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Probability of occupant operation of windows during transition seasons in office buildings

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Abstract: Window operation is not only an important method for improving the indoor thermal environment and air quality, but also a significant way to reduce energy consumption of air-conditioned rooms during off-running periods in transition seasons. The occupants' window-operation behavior is influenced by both objective factors, such as thermal comfort and indoor air quality; and objective sensation, such as psychology and physiology, introducing considerable randomness and uncertainty. A two-month field observation of occupant window-opening behaviors for natural ventilation in an office building during the transition seasons was carried out in Chongqing, China. Multi-factor analysis of variance was conducted in data analysis using SPSS statistical software. The results showed that outdoor air temperature significantly affected window opening among other factors such as outdoor relative humidity, indoor air temperature, indoor relative humidity, and indoor CO_2 concentration, which have much less effect. The main trigger point for opening windows in the transition seasons is from occupants' desire to improve the indoor thermal and air quality environment. A probability model of occupants' window operation was proposed based on logistic regression analysis. Meanwhile, the Monte Carlo simulation results indicate that during transition seasons (when outdoor temperature varied from 15 to 30 °C), the probability of window opening in office buildings follows a normal distribution and increases linearly along with the outdoor temperature growth.

1. Introduction

A comfortable indoor environment at the workplace is important for workers' quality of life, health, and productivity. The behaviors of people seeking to control the indoor environment include adjusting elements of the building structure (e.g. windows, curtains, and sunshades), lighting, and indoor equipment. Among these, window operation is an efficient and common measure to improve the indoor thermal conditions. Understanding the rules and characteristics of window operation by occupants and establishing a model that describes this behavior will be of great value for the improvement of building energy-efficiency research and design, indoor air quality, natural ventilation, thermal comfort, and other relevant factors.

Building energy simulation has become increasingly important in energy efficient design. The popularly-used building energy simulation software packages include Energy Plus, TRNSYS etc. [1] It should be noted that existing building energy simulation programs are based on basic building physical parameters such as the heat transfer coefficient of envelopes, occupant density, efficiency of equipment and systems, and operation schedules. Usually, heating/cooling system operation schedules are determined by two modes: working days and off-working days. To date, the majority of these programs have little consideration of the impact of occupants' behaviors on energy consumption within the building. As a result, relatively large deviations of energy consumption in buildings occur between the predicted and the actual monitored, for both office and residential buildings [2–4]. Therefore there is a need to incorporate occupant behavioral models into the building energy simulation programs in order to improve the accuracy of the simulation results for new building design and existing building retrofit. This should provide reliable results for energy-efficiency strategies to policy-makers.

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2. Background information

Research emphasizing the importance of occupant behaviors emerged in the 1990s and mainly focused on the adaptive thermal comfort [5]. Operations of windows are one of the popular behaviors of occupants to regulate and adapt thermal environments. It has a close relationship with the outdoor weather conditions, including outdoor temperature, solar radiation, and wind speed [6]. Among these weather conditions, outdoor temperature was shown to be the most important factor, whereas solar radiation and wind speed had relatively weaker influences on the behavior of window opening. When the outdoor temperature is less than 15 °C, only a very few people will choose to open a window to improve indoor environments; but when the outdoor temperature is higher than 25 °C, most people will choose to open a window for ventilation [7]. The probability of thermal discomfort is determined, to a great extent, by whether or not a window is open. This indicates that the operation of windows has a significant relationship with the thermal comfort of the occupants.

Some studies have modeled window-opening behavior. Herkel et al. [8] proposed a method that uses the random model to primarily forecast and simulate the open status of windows in office buildings. Yun et al. [9] proposed a calculation rule describing the probability of people's behaviors, with the aim of integrating the probability of window opening into the process of the dynamic simulation of energy consumption. Nicol [10] and Humphries [11] used Probit Analysis to build a random model of the relationship between window opening and outdoor temperature, with the goal of applying this model within simulation software to reduce differences between simulation results and actual conditions as a result of the neglect of occupant behaviors during the simulation process. Macdonald and Strachan [12] introduced Monte Carlo Analysis and Differential Sensitivity Analysis to the simulation of outdoor meteorological parameters and building envelope thermal performance and applied these methods to addressing random variable factors in the simulation software ESP-r. Yun and Steemers [13] developed a random model for the relationship between the probability of window opening of residents and indoor/outdoor temperatures. Haldi and Robinson [14] used three analysis methods including multivariable logistic regression, the Markov process, and survival analysis to analyze the building environment and residents' indoor conditions and built a model of window-opening behavior. Shen et al. [15] presented a longitudinal study observing people's use of windows in cellular offices with a mixed mode of ventilation systems.

Jiang [16] proposed a random weather model – the multivariate time series model – for the randomness of weather conditions during the calculation of air conditioning load in order to decrease the inaccuracy resulting from unstable outdoor weather parameters during energy-consumption simulation. Jiang and Hong [17] studied building thermal heat transfer behavior and its probability distribution using stochastic analysis methods, including a multivariate time series model and state space method and demonstrated that the stochastic model was a promising method. In order to quantitatively study the effect of occupant behavior on building energy consumption, Zhou [18] et al. incorporated the developed random model of occupant behavior into a building energy simulation tool and compared the building simulation results with those of actual monitored data. The commonly used method of incorporating occupancy behavior/occupancy patterns in building simulation tools is to default the patterns and by assumptions [19].

It can be seen that the impact of occupant behavior, especially the behavior of opening doors and windows, on building energy consumption has drawn research attention internationally. However, at present, most probability models of window opening are set up mainly for free-running buildings, with a relatively wider range of outdoor temperatures. A hybrid system is a promising measure to improve the indoor environment. When the air-conditioning system is inoperative, opening/closing the windows during the transition seasons provides suitable natural ventilation for cool rooms. This research aimed to study occupant behavior when operating window systems for the improvement of the indoor environment and the impact of energy efficiency.

3. Experiment settings

A five-storey office building in Chongqing (Fig. 1 and 2) was selected for the experimental study. The building information is listed in Table 1. The monitoring period was between 09:00 and 18:00 on weekdays from September 11 to October 31 in 2012, whilst the weather conditions were those of a typical transition season, with climatic characteristics of daily average outdoor temperature between 15 and 30 °C. The air conditioning system was not allowed to operate during the period, and there was no mechanical ventilation in operation either. Occupants' thermal comfort needs could only be met by natural ventilation via window operations.

During the transition season, the major purposes of opening windows/doors for ventilation are to improve the indoor air quality and thermal comfort. Based on these two requirements, we identified six possible factors that may affect the window opening behavior of occupants: indoor air temperature, indoor air relative humidity, indoor CO_2 concentration, outdoor air temperature, outdoor air relative humidity, and wind speed.

There is no smoking-free policy in office buildings in China. Smoking can produce pungent smoke composed of inhalable particles, CO, nicotine, polycyclic aromatic hydrocarbons, nitrosamine, and other carcinogenic substances [20–22]. Whether or not someone smoking inside the room is an important factor affecting occupants' behavior of opening windows. However, in this study, only non-smoking rooms were selected as experimental sites. In addition, the influence of outdoor noise on window opening was

Fig. 1. Exterior view of the experimental office building.

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Fig. 2. Inside view of an experimental room.

not taken into consideration as the selected experimental office was located in a quiet area.

4. Behavior model

4.1. Window-opening probability

We used a self-developed door/window open status recording device to automatically monitor window opening occurrences caused by the building occupants. Then we used the multi-factor variance analysis method to identify the major influence factors among indoor temperature and humidity, outdoor temperature and humidity, wind speed, and indoor CO_2 concentration. As temperature, humidity and CO_2 concentration are all continuous variables; they are divided into several levels before multi-factor variance analysis. Level divisions indicate the distribution of factors among different levels, as shown in Table 2. In the transition seasons, the temperatures measured are mainly between 15 and 30 °C. We divided them into five levels, i.e. lower than 15 °C, 15 ~ 20 °C, 20 ~ 25 °C, 25 ~ 30 °C, higher than 30 °C. The results of multi-factor analysis are shown in Table 3. The first row in the table represents the calibration model, which is used to identify whether the variance model is significant or not. The observed value of F-statistics is 1.336, and the corresponding Sig. value is 0.021, which is less than 0.05. Therefore, this model has statistical significance. The fourth to the ninth rows in Table 3 shows the statistical test results of outdoor temperature, outdoor relative humidity, indoor air temperature, indoor relative humidity and indoor CO_2 concentration. According to these results, Sig. value of outdoor air temperature is less than 0.05, and Sig. values of outdoor relative air humidity, indoor air temperature, indoor relative air humidity, indoor carbon dioxide concentration and outdoor wind speed are all greater than 0.05. This shows that in office buildings with no significant air pollution source, outdoor temperature t_w is the only factor that influences occupant window-opening behavior in office buildings in the transition seasons.

Table 1
Basic information for the experimental rooms.

Room number	Floor	Type of window	Number of occupants
1	2	Casement window	2
2	2	Casement window	1
3	3	Casement window	4
4	4	Casement window	2
5	4	Casement window	6

Table 2
Level divisions of different influencing factors for opening windows.

Factors	Level 1	Level 2	Level 3	Level 4	Level 5
Outdoor temperature (°C)	<15	15 ~ 20	20–25	25 ~ 30	>30
Outdoor relative humidity (%)	<70	70 ~ 75	75 ~ 80	80 ~ 85	>85
Outdoor wind speed (m/s)	0 ~ 0.5	0.5 ~ 1	1 ~ 1.5	1.5 ~ 2	>2
Indoor air temperature (°C)	<15	15 ~ 20	20–25	25 ~ 30	>30
Indoor relative humidity (%)	<70	70 ~ 75	75 ~ 80	80 ~ 85	>85
Indoor CO_2 concentration (ppm)	<300	300 ~ 500	500 ~ 700	700 ~ 900	>900

1) The existing literature revealed that CO_2 concentrations around 1000 ppm are the boundary value for decision-making on opening windows or not [23]. In office buildings, the indoor CO_2 concentration is generally low when there are no significant CO_2 sources inside the room because of the frequent opening of doors to facilitate mobility. The maximum concentration in our field tests is 829 ppm, lower than 1,000 ppm, which occurred in experimental room 5 on September 14th, 2012.
2) Fig 3 demonstrates outdoor and indoor temperature variations for rooms 2, 3, and 4. From the figure we can see that during the working hours in the transition season, the variation of indoor temperature is relatively small, and the maximum variation is less than 2 °C even when the outdoor temperatures fluctuated greatly with the outdoor windows opened. It was noticed that during the transition seasons, occupants still preferred to open windows when there was no significant differences between indoor and outdoor temperatures and at times when indoor temperatures and air quality were within the acceptable range.

4.1.1. Logistic regression model

As discussed in Section 4.1, the major factor influencing window opening under natural ventilation during transition seasons in the Chongqing area is the outdoor temperature, t_w. Therefore, the probability model of window opening presented in this section is a mathematical expression of the relationship between the probability of window opening and outdoor temperature.

In this section, we describe how we used Binary Logistic regression of the data processing software, SPSS17.0 (SPSS, Inc., Chicago, IL, USA), to process the data acquired in our experiment. We established a mathematical model of the variation of the probability of window opening by occupants according to outdoor temperature variation in an air-conditioner-equipped office building in Chongqing in a free-running mode during transition seasons.

Table 3
The result of the effect among subjects.

Dependent variable: Window status					
1 Source	Type III quadratic sum	df	Mean square	*F*	Sig.
2 Calibration model	15.824a	50	0.316	1.336	0.021
3 Intercept	4.663	1	4.663	19.685	0.000
4 Outdoor air temperature	2.179	3	0.726	3.066	0.029
5 Indoor air temperature	0.933	2	0.466	1.969	0.142
6 Outdoor relative air humidity	0.952	3	0.317	1.340	0.262
7 Indoor relative air humidity	0.079	2	0.040	0.168	0.846
8 Indoor carbon dioxide	2.140	4	0.535	2.259	0.064
9 Outdoor wind speed	0.012	3	0.004	0.016	0.997

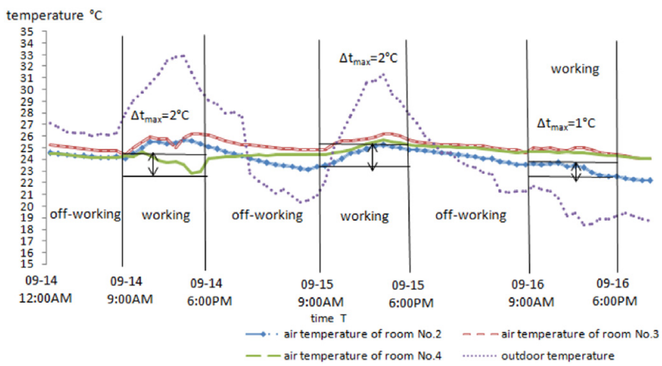

Fig. 3. Variations of indoor and outdoor temperatures during Sep. 14th–16th.

Since the outdoor temperature is regarded as the significant factor influencing window operations, the logistic regression analysis only considers the outdoor temperature factor. The corresponding standard error, Wald value, degree of freedom, significance value, and OR (i.e., Exp. (B), reflecting the influence of independent variables on dependent variables) were calculated. The results are listed in Table 4. We worked out that the corresponding coefficient of the outdoor temperature is 0.156, and the constant is 2.058. The parameter significance value was 0.001, which is less than 0.05 and thus satisfies the requirements of the significance test. So does the Wald value. Therefore, the mathematical relationship between the probability of window opening by occupants in office buildings and the outdoor temperature can be expressed as follows:

$$LogitP = 0.156t_w - 2.058 \tag{4.1}$$

Equation (4.1) represents the relationship between the probability of window opening, p, in the form of Logit:

$$LogitP = \ln\left(\frac{P}{1-P}\right) \tag{4.2}$$

$$\text{Namely,} \qquad 0.156t_w - 2.058 = \ln\left(\frac{P}{1-P}\right) \tag{4.3}$$

Thus, the equation for the probability of window opening, p, under different outdoor temperatures, $t_{w,}$ can be obtained:

$$P = \frac{\exp(0.156t_w - 2.058)}{1+\exp(0.156t_w - 2.058)} \tag{4.4}$$

Table 5 lists the −2 log likelihood values, two pseudo determination coefficients ("pseudo", to distinguish these from the determination coefficients of the linear regression model), the Cox & Snell R^2 and the Nagelkerke R^2. Both value ranges are 0 ~ 1, which is commonly used to compare the fitting of the same data of some different models. The bigger the pseudo-R2 value of a model is, the better data fitting the model predicts. Here, two kinds of pseudo-R2 value are all greater than zero, so they can be accepted. These two values reflect different views of the variation ratio of the dependent variable explained by the independent variable in the current model to the total variation.

Table 4
Variables in the equation.

		B	SE	Wald	df	Significance	Exp (B)
Step 1[a]	Outdoor temperature	0.156	0.046	11.149	1	0.001	0.857
	Constant	2.058	0.937	11.047	1	0.001	22.490

[a] The input variable in step 1 = outdoor temperature.

Table 5
Model summary.

Step	−2 log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	383.146[a]	0.041	0.055

[a] Indicate the degree of freedom adjusted R square.

Table 6 provides the classification used for forecasting by refitting the regression model after introducing the independent variable. Meanwhile, from Table 6, the accuracy of the mathematical model obtained from regression for forecasting closed window status is 65.5%, and that for forecasting window opening is 74.8%. The regression accuracy of the population is 70.15%; hence, the accuracy of regression is relatively high. Therefore, the model well-represents the logical relationship between the window-opening behavior and the outdoor air temperature.

4.2. The verification of the model of the probability of window opening

To verify the model's forecasting accuracy of the probability of window opening, we compared the measured probability of window opening with the values forecast by the model using correlation analysis and determined the degree of correlation between the measured values and the forecasted values according to the value of correlation coefficients between variables.

The degree of correlation depends on the value of the correlation coefficient r. The greater r is, the higher the correlation degree is. Generally, $r = 0$ means zero correlation; $0 < |r| < 0.4$ means low linear correlation; $0.4 < |r| < 0.7$ means significant linear correlation; $0.7 < |r| < 1$ means high linear correlation; $|r| = 1$ means perfect correlation [24].

We used the measured probability of window opening in Experimental Room 1 to verify the proposed probability model of window opening. Table 7 shows the measured and forecasted values for the occurrence of window opening in Experimental Room 1 during working hours (9:00 a.m. to 6:00 p.m.) under different outdoor temperatures. The relevant analytic results are shown in Table 8, and the Pearson correlation coefficient was 0.527. Thus, the two values have significant linear correlation. In addition, the hypothesis-testing significance value for the correlation coefficient is 0.044 (which is < 0.05), illustrating that the two values have a linear correlation and the probability of no linear correlation is less than 0.05. These results indicate that the measured and forecasted values for the probability of window opening fit well, and thus, the accuracy of the model is confirmed. These results also again confirm that window opening behavior is related to outdoor temperature.

5. Monte Carlo simulation model

Occupant window-opening behaviors are influenced not only by objective factors such as thermal comfort temperatures and indoor air quality, but also by subjective psychological and physiological

Table 6
Classification table.[a]

	Observed		Forecasted		
			Window status		Percentage correction
			0	1	
Step 1	Window status	0	93	49	65.5
		1	36	107	74.8
		Total percentage			70.15

[a] The cutoff value is 0.500.

Table 7
The measured and forecasted values of the probability of window opening.

Outdoor temperature (°C)	Window opening and closing frequency		Probability of window opening	
	Open	Close	Measured value	Forecast value
15	42	25	0.63	0.57
17	83	28	0.75	0.64
19	98	57	0.63	0.71
21	113	85	0.57	0.77
23	107	60	0.64	0.82
25	65	22	0.75	0.86
27	28	3	0.90	0.90
29	20	8	0.71	0.92

sensations. This leads to a large degree of randomness of window operation in reality. It poses a great many challenges to solve random problems in real-life. The Monte Carlo method is an ideal method for simulating random problems based on generating random numbers, and thus solving the window operation problems.

It can appropriately simulate the influence of outdoor temperatures on the probability of window opening. The results can be used to analyze and forecast the probability of window opening and thus determine the distribution characteristics of the probability of window opening by simulating random phenomena via the generation of a series of random numbers. We can see the schematic flow chart in Fig. 4.

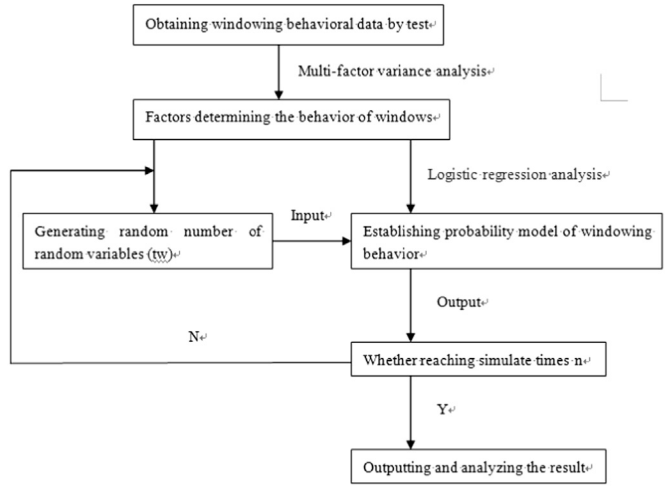

Fig. 4. Simulation of window-opening behavior probability using the Monte Carlo method.

5.1. Generating random numbers

When using the Monte Carlo method to solve actual problems, the first step is to generate a series of random numbers that reflect the variation characteristics of the outdoor temperature. Then the simulation test can be performed. We determined that the outdoor temperature during the working period (9:00 a.m. to 6:00 p.m.) was subject to a normal distribution, $N(20.75, 3.46^2)$, by analyzing the experimental data using SPSS software.

After determining the probability distribution of the random variable (outdoor temperature), we used Excel to load the Crystal Ball, which is an office software suite developed by Decision Engineering Inc [25]. The Crystal Ball is characterized by analytical tools based on an electronic table, including the Monte Carlo simulation (crystal ball), time series forecasting (crystal ball prophet), and the optimal choice (optimized query). The Crystal Ball simulation software is not only easy to use with all the functions of general simulation software but can also be operated in the general environment of a personal computer or work station, and is thus a good tool for computer simulations. In Crystal Ball, the random variables in compliance with certain probability distributions are taken as the Assumption Cell, and the random output variables that require observation are taken as the Forecast Cell. This model simulates multiple circumstances by sampling from the probability distribution of uncertainty factors and provides multiple useful results, including probability distributions, statistical tables, percentage tables, and cumulative graphs which can be used for analysis. Therefore, we sampled a series of random values of the outdoor temperature generated by Crystal Ball, which are in compliance with normal distribution. For every 1000 increased trial samples, we calculated all of the samples' average values and standard deviations until the end of the experiment. Fig. 5 shows the trend diagram of the variation of the average value and standard deviation of random outdoor temperature for different sampling times under the condition of random sampling for 500–10,000 times. It can be seen that the average values and standard deviations of samples tended to be stable once the simulation time was beyond 7000 times. The outdoor temperature distribution fitting generated in less than 10,000 simulation runs is shown in Fig. 6, and again the outdoor temperature was found to comply well with a normal distribution $N(20.75, 3.46^2)$.

Table 8
Correlation analysis results for the measured and forecasted values of window opening.

		Measured value	Forecasted value
Measured probability	Pearson correlation coefficient	1	0.527*
	Significance (bilateral)		0.044
	N	15	15
Forecasted probability	Pearson correlation coefficient	0.527*	1
	Significance (bilateral)	0.044	
	N	15	15

Asterisks represent the 5% level of significance.

5.2. Monte Carlo Simulation of the probability of window opening

When Monte Carlo simulations are performed, the accuracy of the results is affected directly by the number of simulations: the larger it is, the more accurate the results are; and the statistical characteristics of the outputs of the targeted variables are

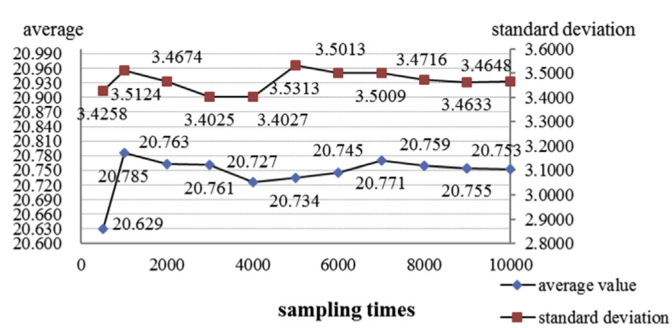

Fig. 5. Variation of the average values and standard deviations of outdoor temperature at different sampling times.

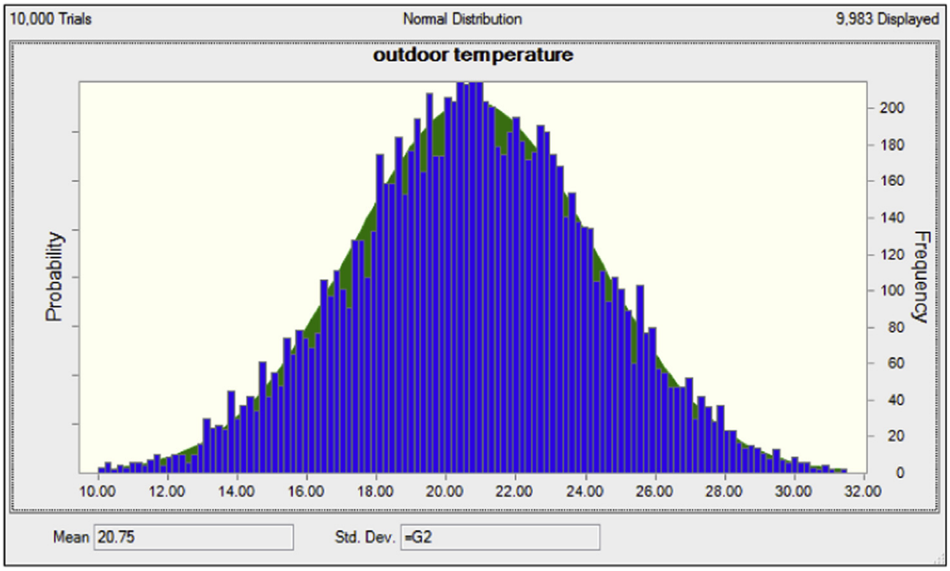

Fig. 6. Fitting diagram of outdoor temperature distribution for 10,000 times of sampling.

significant. Fig. 7 shows the status of the average values and standard deviations of the probability of window opening with increasing simulation duration. As shown in the diagram, the average values and standard deviations of the probability of window opening tended to be stable with a gradual increase in the time of simulation. When the simulation involved 10,000 runs, the average values and standard deviations for the probability of window opening were stabilized. Therefore, within the range of computational capability, we selected the simulation time of 10,000 runs to ensure the use of stable data.

Under the set operating parameters, we ran 10,000 simulation calculations for the probability of window opening in the Crystal Ball software platform, and the probability distribution diagram of window opening probability was obtained. Table 9 lists the forecasted values of the probability of window opening generated by the simulation. The average value is 0.7505, and the standard deviation is 0.0975, which is in compliance with a normal distribution N (0.7505, 0.0975^2).

As shown in Fig. 8, the average probability of window opening is 0.7505, and 90% of the data is distributed across the range less than 0.8738. 10% of the data is distributed within the range smaller than 0.6247; that is, the probability of window opening by occupants inside office buildings in Chongqing during the transition seasons is within the range 0.6247–0.8738 (i.e. most people will choose to open a window during transition seasons).

5.3. *Probability curve of window opening in rooms under natural ventilation mode during transition seasons*

We used a scatter diagram to draw the relationship curve (Fig. 9) between the probability of window opening and the outdoor temperature during transition seasons based on the random outdoor temperature values generated through random sampling and with the model of the probability of window opening, *p*, constructed by Logistic regression analysis. Because the study was conducted in the transition seasons, outdoor temperatures were falling within the range 15 °C–30 °C, therefore, this range has been set for the probability model.

Fig. 9 shows the curve of the probability of window opening. It is almost a linear relationship. During the transition seasons, when the outdoor temperature is low, the probability of window opening by occupants is relatively low. The probability of window opening increases when the outdoor temperature increases. It reached 90% when the outdoor temperature is about 30 °C. This indicates that almost everyone opens a window at this temperature and thus almost all of the room windows will be open.

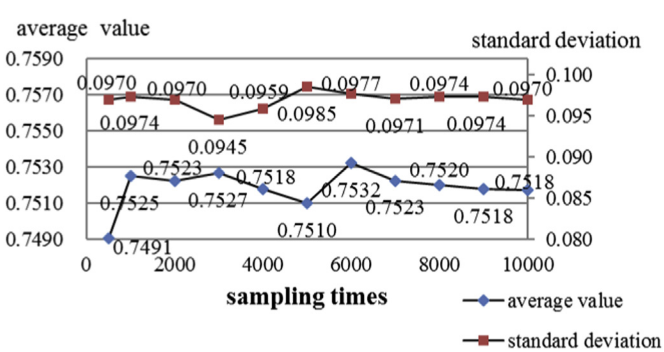

Fig. 7. Variation of the average values and standard deviations of the probability of window opening with increasing simulation times.

Table 9
Statistical results for the forecasted values of the window opening probability.

	Forecasted value
Simulation time	10,000
Benchmark case	0.7518
Average value	0.7505
Median	0.7516
Standard deviation	0.0975
Variance	0.0095
Skewness	0.0014
Kurtosis	3.04
Variable coefficient	0.1299
Minimum value	0.3862
Maximum value	1.1404
False exclusion value	0.0010

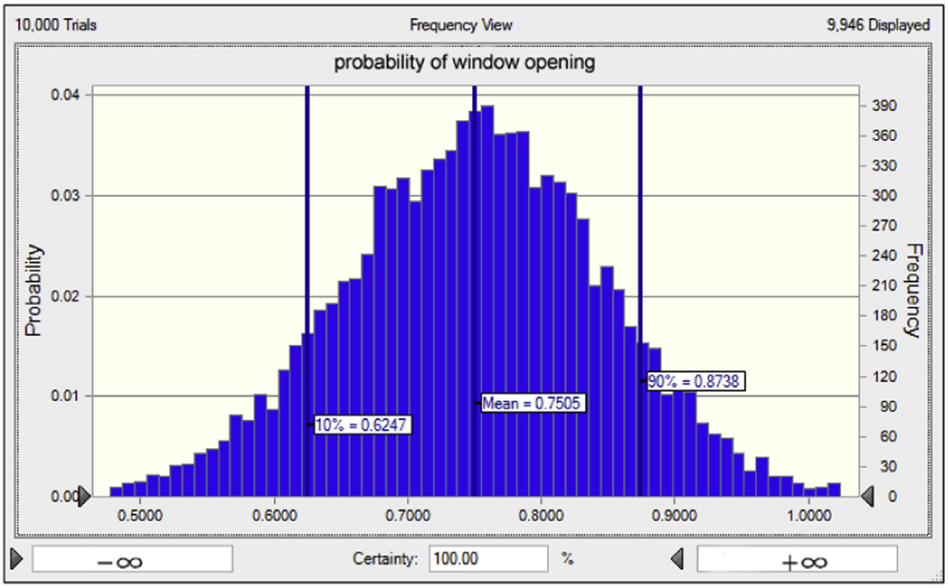

Fig. 8. Forecast diagram of the probability distribution of window opening by 10,000 times of stimulations of models with Crystal Ball.

6. Conclusion

An experimental study to investigate occupant behaviors in operation of windows was conducted in a transition season in Chongqing, China. We draw the conclusions based on the statistical analysis and the Monte Carlo random simulation results as follows:

1) In transition seasons, the behavior of opening windows was observed though the indoor air quality and thermal environment were within the standard comfortable range. This indicates the occupants' psychological demand for opening windows.
2) Using Monte Carlo simulation, we found that the probability of window opening in the office building in Chongqing during the transition seasons followed a normal distribution. In the transition seasons, when there were no other effective indoor environment control measures, the probability of opening windows for the enhancement of natural ventilation increased almost linearly along with outdoor temperature growth.
3) In transition seasons, opening windows for natural ventilation is an energy-efficient and environmentally friendly strategy to improve the indoor environment. It can meet occupants' requirements for both indoor air quality and thermal comfort.

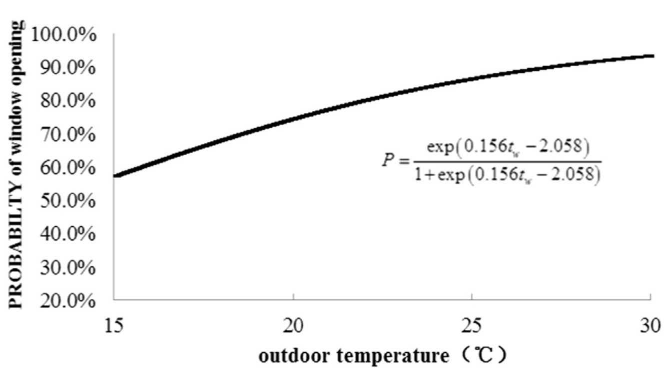

Fig. 9. Relationship between the probability of window opening and outdoor temperature.

However, when the outdoor temperature is beyond the range between 15 °C and 30 °C, there is a bias between the actual indoor thermal environment and occupants' thermal expectation.

Foundation item

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