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Seasonal variation of window opening behaviors in two naturally ventilated hospital wards

Zhenhi Shi^a, Hua Qian^{a,*}, Xiaohong Zheng^a, Zhengfei Lv^b, Yuguo Li^c, Li Liu^d, Peter V. Nielsen^d

^a School of Energy and Environment, Southeast University, Nanjing, 210096, China

^b Jiangsu Province Hospital, Nanjing, 210096, China

^c The Department of Mechanical Engineering, The University of Hong Kong, Hong Kong, China

^d Department of Civil Engineering, Aalborg University, Aalborg, Denmark

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ABSTRACT

Natural ventilation enables personal control, and occupant behaviors in window opening play a decisive role on natural ventilation performance, indoor air quality (IAQ), and/or airborne infection risk in a hospital setting. The occupant behaviors differ significantly from different building types with different functions and living habits. Based on a one-year field measurement in two general hospital wards in Nanjing, China, the effects of air quality (i.e. indoor CO₂ concentration and outdoor PM_{2.5} concentration) and the climatic parameters (i.e. indoor/outdoor temperature, relative humidity, and outdoor wind speed, wind direction and rainfall) on window opening/closing behaviors are analyzed. Indoor air temperature or relative humidity is found to be a dominant factor for window opening behaviors. Seasonal differences are observed for the different influences of physical factors. The outdoor temperature is found to be associated with the window opening probability negatively during the cooling season, but positively during the transition and heating seasons. The indoor relative humidity positively affects the window opening probability during the transition season while a negative impact appears during the cooling and heating seasons. Based on the seasonal variation of window opening behaviors, Logistic regression models in different seasons (cooling, transition and heating seasons) are developed to predict the window opening/closing state and are verified to be promisingly adaptable with results of accuracy bigger than 70%.

1. Introduction

In hospitals, a high ventilation rate has proven to be effective for reducing the cross-infection risk [1–3]. Natural ventilation can provide a much higher ventilation rate with proper utilization than mechanical ventilation, showing a great potential for controlling airborne infection [4–6]. Large ventilation openings were found to help reduce the infection risk of Severe Acute Respiratory Syndromes (SARS) among healthcare workers (HCWs) during the 2003 epidemics in Guangdong Province [7]. The occupants' window opening behaviors play a decisive role on the natural ventilation performance and significantly influence the airborne infection risk and indoor air quality (IAQ) [8], as well as the energy consumption for air-conditioning systems [9–11]. Many factors are known to influence the window opening behaviors, including thermal-driven factors, time-related factors, environment-driven factors, psychological factors and other uncertain factors [12–25,34,35]. Thermal-driven factors, including outdoor climate conditions, indoor air temperature and relative humidity, occupants'

number, clothing condition, gender, etc., are recognized as the most important driving factors in many previous studies [12–17]. Warren and Perkin [12] found that the outdoor air temperature accounted for 76% of the observed variance of window opening status in office buildings, with sunshine for 8% and wind speed for 4%. Fritch et al. [13] developed a stochastic model with outdoor temperature as the only variable based on data of four office rooms from October to May. No significant variations of window opening behaviors were found with wind speeds lower than 5–6 m/s, and its correlation with sunshine was only observed for the south-facing vertical openings [13]. A study in occupied buildings in the UK, Pakistan and throughout Europe suggested that the indoor temperature was a more coherent predictor for window-opening behaviors rather than the outdoor temperature [14]. Huang et al. [15] found that higher indoor temperature in residential buildings promoted people open windows more frequently in winter. Stazi et al. [16] suggested that the need of thermal comfort was a stronger driving factor for undertaking adaptive actions on windows than the need of improving air quality in classrooms. Time-related

* Corresponding author.

E-mail address: qianh@seu.edu.cn (H. Qian).

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factors vary significantly among buildings with different functions. Haldi and Robinson [18] analyzed the window opening behaviors in office buildings and found the interactions with window opening had a significant correlation with occupants' commuter time because window opening or closing behaviors commonly occurred when occupants arrived at or left their offices. Besides, an attempt to take seasonal effects into consideration by adding a factor with 12 levels corresponding to each month of a year did not bring any significant improvement to the model. Barthelmes et al. [19] used K-S test to rank the influencing variables in residential apartment, and results turned out that the time of the day was the most important variable. Windows were opened and closed at certain times of the day (morning and late afternoon hours) regardless of the different day in a week. Jones et al. [20] investigated the impact of season on residential buildings for window opening/closing behaviors, finding that seasonality affected both frequency and drivers of window operation in bedrooms. Same simulation models to predict window operation behavior could be used in spring and autumn. Environment-driven factors, related to the indoor and outdoor environment quality, occupant's perceived illumination, awareness of environmental concern, cognitive resources, building structure and insulation, even geographic areas, are also important driven factors on occupants' interaction with windows [15,16,21–25]. Andersen and Fabi [24] measured 15 Danish residential buildings of window opening behaviors and corresponding environmental conditions during winter, spring and summer. Results indicated that the indoor CO₂ concentration and outdoor temperature were the two single most important variables for window opening prediction. The indoor CO₂ concentration is regarded as a direct indicator for IAQ and ventilation performance since it is a good surrogate for bioeffluents, even for airborne infection risks [26–29]. It is suggested that PM_{2.5} is more hazardous than PM₁₀ as it is more likely to penetrate and deposit deeper in the tracheobronchial and alveolar regions [30]. In recent years, PM_{2.5} pollution has been a predominant problem and caused great health burden in China [31,32]. Previous study showed that the outdoor PM_{2.5} concentration has become a highly concerned factor on residents' interaction with windows in China [25]. Therefore, outdoor PM_{2.5} concentration can be taken as a representative parameter for outdoor air quality in China. Different geographic areas were also supposed to affect occupants' interactions with windows in office buildings [22,25]. Shi and Zhao [25] conducted a field study in 8 naturally ventilated residential apartments in Beijing and Nanjing, and found that the window opening probability had different correlation strengths for the same variable in different cities, especially accounted for the outdoor PM_{2.5} concentration. Besides, household size, disposable income and ethnicity are all found to be influential factors in residential buildings [33].

The characteristics of window opening behavior vary significantly from buildings with different functions. In office buildings, the window opening and closing behaviors are not only driven by thermal comfort needs but also driven by daily routine (time of the day) and habits (arriving and leaving time) [34]. In residential buildings, occupants' daily activities play an important role on window opening and closing behavior. Cooking, cleaning and getting fresh air accounted for 27%, 40% and 33% of the total openings respectively [35]. The day of week does not influence the window opening behavior in residential buildings [19], which is different from that in office buildings. In classroom buildings, the daily routine is also an essential factor and students' interaction frequency with windows is higher during breaks [17]. Few researches are available on the window opening behaviors in hospitals, although many studies focusing on occupants' window opening behaviors have been carried out in residential, office and classroom buildings, etc. [12–14,24–26,36–38]. Studies on window opening behaviors are significantly important in hospital buildings compared to those in other buildings, as ventilation performance is crucial for infection control in hospitals. The interactions with windows in hospitals have the following different characteristics from that in other buildings.

Firstly, the patient group is not fixed and each person has different living habitat, which makes the interactions with windows in hospital buildings a collective behavior. Secondly, patients may have different thermal comfort due to both health and clothing conditions. Nematou et al. [39] conducted an experimental study in 5 big hospitals and 50 shopping centers in Northern Madagascar and confirmed that the comfort temperature was slightly higher in shopping centers than that in hospitals due to the difference of subjects' activity and clothing conditions. Thirdly, the occupation period is mostly 24 h in hospital buildings, which makes the time-related factors differ from other buildings. Besides, the maximum window opening size is limited in many hospital wards for occupants' safety and security. Moreover, the IAQ requirement is generally higher in hospitals than those non-hospital environments. Finally but importantly, inpatients and HCWs would open windows sometimes to cater for their physical or psychological needs even when air-conditioning is on, although windows are usually advocated to be closed to save energy.

This paper aims to investigate occupants' window opening behaviors in hospital wards. Both of the indoor thermal factors (indoor temperature and relative humidity) and outdoor climatic factors (outdoor temperature, relative humidity, wind speed and direction, rainfall, solar radiation, etc.) are analyzed. In terms of the crucial influence of air-conditioning status on the indoor thermal comfort, the window opening behaviors are analyzed by seasons, including the cooling (summer), transition (spring and autumn) and heating seasons (winter). Seasonal statistical models are developed and verified to help evaluating IAQ and energy consumption.

2. Methods

2.1. Field measurement

A one-year field measurement was designed and carried out in a general hospital building in the Jiangsu Province Hospital, Nanjing, China, which holds up to 42,000 inpatients annually. The investigated building is of central corridor type, one of the most common design for general hospitals in China, as shown in Fig. 1. Semi-centralized (with

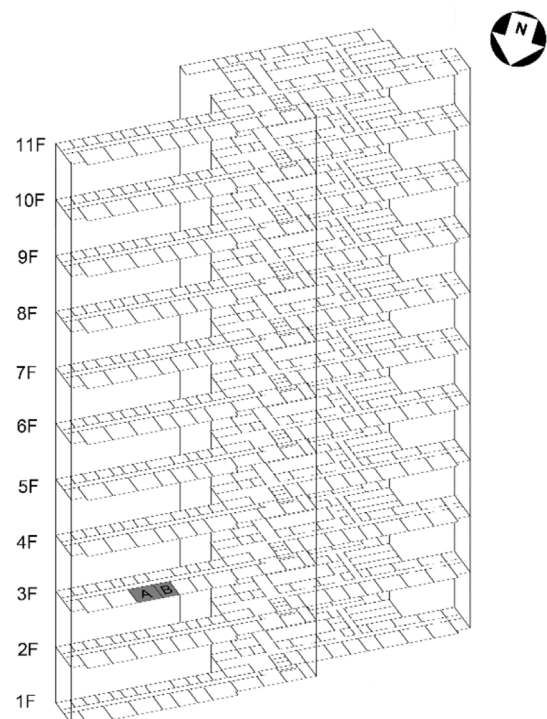


Fig. 1. The spatial distribution of measured wards (grey shaded areas).

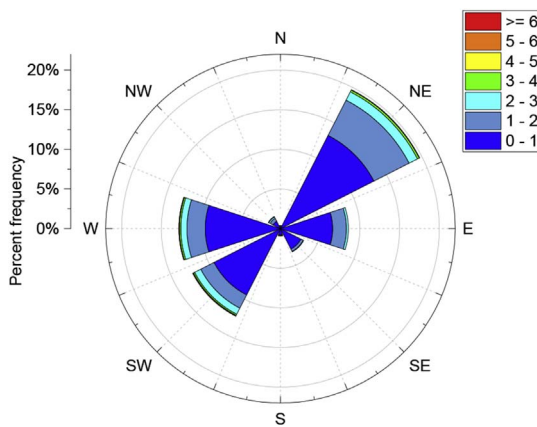


Fig. 2. Wind-rose diagram during the measurement period.

fan coil units) air conditioning systems without fresh air supplement are installed in this building. Occupants can determine when to turn on the air-conditioning and what the setting temperature is with a controlling panel in each ward. Two adjacent wards on the third floor of the ward building were chosen randomly, with dimensions $5.8 \text{ m} \times 7.4 \text{ m} \times 2.6 \text{ m}$ for ward A and $3.5 \text{ m} \times 7.4 \text{ m} \times 2.6 \text{ m}$ for ward B, as shown by the grey shaded areas in Fig. 1. The wards' doors connect to the corridor, and windows connect to the outdoor. Doors are usually open in daytime and closed at night by healthcare workers. Windows are open or closed by inpatients according to their needs. The windows of the measured two wards face northwest. The prevailing wind direction was northeast during the measurement, see Fig. 2. In the interest of inpatients' safety and security, restrictors are installed on windows to control the maximal operable size in the measured hospital. The maximal window opening size in ward A is 190 mm and the minimal size is 25 mm, accounted for a narrow gap on the window frame. The maximal window opening size in ward B is 600 mm due to its broken restrictor. The two measured wards ran as usual during our measurement. In terms of indoor thermal comfort and energy saving, windows are encouraged to be closed when air-conditioning is on, resulting in a high dependency between the occupant behaviors in window opening and air-conditioning states.

The indoor CO_2 concentration, temperature and relative humidity were measured simultaneously by TES CO_2 monitors (1370, TES Corporation, Taiwan), with a recording interval 4 min in measured wards and a calibrating interval 2 months in the lab. The CO_2 monitors were hanged at the height of 0.2 m away from the ceiling and their locations were shown in Fig. 3. The state and opening size of windows were recorded in real time by a self-designed recorder based on laser ranging [40], as shown in Fig. 4. The outdoor air temperature, humidity, wind speed, solar radiation and rainfall were measured by a Vantage Pro2 weather station (DAVIS Inc., Hayward, CA, USA) located on the roof of that building with a recording interval 30 min. The hourly average outdoor $\text{PM}_{2.5}$ concentration were obtained from the "Shanxi Road" air quality monitoring station near the measured hospital [41].

The field measurement was carried out from 2016/08/06 to 2017/08/05 in ward A and from 2017/02/17 to 2017/08/05 in ward B. A recording break of window opening behaviors occurred in 2016/09/06–2016/10/14 due to instrument failure. Since the wards were empty during the Spring Festival holiday (2017/01/27–2017/02/02), data in this period were removed from the analysis. As air-conditioning states made a significant difference in window opening behaviors, the measured periods were categorized by seasons according to the usage of air-conditioning, i.e. cooling, transition and heating seasons. The air-conditioning on-off state was determined by comparing the temperature difference between the measured wards and a vacated room without any occupancy, lighting and equipment. Detailed measuring timetable

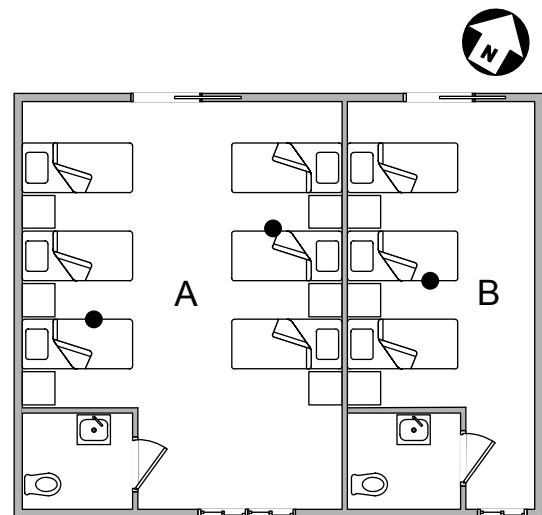


Fig. 3. Schematic diagram of the measured wards and three locations of measurement shown as black dots.

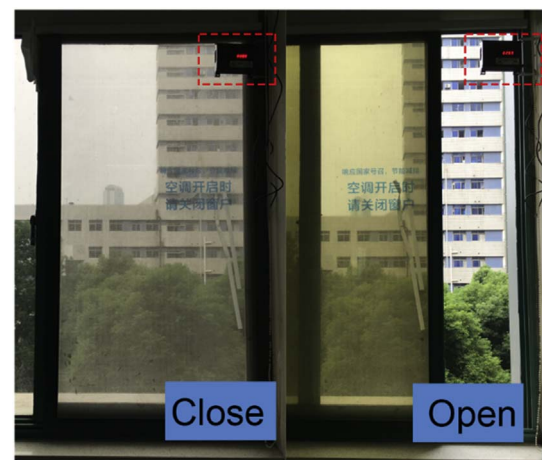


Fig. 4. Features of monitored window and the window-opening recorder, shown within a dotted box.

and corresponding sample size of window opening behaviors are shown in Table 1, excluding those periods without opening size parameters and those periods when the air-conditioning ran intermittently.

To eliminate the non-physical disturbances, data were discarded with frequent window opening and closing behaviors in 10 min. The measured window states were divided into two categories, i.e. closed and open. A total number of 47,686 pieces of data were collected. Proportions of the opening state were 63.3% in summer, 51.9% in autumn, 34.3% in winter and 97.2% in spring in ward A, and 32.0% in summer, 87.5% in winter and 90.8% in spring in ward B during the measurement, see Table 1.

2.2. The stochastic model

The occupants' window opening behaviors can be regarded as a binary variable, with 0 representing close state and 1 representing open state. Logistic regression models are the most popular models for predicting such binary questions [42], which use the maximum likelihood method to fit the logistic equation:

$$\text{logit } P = \log\left(\frac{P}{1-P}\right) = \beta_1 x_1 + \dots + \beta_n x_n + \beta_0 \quad (1)$$

where P is the success probability, and when P is bigger than the classification cutoff value (generally 0.5) the window state is judged to

Table 1
Seasonal timetable and corresponding sample sizes.

Seasonal categories	Ward	Measuring time	Window state	Sample size	%
Summer (cooling season)	A	2016/08/06–	open	6779	63.3
		2016/09/05	closed	3877	36.4
		2017/06/24–	open	1979	32.0
		2017/08/05		4213	68.0
Autumn (transition season)	A	2016/10/15–	open	2618	51.9
		2016/11/20	closed	2431	48.1
Winter (heating season)	A	2016/11/27–	open	4368	34.3
		2017/03/10	closed	8351	65.7
	B	2017/02/17–	open	1437	87.5
		2017/03/10	closed	205	12.5
Spring (transition season)	A	2017/04/13–	open	5600	97.2
		2017/05/21	closed	159	2.8
	B	2017/04/13–	open	5108	90.1
		2017/05/21	closed	561	9.9

be open, otherwise, the window state is considered closed; β_0 is a constant value and β_1, \dots, β_n are partial regression coefficients of the explanatory variables x_1, \dots, x_n respectively. The value $\exp(\beta_i)$ is called *odd ratio*. An *odd ratio* bigger than *unity* means the explanatory variable x has a positive correlation with the dependent variable, while an *odd ratio* smaller than *unity* means the opposite. SPSS 21.0 statistical software was utilized for data analysis and logistic regression modeling.

Correlation test and multi-collinearity diagnosis are carried out before developing logistic regression models as correlation and multi-collinearity problems among variables would make the fitted regression coefficients instable and hard to explain [42]. If the absolute value of Pearson correlation coefficient is bigger than 0.7, the correlation between explanatory variables is indicated to be influential on the variation in regression coefficients. The variance inflation factor (VIF) is computed to assess the multi-collinearity in explanatory variables. A small VIF value (less than 5) means the multi-collinearity is negligible for explanatory variables. The “Backward selection: LR (likelihood ratio)” procedure is also used and the stepwise probability is 0.1 for removal. The explanatory variables with p-value less than 0.05 is recognized statistically significant. The Nagelkeike's R^2 and AUC (Area under ROC Curve) are calculated to estimate the goodness-of-fit of the models. Larger Nagelkeike's R^2 and AUC values suggest a better prediction performance. Influences of different explanatory variables within the same logistic model are identified by the absolute value of the standardized regression coefficient. A larger absolute value of the standardized regression coefficient means a greater impact of the explanatory variable on the dependent variable. The standardized regression coefficient β_{st} can be calculated by Eq. (2):

$$\beta_{st} = \frac{\beta \times SD}{\pi/\sqrt{3}} \quad (2)$$

where β is the partial regression coefficient of the corresponding explanatory variable; SD is the standardized standard deviation.

3. Results and discussion

3.1. Seasonal variation of the measured parameters

Seasonal variations of several measured parameters during the monitoring period are shown in Fig. 5. The top and the bottom scatters represent the maximum and minimum value, the ends of whiskers represent the 5th and 95th percentiles, the top and bottom of the boxes denote the 25th and 75th percentiles, and the dots and the horizontal lines within the boxes stand for the corresponding mean and median values respectively. A “U” shape was observed of the outdoor air temperature ranged from -2°C to 38.4°C , with the lowest value appeared

in winter and the highest showed in summer, see Fig. 5(a). The indoor air temperature showed the similar tendency as the outdoor air temperature. The annual average outdoor humidity was as high as 79.8%, which would strengthen the sense of chill in winter and heat in summer. The highest outdoor average relative humidity appeared in autumn, while the highest indoor average relative humidity showed in summer shown in Fig. 5(b). The indoor relative humidity was generally lower than the outdoor one, especially in winter. The indoor air temperature and relative humidity between wards A and B showed great differences in winter and summer (air-conditioning seasons) and no significant differences in spring (transition season). Variation of the outdoor $\text{PM}_{2.5}$ concentration in Nanjing presented a low-high-low tendency during the measurement with an overall range from 0 to $319 \mu\text{g}/\text{m}^3$, lowest in summer and highest in winter, see Fig. 5(c). The outdoor $\text{PM}_{2.5}$ concentration in Nanjing was substantially lower than that in some northern cities in China. Based on the results, 87% of the daily average $\text{PM}_{2.5}$ concentration during measurement satisfied the threshold value of the daily average $\text{PM}_{2.5}$ concentration stipulated by the current standard in China, i.e. $75 \mu\text{g}/\text{m}^3$ [43]. According to Fig. 5(d), the indoor CO_2 average concentration in ward A was lower than that in ward B in air-conditioning seasons, which was likely attributed to the 25 mm narrow gap on the window in ward A. Though the maximum opening width was only 190 mm in ward A, 79.1% of the CO_2 concentration during the one-year measurement was less than 1000 ppm, the average daily concentration given by Chinese IAQ standard [44], indicating the huge potential for natural ventilation application in general hospitals. Wind speed did not vary by seasons significantly, see Fig. 5(e). The variation range of wind speed was highest in winter, changing from 0 to 5.8 m/s.

Fig. 6 shows variations of window opening size on a 10 min interval in wards A and B. No remarkable relationship between window opening behaviors and the time of the day or week were observed. Window opening behaviors differed in two adjacent wards even in the same period as corresponding indoor parameters including indoor air temperature, relative humidity and CO_2 concentration differing significantly. Comparing the window opening behaviors in wards A [Fig. 6(a)] and B [Fig. 6(b)], adjustment size of window opening was suggested to have an important influence on the occupants' interaction with window opening. The window state in ward A was fully open ($> 150 \text{ mm}$) at 70% of its open time with maximal window opening size 190 mm, while the window in ward B was open in ajar state (30–560 mm) at 91% of its open time with maximal opening size 600 mm. The interaction frequency with the window opening in ward B was found much higher than that in ward A. What's more, the windows were observed to be closed at most of the time in August, November to January, and March, which could partially have associated with the influenza seasons from January to March and July to August in Nanjing [45].

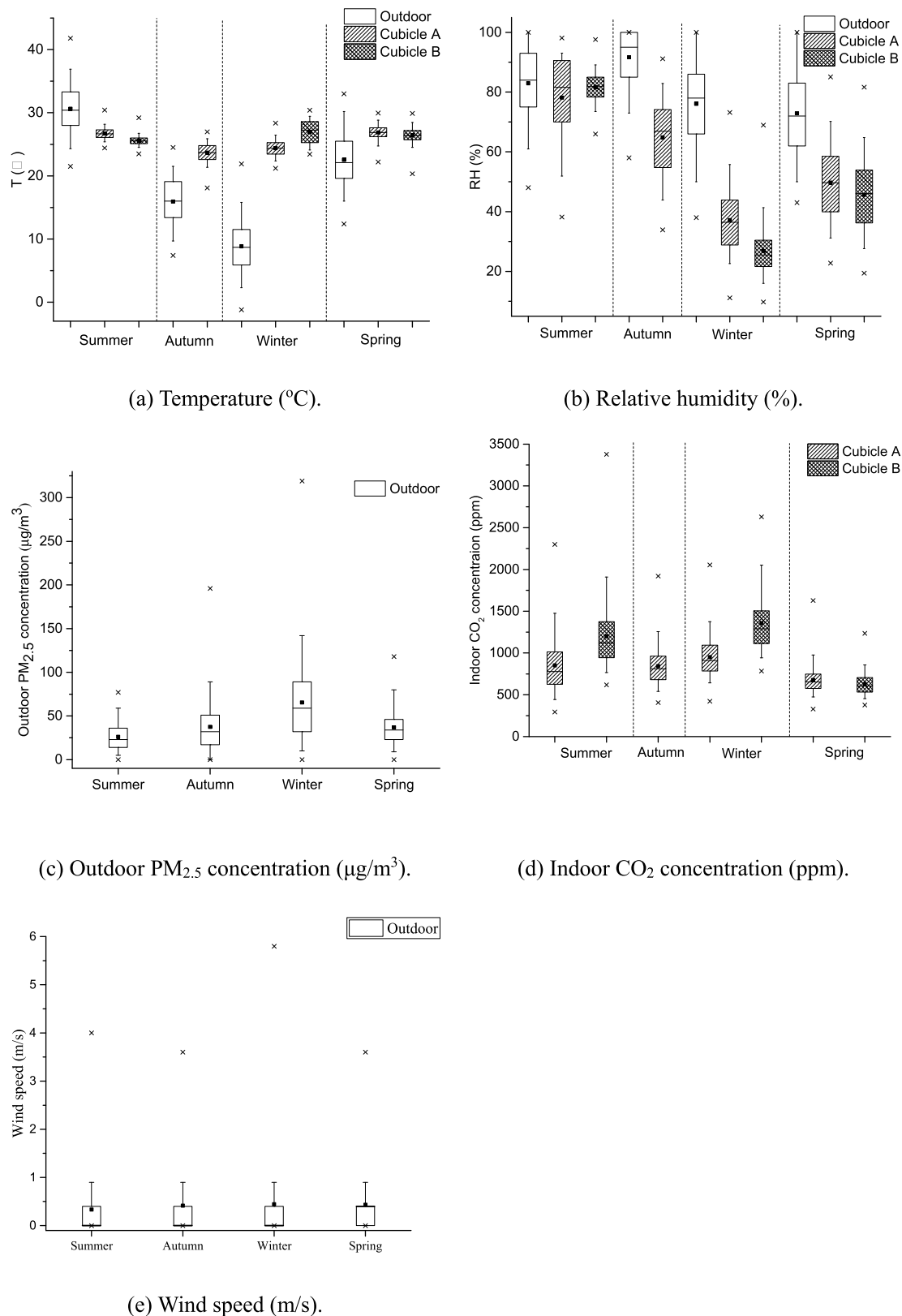


Fig. 5. Seasonal variations of several measured parameters.

3.2. Observed window opening behaviors

Fig. 7 shows the association between the measured thermal-driven (i.e. indoor/outdoor air temperature and relative humidity) and IAQ-driven (i.e. indoor CO₂ concentration and outdoor PM_{2.5} concentration)

factors and the observed probability of window opening, which is the ratio of the number of data in window open state to the total number of data within the specified bandwidth. It is noticeable that some unexpected 0% or 100% values appears mainly due to the sparsity of existing data corresponding to the specific bin width of explanatory variables.

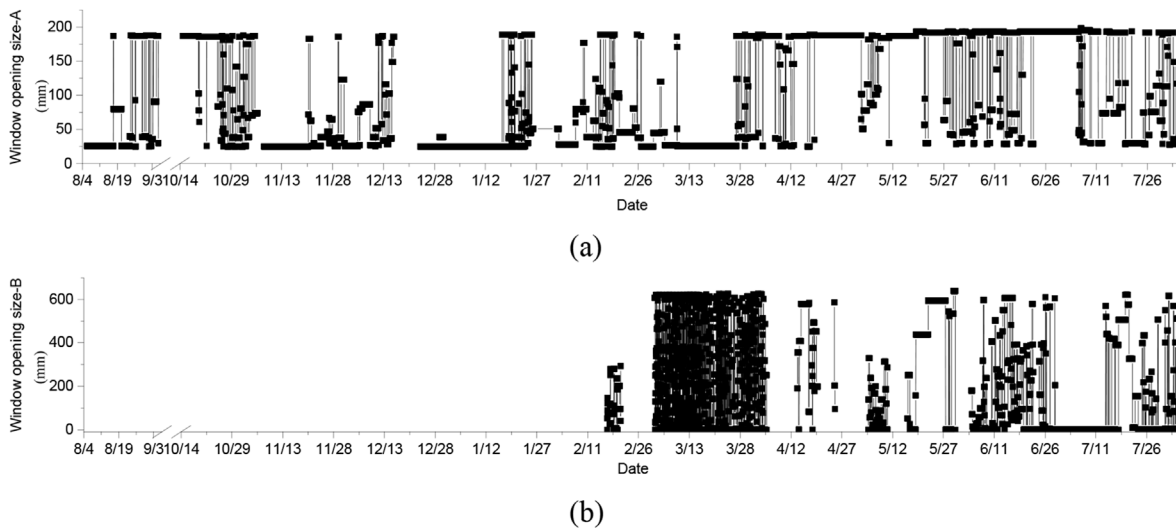


Fig. 6. Variations of window opening size per 10 min in wards A (a) and B (b).

The correlation between the window opening proportion and explanatory variables varies with seasons. As shown in Fig. 7(a), the probability of window opening tends to decrease with the outdoor air temperature in cooling season, as occupants are more likely to close windows to resist the heat with the high outdoor temperature. The window opening probability shows a positive correlation with the outdoor air temperature in transition season. In heating season, the overall trend of scatters goes up gradually. The outdoor temperature ranging from 20 °C to 25 °C could be the most comfortable as the corresponding values of window opening probability reaches the maximum in both air-conditioning and transition seasons. According to Fig. 7(b), the window opening probability is proportional to indoor air temperature in cooling and transition seasons. In heating season, the data in the descending scatters accounted for 71% of the total data, which makes the overall influence negative on window opening behaviors. There is a peak and a valley on each curve representing data in transition and heating seasons, and the valley value might be the occupants' most comfortable indoor temperature, i.e. 23.2 °C in transition season and 26.3 °C in heating season. Fig. 7(c) displays the relationship between window opening probability and outdoor relative humidity. In cooling season, the window opening probability decreases significantly with the increasing outdoor humidity as the high humidity strengthens the hot feeling. In transition season, scatters shows a trend of "U" type with a valley value of about 85%. Opening windows under a high outdoor relative humidity could introduce excess moistures into the indoor environment, which may promote the risk of indoor mold contaminations [46,47]. In heating season, the relationship between window opening probability and outdoor relative humidity is a little vague under some confounders such as the outdoor air temperature, indoor air temperature and humidity. As shown in Fig. 7(d), the window opening probability decreases as the outdoor relative humidity increases in cooling and heating seasons while the correlation between them shows just oppositely in transition season. No significant correlations are found between the window opening proportion and the outdoor PM_{2.5} concentration in Fig. 7(e). However, in residential buildings in Nanjing, the window opening proportion was reported to be negatively related with the outdoor PM_{2.5} concentration [25]. It could be accounted for the difference between individual behaviors in residential buildings and collective behaviors in hospital buildings. The measuring period may also be responsible as Shi's measurements [25] were carried out in 2014 when the average outdoor PM_{2.5} concentration was 73.8 µg/m³, while our study was conducted in 2016 and 2017 when the average outdoor PM_{2.5} concentration was 44.6 µg/m³. Higher PM_{2.5} concentration would degrade the visibility [48] and arouse

people's awareness to prevent the bad outdoor air, e.g. closing the window, even though both of them are higher than the stipulated current standard value of yearly average PM_{2.5} concentration in China, e.g. 35 µg/m³ [44]. Scatters in Fig. 7(f) shows variation trends in a "U" type of window opening proportion in all three seasons with a valley value of about 1500 ppm. When the indoor CO₂ concentration is below 1500 ppm, a negative correlation occurs between the indoor CO₂ concentration and the probability of window opening. The lower proportion of window opening is, the higher the indoor CO₂ concentration would be. When the indoor CO₂ concentration is above 1500 ppm, the correlation between indoor CO₂ concentration and window opening behavior become positive. The indoor CO₂ concentration may act as a result of window opening behaviors when the indoor CO₂ concentration is below about 1500 ppm and turn into a cause when the indoor CO₂ concentration is higher than 1500 ppm at which level occupants might feel uncomfortable in smell and breath. The correlation between wind speed and the window opening probability are shown in Fig. 7(g). In cooling season, wind speed ranging from 0 to 4 m/s has a positive effect on the window opening probability. In transition season, wind speed ranging from 0 to 3.6 m/s has a negative impact on the window opening probability. In heating season, the correlation is positive when wind speed is lower than 2.6 m/s and negative when wind speed is higher than 2.6 m/s. The observed window opening probability is relatively high in prevailing wind direction (about 270°), see Fig. 7(h).

3.3. Logistic regression models of window opening behaviors

Different variation trends found in different seasons make it necessary to model window opening behaviors by seasons. The indoor air temperature (t_{in}), outdoor air temperature (t_{out}), indoor relative humidity (RH_{in}), outdoor relative humidity (RH_{out}), indoor CO₂ concentration (f_{CO2}), wind speed (f_{ws}), wind direction (f_{wd}), solar radiation (f_{solar}) and rainfall (f_{rain}) are considered in modeling. Based on the data from 2016/08/06 to 2016/09/05 in ward A, the logistic regression equation in cooling season is constructed, which is verified by the data from 2017/06/24 to 2017/08/05 in wards A and B. The data in autumn in ward A are used to develop the model in transition season, which is verified with the data in spring in wards A and B. The data from 2016/11/27 to 2017/01/13 in ward A are applied to establish the model in heating season, which is verified with the data from 2017/01/14 to 2017/03/10 in ward A and from 2017/02/17 to 2017/03/10 in ward B. The regression results are shown in Table 2(a)–(c). Some explanatory variables are removed out of the model as they are not significant with corresponding p-values bigger than 0.05. The VIF value less than 5

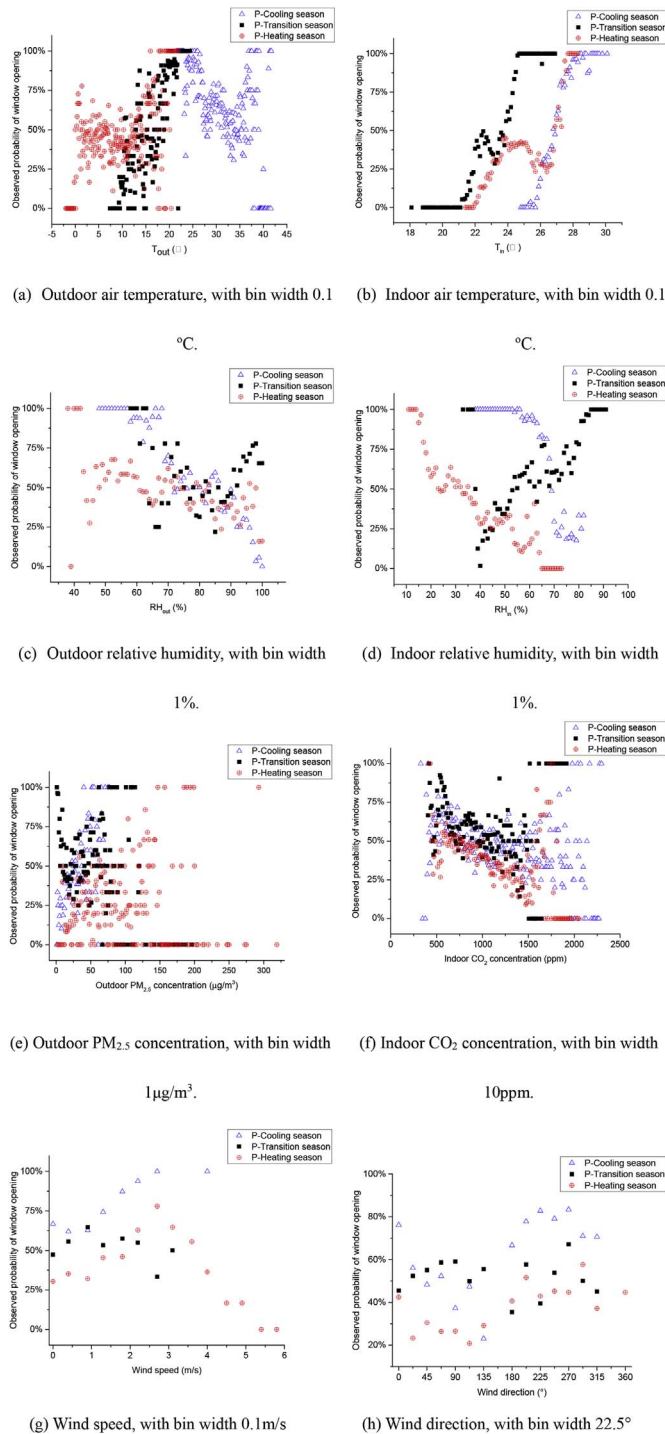


Fig. 7. The association between several measured driven-factors and the observed probability of window opening in ward A.

Table 2a
Multivariate regression results in cooling season.

x_i	β_i	p-value	OR	β_{st}	VIF	-2LR.	R ²	AUC	p-value
t_{in}	1.474 ± 0.075	< .001	4.367	0.657	< 2.0	4093	0.416	0.836	< .001
t_{out}	-0.036 ± 0.015	.019	0.965	-0.067					
RH_{in}	-0.060 ± 0.007	< .001	0.941	-0.276					
f_{solar}	-0.001 ± 0.000	< .001	0.999	-0.155					
f_{WD}	0.001 ± 0.001	.017	1.001	0.047					
β_0	-34.517 ± 2.266	< .001	–	–					

means that no multi-collinearity problem exists in each model. The standardized regression coefficient of each explanatory variable indicates that the influential physical factors for window opening behaviors vary with seasons.

In cooling season, variables of rainfall, wind speed and indoor CO₂ concentration are removed out from modeling as their p-values are bigger than 0.05; outdoor relative humidity is also removed due to the correlation exist between indoor and outdoor relative humidity. The most influential factor is found to be the indoor temperature. The regression coefficient of solar radiation is negative, indicating the negative correlation between window opening behaviors and solar radiation. The multivariate linear logistic regression model of window opening behaviors in cooling season can be expressed as follows:

$$\text{logit } P = \log\left(\frac{P}{1-P}\right) = 1.474t_{in} - 0.036t_{out} - 0.060RH_{in} - 0.001f_{solar} + 0.001f_{WD} - 34.517 \quad (3)$$

In transition season, variables of solar radiation and wind direction are removed out of the model as their p-values are bigger than 0.05; indoor relative humidity and outdoor temperature are also removed as correlation exists between indoor relative humidity and indoor air temperature, and between outdoor air temperature and indoor air temperature. The indoor air temperature is the most significant factor. The wind speed is the least significant factor in the model which ranging from 0 to 3.6 m/s in transition season. The regression coefficient of indoor CO₂ concentration is negative, which indicates the overall decreasing trend of indoor CO₂ concentration with the increase of window opening probability. The logistic regression model of window opening behaviors in transition season can be expressed as follows:

$$\text{logit } P = \log\left(\frac{P}{1-P}\right) = 1.454t_{in} - 0.016RH_{out} - 0.188f_{WS} - 0.020f_{rain} - 0.002f_{CO_2} - 30.755 \quad (4)$$

In the model of heating season, outdoor relative humidity and solar radiation are removed out as they are insignificant. Instead, window opening behaviors are more affected by the rainfalls, followed by the indoor relative humidity. The regression coefficient of indoor CO₂ concentration is negative, which is similar to that in transition season. The wind speed and direction are also the least significant factors in this model. The logistic regression model of window opening behaviors in heating season can be expressed as follows:

$$\text{logit } P = \log\left(\frac{P}{1-P}\right) = -0.328t_{in} + 0.137t_{out} - 0.079RH_{in} - 0.211f_{WS} - 0.016f_{rain} - 0.002f_{CO_2} + 0.001f_{WD} + 11.623 \quad (5)$$

The indoor air temperature or relative humidity contributes as a dominant factor in all the three models. Wind speed and direction are not dominant factors in all the three models, which may due to the small variation of wind speed ranging less than 5.8 m/s and screens mounted on the windows to prevent insects and particles. The solar radiation is significant only in cooling season (summer), which may because that the windows toward northwest without direct sunlight coming in. Verification results of Eqs. (3)–(5) are shown in Fig. 8. The window opening probability fits Eq. (3) in 76.7% in ward A and in

Table 2b
Multivariate regression results in transition season.

x_i	β_i	p-value	OR	β_{st}	VIF	-2LR	R^2	AUC	p-value
t_{in}	1.454 ± 0.045	< .001	4.280	1.132	< 1.6	3391	0.557	0.875	< .001
RH_{out}	-0.016 ± 0.005	.001	0.984	-0.083					
f_{WS}	-0.188 ± 0.078	.016	0.829	-0.063					
f_{Rain}	-0.020 ± 0.003	< .001	0.981	-0.163					
f_{CO2}	-0.002 ± 0.000	< .001	0.998	-0.249					
β_0	-30.755 ± 0.984	< .001	-	-					

Table 2c
Multivariate regression results in heating season.

x_i	β_i	p-value	OR	β_{st}	VIF	-2LR	R^2	AUC	p-value
t_{in}	-0.328 ± 0.042	< .001	0.721	-0.213	< 1.9	3599	0.372	0.823	< .001
t_{out}	0.137 ± 0.015	< .001	1.147	0.255					
RH_{in}	-0.079 ± 0.008	< .001	0.924	-0.381					
f_{WS}	-0.211 ± 0.059	< .001	0.810	-0.073					
f_{Rain}	-0.016 ± 0.001	< .001	0.984	-0.537					
f_{CO2}	-0.002 ± 0.000	< .001	0.998	-0.274					
f_{WD}	0.001 ± 0.000	.017	1.001	0.051					
β_0	11.623 ± 1.137	< .001	-	-					

Note: x_i are explanatory variables; β_0 is a constant; β_i is the partial regression coefficient of each explanatory variable; OR is the odd ratio; β_{st} is the standardized regression coefficient; -2LR is the -2Log-likelihood ratio; and R^2 is the Nagelke's R^2 .

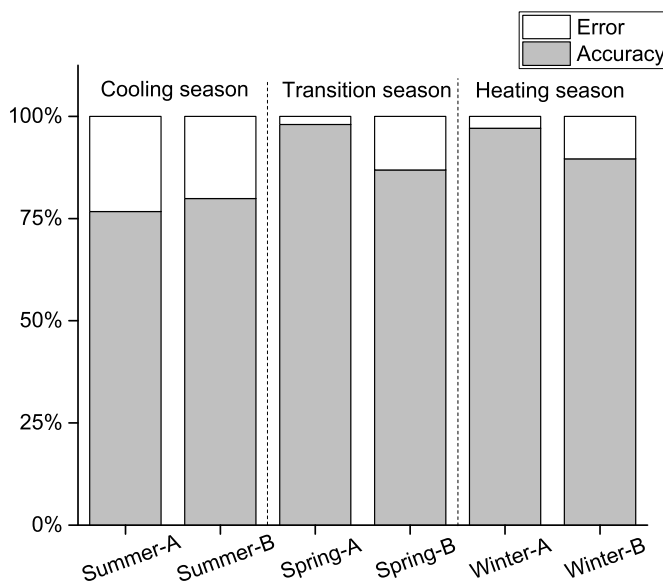


Fig. 8. Verification of the logistic regression models.

79.9% in ward B; the window opening probability fits the Eq. (4) in 98.0% in ward A and in 86.9% in ward B; the window opening probability fits the Eq. (5) in 97.1% in ward A and in 89.6% in ward B. Good accuracy results of the models are achieved though window opening behaviors and indoor variables in wards A and B are significantly different, indicating the promising adaptability of the models proposed in this paper.

3.4. Limitations

Limited by measurement conditions, the sample size of wards (only 2) is small. However, the gathered samples are statistically significant as the patient turnover in the wards is relatively high and window-opening behaviors in the wards are results of collective actions.

The two measured general hospital wards are in the thoracic surgery

department where inpatients are adult men or women, while other departments like obstetrics, pediatric and geriatric departments may have different window opening behaviors. Wards' function, occupant number, the floor height of wards and window orientation are all potential factors that are not considered in our study. As inpatients and HCWs in hospital wards are uniformly dressed, the influences of occupants' clothing conditions on window opening and closing behavior are not concluded. Other individual factors that may influence the thermal comfort like obesity, gender, age are also ignored, as the objective of this study is the collective behavior of window opening and closing in hospital wards, which distinguishes from those in other private indoor environments.

Among all samples of windows in open state, the samples of windows in ajar state accounted for 30% in ward A and as many as 90% in ward B. Occupants may choose to keep the window ajar when the outdoor thermal condition is undesirable but the needs of fresh air exists in indoor environment, indicating the significance of the ajar state in window opening behaviors in further studies, especially for large openings.

4. Conclusions

Based on a one-year field-measurement in two general hospital wards in Nanjing, occupants' interactions with windows are analyzed and modeled. The occupants' interaction with the window opening is affected by the adjustable window opening size. The window with large adjustable opening size is more likely in ajar state and the interaction frequency is much higher. The effects of indoor and outdoor physical variables on window opening behaviors varies significantly by seasons. The probability of window opening decreases with the increase of outdoor temperature during the cooling season but increases during the transition and heating seasons. The window opening probability increases with the indoor relative humidity during the transition season, but decreases during the cooling and heating seasons. Logistic regression models for different seasons are developed to predict the window opening/closing state in general hospital wards. The indoor air temperature or relative humidity is found to be a dominant factor for window opening behaviors in all seasons. Models are verified to be promisingly adaptable with results of accuracy bigger than 70%.

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References

- [1] E.C. Riley, G. Murphy, R.L. Riley, Airborne spread of measles in a suburban elementary school, *Am. J. Epidemiol.* 107 (1978) 421–452.
- [2] Y. Li, G.M. Leung, J.W. Tang, et al., Role of ventilation in airborne transmission of infectious agents in the built environment – a multidisciplinary systematic review, *Indoor Air* 17 (2007) 2–19.
- [3] L.D. Knibbs, L. Morawska, S.C. Bell, et al., Room ventilation and the risk of airborne infection transmission in 3 health care settings within a large teaching hospital, *Am. J. Infect. Contr.* 39 (2011) 866–872.
- [4] H. Qian, Y. Li, W.H. Seto, et al., Natural ventilation for reducing airborne infection in hospitals, *Build. Environ.* 45 (2010) 559–565.
- [5] A.R. Escombe, C.C. Oeser, R.H. Gilman, et al., Natural ventilation for the prevention of airborne contagion, *PLoS Med.* 4 (2007) e68.
- [6] Z.A. Adamu, A.D.F. Price, M.J. Cook, Performance evaluation of natural ventilation strategies for hospital wards - a case study of Great Ormond Street Hospital, *Build. Environ.* 56 (2012) 211–222.
- [7] S. Jiang, L. Huang, X. Chen, et al., Ventilation of wards and nosocomial outbreak of severe acute respiratory syndrome among healthcare workers, *Chin. Med.* 116 (2003) 1293–1297.
- [8] C.A. Gilkeson, M.A. Camargo-Valero, L.E. Pickin, et al., Measurement of ventilation and airborne infection risk in large naturally ventilated hospital wards, *Build. Environ.* 65 (2013) 35–48.
- [9] G. Branco, B. Lachal, P. Gallinelli, et al., Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data, *Energy Build.* 36 (2004) 543–555.
- [10] H.B. Rijja, P. Tuohy, M.A. Humphreys, et al., Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, *Energy Build.* 39 (2007) 823–836.
- [11] K. Schakib-Ekbatan, F.Z. Çakıcı, M. Schweiker, et al., Does the occupant behavior match the energy concept of the building? – Analysis of a German naturally ventilated office building, *Build. Environ.* 84 (2015) 142–150.
- [12] P.R. Warren, L.M. Parkinson, Window-opening behavior in office buildings, *Build. Serv. Eng. Technol.* 5 (1984) 89–101.
- [13] R. Fritsch, A. Kohler, M. Nygård-Ferguson, et al., A stochastic model of user behavior regarding ventilation, *Build. Environ.* 25 (1990) 173–181.
- [14] J.F. Nicol, M.A. Humphreys, B. Olesen, A stochastic approach to thermal comfort - occupant behavior and energy use in buildings, *Build. Eng.* 110 (2004) 554–568.
- [15] K. Huang, G. Feng, H. Li, et al., Opening window issue of residential buildings in winter in north China: a case study in Shenyang, *Energy Build.* 84 (2014) 567–574.
- [16] F. Stazi, F. Naspi, G. Ulpiani, et al., Indoor air quality and thermal comfort optimization in classrooms developing an automatic system for windows opening and closing, *Energy Build.* 139 (2017) 732–746.
- [17] F. Stazi, F. Naspi, M. D’Orazio, Modelling window status in school classrooms. Results from a case study in Italy, *Build. Environ.* 111 (2017) 24–32.
- [18] F. Haldi, D. Robinson, Interactions with window openings by office occupants, *Build. Environ.* 44 (2009) 2378–2395.
- [19] V.M. Barthelmes, Y. Heo, V. Fabi, et al., Exploration of the Bayesian Network framework for modelling window control behavior, *Build. Environ.* 126 (2017) 318–330.
- [20] R.V. Jones, A. Fuertes, E. Gregori, et al., Stochastic behavioural models of occupants’ main bedroom window, *Build. Environ.* 118 (2017) 144–158.
- [21] V. Fabi, R.V. Andersen, S. Corgnati, et al., Occupants’ window opening behavior: a literature review of factors influencing occupant behavior and models, *Build. Environ.* 58 (2012) 188–198.
- [22] F. Naspi, M. Arnesano, L. Zampetti, et al., Experimental study on occupants’ interaction with windows and lights in Mediterranean offices during the non-heating season, *Build. Environ.* 127 (2018) 221–238.
- [23] N. Li, J.C. Li, R. Fan, et al., Probability of occupant operation of windows during transition seasons in office buildings, *Renew. Energy* 73 (2015) 84–91.
- [24] R. Andersen, V. Fabi, J. Toftum, et al., Window opening behavior modelled from measurements in Danish dwellings, *Build. Environ.* 69 (2013) 101–113.
- [25] S. Shi, B. Zhao, Occupants’ interactions with windows in 8 residential apartments in Beijing and Nanjing, China, *Build. Simulat.* 9 (2016) 221–231.
- [26] O.A. Seppänen, W.J. Fisk, M.J. Mendell, Association of ventilation rates and CO₂ concentrations with health and other responses in commercial and institutional buildings, *Indoor Air* 9 (1999) 226–252.
- [27] Q. Zhou, Z. Lyu, H. Qian, et al., Field-measurement of CO₂ level in general hospital wards in Nanjing, *Procedia Eng.* 121 (2015) 52–58.
- [28] ASTM, Standard guide for using indoor carbon dioxide concentrations to evaluate indoor air quality and ventilation, D6245–12, American Society for Testing Materials, 2012.
- [29] S.N. Rudnick, D.K. Milton, Risk of indoor airborne infection transmission estimated from carbon dioxide concentration, *Indoor Air* 13 (2003) 237–245.
- [30] R.D. Brook, B. Franklin, W. Cascio, et al., Air pollution and cardiovascular disease a statement for healthcare professionals from the expert panel on population and prevention science of the American heart association, *Circulation* 109 (2004) 2655–2671.
- [31] Y.L. Zhang, F. Cao, Fine particulate matter (PM_{2.5}) in China at a city level, *Sci. Rep.* 5 (2015) 14884–14895.
- [32] C.B. Song, J.J. He, L. Wu, et al., Health burden attributable to ambient PM_{2.5} in China, *Environ. Pollut.* 223 (2017) 575–586.
- [33] D. Levie, Y.K. De, H.V. Oeffelen, et al., Determinants of ventilation behavior in naturally ventilated dwellings: identification and quantification of relationships, *Build. Environ.* 82 (2014) 388–399.
- [34] S. D’Oca, T. Hong, A data-mining approach to discover patterns of window opening and closing behavior in offices, *Build. Environ.* 82 (2014) 726–739.
- [35] B.C. Jeong, J.W. Jeong, J.S. Park, Occupant behavior regarding the manual control of windows in residential buildings, *Energy Build.* 127 (2016) 206–216.
- [36] R.A.T.G.P. Henze, Stochastic control optimization for a mixed mode building considering occupant window opening behavior, *J. Build. Simulat.* 7 (2014) 427–444.
- [37] S. Herkel, U. Knapp, J. Pfaffert, Towards a model of user behavior regarding the manual control of windows in office buildings, *Build. Environ.* 43 (2008) 588–600.
- [38] B. Jeong, J.W. Jeong, J.S. Park, Occupant behavior regarding the manual control of windows in residential buildings, *Energy Build.* 127 (2016) 206–216.
- [39] M.K. Nematchouaa, P. Ricciardì, S. Reiterb, et al., Thermal comfort and comparison of some parameters coming from hospitals and shopping centers under natural ventilation: the case of Madagascar, *J. Build. Eng.* 13 (2017) 196–206.
- [40] X.H. Zheng, Z.N. Shi, H. Qian, A Kind of Opening Size Recorder Based on Laser Distance Sensor and its Application Method: China, (2016) 10536704. X. 2016-07-08.
- [41] Qingyue Open Environmental Data Center, <https://wat.epmap.org/air/nations>, (2017).
- [42] G. James, D. Witten, T. Hastie, et al., An Introduction to Statistical Learning, Springer, New York, 2003.
- [43] Ministry of Environmental Protection, AQSIQ (State Administration for Quality Supervision and Inspection and Quarantine, PR China), Ambient air quality standards, 2012 GB 3095–2012.
- [44] AQSIQ (State Administration for Quality Supervision and Inspection and Quarantine, PR China), Bureau of Health, SEPA (State Environmental Protection Administration, PR China), Indoor air quality standard, 2002 GB/T 18883–2002.
- [45] M.J. Cunningham, A Study of the Epidemic and Clinical Characteristics of Influenza in Nanjing from 2009 to 2014, Southeast University, 2015.
- [46] R. Quansah, M.S. Reginald, T.T. Hugg, et al., Residential dampness and molds and the risk of developing asthma: a systematic review and meta-analysis, *PLoS One* 7 (2012) e47526.
- [47] H. Viitanen, T. Ojanen, Improved Model to Predict Mold Growth in Building Materials. Thermal Performance of the Exterior Envelopes of Whole Buildings X-Proceedings CD.2–7.12, ASHRAE, DOE, ORNL, Clearwater Beach, USA, 2007 2007.
- [48] T. Luan, X.L. Guo, L.J. Guo, et al., Quantifying the relationship among PM_{2.5} concentration, visibility and planetary boundary layer height for long-lasting haze and fog-haze mixed events in Beijing city, *Atmos. Chem. Phys.* (2017) 1–39.