Occupant monitoring, modelling, and simulation to improve office design and operation

by

Sara Gilani

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Abstract

Building engineers and managers often treat occupants as passive agents despite their important role in building energy performance. Meanwhile, neglecting occupants' preferences may lead to poor implementations of building controls. The overall goal of this research is to improve buildings' energy performance and occupants' satisfaction by considering occupant-building interactions. This research first assessed the impact of static and dynamic occupant modelling approaches in a simulation-based analysis using the existing occupant models. The results showed the discrepancies between these two approaches in predicting the energy performance. The analysis emphasized the importance of using dynamic modelling approach. Given that the existing occupant models are context-specific, the next steps of this research focused on conducting a monitoring campaign. Therefore, the various monitoring methods exist in the literature and the anecdotal evidence were critically reviewed. Among the methods, environmental conditions are more controllable as well as configuring building designs and control systems are more flexible with laboratories and virtual environments. However, researchers can achieve valuable information on the natural occupants' presence and behaviour by in-situ monitoring on a relatively large sample size at a lower cost in long-term studies. This research adopted the in-situ method in a case study. A monitoring campaign was conducted in an office building in Ottawa, Canada. The monitoring study aimed to: (1) extract lessons beneficial for buildings' operation and design, and (2) improve the existing building's operation and occupants' satisfaction. Among the various domains covered in the exploratory analysis, the occupancy-based lighting control was found not to reduce the lighting energy use and satisfy occupants. Therefore, the control system was adjusted to the manual-on/vacancy-off. The results indicated a reduction in the lighting use by a factor of seven. The exploration of several fundamental occupant modelling issues revealed that start date and duration of a study are influential factors on the reliability of models. The findings of this research indicate the great potential of considering occupant-building interactions for the betterment of buildings' energy performance and occupants' satisfaction.

Preface

This thesis is of an integrated-article type, consisting of four journal papers, either published or in review. Should readers wish to refer to the material from this thesis, the current thesis is required to be cited.

The articles included in this thesis are as follows.

- **Article 1:** Gilani Sara, O'Brien William, Gunay H. Burak, Carrizo J. Sebastián. 2016. Use of dynamic occupant behaviour models in the building design and code compliance processes. *Energy and Buildings: Special Issue on Advances in BEM and Sim* 117:260-271.
- **Article 2:** Gilani Sara, O'Brien William. 2016. Review of current methods, opportunities, and challenges for in-situ monitoring to support occupant modeling in office spaces. *Journal of Building Performance Simulation: Special Issue on Occupant Behaviour Fundamentals*.
- **Article 3:** Gilani Sara, O'Brien William, Carrizo J. Sebastián. (2017). Interpreting occupant-building interactions for improved office building design and operation. *ASHRAE Transactions* 123 (2).
- **Article 4:** Gilani Sara, O'Brien William. (In review). Occupants' use of lighting controls in offices: A case study. *Energy and Buildings*.

Slight modifications have been made to the articles in each corresponding chapter. Abstract, introduction, and conclusions of the articles are particularly revised and merged in Chapters 1 and 6 for the integrity of the content and smooth transitions between chapters. Some other revisions, mainly in Sections 4.4.1 and 4.4.2, have also been made to Article 3 in Chapter 4 upon receiving committee members' feedback. A description on the case study in Chapter 5 has been summarized by referring to Chapter 4.

Use of copyrighted material of the aforementioned articles in this thesis is acknowledged as per the corresponding publisher's permission guidelines with respect to the author's rights.

In the co-authored articles, Sara Gilani was the principal contributor to the research methodology conception and design, experiment/monitoring set up and conduct, data acquisition, data analysis and interpretation, and preparing and writing the material presented in the articles, under the supervision of William O'Brien. H. Burak Gunay and J. Sebastián Carrizo provided critical review of and feedback on the manuscript of the corresponding articles.

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1. Introduction

In the past four decades, specific attention has been drawn to occupant behaviour as a source of discrepancies between the predicted and the real building energy and comfort performance (Norford et al., 1994; Neto and Fiorelli, 2008; Demanuele et al., 2010; Dasgupta et al., 2012; Menezes et al., 2012; de Wilde, 2014). Occupants have a significant impact on energy performance of buildings due to their operations of building components and systems (Hoes et al., 2009; Parys et al., 2010; Bonte et al., 2014; Brown, 2015; O'Brien and Gunay, 2015; Gilani et al., 2016). For instance, occupant behaviour can affect annual energy use of commercial buildings by a factor of two to five (Haldi and Robinson, 2011; Clevenger et al., 2014). Energy consumption in residential buildings may differ by a factor of two to four (Gill et al., 2010; Saldanha and Beausoleil-Morrison, 2012). Occupants' significant impact on building energy performance is the case even for buildings equipped with state-of-the-art technologies, as building controls may not be aligned with occupants' preferences and their interfaces may not be designed thoughtfully. In addition, controls' interfaces may not be user-friendly enough to be used and thereby require training (Bordass et al., 1993; Bordass et al., 1995; Galasiu and Veitch, 2006).

Despite the active role of occupants in buildings' performance, designers usually treat occupants as passive agents. However, occupants behave differently from what designers expect them to do (Cole and Brown, 2009; O'Brien and Gunay, 2014). For instance, designers use simplistic schedules as inputs in a simulation-based analysis of design alternatives for code compliance certificate (O'Brien et al., 2016). Meanwhile, occupants frequently respond to discomfort to restore comfort in the easiest way, rather than an energy-efficient way. They may not be as knowledgeable or conscious of buildings' energy performance as designers expect from them (Fedoruk et al., 2015). Therefore, simplifying the underlying uncertainty in occupant behaviours using deterministic assumptions as inputs to building performance

simulation (BPS) tools in a simulation-aided design process causes a gap between the real and predicted building performance.

In recognition of the significance of occupants' impact on buildings, monitoring occupant-building interactions has been performed around the world dating back to 1970s (Hunt, 1979) to derive occupant models. These data-driven occupant models are based on observations of occupancy, environmental conditions, and building components and systems over a period of time. In contrast, default deterministic schedules (e.g. DOE reference office model (Deru et al., 2011), ANSI/ASHRAE/IES Standard 90.1 (2013c), and ANSI/ASHRAE/USGBC/IES Standard 189.1 (2014)) adopted in BPS tools are based on engineering assumptions for ideal operations rather than representative statistical models supported with large datasets (Deru et al., 2011). In modelling studies of occupants' presence and behaviour based on empirical data, models for occupancy (Newsham et al., 1995; Reinhart, 2001; Reinhart, 2004; Wang et al., 2005; Page et al., 2008) and occupants' operation of lighting (Hunt, 1979, 1980; Pigg et al., 1996; Reinhart and Voss, 2003; Reinhart, 2004), window shading devices (Sutter et al., 2006; Inkarojrit, 2008; Haldi and Robinson, 2010), operable windows (Fritsch et al., 1990; Nicol, 2001; Rijal et al., 2007; Herkel et al., 2008; Rijal et al., 2008; Yun and Steemers, 2008; Haldi and Robinson, 2009), plug-in appliances (Gunay et al., 2016d; Mahdavi et al., 2016), heating and cooling devices, and thermostat adjustments, have been developed in correlation with predictive variables.

The two general domains that can benefit from data-driven models of occupant behaviours are: (1) to apply the models in building control systems to improve comfort and reduce energy consumption (Gunay et al., 2016b; Gunay et al., 2016c; Gunay et al., 2017b), and (2) to implement the models in BPS tools in simulation-based design processes for the evaluation of a variety of design alternatives to provide a more representative estimate of what occurs in real situations concerning comfort and energy consumption (Bourgeois et al., 2006; Hoes et al., 2009; Parys et al., 2010; Attia et al., 2011; O'Brien and Gunay, 2015;

Gilani et al., 2016). It is worth mentioning that occupant models can be implemented in BPS tools using averaged or stochastic modelling methods to simulate dynamic occupant-building interactions. While triggers are data-driven fixed thresholds/schedules in the averaged modelling method, probability distributions determine such triggers in the stochastic modelling method.

Therefore, observation of how occupants interact with their built environments in existing buildings is necessary to develop occupant models, however, researchers may benefit from other occupant studying methods as well, such as laboratory and virtual environment methods. In addition to the quantitative analysis in monitoring occupants' presence and behaviour, researchers may also extract qualitative lessons of how occupants interact with buildings (Lopes et al., 2012) and apply their findings in designing new buildings. For instance, Parys, Saelens, and Hens (2011) extracted qualitative conclusions from their surveys, such as: occupants open windows in the winter for fresh air and close windows in the summer for noise.

1.1. Research objectives and questions

Considering the significant role of occupants in building energy performance, this research aims to study occupants and energy flows in the context of an office building as well as to incorporate the exploited lessons for the betterment of buildings' functional operation and design. In general, extracting lessons, both quantitative and qualitative, from occupants' operation of building components and systems in existing buildings is crucial for two aspects: (1) to operate and maintain existing buildings more efficiently for occupants' comfort and building energy performance, and (2) to provide building designers and engineers with recommendations for better design and control of future buildings. The two risks that neglecting occupants in building design and operation processes may cause are: (1) prediction of energy performance may not be a good representative of real situations, and (2) sub-optimal decision-making in designing and operating buildings.

The main objective of this research is to study occupant-building interactions for the prediction and improvement of building energy performance and occupants' satisfaction in office spaces. The overall research questions are:

- What if occupants are not treated as active agents in simulation-based analysis processes?
- How do occupants act in and react to triggers in their built environments? What are the resulting influences on the energy demand of built environments in response to occupants' presence and behaviour?
- In which way can data collection on buildings' energy performance and occupants' presence and behaviour help improve buildings' operation, maintenance, and design?

The following sub-objectives are addressed in this research to explore the above main research questions in the context of private offices. The overall sub-objectives of this research which aimed in each of the articles integrated in this thesis are listed below.

- Article 1 (Chapter 2):
    - To study the impact of conventional and dynamic occupant modelling approaches on building energy performance,
    - To calculate energy consumption of various design alternatives using the static and dynamic models, and
    - To do a design alternative decision-making based on the static and dynamic models.
- Article 2 (Chapter 3):
    - To investigate potential research techniques for collecting data on occupants' presence and behaviour, and
    - To evaluate the feasibility of various data collection methods in studying occupants on site.

- Article 3 (Chapter 4):
    - To perform exploratory analysis on occupants' presence and behaviours and energy flows to investigate the relationship between them in an existing building,
    - To study the impact of contextual factors, such as spaces' orientation, on occupants' presence and behaviour and the consequent building energy use,
    - To extract lessons for the better operation and design from studying occupants' presence and behaviour and energy flows on site, and
    - To explore for deficiencies in building operations resulting in wasting energy and occupants' dissatisfaction and find solutions for them to improve building energy performance and occupants' satisfaction in a case study.
- Article 4 (Chapter 5):
    - To reduce lighting energy use and improve occupants' satisfaction,
    - To develop and verify occupancy and lighting use models,
    - To explore for viable sample size, and
    - To examine the reliability of occupant models in predicting lighting energy use in the case study.

1.2. Theoretical framework

To achieve the objectives of this research, the theoretical framework is framed into two main phases: (1) simulation-based analysis, and (2) experiment-based analysis (Figure 1.1). An overall description of the two main phases of this research project provides a rationale of dividing the theoretical framework into the aforementioned phases.

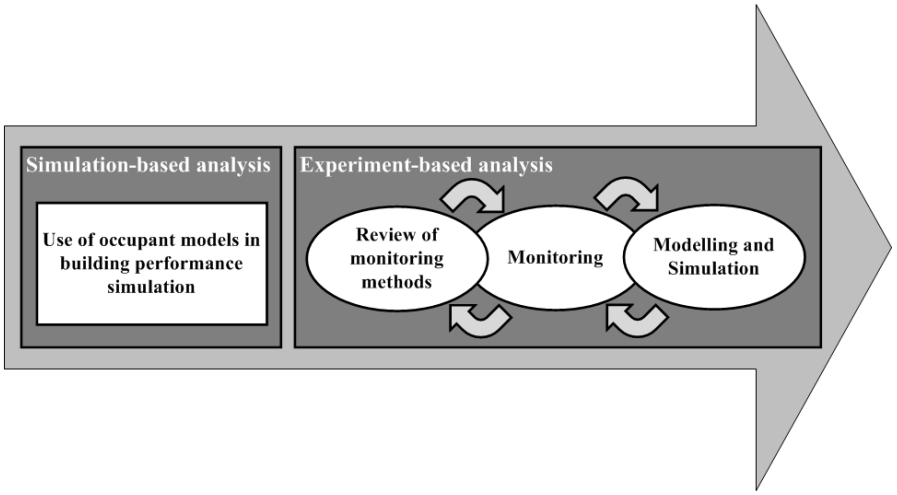

Figure 1.1. Flow chart of theoretical framework.

In the first main phase, existing occupant models were used in building performance simulation. To identify the effect of the conventional and dynamic occupant modelling approaches on the predicted energy use and occupants' satisfaction and design decisions, a comparative analysis of the two modelling approaches was performed. To this end, the energy and daylight performance of a generic perimeter office space in Ottawa, Canada, were evaluated based on the conventional and dynamic occupant modelling using a set of comprehensive performance metrics in a simulation-based analysis. The first phase of this research combined existing occupant models, driven from observational data in different contexts (mostly European countries), whereas climate, culture, and other contextual factors may affect occupants' interactions with buildings. Moreover, the occupant models used for this evaluation were based on field studies in a limited number of peculiar cellular offices (such as with near-south facing windows and easily-accessible motorized blinds). Furthermore, combining these models derived from different studies in one space was the other limitation of this research method.

Therefore, in the second main phase of this research project, an experiment-based analysis was designed. To achieve the objectives of this phase, existing methods in the literature for studying occupants on site were critically reviewed. Likewise, the initial steps for starting a monitoring campaign in an office

building in Ottawa, Canada, were established as per the literature review, whereby personal experience of the researcher to manage this monitoring study was beneficial for the critical review of in-situ monitoring methods as well. Following a few months of data collection while the monitoring study continued, an exploratory research on various domains with respect to the energy flows of the studied offices as well as occupant-building interactions was performed. Based on the outcomes of this exploratory analysis, the lighting control system in the monitored offices was adjusted after about six months to reduce lighting use and improve occupants' satisfaction. The empirical lighting use models were developed and the impact of various lighting control systems on lighting energy use was quantified using the experimental data and simulation.

1.3. Thesis outline

The body of this thesis consists of four main chapters: (1) use of occupant models in building performance simulation, (2) review of in-situ monitoring methods, (3) interpretation of occupant-building interactions, and (4) occupants' use of lighting controls.

Chapter 2: The purpose of this chapter is to provide a better understanding of the influence of assumptions made in representing occupants' interactions with building components and systems over a BPS model's energy use and comfort predictions, as well as their ability to promote better design decisions. To demonstrate the impact of occupant modelling assumptions, the energy and daylight performance of a generic perimeter office space in Ottawa, Canada, are evaluated using industry standard metrics. This chapter has been published as Article 1 (Gilani et al., 2016).

Chapter 3: This chapter focuses on the in-situ monitoring approaches of data collection and the relevant opportunities and limitations to facilitate the monitoring study conducted in the current research in the development of statistical occupant models. The techniques applied in previous studies on occupant behaviour monitoring on site are critically reviewed. Opportunities and challenges of existing monitoring

techniques and the potential to apply new technologies in monitoring studies are discussed, while recommendations for future research are drawn from the previous experience in the literature and the personal experience of the researcher in the initial stages of conducting the monitoring campaign in the current research project. Chapter 3 has been published as Article 2 (Gilani and O'Brien, 2016b).

Chapter 4: This chapter provides insights on how indoor environments are influenced in response to occupant behaviours and offices' characteristics in the case study of this research. These insights are highly beneficial to operate and maintain the existing monitored offices more efficiently and to design new buildings to be more comfortable and energy-efficient. The results of the monitoring campaign conducted in this research on occupants' presence and behaviour, indoor environmental conditions, and energy demand in office spaces are discussed. Chapter 4 has been accepted for publication as Article 3 (Gilani et al., 2017).

Chapter 5: This chapter evaluates the impact of various lighting control systems, including automatic and manual, on lighting electricity use in the case study discussed in Chapter 4. The probabilistic models for occupants' presence and lighting use are developed and the accuracy of the models are evaluated based on the empirical data collected in 25 perimeter offices in the monitored building. These probabilistic models and a set of lighting control systems are implemented in building performance simulation to assess the lighting electricity consumption with various lighting control systems. Chapter 5 has been submitted for publication as Article 4.

Chapter 6: Finally, the conclusions obtained in each aforementioned chapter are discussed in Chapter 6. The major contributions of this research and the recommendations for future research are outlined in this chapter as well.

Chapter 2

This chapter has been published as:

Use of dynamic occupant behaviour models in the building design and code compliance processes.

Gilani S, O'Brien W, Gunay HB, Carrizo JS. *Energy and Buildings: Special Issue on Advances in BEM and Sim*. 2016; 117:260-271.

2. Use of occupant models in building performance simulation

2.1. Introduction

Occupants have a significant impact on energy performance of buildings due to their operations of windows, use of shading devices, lighting control, and thermostat adjustment (e.g. (Parys et al., 2010; Parys et al., 2011; Bonte et al., 2014; Brown, 2015)) while this effect may be neglected by building engineers. For code compliance, the model is often expected to predict performance relative to a reference scenario. The amount of energy savings relative to the reference building may not be a good representative of real situations since current BPS tools report occupants' discomfort without considering occupants' adaptiveness and reactions to discomfort situations (O'Brien and Gunay, 2015). Meanwhile, design practice and code compliance are increasingly relying on BPS tools to predict energy performance and comfort (Attia et al., 2011; Attia et al., 2012).

To account for the important role of occupants on building performance, dynamic interactions between a building and its occupants should be considered using appropriate occupant behaviour (OB) models in the design process. These OB models can be empirically-based and developed from long-term field studies to represent the dynamic interactions between occupants and buildings. There are two possible risks associated with the use of inappropriate OB models and assumptions: (1) energy and other predicted performance results may not reflect what occurs in reality, but perhaps more critically, (2) the results could mislead designers to make sub-optimal design decisions.

Bonte et al. (2014) investigated the impact of occupants' actions on building energy performance and thermal comfort in two different climates by defining two extreme conditions for each of the occupants' actions. They concluded that conventional modelling assumptions underestimate building energy use and overestimate occupants' comfort. Parys et al. (2010) implemented stochastic OB models in building

energy simulations to optimize multiple offices in a commercial building and concluded that energy consumption predicted using the conventional assumptions is higher than that of the stochastic occupant models. However, Parys et al. (2011) drew an important conclusion in a similar study that the uncertainty of single office performance reported by other research may exaggerate total uncertainty because of the diversifying effect of multiple offices at building scale.

Hoes et al. (2009) analyzed the effect of occupant models in the building design process and performed a sensitivity analysis of different design parameters to OB modelling. They concluded that optimization of a building design is achievable by incorporating improved OB modelling in building energy simulation during the design process. Detailed simulation analysis by Tzempelikos and Athienitis (2007) on optimal window size in single-person offices in Montreal showed that without movable shading, the improvement in daylight autonomy was significant for up to window-to-wall area ratios (WWR) of 30% and 50%. Beyond mid-sized windows, there was little improvement to daylighting. Shen and Tzempelikos (2012) found the same optimal WWR as Tzempelikos and Athienitis' (2007) study with automated shading control, for Los Angeles and Chicago. However, it remains unclear how manual blind use affects optimal WWR. In previous research (e.g. (Newsham, 1994; Reinhart et al., 2006; Shen and Tzempelikos, 2012; Tzempelikos and Shen, 2013; Nezamdoost et al., 2014; Dyke et al., 2015)), the effect of manual blind use on the predicted building energy use and thermal comfort has been studied. More recent developments such as the blind modelling efforts of Haldi and Robinson (2010) and the research by Reinhart and Wienold (2011) for a combined analysis of daylighting and thermal performance, demonstrate how different manual blind control strategies affect energy use, visual comfort, and view to the outdoors.

Balancing adequate daylight with minimized visual discomfort is a non-trivial task because ensuring adequate daylight levels during overcast period requires larger windows than during sunny periods. But large windows may cause chronic daylight glare and can have major energy use implications (Ochoa et

al., 2012; Van Den Wymelenberg, 2014). Thus, a considerable number of studies (e.g. (Tzempelikos and Athienitis, 2007; Reinhart and Wienold, 2011)) have focused on assessing facade and controls design using holistic annual performance metrics – considering both comfort and energy - instead of instantaneous daylight analysis under just a handful of sky conditions.

Despite the previous studies, even simplistic consideration of blinds to assess views and daylight availability is not commonplace for simulation-based design. Current modelling guidelines, codes, standards, and rating schemes and metrics regarding daylight and views, all too often focus on potential for daylighting rather than real performance. As eloquently stated by Reinhart et al. (2006), simplistic metrics can lead to designers using "the more the better" rationale for large windows. Clearly, inclusion of blinds would not improve views or daylight availability; though they could mitigate against daylight glare and reduce cooling energy use. Since Reinhart et al.'s (2006) paper, newer versions of the Leadership in Energy and Environmental Design (LEED) have adopted more representative metrics, including spatial daylight autonomy and annual sunlight exposure (IES LM-83-12, 2013). However, previous efforts (e.g. (Reinhart et al., 2006; Reinhart and Wienold, 2011)) have used mostly deterministic occupant models and therefore, questions over real OB control of blinds and diversity modelling remain. For instance, Van Den Wymelenberg (2012) and O'Brien et al. (2013) reported that in reality mean shade occlusions of the numerous studies that have been performed range from 10% to 90% and that while some occupants move their shades more than once per day, frequencies of weekly or less are not uncommon. This diversity in occupant behaviour is in significant contrast to the more common and optimistic modelling assumptions. Due to the rare implementation of dynamic occupant models in design practice, research about the effect of these models on comfort and building energy performance still has a great potential.

This chapter attempts to identify how different OB modelling approaches affect predicted energy use and comfort; and, how these approaches may influence design decisions. First, the methodology used to develop a case study in Ottawa is discussed and an overview of modelling and simulation practice with regards to occupants is provided. Then, the daylight performance and energy results are analyzed using a comprehensive set of existing and developed metrics. Afterwards, the limitations of this study are discussed and the recommendations for future simulation practice are outlined. This chapter concludes that representing occupant interactions with building components using dynamic occupant models is imperative for simulation-supported design and code compliance to predict building performance and design solutions as a better representative of real situations.

2.2. Methodology

This section describes the stochastic OB models, energy and daylight simulations, performance metrics, baseline office model, and the design parameters for the parametric design approach. Several major daylighting design parameters were tested under the static and dynamic occupant modelling approaches. In the next section, the results of the implementation of different occupant models in BPS tool EnergyPlus are used to evaluate their impact on daylight and energy performance and to compare different design strategies.

2.2.1. Occupant behaviour models

To study the impact of occupant behaviour on building design, three empirically-driven probabilistic occupant models were implemented in the EMS feature of EnergyPlus using the scripts available in Gunay et al. (2015b). These models are as follows: (1) Wang et al.'s (2005) presence model, (2) Reinhart's (2004) light switch model, and (3) Haldi and Robinson's (2010) blind use model. Wang et al.'s (2005) presence model allows for an approximation of the vacancy periods instead of assuming constant values for the breaks and lunch periods. Reinhart's (2004) light switch model permits light switch-on

actions at any time of the occupied period. Haldi and Robinson's (2010) blind use model allows for partial or full opening or closing blind events at any time of the occupied period.

Because the models are stochastic, the Markov Chain Monte Carlo method was conducted. Using this simulation method (Gilks et al., 1996; Downing et al., 2013), random numbers between 0 and 1 were generated from the uniform distribution at each timestep. If the random number was lower than the calculated probability, the occupant took action; otherwise the occupant did not take action.

Note that stochastic modelling of the occupancy was necessary for this study, because lighting and blind use depend on the arrival and departure times and the intermediate vacancy durations. Each of occupant models used in this study is briefly explained below.

Based on Wang et al.'s (2005) model for occupancy, the arrival, departure, break times, and the duration of breaks were randomly generated for each day. In this study, the mean arrival and departure times were assumed 9:00 and 17:00, with a standard deviation of 15 minutes. Mean lunchtime and two breaks times were assumed to start at 12:00, 10:30, and 15:00, respectively, with a standard deviation of 15 minutes. The mean vacancy period for two breaks and lunchtime were assumed 15 minutes and one hour, respectively. The vacancy periods were generated randomly for each day using an exponential probability distribution as described in Wang et al.'s (2005) model. An example of an occupancy profile generated by Wang et al.'s (2005) occupancy model is shown in Figure 2.1.

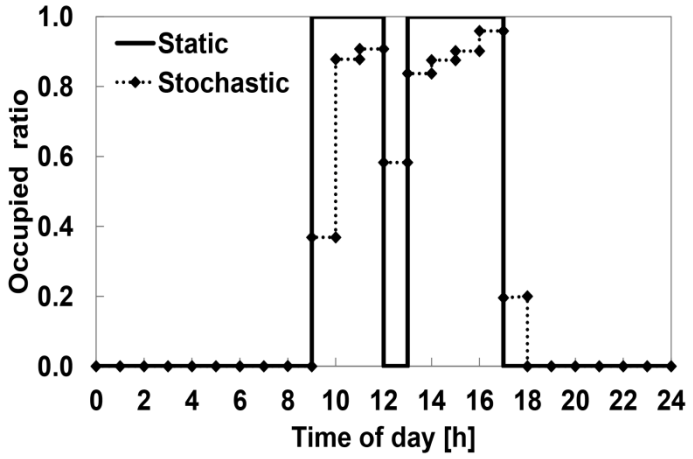

Figure 2.1. An example of stochastic occupancy profile generated compared to the static occupancy profile.

According to Reinhart's (2004) Lightswitch-2002 model for lighting, the probability of light switch-on events was modelled as a function of the workplane illuminance (Figure 2.2). Several studies (Hunt, 1979; Love, 1998; Reinhart, 2004; Lindelof and Morel, 2006) have proven that workplane illuminance is a good predictor for the light switch-on actions. Based on Reinhart's (2004) Lightswitch-2002 model, observing a light switch-on action upon arrival was modelled to be more likely than it was during intermediate occupancy periods. The variation between light switch-on actions upon arrival and during intermediate periods has also been observed in other studies (Hunt, 1979; Love, 1998; Reinhart and Voss, 2003; Gilani and O'Brien, 2017). The light switch-off events are permitted to occur only in the timestep at departure (including intermediate departures). The chances a simulated occupant turns off the lights were modelled to increase as a function of the duration of absence following a departure event, as other studies (Boyce, 1980; Pigg et al., 1996; Reinhart and Voss, 2003; Mahdavi et al., 2008) found that the vacancy period is a key factor to predict light switch-off events.

(a) **(b)**

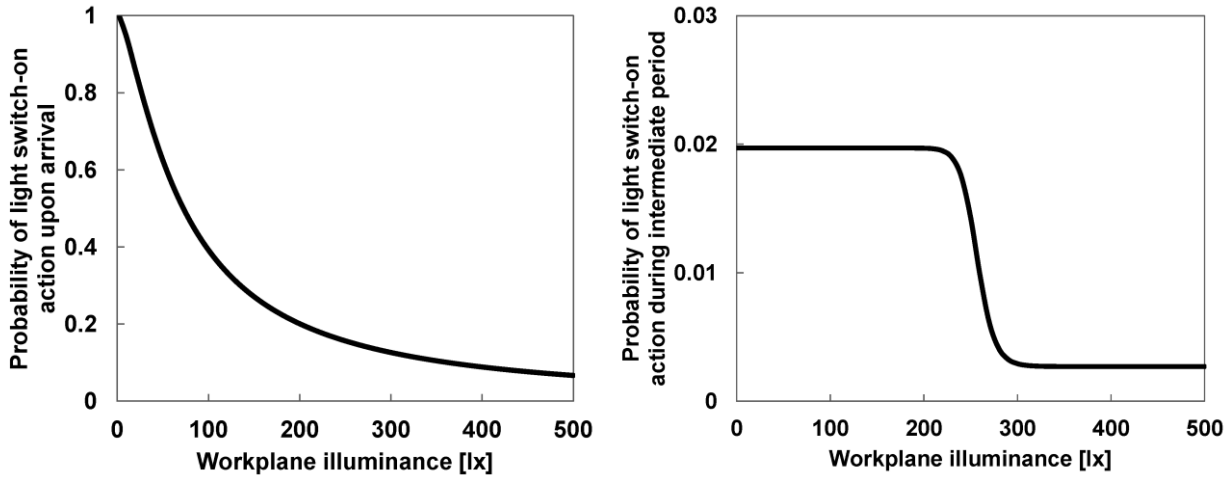

Figure 2.2. Reinhart's (2004) model for light switch-on actions: (a) upon arrival, and (b) during intermediate periods.

Haldi and Robinson's (2010) blind use model is based on six-year monitoring study, where they collected data on various parameters and used forward selection to determine the key influential factors on occupants' blind use. Their model provides a series of logistic regression models as a function of the workplane illuminance and initial blind position to predict the probability of the occupant's action for changing the blind position at arrival and during the intermediate periods in the form of Equation (2.1):

$$p = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}} \tag{2.1}$$

where p is the probability, x_i is the predictor, and β_0 and β_i are the regression parameters as summarized in Table 2.1. If the model predicts that the occupant changes the blind position, it determines whether the occupant will fully open or close the blind based on a series of logistic regression models that depends on the outdoor global horizontal illuminance and/or current blind position based on Equation (2.1). But, if the model predicts a partial blind movement, the magnitude of the movement is sampled from a Weibull distribution, which was found in Haldi and Robinson's (2010) field study as a good fit to estimate the change in blind position. The shape parameter ($\propto$) of the Weibull distribution in Haldi and Robinson's

(2010) blind use model is 1.708 and the scale parameter (λ) of the Weibull distribution that depends on the current shaded fraction ($B_{L,init}$) is calculated using Equation (2.2):

$$\lambda = e^{-2.294+1.522B_{L,init}} \tag{2.2}$$

Table 2.1. Regression parameters in Haldi and Robinson's (2010) blind use model for action and fully closing/opening probabilities.

Occupant behaviour		$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{x_1}$	$\boldsymbol{x_2}$
upon arrival	closing blind	-7.41±0.16	(10.35±0.19)×10^{-4}	2.17±0.16	indoor horizontal illuminance	unshaded fraction
	opening blind	-1.520±0.051	(-6.54±0.46)×10^{-4}	-3.139±0.068	indoor horizontal illuminance	unshaded fraction
during presence	closing blind	-8.013±0.086	(8.41±0.13)×10^{-4}	1.270±0.086	indoor horizontal illuminance	unshaded fraction
	opening blind	-3.625±0.030	(-2.76±0.22)×10^{-4}	-2.683±0.040	indoor horizontal illuminance	unshaded fraction
fully closing blind		-0.27±0.14	-2.23±0.16	-	unshaded fraction	-
fully opening blind		0.435±0.062	(0.91±1.33)×10^{-6}	1.95±0.11	outdoor global horizontal illuminance	unshaded fraction

The input parameters of the probabilistic occupant models were generated randomly, using normally-distributed probabilities based on the mean and standard deviation values provided by the occupant models used in this study. In this analysis, to represent a sample of occupants, 50 run periods as a synthetic occupant population were simulated. Through a sensitivity study, it was found that the mean and dispersion of the data converge within 50 simulations (Gunay et al., 2015b). Note that in the beginning of each run period (i.e. one year) a new set of input parameters — representing a unique simulated occupant — were generated for the occupant models.

2.2.2. Energy and daylight simulation

Simulations performed for this study included creating a typical office model in EnergyPlus and DAYSIM 3.1 (Reinhart, 2010). EnergyPlus was used to evaluate the energy performance of the simulated office space. It should be noted that EnergyPlus also provides the illuminance map for the daylighting analysis in a zone with hourly timesteps. However, in this study, DAYSIM was used as a more accurate daylighting analysis tool (Jakubiec and Reinhart, 2011). The stochastic occupant models were implemented in EnergyPlus, with 5-minute timesteps. For simulating partially-open blind using Haldi and Robinson's (2010) blind use model in EnergyPlus, the blind positions were discretized into five positions: fully open, 1/4, 1/2, and 3/4 closed, and fully closed. This blind position discretization compromises between accuracy and computational cost. Since EnergyPlus is limited to just two blind positions (i.e. open/closed), the window was modelled with four identical vertically stacked pieces. It is worth noting that the properties of window assembly required in EnergyPlus were calculated using WINDOW 7.3, assuming the window frame to be around the whole area of the window (Lawrence Berkeley National Laboratory, 2014) (described in Section 2.2.4).

To analyze the indoor daylight illuminance, annual simulations were performed in DAYSIM 3.1 (Reinhart, 2010), with hourly timesteps as per IES LM-83-12 (2013). In DAYSIM, to calculate the diffuse sky illuminance, the celestial hemisphere is divided into 145 rectangular sky segments that completely cover the celestial hemisphere without any overlap. DAYSIM calculates the direct daylight coefficients for 65 representative sun positions based on the latitude for when the sun is up throughout the year. The direct daylight coefficients for other sun positions are interpolated using the four representative sun positions that circumscribe the sun position at other times of the year (Reinhart, 2006).

The daylighting and energy simulations were coupled using MATLAB. The indoor illuminance was calculated for the five blind positions for the studied WWRs and for the three design options (explained in

Section 2.2.4) using the static shading device in DAYSIM. With knowledge of the blind position from EnergyPlus for each design case at each hour, the indoor illuminance was extracted from the output files generated for that blind position at that hour using DAYSIM. For the blind-closing trigger as per IES LM-83-12 (2013) (explained in Section 2.2.3), the indoor illuminance from direct sunlight obtained using DAYSIM for the 64 points (explained in Section 2.2.3), were defined as schedules for blind-open and closed positions in EnergyPlus. Based on a script in the EMS feature of EnergyPlus, the blind was closed whenever more than one analysis point of the 64 points received at least 1000 lux direct sunlight.

2.2.3. Performance metrics

The performance metrics used in this study for comparing simulation results are as follows:

- Annual lighting, heating, and cooling energy use intensity (kWh/m^2).
- Annual electricity use intensity (kWh/m^2) assuming a coefficient of performance (COP) of 3. This assumption was made to approximate the electricity use for heating and cooling without assuming a specific heating/cooling system.
- Useful daylight illuminance ($UDI_{100\text{-}2000}$); $UDI_{100\text{-}2000}$ is the percent of occupied times when the workplane illuminance is between 100 and 2000 lux (Nabil and Mardaljevic, 2005). It is calculated based on Equation (2.3):

$$UDI_{100-2000} = 100 \times \frac{\sum_{time=1}^{n} \begin{cases} 1 & if\ 100 \leq E_{in} \leq 2000, presence \\ 0 & otherwise \end{cases}}{\sum_{time=1}^{n} \begin{cases} 1 & if\ presence \\ 0 & otherwise \end{cases}} \tag{2.3}$$

where E_{in} is the indoor illuminance (lux) and presence is when there is an occupant in the office.

In this study, $UDI_{100\text{-}2000}$ was evaluated on the illuminance map which had 8 × 8 cells, each cell with dimensions 0.5 × 0.5 m, at a height of 0.8 m. The illuminance sensors were located at the centre of each

cell. First, for each cell of the illuminance map, the $UDI_{100\text{-}2000}$ was calculated using Equation (2.3) and then, the median of $UDI_{100\text{-}2000}$ on all cells (% of occupied period) was computed.

- $UDI_{<100}$ and $UDI_{>2000}$; $UDI_{<100}$ is the percent of occupied times when the workplane illuminance is less than 100 lux (i.e. the space is dark). $UDI_{>2000}$ is the percent of occupied times when the workplane illuminance is higher than 2000 lux (i.e. the space is too bright).
- Daylight Autonomy (*DA*); the percent of occupied period when the workplane illuminance is sufficient (Reinhart et al., 2006). In this study, the required minimum workplane illuminance for the office space was assumed 300 lux which represented a useful indicator of annual daylight illuminance performance in IES LM-83-12 (2013).
- Spatial Daylight Autonomy ($sDA_{300,50\%}$); the percent of floor area that receives at least 300 lux for at least 50% of occupied hours. For this metric, if the Annual Sunlight Exposure (explained next) is not below the required threshold, blinds are controlled hourly to prevent direct sunlight penetration into the space. This daylight metric is approved by IES LM-83-12 (2013) and is required in LEED Version 4.0 (USGBC) to receive the daylight credits. $sDA_{300,50\%}$ must meet at least 55% and 75% of floor area for a "nominally acceptable" and "favourably/preferred" space, respectively. Based on IES LM-83-12 (2013), for an analysis area smaller than 200 ft^2 (18.6 m^2), the hourly blind-closing trigger occurs whenever more than one analysis point on a 2 × 2 ft (0.6 × 0.6 m) grid receives at least 1000 lux direct sunlight. In this study, $sDA_{300,50\%}$ was applied to the static occupant modelling with the blind trigger as per IES LM-83-12 (2013). Also, it was applied to the blind-open/closed static and stochastic cases (as explained in Section 2.2.4) to investigate the daylight performance of these manual blind controls based on $sDA_{300,50\%}$. In the current study, $sDA_{300,50\%}$ was evaluated for the illuminance map (as described for $UDI_{100\text{-}2000}$). For the calculation of spatial daylight autonomy, first the daylight autonomy at the centre of each cell was

calculated based on Equation (2.4). Then, the spatial daylight autonomy was calculated based on Equation (2.5) as follows:

$$DA_{cell} = 100 \times \frac{\sum_{time=1}^{n} \begin{cases} 1 & if\ E_{in} \geq 300, presence \\ 0 & otherwise \end{cases}}{\sum_{time=1}^{n} \begin{cases} 1 & if\ presence \\ 0 & otherwise \end{cases}} \tag{2.4}$$

where DA_{cell} is the daylight autonomy at the centre of each cell (% of occupied period). Note that for the stochastic OB modelling, the DA_{cell} for each cell in the illuminance map was considered as the mean of the 50 simulated occupants.

$$sDA_{300,50\%} = 100 \times \frac{A_{cell}}{A_{floor}} \times \sum_{cell=1}^{n} \begin{cases} 1 & if\ DA_{cell} \geq 50\% \\ 0 & otherwise \end{cases} \tag{2.5}$$

where A_{cell} is the cell area (m^2) and A_{floor} is the floor area (m^2). After finding the spatial daylight autonomy, the median of the daylight autonomy on all cells (% of occupied period) was also calculated.

- Annual Sunlight Exposure ($ASE_{1000,250h}$); the percent of floor area that receives higher than 1000 lux direct solar radiation for at least 250 occupied hours. This daylight metric is also approved by IES LM-83-12 (2013) and is required in LEED Version 4.0 (USGBC) for the evaluation of daylight performance and only applicable to blind open position. In the current study, this metric was applied to the stochastic and static cases with blind open position and the blind trigger as per IES LM-83-12 (2013). According to IES LM-83-12 (2013), $ASE_{1000,250h}$ must be less than 10% of floor area. In this study, the evaluation of $ASE_{1000,250h}$ was performed for the illuminance map (as explained for $UDI_{100\text{-}2000}$). It should be noted that for calculating direct sunlight in DAYSIM, the indoor illuminance was simulated using a zero-bounce method (to eliminate the reflection from other surfaces) with only the direct irradiance in the weather file (to exclude the diffuse sky component). For the calculation of annual sunlight exposure for the whole illuminance map, first the annual sunlight exposure at the centre of each cell was calculated according to

Equation (2.6). Then, the annual sunlight exposure ($ASE_{1000,250h}$) (% of floor area) for the whole space was calculated based on Equation (2.7) as follows:

$$ASE_{cell} = \sum_{time=1}^{n} \begin{cases} 1 & if\ E_{in,dir} > 1000, presence \\ 0 & otherwise \end{cases} \tag{2.6}$$

where ASE_{cell} is the annual sunlight exposure at the centre of each cell (number of occupied hours) and $E_{in,dir}$ is the indoor illuminance from direct sunlight at the centre of each cell (lux). Note that for the stochastic OB modelling, the ASE_{cell} for each cell in the illuminance map was considered as the mean of the 50 simulated occupants.

$$ASE_{1000,250h} = 100 \times \frac{A_{cell}}{A_{floor}} \times \sum_{cell=1}^{n} \begin{cases} 1 & if\ ASE_{cell} \geq 250 \\ 0 & otherwise \end{cases} \tag{2.7}$$

2.2.4. Description of models

For evaluating comfort and energy use under the different occupant models, a parametric study was performed. The parameters that were determined for this study were: WWR (design option 1), window type (design option 2), and blind transmittance (design option 3) (Table 2.2). To this end, the baseline model for EnergyPlus simulation was developed in OpenStudio using the template for office spaces in the climate zone 6A based on ANSI/ASHRAE/USGBC/IES Standard 189.1 (2014). The model's location was assumed Ottawa, Canada where winters are cold, summers are warm and humid, and it is generally sunny year round. The heating and cooling degree days (with balance temperature 18°C) for Ottawa are about 4200°C.day and 300°C.day, respectively. The annual horizontal solar radiation for Ottawa is about 1300 kWh/m^2.

The office room had dimensions W × L × H = 4.0 × 4.0 × 3.0 m, with a south-facing window of different WWR, including the window frame, which was between 20% and 60% in increments of 10%. The window's sill height was 0.8 m for all the analyzed WWRs (Figure 2.3) as a typical window height from

the floor. This study was conducted for just south-facing facades since most existing OB models were developed from observations for this orientation (e.g. (Reinhart and Voss, 2003; Haldi and Robinson, 2010)). The south wall was exposed to the outdoor environment, while all the other surfaces of the room were adjacent to spaces with the same thermal conditions. The visible reflectance of the interior surface of the floor, walls, and ceiling were assumed to be 0.2, 0.5, and 0.8, respectively. The window was assumed to be fixed with thermally-broken aluminium framing with a U-factor of 5.79 W/m^2K (ASHRAE, 2013d) and profile width of 6 cm, regardless of WWR. The window frame was assumed to be just around the whole area of the window, without any dividers. Two glazing systems were considered; where the glazing systems for design options 1 and 3 were the same and modelled on the basis of ANSI/ASHRAE/IES Standard 90.1 (2013c) (Table 2.2). The properties of the glazing systems and different WWRs were calculated using WINDOW 7.3 (Lawrence Berkeley National Laboratory, 2014).

Two kinds of interior blind were modelled in the parametric study, where the blind types for design options 1 and 2 were identical (Table 2.2). It is worth noting that Tzempelikos and Athienitis (2007) concluded that a transmittance of 20% presented the optimal daylight and energy performance, though this value should be 5% if glare is to be kept at a minimum. Therefore, the current work considered 20% transmittance as the second blind alternative.

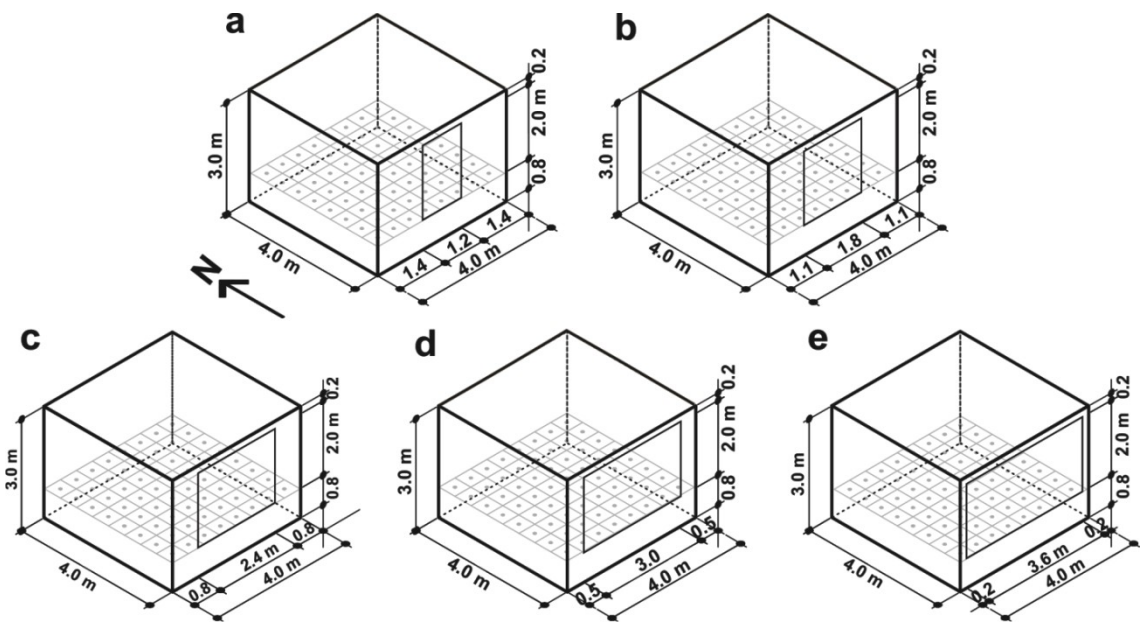

Figure 2.3. Geometry of a generic office room with different window-to-wall area ratios (WWR): (a) WWR of 20%, (b) WWR of 30%, (c) WWR of 40%, (d) WWR of 50%, and (e) WWR of 60%.

Table 2.2. Fenestration system design parameters

Parameters	window-to-wall ratio (WWR) (Area) (m^2)	Window geometry (W×H) (m)	Blind solar/visible transmittance	Glazing performance
Design option 1 (baseline design)	20% (2.4)	1.2×2	0.05	U = 1.64 W/m^2K SHGC = 0.39 VT = 0.44
	30% (3.6)	1.8×2		
	40% (4.8)	2.4×2		
	50% (6.0)	3×2		
	60% (7.2)	3.6×2		
Design option 2 (window type)	20% (2.4)	1.2×2	0.05	U = 0.98 W/m^2K SHGC = 0.56 VT = 0.71
	30% (3.6)	1.8×2		
	40% (4.8)	2.4×2		
	50% (6.0)	3×2		
	60% (7.2)	3.6×2		
Design option 3 (blind transmittance)	20% (2.4)	1.2×2	0.2	U = 1.64 W/m^2K SHGC = 0.39 VT = 0.44
	30% (3.6)	1.8×2		
	40% (4.8)	2.4×2		
	50% (6.0)	3×2		
	60% (7.2)	3.6×2		

The office was assumed to be occupied by one person during the occupied period. For the static schedules, the occupied periods were 9:00 to 12:00 and 13:00 to 17:00. Note that a daylight savings period, starting on the 2nd Sunday in March and ending on the 1st Sunday in November, was applied to the annual run period. The internal heat gains from the occupant, lighting, and electric equipment were assumed to be 120 W, 8.8 W/m^2, and 10 W/m^2, respectively, during the occupied period. Lighting heat gain is based on the lighting power density provided in ANSI/ASHRAE/IES Standard 90.1 (2013c) for an office space. To control lighting for the static occupant modelling, it was assumed that lighting was on whenever daylight illuminance on workplane (E_{wp}) was less than 300 lux during the occupied period. Accordingly, daylight autonomy exactly corresponds with lighting electricity use. In this study, lights were controlled according to the illuminance at the centre of the 0.8m-high workplane. For the static occupant modelling, two blind settings, including fully open and fully closed, were considered. However, for the performance metrics of $sDA_{300,50\%}$ and $ASE_{1000,250h}$, another blind setting based on IES LM-83-12 (2013) with the static cases was also investigated. A summary of the occupancy schedule, and lighting and blind control for the static and stochastic OB modelling approaches are presented in Table 2.3.

Table 2.3. Occupant presence and actions models for stochastic and static occupant modelling

OB model / **OB approach**	**Occupancy**	**Lighting control**	**Blind control**
Stochastic	Wang et al. (2005)	Reinhart (2004)	Haldi and Robinson (2010)
Static: blind open	Weekdays: 9:00-12:00, 13:00-17:00	On if E_{wp}<300lx in occupied period; otherwise off	Always open
Static: blind closed			Always closed
Static: IES blind trigger			Closed whenever more than 1 daylight analysis point receives at least 1000 lx direct sunlight

Fresh air was supplied into the office room at a rate of 7.3 L/s based on ANSI/ASHRAE Standard 62.1 (ASHRAE, 2013b) during the occupied period. To reduce unnecessary mechanical cooling, outdoor air was introduced into the office space at a rate of 100 L/s when the minimum and maximum indoor temperature, minimum and maximum outdoor temperature, and the minimum difference between the indoor and outdoor temperature were 20°C, 24°C, 15°C, 22°C, and 2°C, respectively. The infiltration rate into the office was assumed 0.3 air changes per hour (ACH) which is a common infiltration rate for office buildings (e.g. (Kim and Leibundgut, 2015)). The HVAC equipment of the office was modelled as an air-based ideal load system with heating and cooling capacity of 1500 W as the focus of this study is modelling occupants for early stage design. This heating and cooling capacity was chosen based on a preliminary sizing run. Heating and cooling setpoints were assumed to be: 21°C and 24°C during occupied hours, 15.6°C and 26.7°C during unoccupied hours. These setpoints were based on the template developed for office spaces in OpenStudio according to ANSI/ASHRAE/USGBC/IES Standard 189.1 (2014).

2.3. Results

In this section, the annual daylight and energy performance of the three design options for five different window sizes (as explained in the previous section) are presented. The results include several performance metrics to evaluate how different OB modelling approaches affect the daylight and energy performance. Meanwhile, daylight metrics specified in IES LM-83-12 (2013) are also computed, and the design strategies are compared to determine the effect of OB modelling approaches on simulation-supported design.

2.3.1. Daylight performance

Figure 2.4 shows the distribution of $UDI_{100\text{-}2000}$ for the baseline design (design option 1) with different window sizes under the static and stochastic modelling approaches. This figure shows that for the blind-

open static cases, a larger area near the window is affected by the window (i.e. lower $UDI_{100\text{-}2000}$ and higher $UDI_{>2000}$), especially for larger windows, compared to the stochastic cases. This difference between the static and stochastic cases is because occupants are more likely to close blinds if the window is larger. Figure 2.4 also shows that for the blind-closed static cases, the regions of higher $UDI_{100\text{-}2000}$ is concentrated in the front zone of the space. On the contrary, for the stochastic and blind-open static cases, it is concentrated in the back zone of the space because the front of the space is often too bright (higher $UDI_{>2000}$).

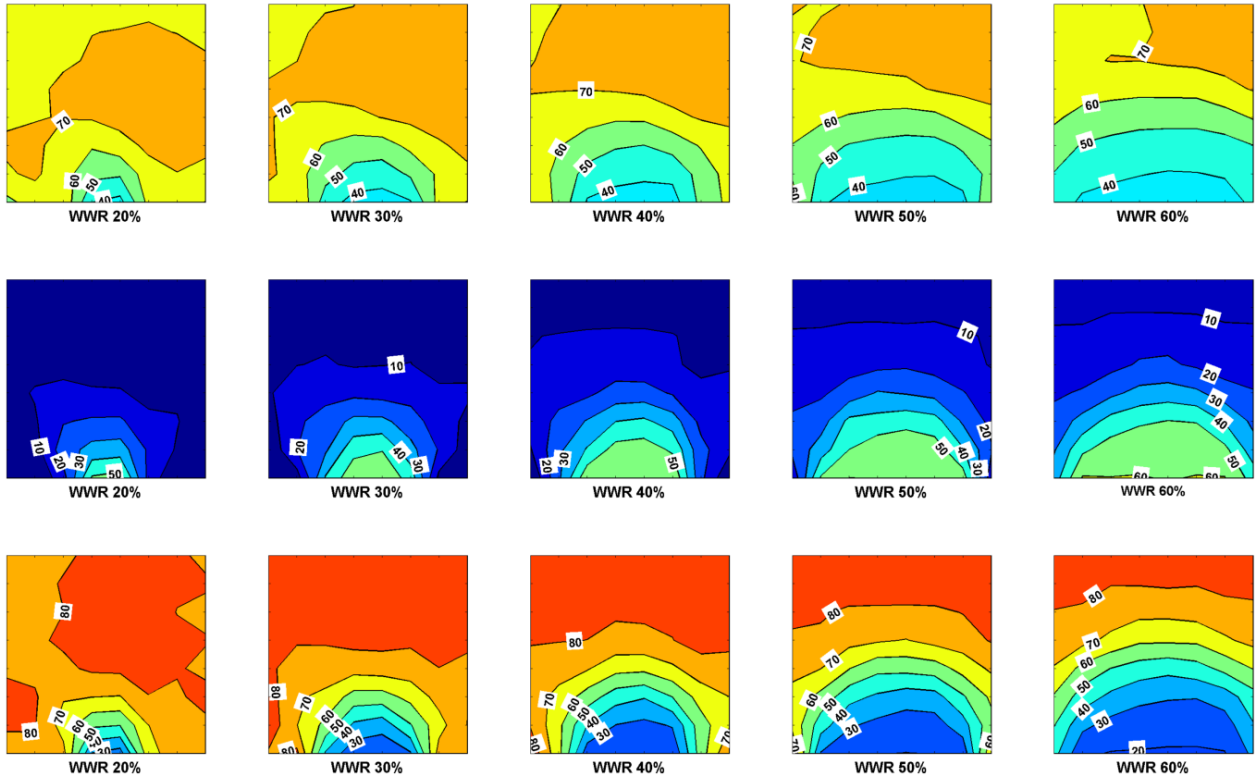

Figure 2.4. Distribution of $UDI_{100\text{-}2000}$ (% of occupied period) for the baseline design under: stochastic OB modelling (top row), blind-closed static OB modelling (middle row), and blind-open static OB modelling (bottom row). (North is up and window is on the south side).

The median of $UDI_{100\text{-}2000}$ on the 64 cells of the illuminance map is displayed in Figure 2.5. Note that in all the graphs presented the results from stochastic cases, the error bars indicate the standard deviation of the results obtained from the 50 simulated occupants. For the stochastic and blind-open static cases,

generally the larger the window, the less the median of $UDI_{100\text{-}2000}$. For the stochastic cases, the lower median of $UDI_{100\text{-}2000}$ for larger windows is due to the higher blind occlusion rates for larger windows as shown in Figure 2.6 (i.e. higher $UDI_{<100}$), which is more noticeable with a glazing system with a higher VT (design option 2). However, for the static cases, the lower median of $UDI_{100\text{-}2000}$ for larger windows is due to higher $UDI_{>2000}$. Using a glazing system or a blind with a higher VT leads to lower $UDI_{100\text{-}2000}$ for larger windows with the stochastic and blind-open static cases and higher $UDI_{100\text{-}2000}$ with the blind-closed static cases. The stochastic cases predict a worse performance for smaller windows than the blind-open static cases, in contrary to larger windows. This difference between the static and stochastic cases is due to the blind closing actions with the stochastic modelling, which can reduce daylight performance for smaller windows, but helps improve daylight performance for larger windows.

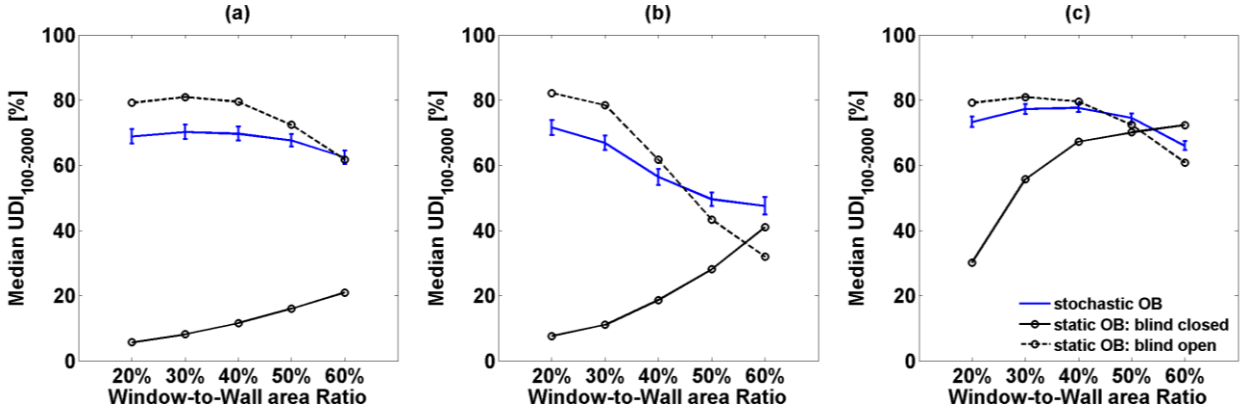

Figure 2.5. Median of $UDI_{100\text{-}2000}$ (% of occupied period) under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

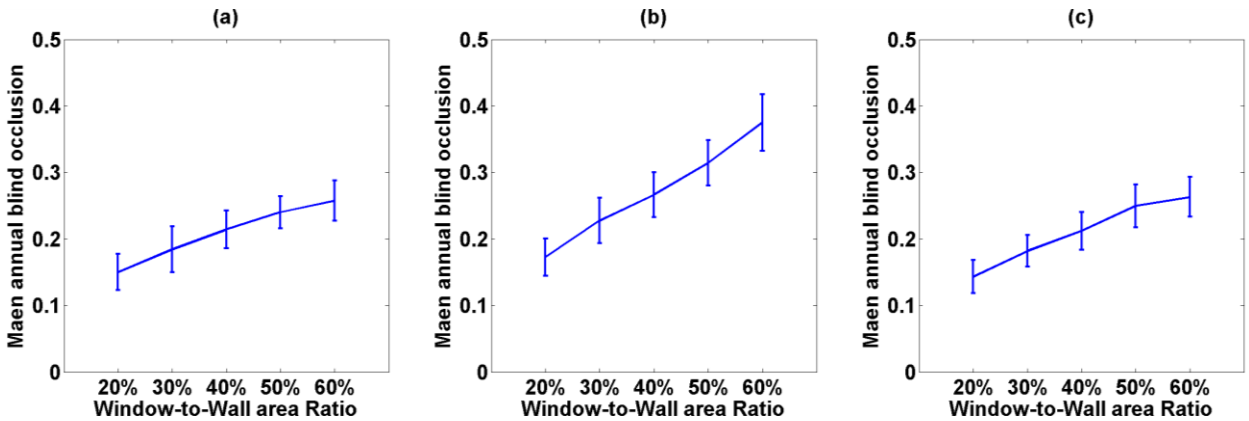

Figure 2.6. Mean annual blind occlusion rate under stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

The median *DA* on the 64 cells in the illuminance map is shown in Figure 2.7. This figure indicates that the trends for *DA* for the stochastic and blind-open static cases are similar, with the exception of design option 2. The blind-open static cases significantly overestimate both the *DA* and the benefit of larger windows compared to the stochastic cases.

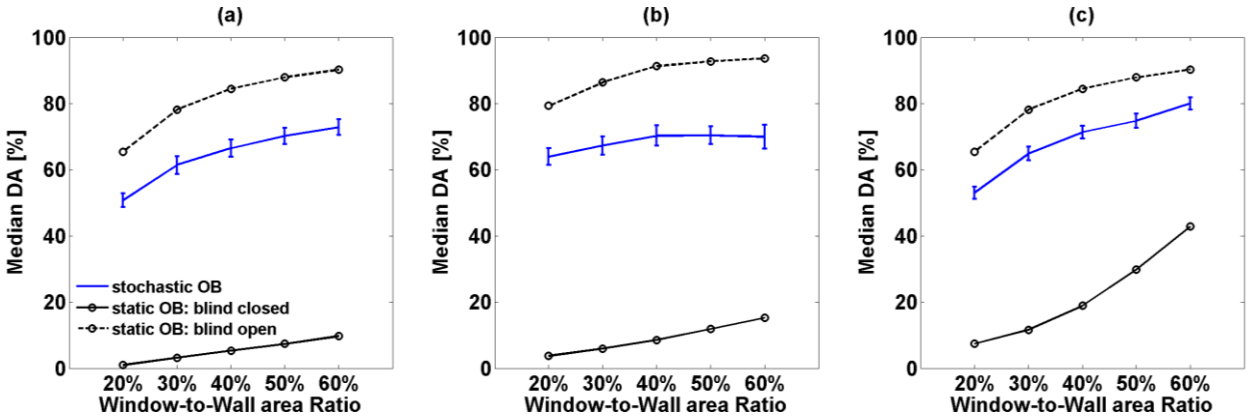

Figure 2.7. Median of DA (% of occupied period) under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

Figure 2.8 displays the daylight performance of the studied design alternatives based on $sDA_{300,50\%}$. In this figure, in addition to the blind-open and closed static cases, another blind closing trigger is shown, based on IES LM-83-12 (2013). It shows that the IES blind trigger cases will not deliver the required threshold

for a nominally-acceptable space for WWR of 20% with design options 1 and 3. The required credit for a favourably/preferred space is achievable with WWRs of 40%, 50%, and 60% under the IES blind trigger. Figure 2.8 also shows that the blind-open static cases yields $sDA_{300,50\%}$ for more than 80% of the floor area for all the considered window sizes. However, the stochastic cases will not deliver the threshold for a nominally acceptable and favourably/preferred space for WWR of 20% of design options 1 and 3, respectively. The stochastic cases predict favourably/preferred-daylit spaces for all the design alternatives with WWRs of 30-60%, which receive the most LEED points for new construction (USGBC).

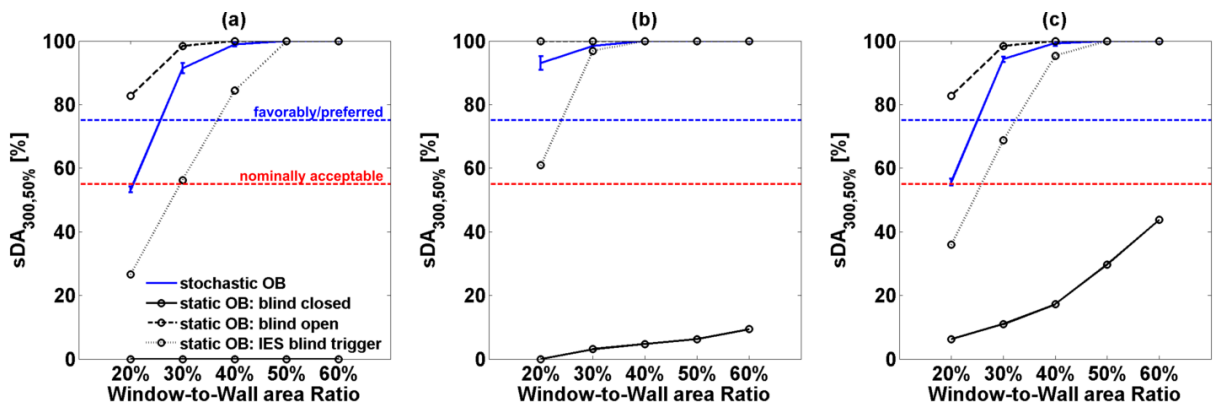

Figure 2.8. $sDA_{300,50\%}$ (% of floor area) under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

Figure 2.9 shows the $ASE_{1000,250h}$ for the studied design alternatives. It shows that larger windows lead to higher values of $ASE_{1000,250h}$ for the stochastic and static cases. Generally, $ASE_{1000,250h}$ exceeds the maximum allowable threshold based on IES LM-83-12 (2013) with the static and stochastic cases. The deviation between $ASE_{1000,250h}$ with the static and stochastic cases increases for larger windows due to higher blind occlusion rates. In this figure, the $ASE_{1000,250h}$ for static cases with blind closing trigger as per IES LM-83-12 (2013) shows that WWR of 20% with design options 1 and 2 deliver the require threshold. Furthermore, Figure 2.9 shows that the stochastic cases predict better daylight performance than the

blind-open static cases based on the $ASE_{1000,250h}$ metric because the occupants tend to close their blinds when daylight conditions are bright.

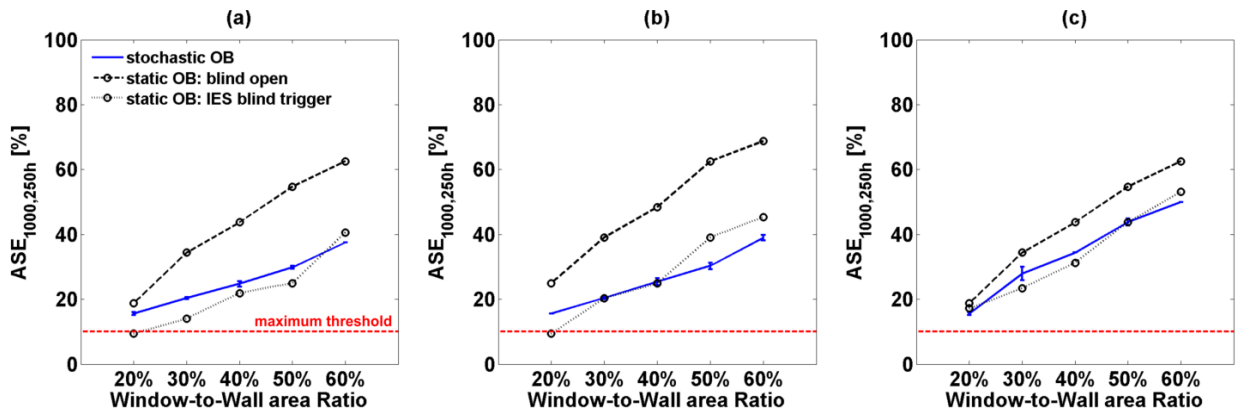

Figure 2.9. $ASE_{1000,250h}$ (% of floor area) under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

2.3.2. Energy performance

Figure 2.10 and Figure 2.11 display the annual heating/cooling and lighting energy use. The results indicate that heating and cooling loads generally increase with larger windows. However, using a glazing system with a higher SHGC and lower U-factor results in lower heating load and significantly higher cooling load for larger windows, especially for the blind-open static cases. Figure 2.10 shows that the stochastic cases predict higher heating loads than that the blind-open static cases. Moreover, the blind-open static cases over-predict the cooling loads relative to the stochastic cases. The deviation between the stochastic and static cases generally increases with larger windows due to the higher blind occlusion rates. Figure 2.10 also shows that the maximum standard deviation in the heating/cooling loads with the stochastic cases are 1 kWh/m^2, 3 kWh/m^2, and 1 kWh/m^2 for design option 1, 2, and 3, respectively. The low standard deviation in the heating and cooling loads is due to the fact that the annual mean blind occlusion levels were almost the same for each occupant and that the annual lighting only plays a small role in heating and cooling loads regarding the assumed internal heat gains from lighting and the annual

lighting use in the current study. Thus, the annual level of resolution does not fully exhibit the stochastic nature of occupants. In addition, the mean annual blind occlusion for the 50 simulated occupants was generally a low value (i.e. about 0.2-0.3) and therefore, the effect of blind on the heating/cooling loads is minor. Moreover, other ways that occupants affect the heating and cooling loads, such as thermostat adjustment, window operation, and plug loads, were not modelled as stochastic in the current study.

As shown in Figure 2.11, for the static cases, the larger the window, the lower the lighting electricity use. Therefore, the near-optimal window size with the blind-open static approach is WWR of 60% from the perspective of lighting electricity use. However, the stochastic cases, where the dynamic occupant-building interaction is taken into account, yield different optimal window size. For design options 2 and 3, WWR of 40% is the near-optimal design due to more frequent occupants' blind closing with larger windows. Figure 2.11 also shows that using a glazing system or a blind with a higher VT leads to lower lighting electricity use for each corresponding window size with respect to the baseline design with the static cases. However, with the stochastic cases, using a glazing system with a higher VT leads to generally higher lighting use for larger windows, which is due to higher blind occlusion rates for larger windows relative to the baseline design. Using a blind with a higher VT results in lower lighting use.

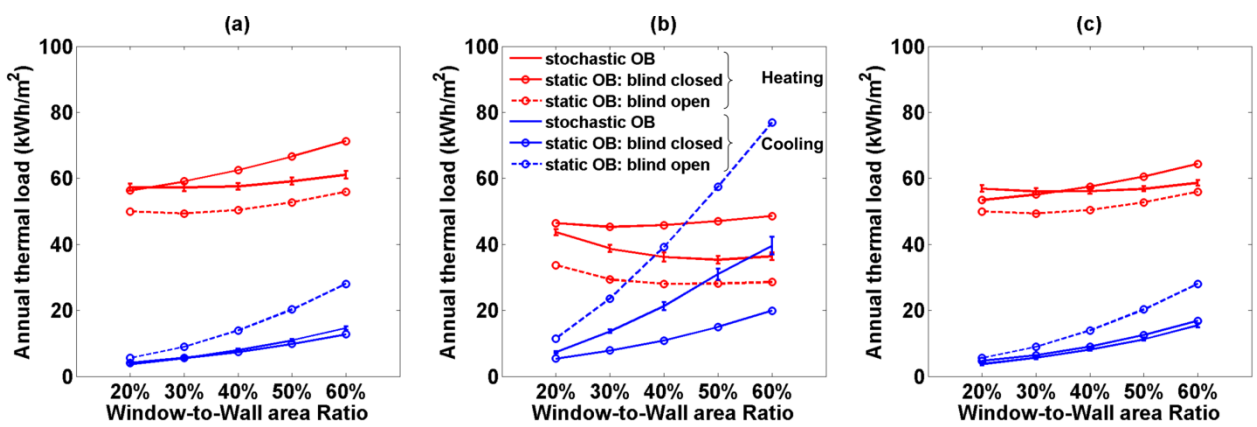

Figure 2.10. Annual heating and cooling loads under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

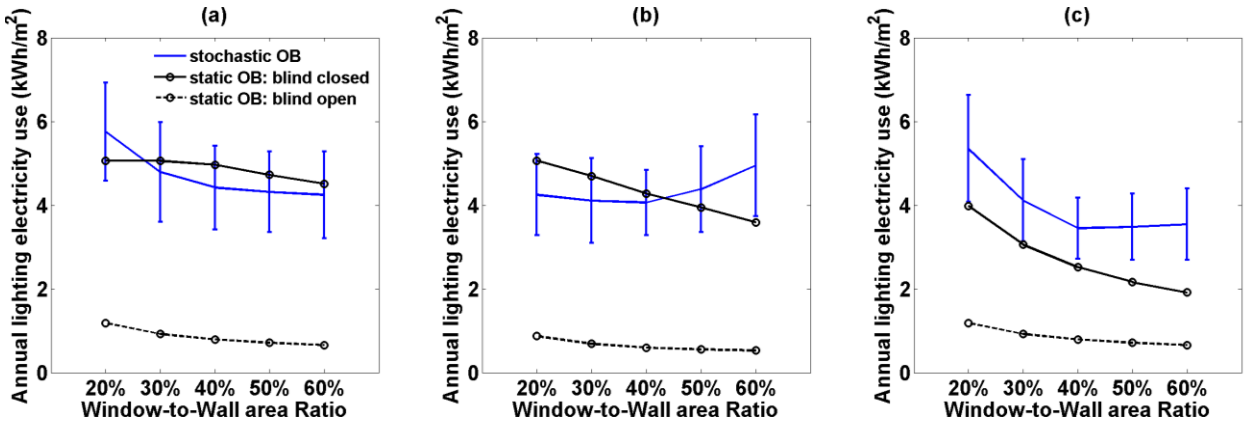

Figure 2.11. Annual lighting electricity use under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

Figure 2.12 displays the annual total electricity use, including heating, cooling, and lighting. Note that this graph is based on a COP of 3 for providing heating and cooling loads. It shows that the energy use predicted by the static and stochastic cases diverges for smaller windows with design option 1 and 3. However, for design option 2, their predictions diverge for both the smaller and larger windows. This figure also indicates that WWR of 20% is the near-optimal window size from an energy perspective for the blind-open static cases. However, with the stochastic cases, WWR of 30%, of the considered window sizes is the near-optimal designs for design option 1 and 3. Furthermore, using a window with a higher SHGC and VT increases the annual total electricity use significantly for larger windows with the stochastic and blind-open static cases. In this case, closing the blind helps decrease the electricity use.

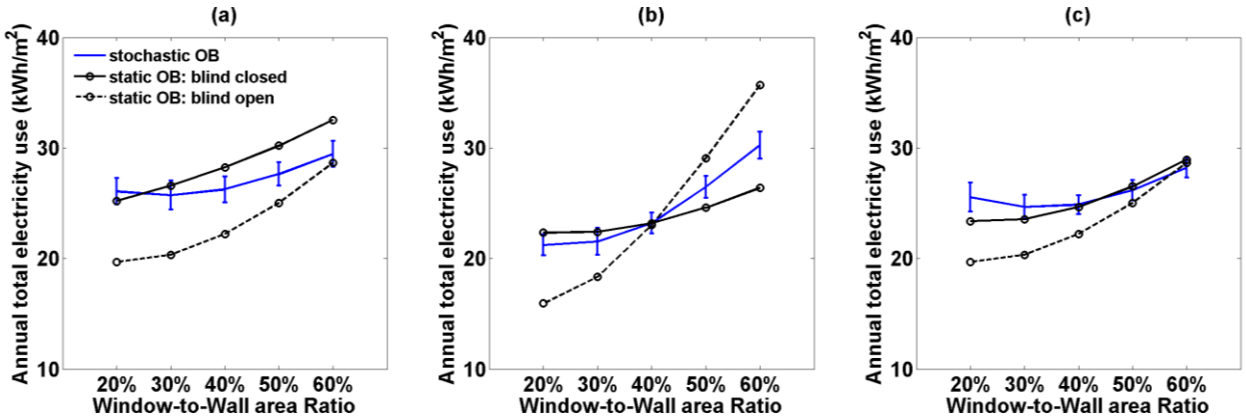

Figure 2.12. Annual total electricity use under static and stochastic OB modelling for: (a) Design option 1 (baseline design), (b) Design option 2 (window type), and (c) Design option 3 (blind transmittance).

2.4. Discussion

The results of this study indicate that there is a deviation between the conventional and stochastic OB modelling approaches in predicting the energy and daylight performance. Conventional occupant modelling failed to capture the influence of building design over occupants' behaviour, and vice versa. The static and stochastic OB modelling approaches yielded different near-optimal design regarding energy consumption. However, they generally led to similar near-optimal designs from daylight perspective based on the set of daylight metrics used in this study. The results of this study necessitate more advanced OB models as requirements for code compliance modelling to prevent the two risks associated with the use of conventional occupant models: unrealistic predicted building performance and sub-optimal designs. Accordingly, the researcher recommends that code and standard development committees, as well as simulationists, begin to examine dynamic models to simulate adaptive behaviours of occupants, either adapting themselves to their environments or adapting their environment to their needs (Gunay et al., 2013). To this end, developing averaged schedule profiles and threshold values to mimic back and forth interactions between occupants and buildings which are supported by large datasets on various building archetypes is recommended. Likewise, BPS tools with a library of occupant models

for simply incorporating them and illustrating probabilistic simulation results are needed to encourage building code and standard development committees to require occupant-related uncertainties in code compliance processes. While the research community has not yet converged on a set of specific models for each occupant action (O'Brien and Gunay, 2014) (and it is not clear if they will or should), it is important for designers and simulationists to begin to think more carefully about the complex occupant-building interaction dynamics. In the current research area, validation of simulation results is also necessary, which requires in-depth future study. A sensitivity analysis could facilitate the calibration of simulation models and minimize the discrepancies between simulation and experiments, while different occupant modelling approaches (i.e. static and dynamic) are tested for simulation (e.g. (Tahmasebi and Mahdavi, 2015)). Developing well-established measures to evaluate a general good agreement between simulation and experimental results is also imperative; for instance, whether a researcher should look at occupants' presence and operations of building components/systems in a micro (e.g. at each timestep) and/or macro (e.g. mean values) scale.

In the current study, there were some important constraints that may affect the energy and daylight performance as well as design ranking. In the following sections, the limitations of the study are outlined.

2.4.1. Methodology limitation

The limitations regarding the performance metrics, simulated model or simulation process are as follows.

- The threshold of 1000 lux for direct solar radiation in $ASE_{1000,250h}$ in IES LM-83-12 (2013) may significantly over-predict glare compared to how occupants have been observed to react to daylight conditions. Reinhart and Voss (2003) reported that in their study all the occupants closed their blinds to avoid direct solar radiation above 50 W/m^2 (~ 5000 lux). Haldi and Robinson's (2010) blind use model indicates that the probability of closing the blind in the next 5 minutes for the indoor illuminance of 1000 lux is quite low (~1%). However, in Haldi and Robinson's (2010) blind use

model, the provided indoor illuminance included the diffuse and direct solar radiation (in contrast to $ASE_{1000,250h}$, which includes only direct solar radiation). Also, the motivation for blind closing actions and positioning remains unclear, whether it was due to glare, thermal discomfort, effort to close the blind, privacy, and social constraints in shared office. Furthermore, if occupants are given some freedom over closing blind, their position, and orientation of their desk, daylight illuminance of 1000 lux is not necessarily a concern – particularly if it only occurs in a small portion of the space. It remains unclear whether it is appropriate to develop illuminance thresholds from blind closing observations, since some occupants may psychologically cope with daylight glare without acting. Therefore, it would be valuable to conduct laboratory and survey-based research on the direct solar radiation threshold that occupants find acceptable, with recognition of adaptive opportunities, such as relocating or reorienting.

- This study was performed on a model of a 4 by 4 meter private office space with a single window. The results using $sDA_{300,50\%}$ for the static cases with the blind trigger as per IES LM 83-12 (2013) indicate that daylight is generally adequate for WWRs of 40-60% to replace electric lighting for more than 50% of occupied hours in more than 50% of the office area. However, the $ASE_{1000,250h}$ metric predicts daylight glare in more than 20% of floor area. In future studies, the same analysis should be performed for deeper spaces or on the whole building scale to investigate the effect of the space depth on the mentioned daylight metrics. Most existing stochastic OB models are limited in scope to small offices and not open-plan offices; therefore developing OB models for such spaces is a critical future research topic.
- This study was conducted for an interior blind and the low blind occlusion rates did not significantly affect the heating and cooling loads. It is necessary to investigate the impact of exterior blinds on the heating and cooling loads using stochastic occupant behaviour models.

- In this study, a workflow between EnergyPlus and the indoor illuminance obtained from DAYSIM was developed in MATLAB. The whole simulation process in EnergyPlus, which included in total 795 annual run periods, was computationally heavy and time-consuming. More efficient tools workflows should be developed in the future so that design feedback can be provided quickly (e.g. at design charrettes). In addition, a user-friendly interface should be developed for the workflow between daylighting and building energy simulation engines and the OB models. Standard methods for visualizing stochastic performance predictions are also required, given that industry is accustomed to single and deterministic predicted performance results.

2.4.2. Occupant model limitation

In this study, three different models based on different monitoring contexts were incorporated. However, it is not clear whether the existing occupant models are applicable beyond their monitoring contexts (e.g. (Schweiker et al., 2011)), such as climate, building geometry, occupants, control systems, and interior layout. Future research should assess the predictive accuracy of the OB models in different contexts. The feasibility of combining different occupant models from different contexts for one space should also be evaluated in future studies. Each of the occupant models used in this study also imposed the following limitations on modelling occupant behaviours.

- Wang et al.'s (2005) model for occupancy requires a certain number of prescribed break intervals. However, in reality the number of intermediate breaks should be modelled as stochastic.
- Haldi and Robinson's (2010) blind use model was developed in peculiar cellular offices with motorized blinds for which the button was easily accessible. Also, there were internal vertical slat blinds and two external blind sets: upper and lower, where the upper one covered with an anidolic system to reflect external radiation. These characteristics may have increased the blind movement actions, especially the upper blind which did not obstruct the view to the outdoors.

- Reinhart's (2004) Lightswitch-2002 model is dependent on the occupancy model's ability to predict the number and timing of the arrival events.
- Reinhart's (2004) Lightswitch-2002 model and Haldi and Robinson's (2010) blind use model are based on illuminance at a single point. This assumption neglects daylight variations within the office and the occupant's ability to rotate or move as an adaptive measure to avoid glare or obtain more daylight.
- Reinhart's (2004) Lightswitch-2002 model and Haldi and Robinson's (2010) blind use model were developed based on field studies in offices with near-south facing windows. However, light and blind use models are affected significantly by window orientation (e.g. (Inoue et al., 1988)). Therefore, the current study was limited to south-facing space. Development of light and blind use models for other orientations is necessary to perform dynamic OB simulation in the design process for other orientations as well.

2.5. Closing remarks

In this chapter, the effect of conventional and dynamic OB modelling approaches on the energy and daylight performance in a simulation-aided design was evaluated. The evaluation was conducted by employing EnergyPlus and DAYSIM models of a south-facing perimeter office space in Ottawa, Canada. The EnergyPlus models were used to represent the energy performance and the DAYSIM models were used to represent the daylight performance. The impact of several design parameters were compared using a set of comprehensive performance metrics. The results showed the deviation between the conventional and advanced OB modelling approaches in the predicted energy and daylight performance. The dynamic OB modelling approach - by capturing the influence of design alterations over the occupant behaviour and vice versa – can predict the energy and daylight performance reflecting real situations.

The following conclusions are drawn which are specific to the case study investigated in this chapter:

- The static and stochastic OB modelling approaches yielded different horizontal distributions of indoor illuminance at workplane height, which may lead designers to a sub-optimal layout design if they use conventional OB models.
- Larger windows caused higher blind occlusion rates under the stochastic OB modelling approach, especially for a window with higher VT. The increase in blind occlusion rates reduces the view and connection to outdoors, despite designers' expectation that larger windows provide better views.
- The stochastic OB cases resulted in higher heating loads than the blind-open static cases, due to higher blind occlusion rates and the resulting lower solar gains. However, the cooling loads were lower with the stochastic OB cases than the static ones.
- With the stochastic cases, due to the blind closing actions by occupants, the lighting electricity use was higher compared to the blind-open static cases.
- From lighting electricity use, WWRs of 60% and 40% were generally the near-optimal window sizes with the static and stochastic cases, respectively.
- The total electrical energy use was generally higher with the stochastic cases than the blind-open static cases, except for WWRs of 50% and 60% using a glazing system with a higher SHGC and VT.
- The maximum difference between the static and stochastic cases in the total electrical energy use was for WWR of 20%, which was about 30 percentage point higher with the stochastic cases relative to the blind-open static cases.
- The near-optimal window size regarding total electrical energy use was WWR of 20% with the blind-open static cases; while the stochastic cases generally suggested WWR of 30% as the near-optimal window size.

This chapter emphasizes the importance of incorporating more advanced OB models as requirements for code compliance modelling to prevent unrealistic predicted building performance and sub-optimal design decisions in the simulated-aided design processes.

As discussed earlier in this chapter, for the simulation-based analysis of the occupants' impact, different occupant models were used for the simulation of a case study located in a context different from the ones that the occupant models were driven from. Combining occupant models originated from various case studies is also questionable. The following chapters are on a monitoring campaign conducted in this research to analyze the energy performance of office spaces as well as to develop occupant models in a single case study. First, next chapter critically reviews the research methods in studying occupants' presence and behaviour, specifically in existing buildings. Afterwards, the following two chapters are on the monitoring study conducted in the current research.

Chapter 3

This chapter has been published as:

Review of current methods, opportunities, and challenges for in-situ monitoring to support occupant modeling in office spaces.

Gilani S, O'Brien W. *Journal of Building Performance Simulation: Special Issue on Occupant Behaviour Fundamentals*. 2016.

3. Review of in-situ monitoring methods

3.1. Introduction

Occupant-related studies can be performed in laboratories (Fanger, 1970; Osterhaus and Bailey, 1992; Velds, 2002; Wienold and Christoffersen, 2006; Konstantzos et al., 2015), existing buildings (Hunt, 1979; Boyce, 1980; Warren and Parkins, 1984; Maniccia et al., 1999), or virtual environments (van Veen et al., 1998; Heydarian et al., 2015; Saeidi et al., 2015).

In laboratory studies, a full-scale experimental environment is constructed which resembles typical spaces of interest, and a number of occupants participate in the study by spending time in laboratory spaces, for example, the climatic chambers of the Technical University of Denmark (ICIEE, 1972), the so-called btga-box of the University of Wuppertal (Schweiker et al., 2012), and the so-called LOBSTER of the Karlsruhe Institute of Technology (Schweiker and Wagner, 2016). Indoor environmental conditions are often tightly controlled in laboratories; whereas in existing buildings, unexpected conditions may appear, such as improperly functioning of stand-alone sensors or deficiencies with operable windows, window shades, lighting, and thermostat adjustments that researchers may not become aware of for an extended period. Laboratory studies ease measuring some variables, such as skin temperature, mean radiant temperature, and local air velocity, which are impractical or costly to measure in in-situ monitoring studies. Furthermore, researchers can manipulate the laboratory space, such as layout, materials, control systems, and orientation (where the environmental chamber is designed to be rotatable), while existing buildings lack this flexibility. However, it is costly to construct and maintain laboratories and to recruit participants. The behaviour of participants may also be influenced and biased, as they are experiencing an unfamiliar environment for a short period of time, which may be insufficient for occupant accustomization. Moreover, the generalizability of the inferences and mathematical models drawn from occupant behaviours in laboratory studies is not well established (Schweiker and Wagner, 2016).

Virtual environments are another approach that have been adopted in occupant behaviour studies in recent years (Heydarian et al., 2015; Saeidi et al., 2015). Virtual environments use computer-generated 3D special effects to mimic the real environment by providing sense of presence as if participants are present in a real space. Previous research found that participants' responses to virtual environments are similar to reality (e.g. (Slater, 2009)). Visual and acoustic domains predominate virtual environments, but replication of thermal conditions inducing occupant behaviours are more challenging. On the other hand, virtual environments provide researchers with flexibility and high control over environmental conditions at a low cost. Similar to laboratory studies, virtual reality is costly for a large sample of participants and long-term studies compared to in-situ monitoring of occupant behaviours.

While laboratory and virtual environments attempt to replicate reality to provide participants with presence sense in real environment (Witmer and Singer, 1998), existing buildings can be considered living laboratories to monitor everyday lives of occupant behaviours in their actual environments. Monitoring occupant behaviours on site is an essential research approach to better understand how occupants react to their built environments and develop data-driven occupant models. Using existing sensors in studied buildings with additional installed sensors, where required, occupants' presence and interactions with building components and systems and influential factors, including indoor and outdoor environmental conditions, can be logged. With the emerging technologies in centralized data management systems, the in-situ monitoring approach is a relatively non-invasive approach where occupants' presence and interactions with buildings are passively recorded with minimized intrusion on occupants' daily life.

Collecting data on occupant behaviours in realistic situations is an imperative ingredient for developing occupant models in occupant behaviour studies. However, conducting monitoring campaigns is a challenging task that requires experience and skill. For instance, sensor-based methods rely on single sensors as proxies for behaviours and comfort, while the occupant decision-making process is complex. Due to the complexity of occupant behaviours, researchers may ignore common-causal variables while

these variables can explain the subtle cause and effect relationships in the observations. For instance, the researcher interviewed an occupant in an office building who closed window blinds and opened operable windows before departure to cool down the space for the next day in the summer. Moreover, retrieving data from stand-alone data loggers, where data acquisition is not stored centrally, can be invasive for occupants. The aforementioned opportunities and challenges must be addressed for in-situ monitoring of occupant behaviours. Furthermore, because of the impacts of the climatic, cultural, and other contextual factors (e.g. building and space characteristics) on the occupant behaviours (O'Brien and Gunay, 2014), in-situ monitoring campaigns must be well documented. Providing such documentation for in-situ monitoring studies will also inform other researchers on whether data-driven occupant models developed based on each specific building are repeatable and applicable to other buildings. Moreover, researchers should decide on well-suited techniques for the designated purposes of monitoring occupant behaviours in existing buildings. The appropriate methods in collecting data from existing buildings should be determined based on the complexity level of analyzing the data obtained from the study and with whom the outcomes of the study are to be communicated (Guerra-Santin and Tweed, 2015a, 2015b).

The objective of this chapter is to facilitate future monitoring studies in office spaces to support the development of statistical occupant models for simulation-based design of new buildings and adjustment of control systems in existing buildings. Likewise, this critical review assisted the researcher to conduct the monitoring campaign of the current research. The monitoring techniques reviewed in this chapter for office spaces are generally applicable to residential buildings. However, occupant behaviours in residential buildings differ from office spaces with regard to types of activities, variety of occupants, autonomy for controlling environmental conditions, and paying for energy consumptions (Guerra-Santin et al., 2009) and thereby require specific considerations. While previous studies (Hong et al., 2015a; Hong et al., 2015b; Yan et al., 2015; Hong et al., 2016) provide comprehensive reviews of occupant behaviours on collecting data, modelling, and simulating occupant behaviours to quantify occupants' impact on

building energy performance, the current study focuses specifically on the in-situ monitoring approaches of data collection and the relevant opportunities and limitations. To achieve the objectives of this chapter, the techniques applied in previous studies on occupant behaviour monitoring on site are critically reviewed. Opportunities and challenges of existing monitoring techniques and the potential to apply new technologies in monitoring studies are discussed, while recommendations for future research are drawn from the previous studies in the literature and the personal experience of the researcher obtained in the initial stages of conducting the monitoring campaign in the current research project. The scope of this study is to encompass those explanatory variables (e.g. air temperature, illuminance, and solar radiation) that can help predict occupants' interactions with building components and systems alongside those which can be modelled in BPS tools.

3.2. Monitoring methods

To apply in-situ monitoring approaches in occupant behaviour studies, observations and surveys are the two general methods that can be employed to collect data. The observation method can be conducted as a covert or overt type. In covert observation, occupants are not notified that their behaviours are being observed, though occupants' unawareness of a study may contradict ethical regulations. In overt observation, occupants are informed of the study. Researchers can record their observations through sensors, notes, photos, video, or tape. Survey studies actively involve subjects in the monitoring study to report about themselves through spoken and/or written communication. The quantitative and qualitative outcomes of such monitoring studies are beneficial for both the adjustment of control systems in the monitored building and implementation in the simulation-based design process. In this section, different in-situ monitoring approaches to study occupant behaviours are discussed, as presented in Figure 3.1.

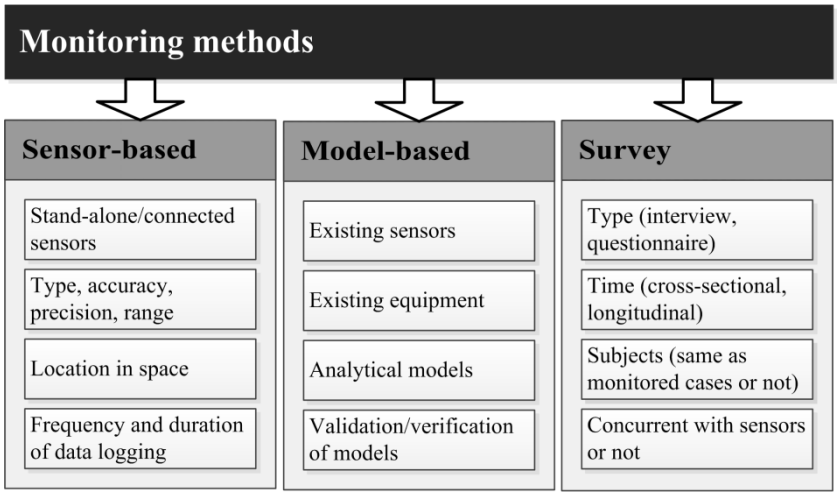

Figure 3.1. Overview of monitoring techniques with the main relevant considerations in applying different techniques to in-situ monitoring studies.

3.2.2. Sensor-based techniques

Sensor-based techniques are generally more efficient and accurate and facilitate obtaining greater sample sizes compared to surveys that involve manual recording of occupant behaviours. Sensor-based techniques are also efficient for buildings that already have such sensors built in. However, costs and effort still become sizable for large or long-term studies. In addition, subtle motivations behind occupant behaviour may not be identifiable by sensor-based techniques. The two common sensor types incorporated in monitoring campaigns are the stand-alone and connected varieties.

3.2.2.1. Stand-alone sensors

Stand-alone sensors operate independently from any other systems for data acquisition, storage, and maintenance. Previous research incorporated these sensors to record occupants' presence and actions and environmental conditions (Figure 3.2). Stand-alone sensors are typically relatively low cost compared to connected sensors, where additional equipment is required for data acquisition and storage, unless connected sensors are already installed and paid for. Furthermore, there is flexibility in locating stand-alone sensors such that standards including ASHRAE Standard 55 (2013a) can be complied with.

Moreover, stand-alone sensors are often more reliable with regard to accuracy and calibration compared to built-in sensors integrated with building automation systems.

However, monitoring occupants on site imposes some limitations for locating stand-alone sensors, as it may be impractical to measure the variables of interest at scientifically appropriate locations. For instance, measuring workplane illuminance and globe temperature in long-term studies is impractical because ideal sensor locations often coincide with occupant spaces. There are some uncertainties in positioning the sensors for measuring illuminance on occupants' desktop, such as occupants' or furniture's shading and monitors' or windows' luminance on sensors. In these cases, mounting illuminance sensors on the ceiling can avoid these issues (Figure 3.3), where ceiling illuminance can be a representative of workplane illuminance that occupants experience. For instance, Tzempelikos et al. (2009) found that there is a correlation between the workplane and ceiling illuminance. However, it is commonplace for simulation tools to calculate and report workplane illuminance. Coupling BPS tools with daylighting analysis tools, such as RADIANCE-based tool DAYSIM (Reinhart, 2010), where the indoor illuminance on the ceiling can be calculated, can address the models developed based on the measurements of indoor illuminance on the ceiling. Locating globe thermometers away from spaces' surfaces may also interfere with occupants' activities. Konis' (2013b) invention of a desktop station attempts to overcome these challenges by providing a platform for globe thermometer and illuminance sensors. Another drawback of stand-alone sensors is that memory and battery life of these sensors are finite and may require frequent data collection. There is also a risk of relocation or even disposal of data loggers by occupants at their convenience. Therefore, the location of installed sensors should be verified frequently and the importance of sensor location should be explained to study participants.

Figure 3.2. Example of using stand-alone sensor for recording light state (on/off), which is magnetically fixed to the lighting fixture.

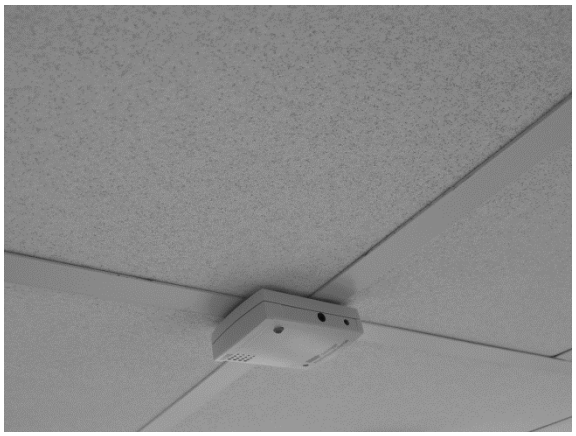

Figure 3.3. Example of stand-alone sensor mounted on the ceiling to measure indoor illuminance.

3.2.2.2. Connected sensors

Connected sensors communicate with remote data management systems for logging and archiving data. Building automation systems (BAS), also known as building management system (BMS), are an instance of centralized building management and operation systems. A wide range of sensors, including built-in and additional ones, can be integrated with the BAS to record occupants' presence and actions and environmental conditions (Reinhart and Voss, 2003; Haldi and Robinson, 2010; Sadeghi et al., 2016). Figure 3.4 shows a typical BAS-integrated built-in sensor at the room level with user interfaces, passive

infrared motion (PIR) sensors, thermistors, humidity, and CO_2 sensors, and some programmable functions. Additional sensors may require a gateway if the communication protocol does not match that of the controllers. Logged data can be collected and stored via the BAS without any impact on the occupants. Other than BAS-integrated sensors, there are numerous products that are targeted at scientific applications that have centralized data management.

Figure 3.4. Example of BAS-integrated built-in sensor on the wall with occupancy, temperature, relative humidity, and CO_2 sensors, and buttons for thermostat setpoint adjustment and light dimming control.

The connection between sensor networks and data acquisition systems can be wired or wireless. While wireless connections are preferable to wired ones as they are more easily installed, especially for retrofitting purposes, wired connections tend to be more reliable due to the limited battery life and range of wireless sensors. However, energy harvesting from light, thermal, or mechanical sources in some emerging wireless sensors (Figure 3.5) may alleviate the drawback of wireless sensors. Moreover, as per anecdotal evidence, wireless sensors may transmit less frequent signals (e.g. to conserve power) and therefore, there is more likely to be a time delay between the measured predictor variables (e.g. illuminance) and occupants' actions (e.g. closing window shades because of the glare issue).

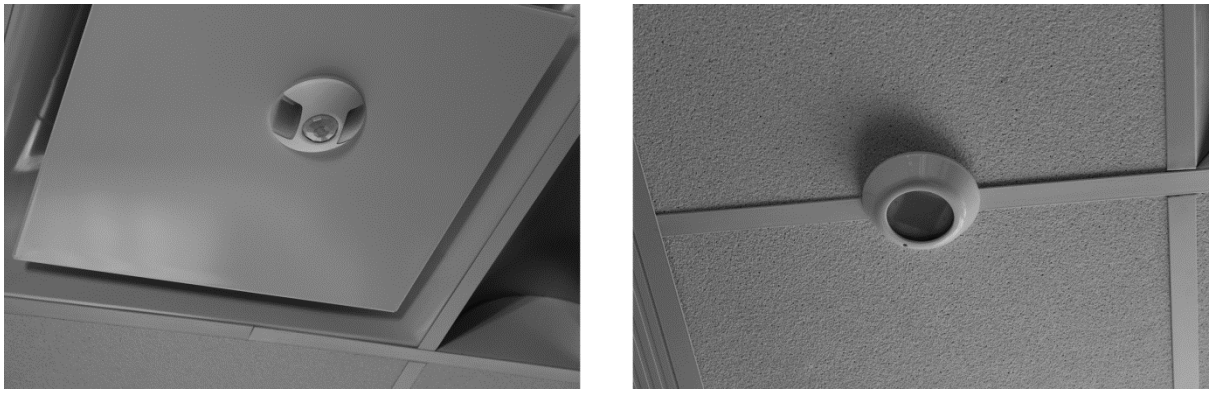

Figure 3.5. Examples of BAS-integrated solar-powered sensors, attached to the ceiling: (left) occupancy sensor, (right) light sensor.

A major advantage of connected sensors is that data can be collected relatively easily and remotely. Moreover, suspicious values caused by faulty sensors or other issues can be identified immediately, in contrast to distributed stand-alone sensors where unexpected results are only discovered upon data collection on site. The required infrastructure costs for connecting control and data acquisition systems can also be reduced by connecting networks of systems using cloud-based services, so-called Internet of Things (IoT) (e.g. (Kovatsch et al., 2012)). Using this new technology, collected data are maintained on remote computers in the cloud with access from any computer via existing network infrastructure. With the IoT, operation and maintenance of networks of data control and acquisition systems is more efficient and reliable than the previous generations of data management systems. However, data storage in the cloud should protect data.

While connected sensors are preferable to stand-alone ones regarding the aforementioned advantages, locations of built-in sensors in spaces may be designated inappropriately for scientific purposes and changing their location is costly and requires intrusive actions. For instance, ASHRAE Standard 55 (2013a) requires measuring air temperature at the height of 1.1 m for seated occupants in the occupied zones away from the occupied zone's boundaries; however, the typical location of built-in thermostat is on the walls at the height of 1.5 m. The field of view of the motion sensors is also affected by the location

of these sensors (Gunay et al., 2016a). Moreover, BAS-integrated sensors may restrict their applications for scientific purposes. For instance, it was discovered that one particular model of wireless BAS-integrated daylight sensors required 100 lux in order to generate the power to send a signal and it did not measure above 1000 lux. These limitations are acceptable for standard lighting controls applications, but pose a major limitation for occupant research.

3.2.2.3. Application of sensors

Detecting occupancy and measuring environmental conditions, such as illuminance level, solar radiation, temperature, relative humidity, and CO_2, with sensors in monitoring studies are the common applications of stand-alone (Figure 3.3) and connected sensors (Figure 3.4 and Figure 3.5) (Foster and Oreszczyn, 2001; Reinhart and Voss, 2003; Sutter et al., 2006; Inkarojrit, 2008; Haldi and Robinson, 2010; Correia da Silva et al., 2015; Langevin et al., 2015). Sensors can also be used to capture occupants' operations on lighting (Figure 3.2), window shading devices (Sutter et al., 2006; Inkarojrit, 2008; Haldi and Robinson, 2010), and operable windows (Herkel et al., 2005; Herkel et al., 2008; Yun and Steemers, 2008; Dutton and Shao, 2010). While using sensors is a reliable technique for recording operable window and blind states, using sensors may restrict occupants from manually opening and closing window shades and operable windows, as the occupants need to be careful not to intervene in proper functioning of the corresponding sensors. Such constraints on using operable windows and blinds might reduce the frequency of occupants' actions. Furthermore, for windows with multiple blinds and/or operable parts, multiple sensors should be installed (e.g. (Haldi and Robinson, 2010)), which could be too laborious and costly for studying a large number of spaces.

Therefore, so-called image-based sensing by recording window and blind positions from the exterior or interior of buildings with photos (e.g. (Rea, 1984; O'Brien et al., 2010; Zhang and Barrett, 2012b; Konis, 2013a; Honnekeri et al., 2014; Meerbeek et al., 2014)) and videos (e.g. (Foster and Oreszczyn, 2001; Reinhart and Voss, 2003; Brager et al., 2004; Sutter et al., 2006)) is more cost-effective and practical for

large sample sizes (Figure 3.6). However, to avoid violating occupants' privacy, low-resolution photos/videos should be taken in a way that occupants cannot be identified from them, which may lead to difficulty in obtaining data from photos/videos (Meerbeek et al., 2014). Furthermore, the position of operable windows left ajar and blind slat angles is difficult to detect from photos and therefore result in this method being less reliable than sensors (Rea, 1984). Using image-based sensing technique also imposes some limitations on the interpretation of data at large scales, that is, more than 50 windows (O'Brien et al., 2010), and long-term monitoring campaigns. For instance, solar reflection on windows, weather conditions (e.g. snow, rain, and fog), and visual obstructions pose constraints that lead to errors in post-processing window and blind positions. Automated image processing using computer vision codes can reduce the amount of manual interpretation of blind positions (O'Brien et al., 2010; Meerbeek et al., 2014).

Figure 3.6. Example of using time-lapse camera for taking photos of the exterior of building.

3.2.2.4. Frequency of data logging

Sampling frequencies among existing occupant monitoring studies vary widely, but requires careful consideration. Normally, environmental conditions, building states, and other continuous variables are logged at a fixed frequency, whereas occupant actions are stored at the time of the event (event-based). Fixed frequency logging should be adequately high that occupant actions can be statistically linked to predictors (e.g. sudden increases in daylight glare). For event-based data logging, Figure 3.7 presents an

example of logged data for occupancy with a motion detector sensor. To convert these raw data to time-step data, using the deterministic approach, the space is assumed occupied whenever the time interval between each two consecutive motion detections is less than a certain time delay (e.g. 10 or 30 minutes). In the probabilistic approach, a cumulative distribution of time intervals between each two consecutive motion detections specifies the probabilistic time delay within a certain confidence interval (Nagy et al., 2015).

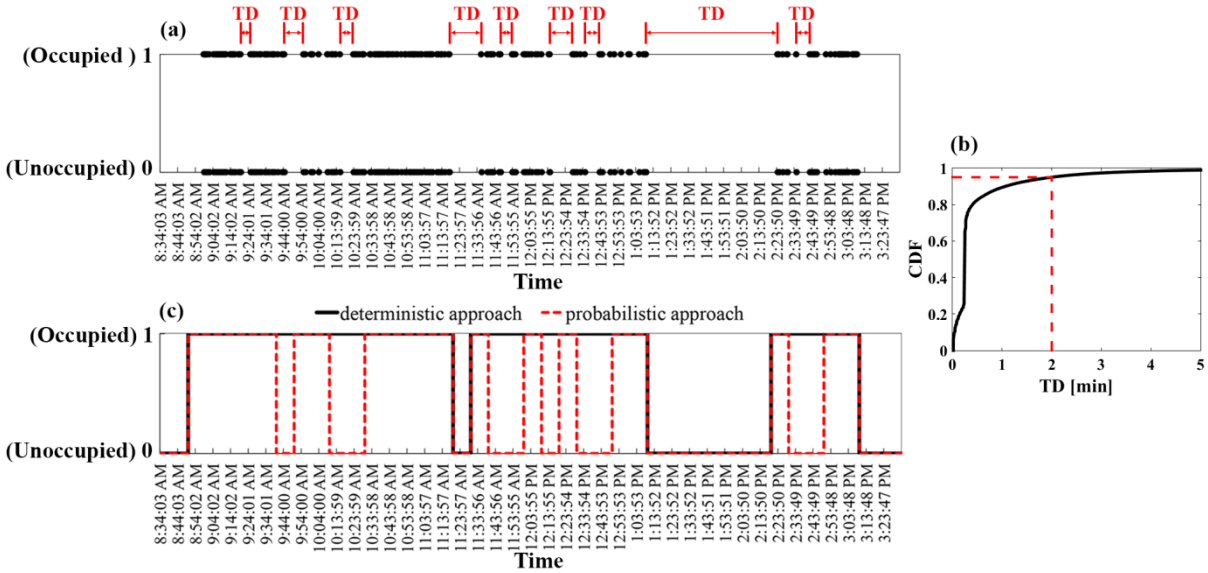

Figure 3.7. Example of occupancy data: (a) logged data by an occupancy sensor showing time delay (TD) between each two consecutive motion detections, (b) cumulative distribution of TD based on 7 months' worth of data, and (c) converted raw data to time-step (10 minutes) data using deterministic and probabilistic approach in calculating TD; where TD is 2 min with confidence interval of 95% using the probabilistic approach, and TD is assumed 10 minutes using the deterministic approach.

Contextual factors may cause occupants' reluctance to interact with building components and systems frequently. For instance, the extent of conditioning in indoor environments may affect occupants' interactions with buildings. Brager and Pigman's (2013) study in an air conditioned building with operable windows, where occupants were satisfied with indoor environmental conditions, revealed that 6%, 38%, and 41% of window users adjust their windows daily, weekly, and monthly, respectively. In these cases, low frequencies of data recording can capture variations in observation (Rea, 1984; Warren

and Parkins, 1984; Foster and Oreszczyn, 2001). On the other hand, the data logging frequency should be high enough as to not to miss two consecutive variations in observation. Low sampling frequencies may fail to capture all changes in occupants' modifications on building components and systems, which may hide key cause and effect events. However, it is important to understand the circumstances that motivated the occupant to act in developing occupant models.

The capacity of data storage and battery life are the other factors in the decision on the data logging frequency – particularly for stand-alone sensors. The frequency of data logging is confined by the duration of continuous data logging with stand-alone sensors, memory capacity, and battery life of these sensors. A typical available stand-alone data logger for recording temperature, relative humidity, and light intensity has a memory of 65 KB with one-year battery life that can record 43 K data points. This specification allows recording frequency of 10 min if data are collected over a year, assuming that all recorded data are transferred once at the end of the data collection. With another available product for measuring temperature with a 16 KB memory, two years battery life, and 8 K capacity of recorded data, a recording frequency of 30 min for a one-year monitoring campaign is feasible.

3.2.2.5. Duration of data logging

Given that occupants' behaviours to adapt themselves to their environments (e.g. changing clothes, drinking hot/cold beverages) and occupants' operations on building components and systems to restore their comfort are seasonally affected, the data logging period should span over an entire year to capture all typical climatic conditions in the building locale. Several previous monitoring studies indicate a significant impact of seasonal variations on occupant behaviours in using lighting (Boyce, 1980), operable windows (Fritsch et al., 1990; Herkel et al., 2005; Herkel et al., 2008), and window shading devices (Mahdavi et al., 2008). Moreover, occupants' operations on building components, such as window shading devices, are infrequently varied. For instance, Rubin et al. (1978), Rea (1984), and Zhang and Barrett (2012a) concluded that blind change position is determined by occupants' long-term

perceptions of sunlight. In these cases, a longer data logging period is required for the development of stochastic occupant models. Otherwise, the number of occupant-related events and corresponding predictors is insufficient to build representative statistical models.

3.2.3. Model-based techniques

In recognition of some of the drawbacks of direct measurement using sensors (e.g. locating them in space that occupants occupy), model-based virtual sensors can replace or supplement traditional sensors. While applying virtual sensors in other fields such as process controls and automobile industry started a few decades ago, this is a novel technique in building sector as emerged in recent years and has not widely spread despite its potential advantages (Li et al., 2011). For instance, virtual sensors have been implemented as a cost-effective method in developing control systems in fault diagnosis and correction occurred in the heating, ventilation, and air-conditioning systems of buildings (e.g. (Li and Braun, 2007a, 2007b; Reppa et al., 2014)).

3.2.3.1. Application of model-based techniques

In some cases, researchers confront variables that are impractical and may be considered as obtrusive to be measured with physical sensors in long-term studies. For instance, measurement of workplane daylight illuminance can be used to predict occupants' operation of shading devices and light switches (Reinhart and Voss, 2003; Haldi and Robinson, 2010). However, in-situ measurement of workplane illuminance is impractical in long-term studies due to shading from occupants or furniture and luminance from windows or monitors on sensors and the inconvenience of sensors' location. Previous studies developed simulation tools to predict workplane illuminance using measured outdoor conditions and building spaces' characteristics (Choi and Mistrick, 1997; Lehar and Glicksman, 2007; Fakra et al., 2011). Researchers may develop the correlation between indoor and outdoor illuminance distribution (Tregenza and Waters, 1983) by high dynamic range (HDR) photographic techniques (Inanici, 2013).

Model-based techniques may also be preferable to commercial sensors because of the limitations with real sensors regarding their accuracy and range of measurements (Reinhart and Voss, 2003). Improper location of sensors can also lead researchers to use model-based techniques. For instance, the location of built-in motion sensors for occupancy may be inappropriate to detect occupants' presence accurately where furniture and space design block the field of view of the motion sensors, or occupants do not move frequently. In these cases, several previous research estimated occupancy by measuring indoor CO_2 concentration (Ke and Mumma, 1997; Wang et al., 1999; Ansanay-Alex, 2013), occupants' use of lighting and electrical equipment (Abushakra and Claridge, 2008; Chang and Hong, 2013; Zhao et al., 2014), or existing information technology networks in buildings (Melfi et al., 2011; Christensen et al., 2014).

Where measuring a specific variable requires deployment of additional sensors and equipment with invasive actions, using model-based techniques is a possible alternative. For instance, several previous studies developed models to estimate occupancy levels based on a number of sensors distributed in buildings and prior information about building usage patterns and occupancy (Lam et al., 2009; Meyn et al., 2009; Dong et al., 2010; Liao and Barooah, 2010). As another example of virtual sensing, in non-intrusive load monitoring process, coined by Hart (1989), power use by individual appliances are calculated measuring building aggregated electrical power consumption and unique electricity use pattern by plug-in appliances, known as power signature analysis (Zoha et al., 2012; Carrie Armel et al., 2013). This process disaggregates electricity use at the zone or building level into end use level, thus this process is a cost-effective as well as non-intrusive method in monitoring plug-in appliance energy use. Measurement of building energy performance at the room level also necessitates multiple meters while model-based techniques can remove the need for installation of additional meters in each space (Ploennigs et al., 2011).

3.2.3.2. Evaluation of model-based techniques

Researchers should be cognizant of the errors that may be caused by virtual sensing. Model-based measurements should be evaluated against direct measurements in the same case studies or spaces with similar characteristics (as explained in Section 3.3.4) (e.g. (Reinhart and Walkenhorst, 2001; Ploennigs et al., 2011)). For instance, Reinhart and Walkenhorst's (2001) validation study on the performance of the daylighting tool DAYSIM in calculating workplane illuminance showed maximum values of 8% and 33% for the mean bias error (MBE) and the root mean square error (RMSE), respectively. This evaluation reveals the deviation between the model-based estimations and the measurements gathered from the ground truth on site. For instance, in occupancy detection studies, taking photos and/or video inside offices is the common used technique as the ground truth (Meyn et al., 2009; Dong et al., 2010; Melfi et al., 2011; Gunay et al., 2016a). However, privacy concerns should be considered in using this technique. Some other research counted occupancy manually (Wang et al., 1999) or used passive (e.g. PIR built-in sensors) or active (e.g. pedometer) occupancy sensors to validate the model (Liao and Barooah, 2010; Chang and Hong, 2013; Zhao et al., 2014).

3.2.4. Surveys

Surveys are the other main research techniques that researchers can use to study occupant behaviours in situ. Surveys can complement sensor-based techniques and reveal subtle cause and effect relationships and phenomena that researchers may not have considered with regard to the complexity of occupant behaviours. This section discusses types, applications, and respondents to surveys. Timing and frequency of distributing surveys and reliability of inferences drawn from surveys are also discussed.

3.2.4.1. Types of surveys

Different research techniques can be used in surveys, such as questionnaires using paper-based (Zhang and Altan, 2011), web-based (Inkarojrit, 2008; Center for the Built Environment (CBE), 2014; Sadeghi et

al., 2016), or physical-based (Konis, 2013b) user interfaces, and interview (Karjalainen, 2009; Zhang and Altan, 2011; Zhang and Barrett, 2012b; Meerbeek et al., 2014). Questionnaires in survey studies are commonly based on predefined questions and answers. Researchers may use their prior knowledge or previous survey studies (Sutter et al., 2006) to design questions. However, interviews allow greater adaptability and customizability mid-way through and may yield greater information compared to pre-designed questionnaires. Zhang and Altan (2011) and Meerbeek et al. (2014) interviewed the participants in their studies in addition to paper-based surveys to understand more deeply about participants' attitudes and feelings in their offices.

3.2.4.2. Application of surveys

Surveys in occupant behaviour studies can be used to improve future designs. In addition, building managers can improve operation and maintenance of buildings by seeking occupants' feedback on their comfort and environmental conditions.

There are also some adaptive actions, such as changing clothing level, consuming a hot/cold beverage, and changing posture that occupants undertake to restore their comfort. These adaptive behaviours and occupants' activity types cannot easily be measured with existing sensors, while surveys can be an appropriate technique in this regard. Several previous studies estimated clothing insulation levels by asking participants to indicate their clothing items (Morgan and de Dear, 2003; Haldi and Robinson, 2008; Honnekeri et al., 2014) while this may violate participants' privacy. Some researchers record participants' clothing unobtrusively (Honnekeri et al., 2014), however, this approach is prone to errors as some clothing layers are unobserved, especially in the heating season. Moreover, survey approaches can be used to perform time use studies (Centre for Time Use Research (CTUR); Lader et al., 2006; GSA Office of Governmentwide Policy, 2012; US Department of Labor, 2014), which are beneficial to develop models of occupants' activities.

In lieu of sensor or model-based techniques, occupant behaviours can be recorded manually by occupants through journaling as another technique in survey studies (Warren and Parkins, 1984; Meerbeek et al., 2014). Researchers may themselves do walk-throughs into spaces of interest for journaling, which also allows them to observe the environment and note any specific features or factors to be recorded (Newsham et al., 1995).

3.2.4.3. Respondents to surveys

Survey subjects can be the subjects involved in the sensor-based data collection campaign (Warren and Parkins, 1984; Sutter et al., 2006; Rijal et al., 2007; Honnekeri et al., 2014; Meerbeek et al., 2014). Survey subjects can also be a sample of another population (Inkarojrit, 2008), whereas recruiting occupants of the buildings where data collection is conducted is preferable so that the influence of contextual factors can be studied as well. In addition, recruiting occupants of the buildings where data are collected will allow researchers to evaluate subjects' responses on their perception of spaces with simultaneous recording of environmental factors. On the other hand, the downside of doing surveys on the same participants in the sensor-based data collection is that they are more frequently reminded of tracking their behaviours; hence the Hawthorne effect (McCambridge et al., 2014) may be exacerbated, where participants may behave differently from their natural behaviours and change their behaviours towards the researcher's expectation and social acceptability. It is worth noting from anecdotal evidence that population sampling may be biased towards occupants who are dissatisfied with their environment as they show more willingness to participate in the study with the hope that their complaints will be acted upon.

3.2.4.4. Timing of surveys

Surveys can be performed before a monitoring campaign commences to obtain prior knowledge about the study. Some previous research relied on conducting a survey prior to data collection to establish the most

suitable predictor variables (Warren and Parkins, 1984; Inkarojrit, 2008; Gunay et al., 2016d). Some researchers carry out survey during measurement or when the data collection phase is accomplished (Warren and Parkins, 1984). However, conducting surveys after the observational study may not provide researchers with knowledge of influential factors to be measured, but can provide researchers with any abnormal report in their collected data. For instance, the researcher had informal discussions with an office occupant who closed the window blind frequently due to the solar radiation on the bookshelves that caused the books to fade. Another occupant did not open the operable window because wind blew debris off the window sill and insect screen. Other occupants turned off the lights and/or closed the window blinds because they felt warm in their offices.

3.2.4.5. Frequency of distributing surveys

Researchers may conduct cross-sectional surveys at one specific time before, during, or after the monitoring period (Rijal et al., 2007; Karjalainen, 2009; Gunay et al., 2016d). Cross-sectional surveys are also the common approach in POE studies where surveys are conducted once shortly after the building is built (Federal Facilities, 2001; Zimmerman and Martin, 2001). Cross-sectional surveys may suffer from occupants forgetting their previous feelings and actions. For example, participants in Warren and Parkins' (1984) and Karjalainen's (2009) studies, took part in the survey just one time while they were asked about their thermal comfort for both the heating and cooling seasons. Bennet and O'Brien (2016) partially solved the recollection bias of one-time surveys by conducting a survey in both the summer and winter term and customizing the questions to suit the season.

On the other hand, longitudinal surveys can address the drawbacks with cross-sectional surveys (Rijal et al., 2007; Haldi and Robinson, 2008). Concurrent measurement of environmental parameters with longitudinal surveys allows researchers to analyze the relationship between environmental conditions and immeasurable variables with current sensor technologies, such as comfort, clothing level, and activity (Morgan and de Dear, 2003; Haldi and Robinson, 2008; Zhang and Barrett, 2012a, 2012b; Konis, 2013a;

Honnekeri et al., 2014). However, there are some limitations with longitudinal surveys. For instance, participants may not completely recall their past comfort conditions in their environments, which is less an issue with longitudinal surveys than cross-sectional surveys. As anecdotal evidence, high frequency of distributing longitudinal surveys may cause occupants to be more reluctant to participate. Pop-up surveys may address this limitation (Haldi and Robinson, 2008; Konis, 2013b).

3.2.4.6. Reliability of surveys

While survey techniques require lower investment with regard to time, cost, and effort of sensor/equipment installation and maintenance, they may be accompanied by errors and/or bias in manual recording of events and comfort level by occupants (Bailenson et al., 2004; Jazizadeh et al., 2011), and thereby achieving less reliability. To minimize participants' biased answers and behaviours towards researchers' expectation and social desirability, researchers should inform participants that the study is seeking real actions and there will not be any judgments on their behaviours as well as collected data will be anonymized by coding for the analysis. Errors with self-reporting in surveys can be lessened by managing time and frequency of distributing surveys during the monitoring period, and recording concurrent responses to questionnaires and occupants' interactions with buildings (Morgan and de Dear, 2003; Haldi and Robinson, 2008; Zhang and Barrett, 2012a; Konis, 2013a; Honnekeri et al., 2014).

3.3. Documenting monitoring studies

Monitoring studies should provide comprehensive documentation of the monitoring process, occupant behaviours of interest, participants, monitored building spaces, and methods used to collect data. A practical monitoring campaign document is required to facilitate future studies to support the development of occupant models using in-situ monitoring approach. A monitoring study document provides valuable information on the reliability and repeatability of the collected data. In addition, accessing to a comprehensive monitoring study document can avoid the usual error sources in data

collection that are likely for researchers to confront. An overview of documentation of a monitoring campaign is presented in Figure 3.8 and is discussed in more details in this section.

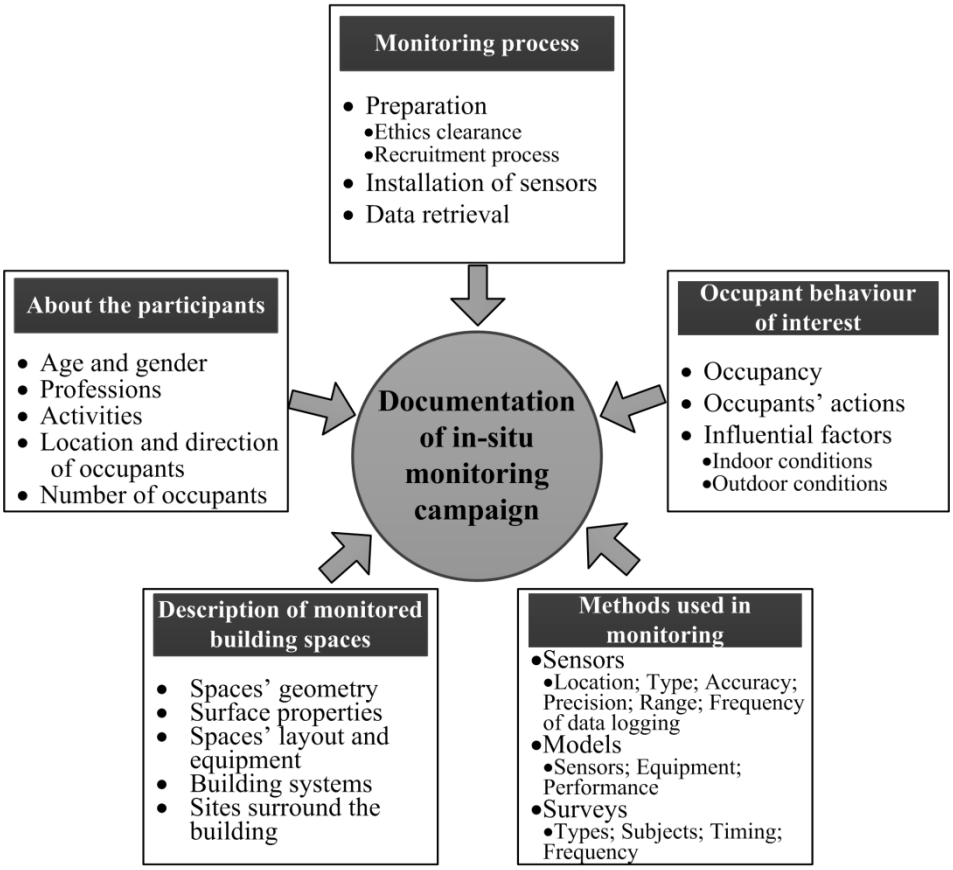

Figure 3.8. Overview of documentation of an occupant behaviour monitoring campaign.

3.3.1. Monitoring process

In the in-situ occupant monitoring process, the three main stages, as presented in Figure 3.9, are: (1) preparation, (2) installation, and (3) data retrieval. Each of these stages requires specific considerations that need to be programmed and organized beforehand to economize on time and effort in monitoring studies. Documenting a monitoring study process will also provide information on how to manage a monitoring campaign for researchers new to this topic while they can also employ and invent techniques

to minimize the challenges with studying occupant behaviours in existing buildings, as discussed in Section 3.4.2.

In the preparation stage of monitoring studies, as per the experience of the researcher, the project should be first assessed by the local facility management and the ethics board to evaluate the necessity of ethics clearance. If ethics clearance is required, the procedure to obtain the ethics approval from the local ethics board is performed.

Afterwards, as per ethics clearance, participants are informed of the study and recruited and then their consent is obtained. Regarding projects where ethics clearance is not required, the project can be performed under the local building management services by informing occupants of the project without the recruitment process. While several previous researchers (Boyce et al., 2003; Boyce et al., 2006; Sadeghi et al., 2016) obtained ethics clearance prior to their study, others (Boyce, 1980; Honnekeri et al., 2014) preferred completing their data collection process without disrupting occupants, involvement in the ethics clearance process, or to minimize the Hawthorne effect (McCambridge et al., 2014). However, tracking occupant behaviours without informing them may violate their privacy and research ethics.

For projects where ethics clearance is required before installing additional sensors and collecting data from stand-alone sensors, researchers should contact each participant to set an appointment for gaining permission to access to their offices. From the personal experience of the researcher, occupants may have a distinct preference about whether their offices are visited while they are present or not. However, for projects without requirement for ethics clearance, researchers can access monitored offices during unoccupied periods without interrupting occupants under the local building management services.

After project completion, researchers should debrief participants and provide them with findings of the project if they request for it. As per the ethics requirements, the findings of a monitoring study should be presented by anonymizing all the collected data, including sensor and model-based techniques and

surveys. However, anonymizing the data may eliminate valuable contextual information where a sample size is limited with regard to data categorization. For instance, participants may be identifiable by their profession, gender, and offices' orientation and floor level.

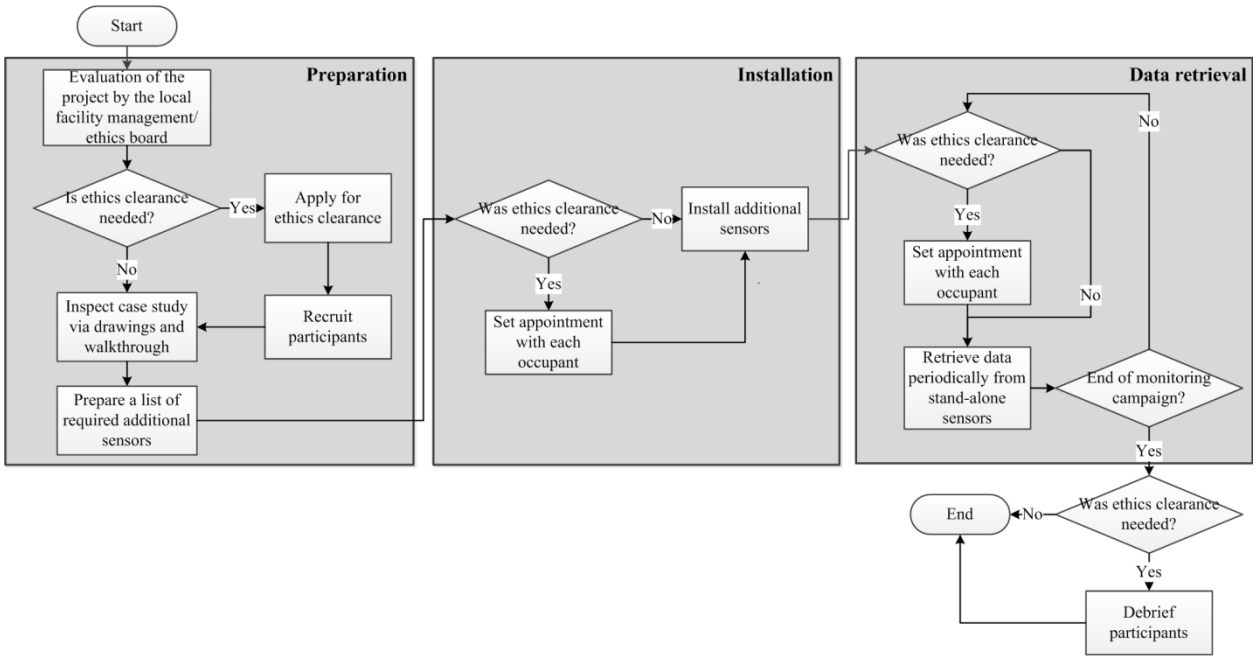

Figure 3.9. Main stages in conducting an in-situ monitoring study.

3.3.2. Occupant behaviours of interest

A monitoring study document should list occupant behaviours of interest, where occupancy is likely an essential element in all monitoring campaigns. The main explanatory variables that can predict how occupants react to their environment are determined based on researchers' prior knowledge, the literature, and/or conducting surveys. Accordingly, a list of applicable techniques are prepared to record occupancy, indoor and outdoor environmental conditions, the state of building components and systems, and plug-in appliances (e.g. computers, fans, space heaters, and fridges), and the state of occupant-related variables (Figure 3.10). Listing all the occupant and building-related parameters and environmental conditions will provide researchers with an overview of the required sensors and equipment. Knowing all the variables of interest and reviewing the literature for existing in-situ monitoring studies will boost the efficiency of

performing such studies, regarding time, effort, and cost. Furthermore, preparing a list of occupant behaviours of interest and the influential factors will ensure sufficient outcomes from data collection to develop occupant models. A summary of previous studies with the relevant measured parameters and the employed monitoring techniques is presented in Table 3.1.

The current study does not review all influential factors on occupant behaviours as several previous studies provided comprehensive reviews on this topic (Gunay et al., 2013; O'Brien and Gunay, 2014). Specifically, on operable windows, Warren and Parkins (1984), Fritsch et al. (1990), Nicol (2001), Rijal et al. (2007), Robinson et al. (2007), Herkel et al. (2008), Rijal et al. (2008), Yun and Steemers (2008), Haldi and Robinson (2009), and Fabi et al. (2012) studied the influential factors on occupant behaviours. On window shading systems, Rea (1984), Inoue et al. (1988), Pigg et al. (1996), Rienhart and Voss (2003), Sutter et al. (2006), Inkarojrit (2008), Haldi and Robinson (2010), Zhang and Barrett (2012a), and O'Brien et al. (2013) researched the explanatory factors. On lighting, Hunt (1979, 1980), Boyce (1980), Pigg et al. (1996), Love (1998), Reinhart and Voss (2003), Reinhart (2004), and Boyce et al. (2006), and on plug-in appliances, Gunay, O'Brien et al. (2016d) and Mahdavi, Tahmasebi, and Kayalar (2016) investigated the parameters that affect how occupants use them. Note that the above list is not inclusive of all occupant behaviours and the relevant references. Prior to designing occupant monitoring campaigns, researchers need to list all occupant behaviours of interest and explore the influential factors. Considerable effort can be saved by thoroughly reviewing the literature to determine whether other researchers established the significance of predictive variables.

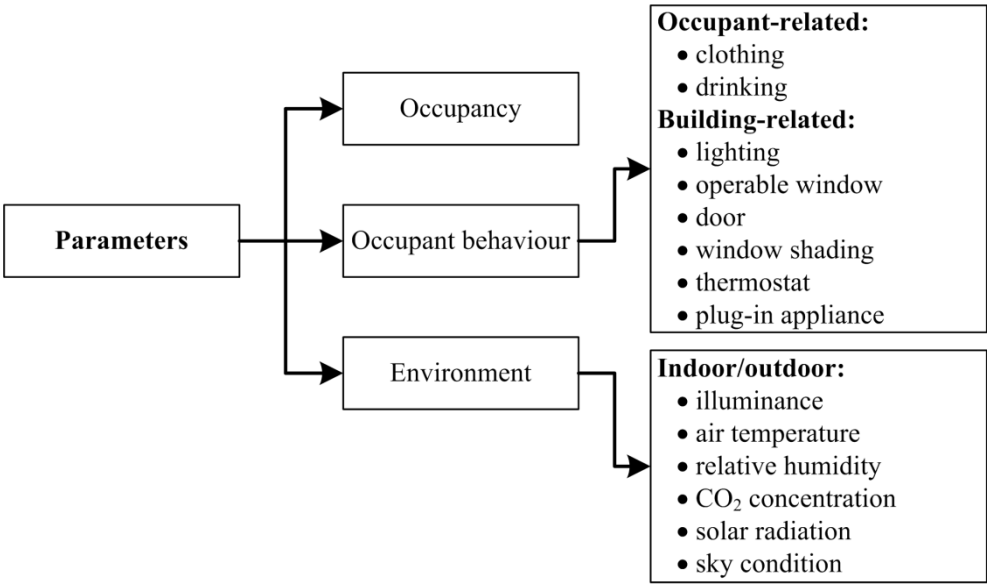

Figure 3.10. A list of parameters that are recorded in in-situ monitoring studies.

Table 3.1. A summary of measured variables and the employed monitoring techniques in the existing in-situ monitoring studies.

Parameter			Monitoring method		
			Sensor-based	**Model-based**	**Survey**
Occupancy			(Pigg et al., 1996); (Love, 1998); (Reinhart and Voss, 2003); (Herkel et al., 2005); (Sutter et al., 2006); (Herkel et al., 2008); (Mahdavi et al., 2008); (Haldi and Robinson, 2009); (Correia da Silva et al., 2015); (Nagy et al., 2015); (Gunay et al., 2016d); (Mahdavi et al., 2016); (Sadeghi et al., 2016)	(Lam et al., 2009) (Meyn et al., 2009); (Dong et al., 2010); (Liao and Barooah, 2010); (Melfi et al., 2011); (Chang and Hong, 2013); (Christensen et al., 2014); (Zhao et al., 2014)	(Boyce, 1980); (Warren and Parkins, 1984); (Newsham et al., 1995); (Yun and Steemers, 2008); (Langevin et al., 2015)
Occupant behaviour	Occupant-related	Clothing			(Morgan and de Dear, 2003); (Rijal et al., 2007); (Haldi and Robinson, 2008); (Zhang and Barrett, 2012a);

					(Zhang and Barrett, 2012b); (Honnekeri et al., 2014);
		Hot/cold drinks			(Haldi and Robinson, 2008)
		Activities			(Lader et al., 2006); (Rijal et al., 2007); (GSA Office of Governmentwide Policy, 2012); (Langevin et al., 2015); (US Department of Labor, 2016); (Centre for Time Use Research (CTUR))
		Comfort			(Warren and Parkins, 1984); (Pigg et al., 1996); (Rijal et al., 2007); (Haldi and Robinson, 2008); (Inkarojrit, 2008); (Rijal et al., 2008); (Yun and Steemers, 2008); (Karjalainen, 2009); (Jazizadeh et al., 2011); (Zhang and Altan, 2011); (Zhang and Barrett, 2012a); (Zhang and Barrett, 2012b); (Konis, 2013a); (Honnekeri et al., 2014); (Meerbeek et al., 2014); (Langevin et al., 2015); (Sadeghi et al., 2016)
	Building-related	Lighting	(Hunt, 1979); (Pigg et al., 1996); (Love, 1998); (Reinhart and Voss, 2003); (Sutter et al., 2006); (Mahdavi et al., 2008); (Correia da Silva et al., 2015); (Nagy et al., 2015); (Sadeghi et al., 2016);		(Boyce, 1980)

		Operable windows	(Fritsch et al., 1990); (Zhang and Barrett, 2012b); (Herkel et al., 2005); (Herkel et al., 2008); (Yun and Steemers, 2008); (Haldi and Robinson, 2009); (Dutton and Shao, 2010); (Honnekeri et al., 2014); (Langevin et al., 2015)		(Warren and Parkins, 1984); (Rijal et al., 2007); (Haldi and Robinson, 2008); (Rijal et al., 2008)
		Door			(Haldi and Robinson, 2008)
		Movable window shading	(Rea, 1984); (Foster and Oreszczyn, 2001); (Reinhart and Voss, 2003); (Inkarojrit, 2008); (Mahdavi et al., 2008); (Haldi and Robinson, 2010); (O'Brien et al., 2010); (Zhang and Barrett, 2012a); (Konis, 2013a); (Correia da Silva et al., 2015); (Sadeghi et al., 2016)		(Pigg et al., 1996); (Haldi and Robinson, 2008); (Meerbeek et al., 2014)
		Heating/ cooling devices	(Honnekeri et al., 2014); (Labeodan et al., 2015)		(Haldi and Robinson, 2008)
		Thermostats			(Karjalainen, 2009)
		Plug-in appliances	(Gunay et al., 2016d); (Mahdavi et al., 2016);	(Ploennigs et al., 2011); (Zoha et al., 2012); (Carrie Armel et al., 2013)	(Gunay et al., 2016d)
Environmental conditions	Indoor	Illuminance	(Boyce, 1980); (Sutter et al., 2006); (Mahdavi et al., 2008); (Haldi and Robinson, 2010); (Konis, 2013a); (Correia da Silva et al., 2015); (Nagy et al., 2015);	(Reinhart and Voss, 2003)	(Pigg et al., 1996)

			(Sadeghi et al., 2016)		
		Temperature	(Morgan and de Dear, 2003); (Reinhart and Voss, 2003); (Herkel et al., 2005); (Sutter et al., 2006); (Rijal et al., 2007); (Inkarojrit, 2008); (Mahdavi et al., 2008); (Rijal et al., 2008); (Yun and Steemers, 2008); (Haldi and Robinson, 2009); (Haldi and Robinson, 2010); (Jazizadeh et al., 2011); (Konis, 2013a); (Honnekeri et al., 2014); (Langevin et al., 2015); (Sadeghi et al., 2016)		
		Solar radiation	(Inkarojrit, 2008); (Correia da Silva et al., 2015); (Sadeghi et al., 2016)		
	Outdoor	Illuminance	(Reinhart and Voss, 2003); (Haldi and Robinson, 2010)		
		Temperature	(Haldi and Robinson, 2010); (Herkel et al., 2005); (Herkel et al., 2008); (Haldi and Robinson, 2009); (Dutton and Shao, 2010); (Honnekeri et al., 2014)		
		Solar radiation	(Foster and Oreszczyn, 2001); (Reinhart and Voss, 2003); (Herkel et al., 2005); (Herkel et al., 2008); (Dutton and Shao, 2010); (Haldi and Robinson,		

			2010)		
		Sky condition			(Rea, 1984); (Inkarojrit, 2008)

3.3.3. About participants

A comprehensive record of occupants and building spaces should be provided in a monitoring study report, as there are mutual interactions between occupants and buildings that affect occupants' comfort and building energy performance (Figure 3.11). To restore comfort, occupants react differently to the specifications of buildings (as explained in Section 3.3.4) that they can modify, such as space layouts, using equipment, and adjustment on building components and systems.

Documenting participants ideally includes occupants' age, gender, profession, and type of activities. The number of occupants in each office space and approximate location and direction of occupants should also be recorded through walk-throughs to each space. Previous studies revealed the differences of age and gender of occupants in their perception of comfort. For instance, Lee (2012) discovered that female and older occupants were less satisfied with the thermal conditions of their environments. The number of people in a space should also be documented, as it has been shown to affect light switching, thermal comfort, and perceived controls of temperature. Boyce (1980) indicated that the number of occupants in a space caused reduction in how often occupants switch lights in open offices. Similarly, Karjalainen (2009) discovered discernible difference in the thermal comfort and perceived control over indoor temperature between single-person, two or three-person, and open-plan offices. The personal characteristics of occupants may also affect the research results. For instance, placid occupants are generally more easily satisfied with the environmental conditions of their environments. Meerbeek et al. (2014) revealed the lower comfort ratings with the occupants who switched the blind control to the manual mode than the users of automatic mode, whereas this may not be related to the control systems since the automatic mode had also the option of manual override. Meerbeek et al. (2014) referred to the fact that users of the manual mode, who were in majority, perhaps were more concerned about their

comfort. Therefore, this user category was more prone to discomfort feelings compared to the automatic mode users who were generally more easily satisfied as they chose automatic control mode.

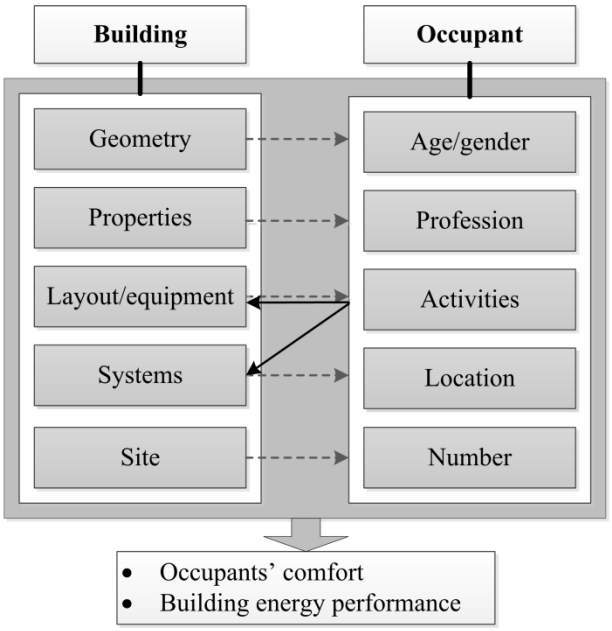

Figure 3.11. Two main domains in in-situ monitoring studies.

3.3.4. Description of monitored building spaces

In recognition of the mutual interactions between occupants and buildings, well-documented specifications of building spaces are necessary in reporting occupant behaviour studies in existing buildings. Monitoring campaigns should be proceeded by inspection of (1) space geometry, (2) surface properties, (3) space layout and equipment, (4) building systems, and (5) site (see Figure 3.11 and Table 3.2), through walk-throughs and architectural, mechanical, and electrical drawings. As occupants may reshape their environment and tweak building components and systems, and some modifications may be performed during constructing a building, researchers should not rely just on drawings and instead should check spaces' layout with available drawings and sketch spaces and/or take photos and notes of them (Zhang and Barrett, 2012b). In case building drawings are unavailable, researchers need to rely heavily on sketching spaces and taking notes and photos. In addition, they may obtain information about building

systems from building facility management, where applicable. Specifications of spaces' surfaces can be measured on site or obtained from manufacturers. Note that while a monitoring study requires almost all the aforementioned information, researchers may specify the information hierarchies as per objectives of each monitoring study.

The geometry of the building(s) and spaces (e.g. floor plan, orientation, dimension, location of windows and window shades, window-to-wall area ratio, and type, size, and location of operable windows and window shading systems) should be recorded since these characteristics can influence behaviour (Rea, 1984). Space layout, furniture type and location, plug-in equipment, location and direction of computer monitors, view to outdoors, and occupants' access distance to control systems (e.g. operable windows, window shades, light switch, and thermostat) should be sketched. The envelope specifications, including U-factors of building envelope, visible transmittance of windows and window shades, solar heat gain coefficient of windows, visible reflectance of interior surfaces, and air tightness are considered for the surface properties.

Researching and documenting building controls hardware and associated logic is critical for in-situ occupant monitoring studies, as subtleties can play an unprecedented role in behaviour. For instance, Boyce et al.'s (2006) study on lighting use in workstations with dimming control and light switching control systems revealed that the dimming control system led to much lower minimum workplane illuminance values than the light switching control system. This observation was because former system allows a reduction in the illuminance level while the latter control system allows for a higher illuminance. Reinhart and Voss (2003) and Sutter et al. (2006) observed that motorized blinds were used more frequently than manually controlled blinds. Heating, cooling, and ventilation systems should also be thoroughly documented. For example, users in air conditioned buildings use operable windows (Rijal et al., 2007) and blinds (Inkarojrit, 2008) much less than in naturally ventilated ones.

The existing sensors and the BAS system, where applicable, should be inspected and documented. Knowing the existing sensors, a list of additional sensors and data loggers that are needed to measure the desired variables is prepared. Existing sensors should be tested with respect to research-grade instruments to verify their accuracy and functionality. Any deficiencies in building components and systems and occupants' interventions (e.g. covering light sensors) to building systems should also be noted by visiting the spaces of interest through walk-throughs. Broken or malfunctioning systems should be repaired. Occupants' interventions should be removed if they consent; otherwise a researcher should take notes of any interventions into building spaces. For instance, anecdotal evidence by the researcher suggests that some occupants unintentionally obstruct existing thermostats that were also measuring occupancy (Figure 3.12). The location of existing built-in sensors should also be checked by researchers, as this may affect proper functioning of sensors (Gunay et al., 2016a).

Figure 3.12. Examples of unintentionally obstructing sensors of built-in thermostats by occupants in an office building.

The characteristics of the urban area around the building to be monitored also affect how occupants use building components. For instance, view of adjacent buildings may interfere with occupants' privacy and thereby preventing them from opening window shading (Foster and Oreszczyn, 2001; Reinhart, 2004; Inkarojrit, 2008). Noise and air pollution may also lead to less frequent window opening actions. For example, Warren and Parkins (1984) reported that noise was the major motivation that caused occupants

to close windows. Occupants may also open window shading devices for the sake of a view to the outdoors. Zhang and Barrett's (2012a) study on window blind use revealed that the majority of occupants highly appreciated the view to outside and thereby opening blinds at least halfway, even when the glare caused visual discomfort for them. Shading of adjacent buildings or reflection from other buildings' facades (Danks et al., 2016) can also influence window shading use pattern. Therefore, the investigation of buildings, streets, and open spaces surround the building of interest is required for in-situ monitoring studies.

Table 3.2. Specifications of building and its site that should be recorded in monitoring studies.

Space geometry	Surface properties	Space layout and equipment	Building systems	Site
• floor plan • orientation of spaces and windows • dimension and location of windows and window shadings • window-to-wall area ratio • type, size, and location of operable windows and window shadings	• U-factor of building envelop • visible transmittance of windows and window shades • solar heat gain coefficient of windows • visible reflectance of interior surfaces • air tightness	• furniture • plug-in equipment • location and direction of monitors • occupants' access distance to control systems (e.g. operable windows, window shades, light switch, and thermostat)	• controls systems: ○ light switches ○ operable windows ○ blinds ○ thermostats • heating, cooling and ventilation equipment • existing sensors • BAS system	• view to outdoors • the neighbourhood: ○ buildings ○ streets ○ open spaces

3.3.5. Methods used in monitoring

Detailed information on the methods used in a monitoring campaign provides valuable information on how accurate and reliable the collected data are. The location, accuracy, precision, and range of variables measured, and the frequency of data logging by the sensors should be documented (as discussed in Section 3.2.2). Evaluated performance of the models as well as the specifications of the sensors and/or equipment used in model-based techniques should be well-documented (as discussed in Section 3.2.3). A

monitoring documentation should also include information on the surveys conducted, such as incorporated techniques, subjects, timing and frequency of distributing surveys (as discussed in Section 3.2.4).

3.4. Discussion

The advantages and disadvantages of different techniques in monitoring studies that a researcher may confront in the three stages of conducting a monitoring campaign (Section 3.3.1) are discussed in this section, as outlined in Table 3.3.

3.4.1. Opportunities

The opportunities provided by in-situ monitoring for occupant behaviour studies are the reality of obtained data, the potential for a large sample size and long-term data collection at relatively low cost, and future sensing technologies.

3.4.1.1. Reality of obtained data

As the existing buildings with their users are the living laboratories in monitoring campaigns, this research approach provides realistic information about occupancy and how occupants experience their environments, use them, and react to them. With a plethora of existing office buildings worldwide, researchers have a great opportunity to obtain realistic data for years to come – particularly with increasing built-in sensing capabilities at higher spatial resolutions. The unprecedented impact of cultural, climatic, and other contextual factors on occupant behaviours can also be discovered in real situations and representative models can be developed in ways that would be hardly possible from other approaches.

3.4.1.2. Cost-effectiveness

By far, the most practical and cost-effective method in long-term recording occupant behaviours and environmental conditions is to use sensors connected to a centralized data management systems in

existing buildings. With these systems, checking proper functionality of sensors can be managed remotely at a reduction in labour costs, and without interrupting occupants. The storage capacity of these systems is generally high and, if needed, can be upgraded at relatively low cost. If additional sensors are required, spaces of interest can be equipped with required sensors at relatively low cost. As an example, given that normally built-in sensors records occupancy and environmental conditions and their price are included in the construction budgeting, it cost the researcher about US$250/office for additional sensors and outdoor cameras to record light, window, and blind states and light intensity. Moreover, recruiting occupants in existing buildings can be as little as nil as they are carrying on with their daily life in contrast to laboratory studies and virtual environments, where participants are recruited for spending a specific period of their time in a different environment.

3.4.1.3. Large sample size and long-term study

Existing studies typically range from just a few (Fritsch et al., 1990) to tens (Herkel et al., 2008) of offices. However, with the evolution in the field of BAS to automatically and remotely archive and maintain a network of sensors and actuators, researchers can pursue a larger sample size. Centralized data management systems also facilitates longer periods of monitoring, which can occur for at least a year to cover all typical climatic conditions, given that occupants' adaptive behaviours and operations on building components and systems are seasonally affected. In this way, data-driven occupant models can be developed and implemented in BPS tools, where annual simulations are generally performed for evaluating comfort and energy performance of buildings.

Likewise, with the advent of on-line distributing questionnaires, a large sample size at a low cost is achievable. For instance, Haldi and Robinson (2008) designed a pop-up survey on occupants' computers, through which each occupant (a sample of 60) filled in the longitudinal questionnaire about 100 times. Konis (2013a) invented a stand-alone polling station for the longitudinal surveys in his monitoring study.

The emerging participatory sensing smart phone applications also facilitate even continuous surveys at large scale (Jazizadeh et al., 2011; Erickson and Cerpa, 2012; Jazizadeh et al., 2013).

3.4.1.4. Novel technologies

The emerging technologies, even in other disciplines such as medicine and computer science, draw a promising future for in-situ monitoring studies in measuring additional occupant behaviours. For example, accelerometers (Mathie et al., 2004; Godfrey et al., 2008; Yang and Hsu, 2010) can be used to record posture and movement, furniture sensor can detect location and number of occupants in a space (Nguyen and Aiello, 2012; Labeodan et al., 2015), smart phones and Wi-Fi/GPS can locate occupants (Biagioni et al., 2011; Lee et al., 2013), and a network of sensors can detect activities (Nguyen and Aiello, 2012; Milenkovic and Amft, 2013). Moreover, new technologies, such as IoT, with lower cost and more capable wireless and energy harvesting sensor networks will ease larger sample size in long-term monitoring studies. The Hawthorne effect in occupant behaviour studies can also be lessened with the emerging technologies, as data retrieval is managed remotely with minimal obtrusive actions in daily life of occupants and reminding them of monitoring their behaviours.

3.4.2. Challenges

The challenges in collecting data in existing buildings are the issues with stand-alone and connected sensors, impediments to achieve a large sample size, the Hawthorne effect, and the errors with self-reporting.

3.4.2.1. Shortcomings of stand-alone sensors

Stand-alone data loggers are criticised by their data and battery capacities, thereby requiring frequent data retrieval and checking which requires a considerable time and effort for a large sample size in long-term studies. There is the risk that sensors fail to function properly before researchers retrieve the logged data,

and thus data for that period are missed. Moreover, potential gradual deterioration of stand-alone sensors' accuracy over time requires periodic recalibration during the monitoring period.

The other shortcoming of these sensors is the risk of relocation. Occupants may choose to move stand-alone sensors to a different location than the researcher's desired location for their convenience. It is not clear to the researcher that data loggers are relocated or interfered during the data collection period.

The installation and data collection phases of using stand-alone sensors also necessitate contacting each participant to book meeting. Setting separate appointment for each occupant to install and collect data is laborious and challenge researchers to conduct a large sample size. Bennet and O'Brien (2016) spent nearly one month visiting to 20 different homes in a medium-sized city. Also, periodic visits remind participants of being observed that may reinforce the Hawthorne effect.

Moreover, the data cleansing process is a necessary pre-processing step for the data analysis to detect and correct any errors with the gathered data. Merging collected data with heterogeneous configurations, sampling frequencies, offsets, and event and time-based data, necessitates modifying data in consistent formats, which is a complex and time-consuming process.

Furthermore, the individual differences between occupants' comfort perceptions and reactions to their environments may be neglected, unlike survey techniques where complex behaviours can be discovered. This shortcoming is also the case for connected sensors.

3.4.2.2. Shortcomings of connected sensors

While installation of stand-alone sensors and data retrieval from them is straightforward, using connected sensors and the required equipment to connect to them and store logged data necessitates special training. In addition, the measurement accuracy, resolution, and range of existing BAS-integrated built-in sensors may not meet the requirements in scientific research. For instance, the designated threshold of illuminance level measured by ceiling built-in sensors may be lower than the potential maximum

illuminance that can occur in too bright spaces. Similar to stand-alone sensors, periodic recalibration of connected sensors is necessary to assure that the accuracy of sensors maintains over time.

The location of built-in sensors also may not be suitable for reliable measurement of variables and moving their location requires invasive actions and cost. For instance, temperature sensors may be located on the exterior walls of spaces, near heating or cooling systems, or direct solar insolation (Figure 3.13 and Figure 3.14) might be incident on them. CO_2 sensors might be located where occupants breathe directly on them (Lee, 2012) and relative humidity sensors may be located near humidity sources. Or, occupants may unintentionally or intentionally locate heating, cooling, and humidity sources near sensors (see Figure 3.15 for unintentional example).

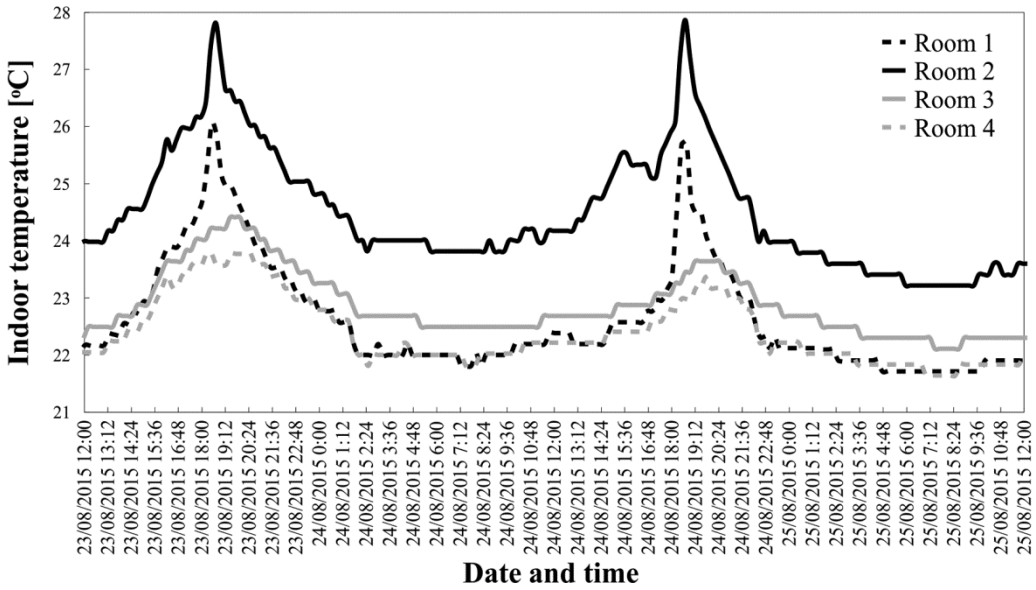

Figure 3.13. Example of spike in temperature recorded by built-in sensors in four typical rooms on the same floor and facade of an office building: Rooms 1 and 2's sensors were hit by direct sunlight around 6pm in August, while Rooms 3 and 4's sensors were not hit by direct sunlight at that time (credit: Justin Berquist).

Figure 3.14. Example of a BAS-integrated built-in sensor that measures temperature and hit by direct sunlight at some time of year.

Figure 3.15. Example of where an occupant unintentionally put kettle near a built-in sensor that measures temperature and relative humidity.

Furthermore, built-in connected sensors may be unintentionally obstructed by furniture or even intentionally obstructed by occupants to override undesirable controls. For instance, the researcher of the current study encountered some occupants in an office building who obstructed light sensors in their offices to prevent automatic light switch due to that the space was too bright or too dark when the lights were automatically switched on or off (Figure 3.16). Some occupants complained of headaches caused by fluorescent lamps (with high-frequency ballast) so that they covered the occupancy sensor of the automatically-controlled lights. A study by Wilkins et al. (1989) showed the impact of fluorescent lamps on occupants' headache, where it reduced by high-frequency ballast fluorescent lamps.

The cost of purchasing and installing additional BAS-integrated sensors may also make it difficult to justify using them for short-term research. Moreover, larger and shared offices require multiple sensors in each occupied zone to record presence and actions of each occupant (Honnekeri et al., 2014).

Similar to stand-alone sensors, data cleansing is necessary for pre-processing of collected data with connected sensors. Where this process is not automated, it will be laborious and prone to errors to detect any corruption in the dataset and convert them into a homogeneous format.

Figure 3.16. Examples of obstructing sensors of light switch by occupants.

3.4.2.3. Risk of reduction in sample size

To develop representative statistical models of occupant behaviours, researchers make an effort to achieve a large sample size and long-term data collection. However, achieving large sample sizes is still quite challenging. Ethics clearance and monitoring techniques adopted by researchers confine the sample size and the duration of study.

Anecdotal evidence indicates that about half of the contacted occupants do not show willingness to participate in (uncompensated) studies. Some occupants express concern for tracking their presence. In addition, for shared offices, each occupant of the space is required to be consent; if one person does not provide consent, the entire space and its occupants cannot be monitored. Therefore, the researcher

recommends identifying a population of at least double the desired sample size when recruiting participants.

Reliability of sensors and logging and archiving systems may also lead to the risk of reduction in the sample size, especially when a failure happens to a single sensor or data logger while concurrent measurements of a variety of variables is needed. In this case, any failure to any part of the network means missing data for that period. Therefore, frequent investigation of proper functioning of the sensors and logging and archiving systems is imperative. Increasing the sample size can also compensates for these failures in collecting data.

The intended sample size may also decline during data collection period because some participants may cease to be involved in the study or may not participate in the questionnaire survey (Warren and Parkins, 1984). Some occupants may move during data collection phase. In this case, researchers should contact new occupants of the spaces to repeat the same ethics procedure to obtain their consent for the continuation of the data collection in their offices and there is the possibility that new occupants may not participate in the study.

3.4.2.4. Hawthorne effect

Performing studies with ethics clearance usually requires consent from occupants. Thus, they may behave differently from before (Hawthorne effect) because they are aware of being observed. For instance, Tiefenbeck (2016) discovered a reduction in the occupants' energy consumption in the first few weeks of the monitoring study.

To minimize the Hawthorne effect, researchers may take advantage of some established techniques. For instance, Boyce et al. (2003) pretended that the study was about all conditions in offices, not just lighting aspect. Mahdavi (2011) introduced their monitoring study to occupants as it was run under the umbrella of the building management services. Meerbeek et al. (2014) postponed the survey phase of their research

to near the end period of the data collection phase to prevent informing occupants in the monitoring study of blind use. However, Meerbeek et al.'s (2014) strategy is applicable to where the local facility management and the ethics board have not considered ethics clearance as a necessary step to launch the data collection phase of monitoring study.

Since periodic visits to spaces to retrieve data from stand-alone sensors may also remind occupants of being monitored and can cause the Hawthorne effect, the researcher recommends researchers to minimize the frequency of periodic visits. With the advancement of BAS technology, the data collection process can be conducted centrally under the local facility management to lessen the Hawthorne effect.

3.4.2.5. Issues with self-reporting

In survey studies, researchers should be aware of the errors with self-reporting techniques. However, researchers can test the reliability of data through asking the same subjects similar questions over the monitoring period to check the consistency in their attitudes, if their responses are not expected to change over time. Occupants can also be asked about phenomena that are redundantly measured with sensors.

Table 3.3. Comparison of opportunities and challenges of different monitoring techniques.

Technique		Opportunities	Challenges
Sensor-based	Stand-alone sensors	• Cost effective • Appropriate for relatively long-term data collection • No need for special expertise in installation and data retrieval • More freedom on choosing the location • Operating independently from any other data acquisition, maintenance, and archiving systems	• Inappropriate for large sample size • Risk of sensor relocation by occupants • Labour intensive • Need for frequent data retrieval and checking proper functioning • Frequent data retrieval reminds occupants of being monitored and thereby reinforcing the Hawthorne effect • Privacy concerns, for example, tracking occupants' presence • Neglecting individual differences between occupants' comfort perceptions and reactions to their environment

	Connected sensors	• Appropriate for long-term data collection • Appropriate for large sample size • Remote data acquisition/control/storage without interrupting occupants	• Expensive and time-consuming at first installation • Need for expertise in connecting sensors to local control systems • Relatively inflexible with the designated location • Privacy concerns, for example, tracking occupants' presence • Neglecting individual differences between occupants' comfort perceptions and reactions to their environment
Model-based		• Appropriate for long-term data collection • Appropriate for large sample size • Reduces number of physical (real) sensors • Potential for fault detection and correction of real sensors • Cost effective • Appropriate for retrofitting purposes • Possibility of remote data acquisition/control/store without interrupting occupants	• Necessity of validation with in-situ measurements • Privacy concerns, for example, tracking occupants' presence • Neglecting individual differences between occupants' comfort perceptions and reactions to their environment
Surveys		• Provide information about individual differences between occupants' comfort perceptions and reactions to their environments • No need for specific equipment • Cost effective • Appropriate for large sample sizes at low cost	• Necessity of ethics clearance • Time-consuming in contacting each participant to obtain her/his consent, where on-line surveys are not incorporated • Labour intensive • Risk of participants not completing the study • Hawthorne effect • Risk of bias and/or self-reporting errors in participants' replies • Possibility of changing occupant of studied spaces during data collection • Inappropriate for long-term data collection • May not result in data that are suitable for constructing statistical occupant models

3.5. Closing remarks

Monitoring of occupants' presence and their actions on building components and systems for the purpose of developing occupant models for BPS can be conducted in the contexts of laboratories, virtual environments, and existing buildings. While researchers have high control over environmental conditions

and can manipulate any configurations of building design and control systems in laboratories and virtual environments, studying occupants in real environments provide insights into the intrinsic nature of how people react to their built environments in reality. However, in-situ monitoring of occupant behaviours is a challenging research approach regarding lack of control over contextual factors and personal spaces. Therefore, researchers should be well informed on the potential of different techniques in capturing these prior to launching data collection on site. It is valuable for researchers to publish any deficiencies and challenges they experience during their monitoring studies to inform other researchers in this field. To assist in this mission, this study critically reviewed existing techniques adopted in monitoring occupant behaviours in existing buildings and the capabilities and limitations with them.

Based on the critical review of different monitoring methods, the following main recommendations are for occupant monitoring studies:

- Sensor-based techniques: The prevalent techniques incorporated in in-situ monitoring for developing statistically representative occupant models are sensor-based, where individual differences between occupants' comfort perceptions and reactions to their environments may not be captured. In contrast, survey techniques can be beneficial in this regard. Among stand-alone and connected sensors, connected ones facilitate large sample sizes and long-term studies where periodic data retrieval are managed and maintained remotely via centralized systems, such as BAS. Therefore avoiding reminding occupants of being observed can alleviate the Hawthorne effect. Where spaces of interest are not equipped with desired sensors, researchers can benefit from stand-alone sensors, which are relatively cost-effective, operate without dependency on any other systems, and require no special expertise for installation and data retrieval.
- Model-based techniques: Using these techniques are plausible where it is impractical to measure variables of interest; accuracy and range of measurements with real sensors are not research-grade; locations of built-in sensors are inappropriate; or where additional sensors and equipment

are required to measure a specific variable. Therefore, these techniques are also appropriate for retrofitting purposes as they reduce necessity for physical sensors. However, validation of model-based techniques with field measurements is necessary.

- Surveys: These techniques can complement sensor and model-based techniques to discover the subtle cause and effect relationships in the collected data, as complex occupants' behaviours are often not realizable from sensor/model-based data. However, solely relying on surveys may not result in mathematical occupant models that are beneficial to BPS tools. Thus, the concurrent use of sensor/model-based techniques and surveys - ideally longitudinal - are recommended to record parameters that cannot be easily measured with sensors such as clothing level and consuming hot/cold beverages. The drawbacks of performing longitudinal surveys, such as considerable time and effort that researchers and participants invest, can be alleviated using the emerging technologies, such as on-line questionnaire distribution that pop up on participants' computers, smart phone applications, and stand-alone polling stations.

Through the exploration of existing methods for studying occupant behaviours on site and the associated opportunities and challenges, a monitoring campaign was conducted in this research. Detailed information of the case study and the techniques used to acquire data are explained in the next chapter. Likewise, the lessons exploited of the monitored offices for operation and design are discussed.

Chapter 4

This chapter has been accepted for publication as:

Interpreting occupant-building interactions for improved office building design and operation.

Gilani S, O'Brien W, Carrizo JS. *ASHRAE Transactions*. 2017; 123(2).

4. Interpretation of occupant-building interactions

4.1. Introduction

Monitoring studies in the literature are mostly focused on deriving probabilistic occupant models for occupants' presence and behaviour from empirical data, rather than measuring energy flows in buildings regarding occupant behaviour or extracting useful qualitative lessons for both design and operation. A literature review also indicates that most research on occupant behaviour by far have been performed in European countries, whereas climate, culture, and other contextual factors may determine occupants' role in using building components and systems (O'Brien and Gunay, 2014). Building orientation also determines energy performance of spaces through which occupants behave differently in interacting with buildings (Rea, 1984; Inoue et al., 1988), while most previous monitoring campaigns were carried out in near south-facing building spaces (Reinhart and Voss, 2003; Haldi and Robinson, 2010).

This research involved conducting a monitoring campaign in an academic building located on Carleton University's campus, Ottawa, Canada. The building had mechanical heating, cooling, and ventilation, but also operable windows. However, it was not operated with hybrid ventilation and the HVAC system continually attempted to maintain the temperature setpoints at all times. The monitored offices were located on perimeter zones in three different orientations. Energy flows of the studied offices as well as occupants' presence and operations of building components and systems were recorded with different sensor-based monitoring techniques, including stand-alone sensors and built-in sensors integrated with the BAS. The methodology of this monitoring campaign, more detailed description of the case study, and the data acquisition process are explained in the following sections. Afterwards, results on occupants' presence and behaviour, indoor environmental conditions, and energy demand in the monitored offices on different orientations are presented and discussed. Based on the analysis of the results, lessons for better design and operation of the existing building are drawn.

4.2. Methodology

Modern building automation systems' hardware and software afford many opportunities to understand the complex relationship between occupants and building performance. However, the resulting volume of data, which is often recorded in 5-minute intervals and up to a dozen or so points per zone, is so vast that it is difficult to convert it into actionable information. This research attempted to manage and translate the substantial data obtained from the BAS-integrated and stand-alone sensors to meaningful information beneficial for building operators and designers.

Monitoring techniques employed in the current research were the sensor-based and image-based ones to detect occupancy, measure indoor environmental conditions, and record occupants' interactions with lighting, thermostats, terminal HVAC system states, operable windows, and window shadings. The collected raw data, including event-based data and data which were sampled at fixed frequencies were cleansed and converted to consistent formats based on a specific timestep. The pre-processed data were merged together to provide concurrent data of correlated variables. For instance, for the analysis of lighting use patterns, which is the focus of the current research (see Chapter 5), in the monitored offices and to develop occupant models, concurrent occupancy, indoor illuminance, and lighting state were required.

The data interpretation phase covered data analysis and development of occupant models. With the univariate and multivariate analysis of the collected data, the existing comfort and energy performance of the individual monitored offices were evaluated. In this process, deficiencies with the building operation were also detected and some recommendations were made which are beneficial for the existing building. In the data interpretation phase, statistically representative models of occupants' presence and behaviour were developed. These models can be incorporated into building automation control systems. Implementation of data-driven occupant models inside control systems has a substantial potential for reduction in building energy consumption while occupants' comfort is maintained by adapting control

schemes to occupancy, occupants' preferences, and occupants' interactions with buildings (Gunay et al., 2016b; Gunay et al., 2016c; Gunay et al., 2017b). The statistical occupant models can also be implemented in BPS tools in the design process of new buildings (Gunay et al., 2015b). An overview of the methodology in this monitoring study is presented in Figure 4.1.

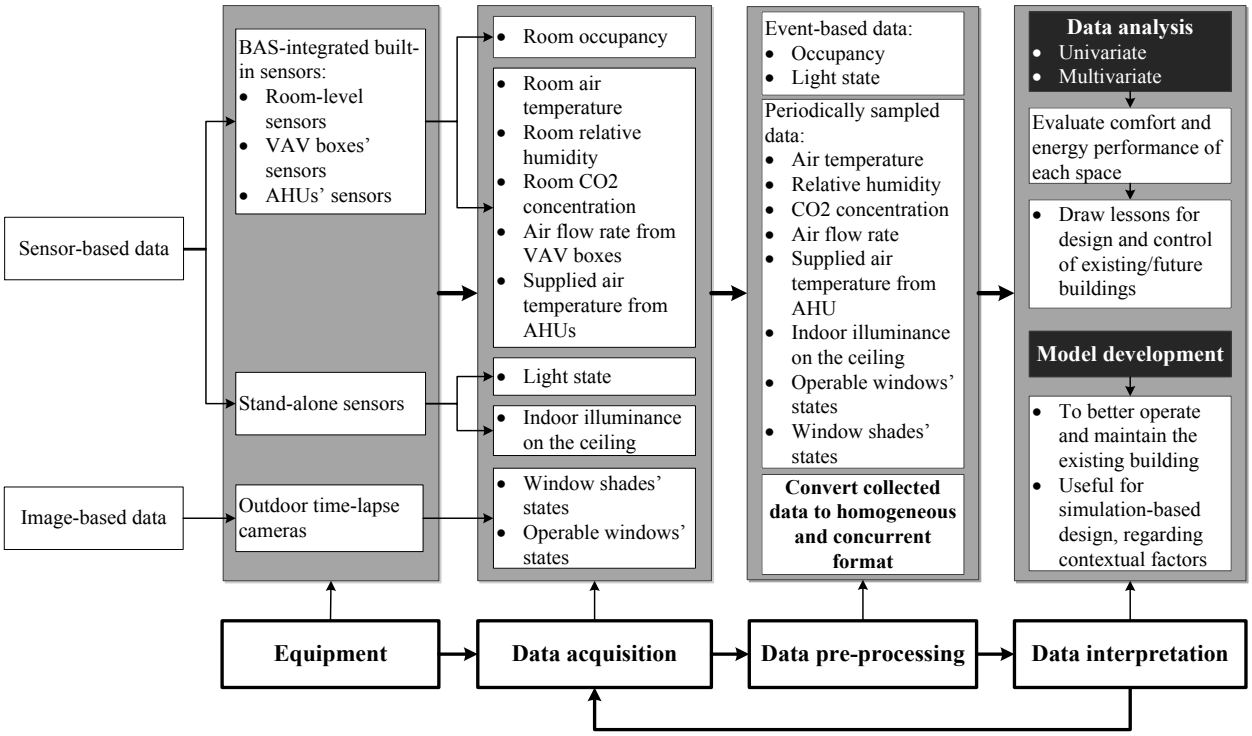

Figure 4.1. Overview of the methodology, as applied to the monitored building

4.3. Monitoring campaign

A description of the monitored building, offices of interest, and the surrounding site and the ethics clearance procedure are presented in this section. Afterwards, detailed information of the variables which were measured and the equipment which were used in this monitoring study are explained.

4.3.1. Description of Case Study

Upon the assessment of the project by the facilities management and planning unit and the ethics board of Carleton University, the researcher applied for the ethics clearance. The ethics protocol was reviewed by Carleton University Research Ethics Board-B, which provided clearance to carry out the research. Upon ethics clearance, 26 occupants were recruited for this project using the consent form approved by the ethics board (see Appendix A). Data acquisition commenced in February 2016. During the first meeting with participants for signing consent forms, the researcher had informal discussions with the participants. Alongside using the architectural and mechanical drawings of the building, the researcher did walk-throughs in the offices, sketched spaces, and took notes and photos on the spaces' layout, equipment, and any deficiencies with or occupants' interference in building components and systems.

The monitoring campaign was conducted in 25 offices in an academic building on Carleton University's campus, Ottawa, Canada. All the participants except for two had private office. The building axes are 37º west from the cardinal directions. For example, the north-most facade is actually N37°W. Hereafter, "south" refers to the south-east facade of the building, "east" refers to the north-east, and "west" refers to the south-west (Figure 4.2). There is no building in the neighborhood, except the north side, where an existing building shades this facade. The south and west perimeter offices of the building overlook a river, while a road passes the east side of the building causing noise pollution for the offices located on this facade.

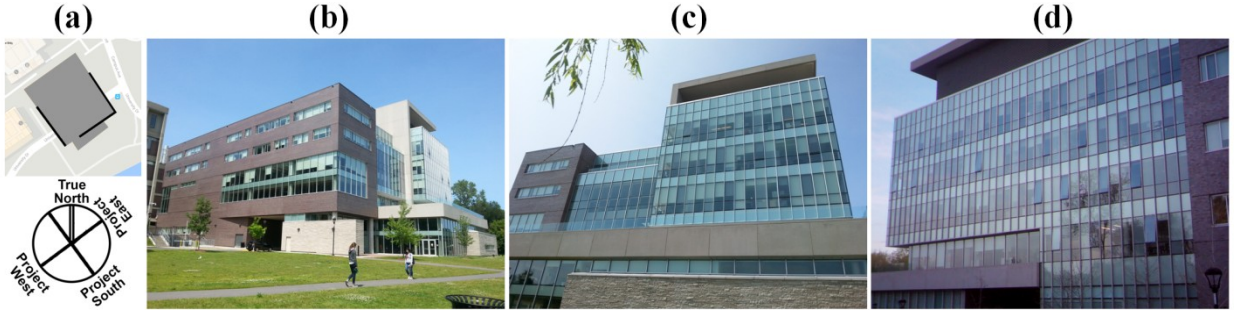

Figure 4.2. The monitored building on Carleton University's Campus: (a) site plan, (b) view to the west facade, (c) view to the south facade, and (d) view to the east facade.

All the monitored cases were perimeter offices from which 14, six, three, and two offices were located on the east, west, south, and corner (south-east) facades, respectively. The WWR of the east, south, and corner offices were about 90%, and for the west offices were about 50%. Only one of the monitored offices, which located on the south facade, did not have any operable windows. All the operable windows of the monitored offices were of an awning type. All the offices had interior roller fabric shades that were controlled independently and manually by a chain beside the window. Table 4.1 presents a brief description of the monitored offices.

The required heating load of the studied offices in the monitored building was delivered by variable air volume (VAV) boxes that supplied warm air into spaces. Eleven of the 17 VAV boxes supplying air into the monitored offices were equipped with reheat coils to heat the supplied air. Each VAV box conditioned two to five offices, except for the corner offices, the south office without an operable window, and three other offices on the east and south facades for which individual VAV boxes were employed. Independently-controlled radiant ceiling panels in each of the studied offices provided supplementary heating capacity.

Each office had stand-alone lighting control with an occupancy sensor, except for three offices where the light switches had already been changed to standard on-off ones at the occupants' request. The lighting control circuit was independent from the BAS that controlled the heating, cooling, and ventilation systems. The default control scheme of the offices' lighting system was occupancy-on/vacancy-off with 15-minute time delay upon departure.

Table 4.1. Characteristics of the monitored offices.

ID	Occupant's profession	Floor	Orientation	Number of occupants	Number of windows*	Number of operable windows	Number of shades
1	Professor	3rd	east	1	3	1	3

2	Professor				3	1	3
3	Administrator	4th			5	1	5
4	Administrator				4	1	4
5	Administrator				3	1	3
6	Professor				3	1	3
7	Professor				3	1	3
8	Administrator	5th			3	1	3
9	Administrator			2	6	1	6
10	Professor			1	5	2	5
11	Professor				3	1	3
12	Professor				3	1	3
13	Professor				3	1	3
14	Professor				3	1	3
15	Professor	4th	south-east**	1	8	2	8
16	Professor	5th			9	2	9
17	Professor	4th	west	1	3	1	2
18	Administrator				3	1	2
19	Professor	5th			3	1	1
20	Professor				2	1	1
21	Professor				3	1	2
22	Administrator				3	1	2
23	Administrator	3rd	south	1	4	0	4
24	Administrator	4th			4	1	4
25	Administrator	5th			3	1	3

* including operable windows
** corner offices

4.3.2. Data Acquisition

In the data collection phase of the project, occupants' presence and operations of light switches, shades, and windows were monitored concurrently. However, mainly occupancy and lighting data were used in Chapter 5, which is focused on lighting use patterns in the monitored offices. The known factors that influence lighting use are occupancy and daylight levels (as discussed in Chapters 2 and 5), rather than clothing insulation and type of activity (regarding metabolic rate). Contextual factors, such as distance to light switch, control system (e.g. whether light switch-off control is automatic or manual), and social constraints (e.g. whether an office is a shared or private office), are the other influential factors that can affect lighting use patterns (Boyce, 1980; Pigg et al., 1996; O'Brien and Gunay, 2014). In the current research, all the monitored offices were private offices except for one. The light switch in all the monitored offices was near the office door (see Figure 5.2). The former lighting control system which was

in use (before the researcher adjusted it) was occupancy-based lighting control system except for three of the monitored offices whose light switches were changed to standard on-off ones at the occupants' request before the current research (see Chapter 5). Likewise, participants' type of activity was the same (i.e. office work) and all the monitored offices had good view to outdoors. Therefore, variables such as view to outdoors, clothing level, and type of activity, all of which are immeasurable with current sensor technologies, were excluded from the data collection in this research. Outdoor environmental conditions, including temperature, relative humidity, and global solar radiation, were measured using a local weather station located on Carleton University's campus.

All the monitored offices had already had built-in thermostats which were integrated with the BAS (Figure 4.3a). These thermostats are equipped with buttons, which are logging setpoint adjustments. All the logged data by the BAS were stored on a local industrial computer connected to the BAS, which was accessible remotely using its IP address. The archived data on the local industrial computer were also stored as backup on cloud servers at specific time intervals. The built-in passive infrared (PIR) motion sensor in thermostats recorded occupancy. Thermistor and humidity sensor measured the indoor air temperature and relative humidity in the offices. All the mentioned variables were sampled at the frequency of 10 minutes. However, occupancy was event-based and was recorded at the time of event occurrence.

While the operative temperature is an influential factor that affects occupants' thermal comfort (which was not the focus of the current research), the researcher measured the air temperature rather than the globe temperature. The ideal spot for locating the globe thermometer prevented researchers from measuring the operative temperature in long-term monitoring studies. However, the inventions of some researchers (e.g. (Konis, 2013b)) can lessen these limitations by making a mini-station to measure the globe temperature on occupants' desktops.

The researcher acknowledges that the measured indoor air temperature deviates from the operative temperature, especially where the differences between the surface temperatures of a building space are significant. For instance, if an occupant is near large windows, the occupant may feel uncomfortable because of the net radiative heat exchange with large windows (which may be significantly warmer or colder than other surface and the air temperature), while the thermostat may show that the indoor air temperature is in the comfort zone.

In the current research, the differences between the indoor air temperature and the operative temperature for the extreme weather conditions in the winter time (i.e. -27ºC [81ºF]) and summer time (i.e. 35ºC [95ºF]) during business hours were calculated. The U-factor of the wall was 0.4 W/m^{2}K (0.07 Btu/hr.ft^2°F) and the U-factor of the window was 2.7 W/m^{2}K (0.48 Btu/hr.ft^2°F). The emissivity coefficients of the wall and window were 0.9 and 0.84, respectively. The interior and exterior surface heat transfer coefficients were assumed 5 W/m^{2}K (0.88 Btu/hr.ft^2°F) and 10 W/m^{2}K (1.76 Btu/hr.ft^2°F) (ASHRAE, 2013d). By knowing the U-factors of the wall and window and the interior and exterior heat transfer coefficients, the heat flux values between the indoor and outdoor were computed for the extreme conditions of the winter and summer time. Afterwards, the interior surface temperatures of the exterior wall and window were obtained given that the heat flux through the wall and window were known, and the setpoint temperature was 22ºC [77ºF]. All the other three walls of the office were adjacent to similar conditioned spaces; and the interior surface temperature of the interior walls was assumed to be 22ºC [77ºF]. Using ASHRAE Thermal Comfort Tool Version 2.0.03 (Huizenga, 2010), the mean radiant temperature was calculated for the typical monitored offices (see Figure 5.2). Afterwards, the operative temperature was calculated assuming the interior convective heat transfer coefficient of 3.1 W/m^{2}K (0.55 Btu/hr.ft^2°F) and radiative heat transfer coefficient of 4.2 W/m^{2}K (0.74 Btu/hr.ft^2°F) (ASHRAE, 2013d). The calculation results showed that the maximum absolute error of assuming identical values for the

indoor air and operative temperature was 1-2ºC (2-3ºF) in the winter time, and 0.2-0.5ºC (0.4-0.9ºF) for the summer time.

The PIR sensors detected motions in a range of 5m (16.4 ft) with a coverage of 100º horizontal and 80º vertical angles. The thermistor measured temperature in a range of 0-70ºC (32-158ºF), with the accuracy of ±0.2°C (0.36ºF), and the precision of 0.1°C (0.18ºF). The humidity sensor measured the relative humidity in 0-100% range. The accuracy of the humidity sensor was ±3% for 20-80% and the precision was 0.1%. The accuracy of humidity sensor was ±3% to ±5% for the 0-20% and 80-100% relative humidity.

The installed light switches in the offices had occupancy sensors to control lighting automatically with the manual override. Since the light switches were not integrated with the BAS, to record light switch-on/off events, stand-alone light on/off data loggers with a light threshold of 65 lx (6 fc) were used for this research (Figure 4.3b). The light state sensors were attached to the lighting fixture in each monitored office. To ensure proper functioning of the stand-alone sensors, periodic visits (i.e. every 1-2 month) to the offices were made. In these periodic visits, logged data were retrieved from the sensors and stored.

The indoor illuminance was measured by stand-alone sensors (Figure 4.3c). The light intensity sensors used in this study were designed for indoor use, with the capability of measuring light intensity in a range of 1-32000 lx (0.09-2972.9 fc). The researcher attached these sensors to the ceiling downwards to measure horizontal illuminance on the ceiling. To check proper functioning, battery life, and memory capacity of data loggers and to transfer data, periodic visits to each office were made. The sensors were attached to the ceiling in each monitored office as there are uncertainties with measuring indoor illuminance on the workplane in long-term monitoring studies, such as furniture's/occupants' shading and monitors'/windows' luminance on sensors (Reinhart, 2001). For instance, Haldi and Robinson (2010) kept indoor illuminance sensors away from the windows to remove window's luminance on sensors. Researchers may measure indoor illuminance at various locations to obtain the mean value of the

workplane illuminance as the most representative of workplane illuminance value. Boyce et al. (2006) measured the illuminance on desktop at various locations in the observed single-person workstations to calculate the mean workplane illuminance. The locations included two spots on desk in each workstation, in the middle of the keyboard, between the keyboard and the monitor, on the monitor, at a point represented face of an occupant in front of the monitor, and on document holders on both sides of the monitor. In some other cases, researchers calculated indoor illuminance using analytical methods with in-situ measuring of the required variables. For instance, Reinhart and Voss (2003) used simulation-based calculation of workplane daylight illuminance using DAYSIM (Reinhart, 2001) based on the in-situ measured direct and diffuse solar radiation for their 10-month field study on occupants' blind and light control in office spaces. Tzempelikos et al. (2009) installed sensors on the ceiling in their field study, as they found that workplane illuminance can be predicted by measuring indoor illuminance on the ceiling.

The majority of the previous research used cameras or videos as a non-invasive technique to record operable windows' and window shades' positions from the exterior of buildings (Rea, 1984; O'Brien et al., 2010; Zhang and Barrett, 2012b; Konis, 2013a; Honnekeri et al., 2014; Meerbeek et al., 2014). In the current research, time-lapse cameras mounted outdoors recorded shades' and operable windows' positions (Figure 4.3d). The field of view of the camera was 42 degrees, with the focus distance of 0.15 m (0.49 ft) to infinity. These cameras were set up to take photos at the frequency of 10 minutes from 6am to 8pm. The photos were periodically transferred from the cameras to a computer system. It is worth noting that regarding occupants' privacy, low-resolution photos were taken. In this way, occupants were not identifiable from photos, however, this may cause difficulty in photo interpretation. For instance, in Meerbeek et al.'s (2014) study, interior blind positions were not recognizable from the low-resolution photos. Furthermore, the position of operable windows left ajar and blind slats is hardly to detect from photos. For example, Rea (1984) analyzed blind positions of a building using photographs, however, the pitch of the venetian blinds was ignored due to the difficulty of determining slat angles from photographs.

In the current research, due to limitations on image interpretation, such as solar reflection on windows, visual obstructions, and weather conditions (Gilani and O'Brien, 2016b), the researcher used photos intermittently to track operable window positions in a number of offices for a partial monitoring period. Improper functioning of the cameras' batteries in cold weather also caused limitation to provide concurrent data with other data which were recorded by stand-alone and BAS-integrated sensors.

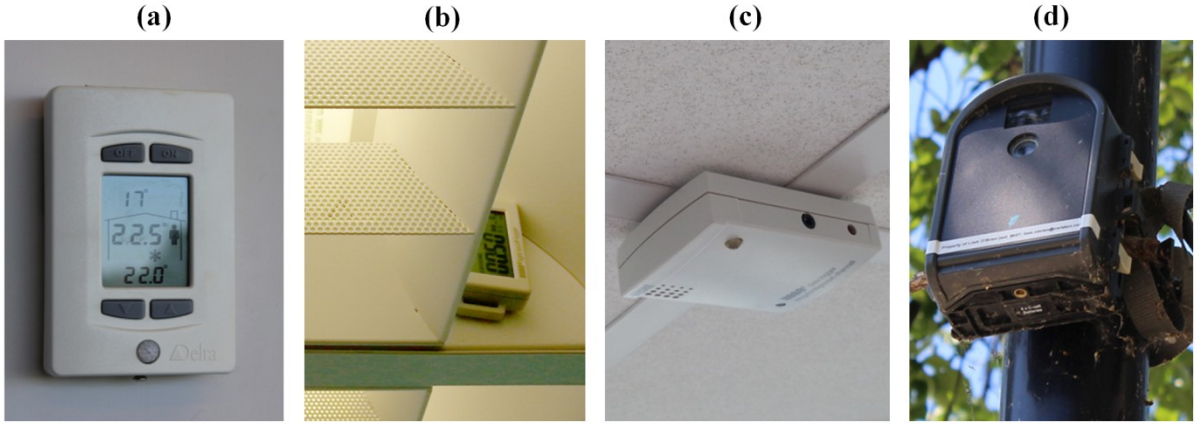

Figure 4.3. Equipment used for collecting data: (a) BAS-integrated built-in sensor for recording occupancy, temperature, and relative humidity, (b) stand-alone light state data logger attached to the lighting fixture, (c) stand-alone light intensity data logger attached to the ceiling, and (d) time-lapse camera for taking photo from the exterior of the building.

4.4. Results and discussion

Results of the monitoring campaign conducted in this research are presented in this section. Occupants' presence and behaviour, indoor environmental conditions, and energy demand in various offices on different orientations are analyzed in this section. Following the results, lessons drawn for building operation and design are discussed.

4.4.1. Occupants' Presence

This section presents results on the relationship between occupants' presence in their offices and indoor environmental conditions. Afterwards, the efficiency of using private offices is discussed.

4.4.1.1. Results

Error! Reference source not found. presents the relationship between the occupied fraction of daytime ours in the monitored west, east, and corner offices and the mean indoor temperature at different times of day between 8am and 6pm during the cooling season portion of the study period (i.e. May to July 2016). It is worth mentioning that Ottawa has warm/hot sunny and humid days in the cooling season. The mean number of business hours that fell into different temperature bins is provided in Figure 4.4d. The monitored building was an academic building occupied by faculty members and administrators, where the winter semester ends late April. Since summertime allows faculty members more flexibility in their scheduling, recruited participants with administration positions are excluded from this analysis. Figure 4.4 represents the presence periods of the nine, three, and two professors used the east, west, and corner offices, respectively. The results in Figure 4.4b indicate that the occupants in Rooms 13 and 14 spent less time in their office as the indoor air temperature increased. This relationship was seen in several other offices, but not all of them. It is not evident from the limited dataset whether this is a correlation or also causation. For instance, warmer weather is both associated with later in the day when occupants are less likely to be present and later in the summer (e.g. August) when occupants are more likely to be on vacation. The researcher's informal discussions with a participant whose office had large windows located on the east facade, revealed that high temperature of some of the offices in the monitored building, even with air conditioning systems on, caused the interviewed participant and other occupants to leave their offices earlier than they normally leave. Figure 4.4d shows the number of business hours with higher indoor temperatures in the east monitored offices with WWR of 90% was more than the monitored offices on the west and corner orientations. The researcher acknowledges that the results presented in this section to indicate the relationship between the occupancy and indoor temperature are not statistically significant enough to draw conclusions, however anecdotal evidence suggests this issue is worthy of future research with a larger sample.

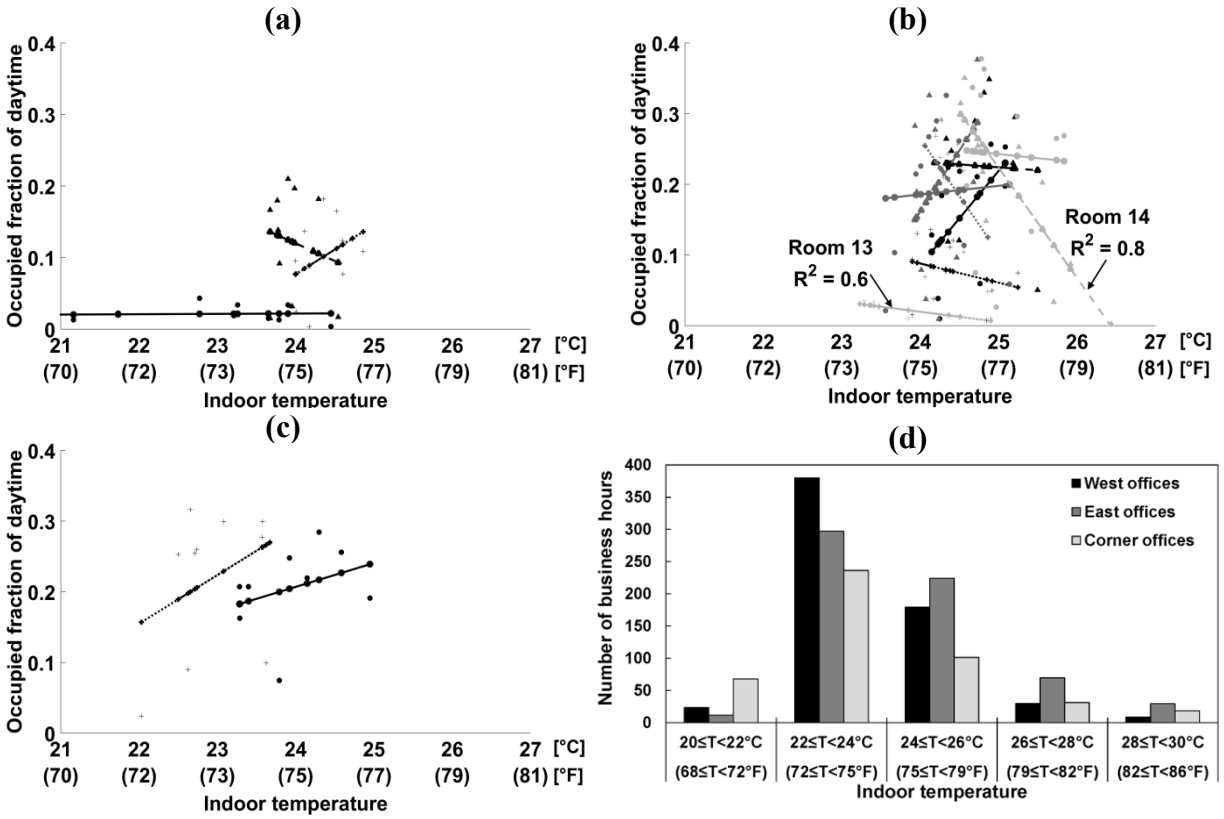

Figure 4.4. Relationship between indoor temperature and occupancy in the monitored offices occupied by professors, in months May to July 2016: (a) occupied fraction of daytime hours in relation to indoor temperature in the (a) west, (b) east, and (c) corner offices; (d) number of business hours averaged over the monitored offices occupied by professors on each orientation at each temperature bin.

Figure 4.5 presents the cumulative distribution of the number of simultaneous occupied offices for the 15 professors participated in this study. This figure shows that 95% of the timesteps, the maximum number of professors who were using their offices at the same time was five. Out of 15 professors, a maximum of 10 were present in their offices simultaneously during the monitoring period. Note that in the monitored building, each faculty member had a designated single-occupancy office, which is the common feature of academic buildings around the world. The researcher acknowledges that there may be bias in the low rate of professors' occupancy, as the results shown in Figure 4.5 are based on summer time (i.e. March to July 2016).

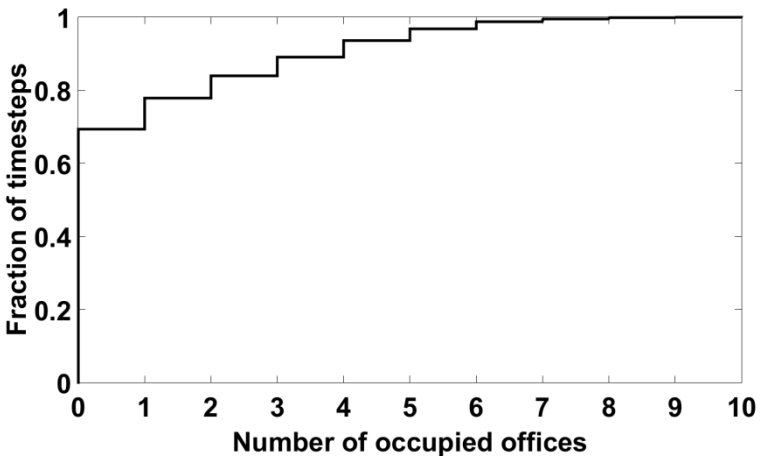

Figure 4.5. Fraction of timesteps with the maximum number of occupied offices, in months March to July 2016.

4.4.1.2. Lessons for Operation and Design

Research on the correlation between occupants' productivity and comfort in their workplaces has proved that poor environmental conditions in offices lead to less productivity (Leaman, 1995; Veitch et al., 2004). Several previous research also report a higher rate of absenteeism in workplaces where occupants were dissatisfied with indoor environmental conditions (Kumar and Fisk, 2002; Issa et al., 2011). To ensure occupants' satisfaction with their workplace, the basic principle is to provide comfortable environmental conditions for buildings' occupants.

Given that faculty members have more flexibility in their time management, providing each faculty member with a single-occupancy office may lead to high cost of infrastructure in academic building while the probability of simultaneous use of offices may not justify assigning one office for each faculty member. Similarly, Haynes' (2008) survey discovered that 50% of the participants with flexible professions, who spend less than 60% of their time with their colleagues, spent less than 60% of their time in their assigned offices. With the concept of lean office design (Franklin, 1999; Danielsson, 2013), designing flexible workplace where occupants use workstations on-demand (i.e. hot desking, office hoteling) can enhance efficiency of office design. However, the acceptance of this design approach by

faculty members requires further research. Designing flexible workplace can reduce overhead costs while it can also ease maintenance as the lack of dedicated desks reduces personal belongings and other items left behind from day to day. With the evolution in the information and communications technology, designers and engineers should facilitate more flexibility, rather than stability in the traditional approach, in designing and managing office spaces.

4.4.2. Occupant Behaviours

This study recorded occupants' operations on lighting, operable windows, and window shades to investigate occupants' interactions with these building components and systems with regard to influential factors. In this section, analysis on the lighting use patterns is presented, followed by some results on the impact of using operable window on indoor environmental conditions and heating demand.

4.4.2.1. Results

Figure 4.6 presents the ratio of lights-on period to the occupied period in each of the monitored offices with the occupancy-on/vacancy-off lighting control system (i.e. the previous control system before the researcher adjusted it in the monitored offices). This analysis excludes the offices where the stand-alone occupancy-based light switches were replaced with standard on-off ones, and the offices where occupants covered the occupancy sensor of the light switches. Figure 4.6 reveals that in some monitored offices, lights were on for about twice the occupied period. This ratio is nine for one of the monitored offices, where further investigations showed that on several days during the monitoring period, lights were not turned off while there was no occupant in the office. This indicates the improper functioning of the lighting control system leading to lighting electricity use at many instances during unoccupied period. On the other hand, in a few offices, as shown in Figure 4.6, lights were on less than the occupied period. This could be because some occupants overrode the auto-on control, for example by taping the occupancy sensor or manual lights switching off. It is worth mentioning that the researcher made notes of the offices

where the occupants covered the occupancy sensor while she was visiting offices every 1-2 months for the data retrieval. However, this is not clear to the researcher that the sensors of the other offices were uncovered for all the time between each two consecutive visits to the offices. This may cause bias in the presented results.

The maximum indoor illuminance measured on the ceiling during occupied period was at the highest value (i.e. 2000 lx (186 fc)) in the corner monitored offices, while it was 1700 lx (158 fc) and 1200 lx (112 fc) in the east and west monitored offices, respectively. The measured ceiling illuminance shows that high WWRs of the corner and east offices led to higher indoor illuminance and probably glare issues during occupied period. It is important to note that for several monitored offices on the east and west facades, the maximum indoor illuminance measured on the ceiling was at a lower value, which may be due to blind occlusion rate, as some previous studies discovered the noticeable impact of orientation on blind positioning (e.g. (Rea, 1984)). In addition to blind position and spaces' characteristics, such as layout, floor plan, reflectivity of interior surfaces, and transmittance of windows, solar radiation is the other influential factor on the indoor illuminance. The amount of solar radiation received in indoor environments varied between the monitored offices on different orientations. Figure 4.7b shows that the ceiling illuminance in the monitored offices on different orientations varied by a factor of four to 11 in the morning, while this variation decreased in the afternoon. Figure 4.7 also shows that the orientation of the monitored offices affected the time they received the maximum indoor illuminance during the day.

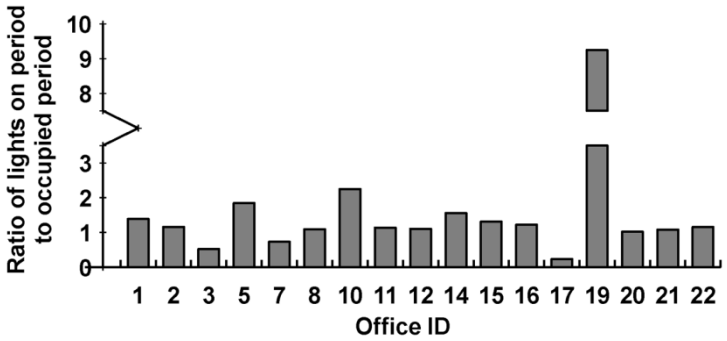

Figure 4.6. Ratio of lights-on period to the occupied period in each monitored office (see Table 4.1).

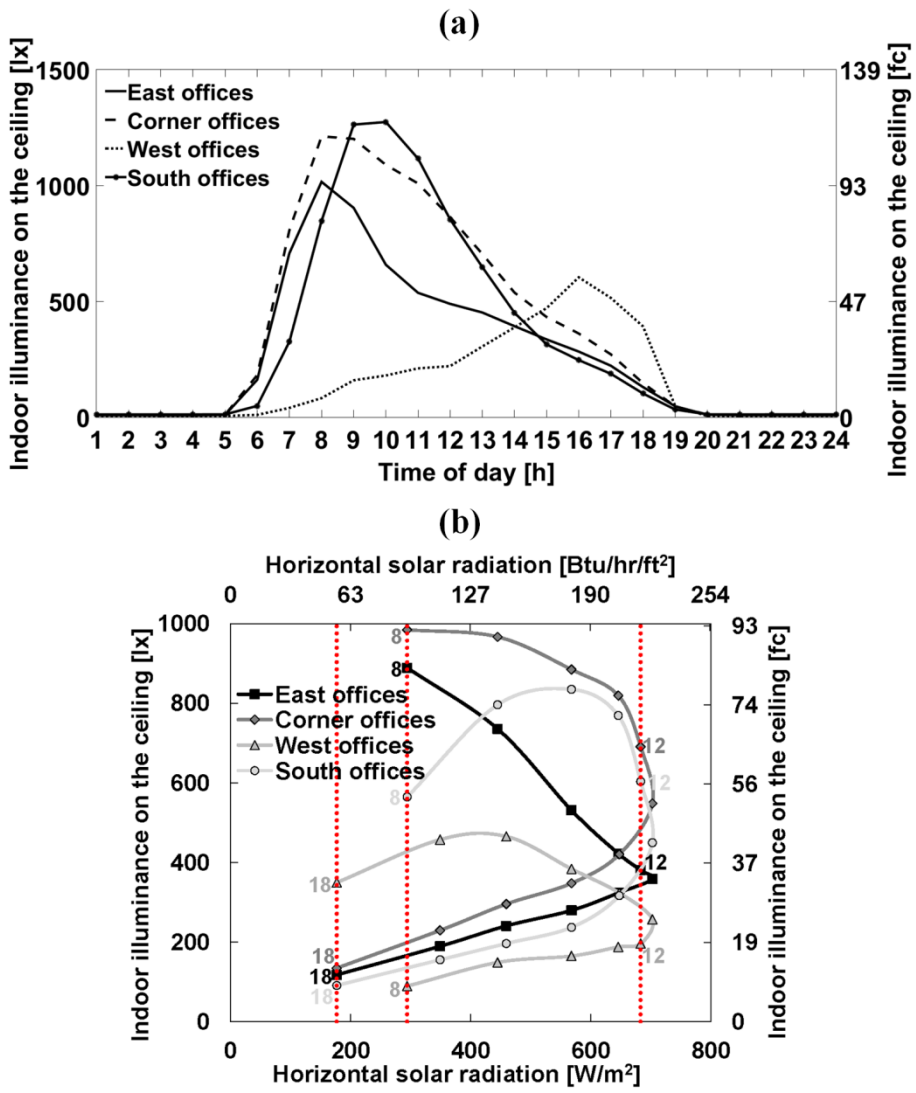

Figure 4.7. Indoor illuminance measured on the ceiling in the monitored offices on different orientations: (a) hourly mean indoor illuminance, and (b) relationship between the horizontal solar radiation and the ceiling illuminance in March to July 2016 (numbers on the graph show time of day).

The analysis of the effect of operable windows on the indoor environmental conditions in two of the monitored offices in the first two weeks of May 2016 is presented in Figure 4.8. As shown in Figure 4.8a, the occupant of Room 9 used an operable window at regular times during the occupied period which helped reduce the indoor temperature even below the setpoint temperature during the occupied period (i.e.

23.5°C [74.3°F]). However, when the indoor temperature exceeded the outdoor temperature (i.e. on May 12th), opening window exacerbated the indoor environmental conditions.

On the other hand, the occupant of Room 6 (Figure 4.8b), opened the window at some point (i.e. May 6th) when the indoor temperature was higher than the setpoint temperature, and then left the window open for a few days. Opening window in Room 6 resulted in a noticeable reduction in the indoor temperature and an increase in the heating energy use even during unoccupied period. While leaving the window open improved the indoor environmental conditions when the outdoor temperature was lower than the indoor temperature, open window led to the increase in the indoor temperature when the outdoor temperature was higher than the indoor.

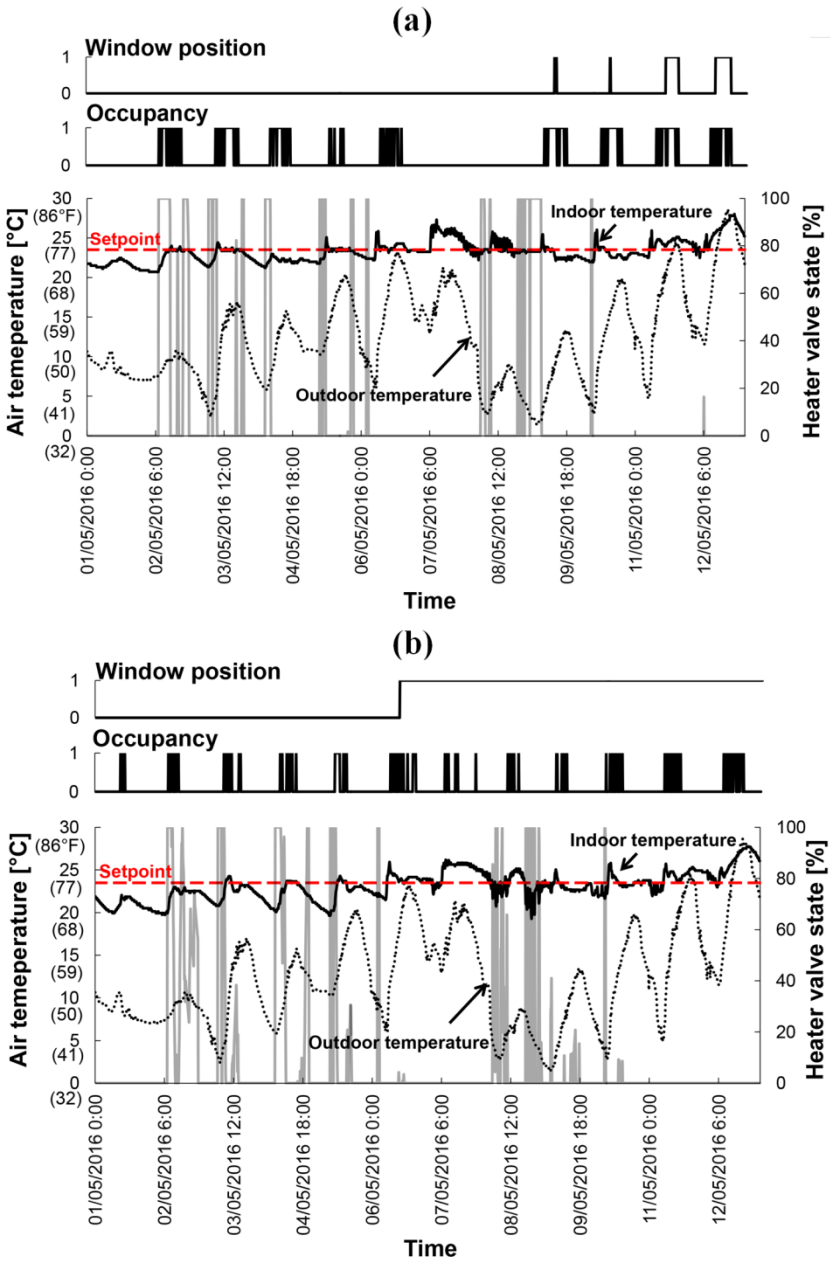

Figure 4.8. Impact of using operable window on indoor temperature and heating demand in two of the monitored offices in May 2016: (a) Room 9, (b) Room 6.

4.4.2.2. Lessons for Operation and Design

The analysis on the lighting use patterns in the monitored offices revealed that the automatic lighting control did not necessarily result in the reduction of the lighting use and improvement of occupants'

satisfaction in the monitored offices. The implications of these observations emphasize the necessity for the periodic control of building systems to ensure more efficient building operations and maintenance. Moreover, building facility managers should facilitate a method for occupants to provide their feedback and act on them at their earliest convenience. The personal experience of the researcher revealed that some occupants taped the occupancy sensor of the light switch in their offices (see Figure 3.16). Some occupants were unsatisfied with the automatic light switches, as their offices were too dark/bright when the lights went off/on automatically. Some occupants preferred task lights to overhead lighting. Some others preferred natural light to fluorescent lamps installed in their offices. The informal discussions of the researcher with the participants in this monitoring campaign revealed that some participants were uncomfortable with fluorescent lamps as these lamps can reportedly cause headache for them.

With regard to the findings of this monitoring study, optimizing building control systems is a necessary work. For instance, Tzempelikos (2010) and Gunay et al. (2017b) discovered that the manual light switch-on is a more conservative lighting control system from both occupants' preference and electricity use. Accordingly, the researcher adjusted the lighting control system in the monitored offices in mid-August 2016 (see Chapter 5). In the updated control system, lights were turned on manually and turned off 30 minutes upon departure unless occupants turned them off manually.

Regarding the impact of opening windows on indoor environmental conditions, occupants may be asked to close operable windows before their departure or janitors may be given the instruction to close operable windows depending on the conditions. Automatic control of closing operable windows or shutting off heating and cooling if occupants leave windows open are the other alternatives.

4.4.3. Heating Demand

The heating demand of the monitored offices was met by the VAV boxes. Each room had additional radiant ceiling panels, which were controlled independently. To compare the heating demand of various

offices on different orientations consistently, positions of the valve of radiant panels of the monitored offices are presented in this section. Note that the results presented in this section are specific to the current case study. However, they can evoke some insights for building design and operation. The heating loads of the monitored offices provide a broad account of the offices' characteristics and occupant behaviours on the heating demand rather than single out the effect of occupants.

4.4.3.1. Results

The percentage of heater valve state in Figure 4.9a indicates that the peak heating demand occurred at different times of day in the monitored offices on different orientations in the current case study. For the east monitored offices, solar radiation in the morning shifted the peak load to later times in the evening. This is also the case for the corner monitored offices. It should be noted that the WWRs of the east and corner offices were about 90% which contributed to passive solar heat gain in these offices in the heating season. On the other hand, the west monitored offices experienced peak heating demand early in the morning.

The box plots in Figure 4.9b presents the distribution of hourly heater valve state averaged on each office on different orientations during business hours (i.e. 8am-6pm) in the heating season (i.e. March and April 2016). The median and interquartile ranges of the heater valve states show the dispersion of the east and south offices' heating demand during the day in the current case study. This dispersion indicates the variations in the heating demand of the east and south offices, while the variations in the heating demand of the corner and west offices were less noticeable. This figure also shows the lower heating demand of the south office with no operable window, which was the only case in the monitored sample with no operable window. The results indicate that solar heat gain in the south-facing offices during the day improved energy performance of these offices in the heating season. On the other hand, the high glazing ratio of the east and corner offices caused higher heat loss leading to relatively higher heating demand in these offices.

To analyze the variations between the east offices shown in Figure 4.9a, the hourly mean heater valve state of each individual office on this facade is presented in Figure 4.9c. Generally, differentiation between the monitored offices' heating demand on the east orientation was more noticeable in the middle of the day, which may be due to various direct solar radiation. The large facade area of Room 3 caused higher heating demand of this room compared to the other monitored offices on the east orientation. On the other hand, the heating demand of Room 9, which had a large facade area compared to the other monitored offices on the same orientation, was low. The lower heating demand of Room 9 compared to Room 3 is due to that Room 9 was a shared and administrative office, where people came by during the day. Similar to Room 9, the heating demand of Room 10 with a large facade was at a lower value. However, Room 10 was assigned for one occupant with administration position where people frequently came by. As per the researcher's periodic visits (for data retrieval from the stand-alone sensors), Room 12's blinds were closed at each visit. Assuming this office's blinds were predominantly closed, this could increase the thermal insulation of the facade and thereby reducing the heating demand of this office. While all the monitored offices on the east facade were occupied during the monitoring campaign, the occupant of Room 13 was on sabbatical. Therefore, without internal heat gain from people and plug load appliances, the heating demand of this office was higher than the other monitored offices on this facade.

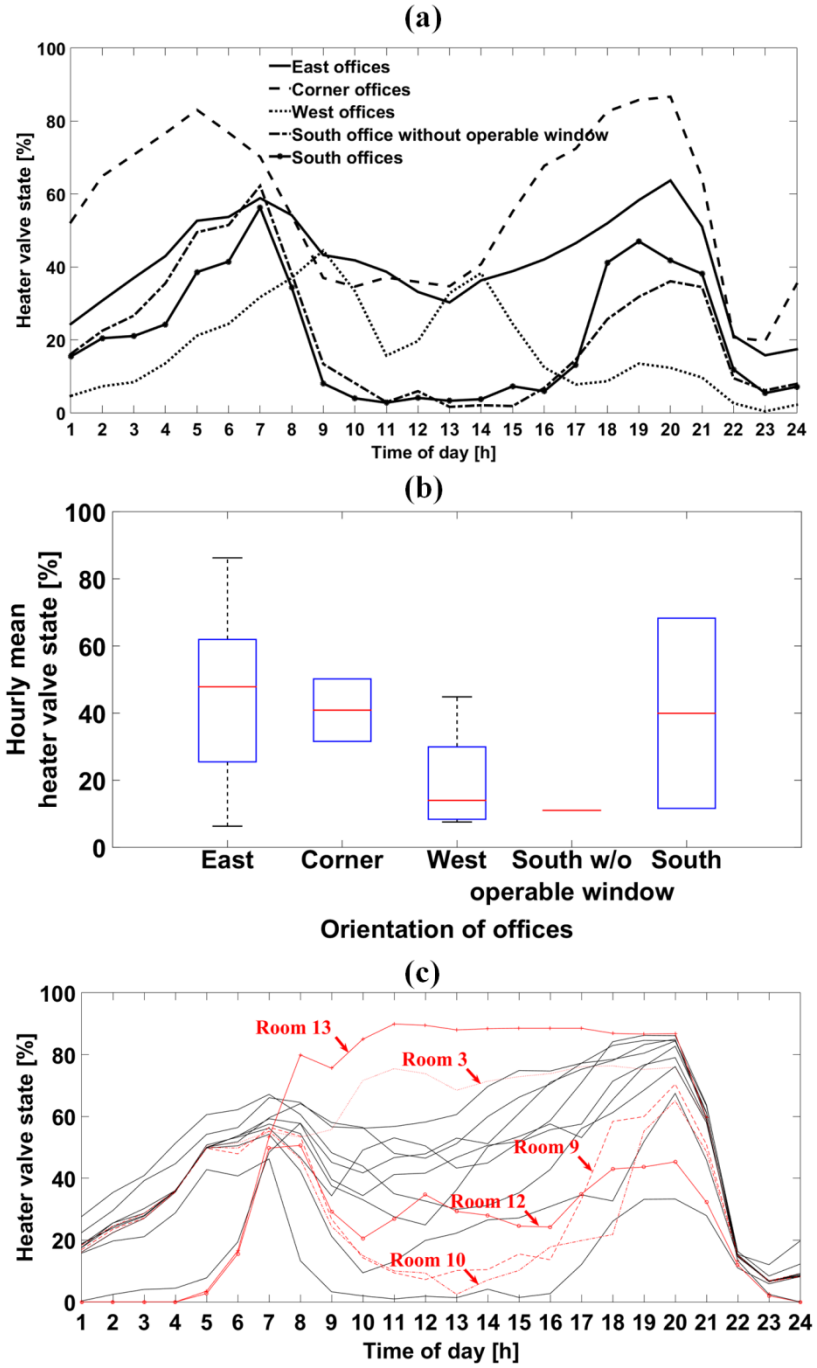

Figure 4.9. Heater valve state in the monitored offices in the heating season (i.e. March and April 2016): (a) hourly heater valve state averaged on all the monitored offices on each orientation, (b) hourly heater valve state averaged on each monitored office during business hours (i.e. 8am-6pm), and (c) hourly mean heater valve state in individual monitored offices on the east orientation.

4.4.3.2. Lessons for Operation and Design

The heating demand results show that the peak heating loads of the monitored offices on different orientations occurred at different times of day in the current case study. Therefore, using morning setback for the east and corner monitored offices and evening setback for the west monitored offices may lead to more efficient operations of the monitored offices with respect to both occupants' comfort and offices' energy performance.

In recognition of the impact of operable windows on the heating demand of offices, designers and operators should pay specific attention in designing operable windows for offices and the control strategy of the positions of operable windows in the heating season, especially upon occupants' departure.

While the analysis of the aggregate data provide operators with valuable information to better control the heating systems of buildings, investigation of the heating demand of each individual office is also imperative. Each office has individual characteristics, such as office use, occupancy, plug load equipment, and positions of operable windows and window shades, that differentiate each office's energy demand from other offices even with the same orientation, properties, and floor area.

4.4.4. Cooling Demand

The cooling loads of the monitored offices are presented in this section. The indoor environmental conditions of the offices are compared as well. Similarly to Section 0, the results presented in this section are specific to the case study of the current research, while they can be beneficial for improved building design and operation. The cooling loads of the monitored offices also take account of the offices' characteristics and occupants' impact on the cooling demand, rather than isolate the occupants' effects.

4.4.4.1. Results

For the analysis of the cooling demand of the studied offices, the cooling load rate of the offices for the months June and July 2016 was averaged on the monitored offices on each orientation. The results are

shown in Figure 4.10a. It is worth noting that the VAV boxes, that supplied air to the studied offices, delivered conditioned air from two air handling units (AHU). Assuming that the conditioned air from the AHUs supplied the air into the rooms with no increase in temperature, the cooling load rate was computed based on the flow rate from each VAV box that supply air to multiple rooms.

As presented in Figure 4.10a, the south monitored office without operable window and the corner monitored offices were at the highest cooling demand in the middle of day (i.e. 2.5 kW (8.5 kBtu/hr) and 1.6 kW (5.5 kBtu/hr), respectively). While the peak cooling load of the east monitored offices occurred early in the morning at a rate of 0.8 kW (2.7 kBtu/hr), for the west monitored offices was about 0.6 kW (2.1 kBtu/hr) in the evening. Compared to the monitored offices on the other orientations, the cooling load rate of the south offices was normally distributed during business hours, with a maximum of 0.9 kW (3.1 kBtu/hr) at midday.

The distribution of hourly cooling load rate averaged on each monitored office during business hours (i.e. 8am-6pm) in June and July 2016 is shown in Figure 4.10b. The results indicate that the cooling load rate of the west monitored offices was at a lower rate than the other monitored rooms (i.e. with the median of about 0.4 kW [1.4 kBtu/hr]), while it was about 1.9 kW (6.5 kBtu/hr) and 1.1 kW (3.8 kBtu/hr) for the south monitored office without operable window and the corner monitored offices, respectively.

The cooling load rates of individual monitored offices on the east orientation are presented in Figure 4.10c. Similar to the aggregate results for these offices on this orientation, each monitored office was at its peak cooling demand early in the morning. Except for Rooms 3 and 9, the cooled air was generally delivered at an identical rate to all the monitored offices on the east orientation. It is worth noting that Room 3 was a single occupancy office with large facade. Room 9 was a shared and administrative office with large windows compared to the other monitored offices on this orientation. The large windows may lead to higher passive solar heat gain and consequently higher cooling demand in these offices.

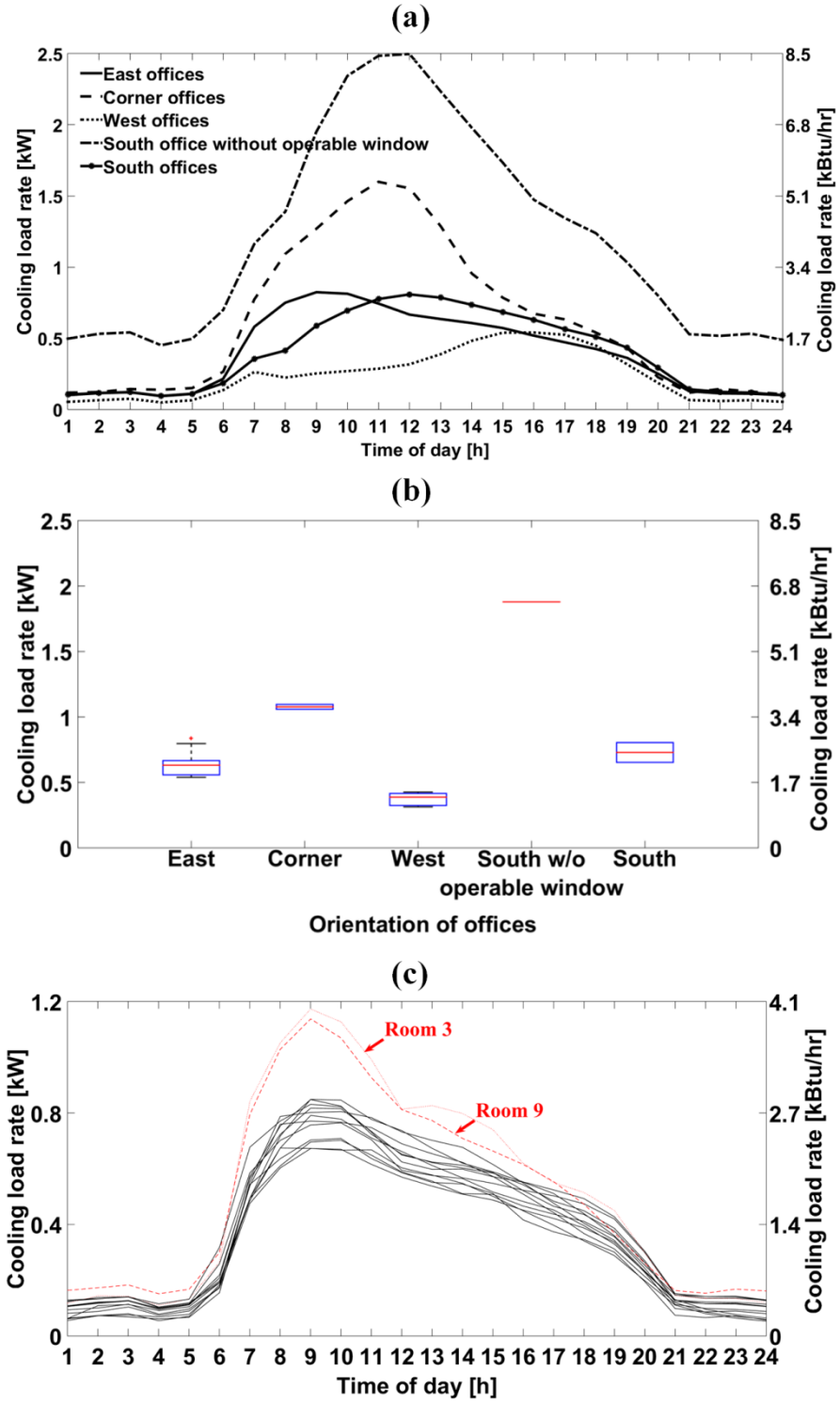
(a)
East offices
Corner offices
West offices
South office without operable window
South offices
Cooling load rate [kW]
Cooling load rate [kBtu/hr]
Time of day [h]
(b)
Cooling load rate [kW]
Cooling load rate [kBtu/hr]
East
Corner
West
South w/o operable window
South
Orientation of offices
(c)
Room 3
Room 9
Cooling load rate [kW]
Cooling load rate [kBtu/hr]
Time of day [h]

Figure 4.10. Cooling load rate in the monitored offices in the cooling season (i.e. June and July 2016): (a) hourly cooling load rate averaged on all the monitored offices on each orientation, (b) hourly cooling load rate averaged on each monitored office during business hours (i.e. 8am-6pm), and (c) hourly mean cooling load rate in individual monitored offices on the east orientation.

A comparison of the indoor temperature of various monitored offices from May to July 2016 during business hours (i.e. 8am-6pm) is presented in Figure 4.11. This analysis revealed that the percentage of business hours that the east, south, and corner monitored offices with WWR of 90% experienced indoor temperature of higher than 28°C (82°F) was more than that in the west monitored offices. Informal discussions of the researcher with the occupants of these offices revealed that even when the air conditioning system was on, occupants felt uncomfortable in their offices and in some cases, occupants used portable fans in the cooling season.

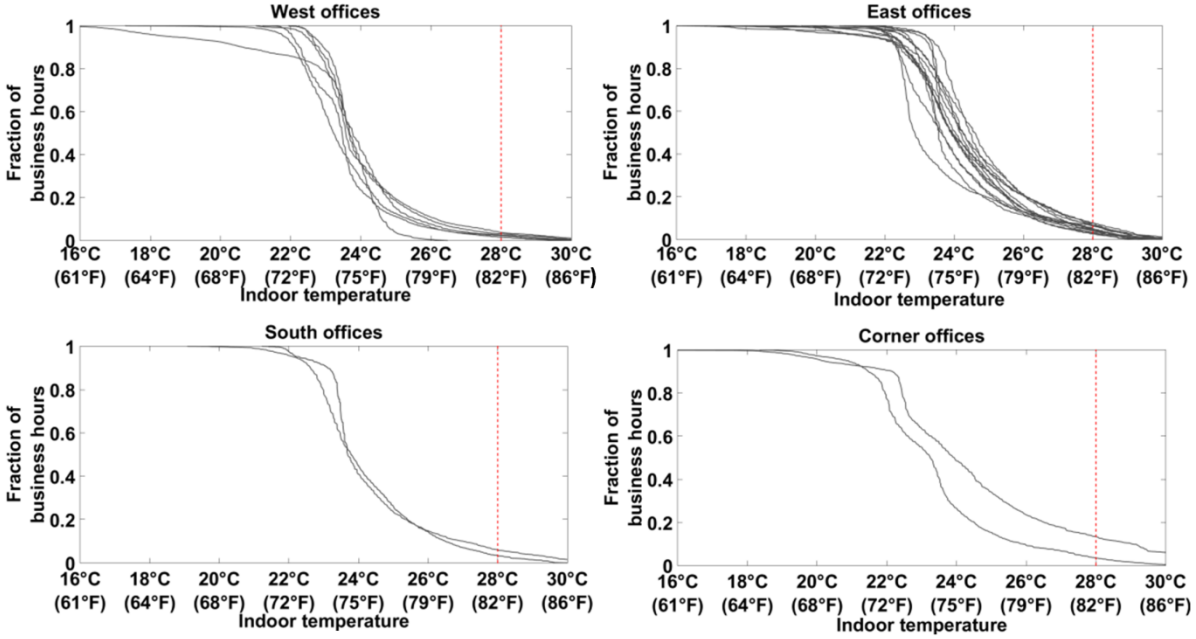

Figure 4.11. Fraction of business hours (i.e. 8am-6pm) in the cooling season (i.e. May to July 2016) when indoor temperature was higher than a specific threshold in the monitored offices on different orientations.

4.4.4.2. Lessons for Operation and Design

Similar to the heating demand, the peak cooling demand occurred at different times of day in the monitored offices on different orientations. This observation suggests time-based setback strategy that

varies based on the offices' orientation for more efficient operation of the monitored offices. Similar to the analysis of heating loads, given that individual offices have specific characteristics, analysis of each office's cooling load can provide valuable information to reduce energy consumption and provide a more comfortable space for occupants.

4.5. Closing remarks

To better understand the mutual interactions between occupants and their built environment and the energy flow, this research conducted a field study in an academic building in Ottawa, Canada. Stand-alone and BAS-integrated built-in sensors recorded occupants' presence and actions, environmental conditions, and energy flows in 25 perimeter offices located on various orientations.

The analysis on the collected data revealed a variety of energy demand and indoor environmental conditions in the monitored offices on different orientations. Furthermore, the occupied period of some of the monitored professors' offices was at a lower rate at higher indoor temperature in the cooling season. Some preliminary results on the impact of using operable windows on indoor environmental conditions and energy demand were presented as well.

This research emphasizes the fact that while the analysis on the aggregate data provide general implications for comfort and energy performance of buildings, analysis of individual spaces is very important. The data analysis on each space reflects the impact of the characteristics of individual offices, (regarding occupancy, occupant behaviour, and space utilization), whereas results based on aggregate data may obscure such cause and effect relationships. In this way, any fault with sensors and/or control systems in each space can also be diagnosed. Likewise, possible occupants' interference in building systems to restore their comfort can be detected, where building facility managers should take actions to modify building systems. Moreover, this study suggests room-level control as the emerging technologies

in monitoring individual spaces has facilitated measuring comfort and energy performance of building spaces at room level.

There were some limitations in this research as outlined below.

- This monitoring campaign was conducted upon receiving the ethics clearance and recruiting occupants. Therefore, the Hawthorne effect may alter participants' natural behaviour towards social desirability due to their awareness of the project. In addition, periodic visits to the monitored offices to retrieve data from the stand-alone sensors may exacerbate the Hawthorne effect.
- Due to the challenges associated with measuring the operative temperature using the globe thermometer, the researcher relied on measuring the air temperature. However, the operative temperature is a significant influential factor on occupants' comfort, especially where the variation between the temperatures of the interior surfaces is noticeable. For example, where the WWR of offices is high, radiant panels provide the heating demand of offices, and occupants' location is near these cold/warm surfaces.

Since the former lighting control system (i.e. occupancy-on/vacancy-off) in the monitored offices led to energy wasting and occupants' dissatisfaction, the researcher adjusted the lighting control system to the manual-on/vacancy-off control system after about six months from the beginning of the monitoring campaign. Next chapter is focused on the analysis of the data collected consequent to this adjustment. The lighting use models developed in this research are explained. The impacts of the previous and adjusted lighting control systems on the lighting use of the monitored offices are also evaluated.

Chapter 5

This chapter has been submitted for publication as:

Occupants' use of lighting controls in offices: A case study.

Gilani S, O'Brien W. *Energy and Buildings*.

5. Occupant's use of lighting controls

5.1. Introduction

In recent years, there has been a surge in the use of automated building systems to provide occupants with a more comfortable indoor environment and to reduce building energy consumption. However, automation may have the opposite effect if occupants' preferences are neglected. In a building energy management system, occupants' comfort is a key parameter while improving buildings' energy performance (Dounis and Caraiscos, 2009; Yang and Wang, 2012). An example of building control systems, which is still being used in private offices in some high-performance buildings, is an occupancy-based lighting control system. For instance, this type of control system was in use in the building which was monitored for the current research, and this study focused on investigating the impact of lighting control systems on the lighting energy use.

Occupancy-based lighting control systems have been investigated to reduce energy use and satisfy occupants in several previous research. For instance, Escuyer and Fontoynont (2001) stated that some occupants prefer occupancy-based lighting controls as they can rely on the lights to be turned on/off automatically rather than having to manually turn them on/off. Guo et al. (2010) and Haq et al. (2014) provided an overview of previous studies (e.g. (Floyd et al., 1996; Maniccia et al., 1999; Jennings et al., 2000; Chung and Burnett, 2001; Maniccia et al., 2001; Von Neida et al., 2001; Galasiu et al., 2007)) on the reduction in lighting energy use with occupancy-based lighting control systems via various research methods of field measurement, simulation, or combination of both methods. For instance, installation of occupancy sensors in Floyd et al.'s (1996) field measurements led to a reduction of 10-19% in the lighting energy use compared to manual control systems. Jennings et al. (2000) achieved lighting energy reductions of 20-26% by replacing manual control systems with occupancy-based light controls in a field study. Chung and Burnett (2001) analyzed the impact of using occupancy-based control systems through

simulation and achieved lighting energy reductions of 26.1-39.1% compared to a baseline design with 14-hour scheduled lights-on period. Similarly, in a simulation-based analysis, Roisin et al.'s (2008) study showed a reduction of 11% in the annual lighting energy use with occupancy-based lighting control systems compared to a base case with scheduled automatic lighting control systems. Maniccia et al. (1999) compared the lighting energy use of an existing building with occupancy-based light control systems to an assumed baseline scenario with lights-on for 10 consecutive hours, where they reduced lighting energy use by 43%. In Von Neida et al.'s (2001) modelling study, lighting energy use decreased by 28-38% relative to the lighting energy used in monitored buildings with manual control systems.

Since the completion of the case study building in 2011, ASHRAE Standard 90.1-2016 (2016) requires that the lighting should not be turned on automatically unless a manual-on control system causes danger to a building space or its occupants. 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 adequate illuminance (Tzempelikos, 2010; Gentile et al., 2016; Gunay et al., 2017b). Furthermore, where automatic building control systems do not account for occupants' reactions to the built environments, occupants' behaviours may not comply with designers' and operators' expectations. For instance, in the monitored building of the current research, occupants were observed to cover motion sensors of light switches to override automatic light switch-on/off (Figure 5.1). Some occupants indicated their offices were too bright or too dark when lights were turned on or off automatically (Gilani and O'Brien, 2016b). The informal discussions of the researcher with the participants of this monitoring study revealed that most of them are satisfied with the manual-on control system following the researcher changed the lighting controls of the monitored offices. Faulty sensors' detection of occupancy (i.e. false positive) and vacancy (i.e. false negative) leads to energy waste and occupants' irritation (Floyd et al., 1996; Guo et al., 2010; Newsham et al., 2017). Other occupants have 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,

2016b). Moreover, automatic control of building systems and components may not give occupants a sense of individual autonomy. It is important to note that the perception of control over environmental conditions affects occupants' satisfaction with their built environments (Leaman and Bordass, 2001; O'Brien and Gunay, 2014).

Therefore, building designers and operators should be cognizant of the preferences of buildings' users when they endeavour to reduce energy use by automating building systems. Dissociating building control systems from their users may suppress the ideal performance of buildings. Built environments host occupants as active agents, where dynamic back and forth interactions between occupants and buildings affect both occupants' comfort and buildings' energy performance. Consequently, comfort and energy performance of existing buildings can 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). For instance, building standards (e.g. (ASHRAE, 2016)) define lighting power densities determined by a space type to represent the lighting energy use, but this approach may neglect the variations between lighting energy use in building spaces with superior and poor daylight performance. A building design can significantly impact occupants' satisfaction and interactions with their built environments, which should be considered in the simulation-based analysis of buildings' energy performance.

The main objective of this research is to examine the impact of lighting control systems, which can be readily applied in existing buildings, on lighting energy use in offices of an existing building. This research also explores the influence of data collection timing in a monitoring campaign on the reliability of probabilistic models. To assess how occupancy-based lighting controls may hinder rather than help improve occupants' comfort and reduce lighting electricity use, the impact of various lighting control systems, including manual and automatic, on lighting electricity consumption are explored in this research. While Tzempelikos (2010) and Gunay et al. (2017b) found that manual control systems lead to

the reduction in the lighting electricity use through a simulation-based analysis, the current research seeks to substantiate this claim with empirical evidence.

Several previous studies (e.g. (Hunt, 1979; Love, 1998; Reinhart and Voss, 2003; Lindelof and Morel, 2006; Correia da Silva et al., 2015)) investigated occupants' interactions with light switches and developed light use models through in-situ monitoring studies. Some research (e.g. (Maniccia et al., 1999; Roisin et al., 2008; Gentile et al., 2016)) implemented different lighting control systems to compare the lighting energy use and/or occupants' satisfation in monitoring or simulation-based studies. To accomplish the main objective of this research project, the impacts of empirical-based models and a set of lighting control systems on lighting electricity use are evaluated in the current research. This assessment requires developing lighting use models, which are derived from empirical data. To this end, a monitoring campaign was conducted in 25 perimeter offices in an existing academic building in Ottawa, Canada, for 15 months.

The obtained results of this monitoring study are also discussed with respect to the simplistic assumptions for light power densities which are suggested by building standards. The findings of this study will provide insights on lighting use patterns in office spaces. These insights will be useful for two aspects of the building life-cycle: (1) in the operation and maintenance of lighting control systems in the existing building, and (2) in the design and operation of new constructions. The ultimate goals of both aspects are to provide a more comfortable environment for occupants as well as to reduce lighting electricity consumption.

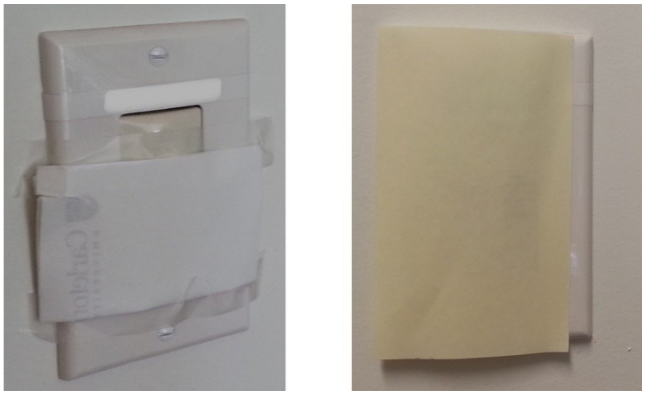

Figure 5.1. Evidence of covering the occupancy sensor of light switches by occupants in the monitored building.

5.2. Monitoring

As explained in Chapter 4, the field study was carried out in 25 perimeter offices in an academic building in Ottawa, Canada which was occupied in 2011 (see Figure 4.2). Upon obtaining ethics clearance, 26 participants were recruited in February 2016. Except for two participants who were using a shared office, all the other participants had private offices. All the offices were occupied by faculty members or administrators. None of the monitored facades were shaded by neighbouring buildings. All the monitored offices had interior roller shades that were controlled manually. Typical floor plans of the monitored offices on different orientations are shown in Figure 5.2. This research covers the data collection period from mid-March 2016 until mid-June 2017.

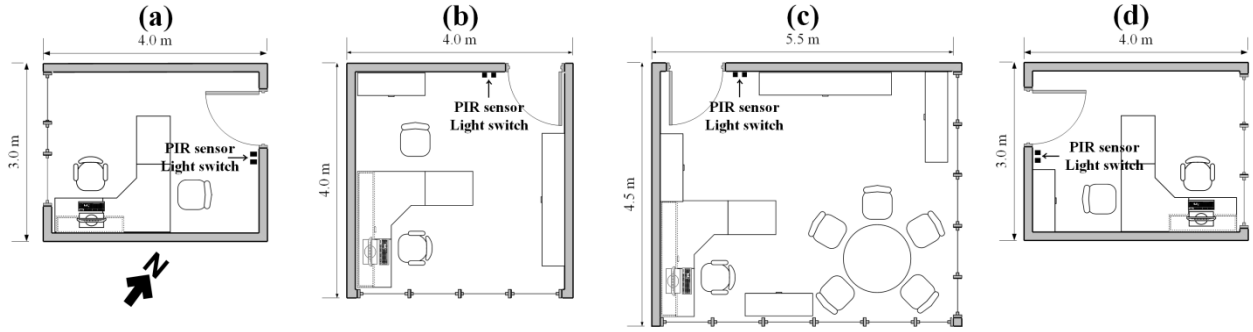

Figure 5.2. Typical floor plans of the monitored offices on different orientations of: (a) west, (b) south, (c) south-east, and (d) east.

Each office was equipped with a built-in thermostat that was also capable of sensing occupancy. Occupancy was sensed using passive infrared motion (PIR) sensors which were integrated with the building automation system (BAS) (see Figure 4.3a).

Stand-alone light intensity data loggers (HOBO U12-012) were installed in each monitored office to record the indoor illuminance as an indicator of daylight availability (see Figure 4.3c). While the shade positions were not recorded with sensors, the indoor illuminance measured in the monitored offices implicitly accounts for this. Due to the uncertainties associated with measuring workplane illuminance in long-term studies (Reinhart and Voss, 2003; Gilani and O'Brien, 2016b), the researcher attached the light intensity data loggers to the ceiling in each monitored office to measure horizontal illuminance on the ceiling. Tzempelikos et al. (2009) found that a linear correlation between the workplane illuminance and the illuminance measured on a spot on the ceiling above the sensor which was located on the desktop. The R-squared of the regression line fit was obtained 0.9 and 0.7 for the two illuminance zones they defined to achieve more accurate results.

As the light switches were not integrated with the BAS, stand-alone data loggers (HOBO UX90-002M), attached to the lighting fixture, were used to record lights' on/off states in each office (see Figure 4.3b). The offices generally had two two-lamp lighting fixtures with T8 32-Watt linear fluorescent bulbs; except for the two corner offices that had four two-lamp lighting fixtures. All the lights in each office were controlled by one light switch. It is worth noting that the corner offices in this study were so bright that the light state data loggers attached to the lighting fixture were not able to detect light states. Therefore, a fiber optic cable, so-called light pipe, was used to remove the effect of daylight. All the monitored offices were already equipped with stand-alone occupancy-based light switches. However, the stand-alone occupancy-based light switches in three of the monitored offices were previously changed to standard on-off ones at the occupants' request. The original lighting control system, prior to the monitoring campaign of the current research, was set to occupancy-on/vacancy-off with 15-minute time delay. After collecting

data for five months from March to August 2016, the researcher converted the automatic lighting control system to the manual-on/vacancy-off with 30-minute time delay using dual in-line package (DIP) switch settings in the light switch of each monitored office (Figure 5.3) as per the direction of building code and standard updates. This lighting control adjustment was implemented in mid-August 2016 and data were collected until about mid-June 2017.

While the BAS was automatically updated with daylight saving time, the data recorded by the stand-alone data loggers for light intensity and light states were processed following data collection to consider daylight saving time before analysing the data.

Figure 5.3. Light switches in the monitored offices, with the cover removed, showing DIP switches (top section) and motion sensor (bottom section). The researcher adjusted lighting control system of the monitored offices using the DIP switch settings in the light switch of each monitored office.

5.3. Modelling

Data-driven lighting use models are a powerful tool for assessing the impact of various lighting control systems on lighting electricity use. Likewise, occupancy is a required input to track: (1) occupants' presence in spaces for occupancy-on/vacancy-off lighting control systems, and (2) occupants' interactions with the lighting. This section explains the methodology used to develop and verify occupancy and lighting use models out of the collected data.

5.3.1. Occupancy

The data collected from mid-March 2016 till mid-June 2017 (i.e. about 450 days) was used to develop occupancy models for each individual office. However, the local industrial computer, which was connected to the BAS to archive data, was down for about two weeks starting from mid-April 2017. Furthermore, the controller of one of the monitored offices (i.e. office 17) stopped logging occupancy due to technical issues for a part of the monitoring period. Therefore, the occupancy model of this office was derived from a shorter period starting mid-July 2016 to mid-June 2017, excluding the second half of April 2017.

5.3.1.1. Model development

To develop occupancy models, the event-based raw data of occupancy recorded by the PIR sensors were converted to time series-based data with presence (i.e. 1) and absence (i.e. 0) at 10-minute timesteps. The time delay for converting occupancy raw data to time series was determined using a probabilistic approach (Nagy et al., 2015). A cumulative distribution of time intervals between each two consecutive motion detections in each office was calculated. Then, the time delay was chosen from the cumulative distribution with a confidence interval of 95% (Gilani and O'Brien, 2016b). For distinguishing between various occupants' habits of active and inactive periods in their offices, time delays were calculated separately for each individual occupant. Based on this approach, it was assumed that the occupant was not in the office if the time interval between each two consecutive recorded occupied instances was higher than the time delay calculated for that occupant (Gilani and O'Brien, 2016b). 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). Using Page et al.'s (2008) model, mobility parameters and profiles of presence probability were generated to predict occupancy as a discrete-time Markov chain. It is worth noting that for the empirical-based analysis of the current building operation, occupancy profiles of each individual office were developed to consider the

diversity of occupants' presence (O'Brien et al., 2016). However, developing a generic occupancy profile can be more applicable in simulation-based design processes.

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 based on Page et al.'s (2008) occupancy algorithm using the collected data in the monitored offices. A Gaussian mixture model was fitted to the probability of presence for each weekday using Equation (5.1):

$$p(presence) = \sum_{i=1}^{n} a_i e^{-(\frac{t-b_i}{c_i})^2} \tag{5.1}$$

where *p(presence)* is the probability of presence at each 10-minute timestep of each week day (i.e. 144 10-minute timesteps per day) and t is the time of day (hour). n is the number of peaks of the Gaussian mixture model fitted to the distribution of presence probabilities. a_i is the probability of presence for each mode, b_i (hour) is the time of day when a_i occurs, and c_i (hour) 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. In this study, a Gaussian mixture model with three peaks (i.e. n = 3) was used to fit the distribution of presence probabilities. It is worth mentioning that O'Brien et al. (2016) found a three-mode Gaussian mixture model fit is a good approximation for occupancy profiles in a building similar to the current one.

The mobility parameter (μ) was the other required input to implement Page et al.'s (2008) model. Mobility parameter, which represents the rate of changes in the occupancy state of an occupant, is calculated using Equation (5.2):

$$\mu = \frac{T_{01} + T_{10}}{T_{11} + T_{00}} \tag{5.2}$$

where 1 represents the presence state, 0 represents the absence state, and the T terms represent the transition probabilities from an occupancy state at the present timestep to the same occupancy state (T_{00} or T_{11}) or the opposite occupancy state (T_{01} or T_{10}) at the next timestep. According to 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 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, similarly to Page et al.'s (2008) model.

5.3.1.2. Model verification

For the verification of the probabilistic occupancy models, the *Brier Score* (*BS*) was calculated using Equation (5.3), as this score is an appropriate metric for the evaluation of the accuracy of probabilistic models where the response is a categorical variable (Brier, 1950; Haldi and Robinson, 2009):

$$BS = \frac{1}{n} \sum_{class=1}^{2} \sum_{ts=1}^{n} (p_{ts,class} - E_{ts,class})^2 \tag{5.3}$$

where *ts* is the timestep, *n* is the number of timesteps, *class* is the category (i.e. two categories of presence and absence for the variable of occupancy), $p_{ts,class}$ is the probability of the considered class to occur at each timestep, and $E_{ts,class}$ is the response to the considered class (i.e. whether the event happened or not) at each timestep. The *BS* calculated for the occupancy of each office is shown in Figure 5.4a. This figure indicates the generally good performance of the probabilistic occupancy models. Equation (5.3) shows that *BS* is zero when the probabilistic occupancy model predicts the correct occupancy state for all the considered timesteps. On the other hand, the *BS* is two for the worst probabilistic occupancy model where the occupancy state of none of the timesteps is predicted correctly (Brier, 1950).

To assess the ability of the probabilistic occupancy models in distinguishing between the presence and absence states for the dichotomous variable of occupancy (i.e. 1 as presence and 0 as absence), the area under the curve (*AUC)* was employed as an indicator (Haldi and Robinson, 2009). The Receiver

Operating Characteristic (*ROC)* curve, which is used to calculate *AUC*, plots the true positive rate (*TPR*) against the false positive rate (*FPR*). For all the monitored offices, the *AUC* was obtained higher than 0.8, indicating that the occupancy models perform accurately in predicting the occupants' presence (Figure 5.4b and c). Hosmer and Lemeshow (2000) state a general rule for the area under the *ROC* curve: (1) *AUC* of 0.5 suggests that there is no discrimination (i.e. the two outcomes have equal probabilities like flipping a coin), (2) An *AUC* of between 0.7 and 0.8 is considered as an acceptable discrimination, (3) *AUC* between 0.8 and 0.9 is considered as an excellent discrimination, and (4) *AUC* of higher than 0.9 is considered as an outstanding discrimination.

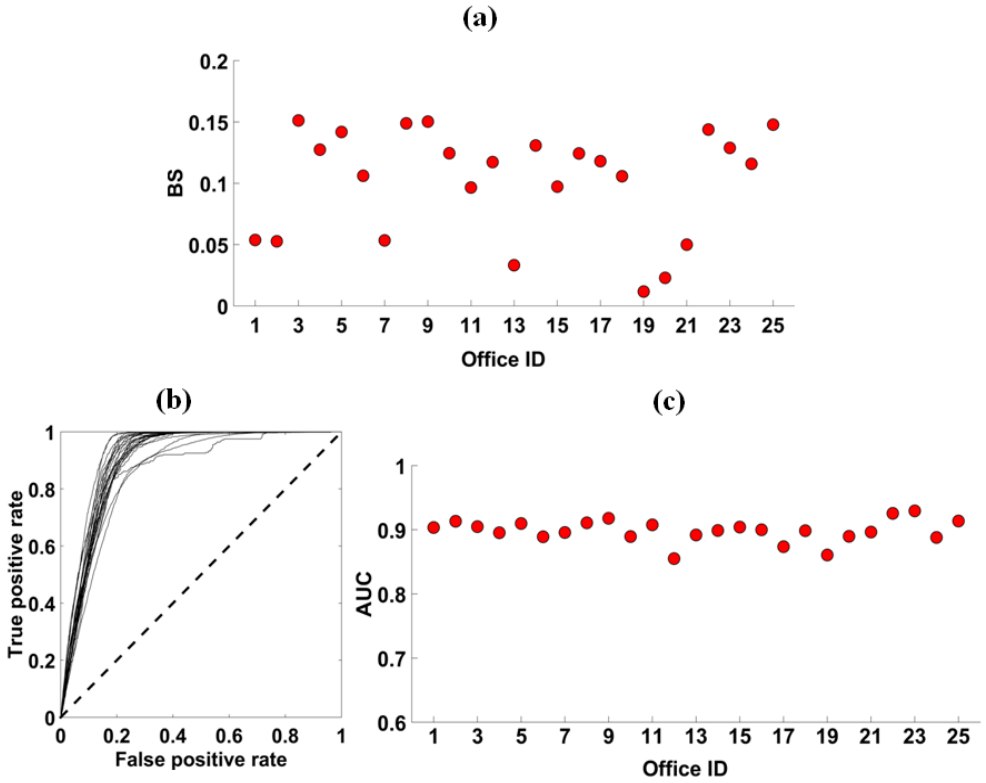

Figure 5.4. Verification of the performance of occupancy models for each monitored office: (a) Brier score (BS) of the probabilistic occupancy model, (b) Receiver operating characteristic (ROC) curves, (c) area under the ROC curve (AUC).

5.3.2. Lighting use

Nine and a half months' worth of data, which covers the monitoring period of mid-August 2016 to the first week of June 2017, was used to develop lighting use models. To generate light switch models, the data from all the monitored offices were aggregated, because number of light-switch actions in each monitored office was insufficient to develop representative statistical models for each office. For instance, light-switch actions occurred at specific values of the relevant predictors or number of actions versus non-actions was imbalanced in some offices. However, the researcher acknowledges that aggregating data from all the monitored offices may suppress the diversity between occupants (Haldi et al., 2016; O'Brien et al., 2016).

5.3.2.1. Model development

Two different light switch-on models were developed in this study: (1) for immediately after any arrival, and (2) for intermediate periods. This is because the current and past studies (Hunt, 1979; Love, 1998; Reinhart and Voss, 2003) found that occupants are more likely to turn on lights upon arrival than during intermediate periods for a given set of daylight conditions. The reason for this is thought to be a combination of relative ease of accessing the light switch when the occupant is already standing, eye adaptation to adjust to the sudden change in light levels, and planned activity as the occupant enters an office.

Previous research (Hunt, 1979; Love, 1998; Reinhart, 2004; Lindelof and Morel, 2006) showed a significant correlation between occupants' light switch-on actions and workplane illuminance. Indoor illuminance measured on the ceiling (E_{in}) was used as the predictor for occupants' interactions with the lighting upon arrival and during the intermediate periods in the current study.

Regarding how often occupants switch off lights, the vacancy period has been proven as a good predictor (Boyce, 1980; Pigg et al., 1996; Reinhart and Voss, 2003; Mahdavi et al., 2008). However, Page et al.'s

(2008) occupancy algorithm does not predict vacancy duration in advance at the time of departure, thus there was no practical method to incorporate vacancy duration to predict light switch-off actions in the building performance simulation (BPS) tool (e.g. EnergyPlus). 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 time of day (*t*).

To estimate the probability of whether an occupant switches on/off lights (i.e. dependent variable) with regard to a relevant predictor (i.e. independent variable), logistic regression models were used because the dependent variable is dichotomous (i.e. whether an occupant takes action or not) (Hunt, 1979, 1980; Love, 1998). The models were built in the form of Equation (5.4):

$$p(event = 1 \mid x) = \frac{e^{\beta_0+\beta_1 x}}{1 + e^{\beta_0+\beta_1 x}} \tag{5.4}$$

where x is the predictor, $p(event = 1 \mid x)$ is the probability of light switch event to occur by the next timestep (i.e. within 10 minutes) for a given value of x, and β_0 is the intercept and β_1 is the regression coefficient of the logistic regression model fitted to the light switch events. The parameters for light switch models are summarized in Table 5.1.

Table 5.1. Parameters of the logistic regression models for estimating the probability of light switch actions.

Light switch model		$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{x}$
Switch-on	Upon arrival	-2.746 ± 0.054	-0.003 ± 0.000	E_{in}
	Intermediate periods	-4.072 ± 0.052	-0.001 ± 0.000	E_{in}
Switch-off		-7.847 ± 0.225	0.314 ± 0.015	t

Note that the methods that can be applied to fit regression models to the observations are: (1) probability of light switch events at each prescribed range of predictor values (i.e. with binning predictor values), and (2) light switch events during the timesteps of interest (i.e. without binning predictor values). In the first

method, the probability of light switch events is calculated at each prescribed bin of predictor values using Equation (5.5):

$$y_{bin(i)} = \frac{\sum_{bin(i)}(a\ AND\ c)}{\sum_{bin(i)}(a\ AND\ b)} \tag{5.5}$$

where the *x* variable on the *x-y* graph is the defined bin of predictor values (i.e. *bin(i)*) and the *y* variable is the probability of light switch actions at *bin(i)*; *a* is the occupancy state (i.e. arrival = 1, intermediate = 1, or departure = 1) by the next timestep (i.e. *ts+1*), *b* is the light state (i.e. on = 1, off = 0) at the present timestep (i.e. *ts*) , and *c* is whether light switch-on/off actions occur by the next timestep. Statements *a*, *b*, and *c* are summarised in Table 5.2. For serving the frequency of variations observed at each bin of the predictor value to fit the regression model, the weighting method should be applied by the number of observations that falls into each bin.

In the second method, the *y* variable on the *x-y* graph is calculated based on Equation (5.6):

$$y_{ts} = \begin{cases} 1, & (a\ AND\ b\ AND\ c) \\ 0, & (a\ AND\ b\ AND\ d) \end{cases} \tag{5.6}$$

where the *x* variable on the *x-y* graph is the predictor value at each timestep, y_{ts} is whether light switch occurs (i.e. 1) or not (i.e. 0), *ts* is the timestep of interest (i.e. when statements *a* and *b* happen), and *d* is when the light switch-on/off actions does not occur by the next timestep. Table 5.2 presents statements *a*, *b*, *c*, and *d*.

Table 5.2. Statements of Equations (5.5) *and* (5.6) *to fit regression models for developing light switch models.*

Light switch model		***a***	***b***	***c***	***d***
Switch-on	Upon arrival	$\text{Arrival}_{ts+1} = 1$	$\text{LS}_{ts} = 0$	$\text{Switch-on}_{ts+1} = 1$	$\text{Switch-on}_{ts+1} = 0$
	Intermediate periods	$\text{Intermediate}_{ts+1} = 1$	$\text{LS}_{ts} = 0$	$\text{Switch-on}_{ts+1} = 1$	$\text{Switch-on}_{ts+1} = 0$
Switch-off		$\text{Departure}_{ts+1} = 1$	$\text{LS}_{ts} = 1$	$\text{Switch-off}_{ts+1} = 1$	$\text{Switch-off}_{ts+1} = 0$

The first method to fit regression models to the observations imposes limitations on the fit model, including: (1) a bin width should be determined which requires considering frequency variations observed

at each bin, and (2) a specific maximum value for predictors should be defined. Therefore, this study employed the second method for developing lighting use models.

5.3.2.2. Model verification

Similar to the assessment of occupancy models, the accuracy of the data-driven light switch models was assessed using the *Brier Score*. The *BS* was calculated as 0.06 for the probabilistic light switch-on model upon arrival and 0.03 for the light switch-on model during intermediate periods based on the aggregate data from all the monitored offices. The *BS* was obtained 0.06 for the light switch-off model. As explained for Equation (5.3), the *BS* ranges from zero (i.e. a thoroughly accurate model) to two (i.e. a thoroughly inaccurate model) for light switch models where two distinct classes (i.e. event occurred and event did not occur) can be mapped. It is worth noting that the number of timesteps (i.e. n) to calculate the *BS* for the light switch-on model during intermediate periods was twice the number of timesteps for the light switch-on model upon arrival and light switch-off model. Therefore, this may cause better performance for the light switch-on model during intermediate periods.

To characterize the performance of light switch models in predicting light switch actions on the aggregate data from all monitored offices, *AUC* values were calculated (Haldi and Robinson, 2009). The *TPR* is graphed against the *FPR* in the curves shown in Figure 5.5. Using MATLAB, the *AUC* value was calculated as 0.74 for the light switch-on model upon arrival and 0.66 for the light switch-on model during intermediate periods. For the light switch-off model, the *AUC* value was calculated as 0.73. Note that the optimal *AUC* value is 1, representing a perfect binary classifier. The obtained values for *AUC* in the current study indicate the acceptable ability of the light switch models in the classification of occupants' light switch actions (Hosmer and Lemeshow, 2000).

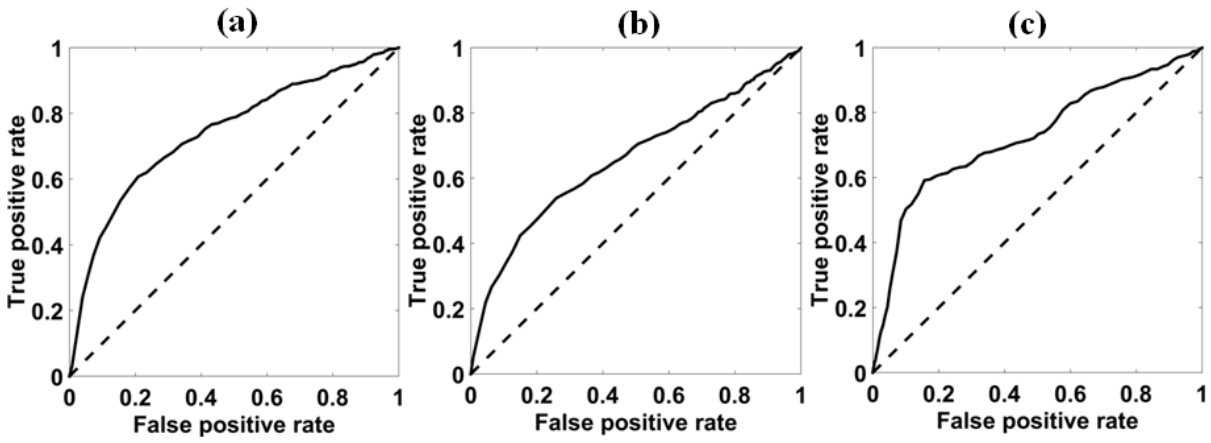

Figure 5.5. ROC curve of light switch models: (a) light switch-on upon arrival, (b) light switch-on during intermediate periods, and(c) light switch-off upon departure.

5.4. Simulation

With the models developed and verified, simulation affords additional capability to further investigate the current topic, such as estimating annual performance. In this study, two sequential lighting control systems were monitored for a partial year. The former lighting control system (i.e. occupancy-on/vacancy-off with 15-minute time delay) spanned a shoulder season (i.e. spring) and summer, while the adjusted lighting control system (i.e. manual-on/vacancy-off with 30-minute time delay) included summer, shoulder seasons (fall and spring), and winter. The limitations of this monitoring study include seasonal variations in daylight availability and occupants' physiological adaptation to seasonal transition from lower daylight availability to higher, and vice versa. Therefore, the lighting use measured for the two lighting control systems was affected unequally. Simulation also facilitated the evaluation of the impact of other lighting control systems on the lighting electricity consumption. Moreover, in the field measurement, the lighting use of the individual offices was compared using the empirical data, while the lighting use of the individual offices is affected by various factors in addition to lighting control systems, such as: offices' layout, orientation, and floor plan; reflectivity of interior surfaces; transmittance of windows; and, solar radiation. These variables were controlled for by simulating a generic office space.

For the simulation-based analysis of this research, a typical office space was simulated. The simulated office had dimensions W × L × H = 4.0 × 4.0 × 3.0 m and a south-facing window with WWR of 40%, sill height of 0.8 m, and an interior roller shade. The interior surface of the floor, walls, and ceiling were assumed to have a visible reflectance of 0.2, 0.5, and 0.8, respectively, similarly to the measured values of the monitored offices using a spectrophotometer. The transmissivity of the window glazing and shade fabric were assumed 0.44 and 0.22 at normal incidence, respectively.

While workplane illuminance is the common parameter to calculate in BPS tools, in the current field study, the horizontal indoor illuminance was measured on the ceiling due to the uncertainties associated with measuring the workplane illuminance in long-term studies. RADIANCE-based daylighting analysis tool DAYSIM (Reinhart, 2001) was used to calculate the annual indoor illuminance on the ceiling. The weather data used for DAYSIM simulations was the Canadian Weather for Energy Calculations (CWEC) for a typical year of Ottawa. The sensor was located in the center of the ceiling, just like in the monitored offices. Window shade use was simulated by Haldi and Robinson's (2010) shade use model, which allows for the partial and full opening or closing of shades. For this simulation, five distinct positions were assumed for offices' shades: fully open, 3/4, 1/2, and 1/4 open, and fully closed. The indoor illuminance on the ceiling (required as an input to the empirical-driven lighting use models) and the workplane illuminance (required as an input to Haldi and Robinson's (2010) shade use model) for the five shade positions were simulated in DAYSIM. Since Haldi and Robinson's (2010) shade use model has been derived from data collected in south-facing office spaces, the current research simulated just a south-facing office.

As the only inputs for simulating occupancy and lighting use based on the data-driven models developed in this study are time and illuminance, a custom MATLAB-based building model was created for more computationally efficient simulation. The output of the DAYSIM simulation was also implemented as input in the MATLAB-based model. To evaluate the impact of lighting control systems on lighting

electricity use, four control systems were implemented in MATLAB as follows: (1) occupancy-on/vacancy-off-15 (i.e. with 15-minute time delay upon departure), (2) occupancy-on/vacancy-off-30 (i.e. with 30-minute time delay upon departure), (3) manual-on/manual-off, where if occupant did not turn off lights upon departure, lights were turned off at midnight, and (4) manual-on/vacancy-off-30 (Table 5.3).

Table 5.3. Lighting control systems

Control system	Name	Switch-on	Switch-off
1*	occupancy-on/vacancy-off-15	occupancy	vacancy (15 minute time delay)
2	occupancy-on/vacancy-off-30	occupancy	vacancy (30 minute time delay)
3	manual-on/manual-off	manual	manual
4**	manual-on/vacancy-off-30	manual	vacancy (30 minute time delay)

* previous lighting control system in the monitored offices
** current lighting control system in the monitored offices

The empirical-based lighting use models for light switch-on actions upon arrival and during intermediate periods and the light switch-off model at departure (explained in Section 5.3.2.1) were implemented in MATLAB. The input coefficients of the probabilistic lighting use models were randomly generated from the normal distribution profiles with the mean and standard error of each coefficient estimate (i.e. β_0 and β_1) at the beginning of each run period (i.e. one year). Note that each run period represented each individual office. The occupancy of each monitored office in the study was simulated in MATLAB using the empirical-driven model developed for that office based on the Page et al.'s (2008) occupancy algorithm (described in Section 5.3.1.1).

To model the probability of different occupants' presence and interactions with lights, the Markov Chain Monte Carlo method was applied over the 25 offices in the monitoring study carried out in this research. Using the Markov Chain Monte Carlo method (Gilks et al., 1996; Downing et al., 2013), random numbers were generated from the uniform distribution in the interval (0,1) at each timestep. If the estimated

probability was higher than the random number, the event of interest occurred; otherwise it did not. 25 one-year run periods were simulated, representing each of the 25 offices, for which the occupancy model was based on each individual office from the case study building, while the lighting use model was based on the aggregate data.

5.5. Results and discussion

This section presents and discusses the results of the lighting use modelling and simulation using the measures of lighting electricity use and duration that the lights were on. The impact of the duration of data collection and rate of changes in light states on the prediction of lighting electricity use are also explored in this section based on the calculation of the intra-class correlation coefficients (*ICC*) and frequency of light switch-on actions.

5.5.1. Modelling and simulation

As indicated by the distribution of annual lighting electricity use for the four investigated lighting control systems presented in Figure 5.6, a 92% reduction in the annual lighting electricity consumption is achievable with the manual-on/vacancy-off control system (i.e. lighting control system 4) compared to the occupancy-on/vacancy-off (i.e. lighting control systems 1 and 2). This result is in line with Gentile et al.'s (2016) field study where they observed a significant reduction of 75% in the lighting electricity use of four monitored offices. Gunay et al.'s (2017b) simulation results revealed a reduction of 70% in the lighting electricity use. Note that ASHRAE Standard 90.1-2016 (2016) allows a reduction in *lighting density power* (*LPD*) where occupancy sensors are used, based on Equation (5.7):

$$LPD_{adjusted} = LPD_{reference} \times (1 - OSR) \tag{5.7}$$

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. According to ASHRAE Standard 90.1-2016 (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 (i.e. $LPD_{reference}$) to 8.29 W/m^2 (i.e. $LPD_{adjusted}$) for an enclosed office with occupancy sensors for which the *OSR* is 0.30. Using the manual-on lighting control system, the *LPD* will be 7.40 W/m^2 (i.e. 11.8 × (1 - 0.30×1.25)). So, the simulated electricity use decreases 11% with the manual-on control system compared to the occupancy-on control using the ASHRAE Standard 90.1-2016 (2016) scheme. However, the simulated lighting electricity use in the current study showed a 92% reduction caused by the manual-on control system. This suggests that the additional reduction factor (i.e. 25%) recommended by ASHRAE Standard 90.1-2016 (2016) should allow more flexibility regarding how well a building space is daylit. A space with poor daylight availability will not benefit from manual-on lighting controls, whereas a well daylit space could benefit substantially more than suggested by ASHRAE Standard 90.1-2016 (2016).

As shown in Figure 5.6, the vacancy-based lights 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). Therefore, if the vacancy-off setup is replaced by the manual-off, it may take weeks or months for occupants to become accustomed to turning off lights manually. The first and second lighting control systems are still being implemented in some modern high performance buildings. For instance, in the monitored building in this research, the first lighting control system was in use for the five years of operation before the researcher adjusted it in the monitored offices. This is despite the fact that ASHRAE Standard 90.1-2016 (2016) requires manual-on lighting control. It is worth mentioning that the committee of the National Building Code of Canada have also required the manual-on lighting control in the upcoming version of this building code. In this research, the third lighting control system (i.e. manual-on/manual-off) shows the potential for reducing lighting electricity use by 31% compared to the first lighting control system and 42% compared to the second.

In addition to reducing lighting energy use, manual control of lighting can enhance occupants' comfort, as stated in previous studies (Boyce et al., 2006; Galasiu and Veitch, 2006; Doulos et al., 2007). In the current research, 24 of the 26 study participants did not express discontent with the adjusted lighting control system (i.e. manual-on/vacancy-off-30). Gentile et al. (2016) also stated that occupants were much more satisfied with the manual-on/vacancy-off lighting control system. In Escuyer and Fontoynont's (2001) study, the main reasons participants mentioned that they preferred manual over automatic lighting controls were to benefit from daylighting, reduce energy, and to relieve their eyestrain caused by a high lighting level. However, in the current study, an occupant, whose office blinds were often closed, stated a preference for the former lighting control system (i.e. occupancy-based light switch-on). This participant stated that with the manual-on lighting control, they have to make an effort to switch on lights when offices become dark and they are still sitting at their desks. Another occupant considered the former lighting control system more efficient when their 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 to be worth conserving energy or they may forget to turn off the lights upon their departure. Furthermore, informal discussions between the researcher and the participants of the monitoring campaign revealed that corner offices were so bright during the day that the switched-on lights were not detectable. Reinhart and Voss (2003) stated that occupants in their study sometimes did not turn off lights as they did not notice that the lights were on due to the high level of indoor daylighting. In such cases, automatic controls of lights switch-off can reduce energy waste where building spaces are too bright and occupants may not notice the lights are on while leaving their offices.

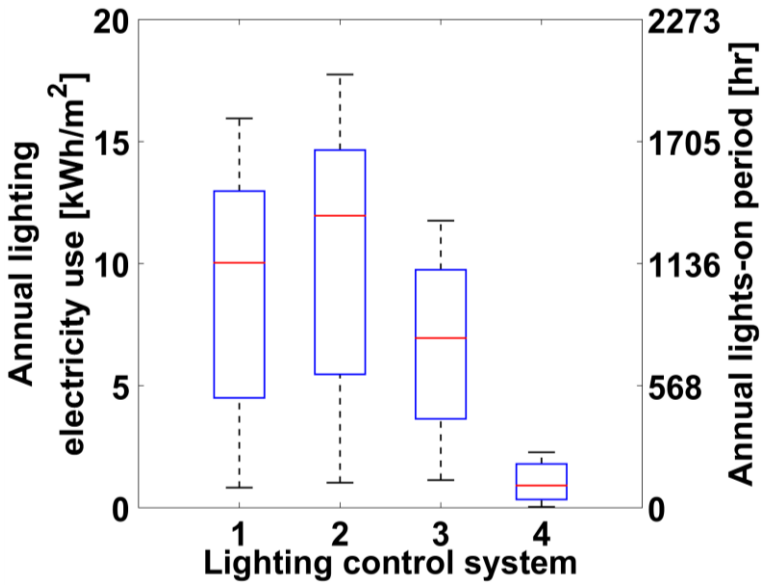

Figure 5.6. Distribution of annual lighting electricity use (kWh/m^2) and lights-on period (hr) for various lighting control systems based on simulation results: (1) occupancy-on/vacancy-off-15, (2) occupancy-on/vacancy-off-30, (3) manual-on/manual-off, and (4) manual-on/vacancy-off-30.

Figure 5.7 presents the simulation results for the relationship between the total annual occupancy period and lighting electricity use where a linear regression model fit to all occupants' corresponding data. The simulation results show that with the manual-on system, the lighting energy use can be reduced by a factor of seven compared to the occupancy-on/vacancy-off.

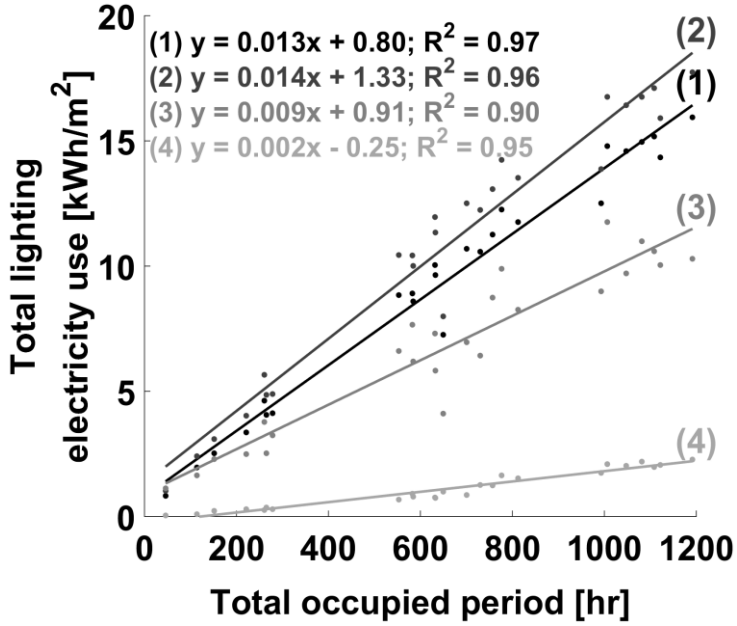

Figure 5.7. Linear regression models fit to the relationship between the annual lighting electricity use (kWh/m^2) and occupied period (hr) for various lighting control systems based on simulation results: (1) occupancy-on/vacancy-off-15, (2) occupancy-on/vacancy-off-30, (3) manual-on/manual-off, and (4) manual-on/vacancy-off-30.

Figure 5.8a presents the lights-on period normalized by the occupied period for five months before and nine and a half months after the researcher changed the lighting control system in the monitored offices. Office 17 is excluded from this figure because its occupancy data had gaps due to technical issues with its controller. The ratio of the lights-on period to the occupied period shown in Figure 5.8b represents the annual output of simulation with lighting control systems 1 and 4 (see Table 5.3). A reduction of 90% is observed with the simulation results with the manual-on/vacancy-off compared to the occupancy-on/vacancy-off. The results of the experiment confirms significant lighting energy savings, showing a 62% decrease in the lighting energy use after changing the lighting control system to the manual-on/vacancy-off compared to the previous lighting control setting (i.e. occupancy-on/vacancy-off). Tzempelikos (2010) and Gunay et al. (2017b) discovered similar conclusions with respect to lighting electricity consumption using manual control systems in a simulation-based analysis, while the current study observed this effect in a field measurement as well (see Figure 5.8a).

Note that Figure 5.8a excludes the three offices for which the original light switches were replaced with the standard on-off ones. The outlier of this distribution with the lights-on period of 21 times the occupied period corresponds to an office whose lights were left on during several nights while the office was unoccupied. However, after adjusting the lighting control system, the ratio of lights-on to the occupied period of this office reduced by a factor of eleven. The simulation results in Figure 5.8b also show that combining lighting data from all offices for developing lighting use models may neglect diversity between occupants' use of lighting, while the observed occupants' behaviours are diverse in reality.

It is important to mention that the researcher acknowledges the noticeable discrepancy between simulation and field measurement results in Figure 5.8, because of: (1) the experimental results before (i.e. control system 1) and after (i.e. control system 4) lighting control adjustment cover different times of year with different potential for daylighting, while the simulation results compares annual lighting use for each of the lighting control systems (i.e. control systems 1 and 4), (2) the experimental results show lighting energy use of each individual monitored office while the simulation used aggregate data for light switch models, (3) light switch-on models were developed using the data which were aggregated from all the monitored offices on various orientations, whereas a south-facing office space was simulated, and (4) window shades were simulated using an existing shade model from the literature rather than shade positions in the monitored offices.

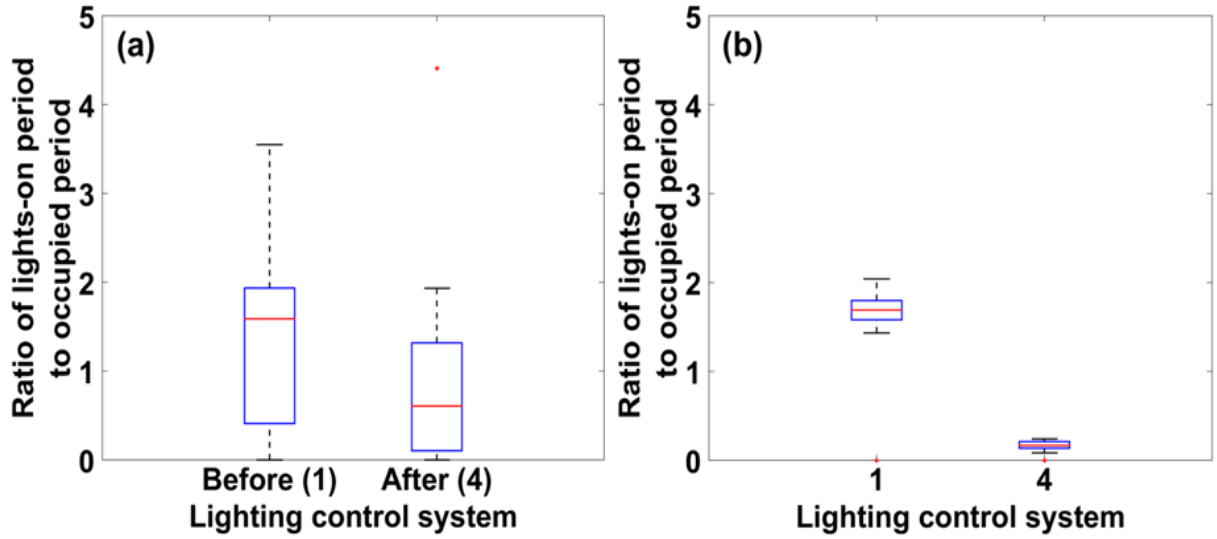

Figure 5.8. Ratio of lights-on to occupied period: (a) experimental results, with five months' worth of data before and nine and a half months' worth of data after adjusting lighting control systems in the monitored offices, (b) one-year run-time simulation results with lighting control systems 1 and 4 (see Table 5.3).

The simulation results in Figure 5.8b indicate that the lighting electricity use can be twice the occupied duration with lighting control system 1. The investigation of light states in the monitored offices with the previous lighting control system (i.e. occupancy-on/vacancy-off) revealed several instances with lights on during unoccupied period. This is because once an office is vacated, its lights are still on for a designated period (i.e. 15 minutes with lighting control system 1). Where occupants leave their offices more frequently during the day and their vacancies last longer than the adjusted time delay for lights to be turned off automatically, lighting electricity use is inevitably higher with the vacancy-off control system (Figure 5.9a). This is especially the case for occupants with higher mobility parameters (Page et al., 2008), because this parameter indicates the frequency that occupants leave and arrive their offices during the day (Figure 5.9b).

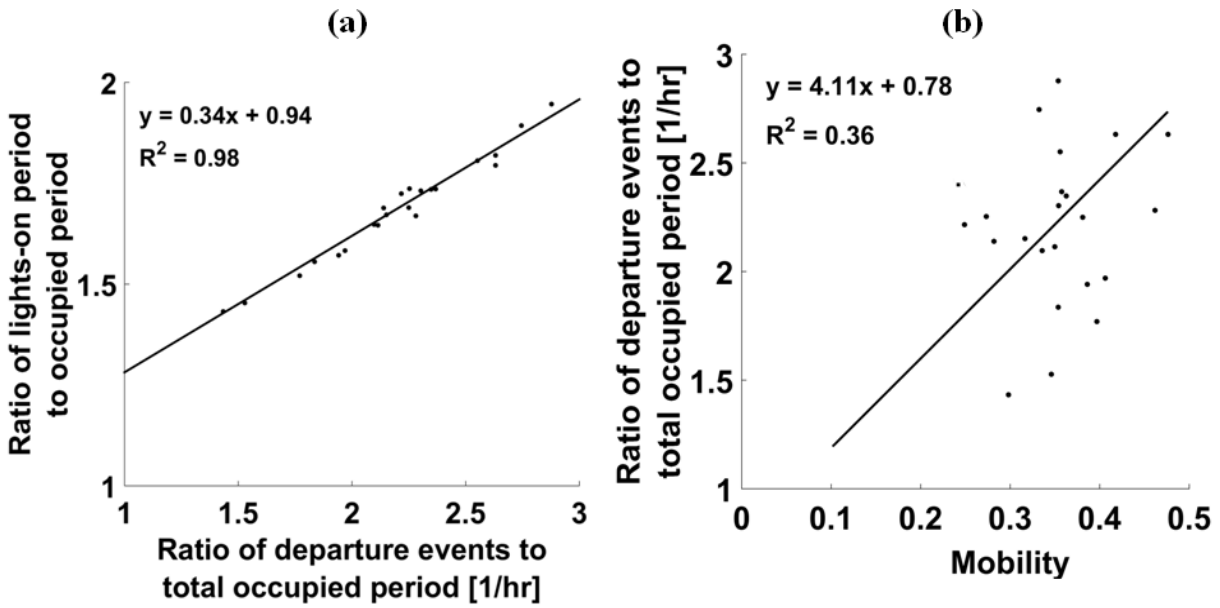

Figure 5.9. Simulation results for the impact of departure events on duration of lights-on where the first lighting control system (occupancy-on/vacancy-off-15) was applied: (a) relationship between the ratio of lights-on to occupied period and the ratio of departure events to total occupied period, , (b) relationship between the ratio of departure events to total occupied period and the mobility parameter.

5.5.2. Monitoring sample size

In general, for occupant monitoring studies, one of the challenges a researcher encounters is determining appropriate sample size including: (1) how many days of monitoring, and (2) how many actions are required to characterize building energy performance and occupants' operations on building systems and components? Given that the light switch models developed in this research are based on nine and a half months' worth of data and the corresponding rate of changes in light states, the researcher acknowledges that the duration and number of events in this monitoring campaign may affect the models and the resulting predicted lighting energy use. However, on the other hand, a minimum sample size required to develop statistically representative models can minimize time, costs, and effort for ethics clearance, participants' recruitment, and logging and processing data. To explore the impact of rate of changes in light states and duration of data collection on the prediction of energy performance, lighting energy use of the group of the individual monitored offices was evaluated assuming different durations for the monitoring study, ranging from two weeks to 39 weeks (i.e. the total monitoring period following the

lighting control adjustment in this research in mid-August 2016). For this evaluation, *ICC* was calculated based on two factor analysis of variance (ANOVA) to assess the lighting electricity use by occupants using Equation (5.8) (Shrout and Fleiss, 1979; Zaiontz, 2017):

$$ICC = \frac{BMS - EMS}{BMS + (k-1)EMS} \tag{5.8}$$

where *BMS* is the mean square between subjects/targets (i.e. 25 monitored offices), *EMS* is the residual or error mean square, and *k* is the number of raters/judges (i.e. 2 to 39 weeks). In this research, subjects were the monitored offices and raters were different periods of data collection. Note that to maintain the consistency of each subject between raters for the *ICC* assessment, the occupancy profile of each participant was generated once, which was used as input to simulate the annual lighting energy consumption of that office with respect to different raters. Lighting control system 4 (i.e. manual-on/vacancy-off-30) was considered for this analysis.

Figure 5.10 shows the *ICC* of lighting electricity use of 25 monitored offices for different weeks' worth of data. This figure shows that after eight weeks starting from mid-August with 191 light switch-on events, *ICC* follows a positive trend starting from a value of 0.86. With respect to the Cicchetti's (1994) interpretation of the *ICC* between 0.60-0.74 as good and 0.75-1.00 as excellent level of significance, the developed data-driven lighting use models built upon eight weeks' worth of aggregate data starting from mid-August were able to predict the lighting energy use of the offices consistently. In other words, the lighting use models were reliable for measuring the lighting use on the group of monitored offices. However, this reliability does not necessarily prove the validity of the developed models (Tavakol and Dennick, 2011). This can also be interpreted as the internal, rather than external, consistency of the lighting energy use predictions on the group of offices between different monitoring periods.

As shown in Figure 5.11, occupants' use of lights varied monthly, which indicates how the monitored perimeter offices benefitted from daylight harvesting during different seasons. The maximum number of

monthly actions of 252 was observed in November 2016. Occupants had also switched on lights more often at the beginning of 2017 when the outdoor illuminance level may have been consistently insufficient. 224 light switch-on events were observed in January and 188 were observed in February. Therefore, the next question that a researcher should ask, when embarking on a new occupant monitoring campaign is: when should I start the campaign and how sensitive are results of partial-year studies to the starting time of year? To investigate how the number of actions may affect the predicted lighting energy use, the reliability testing was performed using the *ICC* metric with the assumption that monitoring campaign began on the first day of different months, except for August when the lighting control system was adjusted in the middle of the month (Figure 5.12). The months March, April, and May 2017 were excluded from this analysis, as the low number of weeks (i.e. number of raters/judges in calculating the *ICC* values) assuming data collection started from these months compared to when data collection was assumed to start from the other considered months may cause bias in the *ICC* calculations. Figure 5.12 indicates the noticeable variation between different numbers of weeks' worth of data for October when the daily rate of changes in light states was higher than the other considered months (see Figure 5.11). However, where it was assumed the data collection started from mid-August or the beginning of September, with the total number of 50 and 117 monthly actions, the *ICC* values generally increase steadily. Figure 5.11 shows that variation in the rate of changes in light states is generally consistent from November 2016 to February 2017 in the winter season when cloudy days are dominant and consequently indoor illuminance is not significantly affected by outdoor conditions. Therefore, the lighting use models, which were developed based on the data collection starting from these months, predicted consistent lighting electricity use on the group of monitored offices. In other words, a higher value was obtained for *ICC*.

This analysis indicates that the required data collection period to develop reliable light use models for predicting lighting energy consumption is influenced by when a researcher plans to start a monitoring

campaign, as the time-dependent potential for daylight results in various occupants' interactions with lights relying on the time of year. Therefore, researchers can achieve savings on time, effort, and costs by having guidance for when to commence data collection in a monitoring campaign. For instance, the duration of data collection in this research assuming it started from the beginning of October, if all else were equal though, could be reduced by a factor of two to reach a consistent growth of *ICC* higher than 0.90 in the prediction of lighting energy use of the group of the monitored offices. It is important to note that, in this study, because of the insufficient number of actions in individual offices, the number of actions was aggregated from all occupants. In this case, a larger number of offices can also reduce the monitoring period as this accelerates the total number of actions. Conversely, if fewer offices had been studied, a longer monitoring period would be required to achieve the same internal consistency. It is worth noting that there is not yet enough research to provide general guidelines for the lighting domain or other domains. However, future studies could perform this analysis continuously to observe how *ICC* and/or other measures change over time.

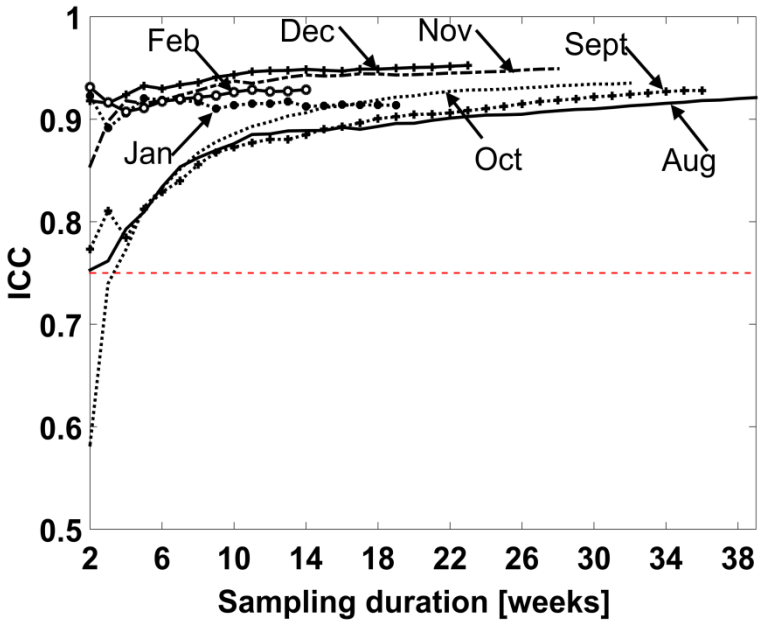

Figure 5.10. ICC of lighting electricity use of 25 monitored offices (i.e. subjects) for different weeks' worth of data (i.e. raters), assuming the monitoring campaign started on the first day of the labeled month except for August when the lighting control system was adjusted in the middle of the month.

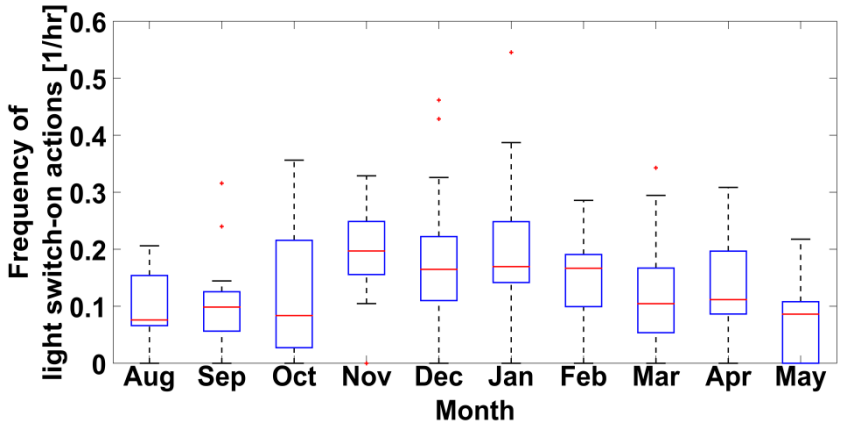

Figure 5.11. Monthly distribution of light switch-on events to the occupied period. The ratio was computed from all occupants for each day of the month.

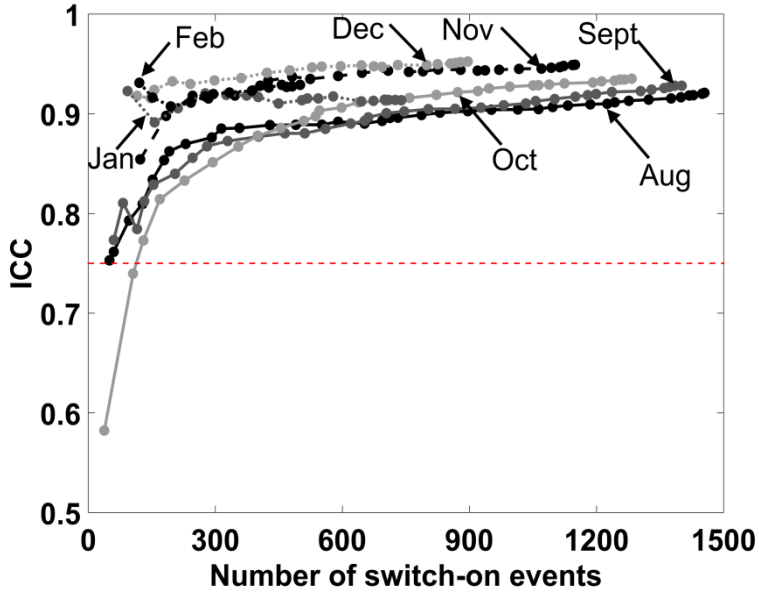

Figure 5.12. The relationship between the ICC of lighting electricity use of 25 monitored offices for different weeks' worth of data and cumulative number of light switch-on actions, assuming the monitoring campaign started on the first day of the labeled month except for August when the lighting control system was adjusted in the middle of the month. The first point in the graph for each month indicates two weeks elapsed after the first day of that month. The next points are spaced in one-week intervals. Note that the number of actions is based on the aggregate data from all monitored offices.

5.6. Closing remarks

The performance of various lighting control systems, including manual and automatic, on the lighting energy use were assessed in the current study via empirical data and simulation. For the simulation-based analysis, probabilistic models for occupants' presence and actions on lights were developed and verified based on a monitoring campaign conducted in 25 perimeter offices in an academic building in Ottawa, Canada.

Key findings from this study are summarized as follows:

- The manual-on/vacancy-off lighting control system was found to reduce lighting electricity use by 62% based on the experimental data and 90% based on the simulation results.
- The manual light switch-on/off lighting control system reduced lighting electricity use by about 36% compared to the occupancy-on/vacancy-off control system based on the simulation results.
- The automatic occupancy-based lighting control systems led to high lighting electricity use, while using daylight sensors can reduce lighting energy use, especially in perimeter offices where daylight can be sufficient to achieve adequate illuminance during business hours.
- The beginning time of year and duration of data collection influenced the number of occupants' interactions with lights and a reliable prediction of lighting energy use.

There were some limitations in this research, which may cause some bias in the obtained results, as listed below:

- Light switch models were developed based on the aggregate data due to the fact that the rate of changes in light states in each office during the monitoring period was insufficient to develop statistically representative model. This method may neglect the variety between occupants' lighting preference and interactions.

- The influence of various factors, such as potential for daylighting at the time of a monitoring study, office layout, orientation, and floor plan, surface materials, and window transmittance, may be neglected by data aggregation for developing light switch models.
- In the monitoring campaign conducted in this research, light states of the fluorescent lamps installed in each office were recorded, while the researcher's walkthroughs to the monitored offices showed that some participants were also using task lights and in some cases, participants stated their preference for non-fluorescent lamps. Therefore, the researcher acknowledges the possibility of bias in the low rate of lighting use recorded in this research.
- For simulating lighting use patterns in MATLAB, 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 occupancy-on/vacancy-off-15 control system 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 researcher acknowledges the bias in the higher lighting electricity use (i.e. a mean increase of 11%) with the simulation results compared to the expected value with this lighting control system.

This research demonstrated that a significant reduction in the lighting electricity consumption can be achieved after changing the occupancy-on/vacancy-off control system to the manual-on/vacancy-off in the monitored offices. Likewise, only two of the 26 participants expressed a preference for the former lighting control system. This research also provided recommendations on data collection timing with respect to probabilistic model reliability. The findings of this research can contribute to the building code and standard development as the observed reduction in the lighting use with the manual-on control system was significantly higher than the scheme suggested by ASHRAE Standard 90.1-2016 (2016) to credit this lighting control system. The lessons learned in this in-situ monitoring study are beneficial for the design and operation of new constructions as well.

In the broader sense, the findings of this research illustrate the importance of controls logic, and not only architectural and/or hardware-related decision-making, during building design and operation. This monitoring campaign achieved a significant reduction in the lighting use of the case study offices with the no-cost upgrade. This research also illustrates how dynamic occupant modelling approach in a simulation-based analysis process can be coupled with building controls logic to evaluate the impact of control decisions for the betterment of building design and operation.

6. Conclusions

6.1. Summary

With the aim of studying occupant-building interactions for the prediction and enhancement of building energy performance and occupants' satisfaction, simulation and experiment-based analysis were employed in this research project. A summary of the conclusions exploited from each stage of this research are outlined as follows.

6.1.1. Use of occupant models in building performance simulation

This research first evaluated the effect of the conventional and dynamic occupant modelling approaches on the energy and daylight performance of a generic office space in a simulation-based analysis. A set of performance metrics was used to compare different design solutions under these two approaches. The results of the first stage of this research showed the below main points.

- Static and stochastic cases resulted in substantially different energy predictions. Specific to the case study analyzed in this research, the maximum difference between the static and stochastic cases in the total electrical energy use was for WWR of 20%, which was about 30 percentage point higher with the stochastic cases than the static cases.
- Static and stochastic cases yielded different near-optimal design from an energy perspective. For instance, the results of the case study investigated in this research showed that WWRs of 60% and 40% generally led to the lowest lighting electricity use with the static and stochastic cases, respectively.
- Using dynamic occupant modelling approach to represent occupant-building interactions is imperative in simulation-aided design process to provide a more realistic prediction of building

energy performance and occupants' satisfaction. However, standard tools are recommended to provide representative outputs (e.g. mean values) for a batch simulation with respect to probabilistic performance predictions to better communicate with building designers and managers in code compliance processes.

6.1.2. Review of in-situ monitoring methods

Alongside establishing the initial stages of conducting the monitoring campaign, the opportunities and challenges associated with studying occupants' presence and behaviour in existing buildings rather than laboratories and virtual environments were also explored in the second phase of this research. The main recommendations made based on the critical review of various monitoring methods in the literature and the anecdotal evidence observed in the monitoring study are as follows.

- Sensor-based techniques: These techniques are the predominant ones used in previous research in creating statistically representative occupant models. However, the individual differences between occupants may be neglected using these techniques. Centralized management of data using connected sensors facilitates large sample size and long-term data collection. On the other hand, stand-alone sensors give more feasible options to researchers to locate them as well as these sensors are straightforward to work with and relatively low-cost.
- Model-based techniques: While the validity of models is the main challenge with these techniques, they are viable techniques that researchers can incorporate into measuring variables which are impractical to measure with the existing physical sensors or where installation of additional sensors in existing buildings requires intrusive actions.
- Surveys: Individual differences between occupants and the subtle cause and effect in the collected data using sensor/model-based techniques can be tracked by surveys. However, concurrent use of

sensor/model-based techniques and surveys are recommended to collect data which can also be beneficial for developing statistical occupant models appropriate for BPS tools.

6.1.3. Interpretation of occupant-building interactions

A monitoring campaign was conducted in this research in 25 perimeter offices in a building on Carleton University's campus, Ottawa, Canada. Occupants' presence and interactions with building systems and components and environmental conditions were collected using stand-alone and BAS-integrated built-in sensors, local weather station, and outdoor cameras. The data analysis of this study revealed lessons useful for the operation of the existing monitored building and design of new constructions. Specifically the following lessons with respect to occupants' presence and behaviour and energy demand of the monitored offices were extracted:

- Automatic control of lighting did not result in a reduction in the lighting use and improvement of occupants' satisfaction.
- An important impact of using operable windows on indoor environmental conditions and energy demand indicated the necessity of closing operable windows in the heating season depending on the conditions.
- Peak energy demand occurred at different times of day in different directions recommended time-based setback strategy that varies for different orientations for more efficiently operation of the monitored offices.
- Analysis of individual offices' energy loads provided valuable information on the impact of the characteristics of offices, the potential for diagnosis of any deficiencies with sensors and control systems in offices, and detection of possible occupants' interference in building systems.

6.1.4. Occupants' use of lighting controls

In the monitoring study conducted in this research, the lighting control system was adjusted after about six months of data collection from the occupancy-on/vacancy-off control system to the manual-on/vacancy-off. The impact of various lighting control systems, including automatic and manual, on the lighting electricity use was evaluated through experiment and simulation-based analysis. Probabilistic models for occupants' presence and lighting use were developed and the accuracy of the models was evaluated based on the empirical data collected in the monitored offices. These probabilistic models and a set of lighting control systems were implemented in building performance simulation to assess the lighting electricity consumption with various lighting control systems. The results indicated the following key points.

- A reduction in the lighting electricity use was achieved by a factor of seven with a manual lighting control system in comparison with the occupancy-on/vacancy-off controls.
- The ratio of lights-on to the occupied period was reduced by 62% and 90% based on the experiment and simulation results, respectively, using the manual-on/vacancy-off control system compared to the occupancy-on/vacancy-off controls.
- In exploring several fundamental occupant modelling issues, this research revealed that duration of a monitoring study influenced the reliability of the models to characterize the lighting electricity use. The starting time of year was the other influential factor on the reliability of the models in predicting the lighting use.

6.2. Research contributions

The major contributions of this research to the existing literature are outlined as below.

Use of occupant models in building performance simulation: This analysis emphasized the importance of incorporating dynamic occupant modelling approach in building simulation to consider the underlying uncertainty in the building energy and comfort performance predicted in a simulation-based analysis. This study can contribute to the code and standard development in considering occupants' impact in code compliance processes. A version of this study has been published in the special issue of the Journal of Energy and Buildings on "Advances in BEM and Sim" (Gilani et al., 2016). In addition, the findings of this study were provided for Hidi Rae Consulting Engineers Inc. through an industrial collaboration.

Review of in-situ monitoring methods: This study did a thorough review of the existing and potential future techniques of in-situ studying occupants' presence and behaviour to support developing occupant models. This critical review can assist in planning for monitoring occupants on site with respect to the challenges and opportunities researchers may confront to save their effort, time, and cost. This review study has been published in the special issue of the Journal of Building Performance Simulation on "Occupant Behaviour Fundamentals" (Gilani and O'Brien, 2016b). The researcher also co-authored a book chapter titled "In situ Approaches to Studying Occupants" in a book titled "Exploring Occupant Behaviour in Buildings" produced as a result of her collaboration with IEA EBC Annex 66.

Interpretation of occupant-building interactions: This research conducted a relatively low-cost and long-term monitoring campaign on a fairly large sample size of 25 offices. Lessons to operate the monitored building more efficiently were extracted, which can also be beneficial for building engineers and managers in designing and operating new constructions. This study has been accepted for publication in ASHRAE Transactions (Gilani et al., 2017) as well as a technical report of this research was prepared for the industrial partner, Rowan Williams Davies & Irwin Inc. In the path of investigating the feasibility of using model-based techniques in the monitoring campaign, the preliminary results on the potential for

virtual daylight sensors has been published in the eSim conference proceedings, IBPSA-Canada (Gilani and O'Brien, 2016a).

Occupants' use of lighting controls: In the monitoring campaign conducted in this research, the automatic lighting control system was adjusted to the manual-on system to reduce lighting use and improve participants' satisfaction with their offices' electrical lighting. The experiment and simulation analysis of lighting control systems showed a significant reduction in the lighting electricity consumption after the lighting control adjustment. Of the 26 participants, only two expressed a preference for the former control system. The findings of this research can also contribute to building code and standard development as the observed lighting use reduction with the manual-on control system was significantly higher than the method used to credit this control system in ASHRAE Standard 90.1 (2016). This research has been submitted for publication to the Journal of Energy and Buildings in addition to an earlier version of this study, which has been accepted for the 15th International Conference of the International Building Performance Simulation Association (Gilani and O'Brien, 2017).

6.3. Recommendations for future work

The main initial and specific questions arose in this research, which require future work, can be outlined as fundamental and applied research topics.

6.3.1. Fundamental research

The Fundamental research topics suggested to be worked on in future are as follows.

- The findings of this research indicated the great potential of considering occupants' presence and behaviour for improving buildings' energy performance while maintaining occupants' satisfaction. The novelty of this research area draws a promising future of building operations and controls that necessitates further research in this area. For instance, building controls can be

managed by a closed-loop control system, rather than an open-loop control system where input to the system is independent from its output. For a closed-loop control system, occupants' reactions to their built environments can be used as input to the control system to adjust the efficiency of the system to the occupants' preferences (i.e. output of the control system) (Gunay et al., 2015a; Gunay et al., 2017a; Gunay et al., 2017b).

- This research adopted in-situ monitoring method to develop occupant models and study occupants' influence on building energy use. Future research on developing mathematical occupant models and building energy performance analysis using other research methodologies is a required research topic. This can be performed in the same contexts (to minimize the impact of other factors) but with different research methodologies, including in-situ monitoring campaigns, laboratories, and virtual environments. The statistical models can be compared analytically and the impact of research methodologies for data collection on occupant behaviours can be quantified. The generalizability of the inferences from each methodology to other methodologies can also be assessed.
- This research showed the prediction of building energy performance and occupants' satisfaction is highly affected by occupant modelling approaches, resulting in uncertainty with a simulation-based analysis. Future research on the quantification of the degree of this uncertainty on different outputs is required. This research could be performed by altering different inputs in a simulation-based analysis. For instance, occupant models, such as occupancy, window shade use, and lighting use, can be altered one at a time to quantify the impact of each occupant model on building energy performance. In the next stage of this analysis, the effect of combined occupant models (e.g. two models at a time, three models at a time) can be evaluated to analyze the mutual interactions between various occupant behaviours. In this stage, the order of implementing various occupant models also needs to be investigated. All the aforementioned analysis can be

performed on single occupants and synthetic populations to quantify occupant-related uncertainties at different scales, such as room level, building level, and city.

- While there are considerable in-situ monitoring studies in the literature, providing well-established methods for data collection and organizing in occupant studies is a required research. For instance, the occupant behaviour researcher community are required to reach a consensus on data collection for studying occupant behaviour in-situ. Best practices in the current research area can facilitate systematic monitoring studies whereby the same procedure and format can be followed in data collection and preparation worldwide. In this way, where ethical regulations allow researchers, they can disseminate their datasets while they can also reproduce analysis on other researchers' datasets.
- A reliable prediction of lighting energy use was found to be influenced by the start date and duration of monitoring study. Further research is necessary to develop methods for determining appropriate sample size respecting the required number of occupants, rate of change in the states of building components and systems, and study duration. To this end, a large dataset with respect to the number of subjects and data collection duration is required. By multiple random sampling from such a large dataset (assuming as a target population), a representative sample size can be determined. Finding an appropriate sample size in this research area is crucial for developing statistically representative occupant models and minimizing cost and effort regarding participants' recruitment, data collection and processing, and the consequent challenges.
- Research on the potential of model-based/analytical techniques to predict variables, which are impractical to be measured with the existing physical sensors, using available datasets as well as to verify the accuracy of existing physical sensors in buildings is a novel research topic in building sector that needs further research. Developing such model-based techniques will reduce in-situ monitoring costs and obtrusive actions for measuring the variables of interest in field

studies. The benefit of model-based techniques is especially advantageous where the occupant behaviour researcher community rely on centralized building management services, such as BAS, for studying occupants. By using model-based techniques, existing logged data (e.g. occupancy) can be used to estimate other variables (e.g. plug-in appliances).

- While the findings of the current research emphasize on the improvement of building design and operation and occupants' satisfaction, the impact of better design and operation of buildings on indoor environment quality (IEQ) and consequently on occupants is a necessary future work. The financial effects of IEQ on occupants' health and productivity are required to be quantified. For instance, medical costs of improving IEQ or health issues caused by poor IEQ should be evaluated. Effect of reducing occupants' absenteeism and increasing occupants' productivity on employers' performance should also be assessed in a financial analysis.

6.3.2. Applied research

The following applied work is recommended as per the specific questions this research confronted.

- A significant deviation was observed between building energy performance predicted by the conventional assumptions and empirical-driven occupant models. Accordingly, incorporating more realistic assumptions on occupants' presence and behaviour needs to be considered in design alternative decision-making processes for the code compliance processes. For instance, averaged schedules obtained from large datasets for various building archetypes can provide better understanding of buildings' energy performance. The other approach that can be implemented in BPS tools is to incorporate threshold values, so that occupants' preferences at each timestep simulation can feed back as input to simulation, rather than a one-way simulation process without considering occupants' response to their environments.

- To accomplish the above mission, the building performance and occupant behaviour researcher community should attend to: (1) the development of a bank of representative and generalizable statistical models, averaged scheduled profiles, and threshold values supported with large datasets, for which conducting more case studies in various contexts and for different building archetypes is imperative, (2) educating and training practitioners in occupant modelling and simulation for the evaluation of buildings' energy performance and occupants' comfort, (3) informing policy makers of the importance of considering occupant-related uncertainties in code compliance processes as a requirement, and (4) development of BPS tools for incorporating occupant models simply in practice, extracting/illustrating probabilistic outputs of simulation results, and speed up simulation for running more advanced occupant models.
- The findings of this research are from a single office building that can be compared with other case studies in the literature. The finding of the current case study may not be generalizable to other cases because of the contextual factors' impact on occupants' presence and behaviour. This limitation highlights the fact that there is still necessity for more case studies in various contexts worldwide. Future sensing technologies, many of which can be borrowed from other fields (e.g. robotics and medicine) and applied to the research area of occupant behaviour, will facilitate monitoring occupant behaviours and influential factors in existing buildings. Remote data management systems, such as BAS to log and restore vast amount of data, draw a promising future for centralized building management and operation.
- The adjustment of lighting control system in the monitored perimeter offices demonstrated a profound reduction in lighting energy consumption using the manual-on control system. This reduction was significantly higher than the value suggested by ASHRAE Standard 90.1-2016 (2016) for light power density. The potential for daylight harvesting in various designed spaces needs to be considered as the other influential factor in addition to space type in determining the

required light power density in building standards. For instances, the impact of how well building spaces with different window sizes and space characteristics on different orientations are designed to benefit from daylight on the lighting electricity consumption with the manual-on control system can be analyzed critically in a simulation-aided design process. This research topic will facilitate quantification of the potential reduction factor for lighting power density (*LPD)* with respect to a building space design in addition to a building space type suggested by ASHRAE Standard 90.1-2016 (2016).

- Aggregate data on light switches from the monitored offices were used to develop occupant models. The behavioural diversity between individual occupants in lighting use needs to be investigated in a longer monitoring period. This necessitates long-term data collection, where the number of offices and the rate of changes in light states in each monitored office should be sufficient to develop occupant models for each individual office and investigate the discrepancies between occupants' preferences.
- A time-based setback strategy based on offices' orientations was suggested in this research, as the peak energy load occurred at different times of day in the monitored offices on different orientations. To investigate this suggestion in-depth, the control system should be tested by implementing it inside building spaces' controllers to evaluate its impact on building energy use and occupants' satisfaction.

Appendix A

Carleton UNIVERSITY
Canada's Capital University

CUREB clearance #: 16-021

Consent Form – Data Collection

Title: Monitoring occupancy and indoor environmental conditions in office spaces in [redacted] Building at Carleton University
Funding Source: General research account and Research Achievement Award (Carleton)
Date of ethics clearance: 01/23/2016
Ethics Clearance for the Collection of Data Expires: 08/31/2016

I _____, choose to participate in a study on "Monitoring occupancy and indoor environmental conditions in office spaces in [redacted] Building at Carleton University". This study aims to measure indoor environmental conditions and log occupancy to better understand how occupants interact with building controls and systems (e.g., light switches and thermostats). The formal research objective is to develop statistically significant mathematical models that describe how occupants adapt to environmental stimuli. The findings of this study can be used to provide a more comfortable indoor environment for the occupants and to reduce energy consumption. **The researcher for this study is Sara Gilani, PhD candidate, at the Civil and Environmental Engineering Department, Carleton University.**
She is working under the supervision of **Professor Liam (William) O'Brien** at the Civil and Environmental Engineering Department, Carleton University.

With your consent, data logger will be installed in your office to log light states. Data logger is a small (about 1 cm by 2 cm by 3 cm) device that measures and logs light switch events and will be attached to the light fixture. The existing wall thermostat in your office will be used to log occupancy, temperature, relative humidity, and carbon dioxide concentration via the Building Automation System (BAS). With your consent, periodic visits (approximately every 1-2 months) to your office will be made to obtain data and confirm proper logging.

With your consent, this study will take low-resolution photos of your office, when you are not in your office, to record the furniture layout and location of wall thermostat. Identifying information (e.g., name plate) will be excluded from the photos.

This research project is deemed to be minimal risk. This research is to passively monitor occupancy in offices without interaction with you. Your identity and information will not be published. The collected data will be analyzed by coding and de-identifying the data collected in offices. The studied offices in this research project will be coded based on their location in [redacted] Building, i.e. east, west, south direction and nominal occupant capacity (e.g. 1, 2, 3, or 4).

You have the right to end your participation in the study at any time, for any reason, up until 15 Jan 2017. You can withdraw by phoning or emailing the researcher or the research supervisor. If you withdraw from the study, all information collected in your office will be immediately destroyed.

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Please retain a copy of this document for your records.

CUREB clearance #: 16-021

All collected data will be encrypted. During collecting data, dataset will be stored on a password-protected desktop computer and backup hard drive in the researcher's designated office space at Carleton.

After project completion, the coded data will be stored on a password-protected desktop computer and backup hard drive in a locked space located in the researcher's designated office space at Carleton.

If you would like to know about the findings of the finished research project, you are invited to contact the researcher to request for it, which will be provided to you.

PERIODIC VISITS

☐ I agree to periodic visits (every 1-2 months) during unoccupied times.

☐ I agree to periodic visits (every 1-2 months) but only during occupied times.

TAKING PHOTOS FROM OFFICE

☐ I agree

☐ I disagree

The ethics protocol for this project was reviewed by the Carleton University Research Ethics Board-B (protocol # 16-021), which provided clearance to carry out the research. Should you have questions or concerns related to your involvement in this research, please contact:

CUREB contact information:
Dr. Shelley Brown, Chair
Carleton University Research Ethics Board-B
613-520-2600 ext. 1505
Shelley.Brown@carleton.ca
You may also contact the Research Compliance Office directly at ethics@carleton.ca

Researcher contact information:
Sara Gilani, PhD candidate
Civil and Environmental Engineering
Carleton University
Tel: (613) [redacted]
Email: saragilani@cmail.carleton.ca

Supervisor contact information:
Liam (William) O'Brien, Professor
Civil and Environmental Engineering
Carleton University
Tel: (613) 520-2600 ext. 8037
Email: liam.obrien@carleton.ca

_____ _____
Signature of participant Date

_____ _____
Signature of researcher Date

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