TIME SERIES CORRELATION BETWEEN OCCUPANTS AND ENERGY CONSUMPTION

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ABSTRACT

Although it is widely acknowledged that occupants play a critical role in building energy consumption, the characteristics of occupants are not well-represented in building simulation over the past decades (IBPSA 1987-2013). Many statistic and data-mining approaches have been applied to develop a reliable occupant model but so far no reliable occupant behavior model is available. Rather than attempting to develop the occupant model, this study aims to present a different perspective to investigate a correlation between the occupant behavior and energy consumption, substantiated by a series of experiments. First, this paper delivers the randomness of occupants' presence and behavior. The degree of randomness was verified using a Normalized Cumulative Periodogram (NCP). Then, the correlation between occupant and energy consumption was studied using the wavelet coherence. It is concluded that the occupants' presence has a degree of randomness, and is not strongly correlated to the energy consumption. The occupants' active action to control a heating/cooling system (turn on/off) is correlated to the energy consumption. In contrast to occupant's presence, the occupants' active action does not follow the random walk, but it has no particular frequency. This study signifies that more attention should be paid to active action than passive action (presence).

INTRODUCTION

Over the past two decades, building energy performance simulation (BEPS) tools have advanced considerably. With the use of BEPS tools, building physics and control logics of mechanical systems can be simulated. However, several studies have shown that a gap remains between simulated prediction and measurements (de Wilde, 2014; Menezes et al., 2012). Since a simulation model is merely a reduced and idealized representation of the reality in a mathematical or abstract form, no model can completely represent a real situation or thermal process in buildings (Park et al., 2010). With regard to the gap between the simulation and measurements, the Occupant Behavior (OB) has gained significant attention from the BEPS community. Recently, three approaches have been reported with regard to modeling occupants: (1) stochastic approach (e.g. Reinhart, 2004; Page et al., 2008; Feng et al., 2014), (2) agent approach (e.g. considering human's sensation, perception, cognition, and psychomotor; Fuji and Tanimoto, 2004), (3) random walk approach (Kim et al., 2014), and (4) data-mining approach (e.g. clustering and regression; Zhao et al., 2014).

The energy and thermal performance of buildings are not only affected by the occupant's presence as a source of heat, but also by their active actions (Mahdavi, 2011). Human beings desire both to control indoor environment based on their free will. The occupants' active actions arise under complex conditions including their thermal comfort, physiological phenomena, psychological state, and interaction with others. In other words, it might be not easy to model the OB by using numerical, experimental or empirical forms. It may requires far more in-depth understanding of the human beings to develop an accurate OB model than we have already acquired.

With this in mind, this study comes from a different direction. Rather than attempting to develop an accurate OB model, this paper reports investigation of the "time-series correlation" between occupants and energy consumption, which has not been studied yet. Please note that this study does not include thermal comfort or other socio-cultural aspects because it would require far more extensive work than what has already been presented in this paper. In other words, so far the majority of current research has been focused on modeling of OB. This study is focused on the "time-series" interaction between occupants and building energy consumption.

The goals of this study are as follows: (1) to investigate the characteristics of 'occupant presence and behavior', (2) to identify the different attitude of each occupant to control indoor condition, and (3) to quantify a time-series correlation between occupants and energy consumption.

EXPERIMENT

The experimental data were collected with real-time monitoring of a laboratory room occupied by 7 people (MS and Ph.D. students) (Figure 1) at OOO university located in South Korea. The occupancy pattern of the laboratory room is informal, and the occupants are free to enter/leave and control the indoor condition according to their own preferences.

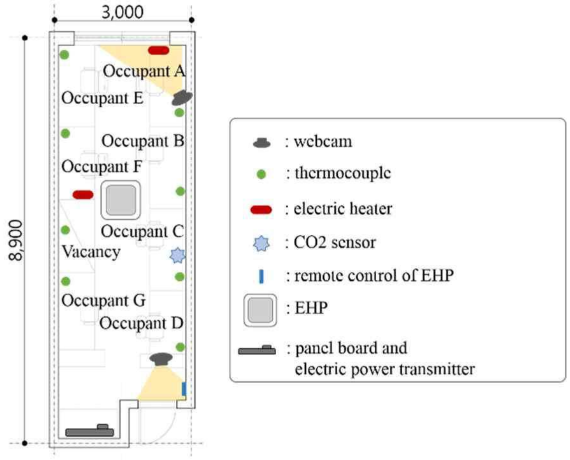


Figure 1 Floor plan and experimental equipment

The indoor temperature in the laboratory is controlled by a ceiling attached electric heat pump (EHP) but no mechanical ventilation is provided. The outdoor air could be induced only by occupant's ventilation actions (e.g. opening/closing a window or door). In addition, two people have individual electric heater under their desks to individual thermal control.

A sampling time was set to 1 minute so that the correlation between occupants and energy consumption can be analyzed without losing any event. The list of monitored behavior and environment is tabulated in Table 1. Occupant's actions (leaving/ entering the room, opening/closing the door and window) were monitored using two webcams (Figure 2).

The experiments were conducted for two weeks (from 23 to 26 February and 2 to 5 March). The CO2 display unit was covered so that occupants couldn't see the current concentration level of CO2 for half of each week at each experiment. This was intended to investigate how occupant's behavior differs when they are provided with information on CO2 concentration level.

Table 1 Monitoring equipment

MONITORING	UNIT	EQUIP.
the number of occupants	number	Webcam
CO2 concentration	ppm	Senselife
window opening ratio	%	Webcam
Action of occupant's opening a window	-	Webcam
Door opening ratio	%	Webcam
Action of occupant's opening a door	-	Webcam
Electricity power consumption of EHP	kW	SEM3010
Action of occupant's controlling a EHP	-	Webcam
Air temperatures at each occupant's desk	℃	DAQ9174
Electricity power consumption by personal heaters	kW	Wattman
Outdoor air temperature	℃	HOBO
Outdoor air relative humidity	%	HOBO

Figure 2 Images recorded by webcams (left: entering the room, right: opening the window)

METHODOLOGIES

Random Walk

The random walk hypothesis is used for verifying the randomness of the time-series data. 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 (1905), has been used in many fields (e.g. ecology, economics, psychology, etc.) to explain observed behaviors as a stochastic activity. Figure 3 shows an example of ten random walks in one dimension, showing the current position on the y axis over time. The mathematical form of random walk for time-series data can be expressed as follows:

$$x_{k+1} = x_k + w_k \quad (1)$$

$$w_k = x_{k+1} - x_k \quad (2)$$

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

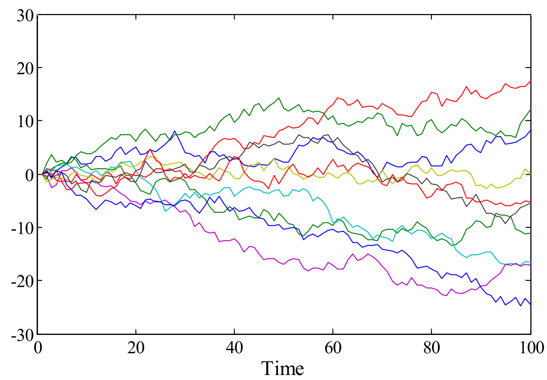


Figure 3 Example of ten random walks

Meanwhile, the time-series data can be characterized by frequency analysis with Fourier transform, which consists of 2π-periodic functions. The time-series w_k can be expressed as a combination of cosine and sine waves and then can be used for checking the periodic behavior. The Normalized Cumulated Periodogram (NCP) is a common method for identifying the periodicity of a given time-series in a frequency domain (Hipel and McLeod, 1994).

For a given n stationary time series $(x_1, \ldots x_n)$, the periodogram function $I(f_j)$, which shows the spectral density of the time-series at each frequency, is calculated as shown in Equation (3) (Hipel and McLeod 1994).

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

where $f_j = j/n$ is the jth frequency ($j = 1, \ldots, N'$), $N' = n/2$, $|\cdot|$ denotes the magnitude, and $i = \sqrt{-1}$. In essence, $I(f_j)$ measures the strength (or spectral density) of the relationship between data sequence x_n and a sinusoid with frequency f_j, where $0 < f_j \leq 0.5$ (Hipel and McLeod, 1994). 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 defined in Eq. (4). 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 time-series data of randomness is not concentrated in the few specific frequencies, but is uniformly distributed within the entire frequency domain. Therefore, it can be said that w_k follows the random walk if it is drawn within a confidence interval along with a straight line joining (0, 0) and (0.5, 1) in the NCP (Hipel and McLeod, 1994). Figure 4 shows the NCP of 500 random numbers (bold blue line) generated by rand function in Matlab, and the dotted lines indicate 95% confidence intervals for testing the random walk.

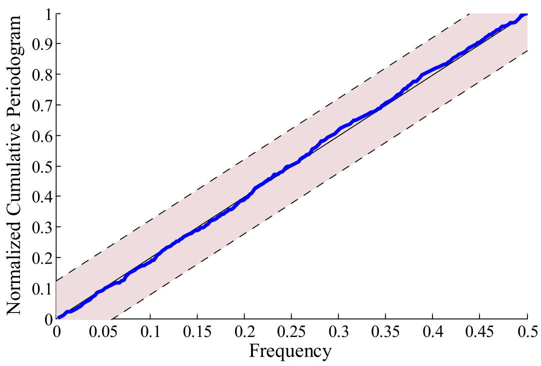


Figure 4 Example of NCP for 500 random numbers

Based on the aforementioned method, Kim et al. (2014) proved that the difference (w_k) in the number of occupants between the previous (k) and current time step (k+1) in two university labs and a library room follow a random walk as discrete random sequences. Please be noted that the random walk hypothesis reported by Kim et al. (2014) is valid not for x_k but valid for w_k.

Wavelet Coherence

As described in the 'Random Walk' section, the data are analyzed in the frequency domain and thus time information is lost after the Fourier transform is applied. To compensate for this, a wavelet coherence method can be used, which allows for the time-series analysis in the two-dimensional plane of time and frequency. In addition, the wavelet coherence can be used to analyze a time-series that contains non-stationary power at many different frequencies (Torrence and Compo, 1998; Percival and Walden, 2000). The wavelet coherence analysis can draw information on dependencies and correlations out of two simultaneous time-series data. In this study, the authors used the wavelet coherence (Grinsted et al. 2004) to quantify the degree of correlation between occupants (presence and behavior) and energy consumption in a room.

A wavelet is a function with zero mean and is localized in both time and frequency space (Farge, 1992). Different types of wavelets can be used (e.g. Morlet, Paul, Meyer, etc.), each having specific characteristics (Percival and Walden, 2000). One particular wavelet, the Morlet, is defined as:

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \quad (5)$$

where ω_0 is the central frequency of the wavelet. The Morlet wavelet (with $\omega_0 = 6$) is appropriate to draw correlation between two time-series data, since it provides a good balance between time and frequency localization (Grinsted et al. 2004). The Morlet wavelet belongs to the family of complex or analytic wavelets; hence, it has both real and imaginary parts, allowing to study both amplitude and phase (Vacha and Barunik, 2012).

The continuous wavelet transform and continuous wavelet power are used for the wavelet coherence analysis. The continuous wavelet transform $W_x(u,s)$, which is obtained by projecting a specific wavlet $\psi(.)$ onto the examined time series, $x(t)$, can be expressed as:

$$W_x(u,s) = \int_{\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi\left(\frac{t-u}{s}\right)} dt \quad (6)$$

The continuous wavelet transform can decompose and then reconstruct a time-series $x(t)$ while preserving the energy of the $x(t)$ (Vacha and Barunik, 2012). For analyzing the covariance or interaction between two time-series, Torrence and Compo (1998) defined the cross wavelet transform of two time series, $x(t)$ and $y(t)$, with continous wavelet transforms W_x and W_y as:

$$W_{xy}(u,s) = W_x(u,s) W_y^*(u,s) \quad (7)$$

where u and s are the position index and the scale, and the asterisk(*) denotes a complex conjugate. The cross wavelet power, which is computed using the cross wavelet transform as $|W_{xy}(u,s)|$, finds areas in the time-frequency space where two time series have a high common power (Vacha and Barunik, 2012).

On the other hand, the wavelet coherence is a measure of the intensity of the covariance of the two time-series in time-frequency space, unlike the cross-wavelet power which is a measure of the common power (Jevrejeca et al., 2003). In other words, the wavelet coherence can detect regions in the time-frequency space where the examined time-series co-move, although they do not necessarily have a common power (Vacha and Barunik, 2012). Using the approach of Torrence and Webster (1999), the squared wavelet coherence coefficient is obtained as follows:

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S(s^{-1}|W_x(u,s)|^2)S(s^{-1}\left|W_y(u,s)\right|^2)} \quad (8)$$

$$S(W) = S_{scale}\ (S_{time}\,(W_n)) \quad (9)$$

where S is a smoothing operator, which consists of a smoothing along the wavelet scale axis (S_{scale}) and a smoothing in time (S_{time}). The squared wavelet coherence coefficient ranges between 0 to 1. The coefficient, which is close to 1.0 or 0.0, indicates a strong (1.0) or weak (0.0) correlation.

The coherence significance levels are estimated using the Monte Carlo method to determine 5% statistical significance level of the coherence (Torrence and Compo, 1998). The edge effect, so called the Cone Of Influence (COI), occurs when dealing with the boundary on a finite length of time-series data. A number of zeroes are padded to deal with discontinuities in the wavelet transform, and the COI is then indicated by opaque regions.

In addition, the wavelet coherence analyzes delays in the oscillation between two time series data using phase differences. Following Torrence and Webster (1999), the phase difference is defined as:

$$\phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}\right) \quad (5)$$

where $\Im\{.\}$ is the imaginary part, and $\Re\{.\}$ is the real part.

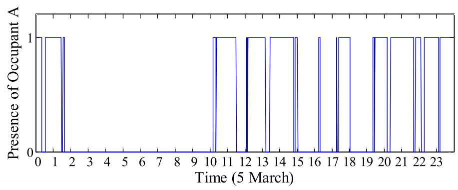
RESULTS

#1: Wavelet coherence analysis for occupant A

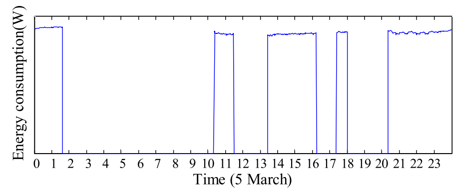
Figure 5 shows Occupant A's time-series presence in a room (Figure 1) and energy consumption of Occupant A's personal electric heater under his desk. Figure 6 shows a wavelet coherence analysis for occupant A. The regions inside the black lines plotted in a warm color indicate that the two time-series data are significantly dependent. The cold color means that they are not dependent on each other. The two time-series data have a similar pattern from 01:30 a.m. to 10:00 a.m. because Occupant A was absent and accordingly the heater was switched off. Therefore, most of the regions before 10:00 a.m. are warm-colored, indicating that two data are dependent and correlated. The arrows in Figure 6 can be interpreted as follows (Vacha and Barunik, 2012):

- arrows pointing to the right (left): two time-series are in-phase (anti-phase), or positively (negatively) correlated.
- arrows pointing upwards (downwards): first (second) time-series leads the second (first) time-series by 90° (first time-series: occupant A's presence, second time-series: ehergy use by personal electric heater).

It is interesting to note that two data are correlated with a period time of a 150 to 240 minutes after 10:00 a.m., even though some regions after 10 a.m. have local correlation with short periods. The short period time (less than 60 minutes) correlations were due to irregular presence or behavior of Occupant A. For example, the presence of Occupant A and energy consumption were correlated at 18:00, with about a period time of 10 to 60 minutes, but they were not correlated with a period time of 60 to 140 minutes, because Occupant A did not turn on the heater until 20:20.



(a) Presence of Occupant A



(b) Energy consumption by Occupant A's electric heater

Figure 5 two time-series data for wavelet coherence analysis

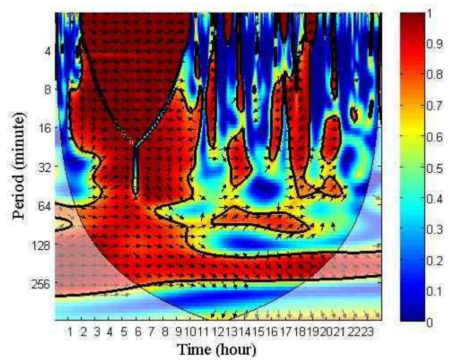


Figure 6 wavelet coherence for occupant A

#2: Difference in occupant preference to indoor condition

As shown in Table 2, the frequency of controlling the indoor environment differs by each occupant. Occupant A showed the highest frequency of actions, tantamount to eight times as much as that of Occupant G, who has the lowest frequency (Occupant A: 87, Occupant G: 10). In addition, Occupant G was never engaged in controlling the indoor condition (except closing the door after someone else's entering). Therefore, each occupant's preference differs in terms of engaging himself/herself to control the indoor condition (door, window, EHP). As a consequence, the indoor environment of the room was controlled by a few people who are willing to control the indoor condition. In other words, the willingness of ventilation action and temperature control differs by each occupant. This implies that OB modeling needs to consider this difference in individual preference.

As mentioned earlier, the CO2 display was not shown purposefully for half of each week. Kim et al. (2013) reported that occupants' behavior changes when such information is provided. In this study, when the CO2 display was shown, most occupants' willingly opened the door or window more frequently than during the period when the display was not shown. However, people who were sensitive to the indoor environment (e.g. occupants A and B), still tried to maintain the indoor/thermal comfort even when the CO2 display was hidden (Table 2). The CO2 concentration was maintained at the level of under 1,500 ppm for most of the time during the experiment (Figure 7).

It is interesting that occupants such as Occupant F and Occupant G are not sensitive to the indoor environmental information. The number of times Occupant F opened the door or the window during the period when CO2 information was hidden is greater than during the period when the CO2 display was shown. This shows a significant difference in individual preference and must be reflected for better prediction and building control in future BEPS or activities such as IEA Annex 66. Please be noted that Occupant D, Occupant F, and Occupant G neither switched the EHP on/off nor controlled the indoor air temperature. Such preference could affect prediction of energy consumption.

#3: Occupant presence and energy consumption

Figure 8 shows the recorded occupancy pattern at a sampling time of five minutes. The height of the blue box means the stochastic range of occupant's presence (A, C). The blue box is vertically high, and this means that the occupancy pattern at each day changes significantly.

During the experiment period, every occupant had a different pattern of presence, and the probability of the presence also differs from each other. The probability that Occupant A was in the room at 20:00 is 100%, but that for Occupant B was 50% (Figure 8).

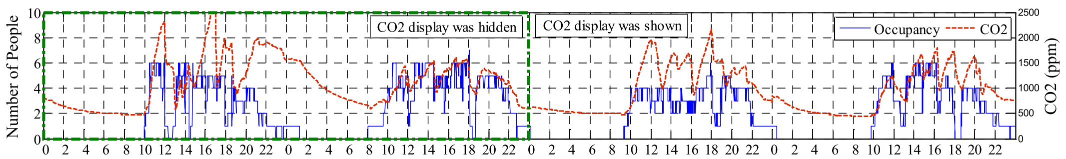
Table 2 Counting the number of occupant actions during the experiment (A/B: when the CO2 display was hidden/shown)

OCCUPANT	DOOR		WINDOW			EHP		
	opening[1)]	closing	opening[2)]	controlling[3)]	closing	turning on	controlling	turning off
A	**11 / 17**	**2 / 9**	**6 / 10**	**8 / 14**	**3 / 5**	**0 / 0**	**2 / 0**	**0 / 2**
B	13 / 19	14 / 16	1 / 1	2 / 0	0 / 0	1 / 1	1 / 1	0 / 0
C	5 / 11	6 / 21	1 / 3	1 / 1	0 / 0	1 / 3	0 / 2	2 / 2
D	7 / 10	10 / 4	0 / 0	0 / 2	0 / 0	0 / 0	0 / 0	0 / 0
E	3 / 0	3 / 3	0 / 0	0 / 0	4 / 0	1 / 0	0 / 0	0 / 0
F	**8 / 3**	**5 / 4**	**3 / 2**	**0 / 0**	**0 / 0**	**0 / 0**	**0 / 0**	**0 / 1**
G	**0 / 0**	**7 / 3**	**0 / 0**	**0 / 0**	**0 / 0**	**0 / 0**	**0 / 0**	**0 / 0**

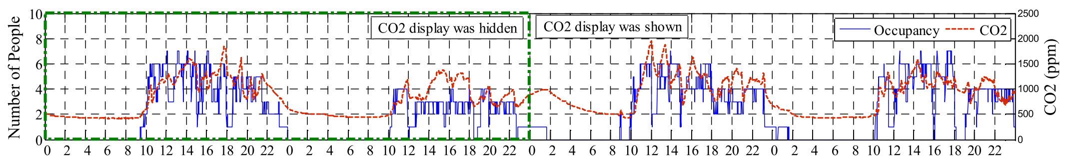
opening[1)]: means that the door was opened for more than 1 minute, and this is considered for the ventilation purpose.

opening[2)]: means that the window opening ratio is over 30%

controlling[3)]: the window is opened under 30% and not fully closed.

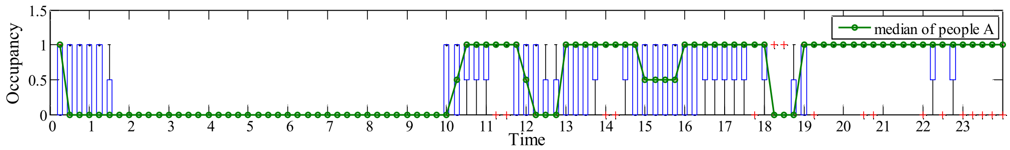


(a) 23 February to 26 February (x axis is time (hour))

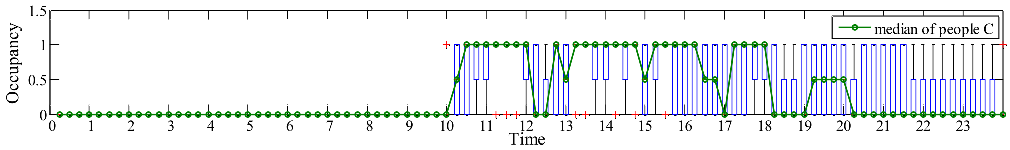


(b) 2 March to 5 March (x axis is time (hour))

Figure 7 Occupant presence and CO2 concentration level



(a) Boxplot of Occupant A's presence



(b) Boxplot of Occupant C's presence

Figure 8 Samples of occupant's presence during the total experiment period (two weeks)

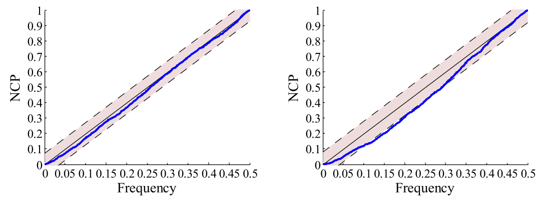
Also, such probability changes depending on the time of the day (e.g. the probability of 'Occupant A' present at15:00 is 50%, but 100% at 21:00).

As described in 'random walk' section, the NCP was used to identify a dominant periodicity of a given time-series in a frequency domain. If the time-series data evenly distribute over the frequency, the time-series can be regarded as a 'random walk'. This means that the events of the time-series do not have the particular periodicity. The random walk hypothesis was applied to each occupant as well as to the entire group of 7 people. The 'random walk' test was conducted for two different periods: one day (2 March) and four days (from 2 March to 5 March).

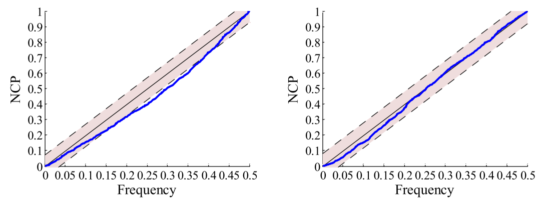
Figure 9 presents the NCP of the pattern (w_k, Equation 2). If the NCP line falls within the 95% confidence interval, the time-series follows the random walk. Occupant A follows the random walk based on one day (2 March), but the NCP line slightly crosses over the confidence interval based on four days (Figure 9 (a)). This implies that Occupant A did not 'always' follow the random walk and there was a slight periodic feature in the presence of Occupant A. Occupant B followed the random walk based on four days, however there was a periodic feature in one day (Figure 9 (b)). The group followed the random walk (Figure 9 (c)) on both cases (one day, four days).

The wavelet coherence was used to identify the dynamic correlation between occupant presence and energy consumption (Figure 10). Half of the experiment period (2 to 5 March) was selected for correlation analysis.

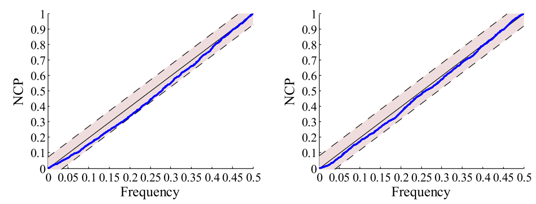
Figure 10 shows the occupancy pattern of the group of 7 people and energy use by EHP. Figure 11 shows the wavelet coherence between the occupancy pattern of the group and energy use by EHP. As shown in Figure 11, most regions are cold-colored and this means that the correlation between occupancy pattern of the group and energy use by EHP is almost negligible. There are two warm-colored regions from 00:00 to 12:00 on 4 March (Figure 11). This is because one occupant switched off the EHP when he left the room (02:00 a.m.), and the other occupant entered the room and turned on the EHP (10:00 a.m.). As shown in Figure 11, it seems not easy to find a strong relationship between occupancy presence and energy use by EHP.



(a) difference between x_k and x_{k+1} (w_k) for Occupant A.
2 March (left) and 2 to 5 March (right)



(b) difference between x_k and x_{k+1} (w_k) for Occupant E.
2 March (left) and 2 to 5 March (right)



(c) difference between x_k and x_{k+1} (w_k) for the group of 7 people
2 March (left) and 2 to 5 March (right)

Figure 9. NCP of difference between x_k and x_{k+1} (w_k)

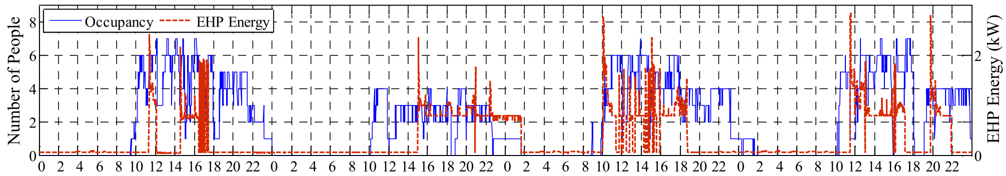


Figure 10 Occupancy pattern of the group and energy use by EHP during 2 to 5 March (x axis is time (hour))

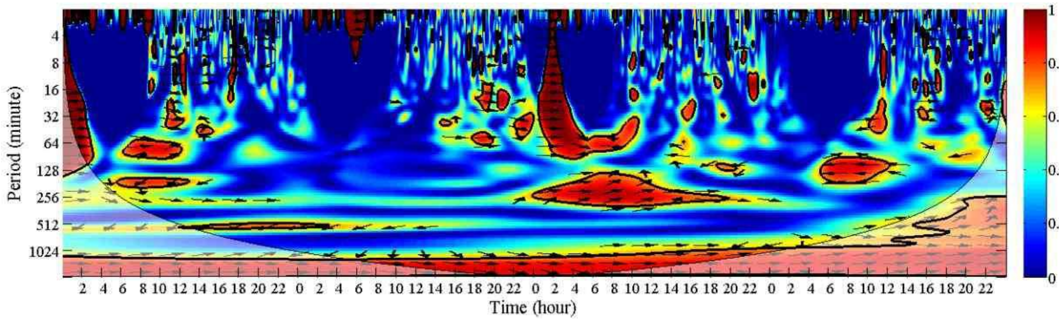


Figure 11 Wavelet coherence between occupancy pattern of the group and energy use by EHP from 2 to 5 March

#4: Occupant behavior and energy consumption

As mentioned earlier, three occupant behaviors were recorded (control of door/window /EHP). First, the occupant behavior was tested in terms of the random walk. As shown in Figure 12, the behaviors (e.g. opening of door/window, control of EHP) did not follow the random walk.

Then, the authors employed wavelet coherence analysis to test correlation between control of the EHP by occupants and energy use by EHP. Figure 13 shows the pattern of the EHP control (1.0 on the left y axis means that an occupant controlled the EHP, 0 means no control). Contrary to the occupant presence (Figure 11), Figure 14 shows that the occupant behavior and energy use by EHP were highly correlated each other for period times of 4 to 128 or 4 to 256 minutes. However, even though the warm regions show long period correlation (4 to 128, 4 to 256 minutes) (y axis), they do not correlate for a long time (x axis). The correlation only occurred at the time when the energy use by EHP changed according to the occupants' behavior (turn on/off). In other words, there is no notable correlation, except the case when the EHP was controlled by occupants.

Due to lack of space, the tiems series correlation between other parameters (e.g. temperatures, CO2, Table 1) and energy use is not included in this paper, which will be reported in elsewhere.

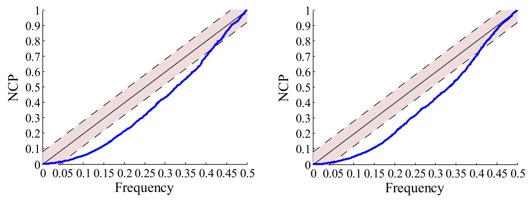


Figure 12 NCP of Occupant behavior: door opening (left), EHP on/off/controlling (right)

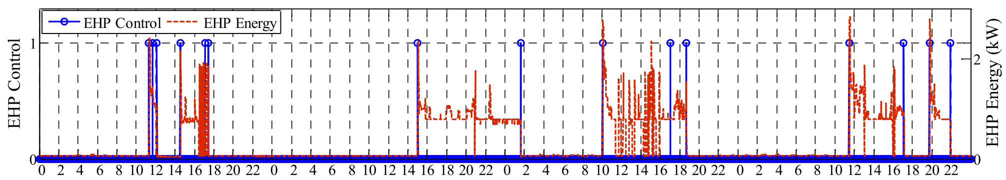


Figure 13 Pattern of occupant's EHP control and energy use by EHP during 2 to 5 March (x axis is time (hour))

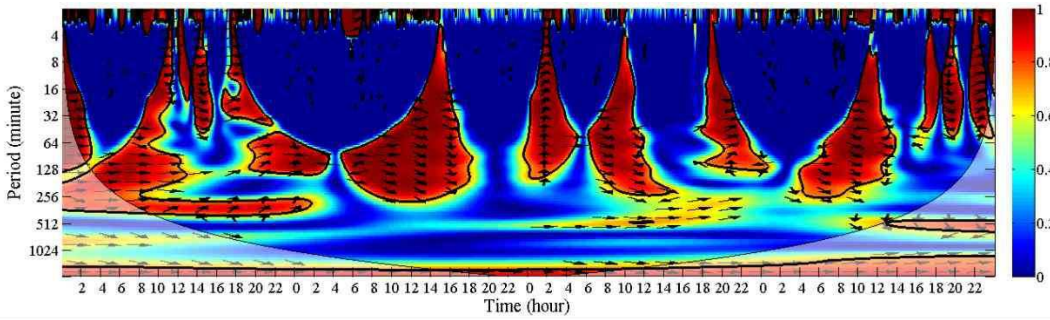


Figure 14 Wavelet coherence between pattern of occupant's EHP control and energy use by EHP during 2 to 5

CONCLUSION

The occupant modeling is not well-represented and remains an unsolved issue in the BEPS. Based on a series of experiments, this paper explored the characteristics of occupants in the perspective of occupant presence/behavior vs. energy consumption. The authors investigated the difference in each occupant's preference in terms of his/her desire to control indoor environment (temperature, CO2 concentration). It was shown that the indoor environment is influenced by 'only a few' occupants in the room who are willing to control the environment.

The randomness of occupant presence and behavior was also tested. It was shown that each occupant presence seems to be close to the random walk, and the group presence strongly follows the random walk. In other words, the occupant presence cannot be easily modeled or predicted. Occupant behavior (control of door/window, control of EHP) doesn't follow the random walk.

The time-series correlation between occupant presence/behavior and energy consumption was investigated using wavelet coherence. It was shown that the occupant presence and energy consumption were not correlated. There was no strong correlation between the occupant behavior and the energy consumption except the case when the EHP was controlled by occupants. In other words, what influences the energy consumption is 'occupants' active action' to control a heating/cooling system (turn on/off). Such active control action has no particular frequency since its frequencies are wide spread. This means that it is hard to predict the control action of occupants in terms of a certain time interval.

In summary, this paper delivers the following: the characteristics of occupant's presence/behavior and their impact on energy prediction. But, it should be noted that this study was conducted in a single laboratory office in a University building in South Korea. The methodologies presented in the paper will contribute to expand our understanding of the OB modeling and contribute to better prediction of building performance.

ACKNOWLEDGEMENT

This research was supported by a grant(15AUDP G02) from Architecture & Urban Development Research Program funded by Ministry of Land, Infrastructure and Transport of Korean government.

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