Research on air-conditioning usage behaviour in offices with different occupancy

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Abstract. Occupant behaviours in the buildings are not only random and uncertain but also related to each occupant’s habitual preference. This leads to the performance gap between actual and expected energy consumption in buildings. Therefore, accurate information and modelling with regard to occupant behaviour are important for reliable energy simulation and energy-saving optimization design. Existing studies on occupant behaviour models in office space usually focus on single-person offices or full-floor buildings, without considering the behavioural differences among offices with different occupancy. Therefore, this study established the air-conditioning usage behaviour models in offices with different occupancy based on questionnaires and measured data. The results show that occupant compromise and clustering effect will increase with the increase of occupancy. Using the established models as input, this study compared the simulation results with that under the standard schedule. The difference rate is as high as 32.19% in winter and 13.07% in the whole year. And for areas with high energy consumption in winter, the gap may be bigger.

1 Introduction

Building energy consumption is mainly affected by six factors: climate, building envelope, building services and energy system, building operation and maintenance, occupant activities and behaviours, and indoor environmental quality of the building according to the International Energy Agency (IEA). Among these factors, occupant behaviour is considered one of the most important findings in IEA EBC annexe 53 [1]. Accordingly, occupant behaviour must be included in energy performance efforts to achieve building energy conservation goals.

Many studies show the significant impact of occupant behaviour on building energy consumption and energy-saving potential. Y. Zhang et al [2] estimated the energy-saving potential of occupant behaviour to be in the range of 10%-25% for residential buildings and 5%-30% for commercial buildings, based on findings of existing research. K. Y. Sun et al [3] conducted a simulation study on the energy consumption of office buildings in four climate zones in the United States and found that the energy-saving effect of single person behaviour is as high as 22.9%. A. C. Menezes et al [4] analyzed the energy performance of an office building in central London and they found the accuracy of the model can be improved to less than 3% of the actual power consumption by combining the actual occupant behaviour monitoring data with the energy prediction model.

When discussing ten problems about occupant behaviour in buildings, T. Z. Hong [5] mentioned that an appropriate mathematical model can reflect the characteristics of randomness and complexity of occupant behaviour to a certain extent. After consulting the existing studies, it is found that the commonly used types of occupant behaviour models can be divided into five types as shown in Table 1. To sum up, the establishment method of the occupant behaviour model has been relatively mature, and each model has advantages and disadvantages.

Exiting studies mostly focus on the single-person space or a full-floor building, and rarely consider the impact of occupant interaction of different occupancy. Occupancy here refers to the number of occupants in the office. Actually, occupant behaviour is affected not only by the indoor environment but also by occupant interaction. C. Wang et al [6] modelled the lighting behaviour of single-person and multi-person offices and found that as the occupancy increased, the lighting habits became more fixed and regular. This phenomenon may also occur in the use of air-conditioning.

Therefore, this study focuses on air-conditioning usage behaviour in offices with different occupancy and established behaviour models, which is helpful to better understand the impact of occupant interaction. On this basis, this study applied the models to the simulation to obtain the gap between the current design standard and the actual use.

<table>
<thead>
<tr>
<th>Model type</th>
<th>Description</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
</table>

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<table>
<thead>
<tr>
<th>Deterministic model</th>
<th>Simplify occupant behaviour into a static and deterministic schedule or specify a certain action trigger point</th>
<th>Simple and can reflect the actual occupant actions</th>
<th>Randomness and complexity are insufficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random model</td>
<td>Use existing statistical data to predict the probability of specific actions and predict the probability at the next moment on the basis of the last moment</td>
<td>Contains behaviours that cannot be explained by external objective variables</td>
<td>Memory limitation; failure of capturing the bimodal features</td>
</tr>
<tr>
<td>Statistical analysis model</td>
<td>Find out the statistical correlation between behaviour and factors according to the observation, and predict the probability under specific environmental conditions</td>
<td>Contact environmental control with occupant behaviour better</td>
<td>Reflect the average characteristics of group behaviour rather than individual behaviour</td>
</tr>
<tr>
<td>Machine learning model</td>
<td>Based on a large amount of data, classify the occurrence frequency, duration and energy consumption results of behaviour</td>
<td>Suitable for analysing a large amount of data and showing excellent adaptability</td>
<td>Can’t describe the behaviour quantitatively; unavailable for simulation</td>
</tr>
<tr>
<td>Agent-based model</td>
<td>Observe occupant behaviour and interaction with each other and with the external environment to establish a system model</td>
<td>Obtain the overall impact of the random and various occupant behaviours</td>
<td>The decision-making process and modelling process are complex</td>
</tr>
</tbody>
</table>

2 Methodology

This study conducted measurements in offices with different occupancy and sent questionnaires to office staff online as a supplement to the experimental data. The obtained data were processed to establish air conditioning usage models. Then these models are applied to find the impact of occupant behaviour on building energy consumption considering the occupant interaction in different occupancy.

2.1 Survey for office staff

According to occupant behaviour studies, occupant behaviour is usually affected by indoor environment and behavioural habits. Between these two driving factors, behavioural habit is more difficult to monitor. Therefore, this study sent questionnaires to office staff all over the country online to extract the typical behavioural patterns. Table 2 shows the main contents and the results were used as a reference for modelling.

Table 2. Main contents of the questionnaire

<table>
<thead>
<tr>
<th>Q1</th>
<th>Please evaluate the factors that affect your air-conditioning related behaviours. (1-5 indicates the degree of influence, of which 1 means no influence and 5 means the greatest influence)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>Indoor temperature</td>
</tr>
<tr>
<td></td>
<td>Air cleanliness</td>
</tr>
<tr>
<td></td>
<td>Habits</td>
</tr>
<tr>
<td>Q2</td>
<td>In winter, if you turn on the air-conditioning as soon as you enter the office, the reasons are:</td>
</tr>
<tr>
<td>A2</td>
<td>(a) Feeling cold. (b) Habits (c) I won’t.</td>
</tr>
<tr>
<td>Q3</td>
<td>In summer, if you turn on the air-conditioning as soon as you enter the office, the reasons are:</td>
</tr>
<tr>
<td>A3</td>
<td>(a) Feeling hot. (b) Habits (c) I won’t.</td>
</tr>
</tbody>
</table>

2.2 Measurement

Measurements were carried out in 4 offices on a university campus in Shanghai. Table 3 presents the occupancy and size of these offices and the duration of the measurement. Besides, the outdoor meteorological data from Nov.1 2020 to Oct.31 2021 were collected from meteorological measuring stations as the weather document for simulation in Energy Plus. The plane layout of the four offices and the layout points of sensors are shown in Fig. 1.

The following variables were measured continuously in the 4 offices: 1) Indoor environment factors measured every 10 min: dry bulb temperature (°C), relative humidity (%) and CO₂ concentration (ppm). 2) Behaviour: air-conditioning state (open/closed) and setting temperature changing (up/down/none). Hawthorne effect may appear when occupants are monitored. To avoid this, most of the data are collected through the cloud platform of the Internet of things (IoT).

Table 3. Overview of measured offices

<table>
<thead>
<tr>
<th>Office index</th>
<th>Occupancy</th>
<th>Size</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>4.5m×10.5m</td>
<td>Dec. 1, 2020-Jan. 9, 2021</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>4.5m×10.5m</td>
<td>May. 7, 2021-Jul. 12, 2021</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>6.3m×8m</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>9m×10.5m</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 1. Layout points of sensors
(a) 4-person; (b) 5-person; (c) 10-person; (d) 16-person
2.3 Establishing the air-conditioning usage model

In this study, we focus on occupant action, such as turning on, turning off, turning up and turning down the air-conditioning. To establish the air-conditioning usage model, the driving factors of these occupant actions need to be determined. At the same time, an appropriate mathematical model can improve the fitting accuracy. Accordingly, the research process can be divided into the following steps.

1) Determine the driving factors of air-conditioning usage model in winter and summer conditions.
2) Based on the obtained behaviour patterns and data characteristics, select the appropriate mathematical model.
3) Establish the air-conditioning usage model in the 4 offices according to the selected mathematical model.

2.4 Model application

Using the established models as input, this study simulated the energy consumption of an office building with different occupancy offices through Energy Plus. The simulation results are compared with the simulation results that use a fixed schedule in the existing national standard as input. In this way, the comparison can reflect the energy-saving potential. The research process can be divided into the following steps.

1) Preparations: a) Establish the geometric model of the case in Design Builder. b) Set the related parameters according to the current standard. c) Use the ideal load system, so the simulation result of energy consumption is the same as the cooling and heating load.
2) In the simulation, the setting temperature is used to reflect the air-conditioning state. Obtain the hourly setting temperature schedule according to the established models through logical flow.
3) Take the schedule obtained and standard schedule as input and bring them into Energy Plus to simulate the energy consumption through the python program.

3 Results

3.1 Air-conditioning usage models

Through the preliminary statistics of the occupant presence with time (Fig. 2) and temperature distribution (Fig. 3) in the offices, it is found that the curve trend of the 4-person office is very similar to the 5-person office, and so is the 10-person and 16-person offices. Accordingly, this study divided the 4 offices into two kinds to simply the modelling, namely, 4-person and 5-person are small-sized offices and 10-person and 16-person are medium-sized offices. In this way, the following modelling and simulation are both carried out for these two types of offices.

A total of 181 valid questionnaires were collected. The average scores for indoor temperature, habits and air cleanliness are 4.01, 2.8 and 1.94. Therefore, the most influential factor is indoor temperature, followed by habits. Combining the survey results with measured data, in winter, the air-conditioning usage behaviour patterns are summarized as follows: turn on the air-conditioning when occupants feel cold and turn off the air-conditioning when they get off work. The driving factor of the former is the indoor environment while the latter is the behavioural habit, so the modelling part will be divided into two parts.

The u-l-k model proposed by C. Wang is suitable for the model of opening events driven by the environmental factor (indoor temperature). The u-l-k model is described in formula (1). As for the closing event, its trigger condition is simple and single, so the basic conditional probability function is suitable for it. The final complete model is shown in Table 4. Air-conditioning usage models in small-sized and medium-sized offices

\[ p_{on} = \begin{cases} 1 - e^{-\frac{(t - \tau)}{\Delta t}}, & \text{if } t < u \\ 0, & \text{if } t \geq u \end{cases} \]

where
- \( p_{on} \) is the probability of some event
- \( u, l, k \) are characteristic parameters
- \( \Delta t \) is the time step
- \( t \) is the independent variable

The valid data on occupant action events are more in summer because of the longer measuring duration and seasonal effect. Therefore, in addition to the behavioural patterns summarized in winter, the adjusting event of the setting temperature and the opening event when entering the office are also considered to obtain a more accurate
description. Similarly, the model is divided into three parts. One part is the opening event when entering the office (behavioural habit), one part is the adjusting event, and the other part is the closing event at leaving moments. The opening and closing events use the basic conditional probability function, and the opening event considers several delay periods. The modelling of the adjusting event is around the setting temperature and there are three settings.

1) The setting temperature in the model is the corresponding indoor temperature when the operating state of the air-conditioning changes;
2) The probability that a certain temperature is the setting temperature is calculated according to formula (2);
\[ P_{\text{setting}} = \frac{\text{changes of the operating state}}{\text{total changes of the operating state}} \]  

3) The setting temperature at each moment in the model after the opening event is randomly generated.

From the statistical results of the data, the \( P_{\text{setting}} \) shows a peak value of right deviation with the temperature. After comparing many mathematical distributions, the final determination is the 2-parameter Weibull distribution, as shown in formula (3). The final complete model is shown in Table 4. Air-conditioning usage models in small-sized and medium-sized offices

\[ p_t = \frac{b}{a} t^{\frac{b-1}{a}} e^{-(t/a)^b} \]  

where
- \( t \) is the temperature (°C)
- \( p_t \) is the probability that \( t \) is setting temperature
- \( a, b \) are characteristic parameters

<table>
<thead>
<tr>
<th>Season</th>
<th>Description</th>
<th>Model of the small-sized office</th>
<th>Model of the medium-sized office</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>Opening event during office hours</td>
<td>[ p_{\text{on}} = \begin{cases} 1 - e^{\left(\frac{21-t}{0.12}\right)^{2.29}} &amp; \text{, if } t &lt; 21 \ 0 &amp; \text{, if } t \geq 21 \end{cases} ] (4)</td>
<td>[ p_{\text{on}} = \begin{cases} 1 - e^{\left(\frac{25-t}{0.2}\right)^{3.23}} &amp; \text{, if } t &lt; 25 \ 0 &amp; \text{, if } t \geq 25 \end{cases} ] (5)</td>
</tr>
<tr>
<td>Closing event</td>
<td>[ p_{\text{off}} = \begin{cases} 0.857 &amp; \text{, at leaving moment} \ 0 &amp; \text{, other time} \end{cases} ] (6)</td>
<td>[ p_{\text{off}} = \begin{cases} 0.763 &amp; \text{, at leaving moment} \ 0 &amp; \text{, other time} \end{cases} ] (7)</td>
<td></td>
</tr>
<tr>
<td>Opening event</td>
<td>After entering office</td>
<td>[ p_{\text{on}} = \begin{cases} 0.411 &amp; \text{, at entering moment} \ 0.788 &amp; \text{, within 1 h after entering} \ 1 &amp; \text{, within 2 h after entering} \end{cases} ] (8)</td>
<td>[ p_{\text{on}} = \begin{cases} 0.603 &amp; \text{, at entering moment} \ 0.792 &amp; \text{, within 1 h after entering} \ 1 &amp; \text{, within 2 h after entering} \end{cases} ] (9)</td>
</tr>
<tr>
<td>Summer</td>
<td>Adjusting event (the probability of setting temperature)</td>
<td>[ p(t) = \frac{18.73}{26.12} \cdot \left(\frac{t}{26.12}\right)^{17.73} e^{-\left(\frac{t}{26.12}\right)^{16.73}} ] (10)</td>
<td>[ p(t) = \frac{24.29}{26.54} \cdot \left(\frac{t}{26.54}\right)^{21.29} e^{-\left(\frac{t}{26.54}\right)^{24.29}} ] (11)</td>
</tr>
<tr>
<td>Closing event</td>
<td>[ p_{\text{off}} = \begin{cases} 0.638 &amp; \text{, at leaving moment} \ 0 &amp; \text{, other time} \end{cases} ] (12)</td>
<td>[ p_{\text{off}} = \begin{cases} 0.617 &amp; \text{, at leaving moment} \ 0 &amp; \text{, other time} \end{cases} ] (13)</td>
<td></td>
</tr>
</tbody>
</table>

### 3.2 Impact of different occupancy

As mentioned earlier, the visible and invisible interaction among occupants will affect their energy consumption behaviour. The impact is shown in the difference in air-conditioning usage model between small-sized and medium-sized offices.

In the model of the opening event in winter, the \( u \) and \( k \) of the medium-sized office are significantly higher.
and the fitting curve is also "steeper" than those of the small office. And in the model of the setting temperature in summer, the \( a \) of medium-sized office which shows the most comfortable temperature is also a little higher. From these results, the occupants in the medium-sized office tend to act at higher room temperature whether in winter or summer and this may result from the "occupant compromise" which is mentioned in Z. P. Deng’s study [7]. The setting temperature in a multi-person office is a trade-off decision, that is, some occupants may compromise with a preference of others. Furthermore, the gap between the two types of offices in winter is more obvious than that in summer, which is related to the priority of various adaptive behaviours when occupants feel hot or cold. In winter, occupants have fewer heating methods, usually only drinking hot water and turning on air-conditioning, while opening windows and mechanical ventilation are available in summer, so office occupants rely more on air-conditioning in winter.

In addition, in winter, the \( l \) of the medium-sized office is higher, that is, the corresponding temperature range of the probability (0–1) of the opening event is narrower. In summer, the \( b \) of the medium-sized office is higher, that is, the selection range of the setting temperature is more concentrated. These reflect a phenomenon that with the increase of occupancy, the randomness of the action decreases and the driving temperature of the action becomes more stable. And S. Karjalainen’s study has similar findings [8]. He analyzed the interview and survey results of single, 2-person, 3-person and multi-person offices in Finland, and found that with the increase in occupancy, the perception of indoor temperature becomes slower.

### 3.3 Simulation results

In this section, the geometric model of an office building with three rectangular standard floors is established in Design Builder. In this model, the middle layer is selected to reflect the simulation effect of the above behaviour models, which has four small-sized (4-person) offices and four medium-sized (13-person) offices in different directions (Fig. 4). And the duration of the simulation is the heating season (Dec.1 – Feb.28) and cooling season (May.1 – Sep.30).

![Fig. 4. The layout of the medium layer](image)

To simulate the energy consumption, the first step is to get the setting temperature schedule according to the above behaviour models. **Fig. 5** illustrates the workflow to determine the hourly setting temperature schedule. For each moment, the setting temperature is determined through three random processes which contain opening, closing and adjusting events. After many circles, a complete schedule for the heating and cooling season will be obtained. The obtained schedule and the standard schedule are simulated 200 times respectively to reduce random errors. According to formula (14), the simulation results are converted into difference rates which facilitate a better comparison.

\[
D(n) = \left( \frac{E_B - E_n}{E_B} \right) \times 100\% \quad (14)
\]

where
- \( D(n) \) is the difference rate between the model schedule and the standard schedule of each simulation
- \( E_B \) is the energy consumption under the standard schedule
- \( E_n \) is the energy consumption under the model schedule

As shown in **Fig. 6** and **Fig. 7**, the difference rate in winter fluctuates between 25% and 40%, and that in summer fluctuates between 11.2% and 12.3%. The
average in winter is 32.19%, in summer is 11.81% and for the whole year is 13.07%. Since the difference rates are positive, the energy consumption is obviously lower than that under the current standard schedule whether in winter or summer. In addition, although the difference rate in winter is more obvious, the result depends more on summer because the proportion of energy consumption in winter is relatively small.

5 Conclusion

Occupant behaviour is known to be one of the major factors affecting energy consumption in buildings. This study focuses on air-conditioning usage behaviour in offices with different occupancy and carried out a series of measurements and modelling. Comparing the model results, the impact of different occupancy is reflected in occupant compromise and clustering effect. It can be inferred that with the increasing of occupants, there is finally no need to consider personalized control. Applying the established models into the simulation, the results show that the overestimation of energy consumption caused by using the fixed standard schedule is as high as 32.19% in winter and 13.07% for the whole year. And these established models can provide a more objective and accurate basis for the prediction, evaluation and optimization of building energy consumption, and can provide a reference for engineering design and standard establishment in the future.

However, owing to the limitation of samples, more research is needed to verify the conjecture of this study. Besides, this study only focuses on the air-conditioning usage behaviour, but the energy-related occupant behaviours are various and the energy consumption is a comprehensive result, so there is still a need for more studies on occupant behaviours.

References