Statistical Analysis of Occupancy Behavior in Open Office Spaces Using Measured Lighting Switch Data

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ABSTRACT

Discrepancies between the actual measured building energy consumption and simulated results from computer based building energy modeling programs (BEMPs) can be attributed to many factors. One of the most important factors is occupancy behavior in buildings. Occupancy behavior has significant impact on energy use and operational controls of buildings and their energy service systems as they are designed and operated to provide comfort and healthy working environment for occupants. This study used statistical methods to analyse occupancy data measured in five-minute interval for each open-plan office space (cubicle) located on three floors of an office building. Five typical occupancy patterns were identified based on the average daily 24-hour profiles of an occupant's presence in a cubicle, which include one-square curve, one-valley curve, two-valley curve, variable curve, and flat curve. The average occupancy profile together with the probability distributions of duration and number of times an occupant absent from his cubicle are key parameters that define the occupancy model. The statistical results also reveal that the number of an occupant absent from his cubicle decreases with the total daily working hours, and the duration of absence from cubicle decreases with the frequency. Furthermore, the occupancy patterns are slightly influenced by the location of cubicles in the building – occupants close to windows or isolated corners tend to leave office less often. The developed occupancy model captures the stochastic nature of occupants moving in and out of cubicles and thus can be used to predict more realistic occupancy schedule which is crucial to improve the accuracy of evaluating energy saving potentials of occupancy based technologies and controls using building simulations.

KEYWORDS

Building energy performance, Building simulation, Occupant behavior, Occupancy patterns, Statistical analysis

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INTRODUCTION

The building energy simulation tools are widely applied recent years for energy-saving proposals of new construction designs and existing building retrofits. However, the simulated results can sometimes deviate significantly from measured data. Such discrepancies can be attributed to several factors. One of the most important factors is occupant behavior in buildings. Several studies, such as Haas et al. (1998), Pfafferott and Herkel (2007), and Tanimoto et al. (2008)demonstrated that building occupancy behavior has significant impact on energy use and operational controls of buildings. In recent years, more personal control systems and devicesare induced for energy efficiency improvement to achieve energy savings. Accurately estimating the energy and comfort impact of these personal controlled systems and technologies rely on accurate predicting of how frequent and how long occupants stay in their offices. How to obtain realistic and stochastic occupancy is a key issue for building energy simulations to accurately evaluate performance of occupancy based controls. Currently, most simulation tools apply monotonous occupancy schedules to represent the time when occupants are in offices. However, occupancy behavior may change significantly according to the season, weather, time, and personality. Therefore it is not surprising that simulated energy use deviates from actual consumption in most situations. Although various occupancy models, including Fritsch et al. (1990), Page et al. (2007),Wang et al. (2011), andSantin (2011), were developed in order to predict the occupancy in the building, they usually lack validation using adequate field measurement data.This study uses statistical method to analyze lighting switch data collected from open office spaces of an office building to identify variations of occupancy behavior. Various occupancy patterns and characteristics are identified and a robust occupancy model is being developed to generate more realistic occupant schedules. The results of this study can be used to further understand and evaluate the impacts of occupant behavior on building energy performance, and to improve the accuracy of predicting actual energy use of buildings with simulation tools.

DATA COLLECTION AND ANALYSIS METHODS

A total of 200 lighting switch sensors were installed on open office cubicles of three floors, Floor A, Floor B, and Floor C,in an office building. The installed switch numbers of each floor are 104, 47, and 49, respectively. The occupancy sensor detects movement of the occupant and controls the lighting switch for each cubicle. The switch events were recorded as “1” and “0” indicating the cubicle is occupied and unoccupied. The data collected for weekdays, weekends, and holidays from May through November in 2011 was used. The data may be incorrect for a few cases due to the sensor sensitivity and coverage. The switch sensors sometimes are triggered by people walking outside cubicles, or aren’t triggered at all when occupants do not move much in the cubicles. However, they occur relatively infrequent and should not have noticeable impact on data analysis results. As the investigation continued, some days were further excluded due to the control system going offline temporarily which resulted in incomplete data collection. The final data used in this study include 76 weekdays and 34 weekends and holidays.

Statistical methods are applied in this study to investigate and analyze the occupancy data. The working hours of each occupant in each day can be obtained by accumulating the “switch on” events and then the total working hours in each month can be calculated by adding up the hours of each day. Additionally, the occupancy patterns of three floors are respectively illustrated according to the probabilities of “switch on” events andcan be classified into five different types. By accumulating the probabilities of five different patterns individually and then dividing by the numbers of each occupancy pattern, the average occupancy pattern can be therefore determined. According to the “switch off” events, the occupant stays in or moves out the cubicle can be distinguished and therefore the daily absence times and absence minutes can be determined.

RESULTS

The profiles of occupant working hours for each floor are discussed firstly. For Floor A and Floor C, most occupants work 2 to 6 hours a day. As for Floor B, it is noticeable that the occupancy behavior is totally different from other two floors. The average working hours of Floor B is almost half compared with the Floor A and Floor C. This may be deduced that different agencies with different job categories work on different floor. Figure 1 displays the average daily profiles of “switch on” of each floor during weekdays. The occupancies for the three floors generally begin arriving at 6 AM and leave by 6 PM during weekdays. It can be found that the occupancy of each floor has a noticeable dip around noon which can be attributed to occupants leaving for lunch. In addition, the spikes that occur in the evening are attributable to the night cleaning crews. Compared to the occupancies in the weekdays, the occupancy of Floor A is less than 3% and almost equal to 0% for Floor B and Floor C in the weekend. Therefore, this study only focuses on the investigation and analysis of data collected for weekdays.

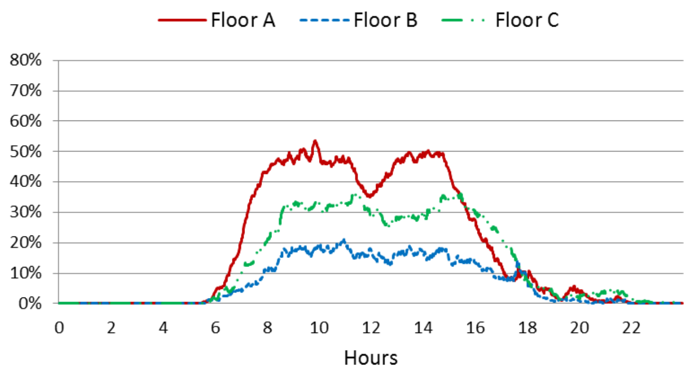

Figure 1*The average daily profiles of “switch on” of each floor during weekdays*

The occupancy behavior can be classified into five different patterns, as illustrated in Figure 2. It can be seen that these occupancy behavior patterns are very different from each other. For Figure 2(a), the pattern is close to a single-square curve. It indicates that the occupant may leave the cubicle any time in office hours with equal probability. As for Figure 2(b), the occupancy behavior pattern is similar to Figure 2(a) except an observable deep valley occurring during the noon. The period is around 1 to 1.5 hours. This can be resulted from the occupant leaving the cubicle for lunch. Therefore, this kind of pattern can be defined as the occupant doesn't move in and out the cubicle frequently but will leave for lunch during noon. As for Figure 2(c), there are two noticeable valleys in this pattern. In addition to the valley occurred in the noon, one of the valley appears in the morning. This can be attributed to the longer absence of occupant, such as attending meetings or going outside. However, this valley observed in this study not only occurs in the morning but also in the afternoon, just not shown here. As for Figure 2(d), it can be seen that the pattern varies significantly and there is no regulation like Figure 2(a)-(c). This kind of pattern represents the occupant leaves the cubicle very frequently during the working time and with a longer leaving period. As for Figure 2(e), the occupancy behavior pattern is flatness. This can be attributed to that the cubicle is occupied for public usage, such as print station, coffee shop, or office supply room. Therefore, this kind of pattern will not be further discussed in this study.

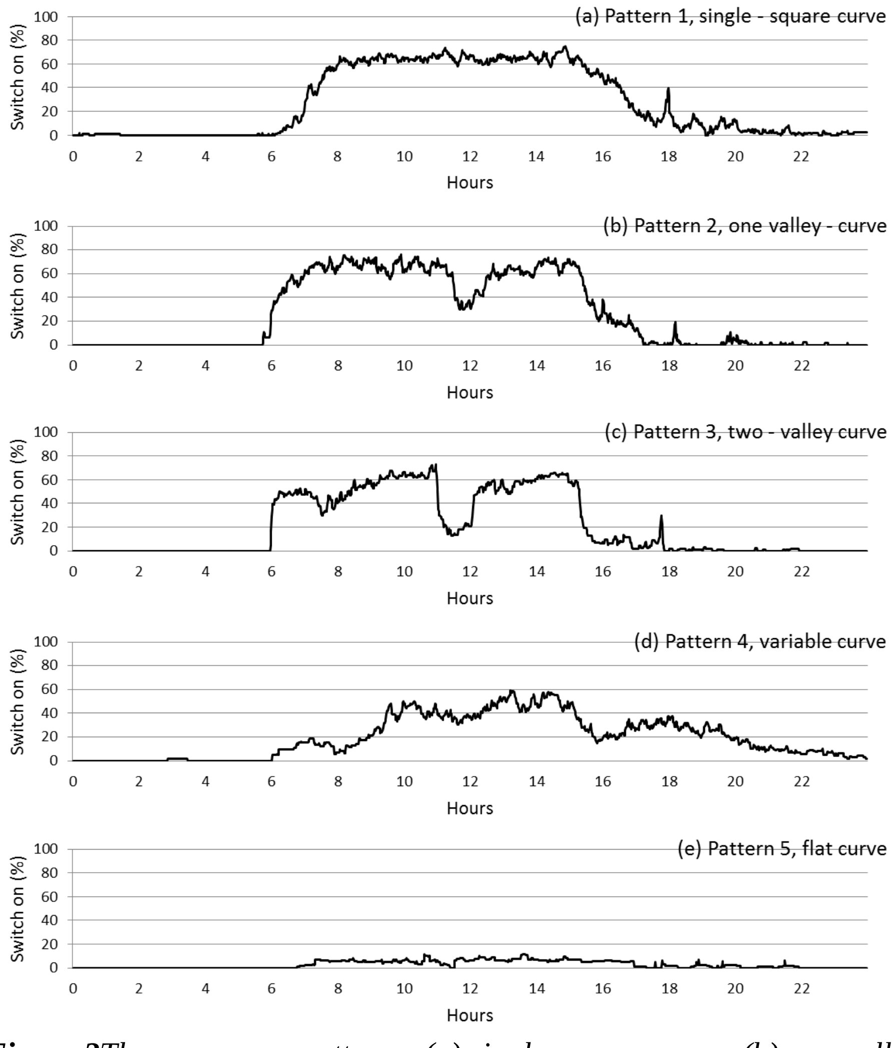

Figure 2*The occupancy patterns: (a) single-square curve; (b) one-valley curve; (c) two-valley curve; (d) variable curve; (e) flat curve*

The occurrence percentages of each pattern are similar for Floor A and Floor C. Pattern 2 is the most typical occupancy behavior pattern, about 45% and 39% respectively, in Floor A and Floor C. The most occupancy behavior pattern in Floor B is pattern 5 which occurrence percentage is about 38%. This significant difference can be attributed to different agencies working on different floor.The daily absence times of each occupancy behavior pattern are displayed in Figure 3.The designations of patterns 1 to 4 shown in this figure are corresponding to the Figures 2(a)-(d), and these designations will be further used in the later discussion. It can be found that the peak of each occupancy behavior pattern shifts and decreases with the daily absence times. The most typical daily absence times for each pattern are1, 4, 5, and 9. For pattern 1, there are a total of 5 days the occupant never leaves the cubicle at all. Compared with pattern 1, although the peak of the other patterns are less than that of pattern 1, each of the total absence times of patterns 2 to 4 is almost greater than those of pattern 1 except the less daily absence times cases.

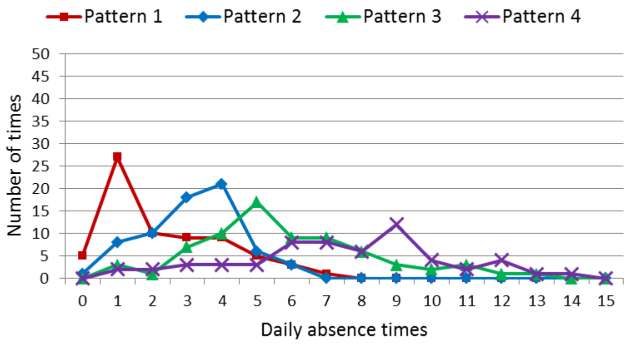

Figure 3 *The daily absence times for each occupancy behavior patterns*

The times of absence minutes,shown in Figure 4, almost concentrate in 10 to 29 minutes for all the occupancy behavior patterns except pattern 4. For pattern 4, the most case of absence minutes occurs in 0 to 9 minutes. Additionally, it is noticeable that the occurrence times decreases with the longer absence minutes for all the patterns. The shorter period can be deduced that the occupant leaves the cubicle to take a break, go to restroom, or walk around. While the longer period can be attributed to that the occupant goes to meeting, have lunch, or goes outside for business.

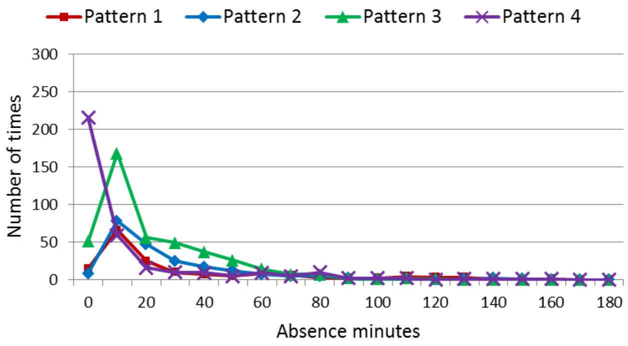

Figure 4*The number of times of absence minutes for each occupancy patterns*

The total numbers of absence times and average absence minutes of these time periods for pattern 2 are illustrated in Figure 5. The numbers of absence times shown here are the accumulated numbers within the 76 days period, and the absence minutes are the average values.The occupant leaves the cubicle more often with the short duration in the afternoon. This may be due to the less concentration or more tiredness of occupant resulting in the occupant walk around or go to restroom more often. Furthermore, the average absence minutes in the time period 11:30 AMto 1:30 PM is significant longer than the others. The reason is the occupant leaves the cubicle for lunch. However, the average absence minutes in the time periods of 8:00 to 11:30 AM and 1:30 to 6:00 PM are almost the same.

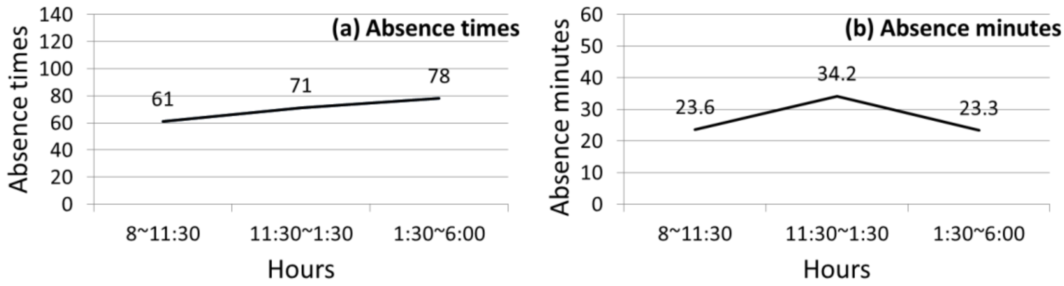

Figure 5*The occupancy behavior variations of pattern 2 for three time periods: (a) absence times; (b) average absence minutes*

The accumulated numbers of absence minutes of each time period for pattern 2 are illustrated in Figure 6.The most typical absence minutes occurred for all three time periods is 10 to 19 minutes. For the time periods of 8:00 to 11:30 AM and 1:30 to 6:00 PM, the curves drop drastically after the peak and then descend slowly. Compared with the time period of 1:30 to 6:00 PM, more times of longer absence occur in the time period of 8:00 to 11:30 AM. For the time period 11:30 AM to 1:30 PM, the curve declines more smoothly after the peak and the times of longer absence are higher than the other two time periods. It indicates that the occupant may spend over 10 minutes and even sometimes almost 2 hours for lunch.

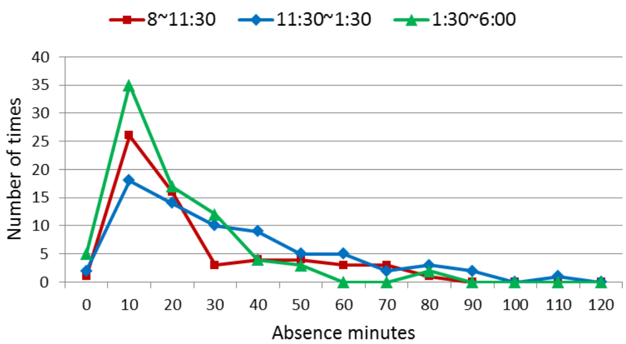

Figure 6*The number of times of occupancy pattern 2 for three time periods*

DISCUSSIONS

Several occupancy behaviors in an office building are observed and investigated in this study. Firstly, the occupancy of cubicles for a typical 8-hour weekday for the three floors mostly begins around 8 to 9 AM with a dip around noon, and then begins decreasing around 4 to 6 PM. The occupancy levels during weekdays for Floor B are very different from the other two floors, which can be attributed to different agencies working on different floors. Secondly, the occupancy behaviors can be classified into five different patterns according to the occupancy variation, appearance duration in the cubicle, and occupant personality. The occupancy behavior occurred the most among all occupants on cubicles of the three floors is pattern 2, which indicates that most of the occupants leave their cubicles for lunch around noon, in addition to other longer events, such as attending meetings or going outside. Thirdly, the most typical of daily absence times for pattern 1 to pattern 4 is 1, 4, 5, and 9 times. The absence minutes for each absence are almost within 10 to 29 minutes for all the occupancy behavior patterns. The absence times decreases with the longer absence minutes for all patterns. Finally, the occupants leave the cubicle more often in the afternoon but with shorter absence minutes. In other words, the occupants leave the cubicle less frequency but with longer absence minutes. Moreover, the average absence time of occupancy is longer during noon due to lunch. This study also observes that the occupancies are slightly influenced by the location of the cubicle on each floor. However, job category may have more influences on the occupancy behavior than location of cubicles. It is unfortunate that no data, due to privacy concerns, is available to further relate job characteristics to occupancy behavior.

Our analysis covered the impact of cubicle location on the occupancy behavior. Occupants close to windows or isolated corners tend to leave office less often. However, due to the privacy and security concerns of the studied building which is a Federal building, floor plans and detailed analysis results cannot be disclosed. For occupants close to windows, comfort such as view and opening windows for fresh air and temperature control is readily available, they can adjust as necessary to feel more relaxing during work or break. For occupants in isolated corners, better privacy or quiet surrounding allow them to focus more on work and leave office less often.

CONCLUSIONS

Measured lighting switch data, representing status of occupancy, collected from 200 cubicles on three floors of a commercial office building are statistically analyzed in this study. The occupancy levels are identified and the occupancy behavior can be classified into five different patterns. The daily absence times and absence minutes of each occupancy behavior pattern are further calculated and analyzed. Based on the results, a mathematical model to describe the occupancy patterns, including the probability of occupant appearance and duration, is under development. The occupancy model can be used to generate more realistic occupancy schedulesfor open office spaces that can be used in building energy simulations. In addition to the lunch during noon, more occupancy events such as meeting, short visit, walking around, and late night cleaning can be taken into account in the model to capture the actual occupancy variations in the building. The more detailed occupancy schedules can be approached and can replace the monotonous ones used in the building energy simulation tools before. Therefore, the predicted occupancy levels can be applied in building energy models to better assess the impacts of occupant behavior on building energy performance and to improve accuracy of simulated results. This method can also be used to validate and enhance other building occupancy models. However, more case studies and measured data analyses need to be conducted. The analysis methods used in this study can also be adapted to study the occupancy behavior of private offices and other building types like residential.

ACKNOWLEDGEMENTS

The authors thank Joy Wei and Abby Enscoe for providing the lighting switch data and answering our questions. This work is supported by the Bureau of Energy, Ministry of Economic Affairs, Taiwan, and the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Program, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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