Modelling and Simulation of Lighting Use Patterns in Office Spaces

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Abstract

While building engineers attempt to automate building systems in modern high performance buildings, their efforts may lead to inverse consequences with respect to comfort and energy performance of buildings where they neglect occupants' preferences. The objective of this research is to evaluate the impact of various light control systems, including automatic and manual, on lighting electricity use. To this end, probabilistic models for occupants' presence and actions on lighting were developed based on empirical data being collected in 25 perimeter offices in a building. These probabilistic models and a set of light control systems were implemented in building performance simulation (BPS) tool EnergyPlus to assess lighting electricity consumption with various lighting control systems. The results indicate a reduction in lighting electricity use by a factor of seven with manual light control in comparison with the occupancy on and vacancy off. The ratio of lights on to the occupied period is reduced by 76% and 90% based on the experiment and simulation results, respectively, using the manual on and auto off control system compared to the auto on and off.

Keywords: occupant behaviour, light control system, experiment, empirical-based model, building performance simulation.

Introduction

In recent years, there has been a surge in incorporating automated building systems to provide occupants with a more comfortable indoor environment and to reduce building energy consumptions while this may have the opposite consequence where occupants' preferences are neglected (e.g. Dounis and Caraiscos, 2009). For instance, occupancy-based lighting control may be considered to save energy as well as fulfilling occupants' satisfaction. Escuyer and Fontoynont's (2001) study states that some occupants prefer occupancy-based lighting control as they can rely on occupancy sensors to switch on/off lights rather than taking care of light switch on/off.

However, building standards (e.g. ASHRAE 2016) recommend that the lighting should not be turned on automatically upon occupancy. Occupancy-based light switch on by any occupants' arrival events and movements in their workspaces is not an energy-efficient strategy when indoor daylight can maintain occupants' visual comfort (e.g. Tzempelikos, 2010; Gunay et al., 2016).

Furthermore, built environments host occupants as active agents, where dynamic back and forth interactions affect both occupants' comfort and buildings' energy performance. Consequently, comfort and energy performance of existing buildings substantially deviate from theoretically logical estimations computed by simplistic assumptions with respect to occupants' presence and actions on building systems (Dasgupta et al., 2012; Korjenic and Bednar, 2012; Menezes et al., 2012; de Wilde, 2014).

Where automatic building control systems are not taking account of occupants' reactions to built environments, occupants' behaviors may not comply with designers and operators' anticipation. For instance, anecdotal evidence is that occupants cover motion sensors of light switches to override automatic light switch on/off (Figure 1). Some occupants indicated their offices are too bright or too dark when lights are turned on or off automatically. Some occupants stated their preference for task lights as they get headache with fluorescent lamps installed in their offices (Wilkins et al., 1989; Gilani and O'Brien, 2016).

Moreover, the perception of control over environmental conditions affects occupants' satisfaction with their built environments (Leaman and Bordass, 2001; O'Brien and Gunay, 2014).

The objective of this research is to investigate lighting use patterns in office spaces. The impacts of empirical-based and a set of light control systems on lighting energy consumption are evaluated. To this end, a monitoring campaign is being conducted in an office building. The findings of this study will provide insights on lighting use patterns in office spaces. These insights will be useful for two aspects: (1) in the operation and maintenance of lighting control systems in the existing building being monitored, and (2) in the design process of future buildings. The ultimate goals of both aspects are to provide a more comfortable environment for occupants and to save lighting energy consumption.

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Figure 1. Evidence of taping occupancy sensor of light switch by occupants in an office building (taken from (Gilani and O'Brien, 2016)).

Experimental setup

The field study is being carried out in 25 perimeter offices in an academic building upon obtaining the ethics clearance. Built-in wall thermostats, already installed in each office, are recording occupancy. These thermostats are equipped with passive infrared motion (PIR) sensors and are integrated with the building automation system (BAS) (Figure 2a). The distance range and the coverage horizontal and vertical angles of the PIR sensors are 5 m, 100º, and 80º, respectively.

As the light switches are not integrated with the BAS, stand-alone data loggers with a light threshold of 65 lx, attached to the lighting fixture, are being used to record lights' on/off state in each office (Figure 2b). All the monitored offices are already equipped with stand-alone occupancy-based light switches. However, the stand-alone occupancy-based light switches in three of the offices being monitored were already changed to the standard on-off (single-pole) ones at occupants' request. The lighting control were set to occupancy on and vacancy off with 15 minute time delay upon departure. After collecting data for five months, the authors converted the automatic lighting control to the manual on and vacancy off with 30 minute time delay. This lighting control adjustment was implemented in mid August 2016 and data have been collected since then.

Stand-alone light intensity data loggers with measurement range of 1-32000 lx are measuring the indoor illuminance installed in each monitored office (Figure 2c). Due to the uncertainties associated with measuring workplane illuminance in long-term studies, the authors have attached the light intensity data loggers to the ceiling in each office being monitored.

(a) (b) (c)

Figure 2. Sensors used in the experiment: (a) BAS-integrated built-in sensor for recording occupancy, (b) stand-alone light state data logger attached to the lighting fixture, (c) stand-alone light intensity data logger attached to the ceiling.

Modelling

To assess the impact of various light control systems on lighting electricity use, occupancy is a required input to track: (1) occupants' presence in spaces for occupancy on and/or vacancy off light control systems, (2) occupants' interactions with the lighting.

To this end, the event-based raw data of occupancy recorded by the PIR sensors were converted to presence (i.e. 1) and absence (i.e. 0) time series of 10 minute timesteps. The time delay was determined with confidence interval of 95% by calculating the cumulative distributions of time intervals between each two motion detections (Nagy et al., 2015). For distinguishing between various occupants' habits of active and inactive periods in their offices, time delays were calculated separately for each individual occupant. To generate the occupancy profiles, Page et al.'s (2008) occupancy algorithm was implemented, as the accuracy and reliability of this model have been validated in previous studies (Page et al., 2008; Liao and Barooah, 2010).

In recognition of the variations between the occupancy on different weekdays, especially for the offices occupied by faculty members, the probability of presence at each 10-minute timestep was calculated for each weekday individually as per Page et al.'s (2008) occupancy algorithm using the collected data in the monitored offices. A Gaussian model with three modes was fitted to the probability of presence for each weekday using Equation (1):

$$p(presence) = \sum_{i=1}^{n} a_i e^{-(\frac{t-b_i}{c_i})^2} \qquad (1)$$

where $p(presence)$ is the probability of presence at each 10-minute timestep of each day of week (i.e. 144 10-minute timesteps per day). n is the number of peaks (i.e. three in the current study) of the Gaussian model fitted to the distribution of the probability of presence. a_i is the maximum probability of presence for each mode, b_i is the timestep where a_i occurs, and c_i is the standard deviation from b_i. The Gaussian parameters (i.e. a_i, b_i, and c_i) were calculated individually for each of the 25 monitored offices.

Furthermore, as per Page et al.'s (2008) occupancy model, the mobility parameter was computed for each timestep after removing long absences lasting more than one day unless they were relevant to weekends. Afterwards, the mobility parameter was averaged over all the timesteps between the mean first arrival and the mean last departure for each individual occupant.

Figure 3 shows an example of the profiles of weekly probability of presence for one of the participants in the monitoring study, whose mobility parameter was obtained 0.38. The Gaussian parameters of this example are presented in Table 1.

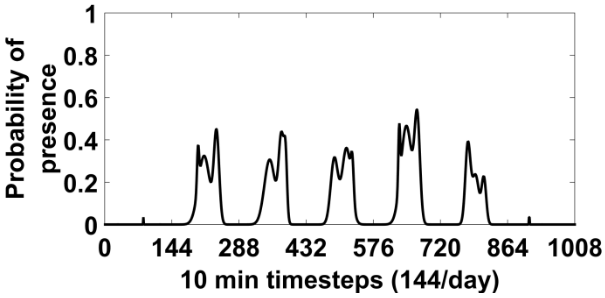


Figure 3. An example of the profiles of weekly probability of presence in one of the monitored offices, with the mobility parameter of 0.38. The parameters of the Gaussian model for each weekday have been provided in Table 1.

Table 1. Parameters of the three-mode Gaussian models fitted to the profiles of weekly probability of presence, for the office shown in Figure 3.

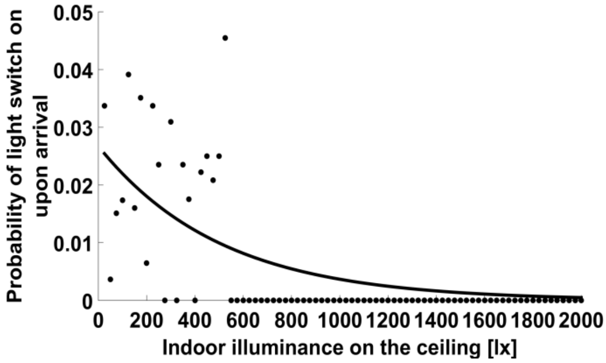
	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.
a1	0.000	0.421	0.243	0.179	0.471	0.233	0.070
b1	4.67	15.98	16.67	16.51	15.73	12.54	7.75
c1	0.359	1.32	0.749	0.713	1.36	1.76	0.098
a2	0.034	0.325	0.409	0.309	0.275	0.372	0.000
b2	13.83	11.53	15.21	10.07	9.27	9.79	12.27
c2	0.069	2.88	1.40	1.82	0.457	1.29	0.179
a3	0.000	0.191	0.307	0.361	0.467	0.215	0.000
b3	19.72	9.36	10.99	14.43	11.84	15.54	19.53
c3	0.327	0.511	2.69	2.26	2.80	1.135	0.219

Light use models were developed based on one and a half months' worth of data collected in each office, which covers the monitoring period of mid August 2016 to the end of September 2016. Since the number of each occupant's actions on lights during this period was insufficient to develop representative statistical models for each office being monitored, light use models were made using the aggregate data combined from all the monitored offices. Indoor illuminance was considered as the influential factor to predict occupants' interactions with the lighting upon arrival and during the intermediate period. Previous research (Hunt, 1979; Love, 1998; Reinhart, 2004; Lindelof and Morel, 2006) proved a significant correlation between occupants' light switch on actions and indoor illuminance.

To estimate the probability of whether an occupant switch on lights upon arrival (i.e. dependent binary variable) with regard to the indoor illuminance (i.e. independent variable), logistic regression model was used in the form of Equation (2):

$$p(light\ switch\ on|arrival) = \frac{e^{\beta_0+\beta_1 E_{in}}}{1+e^{\beta_0+\beta_1 E_{in}}} \qquad (2)$$

where $p(light\ switch\ on|arrival)$ is the probability of light switch on events in the next 10 minutes upon arrival as a function of the indoor illuminance measured on the ceiling (E_{in}). β_0 is the intercept and β_1 is the regression coefficient of the logistic regression model fitted to the light switch on events at different bins of indoor illuminance (i.e. 25 lx) measured on the ceiling (Figure 4). For serving the frequency variations observed at each bin of the indoor illuminance to fit the regression model, the weighting method was applied by the number of observations fell into each bin. Accordingly, Figure 5 represents the number of timesteps at each bin of the indoor illuminance when occupants arrived and lights were off. In total, 3686 timesteps (614 hrs) with the indoor illuminance between 0 and 2000 lx at 25 lx bins were observed, where at 61 timesteps occupants switched on lights.



	Coefficient	Standard error	p-Value
β_0	-3.595	0.183	0.000
β_1	-0.002	0.001	0.004

Figure 4. Probability of light switch on upon arrival with the logistic regression model of:

$$p = \frac{e^{-3.595-0.002E_{in}}}{1+e^{-3.595-0.002E_{in}}}$$

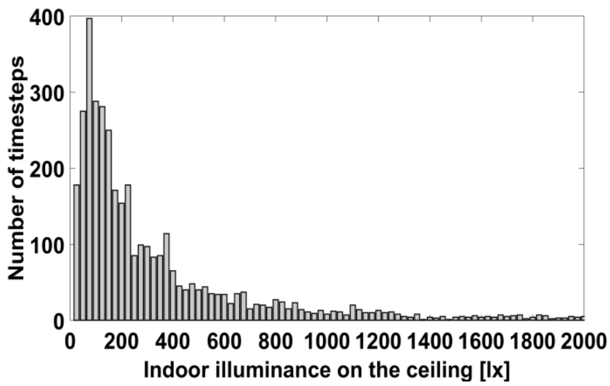
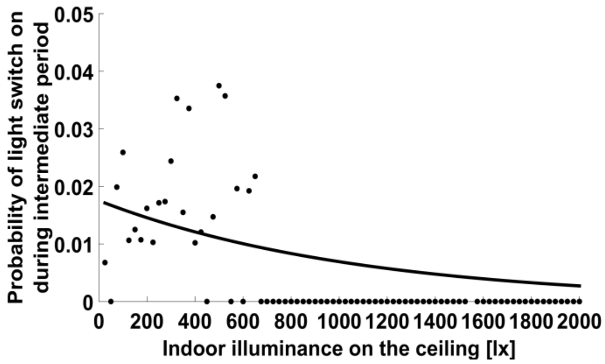


Figure 5. Number of timesteps at each bin of the indoor illuminance measured on the ceiling (i.e. 25 lx), when occupants arrived in their offices and lights were off.

The statistical model to predict the probability of occupants' light switch on actions during the intermediate period was developed using logistic regression model based on Equation (3):

$$p(light\ switch\ on|intermediate\ period) = \frac{e^{\beta_0+\beta_1 E_{in}}}{1+e^{\beta_0+\beta_1 E_{in}}} \qquad (3)$$

where $p(light\ switch\ on|intermediate\ period)$ is the probability of light switch on events during the intermediate period as a function of the indoor illuminance measured on the ceiling. β_0 is the intercept and β_1 is the regression coefficient of the logistic regression model fitted to the light switch on events at different bins of the indoor illuminance measured on the ceiling (Figure 6). Similar to the light switch on model upon arrival, weighting method was used to fit the regression model with respect to the number of timesteps at each bin of the indoor illuminance during the intermediate period when occupants were present in their offices and lights were off (Figure 7). Out of total 6297 timesteps (1050 hrs), 84 times occupants turned on lights.



	Coefficient	Standard error	p-Value
β_0	-4.027	0.146	0.000
β_1	-0.001	0.000	0.016

Figure 6. Probability of light switch on during intermediate period with the logistic regression model of: $p = \frac{e^{-4.027-0.001E_{in}}}{1+e^{-4.027-0.001E_{in}}}$

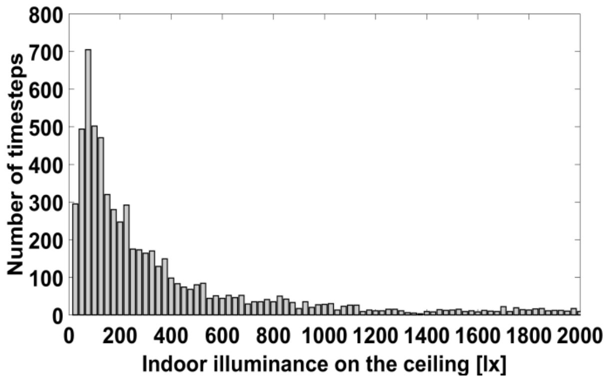
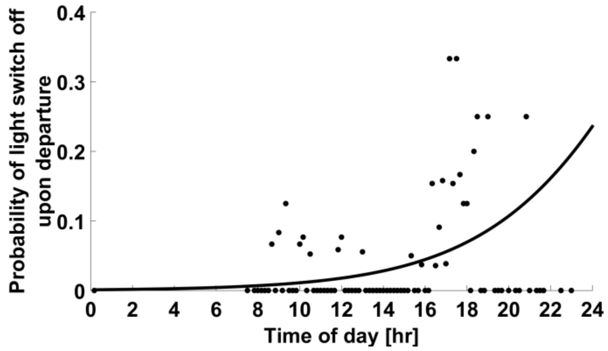


Figure 7. Number of timesteps at each bin of the indoor illuminance measured on the ceiling (i.e. 25 lx), when occupants were present in their offices and lights were off.

For how often occupants switch off lights, vacancy period has been proven as a predictor (Boyce, 1980; Pigg et al., 1996; Reinhart and Voss, 2003). However, there is no computationally efficient way to incorporate a light switch off model as a function of vacancy duration in EnergyPlus where Page et al. (2008)'s occupancy model does not provide a prediction of vacancy durations at the time of departure. Therefore, to implement an empirical-based model for light switch off events in simulation, a light switch off model was developed as a function of the time of day (i.e. predictor) as presented in Figure 8. Figure 9 shows the number of observations at each 10-minute bin for the time of day when occupants left their offices and lights were on. In total, 1208 timesteps were observed where 37 times occupants switched off lights upon departure.



	Coefficient	Standard error	p-Value
β_0	-6.845	0.941	0.000
β_1	0.236	0.061	0.000

Figure 8. Probability of light switch off as a function of time of day with the logistic regression model of: $p = \frac{e^{-6.845+0.236t}}{1+e^{-6.845+0.236t}}$ *where t is time of day.*

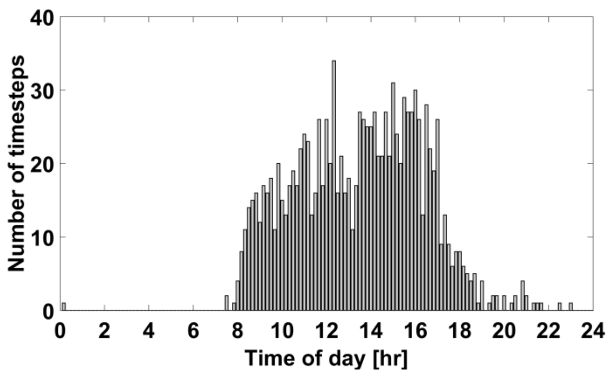


Figure 9. Number of timesteps at each bin of day time (i.e. 10 minutes) when occupants left their offices and lights were on.

Simulation

To evaluate the impact of different light control systems on lighting electricity consumption, a typical office space with dimensions W × L × H = 4.0 × 4.0 × 3.0 m and a south-facing window with window-to-wall area ratio of 40% and sill height of 0.8 m was simulated in EnergyPlus (Figure 10). The interior surface of the floor, walls, and ceiling were assumed to have a visible reflectances of 0.2, 0.5, and 0.8, respectively. The transmissivity of the window was assumed 0.44 at normal incidence.

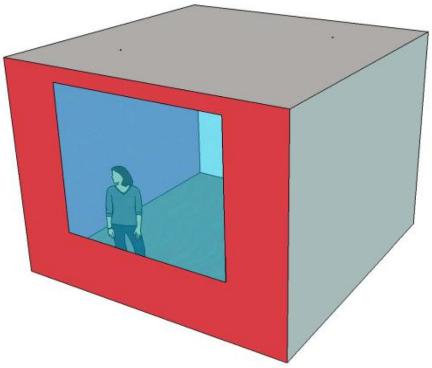


Figure 10. Geometry of the simulated office.

While workplace illuminance is the common parameter to calculate in BPS tools, in the experiment conducted in this research, the indoor illuminance was measured on the ceiling vertically downwards due to the uncertainties associated with measuring the workplane illuminance in long-term studies. As this proxy variable was impractical to be simulated in EnergyPlus, RADIANCE-based daylighting analysis tool DAYSIM (Reinhart, 2001) was used to calculate annual indoor illuminance on the ceiling. The sensor was located in the middle of the ceiling. Window shades were assumed open. The output of DAYSIM was implemented in EnergyPlus as an input.

To evaluate the impact of light control systems on lighting electricity use, four control systems were implemented in EnergyPlus as follows: (1) auto on and off with 15 minute time delay upon departure, (2) auto on and off with 30 minute time delay upon departure, (3) manual on and off where if occupant did not turn off lights upon departure, lights were off at the end of that day, and (4) manual on and auto off with 30 minute time delay upon departure (Table 2).

Table 2. Lighting control systems

Control system	Switch on	Switch off
1	Auto (occupancy)	Auto (vacancy 15 minutes)
2	Auto (occupancy)	Auto (vacancy 30 minutes)
3	Manual (model-based)	Manual (model-based)
4	Manual (model-based)	Auto (vacancy 30 minutes)

The three empirical-based lighting models, explained in the previous section, were implemented in the Energy Management System (EMS) application of EnergyPlus. The input coefficients of the probabilistic lighting models were randomly generated from the normal distribution profiles with the mean and standard deviation of each coefficient (i.e. β_0 and β_1) at the beginning of each run period (i.e. one year) represented each occupant. Occupancy profile of each participant were the empirical-driven model developed for each participant using Page et al.'s (2008) model. The occupancy models were also implemented in the EMS application of EnergyPlus.

To model the probability of different occupants' presence and interactions with lights, the Monte Carlo technique was applied over the 25 participants in the monitoring study being carried out in this research. 25 one-year run periods were simulated representing each of the 25 participants.

Results and discussion

As the distribution of annual lighting electricity use for the four investigated lighting control systems presented in Figure 11, a 91% reduction in the annual electricity consumption is achievable with the manual on and auto off control system compared to the occupancy on and vacancy off (i.e. lighting control systems one and two). Note that ASHRAE Standard 90.1 (2016) allows to reduce the *lighting density power* (*LPD*) where occupancy sensors are used based on Equation (4):

$$LPD_{adjusted} = LPD_{reference} \times (1 - OSR) \qquad (4)$$

where $LPD_{adjusted}$ is the adjusted lighting power density, $LPD_{reference}$ is the reference lighting power density determined based on spaces' type, and *OSR* is the *occupancy sensor reduction* factor. As per ASHRAE Standard 90.1 (2016), *OSR* can be increased by 25% where the manual on lighting control system is used. For instance, the *LPD* can be reduced from 11.8 W/m^2 ($LPD_{reference}$) to 8.29 W/m^2 ($LPD_{adjusted}$) for an enclosed office with occupancy sensors. Using manual on lighting control system, the *LPD* will be 7.40 W/m^2. So, the electricity use decreases 11% with the manual on control system compared to the auto on control. However, the electricity savings in the current results indicated a 91% energy savings caused by the manual on control system . This indicates that the additional reduction factor (i.e. 25%) suggested by ASHRAE Standard 90.1 (2016) should allow more flexibility regarding how well a building space is daylit. A space with poor daylight quality will not benefit from manual on lighting controls whereas a well daylight space will benefit noticeably.

As shown in Figure 11, the auto light switch off can reduce electricity use compared to the manual off where manual on lighting control system is implemented. However, occupants may take less responsibility for turning off the lights because they rely on automatic control (Pigg et al., 1996). The first and second lighting control systems are being implemented in some modern high performance buildings while building standards (e.g. ASHRAE 2016) recommend manual on lighting control. For instance, in the monitored building in this research, the former one was the previous light control system before the authors adjusted it in the monitored offices. The third light control system (i.e. manual on and off) shows the potential for reducing lighting electricity use by 36% and 44% compared to the first (i.e. auto on and off with 15 minute time delay) and the second (i.e. auto on and off with 30 minute time delay) light control systems, respectively. Tzempelikos (2010) and Gunay et al. (2016) discovered similar conclusions with respect to lighting electricity consumption using manual control systems.

In addition to save on lighting energy, manual control of lighting can enhance occupants' comfort. Informal interview of the authors with the participants of this monitoring study revealed that most of them are satisfied with the adjusted light control system. However, an occupant whose office's blinds are often closed stated the preference for the former light control system (i.e. occupancy-based light switch on). This participant stated that with occupancy on lighting control, occupants do not need to care about switching on lights when offices become dark and they are sitting at their desks. Another occupant considered the former one more efficient where hands are full.

While occupants' control over building systems can enhance their perceived comfort, this may lead to inefficiencies in the building energy use (Inkarojrit, 2008; Gunay et al., 2014). For instance, occupants may leave their lights on upon their short-term departure during the day (Boyce, 1980; Love, 1998) as they may not consider it being worth of conserving energy or may forget to turn lights off upon their departure. Furthermore, the interview of the authors with the participants in the monitoring campaign revealed that corner offices are so bright during the day that the switched-on lights are not detectable. It is worth noting that the corner offices were so bright that the light state data loggers attached to the lighting fixture were not able to detect light states without an additional component to remove the effect of daylight. In such cases, automatic control of light switch off can economize on lighting use compared to solely manual control.

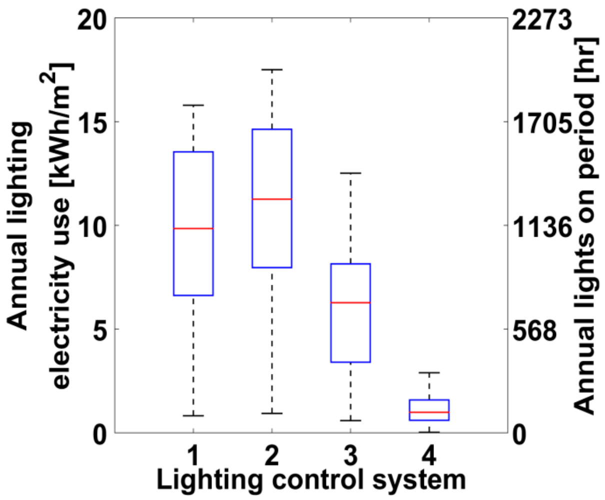


Figure 11. Distribution of the annual lighting electricity use (kWh/m^2) and lights on period (hr) for various control systems: (1) auto on and off with 15 minute time delay, (2) auto on and off with 30 minute time delay, (3) manual on and off based on the empirical models, and (4) manual on based on the empirical models and auto off with 30 minute time delay.

Figure 12 presents the relationship between the total annual occupancy period and lighting electricity use where a linear regression model fit to all occupants' corresponding data. The positive constant term of the linear models fit for the first, second, and third lighting control systems indicates that the demand for lighting rarely reaches zero even at hypothetical-zero occupancy. The investigation of lighting states in the monitored offices with the previous lighting control system (i.e. auto on and off) also revealed several instances with lights on during unoccupied period. With manual on system, the lighting use can be reduced by a factor of seven compared to the auto occupancy on and vacancy off.

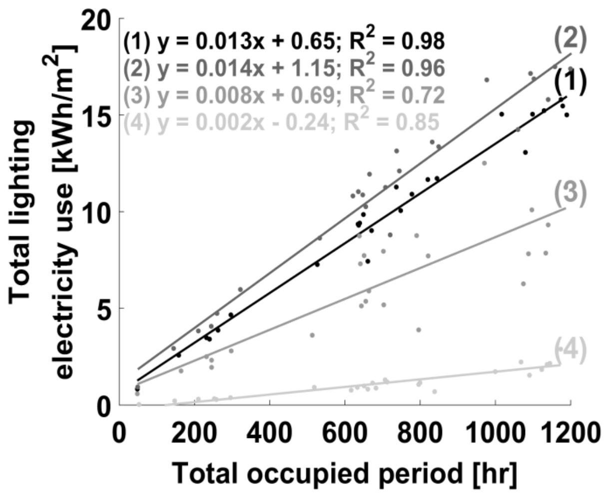


Figure 12. Linear regression models fitted to the relationship between the annual lighting electricity use (kWh/m^2) and occupied period (hr) for various control systems: (1) auto on and off with 15 minute time delay, (2) auto on and off with 30 minute time delay, (3) manual on and off based on the empirical models, and (4) manual on based on the empirical models and auto off with 30 minute time delay.

Figure 13a presents the lights on period normalized by the occupied period for one and a half months before and after the authors changed the light control system in the offices being monitored. The ratio of lights on period to the occupied period shown in Figure 13b represents the annual output of simulation in EnergyPlus with light control systems one and four (see Table 2). A reduction of 90% is observed with the simulation results with manual on and vacancy off compared to the occupancy on and vacancy off. The results of the experiment approves this reduction, showing 76% decrease in the lighting use after changing the light control system to manual on and vacancy off compared to the previous light control setting (i.e. occupancy on and vacancy off). Note that Figure 13a excludes the three offices for which the original light switches were replaced with standard on-off (single-pole) ones. In this figure, the outlier and the maximum ones are relevant to two offices where the investigation of the light states shows the improper functioning of the light control to switch off lights during unoccupied period.

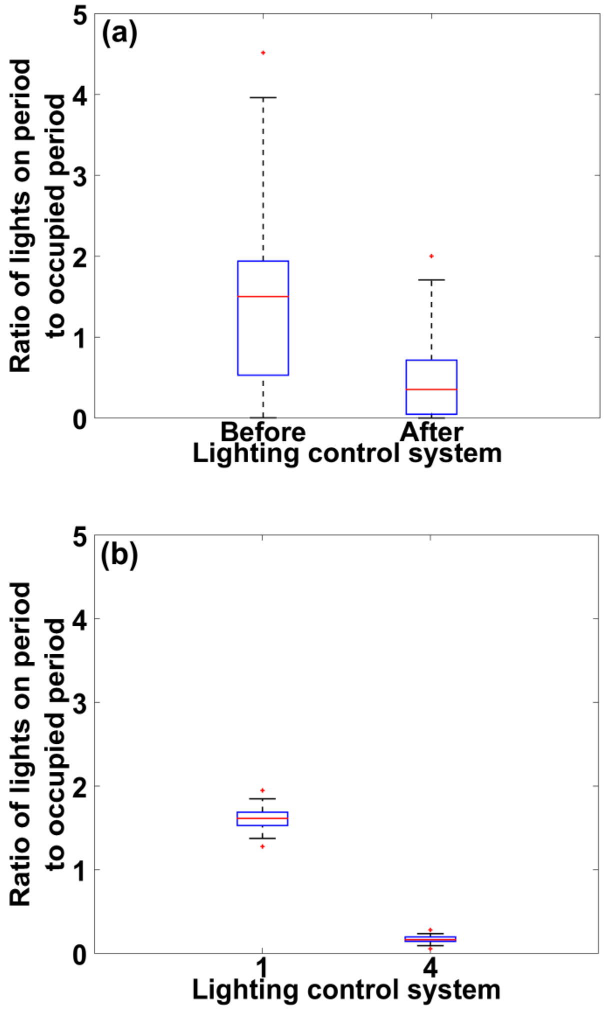


Figure 13. Ratio of lights on period to the occupied period: (a) experimental results, with 1.5 months' worth of data before and after adjusting light control system in the monitored offices, (b) one-year run-time simulation results with light control systems 1 and 4 (see Table 2).

The simulation results in Figure 13b indicates that the lighting electricity use increases as much as twice the occupied duration with the light control system one. This is because that once an office is vacated, its lights are still on for a designated period (i.e. 15 minutes with light control system one). Where occupants leave their offices more frequently during the day and their vacancies last longer than the adjusted time delay for lights to be auto off, lighting electricity use is higher inevitably with vacancy off control system (Figure 14). This is especially the case for occupants with higher mobility parameters (Page et al., 2008) that can be considered as a representative of how often occupants leave and arrive their offices during the day (Figure 15).

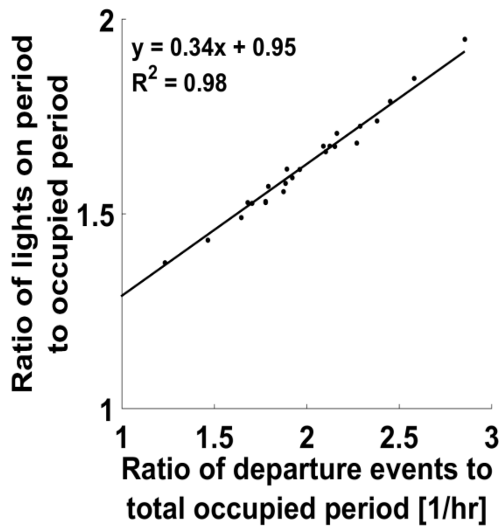


Figure 14. The relationship between the ratio of lights on period to the occupied period and the ratio of departure events to the total occupied period, where the first light control system (auto on and off with 15 minute time delay) is applied.

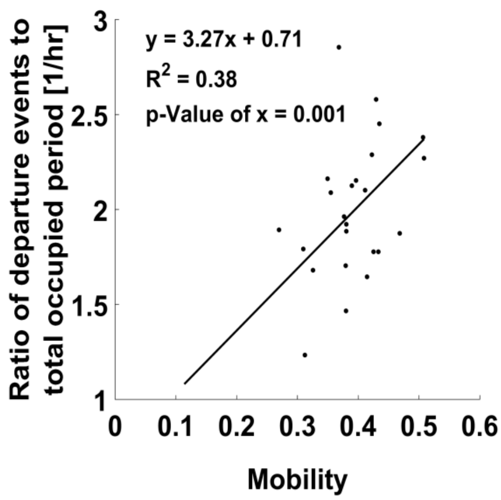


Figure 15. The relationship between the ratio of departure events to the total occupied period and the mobility parameter, where the first light control system (auto on and off with 15 minute time delay) is applied.

There were some limitations in this research, that may cause some bias in the exploited results, as follows.

- In the monitoring campaign being conducted in this research, light states of the fluorescent lamps installed in each office are being recorded while the authors' walkthroughs to the monitored offices show that some participants are also using task lights and in some cases, participants stated their preference for non-fluorescent lamps. Therefore, the authors acknowledge the possibility of bias in the low rate of lighting use recorded in this research.

- The authors adjusted light control system in the summer time, before the start of the new academic year, and when the daylight level can provide occupants' visual comfort. Therefore, the low lighting use during this one and a half month period (after adjusting light control system) in the monitored offices presented in this article may be bias because of the quiet summer term and long summer days with sufficient sunlight during the business hours.

- For simulating lighting use patterns in EnergyPlus, the timestep was set 10 minutes, the same as the frequency of data logging in the monitoring campaign. This prescribed timestep results in that with the light control system one where lights should be off with a time delay of 15 minutes, the lights are still on 5 more minutes upon each departure unless occupants arrive their offices earlier than that. Therefore, the authors acknowledge the bias in the higher electricity use with simulation compared to the expected value with this light control system.

Conclusion

With the aim of assessing the performance of lighting control systems, various lighting controls including manual and automatic were implemented in BPS tool EnergyPlus. To this end, probabilistic models for occupants' presence and actions on lights were developed based on a monitoring campaign being conducted in 25 perimeter offices. The results of this evaluation indicate that:

- Manual on and vacancy off lighting control system leads to a reduction in the ratio of lights on period to the occupied period by a factor of 4 and 10 based on the experiment and simulation results, respectively.

- A reduction of 91% in the annual lighting electricity use is achievable using manual on and vacancy off lighting control system in comparison with the occupancy on and vacancy off.

- Manual light switch on and off reduces lighting electricity use by about 40% compared to the occupancy on and vacancy off lighting control system.

- Automatic occupancy-based light switch on control leads to a high lighting electricity use, while using daylight sensors can customize on lighting demand, especially in perimeter offices where daylight can be sufficient to respond to visual comfort during business hours.

The future necessary research extracted from this research are as follows.

- Light switch models were developed based on the aggregate data due to that the rate of changes in light states in each monitored office during one and a half month's worth of data were insufficient to develop statistically representative model. This method may neglect the variety between occupants' lighting preference and interactions. The authors are continuously collecting data to develop models for each individual occupant.

- It is necessary to determine whether a light use model developed based on aggregate data can be representative of individual light use patterns. This necessitates long-term data collection, where the number of offices and the rate of changes in light states are important factors for this purpose.

- Page et al.'s occupancy model does not predict vacancy durations at the time of departure, and thus vacancy duration could not be used and implemented into EnergyPlus as a predictor for manual light switch off events. Instead, time of day was used as the predictor. Lighting use patterns with respect to various occupancy models is a necessary research.

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