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Predictability of occupant presence and performance gap in building energy simulation[1]

Abstract

Occupant behavior is regarded as one of the major factors contributing to the discrepancy between simulation prediction and real energy use. Over the past several decades, occupants have been represented as fixed profiles of occupant presence in building energy simulation tools. Recently, stochastic models have been introduced to account for dynamic occupant presence. This stochastic approach is based on the premise that occupant presence can be described by empirical and probabilistic transition rules, e.g. Markov Chain.

This paper presents evidence that occupant presence in some rooms and buildings follows a "random walk" pattern. In other words, occupant presence in certain types of buildings cannot be predicted stochastically. In this study, occupants' presence in two laboratories and three reading rooms at two universities was monitored. The hypothesis of the random walk pattern was tested using the Normalized Cumulative Periodogram (NCP) method. Based on a series of six experiments, it is shown that each occupant's presence in the five locations follows a random walk pattern. Three different occupant models (fixed ASHRAE model, Markov Chain model, and Random Walk model) were applied in EnergyPlus simulation runs. The adjusted R^2 for three experiments between the fixed AHSRAE model and the random walk model, and between the Markov chain model and the random walk model are 0.54, 0.02, 0.01 and 0.86, 0.19, 0.41, respectively. This does not negate the need for the fixed ASHRAE model or the MC model. Rather, this signifies that, for a certain type of building, another occupant presence model should be introduced, e.g. the RW Model.

Keywords: occupant presence, occupant behavior, random walk, energy prediction, performance gap, Normalized Cumulative Periodogram

[1] This paper was significantly revised based on the short version, which was presented at the CUE2015- Applied Energy Symposium and Summit 2015: low carbon cities and urban energy systems in Nov 2016, Fuzhou, China.

1. Introduction

Building occupancy is a key factor for accurate prediction of building energy use and energy saving potential with regard to occupancy-related systems and controls [1-4]. Specifically, lighting, plug loads, ventilation and internal heat gain or loss greatly depends on the level of occupancy within a building [5]. Chang and Hong [6] proved that the presence of occupants leaving their cubicles and the corresponding durations of absence had significant impact on the total energy use and controls of an office building. The occupancy diversity factors measured in [7] differ as much as 46% from those published in ASHRAE 90.1 2016 [8] energy cost method guidelines, a document referenced by energy modelers regarding occupancy diversity factors for simulations. This discrepancy may result in misleading simulation results and may introduce inefficiencies in the final equipment and systems design [7].

In most building energy simulation tools, occupant presence is still represented as a fixed schedule of occupant presence [8]. To overcome this limitation, a number of occupant presence and behavior models have thus far been developed based on stochastic approaches to describe window operations [9-14], blinds [15-19], lighting [19-22], and occupant presence [4, 23-26].

Page et al. [23] proposed a stochastic Markov Chain model to predict occupant presence in private offices. The model has proven its capacity to realistically reproduce key properties of occupant presence such as times of arrival and departure [23]. Richardson et al. [24] developed a realistic stochastic model that generates occupancy time-series data for UK households at a ten-minute resolution and takes account of differences between weekdays and weekends. From a case study of an office building, Wang et al. [4] developed a model that can produce realistic occupancy variations in an office building for a typical workday with key statistical properties of occupancy such as the time of morning arrival and evening departure, lunch time, periods of intermediate walking-around, etc. Sun et al. [25] developed a stochastic model to describe overtime occupancy data from an office building. The overtime model [25] was used to generate an overtime occupancy schedule as an input for an energy model of a second office building. Feng et al. [26] developed a software module to predict four levels of occupant presence based on a Markov chain approach.

As noted above [4, 23-26], the Markov chain occupant presence model is based on the premise that a future state can be predicted by a present state and the probabilities of an event occurrence. A statistical relationship between the future state and the present state is established based on extensive observed data [4, 23-27]. It is intuitively obvious that the Markov Chain occupant presence model could be applied to process-driven buildings such as offices and households where occupant presence can be easily defined by fixed profiles of occupant presence [4, 23-27]. It is noteworthy that such stochastic occupant presence studies have been conducted in process-driven buildings such as offices [4, 5, 9-12, 14-23, 25, 28-30], residences [13, 24, 31, 32], and dormitories [33]. However, it is questionable whether a stochastic occupant presence model can be applied to a different type of buildings, e.g. a random walk driven building where occupant presence follows a random process. To date, there is no complete occupant presence model that considers the degree of randomness in occupant presence.

This study aims to demonstrate that the aforementioned stochastic model is not suitable for the prediction of occupant presence in a random walk driven building, and that a new occupant presence model should be introduced. Employing a series of six experiments, the authors gathered occupant presence data in two laboratories of Sungkyunkwan University and three library rooms of Kangwon University, South Korea. These five spaces were purposefully selected, because the authors assumed that the occupants' presence in these five spaces might differ from that in process-driven buildings, but rather might be close to that in random walk driven buildings. Normalized Cumulative Periodograms (NCPs) were used to investigate the predictability of occupant presence in the five spaces. An NCP delivers a graphical representation that allows to assess whether time-series data (e.g. occupant presence data) have a periodicity (predictable), or they do not (not predictable). Three occupant presence models (fixed ASHRAE model, Markov Chain model, and Random Walk model) were applied in EnergyPlus simulation runs in order to show the importance of appropriate occupant presence model for predicting building energy use.

2. Random walk

A random walk is a mathematical formalization of a path that consists of a succession of random steps. The term "random walk", first introduced by Pearson [34], has been used in many fields (e.g. ecology, economics, psychology, etc.) to explain observed time-series behavior [35]. Fig. 1 shows an example of twenty random walks in one-dimension, showing the current position on the y-axis over time. The mathematical formula of a random walk for time-series data is as follows [36]:

$$x_{k+1} = x_k + w_k \tag{1}$$

$$w_k = x_{k+1} - x_k \tag{2}$$

where $x_k$is the state of the kth time-step, x_{k+1} is the state of the $(k+1)$th time-step, and w_k is the difference between x_k and x_{k+1}, meaning the difference in the state over time.

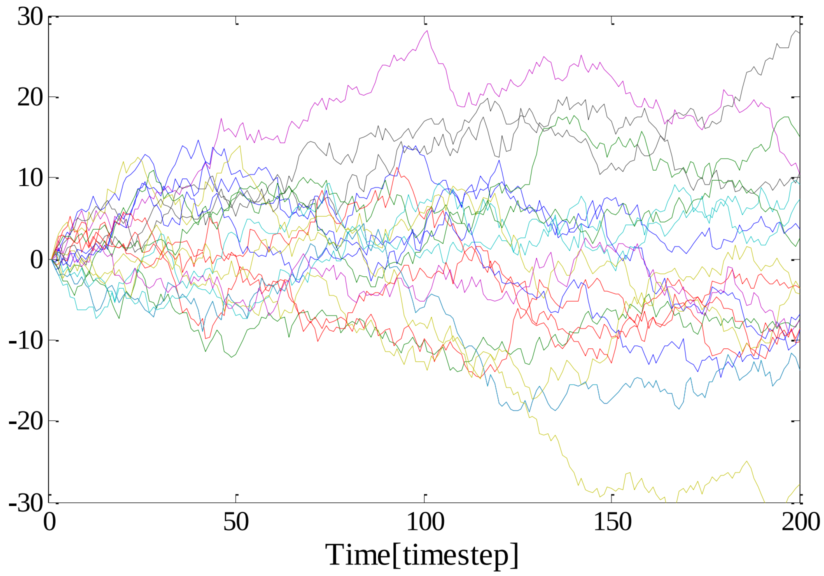


Fig. 1 Example of twenty random walks

The time series w_k (Equation (2)) can be characterized by a frequency analysis with a Fourier transform. The term w_k can be expressed as a combination of cosine and sine waves and can then be used to examine the periodic behavior of the time series. The NCP is a common method used to identify the periodicity of a given time-series in a frequency domain [37].

For a given n stationary time-series $(x_1, \dots, x_n)$, the periodogram function $(I(f_i))$, which shows the spectral density of the time-series at each frequency, is calculated as shown in Equation (3) [37].

$$I(f_j) = \frac{2}{n}\left|\sum_{l=1}^{n} x_l \exp(-2\pi i f_j l)\right| = \frac{2}{n}\left[\left(\sum_{l=1}^{n} x_l \cos(2\pi f_j l)\right)^2 + \left(\sum_{l=1}^{n} x_l \sin(2\pi f_j l)\right)^2\right]^{1/2} \quad (3)$$

where $f_j = j/n$ is the jth frequency ($j = 1, \dots, N'$), $N' = n/2$, $|\cdot|$ denotes the magnitude, and $i = \sqrt{-1}$. Essentially, $I(f_j)$ measures the strength (or spectral density) of the relationship between data sequence x_n and a sinusoid with frequency f_j, where $0 < f_j \leq 0.5$ [36]. Finally, the NCP of frequency is defined as Equation (4).

$$C(f_k) = \sum_{j=1}^{k} I(f_j) \Big/ nc_0^2 \quad (4)$$

where $C(.)$ is the NCP and c_0^2 is the estimated variance. The randomness of w_k can be identified if the power spectrum density of w_k is evenly distributed over the frequency in the

NCP. The random time-series data are not concentrated in the few specific frequencies, but are uniformly distributed over the entire frequency domain. Therefore, it can be said that w_k follows a random walk if it is drawn within a confidence interval with a straight line joining (0, 0) and (0.5, 1) in the NCP [37]. For example, 1,000 random numbers were generated by the "*rand*" function in Matlab and were recorded at a rate of one number per minute. Fig. 2 shows the NCP for 1,000 random numbers (bold blue line), where the dotted lines indicate 95% confidence intervals for testing the random walk [35].

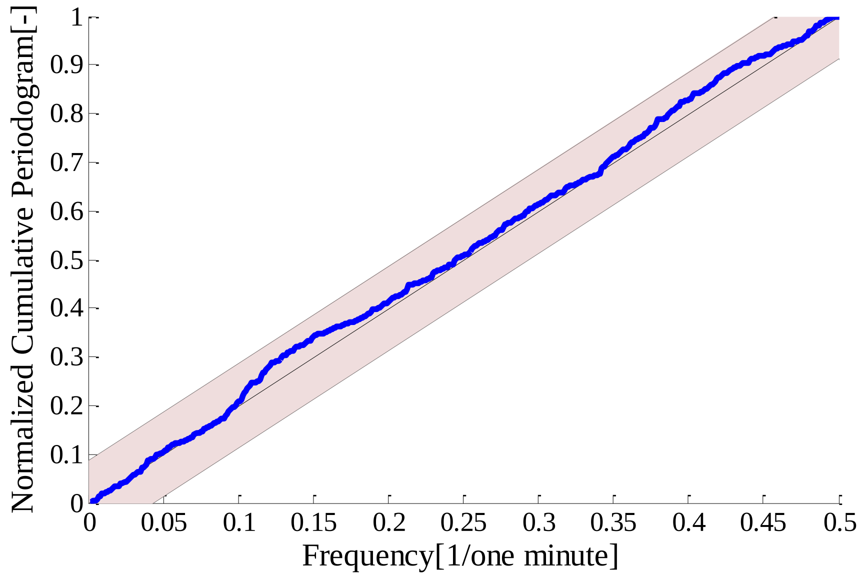


Fig. 2 Example of NCP for 1,000 random numbers

Fig. 3 shows the calculation steps for NCP. In Step 1, the time-series data of interest are collected and x_k, x_{k+1}, and w_k are calculated (Equations 1-2). Then, $\frac{n}{2}$ outputs are obtained from the periodogram function (Equation 3, Step 2). In Step 3, $\frac{n}{2}$ NCPs are obtained from Equation (4). In Step 4, the calculated NCPs are plotted as shown in Fig. 2.

Step 1.
Collect time series data and calculate x_{k+1}, x_k, and w_k
- Equations (1)-(2)

↓

Step 2.
Calculate the periodogram function $[I(f_j)]$
- Equation (3)

↓

Step 3.
Calculate normalized cumulative periodogram (NCP) or $[C(f_k)]$. The number of NCPs is equal to n/2.
- Equation (4)

↓

Step 4.
Draw the NCPs calculated from Step 3
- Fig. 2

Fig. 3 NCP calculation steps

3. Experiments

The occupants' presence in two laboratories at Sungkyunkwan University and three reading rooms at Kangwon University (Fig. 4) was monitored, as presented in Table 1. The arrival and departure times of the occupants were recorded using webcams. Based on the recorded scenes, the occupants' presence was calculated at sampling times of 10 minutes (Case A) and 1 minute (Cases B, C, D, E, and F) (Table 1). The original purpose of the Case A experiment was to study the cognitive responses of occupants, while the studies of Cases B to F were conducted to investigate the predictability of the occupants' presence. While different sampling times were applied, the authors assumed that it was worthwhile to include all experiments in this paper. Fig. 5 shows samples of recorded images.

Table 1 Overview of six experiments

Experiment	Name and use of space		Max. number of occupants during experiment	Measurement period and date	Sampling time
A	Laboratories in Sungkyunkwan University	U-lab.	9	4days June 7^{th} - 8^{th} (Th., Fri.), June 19^{th} - 20^{th} (Tue., Wed.)	10 min.
B		BS-lab.	6	5days	1 min.

				Feb 26th - 28th (Tue.-Th.) March 1st (Fri.), March 4th (Mon.)	
C		BS-lab.	7	8days Feb 23rd - 26th (Mon.-Th.) Mar 2nd - 5th (Mon.-Th.)	1 min.
D	Reading rooms in Kangwon University	Room#1	31	2days Oct 21st – 22nd (Sun.-Mon.)	1 min.
E		Room#2	10	2days Oct 21st - 22nd (Sun.-Mon.)	1 min.
F		Room#3	15	1day Oct 22nd (Mon.)	1 min.

(a) U-laboratory at Sungkyunkwan University

(b) BS-laboratory at Sungkyunkwan University

(c) Three reading rooms at Kangwon University

Fig. 4. Photos of laboratories and rooms

(a) U-laboratory at Sungkyunkwan University

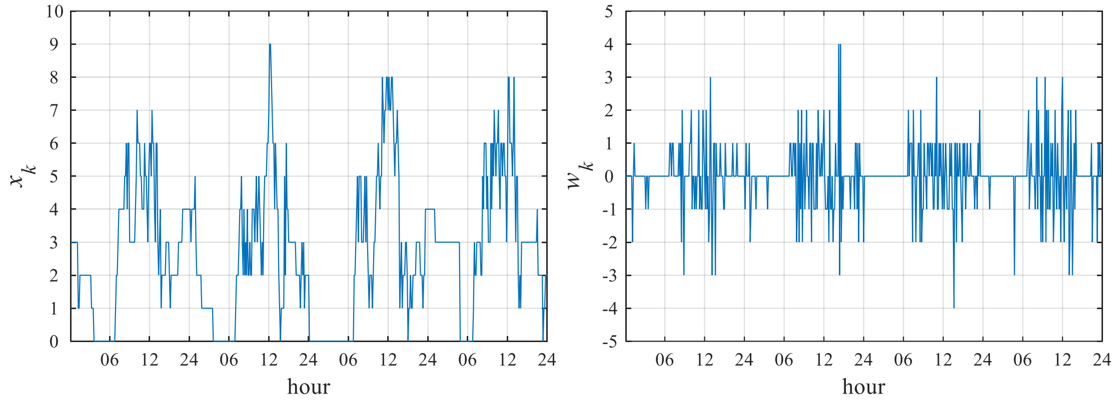
(b) BS-laboratory at Sungkyunkwan University

(c) Three reading rooms at Kangwon University

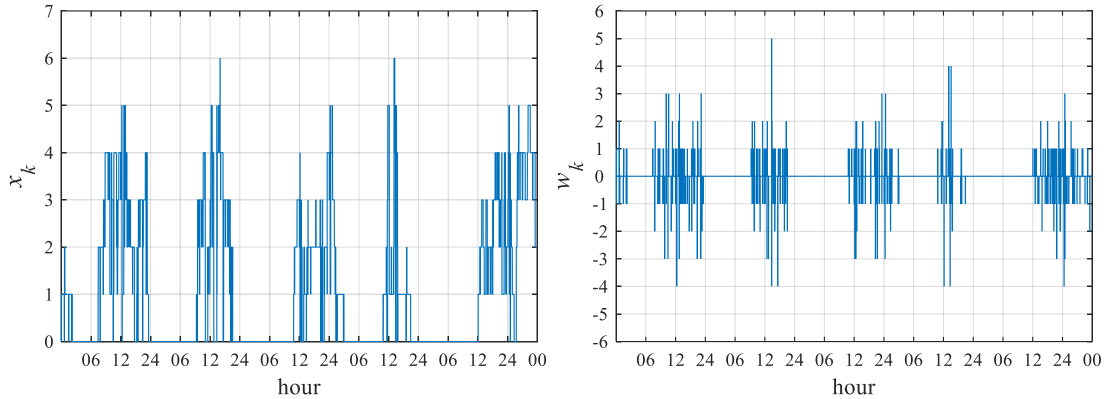
Fig. 5 Images recorded by webcams

In Experiments A, B, and C (Table 1), there were no strict office hours. Graduate students were able to enter and leave the labs according to their own preferred timing. In the case of the library reading rooms (Experiments D, E, and F, Table 1), the library opens at 8:30 A.M. and closes at 11:00 P.M.

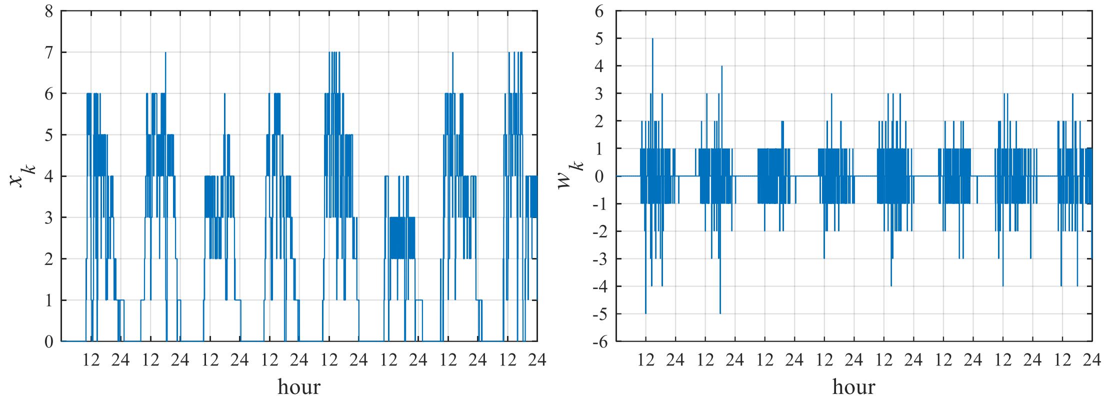
Fig. 6 shows the occupants' presence for each experiment. For the laboratories, the rooms were occupied until late at night, which is typical for university research laboratories. Meanwhile, in the case of the reading rooms at Kangwon University, the library operating hours were more restricted. Please note that each experiment (Fig. 6) has different measurement period (Table 1).



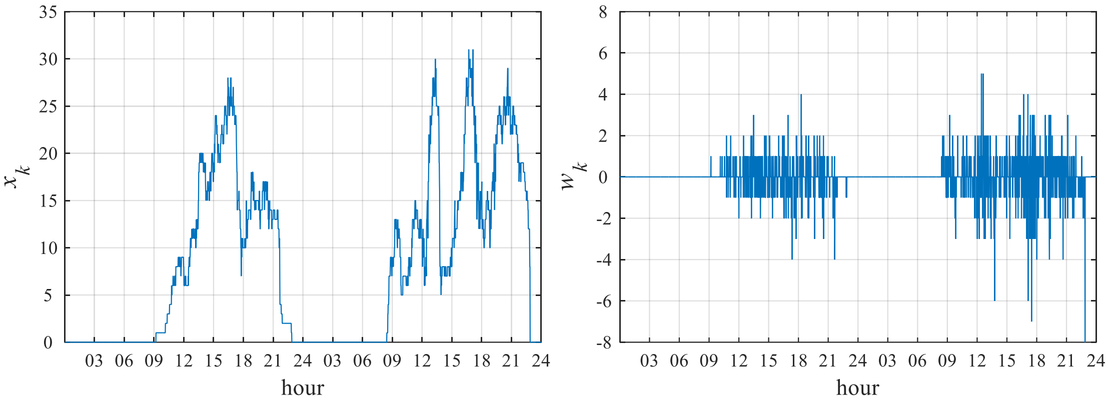
(a) Experiment A



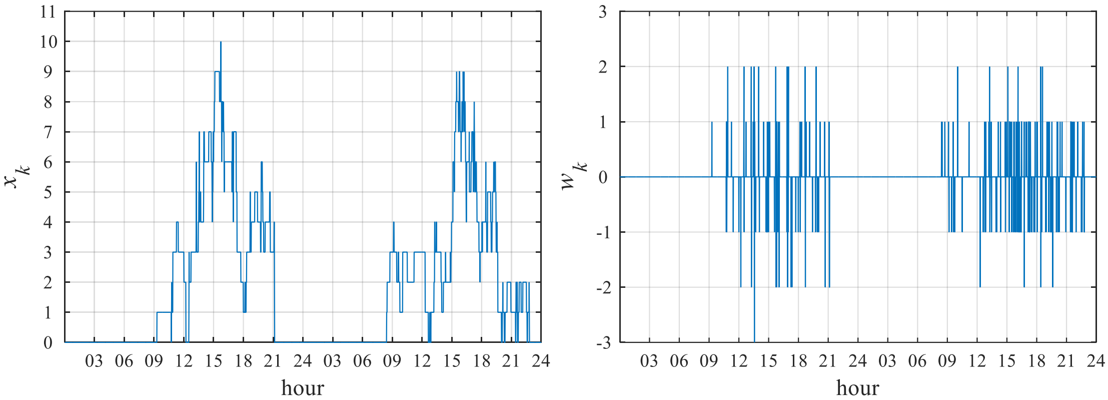
(b) Experiment B



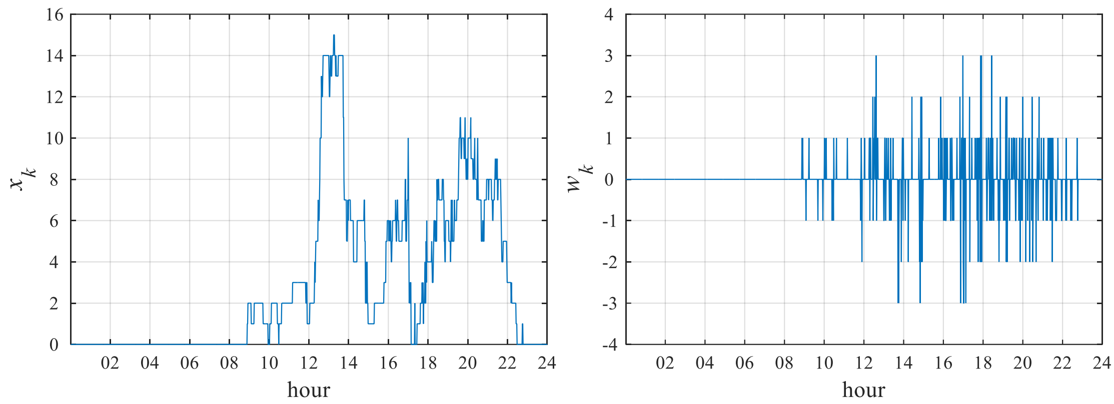
(c) Experiment C



(d) Experiment D



(e) Experiment E



(f) Experiment F

Fig. 6. Occupants' presence (x_k) (left) and variation in occupants' presence (w_k) (right)

4. Results

To verify whether or not the occupants' presence followed a random walk, the occupants' presence (x_k) (Equation 1) and the variation in the occupants' presence (w_k) (Equation 2) were tested by the NCP. It is worth noting that the x-axis in the NCP plot usually represents a frequency. However, it has been purposefully replaced with a period for the sake of clarity (Fig. 7, Table 2). Because of this replacement, the period on the x-axis is in descending order, as the period is the inverse of frequency. It should be noted that a difference is observed in the minimum and maximum values of the x-axis between Experiment A and the other experiments (Experiments B, C, D, E, and F) (Fig. 7) because of differences in the sampling times for the experiments (Table 1).

As shown in Table 2 and Fig. 7(a), the NCP of the occupants' presence sharply increases in the range of periods between 1,440 min and 160 min. In other words, 88% of the periodicities of the occupants' presence (x_k) in Experiment A are longer than 160 min, which is equivalent to 2.67 hours. In other words, it can be inferred that 88% of the occupants' presence in Experiment A has a periodicity longer than 2.67 hours (Table 2).

Interestingly, 59.9% of the frequencies in the occupants' presence (w_k) (Fig. 7(a)) are located inside the 95% confidence limit in the NCP plot. The other 40.1% of the frequencies are distributed close to the confidence interval (Fig. 7(b)). This means that the spectral density of w_k is evenly distributed over all periods (or over all frequencies). This indicates that the difference (w_k) between x_k and x_{k+1} is random. Thus, w_k in Experiment A is unpredictable and follows a random walk. Clearly, this means that w_k cannot be predicted by any stochastic model. It is important to note that because the sampling time for Experiment A (Table 1) is 10 minutes, the confidence limit shown in pink in Fig. 7(a) is wider than that for the other confidence limits (Experiments B, C, D, E, and F).

The results of experiment B are similar to those of Experiment A. As shown in Fig. 7(b), the cumulative periodogram of the occupants' presence (x_k) in Experiment B sharply increases in the range of periods between 1,440 min and 160 min. As shown on the right side of Fig. 7(b), the spectra of w_k are evenly distributed over all the periods (or over all the frequencies) near the shaded confidence region, similar to those of Fig. 7(a). It can be concluded that the variation in the occupants' presence (w_k) in Experiment B is equivalent to, or close to, a random walk. In other words, the occupants' presence at the next time step cannot be predicted, because since w_k is unpredictable.

As shown on the left side of Fig. 7(c), the NCP of the occupants' presence sharply increases up to the location at (160, 0.85). The spectra of w_k (right side of Fig. 7(c)) are located slightly outside of the lower dotted line. However, the degree of deviation from the confidence interval is not significant. It can be said that the occupants' presence (x_k) in experiment C *marginally* follows a random walk.

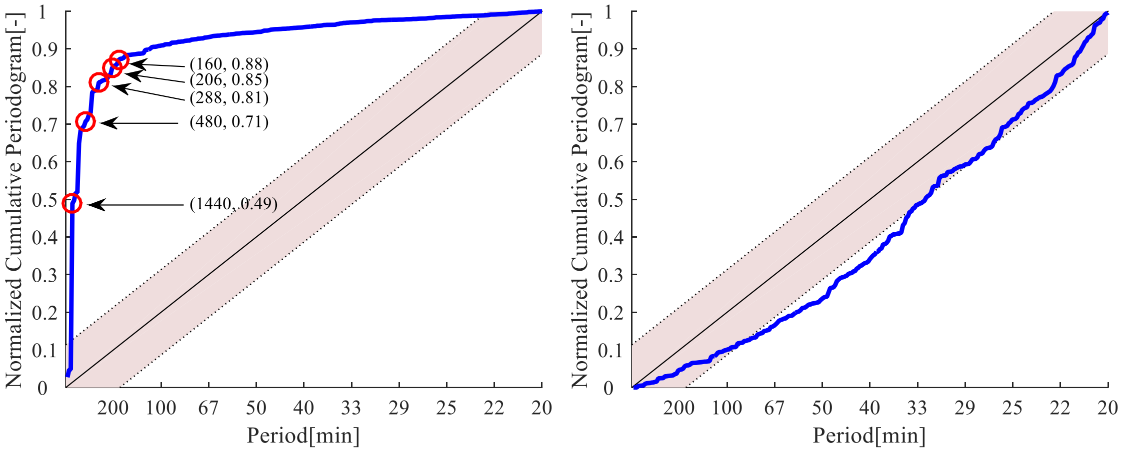
As shown on the left side of Fig. 7(d), the NCP of the occupants' presence (x_k) rapidly increases close to the point at (160, 0.94). The NCP of the variation in the occupants' presence (w_k) (right side of Fig. 7(d)) is shown inside the confidence limits. This indicates that the variation in the occupants' presence (w_k) in Experiment D follows a random walk.

With regard to the occupants' presence (x_k) in Experiments E and F (left sides of Figs. 7(e) and 7(f)), the cumulative periodogram curves sharply increase, similar to those in other experiments (A, B, C, and D). The NCPs of the variation in the occupants' presence (w_k) (right sides of Figs. 7(e) and 7(f)) show a random sequence. It is important to note that the NCP of the variation in the occupants' presence (w_k) (right side of Fig. 7(f)) slightly deviates from the lower bound of the confidence limits near the periods of 5.5 and 3.3 min. However, the degree of deviation is negligible.

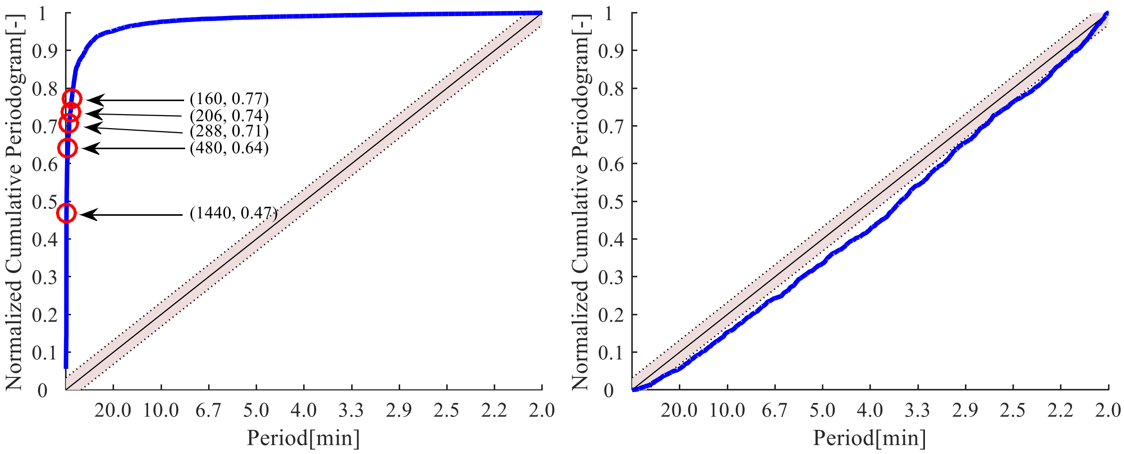
Table 2. NCP of the occupants' presence (x_k)

Index	Period (min)	Period (hours)	Exp. A NCP (-)	Exp. B NCP (-)	Exp. C NCP (-)	Exp. D NCP (-)	Exp. E NCP (-)	Exp. F NCP (-)
1	1,440	24.0	0.49	0.47	0.67	0.72	0.65	0.45
2	720	12.0	0.65	0.60	0.70	0.76	0.74	0.46
3	480	8.00	0.71	0.64	0.74	0.82	0.76	0.64
4	360	6.00	0.79	0.68	0.76	0.83	0.81	0.73
5	288	4.80	0.81	0.71	0.78	0.86	0.85	0.74
6	240	4.00	0.82	0.72	0.79	0.90	0.87	0.79
7	206	3.43	0.85	0.74	0.81	0.92	0.88	0.83
8	180	3.00	0.87	0.76	0.84	0.94	0.89	0.86
9	160	2.67	0.88	0.77	0.85	0.94	0.90	0.89
10	144	2.40	0.88	0.79	0.86	0.95	0.91	0.89

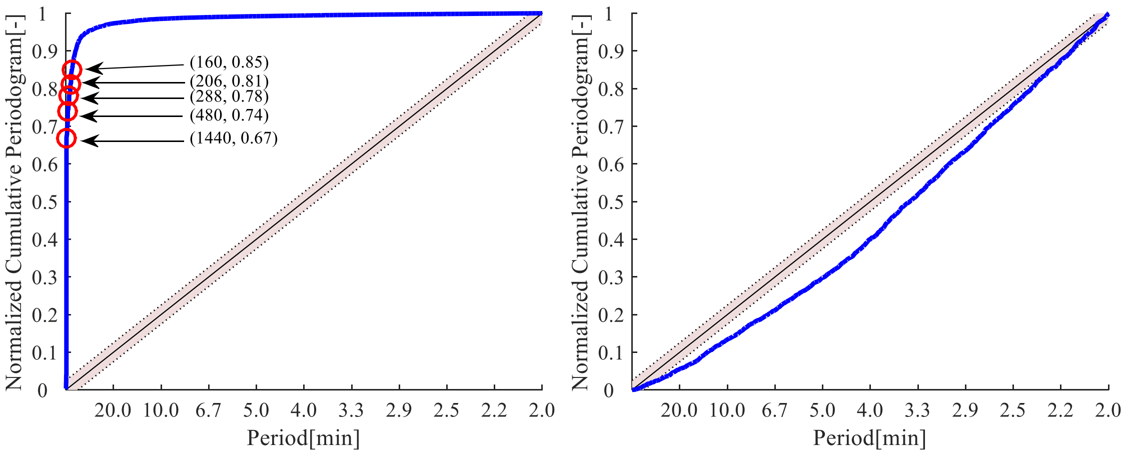
* Indices #1, 3, 5, 7, and 9 correspond to the red circles in Fig. 7.



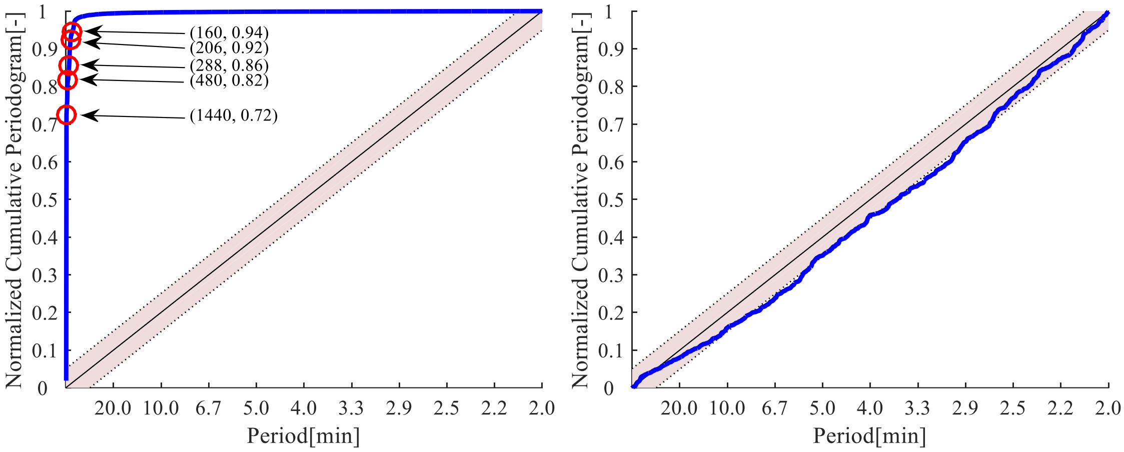
(a) Experiment A



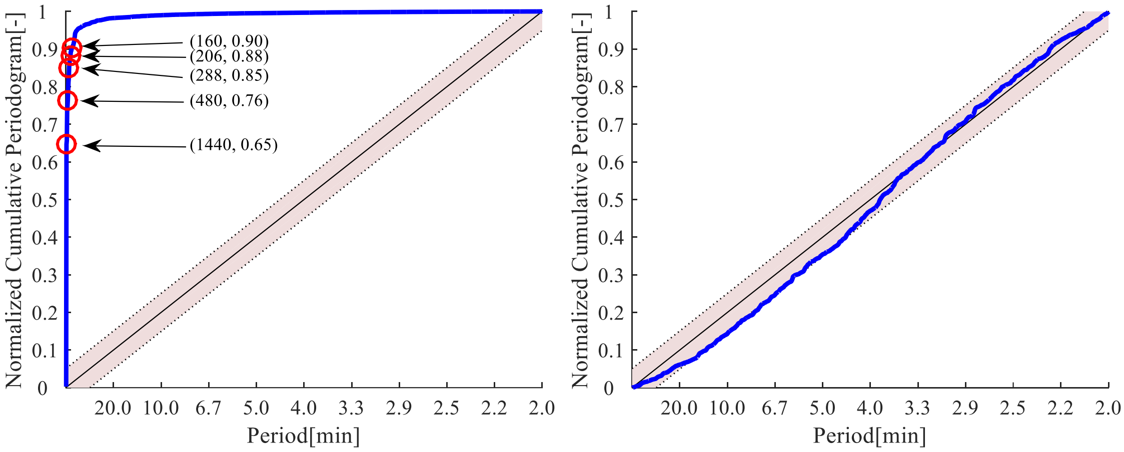
(b) Experiment B



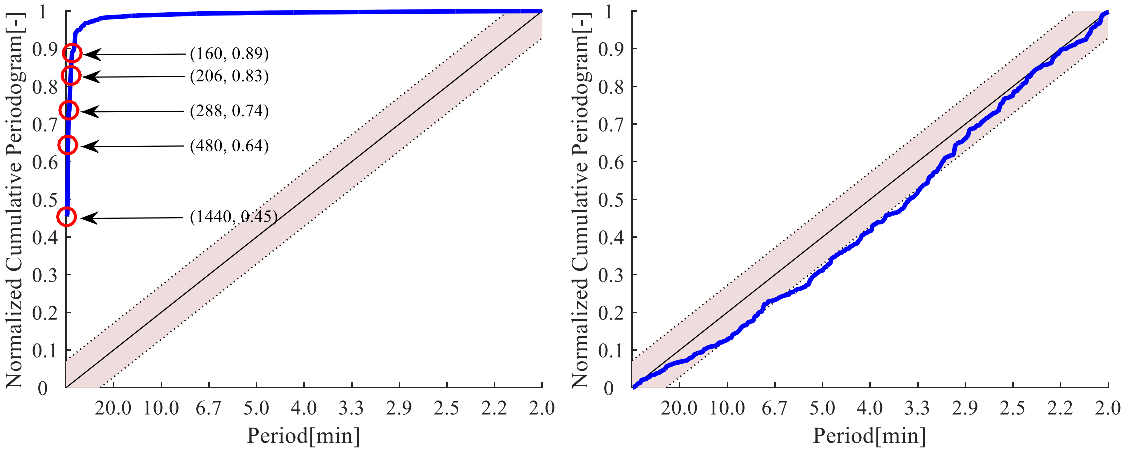
(c) Experiment C



(d) Experiment D



(e) Experiment E



(f) Experiment F

Fig. 7. NCP of occupants' presence (x_k) (left) and variation in occupants' presence (w_k) (right)

In summary, the results of the six experiments confirm the evidence of the random walk. This output is contradictory to the prediction of occupant presence by the Markov chain model. However, as mentioned in Section 1, stochastic prediction models were based on measured data in process-driven buildings, whereas the "random walk" case studies in this current study used data from university labs and library reading rooms, which are not process-driven. This means that the occupant modeling approach must be determined based on the characteristics of building occupants.

5. Energy simulation with three different occupant models

Occupants' presence and interaction with various building components significantly affect the energy simulation [5]. Clevenger and Haymaker [38] studied uncertainty in occupant presence and behavior in building energy simulation models, using various occupancy schedules and environmental preferences and found that the energy consumption differed 150% (or more) if the occupant-related inputs were maximized and minimized, even for typical occupancy patterns.

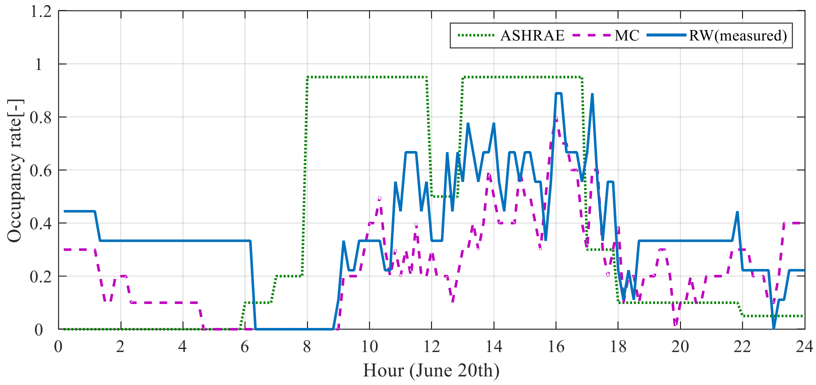
In order to show the importance of appropriate occupant presence models for predicting building energy use, the authors conducted a series of EnergyPlus simulation runs with three occupant models: fixed ASHRAE [4], Markov chain (MC), and Random Walk (RW). The simulation cases were made for Experiments A to C (Tables 1, 3).

The fixed ASHRAE model uses the office occupancy schedules suggested in ASRHAE Standard 90.1-2016 [4]. For the MC model, the authors used part of the measured data (Table 3). It is worth noting that Experiments D, E, and F (Table 1) were excluded from this simulation study, because the measurement period (1-2 days) was insufficient for developing an MC model. The RW model employs the measured occupancy data.

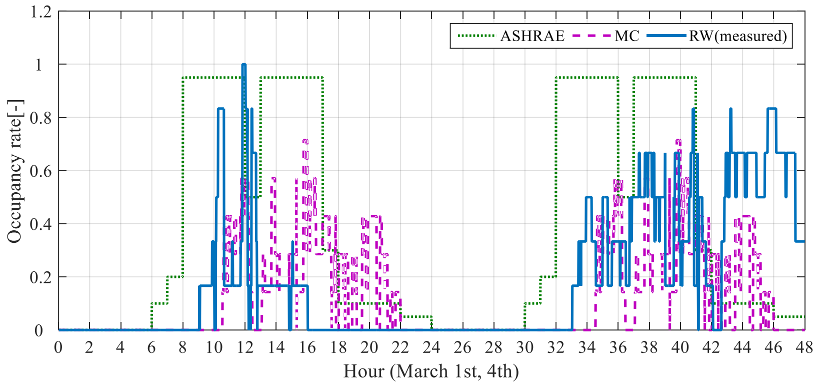
Table 3 Training and validation period for Markov chain (MC) models

Experiment	Training period (for development of MC model)	Validation period (for cross-comparison of occupant presence and energy simulation between three models)
A	June 7th (Th.), 8th (Fri.), 19th (Tue.)	June 20th (Wed.)
B	Feb 26th (Tue.) – 28th (Thu.)	March 1st (Fri.), 4th (Mon.)
C	Feb 23rd (Mon.) – 26th (Thu.), Mar 2nd (Mon.)	Mar 3rd (Tue.) – 5th (Thu.)

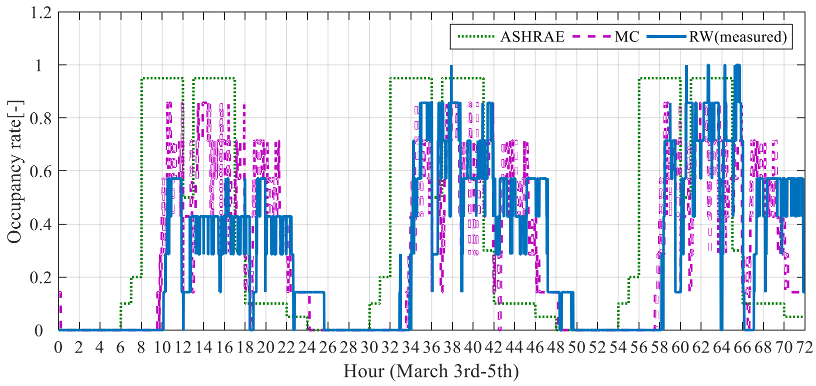
Fig. 8 shows a comparison of the three occupant presence models during the validation period (Table 3). Significant differences are observed in the prediction of the occupants' presence between the three models. Obviously, this does not negate the need for the fixed ASHRAE model or the MC model. Rather, this signifies that an additional occupant presence model should be introduced for a certain type of building, e.g. the RW Model.



(a) Experiment A



(b) Experiment B

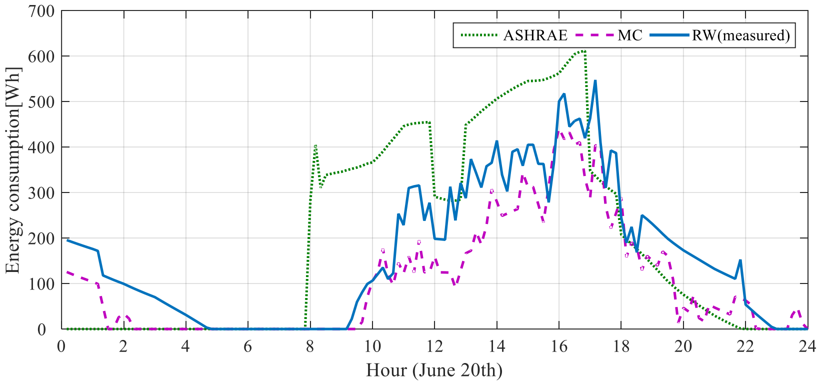


(c) Experiment C

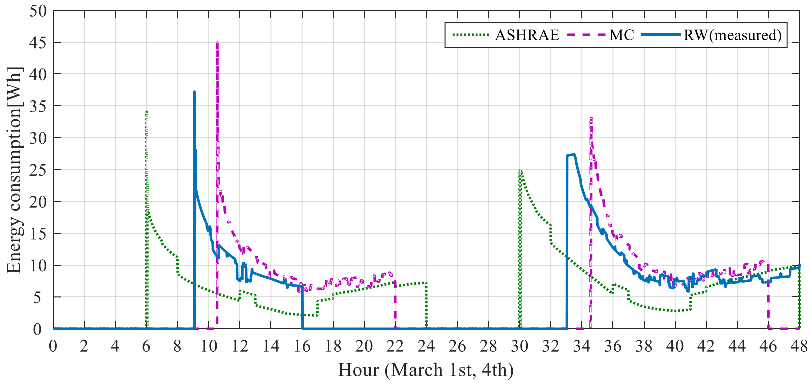
Fig. 8. Comparison of three occupant presence models

Using the aforementioned three occupant presence models, the authors conducted EnergyPlus simulation runs for Experiments A-C. The EnergyPlus simulation models were developed for U-lab and BS-lab (Table 1). All simulation inputs except the number of occupants were equally applied for fair comparison. The indoor temperatures in U-lab and BS-lab were controlled by ceiling mounted electric heat pumps (EHPs) at 22°C. The EHPs were only operated if an occupant was present in a space.

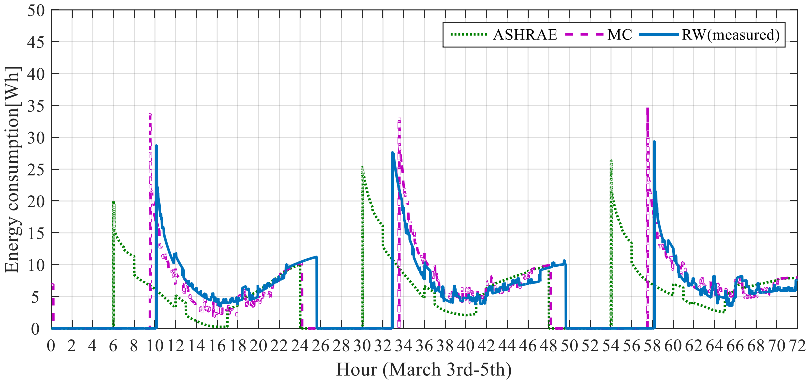
Figs.9-10 show the energy simulation results during the validation period (Table 3). As indicated in the adjusted R^2 in Fig. 10, a significant difference is observed between the three occupant presence models. In Experiments A to C (Figs.9-10), the on/off operation of the EHPs was determined by the occupants' presence. Therefore, the occupants' presence (Fig. 8) is the only variable that can account for the gap between three predictions. For the types of buildings in which occupant presence follows a random walk pattern, careful attention must be paid. The fixed ASHRAE model or the MC model could lead to a performance gap between actual and expected energy consumption for this type of building.



(a) Experiment A

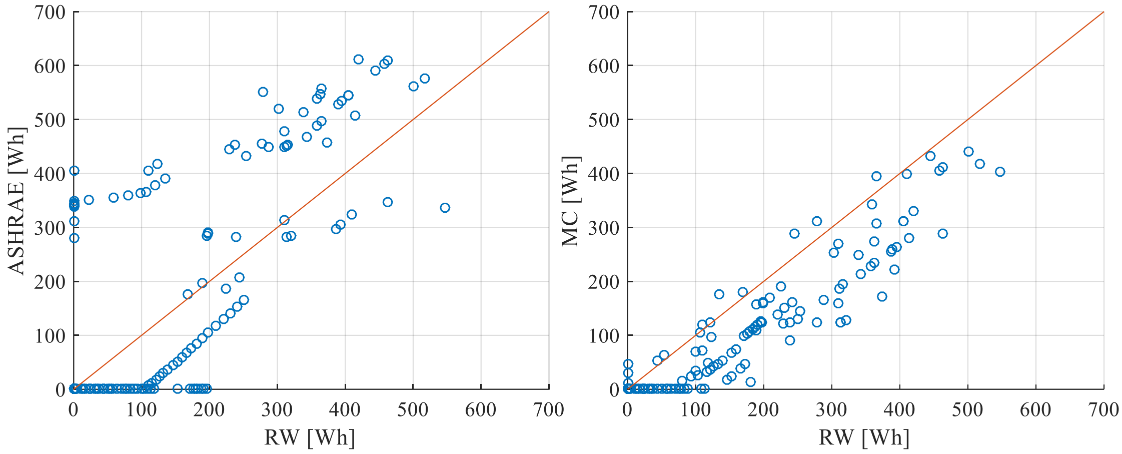


(b) Experiment B



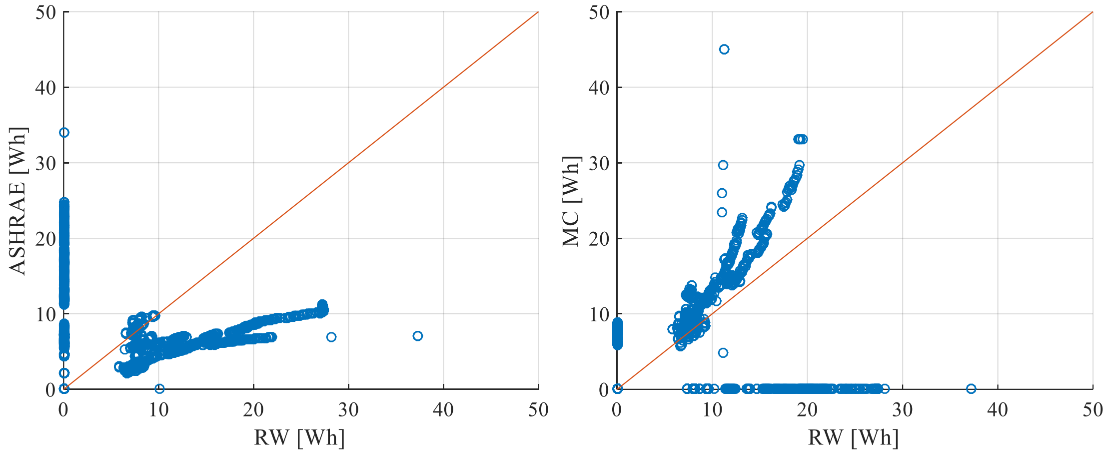
(c) Experiment C

Fig. 9. Energy simulation results



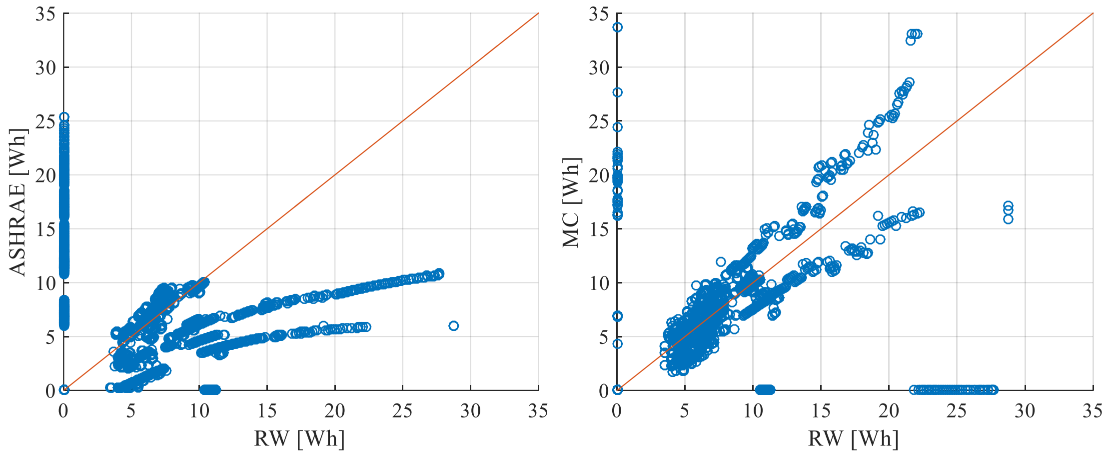
Adjusted R^2: 0.54　　Adjusted R^2: 0.86

(a) Experiment A



Adjusted R^2: 0.02　　Adjusted R^2: 0.19

(b) Experiment B



Adjusted R^2: 0.01 Adjusted R^2: 0.41

(c) Experiment C

Fig. 10. Comparison of energy prediction among the three models

6. Discussion

Fig. 11 illustrates the findings of this paper. The x-axis represents the degree of randomness in occupant presence. In other words, the x-axis refers to the degree of predictability of occupant presence. If a building is located at the far left of the x-axis, a stochastic model (e.g. Markov chain model) can predict occupant presence to some extent. Process-driven buildings such as K-12 school buildings, offices, factories, etc. are located at the far left of the x-axis, in which high stochastic predictability is inherent. Occupant presence in other building types located at the right of the x-axis is more likely to follow a random walk. Examples include university labs and reading rooms, as shown in this paper. Obviously, any stochastic model can fail to predict occupant presence in random walk driven buildings.

As shown in Fig. 11, the stochastic characteristics of occupant presence can vary according to building type (specifically, room [space] type rather than building type). To date, studies conducted on the "random walk" (or unpredictability) of occupant presence have been insufficient. More studies need to be carried out to characterize occupant presence according to building types, and to develop a new prediction model for random walk-driven buildings.

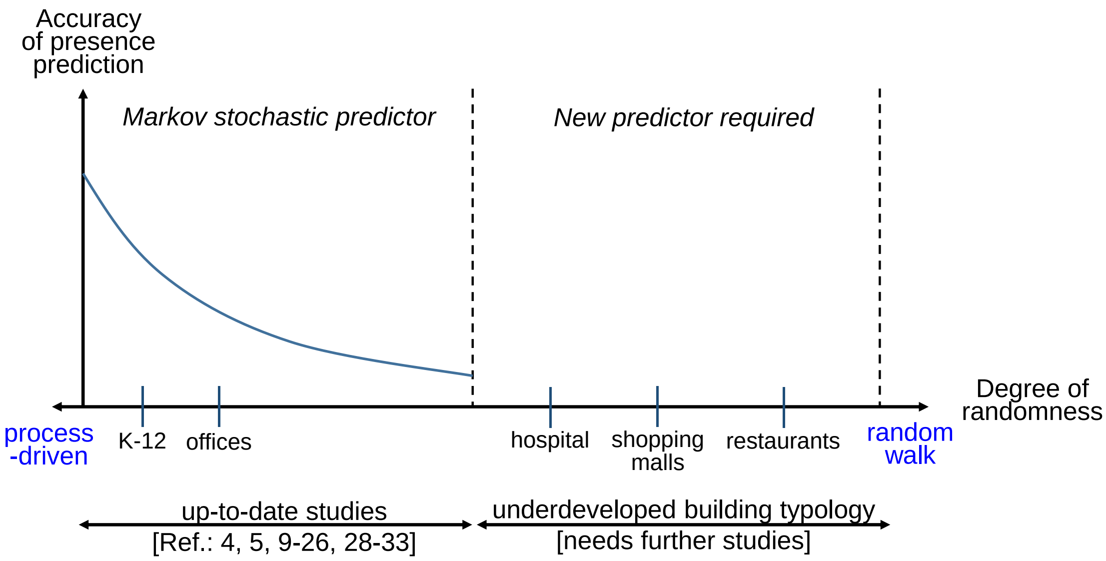


Fig. 11 Predictability of occupant presence according to building types (the location of building types on x-axis can vary) [4, 5, 9-26, 28-33]

7. Conclusion

Occupant presence and behavior are known to be a major reason for the performance gap between actual and expected energy consumption in buildings. Accurate information and modeling with regard to occupant presence and behavior is important for reliable energy simulation. The aim of this study is to propose a new occupant presence model based on the so-called random walk pattern.

A series of experiments was conducted to obtain occupancy data in two laboratories and three reading rooms at two different universities. The degrees of randomness of the occupants' presence in the five spaces were verified using Normalized Cumulative Periodogram (NCP). The NCP results show strong evidence of the random walk pattern with regard to occupant presence in real-life situations. This means that it is difficult to predict the variation in the number of people over a certain time interval for this type of buildings.

According to energy simulation results using the three occupant presence models (fixed ASHRAE model, Markov Chain model, and Random Walk model), a significant difference is observed in energy prediction among the three models. In other words, the performance gap is influenced by the characteristics of the occupants' presence. This also indicates that it is important to use an appropriate occupant presence model for predicting building energy use, depending on the 'occupant presence' characteristics.

Contrary to previous works (fixed ASHRAE model, Markov Chain model), this study presents a new concept: “random walk” occupant presence model. However, it should be noted that this study was performed in two laboratories and three reading rooms at two universities; such buildings significantly differ from process-driven buildings such as K-12 schools, offices, factories, etc. Accordingly, as suggested in Fig. 11, more work on occupant presence model needs to be performed, depending on the types of buildings (process-driven vs. random walk-driven).

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