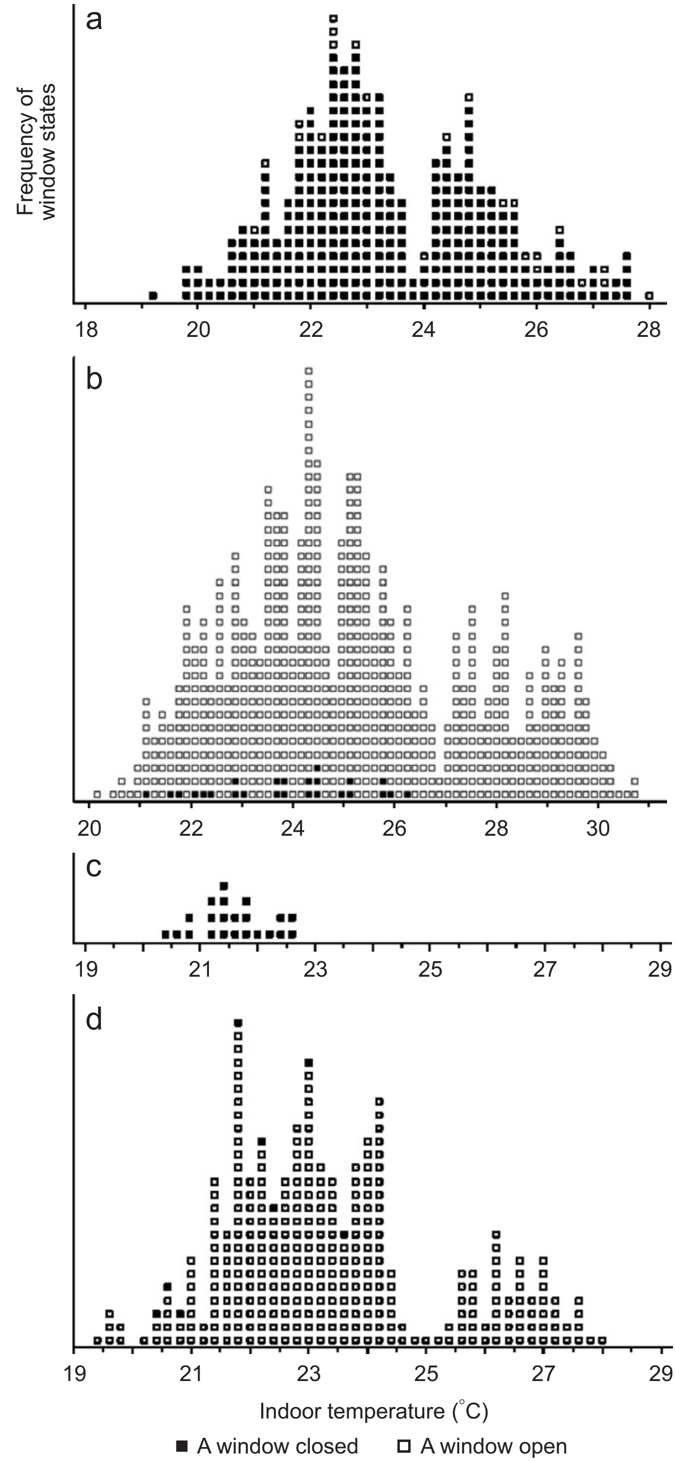

Fig. 6. The frequency distributions of a window state with corresponding indoor temperature during the intermittent period. (a) Total offices without night ventilation with a previous window state being closed. (b) Total offices without night ventilation with a previous window state being open. (c) A night ventilated office with a previous window state being closed. (d) A night ventilated office with a previous window state being open.

hours. The proportions of a window from closed to open in offices without night ventilation with the inside temperature even over 22 °C were quite low. The change activities of a window position from open to closed were also few. In particular, when the room temperature was over 26.3 °C, it was observed that a window always stayed open.

The open window in the night ventilation office (office 6) during the intermittent period was rarely closed. The window was still open with the inside temperature of 19.3 °C (the lowest recorded temperature during intermittent hours). Also, no data of a window shifting from open to closed with the corresponding temperature of over 23.7 °C was monitored (23.7 °C is the highest recorded temperature of a window state changing from open to closed during intermittent hours). No opening events of a closed window in the office with night ventilation took place during the intermittent period in this particular case. This might be explained by the relatively low range of the corresponding inside temperatures (i.e., the office remained relatively cool). It should be also mentioned that the number of the monitoring samples was limited to 22 (Fig. 6(c)).

In most times (90%) night ventilation was realised in office 6 when the previous state window state was open (Fig. 7). There were only a few cases in office 6 that the window was closed on departure even when the room temperatures were below 23.6 °C. On departure a closed window was observed just four times with the previous window state being closed. The corresponding temperatures were all of below 22 °C. In this specific case night cooling was not deployed.

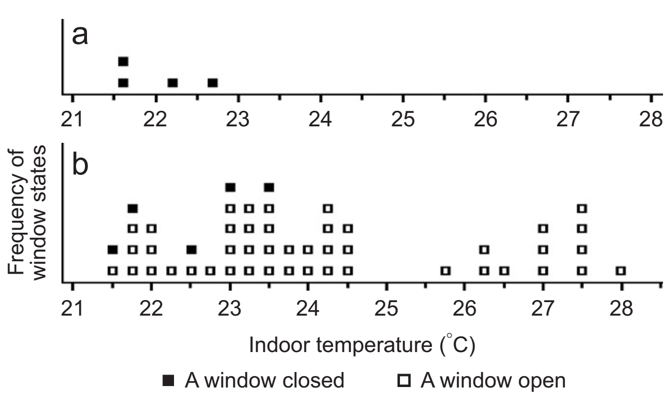

Fig. 7. The frequency distributions of a window state in office with night ventilation on departure. (a) Total offices without night ventilation with a previous window state being closed. (b) Total offices without night ventilation with a previous window state being open.

The analysis provided the general trends of window-opening behaviour patterns in relationship with both the time of day and indoor temperatures. However, it was not possible to derive any specific thresholds of changing window states. At the same time, it was also found that occupant behaviours of window control are more likely to be stochastic, not deterministic.

As Nicol [5] stated, there is a stochastic rather than a precise relationship between the use of environmental controls by occupants and the physical conditions. Consequently, the assumption that a window is open whenever the indoor stimulus is over a certain threshold of inside temperature is not adequate, nor precise. In this study, therefore, the stochastic approach was applied in order to derive time-dependent transition probability models relating the indoor stimulus to the occupant interaction with window control.

5.2. Transition probability model of window control

Probability models for offices with and without night ventilation were derived through probit and ordinary linear analysis of the monitoring data. Probit analysis is the natural complement of ordinary linear regression to describe the relationship between the binary or categorical-dependent variable and a set of independent variables [8,9]. A normal distribution is used in probit analysis to provide a probability model. Because the nature of a dependent variable in this study is fundamentally binary, (i.e., a window is open or closed), probit analysis was selected for the primary regression method. The probability models for each regression models are as follows:

For probit analysis:

$$P = \frac{e^{a+bt}}{1+e^{a+bt}}. \quad (1)$$

For ordinary linear analysis:

$$P = a + bt, \quad (2)$$

where a and b are regression constants and t is indoor temperature.

Table 2
Descriptions of the probability models derived from the field study

	Abbreviations	Time of day	Window state		Comparison
			Previous	Current	
Office without night ventilation	$P_{\text{C–O(Arr)}}$	Arrival	Closed	Open	$P_{\text{C–C(Arr)}} = 1-P_{\text{C–O(Arr)}}$
	$P_{\text{C–O(Int)}}$	Intermittent	Closed	Open	$P_{\text{C–C(Int)}} = 1-P_{\text{C–O(Int)}}$
	$P_{\text{O–C(Int)}}$	Intermittent	Open	Closed	$P_{\text{O–O(Int)}} = 1-P_{\text{O–C(Int)}}$
Office with night ventilation	$P_{\text{C–O(Arr)}}$	Arrival	Closed	Open	$P_{\text{C–C(Arr)}} = 1-P_{\text{C–O(Arr)}}$
	$P_{\text{O–O(Int)}}$	Intermittent	Open	Open	$P_{\text{O–O(Int)}} = 1-P_{\text{O–C(Int)}}$
	$P_{\text{O–C(Dep)}}$	Departure	Open	Closed	$P_{\text{O–C(Int)}} = 1-P_{\text{O–O(Int)}}$

Each probability model of the operation of a window was obtained, having considered the effects of indoor temperatures and the time of day. To reflect the time of day effects, separate probability sub-models for the start, intermittent and end of the period of occupation were established.

It is clear from Section 5.1 that the previous state of a window has a significant effect on the subsequent window state. Therefore, the probability functions of shifting a window state from closed to open or from open to closed for different periods of occupation were proposed. It enables the prediction of the current window state in relation to the previous window state.

The time-dependent probability models considered are summarised in Table 2. For offices without night ventilation, the probability of closing a window at the end of the period of occupation was observed to be 100%. So, the previous window state for the start of the period of occupation was kept closed.

Although office 6, three states of a window position (i.e., closed, slightly open and widely open), were recorded, probability models to predict the change of three states of a window has not a sufficient statistical significance. Rather, the two-state model was developed and presented here.

5.2.1. *Office without night ventilation*

First, we investigated indoor and outdoor temperatures as the driving variables for window control activities by occupants. The regression models at arrival and during the intermittent period are given in Table 3. To assess the regression models, we used "*G*-statistic" for the overall model test; "*Z*-statistic" for independent variable test; and "Pearson statistic for goodness-of-fit test" in probit analysis. In ordinary regression analysis, a *F*-statistic method was used for the overall model test; a *T*-statistic method for independent variable test; and R^2 (coefficient of determination or explained variance) for substantive significance test [10,11].

The probit analysis for occupants' arrival reveals that the regression model based only on indoor temperature is statistically significant. Although the *P*-values from *G*-statistic in two models are less than 0.001, the result of the *Z*-statistic for outdoor temperature, with a *P*-value of 0.937, suggests that the window control patterns at occupants' arrival are not related with outdoor temperature. The Pearson's goodness-of-fit test (*P*-value = 0.594) for the regression model using indoor temperature supports that the model has predicative ability.

The close relationship between window control patterns and indoor temperature during the intermittent hours are confirmed by R^2 values (i.e. 0.635 for the window state change from open to closed and 0.628 for the window state change from closed to open). In addition, *P*-values, calculated from the *F*-statistic and *T*-statistic, are all less than 0.005. This indicates a statically significant relationship with indoor temperature. However, there is poor

Table 3
Regression results and statistical tests of window control for offices without night-time ventilation as a function of indoor and outdoor temperatures

Model	Probability model	Driving variable	Overall model test			Pearson's goodness-of-fit test			Independent variables test			
			Log-likelihood	*G*-statistic	*P*-value	χ^2	*P*-value		Regression coefficient	S.E.	*Z*-statistic	*P*-value
$P_{C-O(Arr)}$	$P_{C-O(Arr)}=\frac{e^{a+bt}}{1+e^{a+bt}}$	Indoor temperature	−87.404	26.335	0.000	88.156	0.594	Constant (a)	−4.849	1.075	−4.51	0.000
								Indoor temperature (b)	0.218	0.045	4.77	0.000
	$P_{C-O(Arr)}=\frac{e^{a+bt+ct_{out}}}{1+e^{a+bt+ct_{out}}}$	Indoor and outdoor temperatures	−87.401	26.341	0.000	145.635	0.516	Constant (a)	−4.842	1.079	−4.49	0.000
								Indoor temperature (b)	0.220	0.053	4.17	0.000
								Outdoor temperature (c)	−0.003	0.038	−0.08	0.937
Model	Probability model	Driving variable	Analysis of Variance						Independent variables test			
			Sum of squares	Mean square	*F*-statistic	*P*-value	R^{2a}		Regression coefficient	S.E.	*T*-statistic	*P*-value
$P_{O-C(Int)}$	$P_{O-C(Int)}=a+bt\ (t\leqslant 30)$	Indoor temperature	0.004	0.004	13.87	0.006	0.634	Constant (a)	0.209	0.049	4.29	0.003
								Indoor temperature (b)	−0.007	0.002	−3.72	0.006
	$P_{O-C(Int)}=a+bt_{out}$	Outdoor temperature	0.000	0.000	0.00	0.975	0.000	Constant (a)	0.040	0.046	0.87	0.400
								Outdoor temperature (b)	0.000	0.001	0.03	0.975
$P_{C-O(Int)}$	$P_{C-O(Int)}=a+bt\ (t>20)$	Indoor temperature	0.038	0.038	10.11	0.019	0.628	Constant (a)	−0.629	0.226	−2.79	0.032
								Indoor temperature (b)	0.030	0.010	3.18	0.019
	$P_{C-O(Int)}=a+bt_{out}\ (t_{out}>15)$	Outdoor temperature	0.015	0.015	4.76	0.052	0.302	Constant (a)	−0.115	0.088	−1.31	0.216
								Outdoor temperature (b)	0.009	0.004	2.18	0.052

[a] R^2 refers to the proportion of explained variance by independent variable.

Table 4
Regression results and statistical tests of window control on occupants' arrival for individual offices without night-time ventilation as a function of indoor temperature

Model	Probability model	Office number	Overall model test			Pearson's goodness-of-fit test			Independent variables test			
			Log-likelihood	G-statistic	P-value	χ^2	P-value		Regression coefficient	S.E.	Z-statistic	P-value
$P_{C-O(Arr)}$	$P_{C-O(Arr)} = \frac{e^{a+bt}}{1+e^{a+bt}}$	1	−18.327	6.645	0.104	15.787	0.730	Constant (a)	−4.636	2.518	−1.84	0.066
								Indoor temperature (b)	0.174	0.108	1.61	0.108
		2	−5.432	6.459	0.026	12.081	0.209	Constant (a)	−7.864	3.53	−2.23	0.026
								Indoor temperature (b)	0.325	0.140	2.32	0.020
		3	−5.283	2.438	0.118	24.956	0.096	Constant (a)	−5.775	4.935	−1.17	0.242
								Indoor temperature (b)	0.272	0.192	1.41	0.158
		4	−9.099	4.453	0.035	18.124	0.641	Constant (a)	−8.250	5.073	−1.63	0.104
								Indoor temperature (b)	0.420	0.233	1.80	0.072
		5	−34.978	6.072	0.014	52.847	0.259	Constant (a)	−3.758	1.802	−2.09	0.037
								Indoor temperature (b)	0.173	0.077	2.24	0.025

correlation between the window control patterns with outdoor temperature. In particular, the regression model with outdoor temperature for the window state from open to close is not significant (e.g. R^2 is less than 0.001 and a P-value in analysis of variance is 0.975). After identifying this, the regression models based only on indoor temperature are given in Tables 4 and 5.

There is a marked difference in the predicted probabilities of opening a window between different offices at the start of a period of occupation. Fig. 8 shows the predicted probabilities of a window from closed to open on arrival. These were drawn using Eq. (1) and statistical tests and constants of each office are presented in Table 4. The variation of the probabilities between offices 1 and 4 was the biggest. The predicted probabilities of window open at the temperature of 23 °C were 35% for office 1 and 80% for office 4. This large spread could be understood by the difference in individual occupants' control of a window. The occupant in office 4 was a more active in interacting with a window while the occupant in office 1 rather passively adjusted a window (Fig. 2).

The probability of $P_{C-O(Arr)}$ for all offices (1–5) lies in between probability curves of offices 1 and 4. In particular, P-value for the probability model for the total office, obtained from G-statistic in Table 3, is less than 0.001, confirming the statistical significance of the gained model. It is also of interest to observe that the expected probability of a window opening in office 5, which it was occupied by two people, has a similar pattern to the average of all the offices (1–5).

All observations during the intermittent hours were transformed to 1 h averaged indoor temperatures along with corresponding window states and were grouped into temperature bins with 1° interval. For example, the temperature bin of 21 °C contains the observed data, of which indoor temperatures are from 20.50 to 21.49 °C. The ratio of the number of window state change events to the total of each bin is plotted against temperature bins (Fig. 9). The intermittent probability models for offices without night ventilation were based on this plotted data and the regression models with statistical results are shown in Table 3.

The inverse relationship between the frequencies of closing an open window and indoor temperatures were found during the intermittent hours. The derived probability model also confirmed that changing an open to closed window were rare events. The highest probability observed was only 7% with the temperature range from 21 to 30 °C. No observation of closing was made for temperatures over 27 °C.

The gradient of the intermittent probability model of opening a closed window was positive but modest. The time of day effects were apparent. The probabilities of opening a window were much lower than those of the start of a period of occupation.

5.3. Office with night ventilation

Figs. 10 and 11 summarise the results of probit and ordinary linear regression models for an office with night ventilation. The values of each constant and corresponding statistical test results are given in Table 5. In cases of the intermittent period and the end of a period of occupation once a window had been closed, the window state was not changed. Also, the window, which had been open on the departure, remained open at the start of a period of occupation. Consequently, regression analyses for those cases were not carried out.

There were limited data for cases where a window was closed on occupants' arrival. Although the probability model of opening a closed window on the arrival should not be considered precise (a P-value from Z-statistic for indoor temperature in Table 5 is 0.300), the prediction by this model seems plausible. A P-value from G-statistic for this regression model is 0.091. The statistical test results of the regression models for during intermittent hours and on occupants' departure in Table 5 show that these models are statistically (i.e. P-values in overall model test and analysis of variance are less than 0.05) and substantively

Table 5
Regression results and statistical tests of window control for night-time ventilated office as a function of indoor temperature

Model	Probability model	Overall model test			Pearson's goodness-of-fit test			Independent variables test			
		Log-likelihood	*G*-statistic	*P*-value	χ^2	*P*-value		Regression coefficient	S.E.	*Z*-statistic	*P*-value
$P_{\mathrm{C-O(Arr)}}$	$P_{\mathrm{C-O(Arr)}} = \frac{e^{a+bt}}{1+e^{a+bt}}$	−3.074	2.850	0.091	1.897	0.594	Constant (a)	−38.622	37.491	−1.03	0.303
							Indoor temperature (b)	1.823	1.758	1.04	0.300
$P_{\mathrm{O-O(Dep)}}$	$P_{\mathrm{O-O(Dep)}} = \frac{e^{a+bt}}{1+e^{a+bt}}$	−13.264	5.979	0.014	32.162	0.837	Constant (a)	−11.264	6.777	−1.66	0.096
							Indoor temperature (b)	0.543	0.298	1.82	0.069
Model	Probability model	Analysis of Variance						Independent variables test			
		Sum of squares	Mean square	*F*-statistic	*P*-value	R^2		Regression coefficient	S.E.	*T*-statistic	*P*-value
$P_{\mathrm{O-C(Int)}}$	$P_{\mathrm{O-C(Int)}} = a + bt$ $(t \leqslant 26)$	0.017	0.017	11.07	0.013	0.613	Constant (a)	0.444	0.124	3.59	0.009
							Indoor temperature (b)	−0.017	0.005	−3.33	0.013

(i.e. a *P*-value in Pearson's goodness-of-fit is over 0.05 and R^2 for the intermittent model is 0.613) significant. This is despite a modest number of cases.

The occupant behaviour model enables us to predict whether night ventilation would be exercised on an occupant's departure as a function of corresponding inside temperatures. Over 90% probability of applying night cooling is expected with the inside temperature of 24 °C with the previous window state of open.

The rare events of closing an open window are predicted by the developed ordinary linear regression model, which is consistent with the case of offices without night ventilation. No window is predicted to be closed with a temperature of over 26 °C.

6. Discussions

This study develops time-dependent window-opening behaviour models for offices with and without night ventilation through the analysis of field study data in summer. It was revealed that occupant's interaction with window controls can be accounted for as (i) a function of the indoor temperatures, (ii) previous state of a window opening and (iii) time of day effects.

One important application of the developed models would be their integration with dynamic building simulations. Generally, current building simulations handle occupant interactions in deterministic ways based on a predefined schedule. As a result, they lead to errors in the prediction of both the indoor thermal conditions and energy demands [12]. One criticism of the Nicol's model [5] is that it cannot predict when and how long a window is open because there is not any relationship between the previous and current state of individual windows [13]. Therefore, it is not able to estimate what can take place once a window is open or closed. However, the time-dependent model developed in this study estimates the current window state in relation to the previous window state. So, the developed model can be applied to statistical dynamic energy simulations considering the effects of the previous state of a window on the current state.

The simulation that combines the building physics algorithm with a stochastic occupant model would contribute to more realistic evaluations of building thermal performances. In fact, this hybrid nature of simulation is identified as one of the challenges of the building simulation [14].

This study also provides evidence that each individual responds differently to the thermal stimulus, thus resulting in different interactions with the control of a window. For instance, there was a marked contrast in occupant behaviour patterns between offices 1 and 4 (Figs. 2 and 8). The occupant in office 4 was more frequently changing the state of the window and seemed more responsive to the intensity of the indoor temperature than the user in office 1. The proportion of changes in window at arrival times in office 1 was only 29%; for office 4 was 85%. According to individual regression models for arrival, the probability of a window being open for office 1 is 0.39 at an indoor temperature of 24 °C; for office 4 is 0.86.

When the window control model based on all occupants' responses is integrated into a deterministic model of building energy analysis, it would enable us to identify the real effects of occupant behaviour on the thermal and energy performances of buildings. In addition, the integrations of two prediction models based on offices 1 and 4 would reveal the possible range of occupants' impact on building performance. These models for offices 1 and 4 generate two outermost prediction curves as shown in Fig. 8. For instance, the integration of the office 4 model into building simulation would show the performance of the building, in which its occupant actively adjusts the state of the window for controlling the indoor environment.

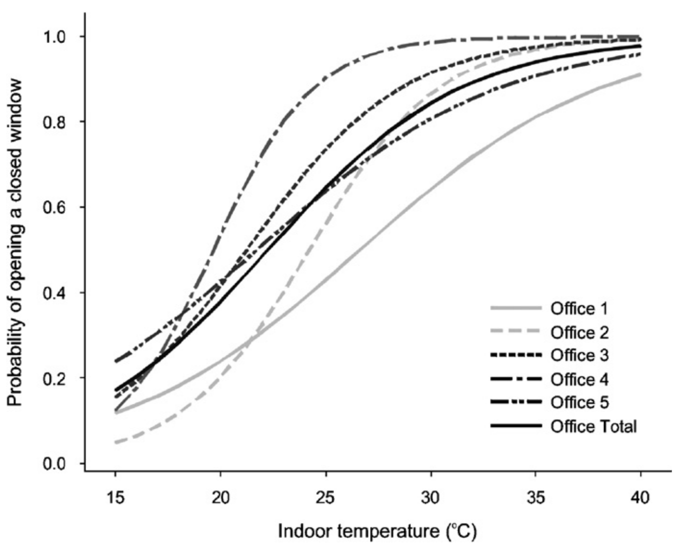

Fig. 8. The prediction of probabilities of opening a closed window for offices without night ventilation on arrival.

It seems that how an occupant recognises the effectiveness of a window as an environmental controller is an important factor in the occupant interaction with the opening of a window. Fig. 12 illustrated a clear difference in occupants' perceived control over their environments. The occupant in office 4, who actively opened a window, felt that the control over the local air quality and thermal environment was generally high. In contrast, the occupant in office 1 recognised the ability to adjust the environmental conditions quite low particularly in the afternoon. The comment by the occupant in office 4 suggests that the positive appreciation of a window as an effective environment measures might result in more active interaction with a window.

> I am lucky to be in an East facing office as the temperature is usually pleasant throughout the day … so I can control my environment. I also have control of the amount of fresh air I get as I have a window … and plenty of green plants to give me extra oxygen during the day! I am very happy NOT to have air-conditioning in this office as I find that artificial environment very uncomfortable and many people catch colds, etc easily in air-conditioned offices.

It should be also mentioned that security has been a key factor of deploying night ventilation by occupants. An occupant in building B, in which was absent from security problems due to the careful design of a window system, was able to open a window for night cooling on departure. In contrast, the security measures of building A included closing windows on departure. It seems that designing with the consideration of both security and environmental

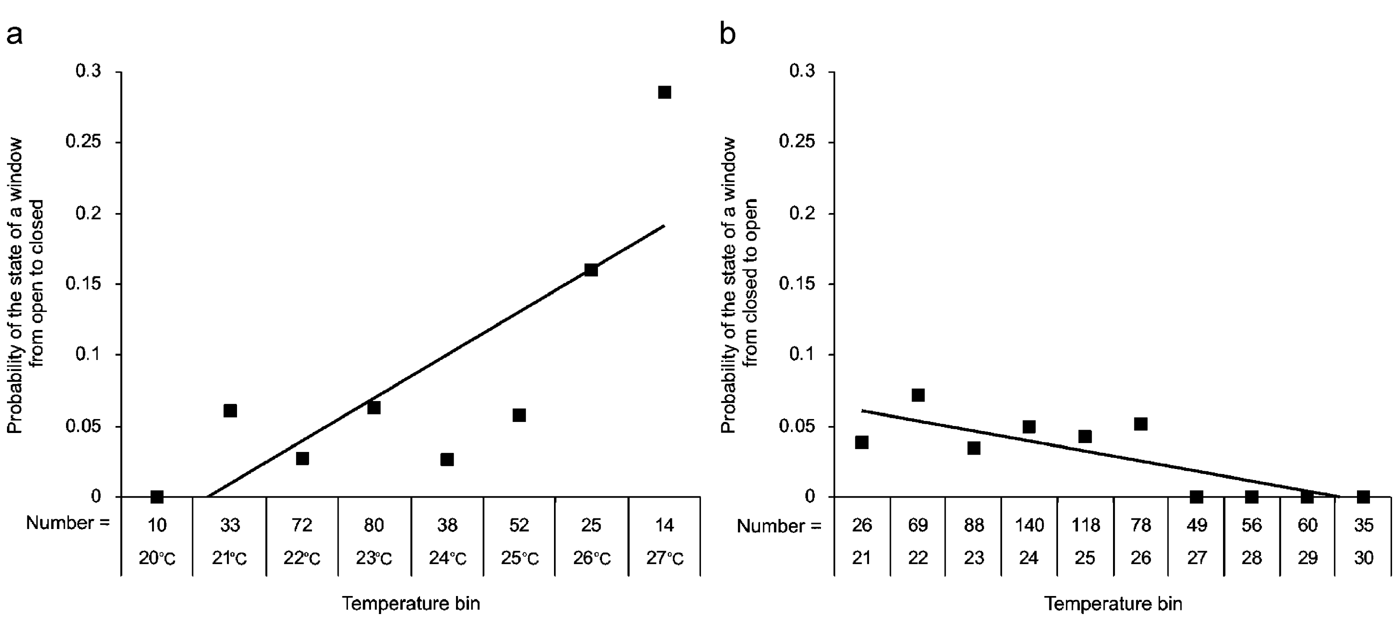

Fig. 9. The observed probability and fitted regression line of a window state change in offices without night ventilation during intermittent hours. (a) The state of a window from closed to open. (b) The state of a window from open to closed.

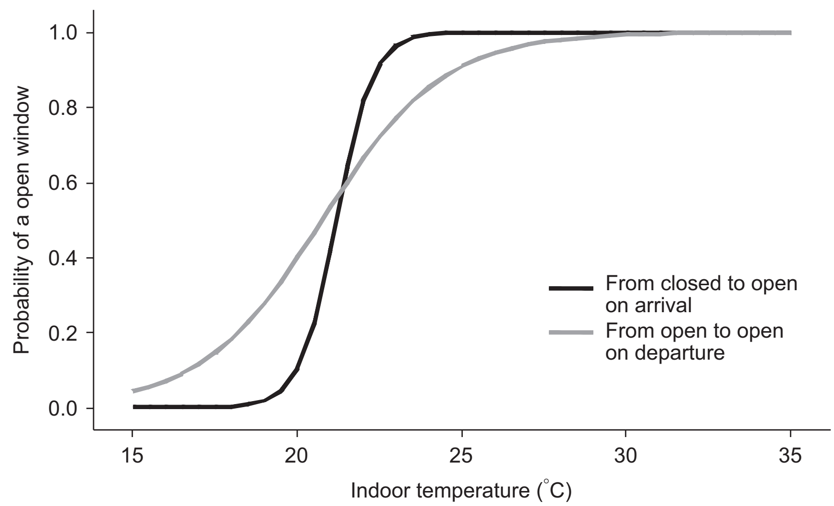

Fig. 10. The predicted probabilities of a window state being open for office with night ventilation on arrival and departure.

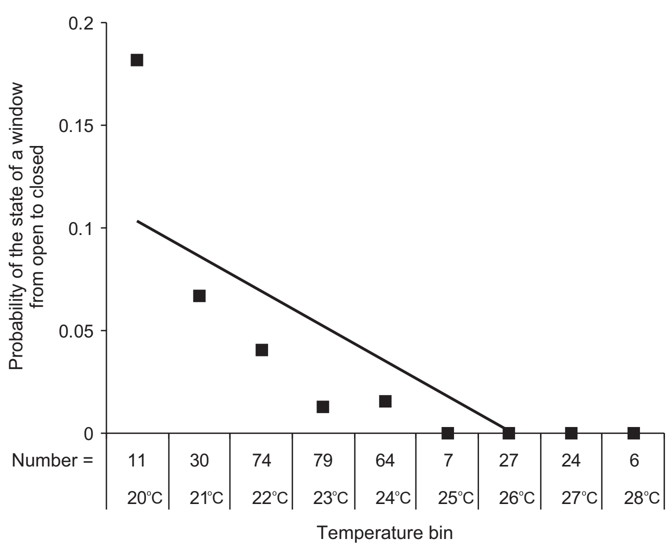

Fig. 11. The observed probability and fitted ordinary linear regression curve of closing an open window.

aspects would lead to the successful application of night ventilation in practice.

In this study, the physical variable to predict the operation of a window by an occupant is confined to the indoor temperature. There are other physical stimuli such as air movement and solar intensity which might affect the behaviour of an occupant. Other than physical variables, which can be easily measured and quantified through the field study, the previous study by Warren and Parkins [3] identified the need for fresh air as another main reason for opening a window. Also the different building designs and environmental strategies could bring about different occupant behaviour patterns. Research to reveal the effects of physical (particularly indoor air quality) and non-physical variables on the occupant behaviours patterns is not included but warrant further investigations. In this paper, whether the occupant behaviour is dependent on the window technology is not dealt with, but further research should address this question.

7. Conclusion

The occupant behaviour patterns with regard to the control of a window in offices with and without night ventilation in Cambridge, UK, were monitored from 13 June to 15 September 2006. Observing that there were large variations in the indoor temperature distributions of the offices under the same weather conditions, window-opening behaviours were explained by indoor stimuli, (i.e. indoor air temperatures). Statistically and substantively significant correlation between the window-opening patterns and indoor air temperatures were found.

There were marked differences in window-opening behaviour patterns according to the time of day. At the start of period of occupation, the average frequency of a window shifted from closed to open for offices without night ventilation was observed 61%. It increased to 76% in the office with night ventilation. The window state on arrival of an occupant had a considerable impact on the subsequent window state during the intermittent hours. A change of a window state in both offices with and without night ventilation barely occurred during the intermittent period. For example, only 7% of the intermittent hours with a closed window in offices without night ventilation shifted to an open window and 3% of those with an open window changed to a closed window. At the end of period of occupation, windows in offices without night ventilation were always closed as a security measure. In contrast, a tilt and turn window with an external louver and bug-screen enabled night ventilation to be exercised in most of the monitoring period.

Two probability models of window-opening behaviour patterns in summer for offices with and without night ventilation occupied by one or two people were obtained from the analysis of monitoring data. Each model is

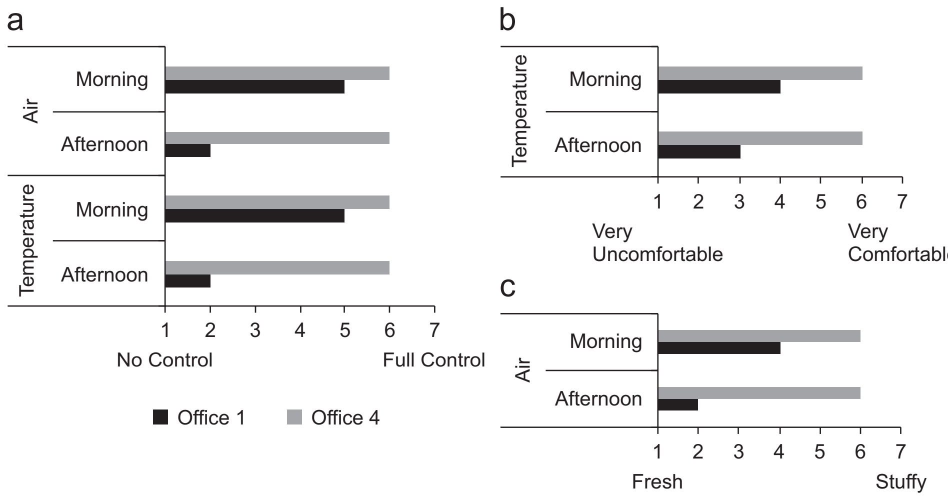

Fig. 12. The occupant perceived controllability over and evaluation of the local environment. (a) The controllability over the environment. (b) The perception of thermal comfort. (c) The perception of air freshness.

comprised of separate probability sub-models for the start, intermittent hours and end of occupation. It predicts the probability of changing a window state from open to closed or from closed to open as a function of indoor temperature and the previous window state.

The outcomes of the study could be a foundation for more realistic evaluations of the thermal performance in naturally ventilated buildings, and also give an insight into occupant behaviour patterns regarding ventilation in summer.

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