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Abstract
Occupancy profile is one of the driving factors behind discrepancies between the measured and simulated energy consumption of buildings. The frequencies of occupants leaving their offices and the corresponding durations of absences have significant impact on energy use and the operational controls of buildings. This study used statistical methods to analyze the occupancy status, based on measured lighting-switch data in five-minute intervals, for a total of 200 open-plan (cubicle) offices. Five typical occupancy patterns were identified based on the average daily 24-hour profiles of the presence of occupants in their cubicles. These statistical patterns were represented by a one-square curve, a one-valley curve, a two-valley curve, a variable curve, and a flat curve. The key parameters that define the occupancy model are the average occupancy profile together with probability distributions of absence duration, and the number of times an occupant is absent from the cubicle. The statistical results also reveal that the number of absence occurrences decreases as total daily presence hours decrease, and the duration of absence from the cubicle decreases as the frequency of absence increases. The developed occupancy model captures the stochastic nature of occupants moving in and out of cubicles, and can be used to generate a more realistic occupancy schedule. This is crucial for improving the evaluation of the energy saving potential of occupancy based technologies and controls using building simulations. Finally, to demonstrate the use of the occupancy model, weekday occupant schedules were generated and discussed.

Keywords
Building simulation, occupancy model, occupancy pattern, occupant schedule, office buildings, statistical analysis

1 Introduction

Building energy simulation tools have been widely applied in recent years in energy saving proposals for new construction designs and existing building retrofits. However, simulated results sometimes deviate significantly from measured data. Such discrepancies can be attributed to several factors. One of the most important is occupant behavior in buildings. Many studies demonstrate that building occupancy profiles have a significant impact on energy use and the operational controls of buildings. An investigation into the impact of consumer behavior on residential energy demand found that consumer behavior is the most important issue with respect to energy consumption in households (Haas et al. 1998). A simulation of user behavior for the low energy office building design process, which applied a statistical method, found that realistic user behavior should be incorporated into passive cooling design concepts (Pfafferott and Herkel 2007). A methodology that takes into account the variation in occupant behavior and schedules was proposed to estimate the cooling demand in residential units (Tanimoto et al. 2008). Its authors concluded that occupant behavior is a significant factor in residential cooling requirements, though the methodology needs further validation to confirm its plausibility.

Various modeling approaches have been developed for use in building energy performance simulations to predict occupancy characteristics in different types of buildings. A stochastic user behavior model generates a time series of window operations by using Markov chains (Fritsch et al. 1990). However, the lack of adequate measurements makes computing the Markov matrices impossible. The use of stochastic models to capture human behavior and occupant interaction within a building attempts to simulate multiple influences that occupants can have on a building in terms of resource consumption (Page et al. 2008). The results sometimes overestimate and other times underestimate the weekly total energy use and peak demands. A model that combines user presence and interaction in a building showed that improved modeling of user behavior in numerical simulations can optimize overall building performance (Hoes et al. 2009). A model of activity and location schedules was developed, using a system of USSU - User Simulation of Space Utilization, to generate movement patterns that provide a representation of human activities in office building spaces (Tabak 2008). However, there were obvious differences between the observed and predicted human activity behavior related to the number of times a workplace was used during a working day. A model based on Markov chains that simulates the movement of occupants inside an office building can produce more realistic occupancy variations, nonsynchronous change of occupancy in time, and an uneven distribution in space (Wang et al. 2011). However, more validation and calibration approaches must be carried out with specific occupant-movement patterns. Behavioral patterns associated with energy spent on heating were determined statistically, and household and building characteristics were identified (Santin 2011). It appears difficult to establish relationships between behavioral patterns and energy consumption.

Recent years have seen the introduction of systems and devices that can be controlled on a personal basis. These efforts to improve energy efficiency and increase energy savings include lighting, office equipment, thermostats for heating, ventilation, and air conditioning, windows, and blinds. Accurately estimating the savings and impacts of these systems and technologies requires the accurate prediction of how often and how long occupants stay in their offices. Therefore, the impact of occupancy profile on building energy performance becomes more important. The occupancy pattern defined in the present study is the frequency of an occupant leaving his/her cubicle and the corresponding duration of the absence. It is part of the broader occupant behavior which includes occupant's interactions with building envelope and energy systems. A method for obtaining realistic and stochastic occupancy is a key concern for building energy simulations, in order to precisely evaluate the performance of occupancy-based controls. Currently, most simulation tools apply fixed or predefined occupancy schedules to represent the time when occupants are present. However, occupancy pattern can change significantly according to the season, weather, time, and personality. It is therefore not surprising that simulated energy use deviates from actual consumption in most situations. Although various occupancy models have been developed to predict occupancy profiles in buildings, they usually lack validation from adequate field-measured data.

This study uses statistical methods to analyze lighting-switch data collected from the open office spaces of an office building to identify variations in occupancy patterns. 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 understand further and evaluate the impact of occupancy patterns on building energy performance, and to improve the accuracy of predicting the actual energy use of buildings with simulation tools.

2 Data collection

A total of 200 lighting switch sensors were installed in open office cubicles on three floors of an office building. The numbers of switches installed on each floor are listed in Table 1. Each cubicle had a single, workstation-specific suspended fixture with a built-in occupancy sensor. The sensor detected occupant movement and controlled the lighting switch for each cubicle. The light was activated (switched on) if the cubicle was occupied, and deactivated (switched off) if unoccupied. All occupancy sensors were calibrated and control systems were commissioned before data were collected. The lighting control system recorded a daily log of sensor switch events, including the presence and absence of occupants, every five minutes. Switch events were recorded as 1 or 0, indicating the cubicle was occupied or unoccupied, respectively. In this study, each cubicle was assumed to be unoccupied until the occupant arrived for the first time in the morning. After the first occupancy event, the data was filled in with 1 or 0, based on the most recent event for each cubicle.

This study used data collected for weekdays, weekends, and holidays from May through November in 2011. In a small number of cases there may be some errors in the data due to sensor sensitivity and coverage. Switch sensors sometimes are triggered by people walking past cubicles, or fail to trigger if occupants remain overly static in their cubicles. Although these cases cannot be excluded in this study, their occurrence is relatively infrequent and should not have a noticeable impact on the results. The collected data for weekdays were processed in parallel with data for weekends and holidays to provide a more accurate view of occupancy profiles. The goal was to obtain general occupancy trends and patterns for a large number of office cubicles to allow for comparisons across each floor. Data were processed for as many valid days as possible, including time periods during and after commissioning. Exclusions were made due to missing or incomplete switch data files and insufficient switch-number information. Some days were excluded due to the control system going offline temporarily, which resulted in incomplete data collection. The final data used in this study includes 76 weekdays and 34 weekend days and holidays.

3 Analysis methods

Once the collected data were finalized, they were statistically analyzed to identify occupancy patterns during weekdays and weekends. The number of daily absences and their durations were determined, and the occupancy variations were distinguished.

The switch-on events were recorded every minute. Therefore, the presence duration of each occupant can be obtained by accumulating the number of switch-on events. The total monthly presence hours were calculated by adding up the daily presence hours. The average daily presence hours of each occupant were determined by dividing the total presence hours in each month by the number of data-collection days in that month. Thus, the profiles of occupant presence hours of the three floors were determined. Additionally, the daily occupancy profiles of each floor during weekdays and weekends were obtained by averaging the probabilities of switch-on events for each cubicle each month.

A total of 200 occupancy patterns of three floors are illustrated according to the probabilities of switch-on events. Different occupant's behavior results in different occupancy patterns. Based on the variations of each occupancy pattern curve, these 200 occupancy patterns were classified into five types: a single-square curve (Fig. 4(a)), a one-valley curve (Fig. 4(b)), a two-valley curve (Fig. 4(c)), a variable curve (Fig. 4(d)), and a flat curve (Fig. 4(e)). A valley was identified when the switch-on profile started to drop and then rise when the difference between the maximum and minimum switch-on percentage values exceeded 20%. A single-square curve occupancy pattern was defined if there wasn't a valley apparent from the switch-on profile. Similarly, the one-valley curve and two-valley curve occupancy patterns were defined if the valley occurred once or twice in the switch-on profile, respectively. Finally, the variable-curve occupancy pattern was defined if the valley occurred twice or more. After all occupancy patterns were determined, the occurrence percentages of each occupancy pattern could be calculated by counting the frequency of each occupancy pattern for each floor. By accumulating the probabilities of the five patterns individually, and then dividing by the total number of each occupancy pattern, the average occupancy pattern was determined. Daily working hours were divided into four two-hour time periods. The occurrence times of each occupancy pattern for each time period on the three floors were collected to determine the occurrence percentages of each occupancy pattern, and the relationships between occupancy and working time period.

The number of daily absences and absence durations of each occupancy pattern were calculated to further understand the characteristics of each occupancy pattern. Switch-off events tracked when the occupant vacated the cubicle. Accumulating these events provided time and duration information and allowed further understanding of their relationship. According to the results, a noticeable valley usually occurred during noon in the occupancy patterns. Therefore, daily working hours were re-divided into three time periods: 8-11:30 a.m., 11:30 a.m. -1:30 p.m., and 1:30-6 p.m. The number of daily absences and absence durations in each time period were summarized to investigate when the valley occurred in the occupancy pattern.

4 Results

The profiles of occupant presence hours for each floor are shown in Fig. 1. The working time is divided into four periods, every two hours. The percentages of occupant presence hours for each floor were very different. For Floors A and C, most occupants, 40% and 31% respectively, stayed in their cubicles for 4 to 6 hours per day. Only a few occupants stayed over 6 hours. On Floor B, occupancy pattern was significantly different from Floors A and C. Most occupants, about 66%, on Floor B stayed in their cubicles for around 2 hours per day. There was no one staying for more than 6 hours. The average presence hours of Floor B were almost half those of Floors A and C. This may indicate that different agencies with different job categories work on different floors. The occupants of Floor B may work half-time, or work at home or outside the office part of the time. Therefore, a working occupant may not always be in his or her cubicle. Furthermore, this study observed that occupancy patterns were influenced slightly by the location of the cubicle. Longer occupancy periods occurred in more isolated cubicles that had more privacy, or cubicles that were near windows. However, job category may have more impact on occupancy pattern than location of the cubicle. Unfortunately, private information like job category for each occupant was not available for this study.

The average daily weekday switch-on profile of each floor is shown in Fig. 2. In general, the occupants of each floor arrived at and departed from the office between 6 a.m. and 6 p.m. on weekdays. The switch-on percentage of each floor increased in the morning and reached a peak value at around 9 a.m. The maximum values of Floors A, B, and C are about 48%, 16%, and 32%, respectively. A higher switch-on percentage means higher occupancy. The increase in switch-on rate of Floor A was greater than that of Floors B and C. Fig. 2 also shows that the switch-on percentage of each floor has an obvious drop at around noon, attributed to occupants leaving the office for lunch. Also, it can be seen that the switch-off rate of Floor A is greater than that of the other two floors. The occupants of each floor began to leave work approximately between 3 p.m. and 4 p.m. Compared with the decrease in switch-on rate of Floors B and C, the decrease in switch-on rate of Floor A is greater. In addition, several spikes occurred after 6 p.m. This can be attributed to the cleaning crews in the evening. The cleaning schedules of Floors A, B, and C are 6:35 p.m. to 8 p.m., 5:05 p.m. to 6:30 p.m., and 9:25 p.m. to 10:50 p.m., respectively. The spikes occur within these time periods and the switch-on percentage of each floor is about 5%. As for weekends, the average daily profiles of switch-on events for each floor are shown in Fig. 3. Compared with the weekday profiles, the weekend switch-on percentages are quite low for all three floors. The switch-on percentage of Floor A was less than 3% and for Floors B and C was almost equal to 0%. Therefore, this study only focuses on the investigation and analysis of data collected for weekdays.

The numbers of lighting-switch sensors installed on Floors A, B, and C were 104, 47, and 49, respectively. This led to 200 occupancy profiles. The collected occupancy profiles can be classified into five patterns by occupancy variation, presence duration in the cubicle, and occupant personality, as shown in Fig. 4. These occupancy patterns are very different from one another. In Fig. 4(a), the pattern looks like a single-square curve. The percentage of occupants stay in the cubicle is more than 60% within daily working hours except two time periods: one from 6 to 8 a.m. when occupants arrive at the office, and the other from 4 to 6 p.m. when occupants get off work. Fig. 4(a) indicates that occupants leave their cubicles fewer times and with shorter duration during working hours. Alternatively, this pattern can be interpreted as the stationary time in which an occupant does not leave or enter their cubicle frequently. Several spikes occur after 6 p.m., the reason for which is discussed in our description of Fig. 3. Fig. 4(b) shows an occupancy pattern similar to Fig. 4(a), except for an observable deep valley occurring at midday for a period of approximately 1 to 1.5 hours. This can result from the occupant leaving for lunch. The occupant leaves the cubicle after approximately 11:30 a.m. for lunch and then returns to the cubicle at approximately

1 p.m. This pattern can be interpreted as the occupant not leaving or entering the cubicle frequently, but leaving for lunch at midday. Fig. 4(c) shows two noticeable valleys in this pattern. In addition to the valley that occurs around noon, another valley appears in the morning. This can be attributed to a longer absence by the occupant, such as attending a meeting or leaving the building. However, the valley observed in this study not only occurs in the morning but also in the afternoon (although it is not shown in Fig. 4(c)). Fig. 4(d) shows a significant variation in the pattern. There is no regular pattern as with Figs. 4(a)-(c). This pattern shows the occupant leaving the cubicle frequently during work time and being absent for longer amounts of time. Fig. 4(e) shows a flat occupancy pattern; the cubicle seldom appears occupied and the occupied duration is short. This can be attributed to a cubicle used for public usage, such as a print station, coffee shop, or office supply room. This kind of pattern will not be discussed further in this study.

Based on the number of occupants on each floor in Fig. 2, the occupancy patterns of all occupants were further identified. Fig. 5 shows occurrence percentages of each occupancy pattern for the three floors. The designations of Patterns 1 to 5 shown in this figure correspond to Fig. 4(a) to (e) as discussed above, and these designations will be further used in later discussion. Compared with Floor B, the occurrence percentages of each pattern are similar for Floors A and C. Pattern 2 is the most typical occupancy pattern, about 45% and 39% for Floors A and C respectively. For Floor B, however, the highest occupancy pattern is Pattern 5, with an occurrence percentage of about 38%. This significant difference can be attributed to different agencies working on different floors, as discussed above.

The occurrence percentages for each occupancy pattern for the three floors in four time periods are listed in Fig. 6. Circles displayed in this figure indicate the occurrence times of the pattern. Larger circles represent higher occurrence times. Occurrence percentages of Pattern 2 for each floor were found to be higher than those of other patterns when occupants stayed in their cubicles for 2 to 8 hours per day. This indicates that most occupants of each floor left for lunch during the noon hour. The second highest is Pattern 1, which represents occupants who did not leave or enter their cubicles frequently. Additionally, the occurrence percentages of Pattern 1 for each floor were higher than those of Patterns 2 to 4 when occupants stayed in their cubicles for less than 2 hours per day.

The analysis results described above are occupancy patterns that only represent the overall characteristics of cubicles occupied on each floor. It is still very approximate for use as an occupancy schedule in building simulation tools. For example, the switch-on percentage of Pattern 1 was about 60% during the working hours of 8 a.m. to 6 p.m. This indicates that the probability of an occupant in the cubicle was about 60%. However, the number of daily absences and absence durations still cannot be obtained via this occupancy pattern. An occupant's number of daily absences and absence durations can have significant impact on energy usage and cause substantial differences between measured and simulated energy use. To obtain more accurate simulation results, a more realistic occupancy schedule — including presence and absence durations of occupants, and the number of absences in the cubicle — is required for use in the simulation. Therefore, the number of daily absences and absence durations of each occupancy pattern were further identified and detailed, as follows.

Fig. 7 represents the accumulated number of daily absences within the 76-day period for Patterns 1 to 4. The days when the occupant did not arrive at the office are excluded. For example, if the number of daily absences and the number of occurrences were 4 and 9, respectively, this represents a total of 9 days when the occupant left the cubicle 4 times per day. In this figure, it can be found that the maximum number of occurrences of each occupancy pattern shifted and decreased with the number of daily absences. The most typical numbers of daily absences of each pattern are 1, 4, 5, and 9, respectively. For Pattern 1, there are a total of 5 days when the occupant never left the cubicle. Although the peaks of the other patterns were less than that of Pattern 1, each of the total number of absences of Patterns 2, 3, and 4 was almost greater than those of Pattern 1, except the cases with none or one daily absence. More daily absences indicate that the occupant entered or left the cubicle more frequently.

The accumulated numbers of durations of each absence within the 76-day period for each pattern is shown in Fig. 8. The absence durations concentrate in a 10-to-29-minute span for all occupancy patterns except Pattern 4. For Patterns 1 and 2, most absence periods were 10 to 19 minutes in duration, and their occurrence percentages were 41% and 37%, respectively. For Pattern 3, most absences lasted 20 to 29 minutes, and the percentage was 56%. For Pattern 4, most absences were 0 to 9 minutes, and the percentage was 62%. For all patterns, occurrence times decreased with longer absence minutes. It can be deduced that for shorter-duration absences, the occupant leaves the cubicle to take a break, go to the restroom, or walk around. Longer periods can be attributed to meetings, lunch, or outside business.

The outlines of occupancy profiles in Patterns 1 to 3 were similar except for one and two significant valleys in Patterns 2 and 3. To further understand occupancy patterns, Pattern 2 was further investigated as follows. The working time in a day was divided into three periods: 8 to 11:30 a.m., 11:30 a.m. to 1:30 p.m., and 1:30 to 6:00 p.m. The total number of absences and average absence durations for these time periods for Pattern 2 are illustrated in Fig. 9(a) and (b). The number of absences shown here are the accumulated numbers within the 76-day period, and the absence durations are the average values. The number of absences increased as the day progressed. The occupant left the cubicle more often and with a shorter duration in the afternoon. This may be due to the dwindling concentration of an occupant or increasing fatigue, resulting in the occupant walking around or going to the restroom more often. The average absence duration from 11:30 a.m. to 1:30 p.m. was significantly longer than the others, as this is the lunch period. However, the average absence durations from 8 to 11:30 a.m. and 1:30 to 6:00 p.m. were almost the same.

The accumulated numbers of absence minutes of each time period for Pattern 2 is illustrated in Fig. 10. The most typical absence duration for all three time periods was 10 to 19 minutes. The percentages for each time period were 43%, 25%, and 45%. Fig. 10 shows that occurrence times decrease with longer absence minutes. This corresponds to the result mentioned before. However, the occurrence times of absence minutes for different time periods can be further distinguished. For the time periods of 8 to 11:30 a.m. and 1:30 to 6:00 p.m., the curves dropped drastically after a peak and then descended slowly. Compared with the period of 1:30 to 6 p.m., more absences of longer duration occurred from 8 to 11:30 a.m. It can be deduced that there were more meetings or longer events in the morning. For the time period 11:30 a.m. to 1:30 p.m., the curve declined more smoothly after the peak and the times of longer absences were higher than the other two time periods. This figure indicates that the occupant may spend over 10 minutes and sometimes almost 2 hours for lunch.

5 Discussion

Cubicle occupancy for a typical 8-hour weekday for the three floors mostly begins between 8 and 9 a.m., with a dip around noon, and then begins to decrease from 4 to 6 p.m. Spikes, caused by the late-night cleaning crews after most occupants have left in the evening, are also observed. Weekend occupancy levels for cubicles on all three floors are fairly low and can be neglected. Furthermore, weekday occupancy levels for Floor B are very different from the other two floors, which can be attributed to different agencies working on different floors, with occupants on Floor B working part time, going out for business more often, or working from home part of time. Due to privacy and security concerns, no further data is available to allow further verification.

200 occupancy patterns for the three floors were collected in this study. These collected patterns can be classified into five patterns according to occupancy variation, appearance duration in the cubicle, and occupant personality. The five identified occupancy patterns are: Pattern 1 (single-square curve), Pattern 2 (one-valley curve), Pattern 3 (two-valley curve), Pattern 4 (variable curve), and Pattern 5 (flat curve). Statistical results show that the most common occupancy among all occupants is Pattern 2, which indicates that most occupants leave their cubicles for lunch around noon, in addition to other longer events, such as attending meetings or going outside. The second most popular occupancy is Pattern 1, in which occupants do not leave or enter their cubicles frequently. Additionally, the occurrence percentages of Pattern 1 for each floor are higher than those of other patterns when occupants stayed in their cubicles for less than 2 hours per day.

The number of absences and absence duration for each occupancy pattern are identified. More daily absences mean an occupant moves in and out of the cubicle more frequently. The most typical numbers of daily absences for Patterns 1 to 4 are 1, 4, 5, and 9, respectively. Additionally, the absence durations for each absence are mostly from 10 to 29 minutes for all occupancy patterns. The number of absences decreases with the longer absence duration for all patterns. For a short absence duration, it can be deduced that an occupant leaves the cubicle to take a break, go to the restroom, or walk around. On the other hand, a longer period can be attributed to an occupant attending a meeting, having lunch, or going outside.

Finally, the working time in a day is divided into three periods for further analysis of occupancy patterns. Occupants leave the cubicle more often in the afternoon but for shorter durations. In other words, the occupants leave the cubicle less often but for longer. The average absence at midday is longer due to lunch. However, the average absence durations in the morning and afternoon are almost the same.

This study also observes that occupancy patterns are slightly influenced by cubicle location. Longer occupancy periods occur in more isolated cubicles that have more privacy or are near windows. However, job category may have more influence on occupancy pattern than cubicle location. Due to privacy concerns, no data is available to further relate job characteristics to occupancy patterns.

6 Occupancy model and schedule generation

Based on the results, a stochastic occupancy model of each pattern is developed with three key elements: (1) the cumulative distribution function (CDF) of the number of daily absences, (2) the CDF of each absence duration, and (3) the probability distribution function (PDF) of the start time of each absence.

For an open-plan office with a certain number of cubicles, assuming one occupant per cubicle, a profile of occupancy patterns must first be determined by energy modeling. Then occupancy schedules for a weekday can be generated by the following steps, using Patterns 1 and 2 as examples. First, a uniform-distribution random number between 0 and 1 is generated, and it is used as an input to the inverse function of the CDF of the number of daily absences in Fig. 11(a) to find the corresponding number of daily absences. For each absence, a uniform-distribution random number between 0 and 1 is generated, and it is used as an input to the inverse function of the CDF of the daily absence duration in Fig. 11(b) to find the corresponding daily absence duration in minutes. Finally, for each absence, a uniform-distribution random number is generated and used to calculate the start time of each absence. After that, the end time of each absence can be determined by adding the absence durations previously calculated. For Pattern 1, according to Fig. 4(a), the absence start time can be assumed to be uniformly distributed between 8 a.m. and 4 p.m. For Pattern 2, the absence start time is not uniformly distributed, as there is a deep valley at around noon, as shown in Fig. 4(b). Therefore, the distribution of number of absences is determined by the relative probability of occurrence in the three time periods: morning, noon, and afternoon, based on Fig. 12. For each absence in either of the three time periods, the same procedure as Pattern 1 is used to determine the absence start time.

Three generated weekday occupant schedules of Pattern 1 are shown in Fig. 13. The value 1 in the figure indicates the occupant is in the cubicle, while 0 indicates the occupant is away from the cubicle. It can be seen that for Pattern 1, there is mostly one daily absence, lasting 10 to 30 minutes. Three generated weekday occupant schedules of Pattern 2 are shown in Fig. 14. As with the occupant schedules of Pattern 1, most absence durations last 10 to 30 minutes, but the number of daily absences are increased to 3 or 4, and one absence occurs during noon.

7 Conclusions

This study statistically analyses information collected from 200 cubicle offices on three floors of a commercial office building. It used measured lighting-switch data to represent the occupancy status of cubicles. Occupancy levels were identified and occupancy profiles were classified into five patterns as displayed in Figs. 4(a)-(e). The number of daily absences and absence durations for each occupancy pattern were further calculated and analyzed. Based on these results, a mathematical model to describe the occupancy patterns, including the probability distributions of the number of absences and absence duration, was developed. The occupancy model can be used to generate more realistic occupant schedules for open-plan cubicle offices, for use in building energy simulations. In addition to lunch breaks, more occupancy events such as meetings, short visits, walking around, and late-night cleaning can be taken into account in the model to better capture the stochastic nature of actual occupancy variations in the building. These more detailed occupancy schedules can replace the fixed or predefined ones currently used in building energy simulations to better assess the impact of occupancy patterns on building energy performance, and to improve the 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 are needed. The analysis methods used in this study can also be adapted to study the occupancy patterns of private offices and other building types, such as residential.

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Table 1 Number of lighting switches on three floors of an office building

Building Floor	Number of Switches
Floor A	104
Floor B	47
Floor C	49
Total	200

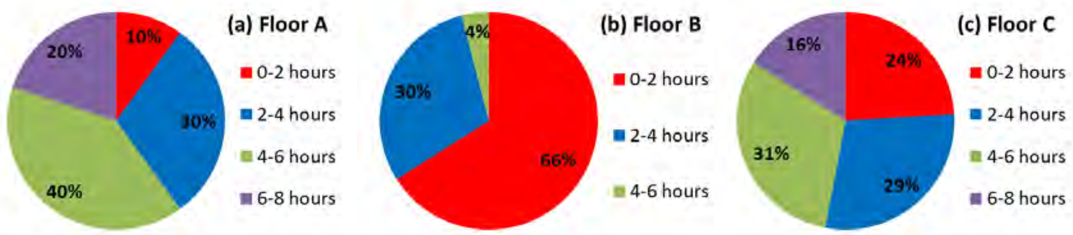

Fig. 1 Profile of presence hours for each floor: (a) Floor A; (b) Floor B; (c) Floor C

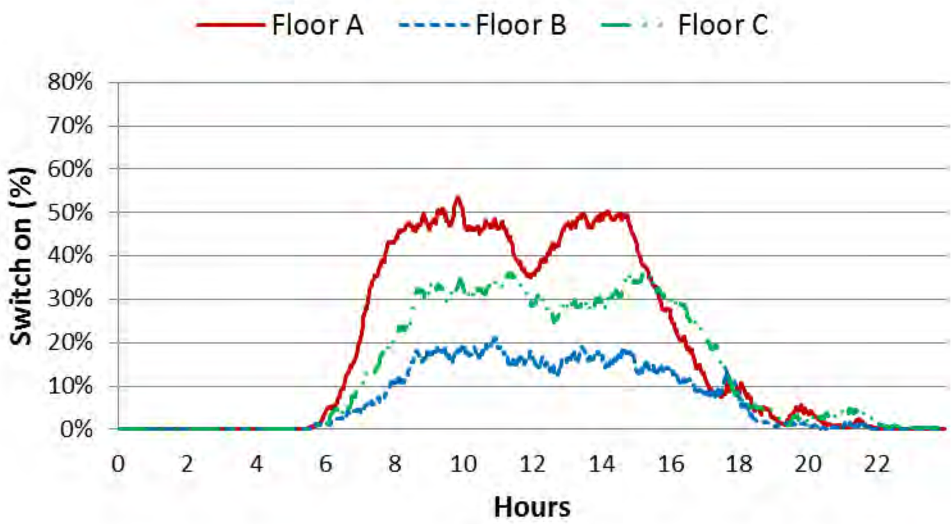

Fig. 2 The average daily weekday profile of switch-on events for each floor

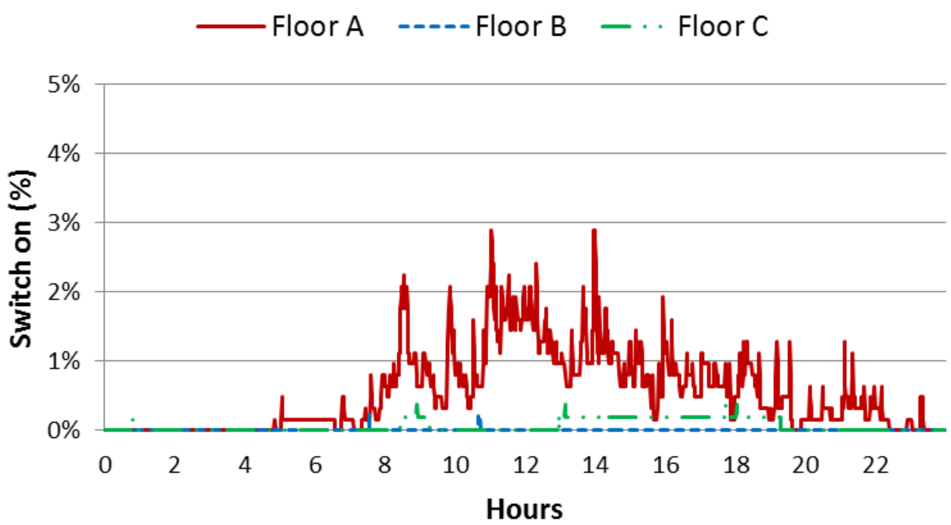

Fig. 3 The average daily weekend profile of switch-on events for each floor

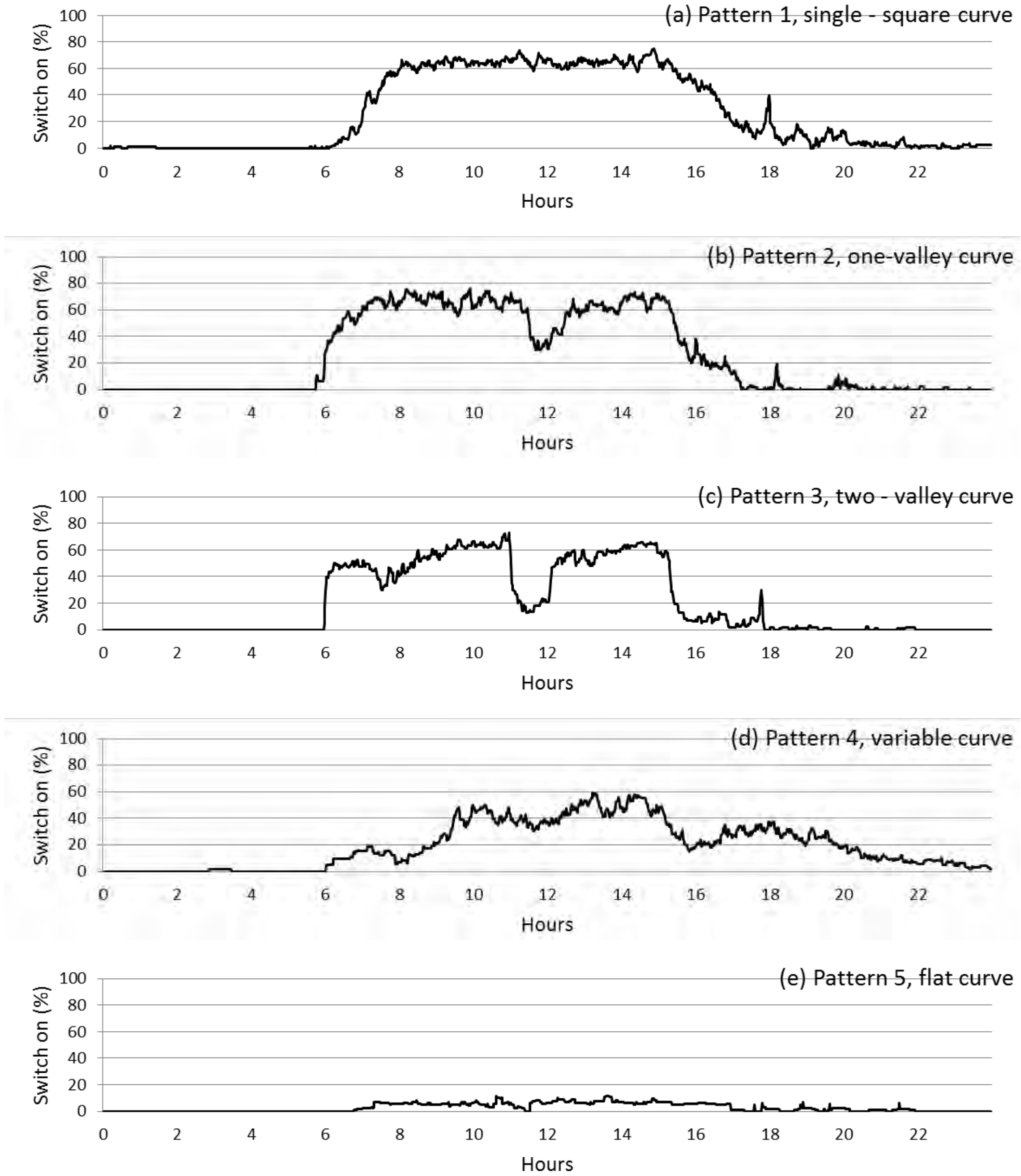

Fig. 4 The occupancy patterns: (a) single-square curve, (b) one-valley curve, (c) two-valley curve, (d) variable curve, (e) flat curve

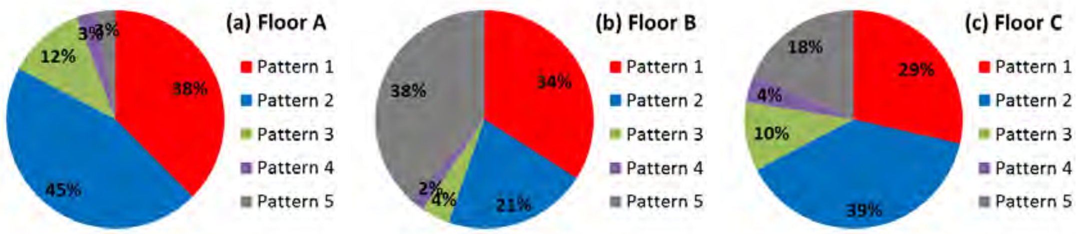

Fig. 5 The occurrence percentages of each occupancy pattern: (a) Floor A; (b) Floor B; (c) Floor C

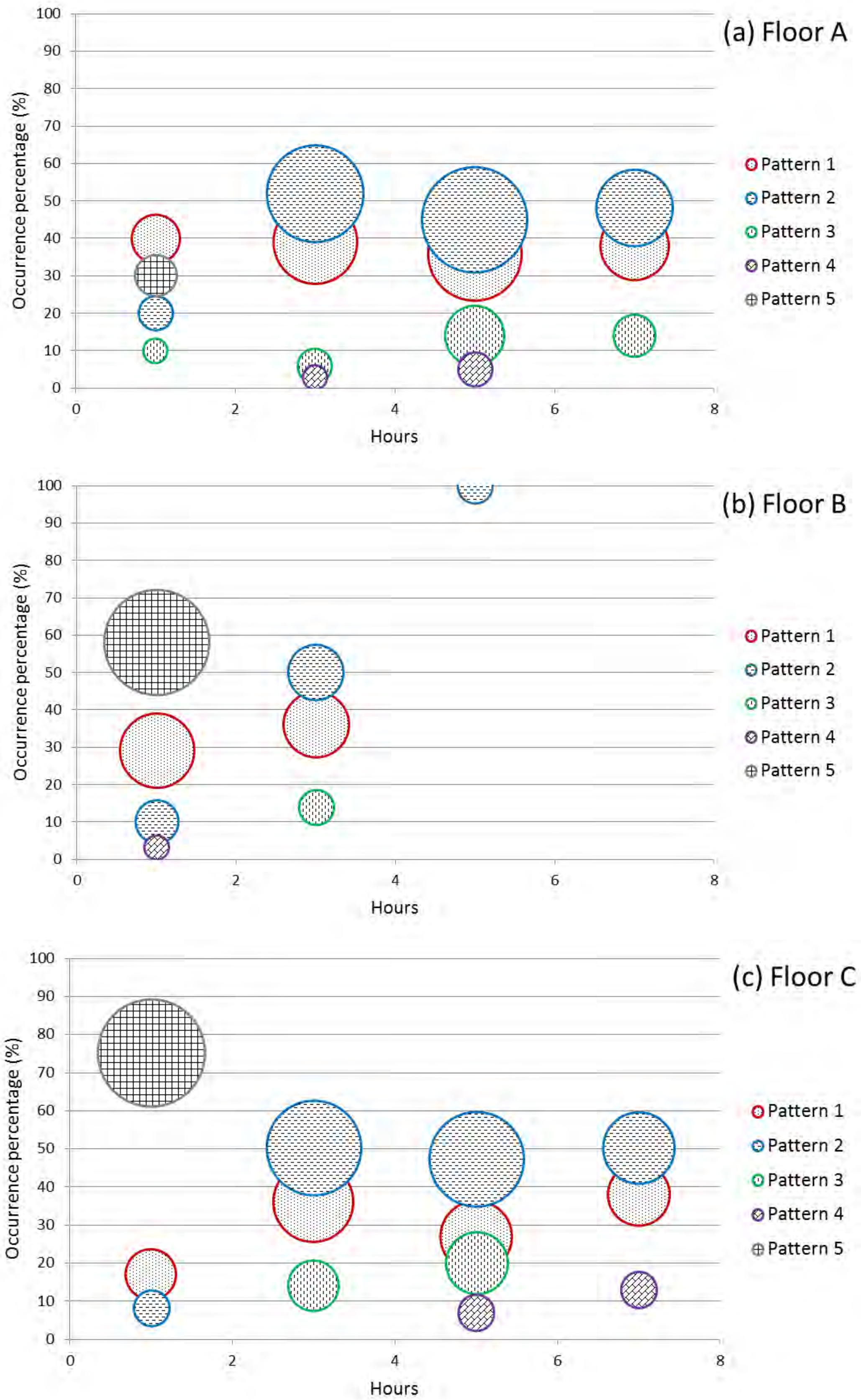

Fig. 6 The occurrence percentages of each occupancy pattern in four time periods for each floor: (a) Floor A; (b) Floor B; (c) Floor C. Larger circles represent more occurrences

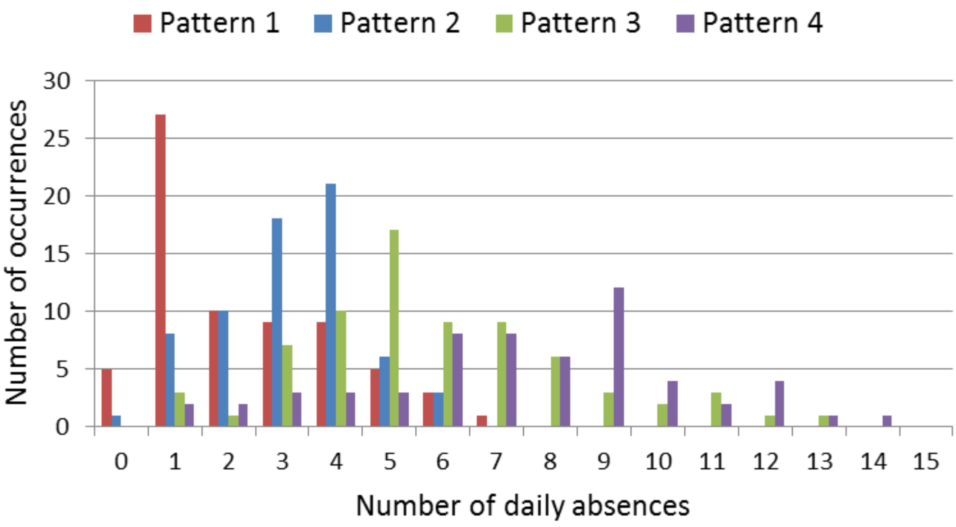

Fig. 7 The accumulated number of daily absences for each occupancy pattern in a 76-day period for Patterns 1-4

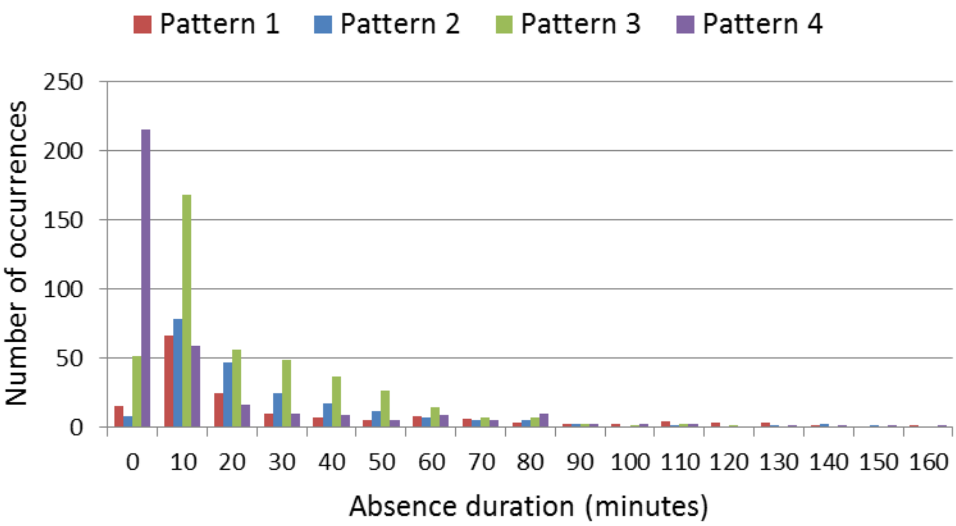

Fig. 8 The accumulated number of occurrences of absence duration for each occupancy pattern over a 76-day period

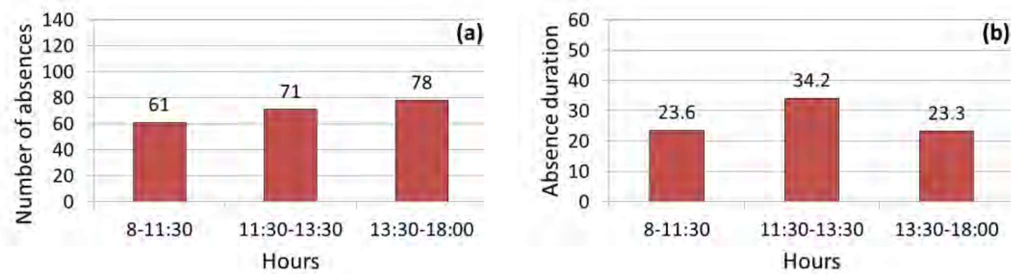

Fig. 9 Total number of absences and average absence duration of three time periods for Pattern 2 over a 76-day period: (a) number of absences; (b) absence duration in minutes

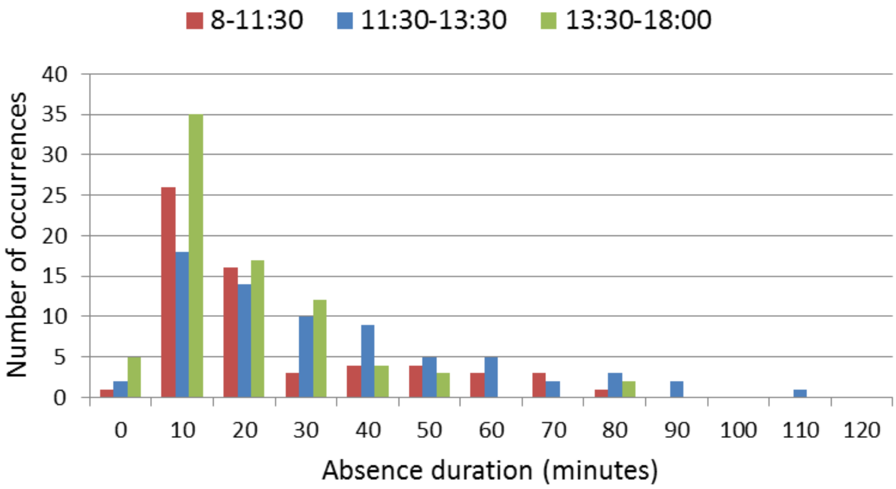

Fig. 10 The accumulated number of occurrences of each absence duration for occupancy Pattern 2 for three time periods over a 76-day period

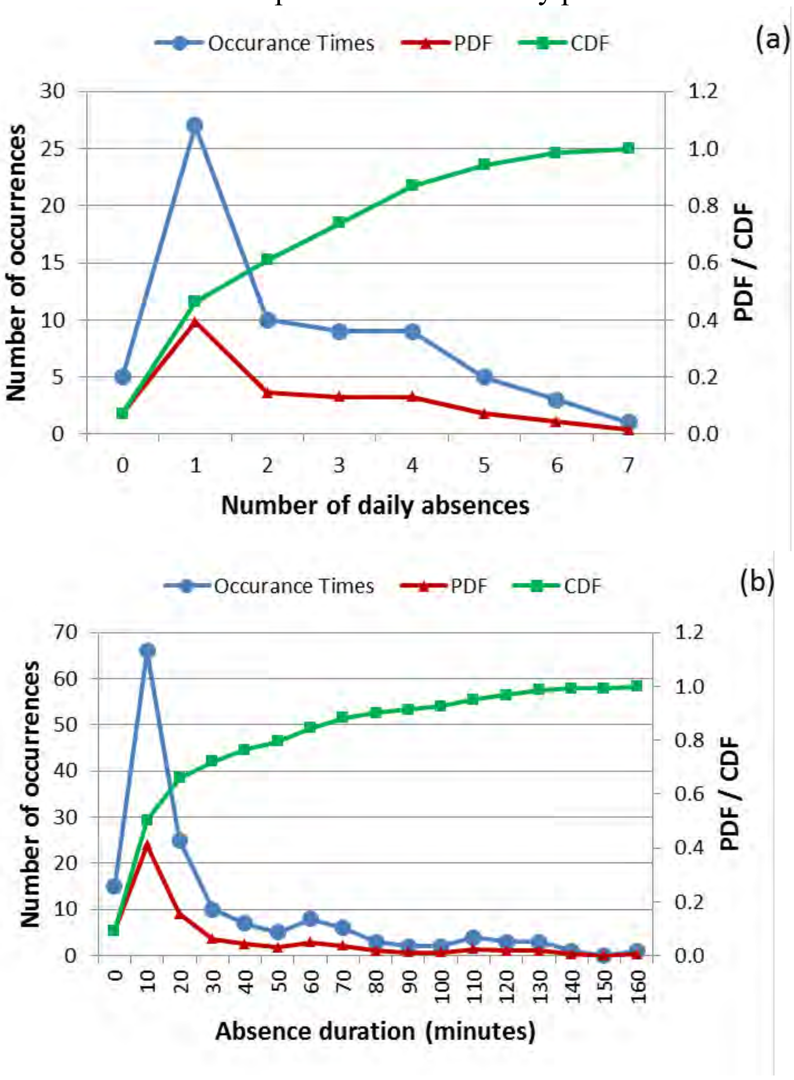

Fig. 11 The curves of occurrences, probability distribution function (PDF), and cumulative distribution function (CDF) of Pattern 1: (a) number of daily absences; (b) absence duration

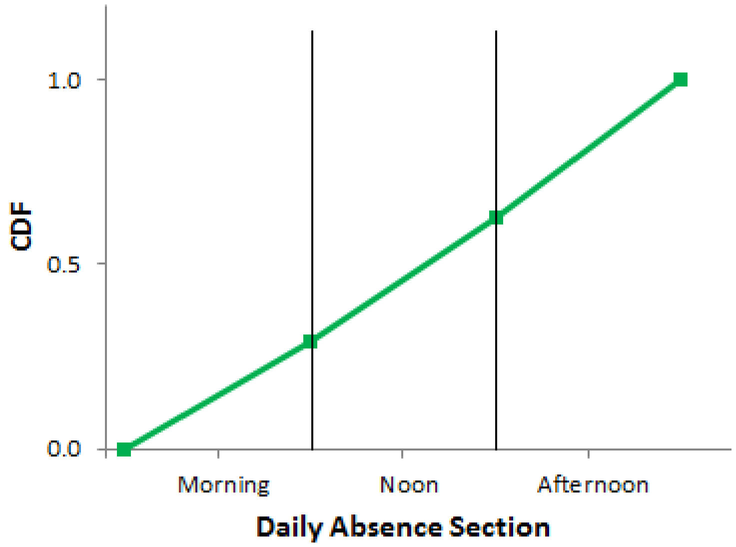

Fig. 12 The curve of cumulative distribution function (CDF) of daily absence section for Pattern 2

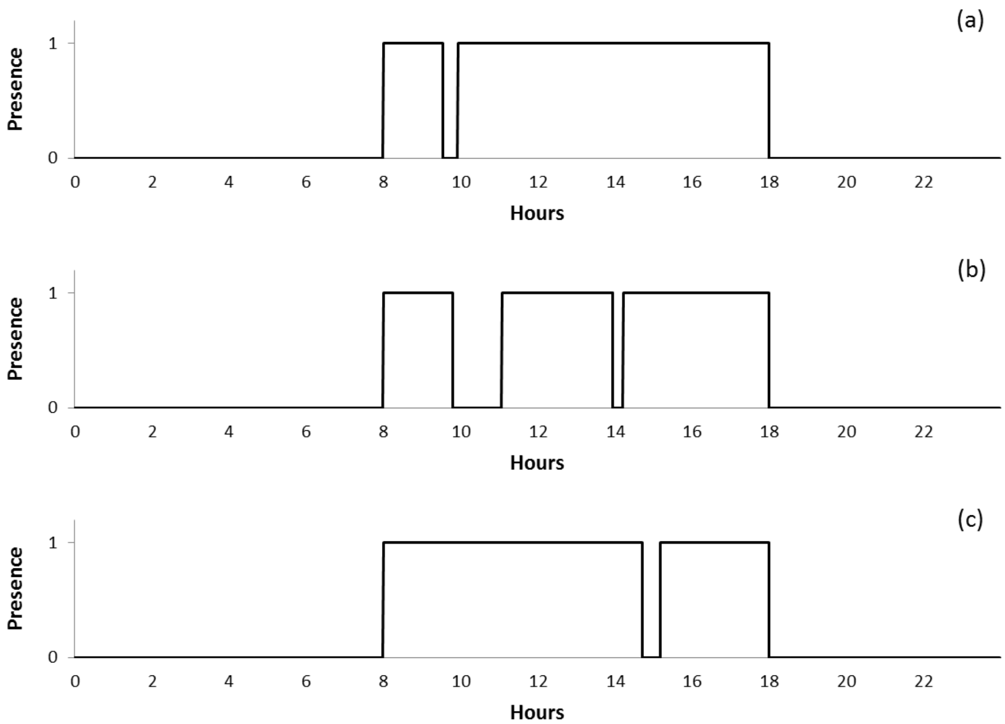

Fig. 13 Three generated weekday occupant schedules for Pattern 1

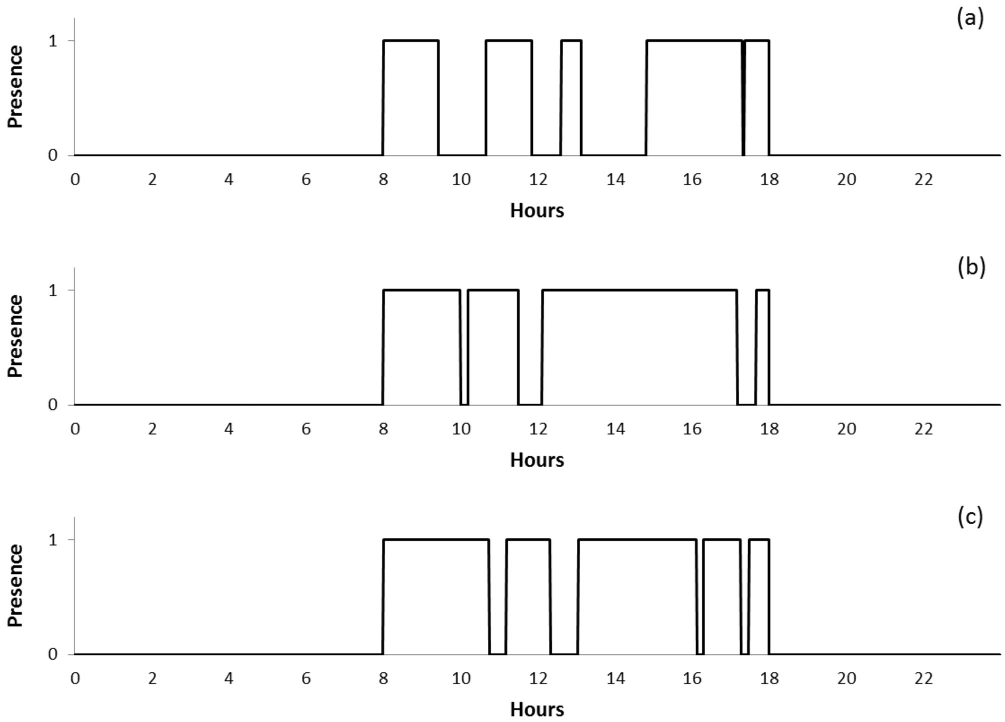

Fig. 14 Three generated weekday occupant schedules for Pattern 2