Occupancy Driven Uncertainty in Electric Lighting Use: Modeling a Case Study

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ABSTRACT

Uncertainty in building occupancy can lead to significant variations in electric lighting use. In its first six months of operation, the National Renewable Energy Laboratory's Research Support Facility (RSF) exceeded its modeled electric lighting energy budget because of unanticipated occupancy patterns in the evenings. This experience highlights the potential usefulness of modeling occupancy uncertainty and its impact on loads such as lighting energy use, while at the same time pointing out the difficulty of appropriately bracketing and quantifying all reasonable scenarios. In this paper we build on the RSF example to develop models for uncertainty in electric lighting use caused by uncertainty in building occupancy and interactions with lighting controls, especially in office buildings with open work space. The models so developed may be used by engineers and architects to understand how lighting control strategies affect energy usage under occupancy uncertainty. We also use our models to reflect on the RSF modeling process, and subsequent experience with the physical building and lighting use mitigation strategies.

Introduction

Building energy simulations are typically relied upon to provide a design-point calculation of the building energy consumption, but rarely are the simulations utilized to assess real-world performance variation. Most building operators recognize that there is some level of uncertainty in building use, operations, and weather conditions, often leading to a significant difference in predicted and actual energy consumption (Clevenger & Haymaker 2006). Additional uncertainties and inaccuracies arise from the simplifications necessary to model complex building geometries, equipment, and controls systems in an energy simulation program (Wit & Augenbroe 2002). These two types of uncertainty lead to challenges in the design process, particularly in the case of design optimization and decision making (Eisenhower et al. 2011; Hopfe 2009; Jacob et al. 2010; C. Struck & P. Kotek 2009; Christian Struck et al. 2007). Much of the current literature uses uncertainty as a means to assess the sensitivity of the building's energy performance to variation in a large number of variables (Eisenhower et al. 2011; Wit & Augenbroe 2002), or to a limited subset of variables, such as construction materials (C Struck & J Hensen 2006), and schedules (Clevenger & Haymaker 2006; Zhao et al. 2011). Occupant behavior, which in energy simulations is modeled using schedules, presents a particularly interesting challenge since occupants not only impact energy use directly, but also interact with lighting and other control systems. Recent experience at the National Renewable Energy Laboratory's Research Support Facility (RSF) highlights the importance and difficulty of capturing such model uncertainties. Capturing and appropriately modeling uncertainty within a building will allow for better prediction of actual energy usage as well as allowing designers to incorporate systems to help mitigate uncertainty in energy usage.

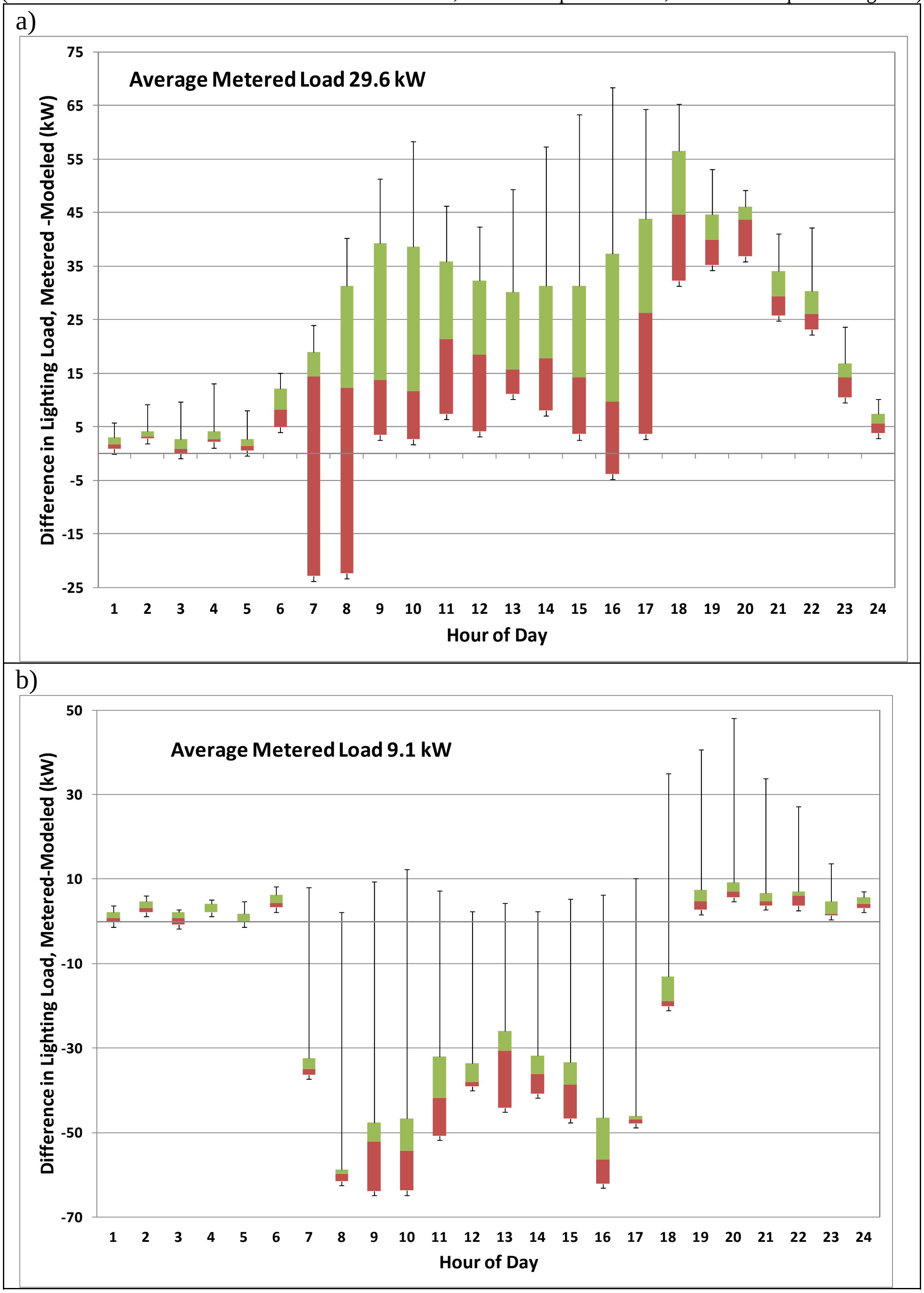
The National Renewable Energy Laboratory is home to the Research Support Facility (RSF), which began operating in mid 2010. The RSF was designed with an extremely demanding energy target (35 kBtu/sf/yr normalized including a data center, approximately half of typical office buildings in the Denver metro area (Guglielmetti 2011)). According to the 2003 Commercial Building Energy Consumption Survey (CBECS), lighting directly accounts for 25% of an office building's site energy use, and 39% of its electricity use, on average (EIA 2003). Thus, detailed attention was paid to the design of the RSF's lighting systems, particularly in the open offices and corridors, where very high levels of daylighting are used to minimize this energy end use. Additionally, an aggressive electric lighting control sequence was implemented to try to limit use outside typical work hours by automatically sweeping off a majority of lights (with the exception of a single light over entrances, exits, and stairwells).

Within the first few months of operation it was observed that the lighting energy use was significantly higher than expected, primarily on weekdays outside of prime working hours (8am – 5pm). Part of this was attributed to cleaning and maintenance crews working from 6-10pm, turning the lights on, but not switching them off so that they stayed on until the next sweep at 8 or 10pm. This pattern is evident in Figure 1, which shows the deviation between the expected and actual lighting use broken down into day types (weekday and weekend/holiday), hour and month. The median values in Figure 1a demonstrate that the predicted weekday lighting use was accurate from hours 1-16 and 23-24, but in hours 17-22 a significant unexpected shift was observed. The large variances in hours 7-17, and to some extent, the additional energy use seen in those hours (a moderate positive shift of the median value) is attributable to variations in daylight availability, which are particularly pronounced in January. In contrast, there is little variance in electric lighting use in hours 17-22, but rather a more deterministic shift associated with the unanticipated presence and behavior of occupants during these hours. As a fraction of the averaged metered load for January the variance can be significant particularly during hours 7-17 while the variance outside of these hours is small in relation to the average load. The amount of variance in relation to the average is even larger for the weekends but it is a much smaller average load.

Overall, the data shown in Figure 1 shows that the lighting energy use of open-plan, daylit office buildings varies day-to-day and hour-to-hour, in response to both weather and occupant interactions. It is also easy for even a highly engaged design team to miss entire occupant populations and their likely behaviors. This case study highlights the need for a better understanding of the (stochastic) relationships between weather, occupants, controls, and electric lighting use; and also the need to somehow capture possible occupancy patterns outside of the primary use of the space. Understanding these relationships further will help both in the design phase and the actual building use phase. By developing better understanding, including stochastic relationships, building designers will be able to incorporate uncertainty into the design phase and create designs which help mitigate future energy use uncertainty. Additionally the understanding will be useful when a building is in operation for the ability to test out new lighting control strategies to reduce unwanted variation not initially captured or controlled after the design phase.

Figure 1. Difference between Metered Load and Modeled Load, a) January 2011 Weekdays, b) January 2011 Weekends/Holidays.

(The whiskers show the minimum and maximum values, the second quartile is red, and the third quartile is green.)



The need for modeling occupant behavior is well recognized in the literature (Bourgeois et al. 2005; Wang et al. 2005; Clevenger & Haymaker 2006), and many models have been proposed. Furthermore, the potential impact on lighting use has also been investigated (Clevenger & Haymaker 2006; Bourgeois et al. 2005). Only two of these works have investigated the uncertainty with occupant behavior (Zhao et al. 2011; Clevenger & Haymaker 2006); One of these is primarily focused on the development of advanced models to incorporate uncertainty into the occupant behavior while the other takes a much simpler high/medium/low approach to understand the sensitivity of total energy use. Occupant behavior has been statistically investigated by a variety of authors under very specific conditions not representative of the open office environment. Wang et. al looked into developing a statistical occupancy model for a single office and determined that vacancy, not occupancy, could best be modeled with an exponential distribution (Wang et al. 2005). Others have taken multiple sets of commercial building office data and tried to link occupancy and lighting usage statistically but are limited to manual controls (Rubinstein et al. 2003; Mahdavi & Pröglhöf 2009) but have shown that occupancy and lighting may be correlated further through the total illuminance available upon arrival (Mahdavi & Pröglhöf 2009). While these studies have shown that occupancy and lighting can be potentially modeled with statistical models they have all been limited to manual controls and primarily private offices.

In this paper, we model, measure, and study the interaction of occupant behavior and electric lighting energy use in open office spaces typical of the RSF. Detailed occupancy and lighting use data was collected from several RSF spaces, post the interventions (training of the custodial staff operating during the evening hours) taken to address the initial measured to model deviations seen in the evening hours. The next section describes the spaces in which the data were collected. We then go on to analyze the data in an initial attempt to gain understanding into the possibility of developing probabilistic models. Additionally we note the challenges and limitations of the current data set and the data needs to develop more detailed models. While uncertainty in daylight availability should ultimately be folded into these models as well, that is outside the scope of this paper, although we hope to take up that question as future work.

Modeling Occupancy Effects on Electric Lighting Use

In this section we focus on describing the space both monitored and modeled. We first present the space and describe the lighting design and operation, followed by a description of the data collection that was performed. Finally we statistically investigate two primary spaces to try to further understand the interaction of occupancy with lighting use and develop statistical models for quantifying the occupancy effects on electric lighting use.

RSF Space Descriptions

We investigated two spaces: a large open office and a kitchen serving the open office (Figure 2). The RSF is divided into east and west wings. All the data collected in this study comes from the east wing. During the design-build contract period, the open office space lighting was modeled, designed, and commissioned for aggressive electric lighting energy savings through the use of coordinated daylighting, ambient and task electric lighting, and ambient lighting control schemes. The integrated design of the building relies heavily on space programming and the details of the interior finish. All office surfaces are light in color, and most occupants are located in cubicle workstations with low walls. Semi-private offices are located on the north wall to minimize their impact on the daylight saturation of the rest of the space. Along with daylight redirection technologies, the overall design gives very high daylight saturation that conforms to the LEED IEQc8.1 daylighting requirements. The open office was iteratively designed and modeled to maximize daylight saturation. The final daylighting design, control equipment, and sequences were modeled in detail to predict actual, required ambient lighting power density and usage schedules for different space types.

The lighting controls ensure that the space lives up to its potential in terms of electric lighting energy use savings. The open office wings are sixty feet wide, and are divided in two electric lighting switching zones. The perimeter zones use a bi-level switching control that turn the lights on, half-on, or off to daylight availability. These systems account for one third of the installed lighting power density. In the core of the open office space, a continuous dimming system takes advantage of available daylight. These lights are never fully turned off by the dimming controls, but only in response to manual switching. The specific control design is for lights to be turned on manually by occupants if needed as they enter the space in the morning, guided by always-on night lights near entrances and light switches. As daylighting increases throughout the day, electric lighting in all offices and corridors will dim or switch off in response. Manual on/off capability by occupants is always enabled. At 6:30 pm, a timed event cause all open office and corridor lighting to blink, warning occupants that the lights will turn off in five minutes. Occupants can override the sweeps, which occur every two hours throughout the night, that is, at 6:30pm, 8:30pm, etc. All enclosed spaces such as kitchens and closed offices are controlled based on local occupancy control. The kitchens are true occupancy sensors in that if the light switch is in the on position then the lights will turn on when occupancy is detected. The closed offices use vacancy sensors that must be manually turned on at each arrival.

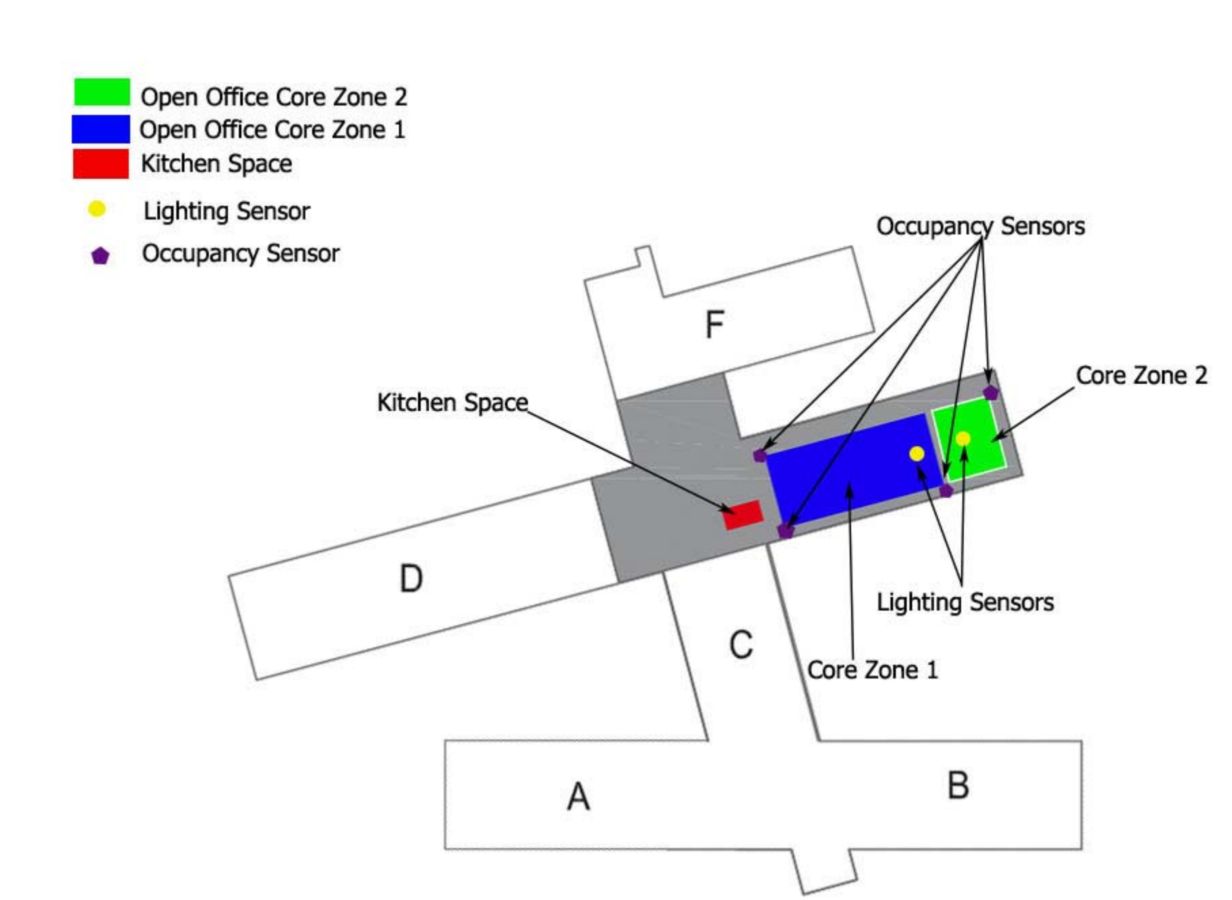
The kitchen lighting design accounted for daylight availability and occupancy-triggered controls, but was not modeled aggressively from a daylighting point of view because of both location and size. There are no daylighting controls, and occupancy sensors were modeled with a simple 10% LPD reduction as recommended by ASHRAE 90.1. The kitchen is comprised of undercabinet and overhead lighting that is controlled via line voltage, manual switching and auto-off overrides triggered by the switch being on but the space vacant. The occupancy sensor turns lights on automatically only if the manual switch is in the on position.

RSF Occupancy and Lighting Data Collection

A challenge in creating occupancy-lighting models is that underlying any data set is a lighting control scheme that influences occupant interaction with a lighting system. This underlying occupancy-lighting system interaction limits the applicability of a model, built upon building specific real-world data, that can be used for effective prediction of a new lighting control scheme. Although this underlying challenge is significant, we can still use data to drive the development of the models while keeping in mind how the data factors into the model development. Due to the large space size of the open office space it is not possible to achieve full coverage occupancy logging. Rather, occupancy loggers are used to track whether people are entering or exiting the space. Although this limits the true knowledge of occupancy it is still of relevance for determining the interactions of people with the lighting system.

The kitchen space is small enough to have full coverage with the occupancy loggers allowing for direct capture of lighting use and occupancy. The monitoring of lighting usage in this space provides interesting insight into the impact of daylighting on occupant behavior. As previously mentioned the kitchen spaces were not designed with aggressive daylighting but do receive some low level daylighting (~5 fc) that may impact the observations seen with logged data. The location of the occupancy and lighting sensors are highlighted in Figure 2 for the open office space type considered. The occupancy and lighting sensors are not displayed within the kitchen space due to the relatively small size. All spaces were monitored from January 7 through February 12, 2012 using WattStopper IT-200 occupancy and light loggers.

Figure 2. Approximate Location of Lighting and Occupancy Sensors in Open Office Space and Location of Spaces within RSF Building

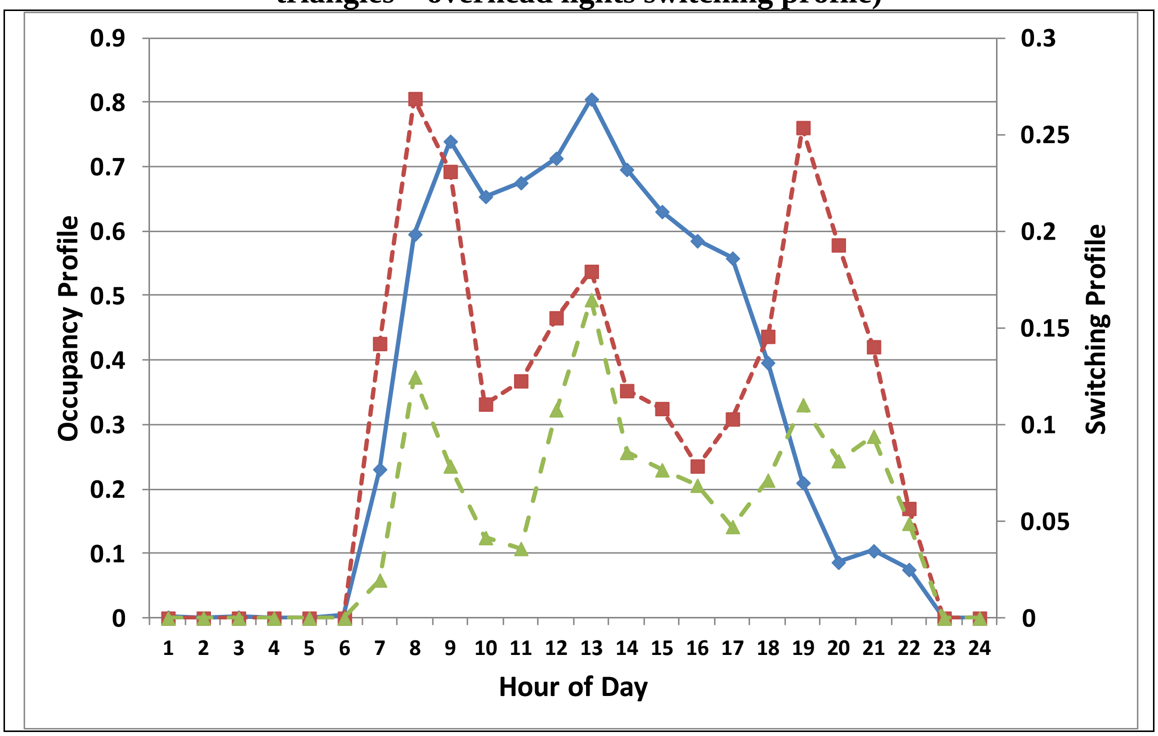


RSF Occupancy and Lighting Data Analysis

In this section the occupancy and lighting use variations are investigated as a function of day type and time of day. Specific concern is paid to what type of statistical model will best fit the data and how well occupant level variation can be used to explain lighting use variance.

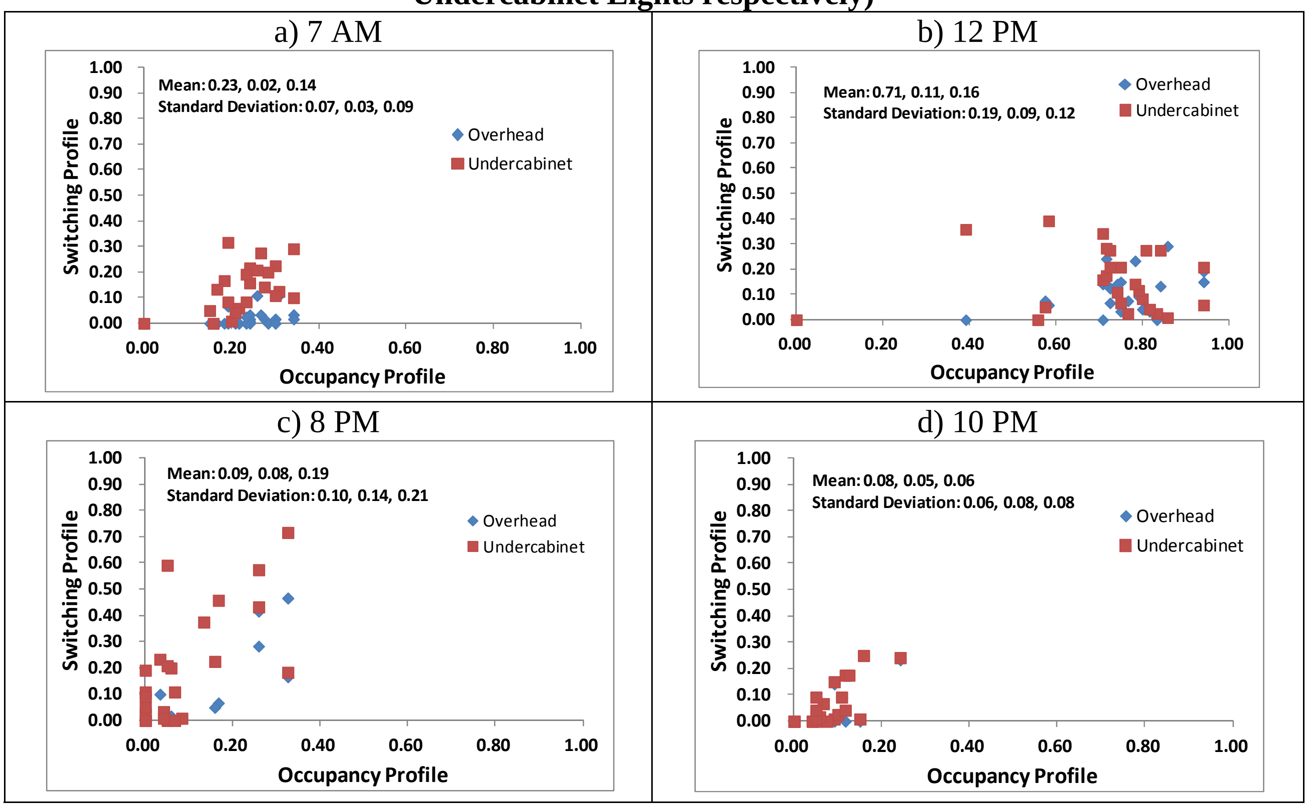
Kitchen space analysis. The first step was a simple breakdown of the variations observed for weekdays and weekend/holidays. The data are grouped by hour and utilize a method where an occupancy of 1 for a given hour means the space was fully occupied for the hour, if 0.5 then it was occupied 50% of the time which may be exaggerated due to the timeout settings (five minutes) of the loggers. The same structure applies to lighting for the kitchen space. While observing the kitchen space on weekend days only limited occupancy was observed with zero lighting usage. Figure 3 displays the average weekday occupancy and lighting usage for the kitchen space. The data shows that from 11PM-6AM the occupancy is zero and lighting usage is zero or very low. When the typical work day starts both occupancy and lighting increase in the morning, decrease until a lunchtime peak, then in the afternoon it is observed that occupancy is generally very small but lighting usage is seen to spike at 7PM, most likely associated with custodial staff presence. The results also indicate a change in behavior with the presence of daylighting. As noted the kitchen spaces do have a small amount of dayligthing allowing users to most likely perform quick tasks (opening refrigerator, throwing out trash, etc.) without turning on the lights but more lengthy tasks (preparing coffee and meals) will likely require turning on some form of lighting. Because of this we investigated specific hours to look at a more detailed level of occupancy lighting interactions at key hours.

Figure 3. Average Hourly Weekday Occupancy and Lighting Usage for the Kitchen Spaces (solid line – occupancy, dashed squares– undercabinet lights switching profile, dashed triangles – overhead lights switching profile)



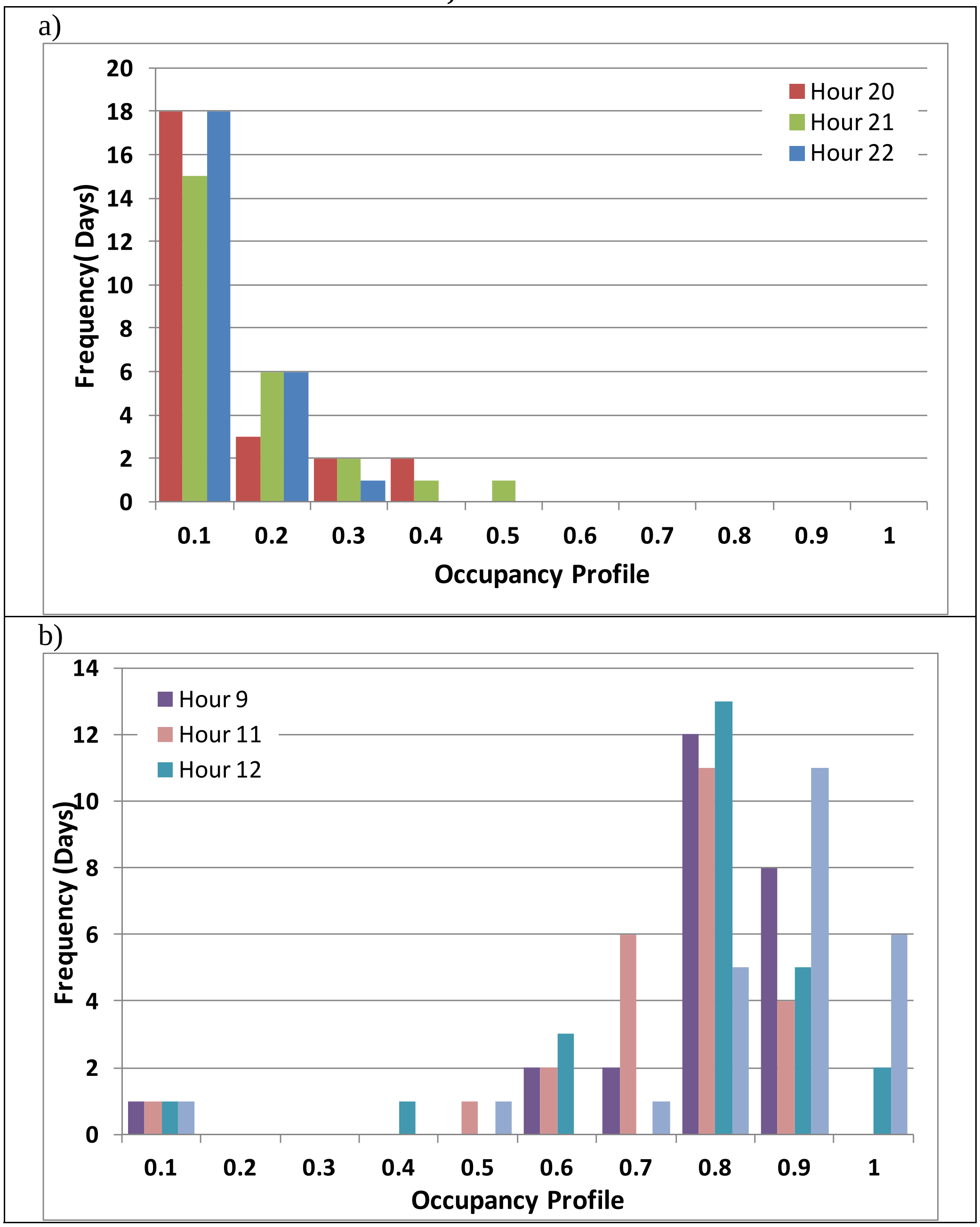
Further investigation into the data used in figure 3 reveals additional interesting conclusions about occupancy interactions with lighting. For key selected hours the occupancy profile for each weekday is plotted against the switching profile on weekdays for both the overhead (two-thirds of the total kitchen fixture light output) and undercabinet lights (one-third of the total light output). The switching profile represents the fraction of the time within a given hour that the lights are on to full power output (i.e. if the switching profile is point 0.5 the lights were on 50% of the time for that hour, if at full power, or were on the full time at 50% power). Figure 4a and 4d exhibit what initially appears to be a relatively strong correlation of low occupancy to low lighting but upon investigating other hours this breaks down. Figure 4b and 4c are the hours of 12PM and 8PM respectively both have similar mean lighting levels but significantly different mean occupancy profiles. It should be noted that for any given hourly or total weekday set of occupancy lighting data, no simple linear correlation could be found with an R^2 value greater than 0.5. This result significantly differs than that reported in (Mahdavi & Pröglhöf 2009) where a much more significant correlation could be found. Our initial conclusion is that two underlying effects are occurring that are not captured here: daylighting and task. With respect to daylighting it can be seen in Figure 3 with the significant decreases in lighting without significant decreases in occupancy. The task effect can be seen at the prime lunch hours 12 and 1 PM where the lighting also peaks while the daylighting is also at a maximum indicating that even though there is some daylighting more complex tasks in the kitchen like preparing lunch leads to more lighting usage. This result is similar to what was previously reported where a strong correlation was seen between illuminance level and relative frequency of switching on lights (Mahdavi & Pröglhöf 2009).

Figure 4. Relationship of Occupancy to Lighting Switching Profile for Hours: a) 7AM, b) 12PM, c) 8PM, d) 10PM (Mean And Standard Deviations for Occupancy, Overhead, and Undercabinet Lights respectively)



While the results shown above demonstrate that more complex interactions may be needed further study was taken to investigate how a joint occupancy lighting model, a probabilistic model that includes uncertainty in occupancy that drives the uncertainty in lighting usage, may be developed. The first step was to assess the probabilistic distribution of both occupancy and lighting. Selected hours are plotted in figure 5 for the occupancy distributions which display a strong dependence on time of day. Such histograms show that occupancy profile may best be represented by a beta distribution where the two shape parameters would be time dependent.

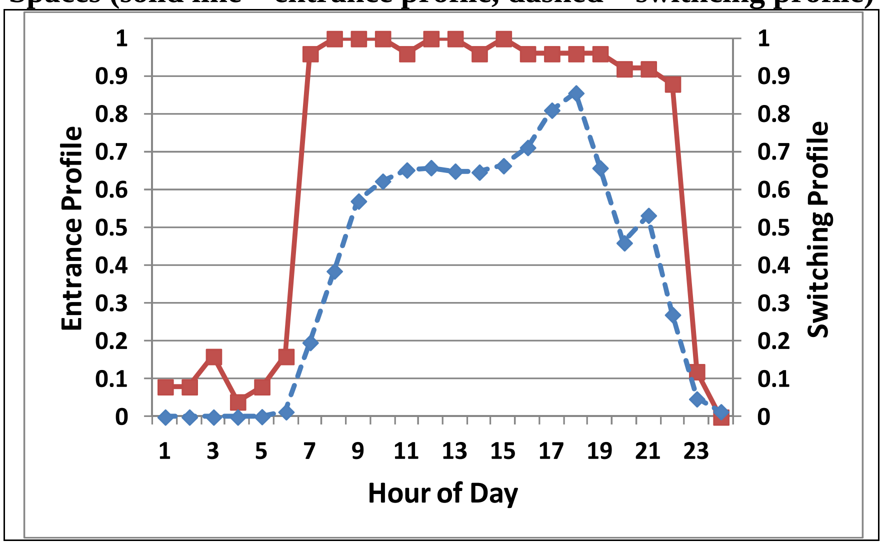
Figure 5. Kitchen Weekday Occupancy Histograms: a) Hours 20, 21, and 22, b) Hours 9, 11, 12 & 13



Similarly we investigated the lighting profiles and it was revealed that all followed an exponential type distribution for the kitchen space. We stopped short of developing the distributions proposed due to the need for further investigation of additional effects.

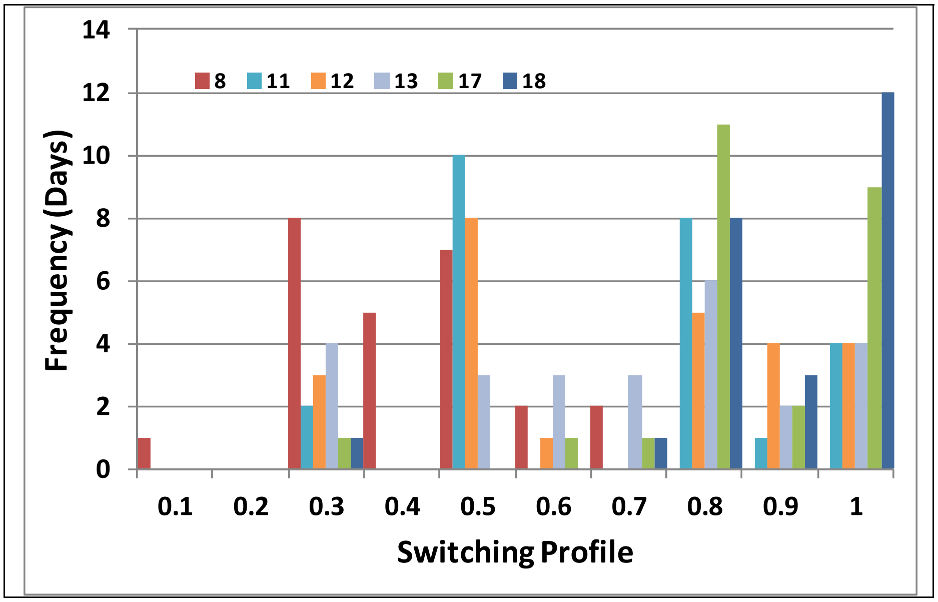
Open office space analysis. Similar to the kitchen space we investigate the monitored lighting usage within the open office space. As noted the occupancy sensors cannot provide full occupancy coverage but rather provide an indication of someone entering the space, deemed the entrance profile. Again it should be mentioned that the open office space type in the RSF was designed to achieve high levels of daylighting throughout the space. Figure 6 presents the weekday variation in switching profile and entrance profile for the open office space. From Figure 6 the impact of daylighting can mildly be observed due to the less than 100% switching profile during near maximum peak occupancy. It also becomes clear that the late afternoon, early evening hours have significant lighting use potentially reflecting occupant behavior differences between groups who arrive early versus stay late at work, although this could also be linked to daylighting and highlights the need for additional monitoring of daylighting illuminance levels. As mentioned previously this is also compounded with cleaning and maintenance crews working primarily in the evening hours.

Figure 6. Average Hourly Weekday Entrance and Switching Profiles for the Open Office Spaces (solid line – entrance profile, dashed – swithcing profile)



In addition to observing the hourly trends a similar investigation into the frequency distributions of the switching profiles to that of the kitchens was performed. The impact of daylighting is strongly observed in Figure 7 by observing the frequency distributions associated with various times of the day. In the early hours the switching profile is typically low while during the middle of the day (peak daylighting) the switching profile follows almost a unform distribution, with the late evening hours having high levels of switching profiles. Figure 7 reveals a novel progression that seems to be previously unrecognized in the literature of a highly time and occupant dependent statistical distribution that changes distribution type depending on the level of daylighting but also on the occupant. The first effect, daylighting, is linked to the time of day where it can be observed that switching profiles frequency distributions vary as a function of the time of day. Particularly of interest are the potentially uniform distributions during hours of peak daylight. The second effect, the occupant, which is just primarily qualitative at this point is based upon the assumption that office workers working later into the evening may have different lighting desires than those arriving early in the morning. This effect is certainly intertwined with the first effect and further justifies the need for further study. Based upon these results further investigations are warranted to also try to track illuminance levels in the space as well as come up with a way to get a more realistic grasp on the actual occupancy.

Figure 7. Variation in Open Office Switching Profile Frequency Distribution as a Function of Hour of Day



Conclusions

Through the detailed data collection and statistical modeling performed within it was shown that using occupancy as the sole variable for describing lighting use variations was not adequate. In particular the kitchen space where a small amount of daylighting is available lighting use did not correlate with occupancy or with hours of maximum daylighting indicating that additional factors are important. One potential factor is the task of the occupant in conjunction with the available daylighting leads to different lighting use scenarios. For the open office space type daylighting seems to be a much stronger factor in affecting the interaction of occupants with a lighting system. Of particular interest is the changing frequency distribution of the switching profiles which ranges from exponential to normal to uniform depending on the time of day and daylighting. This dynamic suggests that further studies are needed for both space types to get a full understanding how occupant uncertainty leads to lighting uncertainty particularly in the presence of daylighting and spaces where occupants perform a variety of different tasks.

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