Typical Heating and Cooling Occupant Behavior Patterns of Office Buildings Based on Large Scale Survey

ABSTRACT

Due to the diversity and randomness of heating and cooling usage behavior in buildings, occupant behavior can lead to great variation in building energy consumption. In the study of occupant behavior modeling, the characteristic parameters obtained from limited case studies are difficult to fully reflect the diversity and distribution characters of occupant behavior of large population. In practical engineering applications including energy efficiency design, standard formulation and technology evaluation, the typical behavior patterns based on large-scale crowd statistics are also required as the input of the modeling to ensure that the energy simulation results are consistent with the actual building energy use. This paper conducted a large-scale questionnaire survey about the preferences and habits of occupant behavior in China. Based on the behavior characteristics, the heating and cooling switching behaviors and temperature set point adjusting behavior were classified as several typical behavior patterns using cluster analysis methods. The conditional probability functions and characteristic parameters for the typical behavior pattern were also obtained to provide input for the occupant behavior model.

KEYWORDS

Occupant behavior, building energy consumption, heating and cooling behavior, typical behavior pattern, survey

1. INTRODUCTION

Among various parameters that affecting building energy use, the impact of human behavior on building energy consumption is non-negligible and has received increasing attention. It influences energy use in multiple ways, such as occupancy-based thermal gain, appliance operation schedules, heating and cooling set points, etc. Unlike deterministic parameters, the occupant behavior in buildings is usually random (Fabi et al. 2013, Lee et al. 2014). Due to differences in personal perceptions of the environment and living habits, it can lead to different behavioral outcomes (Reinhart and Voss 2003, Al-Mumin et al. 2003).

In order to extract typical behavior patterns from diverse behavior and quantitatively simulate occupant behavior, various studies have been carried out. Ren et al. (2015) used cluster analysis to classify five types of households according to the monitored indoor temperature curves. Carmo et al. (2016) applied clustering and regression analysis methods to acquire three heating behavior patterns based on the measured energy consumption. Haldi et al. (2016) monitored indoor environment of offices and used questionnaires to record occupant behavior, and obtained the probability distribution of parameters in the occupancy model using generalized linear regression.

However, the typical behavior patterns obtained from limited case studies are difficult to fully reflect the diversity of occupant behavior of large population. In practical engineering applications of occupancy models, the typical behavior patterns of large population are required as the input of the modeling instead of accuracy and personalization of individuals (Feng 2016). Hence, it is necessary to obtain data with a wide coverage of the population through questionnaire survey as a basis for extracting typical behavior patterns and distribution.

This paper conducted a large-scale questionnaire survey about the preferences and habits of occupant behavior in China. Based on the behavior characteristics, the heating and cooling switch actions and temperature set point adjusting behavior were classified as several typical behavior patterns using cluster analysis methods. The probability distribution and characteristic parameters for each pattern in the occupancy model were also provided.

2. METHODS

The purpose of this study is to identify the typical behavior patterns based on behavioral characteristics. The technical framework of this study can be generalized as the following:

1) The questionnaire survey was conducted to obtain the heating and cooling behavior patterns of large population. The questionnaire was designed in accordance with the occupant behavior model proposed by Wang (2014).

2) From the responses to the survey, several typical behavior patterns were obtained using cluster analysis based on behavioral characteristics.

3) The probability distribution and characteristic parameters for typical behavior patterns were provided and input into the occupant behavior module in DeST (Feng 2015) to simulate the energy consumption.

2.1. Occupant behavior survey

Participants of the study were 1180 individuals from across the China (560 males, 571 females, 49 unanswered; Mage = 34.37, ranging from 19 to 65), who were recruited from cold areas (28.75%), hot-summer and cold-winter zones (48.60%), and hot-summer and warm-winter zones (21.63%). Participants reported working in positions such as administrators (30.03%), technician (27.74%), researchers (19.00%), students (10.77%), sales (6.96%) and others (5.51%). The questionnaire survey was distributed through the internet to get a wide coverage of the population.

Participants reported their habit and preference of heating and cooling control behaviors, such as under what occasion they would turn on or off the air-conditioning, or adjust the temperature in their offices (Table 1). The questionnaire also contained workspace environment questions and demographics questions. Multiple choices were allowed in the survey when related to behavioral options.

Table 1. *Measures in the questionnaire*

Heating and cooling behaviors	*Personal workspace and interaction with colleagues*	*Demographics*
Control privilege	Workspace types	Occupation
Control ways	Arrival and departure time	Age
Heating switching on/off modes	Working hours	Gender
Frequently-set heating set point	Coworker numbers	Region
Cooling switching on/off modes	Frequency of discussion	Education
Frequently-used cooling set point	Decision making ways	
Temperature set points adjusting modes		

2.2. Cluster analysis of occupant behavior

This paper extracted typical behavior patterns based on behavioral characteristics, and used the survey results as cluster samples. Figure 1 shows the clustering algorithm.

Input: Sample set D=$\{x_1, x_2, \dots, x_m\}$; Number of clusters k
Process:
Select k samples from D as the initial mean vector $\{\mu_1, \mu_2, \dots, \mu_k\}$
repeat
  For $C_i = \emptyset (1 \leq \mathrm{i} \leq \mathrm{k})$
  for $\mathrm{j} = 1,2, \dots, \mathrm{m}$ do
    Calculate the distance between the sample x_j and each mean vector μ_i: $d_{ji} = \left\| x_j - \mu_i \right\|_2$;
    Determine the cluster mark of x_j based on the nearest mean vector: $\lambda_j = \arg \min_{i \in \{1,2,\dots,k\}} d_{ji}$;
    Divide the sample x_j into the corresponding cluster: $C_{\lambda_j} = C_{\lambda_j} \sqcup \{x_j\}$;
  end for
  for $\mathrm{i} = 1,2, \dots, \mathrm{k}$ do
    Calculate new mean vector: $\mu_i' = \frac{1}{|C_i|} \sum_{x \in C_i} x$;
    if $\mu_i' \neq \mu_i$ then update the current mean vector μ_i to μ_i'
    else keep the current mean vector unchanged
    end if
  end for
until current mean vector is not updated
Output: Cluster division $C = \{C_1, C_2, \dots, C_k\}$

Figure 1*. The clustering algorithm flow*

In the questionnaire, the options of each behavior mode are either 0 (unselected) or 1 (selected), which are defined as categorical attributes in the clustering algorithm. Hence, this paper applied VDM (Value Difference Metric) distance (Stanfill and Waltz, 1986) to calculate the distance between the categorical attribute values of different behavior modes, shown as Equation (1). And then, the distance between two samples is calculated by Minkowski distance, shown as Equation (2).

$$\mathrm{VDM}_2(0,1) = \sum_{i=1}^{k} \left| \frac{m_{u,0,i}}{m_{u,0}} - \frac{m_{u,1,i}}{m_{u,1}} \right|^2 \tag{1}$$

where $m_{u,0}$ – The number of samples with value 0 on attribute u; $m_{u,0,i}$ – The number of samples with value 0 on attribute u in the i-th clustering sample; k – The number of clustering samples.

$$\mathrm{MinkovDM_P}(x_i, x_j) = \left[\sum_{u=1}^{n} \mathrm{VDM}_2(x_{iu}, x_{ju})\right]^{\frac{1}{\mathrm{p}}} \tag{2}$$

where x_i – The i-th clustering sample; x_{iu} – The value on attribute u in the i-th clustering sample; n – The number of categorical attributes; p – Norm, takes 2.

2.3. Heating and cooling occupant behavior modeling

In the occupant behavior model proposed by Wang (2014), driven factors of heating and cooling behavior could be divided into event and environment factors. Whether the switching action occurs is described as a probability function of event or environmental parameters. For instance, “turn on AC when entering office” and “turn on AC when feeling hot” are described as Equation (3) and Equation (4), respectively.

$$P_{on} = \begin{cases} p & if\ \tau = \tau_0 \\ 0 & if\ \tau \neq \tau_0 \end{cases} \tag{3}$$

where P_{on} – the probability for occupants to turn on AC; τ – the current time in simulation; τ_0 – the moment when related event happens.

$$P_{on} = \begin{cases} 1 - e^{-\left(\frac{t-u}{l}\right)^k \Delta\tau} & if\ t > u \\ 0 & if\ t < u \end{cases} \tag{4}$$

where t – the indoor temperature (◦C); $\Delta\tau$ – the time step in simulation; *u,l,k* – the constant parameters that could be determined by data fitting after field measurements.

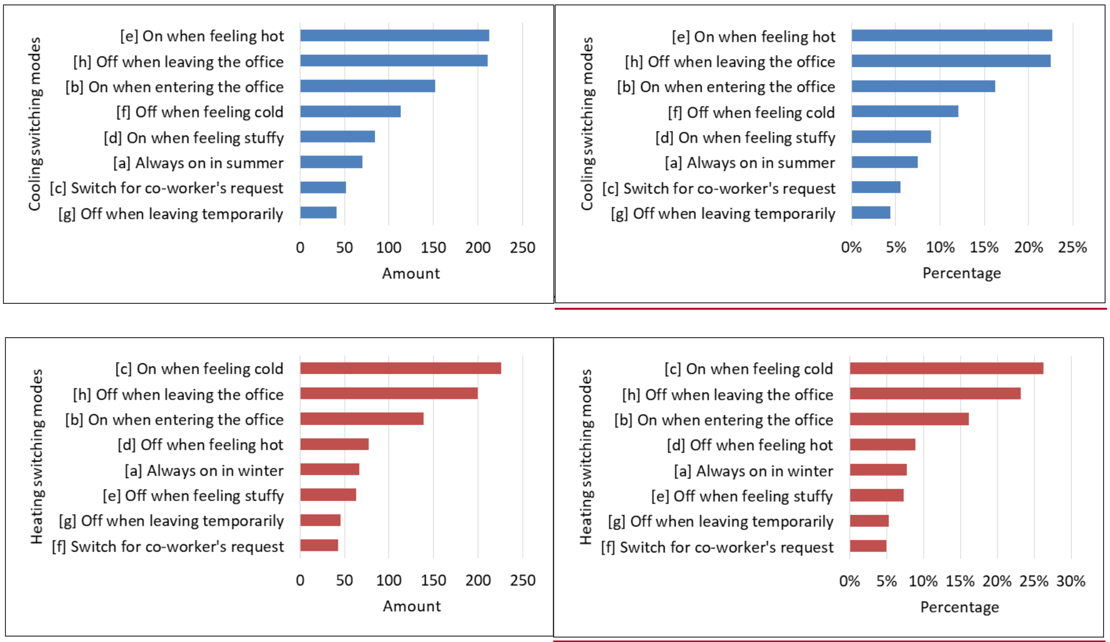
Coupling calculations of occupant behavior models and building thermal processes have been implemented in DeST (Feng 2015). The occupant behavior simulation performs an alternating calculation of the three sequences of occupant behaviors, equipment operating status and environmental conditions, therefore obtaining the equipment operating schedule, indoor environmental conditions, and building energy consumption at each time step in the room.

3. RESULTS

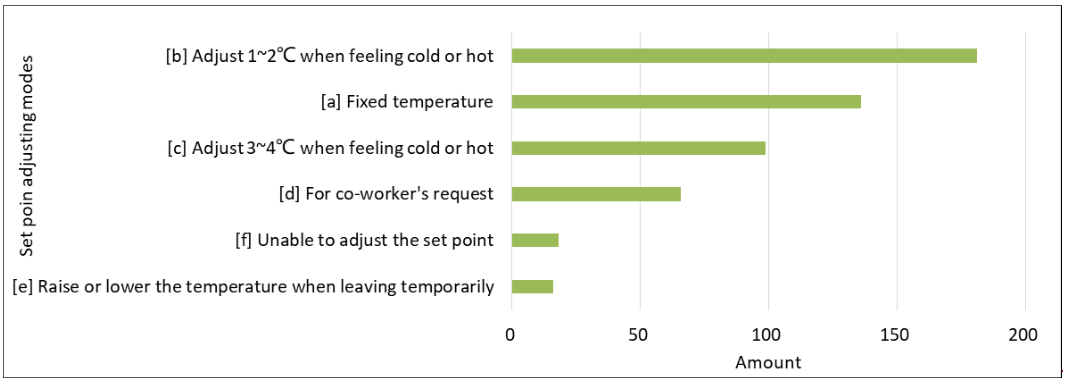
The large-scale survey was conducted across from China (1180 respondents), and the heating and cooling behavior of occupants might differ depending on the climate zone in which they live. The following section studied the heating and cooling occupant behavior in hot-summer and cold-winter zone (573 respondents), while other climate zones could be studied following this technical approach.

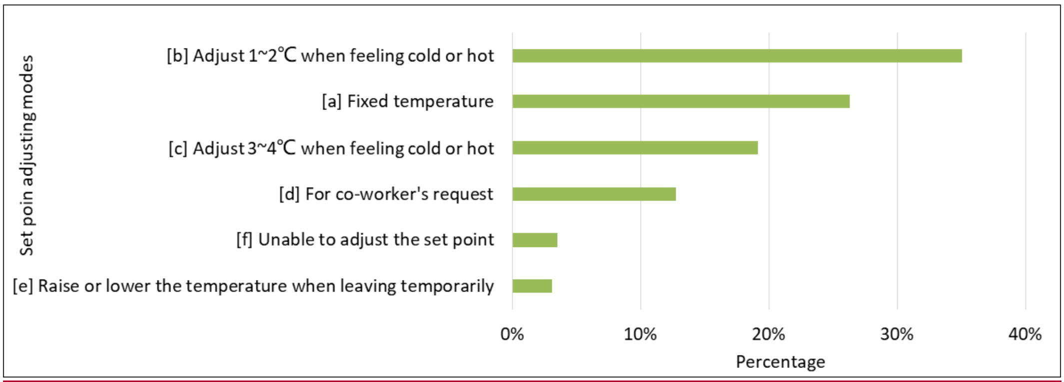
3.1. Typical heating and cooling behavior patterns

The amount of each heating and cooling behavior mode in the questionnaire was counted, shown in Figure 2. The survey results suggest that the sensation of hot or cold is the most important factor that causes the occupants to turn on AC or heating in the offices. The switching off behavior is mainly affected by the event of leaving the office, while few people would turn off cooling or heating when they leave temporarily for a meeting or lunch. Similar results can be found in the survey results of the temperature set point adjusting behavior. Since there are multiple occupants in an office, the request from co-workers or managers is also one of the non-negligible factors that influences occupant behavior.



(a) (b)





(c)

***Figure 2**. Survey results of the cooling switching (a), heating switching (b) and temperature set point adjusting modes(c) in the offices*

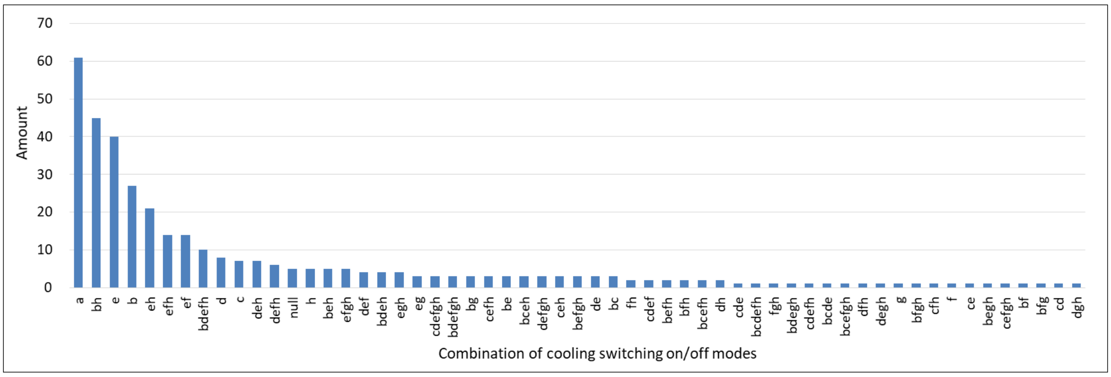


***Figure 3**. Survey results of the combined cooling switching mode*

Since the questionnaire allows for multiple choices, the combinations of behavior modes are diverse and scattered distributed, shown in Figure 3. The label in the x axis is in correspondence with the behavior mode in Figure 2. Table 2 and Table 3 provide the clustering results of cooling and heating switching behavior patterns and their population distribution. It can be seen that the typical patterns extracted based on behavioral characteristics can represent the common behavioral habits of the population. In several patterns such as "AC On when [e] feeling hot", the lack of a switching off behavior indicates that the occupant ignores it and has the co-worker or operation manager to turn off the AC, which is common in the offices. The listed typical heating and cooling behavior patterns can be used for further occupant behavior simulation and building energy analysis.

***Table 2.** Cluster analysis results of cooling switching behavior*

Cluster	*Typical cooling switching patterns*	*Proportion of population*
1	On when [b] entering the office, Off when [h] leaving	23.3%
2	On when [e] feeling hot, Off when [f] feeling cold and [h] leaving	20.0%
3	On when [e] feeling hot	18.9%
4	[a] Always on in summer	16.9%
5	On when [b] entering the office	10.8%

6	On when [c] coworker request or [d] feeling stuffy, Off when [h] leaving	10.0%

Table 3. *Cluster analysis results of heating switching behavior*

Cluster	*Typical heating switching patterns*	*Proportion of population*
1	On when [c] feeling cold, Off when [h] leaving	31.9%
2	On when [c] feeling cold	24.1%
3	[a] Always on in winter	16.9%
4	On when [b] entering the office	12.3%
5	On when [b] entering the office, Off when [h] leaving	12.0%
6	Others	2.7%

3.2. Case study

In order to illustrate the application of typical behavior patterns in occupant behavior modeling, this paper simulated the cooling occupant behavior of an office in Shanghai. A four-story office building model was built in DeST. Figure 4 shows the layout of the fourth floor, where Room 441 is the studied case. The envelope was designed in accordance with the domestic design standard.

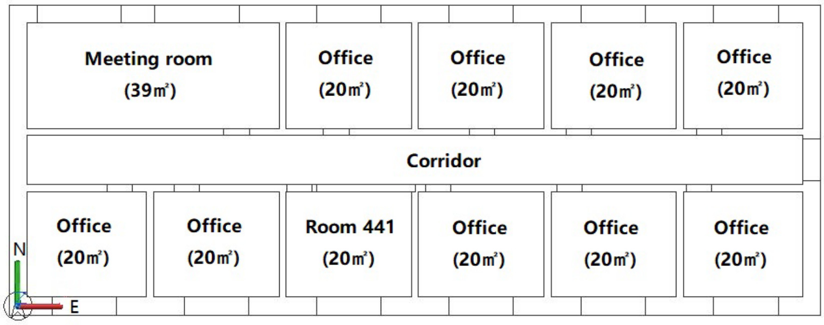


Figure 4*. Layout of the fourth floor of the office building in Shanghai*

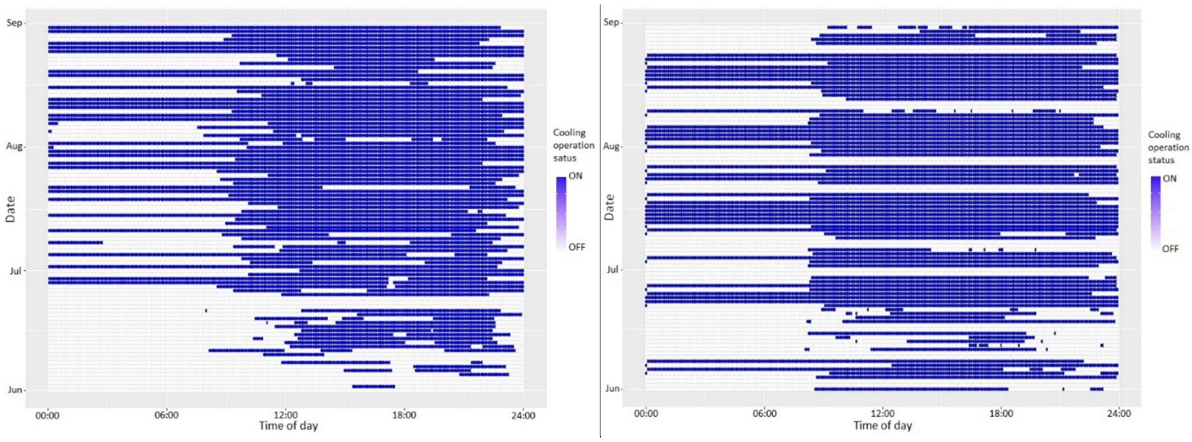
There were five occupants in the office and their behavior patterns were different. Based on the survey of the occupants in this case, the cooling switching behaviors of two occupants were described by the pattern of "On when [b] entering the office, Off when [h] leaving" and the other three occupants were described by "On when [e] feeling hot, Off when [f] feeling cold and [h]leaving" in Table 2. The parameters in the occupancy model were determined by fitting the measurement data from June 1th to August 31st, referring to the method of Ren et al. (2015). The cooling behavior pattern and model parameters are shown in Table 4. The cooling set point was set between 25°C to 27 °C.

Table 4. *Models and parameters for cooling behavior in the simulation case*

Cooling switching modes	*Occupancy models*	*Feature parameters*
[e] On when feeling hot	$P_{on} = \begin{cases} 1 - e^{-\left(\frac{t-u}{l}\right)^k \Delta\tau} & if\ t > u \\ 0 & if\ t < u \end{cases}$	u=27, l=4.28, k=1.85
[b] On when entering the office	$P_{on} = \begin{cases} p & if\ \tau = \tau_0 \\ 0 & if\ \tau \neq \tau_0 \end{cases}$	p=0.49

[f] Off when feeling cold	$P_{off} = \begin{cases} 1 - e^{-\left(\frac{u-t}{l}\right)^k \Delta\tau} & if\ t < u \\ 0 & if\ t > u \end{cases}$	u=26, l=3.40, k=4.56
[h] Off when leaving the office	$P_{off} = \begin{cases} p & if\ \tau = \tau_0 \\ 0 & if\ \tau \neq \tau_0 \end{cases}$	p=0.60

The actual and simulated operation schedule of cooling in the studied room are shown in Figure 5. Although the simulation results are not exactly the same as the measured values, they are very similar in general. Table 5 shows the cooling operation hours and the number of turn-on times in the measurement and simulation cases. It can be seen that the cooling related statistical indicators of the simulation results are close to the measured results, and the differences can be statistically explained and accepted.



(a) (b)

Figure 5. *Actual (a) and simulated (b) operation of cooling in the studied room*

Table 5. *Comparison of measurement and simulation results*

	Time step	Total hours (h)	Cooling operation hours (h)	Cooling turn-on times	Cooling operaion hours difference	Cooling turn-on times difference
Measurement result	5 min	2206	1246	94		
Simulation result	5 min	2206	1259	87	1.02%	7.40%

It can be concluded that the selected behavior pattern can reflect the practical behavior of the occupants in this case. Hence, the typical behavior patterns obtained by large-scale survey clustering can be used as the input for heating and cooling behavior simulation in office buildings.

4. DISCUSSION

This study presented a novel method for obtaining typical behavior patterns based on the results of large-scale survey. However, the limitation is that the distribution of the survey samples in each climate zone is uneven, future work should collect more samples to study the impact of the climate zone on the typical behavior patterns.

Another issue in this study is that the multiple behavior patterns and negotiation process between several occupants in an office were not considered in the case study, which may lead to different behavioral outcomes and simulation results. This could be included in future research.

5. CONCLUSION AND IMPLICATIONS

Based on the large-scale survey in China, six typical behavior patterns for heating and cooling were obtain by cluster analysis, and their population distribution was also provided. Through a case study of cooling behavior simulation, the typical behavior patterns were preliminarily verified to be reasonable and accurate in describing the occupant behavior in offices. It can be used as the input of occupancy model to simulate the equipment operating status in DeST.

For each pattern, further efforts could be made to collect and analyze measurement data in different climate zones and generate the corresponding occupancy models and parameters. Typical behavior patterns and models can be applied to the simulation analysis of building design, technical evaluation and standard formulation to reflect the energy use behaviors of the large population.

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