Energy and Buildings 67 (2013) 587–595

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Revealing occupancy patterns in an office building through the use of occupancy sensor data

Carlos Duarte [a,*], Kevin Van Den Wymelenberg [a], Craig Rieger [b]

[a] University of Idaho, College of Arts & Architecture, Integrated Design Lab, 306 S. 6th St., Boise, ID 83702, United States
[b] Instrumentation, Controls and Intelligent Systems, Idaho National Laboratory, PO Box 1625, Idaho Falls, ID 83415, United States

ARTICLE INFO

Article history:
Received 22 February 2013
Received in revised form 13 August 2013
Accepted 27 August 2013

Keywords:
Occupancy patterns
Office building
Energy simulation
Data mining

ABSTRACT

Energy simulation programs like DOE-2 and EnergyPlus are tools that have been proven to aid with energy calculations to predict energy use in buildings. Some inputs to energy simulation models are relatively easy to find, including building size, orientation, construction materials, and HVAC system size and type. Others vary with time (e.g. weather and occupancy) and some can be a challenge to estimate in order to create an accurate simulation. In this paper, the analysis of occupancy sensor data for a large commercial, multi-tenant office building is presented. It details occupancy diversity factors for private offices and summarizes the same for open offices, hallways, conference rooms, break rooms, and restrooms in order to better inform energy simulation parameters. Long-term data were collected allowing results to be presented to show variations of occupancy diversity factors in private offices for time of day, day of the week, holidays, and month of the year. The diversity factors presented differ as much as 46% from those currently published in ASHRAE 90.1 2004 energy cost method guidelines, a document referenced by energy modelers regarding occupancy diversity factors for simulations. This may result in misleading simulation results and may introduce inefficiencies in the final equipment and systems design.

1. Introduction

1.1. Background

Energy simulation is an effective tool that helps building owners estimate and evaluate energy consumption for their buildings prior to construction or a major renovation. Energy simulation software can produce hourly energy consumption data by end use (lighting, heating, cooling, plug loads, etc.) for an entire year. In order to estimate performance of an actual building, models require inputs such as building size, shape, orientation, construction materials, heating, ventilation, and air-conditioning (HVAC) system size and type, interior and exterior lighting, and other physical parameters [1]. These physical inputs are relatively easy to find and can often be extracted from architectural and engineering plans. On the other hand, there are inputs that vary with time such as plug loads, lighting, blind position, ventilation rates, and heating and cooling loads [2]. Many of these inputs vary with time because they are occupancy related, others are weather dependent, and some are influenced by both. For example, lighting and plug loads, and in some applications fresh air requirements, greatly depend on the level of occupancy within a building [3]. That is, people usually operate electric lights, computers, and other common office devices when in a space, and this equipment is often turned off or in sleep mode when the space is not occupied. Therefore, building occupancy is considered an important basic factor in energy simulations [4]. Furthermore, HVAC equipment utilization is affected by occupant heat load, and in some cases by occupant-driven carbon dioxide (CO_2) levels, as well as the component heat gains of lighting and plug loads. Of course, weather also affects the level of operation of HVAC equipment.

The definition of the number of people that occupy a particular space and for what duration is difficult to characterize because human behavior is considered stochastic in nature [4–8]. Occupants do not arrive and leave at the same time every day. Occupants' locations within the building varies throughout the day and this distribution can be valuable information when evaluating demand control strategies [9–12]. For a constructed and occupied building, the energy modeler can obtain estimated occupancy schedules (business hours) from tenants and make adjustments accordingly in the energy simulation of a major energy renovation, or retrofit. However, even in this case, building occupancy schedules are based upon generalized assumptions and depend on the experience of the modeler to obtain accurate simulation results. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard 90.1-2007 provide guidance for the minimal requirements of energy-efficient new building design. This

* Corresponding author. Tel.: +1 208 401 0646/+1 208 599 4525.
E-mail addresses: duar3288@vandals.uidaho.edu (C. Duarte), kevinv@uidaho.edu (K. Van Den Wymelenberg), craig.rieger@inl.gov (C. Rieger).

0378-7788/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.enbuild.2013.08.062

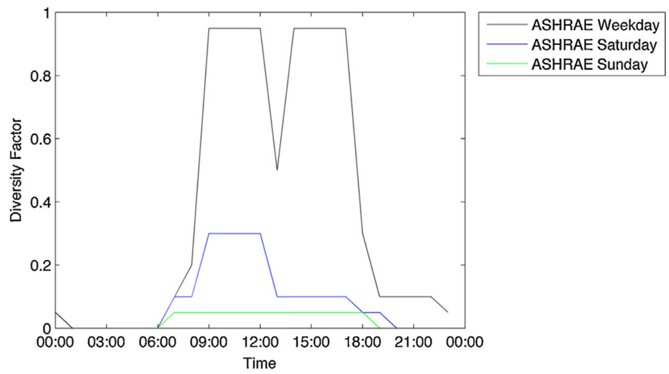

Fig. 1. ASHRAE 90.1-2004 recommended occupancy diversity factor by day type.

standard leaves the determination of occupancy schedules up to the modeler and approval up to the rating authority [13]. Again the modelers' experience will greatly influence the accuracy of simulation results. Modelers often refer back to ASHRAE 90.1-2004 which includes standardized occupancy diversity factors in tables for different building types and zones by hour of day [14]. Fig. 1 shows the ASHRAE 90.1 2004 recommended diversity factor for use with an "office occupancy" when actual schedules are not known. The published office diversity factor does not differentiate for private offices or open floor plan offices. It is important to note that most of these schedules were last updated in ASHRAE standard 90.1-1989 which included a few addendums and added a 5% factor for emergency lighting during all unoccupied hours [13]. The graph shows the factor for weekday hours reaches a value close to 100%, with an approximately 50% drop during the noon hour.

In the case of buildings that are still in the design phase, energy simulation tools aid with the selection of design parameters that are the most effective and efficient for the building like building shape design, HVAC system configuration, air handling unit (AHU) design, cooling/heating source plant design, and transmission and distribution systems [15]. The simulation tools can be critical for design analysis and decision making when pursuing extremely efficient building designs and net zero-energy buildings [16]. Therefore, accurate occupancy schedules for the zones are important in order to choose the right system types and sizes, building configurations, and control strategies for the designed building. That is why there has been an increase in research of occupancy levels in buildings in recent years. Researchers recognized that human interactions with their built environment greatly impact energy consumption in a building [17–20]. Energy modelers account for the variability in occupancy throughout the day and other simulation inputs that vary with time using diversity factors or profiles.

1.2. Occupancy diversity factors

Diversity factors are hourly fractions for a 24-h day. A profile for each day of the week can be created and combined to make up a representative week of general occupancy or specific equipment operation profiles in a building. The diversity factor for each workweek, generally Monday through Friday, are often treated identically with weekend days having a different profile. Alternatively, each day of the week can be differentiated in order to represent intricacies in occupancy or equipment operation profiles in an office building. In the same way each zone type will often have different profiles in order to represent the intended use of the space with regards to energy factors. The profiles have a range from zero to one where zero represents no usage of the equipment or no people in the zone and one represents peak equipment usage or the maximum design level of people in the building or zone [21]. In the case of HVAC equipment, the occupancy diversity factor is used to multiply the design cooling/heating load in an energy simulation because occupancy will not always be at the maximum design level and it is a way to account for the variable heat gains throughout the day. Diversity factors are lower during hours when people are not present and ramp to a maximum value during hours when people are most present or in the case of some types of HVAC equipment, when weather is at or beyond an extreme design condition.

Occupancy diversity factors have not been studied as extensively as lighting [22–25] and plug loads [26–31] diversity factors. Some reasons for fewer studies of occupancy is limitations accessing existing occupancy datasets and challenges interpreting the data. Due to the random nature of individuals' behavior and challenges accessing accurate data, current studies include the creation of deterministic schedules where a standard workday profile is the same for the whole workweek and both weekend days have the same profile. Depending on the available data, this method assumes no change in occupancy schedules throughout the year. These are referred to as *deterministic* models. In more complex and sophisticated *stochastic* occupancy models, schedules for one week are not the same as the next [4–8]. Stochastic models use various probabilistic methods like non-homogenous Poisson processes, inhomogeneous and homogeneous Markov chains to create the dynamic schedules. The developers of these models acknowledge a few deficiencies, e.g. inability to simulate long periods of absence accurately [5] or the fact that that occupancy levels are decoupled from time of day [6]. The following sections will describe selected deterministic and stochastic occupancy models.

1.2.1. Deterministic diversity factors

In 2010, Davis and Nutter reported on building occupancy data through the use of building security cameras, doorway electronic counting sensors, semester classroom scheduling data, and manual tabulation [1]. The eight university buildings surveyed include classroom, office, commons, laboratory, and service areas but did not calculate the diversity factor per space type. Instead they characterized the whole building into administrative, library, physical education, architecture, research, or classroom building types. They calculated the total number of people inside each building every hour and divided it by the maximum occupancy capacity for the respective building to obtain occupancy profiles for each day. In each building, the occupancy profiles were averaged together if the profiles were generally the same for the different days. The administration building will be provided as an example since it most closely relates to the study described in this paper. For the administration building, Monday, Thursday, and Friday were averaged together because there was relatively little variance in the occupancy factors for each of these days at a particular hour. Saturday and Sunday were also averaged together. For each workday, occupancy spanned from 6:00 am to 6:00 pm with a maximum of about 0.7, or 70% of the maximum occupancy, while the weekend figure peaked at about 0.1.

A study done by Mahdavi did not necessarily focused on the occupancy in a building but rather on the interactions occupants had with their built environment. The researcher describes the control-oriented occupant behavior in private offices for two buildings [17]. He installed various equipment to monitor occupancy, temperatures, relative humidity, illuminance, air velocity, global irradiance, status of electrical fixtures, and position of shades. His results show that occupants' interaction with their built environment depended on both indoor and outdoor conditions. With regards to occupancy, Mahdavi had occupancy sensors installed for 42 private offices, 13 scientific staff offices and 29 typical commercial offices, logging at 5-min intervals. The occupancy data shows an 8:00 am 8:00 pm work schedule with a maximum of about 0.6 for typical commercial offices and about 0.48 for scientific staff offices.

The data also shows a noticeable decrease from a peak starting at about 12:00 pm, presumably when occupants leave for lunch break.

1.2.2. Stochastic diversity factors

Wang et al. used probabilistic methods to evaluate approximately one year of occupancy data for 35 private offices in a large commercial office building [6]. They used a non-homogeneous Poisson process model, a model used to simulate random behavior with data that has an exponential distribution. They plotted the occupancy interval and vacancy interval in minutes for the private offices to obtain the two parameters, one for the occupancy data and one for the vacancy data, needed for their exponential distributions. The parameter for occupancy was found to be statistically invalid while the vacancy parameter was tested to be valid. Wang et al. continued with their methods and found a reasonable diversity factor for a single day. The simulated data show that occupants start to arrive at about 8:00 am and are completely vacated by 9:00 pm with a maximum diversity factor of about 0.75. This is without taking into account the initial peak that reached 0.9 that resulted from the model during the simulated arrival times of occupants. Some of the drawbacks with this model are that it does not take time of day into account and this model is only valid for nominally occupied hours of 8:00 am to 5:00 pm. Other hours are assumed to be zero including hours during the weekends.

Page et al. aimed to account for the time of day for an improved stochastic model. They developed their model using the Markov chains [5]. In the Markov chain method, the next state of the system being analyzed is only dependent on the current state of the system. When this method is applied to occupancy in a private office there are only two states to consider, occupied and not occupied. If the current state is occupied, it has x probability that it will change to a vacant state and $1 - x$ that it will stay occupied in the next time step. Page et al. found the four probabilities of transition that are associated for each hour of the day thus giving time of day priority in the calculation of the diversity factor for a particular day. The researchers obtained the probabilities of transitions from measuring the occupancy in five private offices in a research building. They were able to simulate a whole week using the Markov chain method. The diversity factor started out at about 8:00 am and went back to zero at 6:00 pm with a maximum of approximately 0.65 for workweeks and about 0.1 for the weekends. This model showed variability on a day-by-day basis and was able to model hours that are perceived to have low or no occupancy, during after work hours and on weekends. A shortfall of this model is that it underestimated occupants' periods of long absences, specifically those greater than 24 h (business trips, vacations, illness etc). Page et al. tried to improve this aspect by adding a step into their algorithm that allowed simulated occupants to enter a long absence at any given time. Entering a long absence at any given time may be the best approach to model business trips and people becoming ill because this can be treated as random behavior. In the case of vacations, this might not be true. People might have seasons or months with predictably more or less travel, due in part to holidays or weather. Therefore, seasonal variations in occupancy need to be identified in order to adjust stochastic models to properly account for long absence periods.

1.2.3. Other occupancy studies

In other occupancy studies, researchers have used different detection sensors to estimate the number of occupants [32–35]. In these studies, researchers use CO_2 sensors, volatile organic compound (VOC) sensors, motion sensors, ambient light sensors, temperature, relative humidity, and acoustic sensors to determine the amount of people in a zone [33,35,36]. They applied algorithms to analyze the data and found that temperature and relative humidity were not good indicators for occupancy levels in a zone but the rest of the sensor types were. Since it is hard to predict how occupants will move within a building, Li et al. monitored occupancy using radio frequency identification RFID tags [34]. This tags recorded where each occupant was located at any given time to support improved HVAC operation. Finally, Benezeth et al. [32] developed a vision-based system where not only is human presence detected, but the system also characterized human activity and adjusted HVAC conditioning accordingly [32]. While these studies used advanced occupancy detection systems to control HVAC conditions, no summary data were available regarding occupancy diversity factors.

1.3. Purpose of study

Recent energy simulation research has reported to have substantial error when compared to actual building performance [37,38]. In fact, ASHRAE 90.1 Appendix G states "neither the proposed building performance nor the baseline building performance are predictions of actual energy consumption . . . due to variations such as occupancy, building operation and maintenance, weather . . . and the precision of the calculation tool" [14]. While modeling error can be attributed to several factors, reducing error by using reasonable occupancy profiles is desirable. This paper aims to contribute to the research on occupancy diversity factors for commercial office buildings by providing detailed analysis of private office and summary of open office occupancy patterns and as well as for other commercial office building space types. It revealed a need for improved reference material for energy modelers regarding occupancy diversity profiles for commercial office buildings space types. The literature review did not reveal any data on occupancy patterns analyzed by month and we feel there is justification for seasonal variance. This paper introduces new deterministic occupancy diversity factors for common commercial office building space types using data from a large multi-tenant office building. Furthermore, the results may be useful for developers of stochastic models as well.

The rest of this paper is organized as follows. Section 2 describes the building and sensors used to obtain the occupancy data, how the data were preprocessed, the methods used to calculate the diversity factors, and the description of the statistical analysis to identify the need for unique diversity factors. Section 3 includes graphical representations of the occupancy diversity factors. A variety of graphs are used to show how the diversity factors differ throughout the year and for the different weekdays. Sections 4 and 5 summarize key findings and discuss further research needed.

2. Methods

2.1. Building and sensor description

Occupancy sensor data were collected from a 195,000-ft^2, 11-story speculative commercial office building located in Boise, Idaho. The tenants of these offices include firms that are in the business of law, policy, financial, utility, software, logistics, and realty. Thus, even though data come from just one building, the data represent a wide range of tenants. According to the Commercial Building Energy Consumption Survey, this building's principal building activities are categorized as 100%.

A total of 629 occupancy sensors are located throughout the building comprising private and open plan offices, conference rooms, lobbies, hallways, reception areas, and supporting spaces such as mechanical and electrical rooms. The majority of occupancy sensors ($n = 223$) are located in private offices, followed by open plan offices. Table 1 shows the sensor count for each space type. Fig. 2 shows two representative floors of the building color-coded

Table 1
Occupancy sensor count by space type.

Space type	Sensor count
Private offices	223
Open plan offices	77
Storage, data closets, servers room	74
Conference rooms	64
Hallways	52
Bathrooms	44
Support rooms (fan, mechanical, electrical)	30
Stairwells	18
Break rooms	17
Lobbies	17
Workrooms	13
Total	629

by space type. Fig. 2a illustrates a representative private office floor plan and Fig. 2b a representative open office floor. The two floor plans are equal in square footage but private offices dominated floor plans have substantially more occupancy sensors. It is more complicated and involves more uncertainty to use occupancy sensors in open office areas to derive diversity factors. Data collection spanned approximately two years (November 2009–October 2011).

Occupancy sensors detect activity in their coverage area and return a control signal that indicates occupancy status. The technology types commonly found are infrared, ultrasonic and a hybrid class incorporating both technologies. Infrared occupancy sensors detect line-of-sight temperature changes while ultrasonic sensors use Doppler principle to detect movement [39]. In this study, data were collected with the preexisting ceiling-mounted passive infrared occupancy sensors. The coverage area is about 24 ft in diameter with a 360° line-of-sight. The sensors report change of state and are designed to control light fixtures based on a

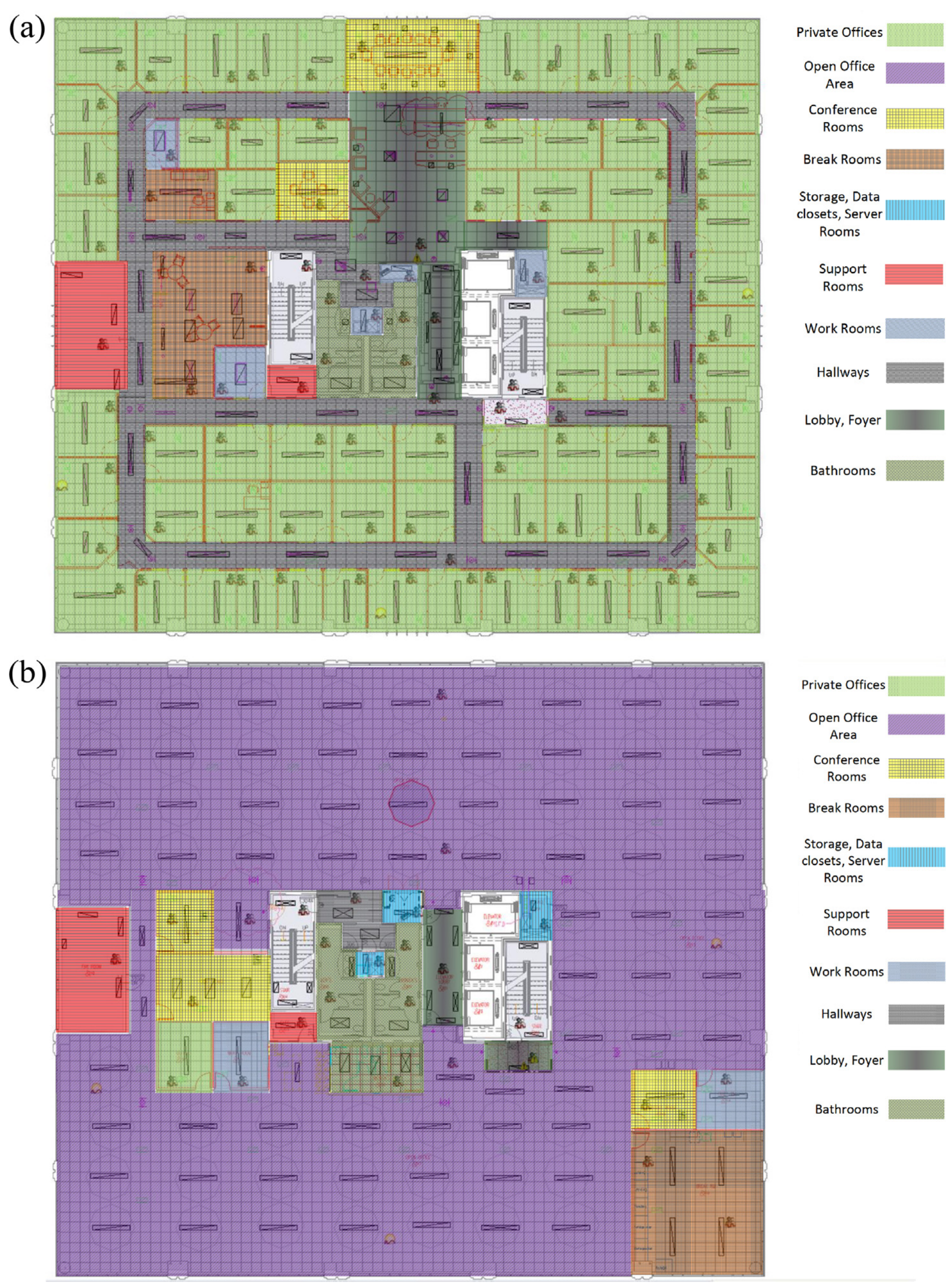

Fig. 2. (a) Representative private office floor plan and (b) representative open office floor plan.

predetermined time delay for this particular building. It is important to note that occupancy sensors do not count people; rather they report time-stamped changes of state.

2.2. Data cleaning and processing

The building control system records two separate logs for each sensor. One log is time-stamped to correspond to a real-time occupancy state of the space. An occupied state is recorded as soon as the sensor detects the presence of a single occupant and records an unoccupied state as soon as it does not detect presence. The second log records the predetermined unoccupied lighting switch time delay. The data analysis reported here was conducted on the real-time state of the space, not the time-delayed state. The overall state of the space was converted to minute-by-minute data such that the each minute was assigned a value of zero for unoccupied and one for occupied. If the majority of the minute was in either state then the dominant state was assigned to the entire minute.

Any part of a single sensor's data that registered as continuously occupied for 48 h or more was replaced with a null value for that period. This was done to reduce the likelihood of including faulty sensors' data or data from periods of sensor malfunction. The opposite failure may also have occurred (sensors fault-off rather than fault-on) but it was not possible to protect against this because it is reasonable for a space to correctly register long unoccupied periods (e.g. weekends, vacations, or business trips). There were a total of 153,980 sensor-days of data for private offices. The equivalent of 3940 sensor-days (2.56%) were removed from the analysis due to filtering out the fault-on sensor data. Table 2 shows a summary for the rest of the occupancy sensors in other space types. We expect a similar small amount of fault-off sensor data; however, as stated, these could not be removed reliably. The building was approximately 95–100% leased during the study period; therefore the entire building was included in the analyses.

The private office occupancy diversity factor was obtained by adding all the private office sensors in an occupied state for a given minute and dividing by the total number of private office sensors. For example, there are 223 sensors for private offices, if 44 sensors registered an occupied state at 8:01 AM, then the diversity factor at 8:01 AM is 44/223 or 0.2. The occupancy diversity factor is essentially the percentage of sensors that registered an occupied state for a particular space type at a particular time. The occupancy diversity factor profile accumulates minute-by-minute data for longer time periods.

2.3. Statistical methods

Descriptive statistics and two-sample *t*-tests (95% confidence interval) were used in order to determine if there were statistically significant differences between each month of the year, day of the week, or hour of the day by space type. Performing *t*-tests between all months (7:00 AM to 6:00 PM on weekdays), between days of the week and between hours, were conducted to determine the meaningful differences. Holidays, as defined by the United States (US) federal government were omitted from monthly comparative analysis. Descriptive statistics provide a starting point to summarize the data in the study to identify features that are relevant to simulation models. Monthly and day type profiles are reported including individual weekdays, holidays, and days after and before holidays. Within the weekday profiles, the critical features examined were the start of a workday, lunch and break periods, and end of a workday and peaks. These features were compared with other occupancy pattern studies to show how findings compare with each other.

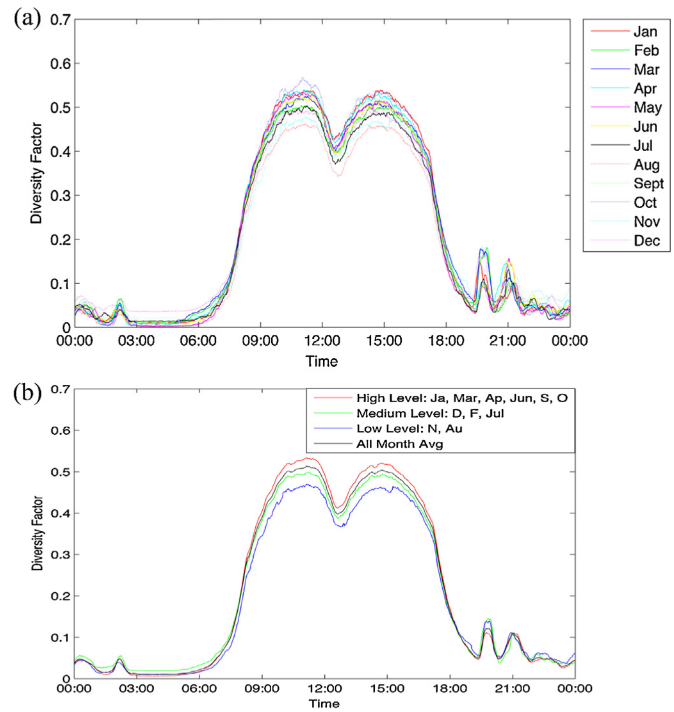

Fig. 3. (a) Private office diversity factory for each month and (b) mean of high, medium, and low levels for all months.

3. Results

Fig. 3a shows the average diversity factor by hour for each month. Note that the scale is different from Fig. 1. The graphs have been filtered to show weekdays only, excluding Saturdays, Sundays, and US holidays. The months seem to cluster at three different diversity factor profile levels. A calculation of *t*-tests and their resulting *p*-values suggests the months of January, March–June, September, and October cluster together to form the high profile level. December, February, and July cluster to form the medium profile level, and November and August form the low profile level. Fig. 3b displays the mean for each of these three clusters along with the mean for all the months combined.

Mondays tended to have the highest-level of occupancy of all weekdays, Fridays have the lowest, with Tuesday, Wednesday and Thursday having no discernible difference. The diversity factors for weekday types are shown in Fig. 4a. From this graph, it is revealed that occupancy returns to approximately the same level after lunch as before lunch in private offices, with the exception of Fridays, where the afternoon occupancy level drops by a mean of about 5%. These graphs represent weekday data and exclude holidays. Fig. 4a illustrates the average of the days for all months. The profiles for weekdays peak between 0.5 and 0.55 for private offices. The averaged data in Fig. 4a is smooth, however Fig. 4b shows the variability on a month-to-month basis for Monday, Friday–Sunday. The variability of the diversity factor peaks is between 0.42 and 0.6. The omitted days fall in between Monday and Friday and were excluded to improve legibility.

We examined weekends to determine if there were any noticeable patterns useful for energy modelers. Fig. 4b also shows the plots for Saturdays and Sundays averaged by month and indicates that weekend days tend to cluster together. Weekend days typically peak at about a 0.1 diversity factor.

Fig. 5a shows occupancy diversity factors for US holidays. Due to the variability, it is difficult to decipher the specific holidays, therefore the following list states the holidays in order from the highest diversity factor peak to the lowest peak: Columbus Day,

Table 2
Faulty occupancy sensor analysis.

Space type	Sensor count	Sensor count with at least one faulty period	Total count of faulty instances for all sensors	Sum of fault sensor-days for all sensors	Average number of sensor-days per faulty instance
Private offices	223	197	536	3940.0	7.4
Open plan offices	77	73	266	2429.2	9.1
Storage, data closets, servers room	74	42	96	895.4	9.3
Conference rooms	64	45	124	1064.4	8.6
Hallways	52	51	211	1547.5	7.3
Bathrooms	44	44	139	994.4	7.2
Support rooms	30	8	12	344.2	28.7
Stairwells	18	15	56	834.4	14.9
Breakrooms	17	16	61	432.4	7.1
Lobbies	17	14	66	415.2	6.3
Workrooms	13	11	103	740.3	7.2
Total	629	516	1670	13,637.5	113.0

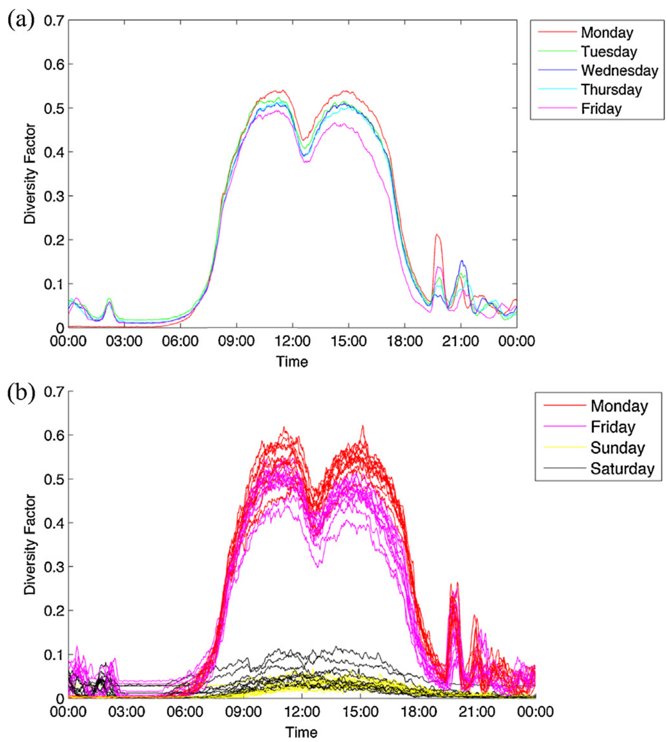

Fig. 4. (a) Average private office diversity factor profile for weekdays and (b) private office diversity factor by weekday for each month.

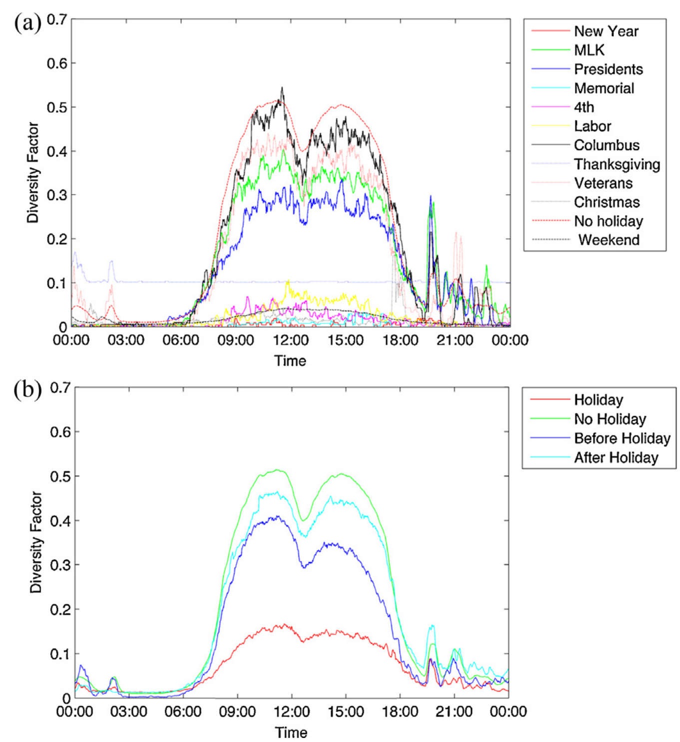

Fig. 5. (a) Average private office diversity factor for holidays (b) average diversity factor for days before and after holidays.

Veterans Day, Martin Luther King Jr. Day, Presidents Day, Labor Day, Independence Day, Christmas Day, Memorial Day, New Years Day, and Thanksgiving. Fig. 5a also includes the average workday and weekend day profiles for comparative purposes.

In addition, Fig. 5b shows the private office diversity factor on holidays, as well as one day before and after the holidays, along with the typical workday profile.

Finally, the diversity factors for each of the space types were examined in a similar fashion to private offices. Fig. 6 shows the diversity factor for selected space types. These profiles are filtered to show weekdays only, excluding holidays, but including all months.

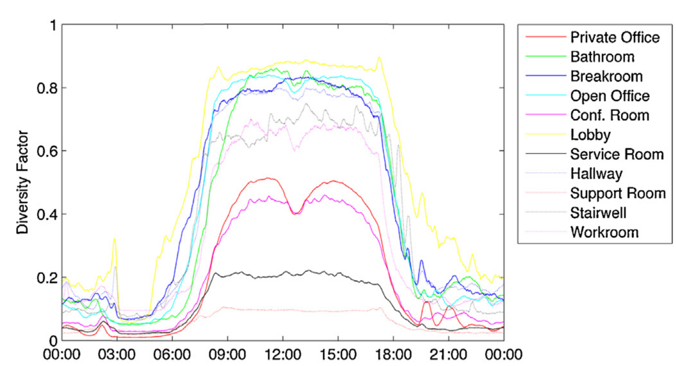

Fig. 6. Occupancy diversity factor shown by space type; weekend, all months, excluding holidays.

4. Discussion

4.1. Comparing ASHRAE references to measured data

By comparing ASHRAE reference private offices diversity factors to the data collected in 223 private offices from an operating

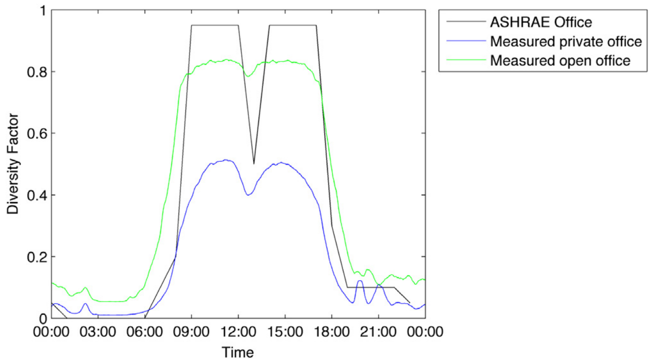

Fig. 7. Comparing ASHRAE 90.1 2004 references to current research.

multi-tenant commercial office building, one can see that both profiles have the same important characteristics in occupancy diversity factors (see Fig. 7). That is, the diversity factor starts to increase around 7:00 AM, dips at noon, rises again after noon and drops near the end of the workday. However, there are important differences as well. In the 90.1 2004 ASHRAE guidelines, the diversity factor decreases at about 5:00 PM, whereas the measured data reaches a peak value after the lunch hour at 3:00 PM, after which it decreases. Most importantly, the measured private office diversity factors do not come close to the 95% occupancy level as recommended in 90.1 2004, rather they peak at 50%. The open office data from Fig. 7 also do not reach much beyond a 0.8 peak. If energy models are to reflect accurate results for energy predictions and come closer to matching real world energy billing data, using diversity factors resemble these contemporary real world data may prove beneficial. The results herein support research that found the peak value for private office profiles ranging between 60% and 70% [1,17,40].

It was hypothesized that summertime occupancy diversity factors may shift and start to increase and decrease earlier in the day. As shown in Fig. 3a, this does not seem to be the case for this dataset. These data suggests that people generally have an established work schedule independent of season. However, Fig. 4a shows that the day of the week has a significant difference with the middle of the week following a similar profile but statistically higher occupancy on Mondays and early departure on Fridays (∼30 min earlier). Also in Fig. 4, small but consistent peaks and valleys appear after about 7:00 PM. These features likely correspond to the maintenance staff cleaning offices. The curves suggest that there is little variability in the cleaning schedule.

4.2. Significantly different occupancy diversity factors

It was interesting to find that October has the highest diversity factor profile of all the months for private offices, with August having the lowest. It was hypothesized that July or August would have the lowest occupancy due to vacations. These data suggest that people tend to wait until the end of summer to do their major traveling. November also has a low diversity factor profile, which is likely due to people taking extended vacations near the Thanksgiving holiday. Expanding on this idea, we examined four other extended vacations near holidays.

Fig. 5b illustrates the day before and after holidays also have a lower diversity factor profile than a typical workday. Interestingly, the days before holidays have similar features as Friday profiles such that the diversity factor does not reach the same peak after the lunch hour as before the lunch hour and occupancy drops about 30 min earlier on average.

Results from private offices during the weekend were expected to be low. The profile for Saturdays and Sundays reach a peak of just 0.1 or lower, a value that is likely due to the cleaning or maintenance staff occupying a few offices intermittently or occasional worker occupancy.

Holidays were also expected to be low. The data were filtered to show only US federal holidays, however each company or individual occupant might have a different policy or view on these holidays. For example, these data suggest that the majority of organizations do not observe Columbus Day, whereas there is virtually no occupancy on Memorial Day, Thanksgiving, Christmas, and New Years Day (Fig. 5a). There is minimal activity for Independence Day and Labor Day, almost resembling a weekend schedule. President's Day, Washington's Birthday, and Martin Luther King Jr. Day reach a peak value above 0.3, about 25% below that of a typical workday.

Fig. 5a shows a flat line minimum value for Thanksgiving day that is higher than expected. This was considered to be the zero reference value because a constant minimum value was clearly shown. This discrepancy could have been due to a few faulty sensors for that particular day, i.e. the sensors registered an occupied signal for more the 24 h but less than 48 h, and thus, the filter routine did not remove these sensors.

4.3. Other room types

Fig. 6 reveals that common areas such as lobbies, bathrooms, open office areas, break rooms, hallways, workrooms, and stairwells tend to have higher peak values and flatter profiles. Most of them have an average value of 0.75–0.88. While this is somewhat surprising, it can be explained in part by the fact that there are a limited number of sensors in these space types and they also have frequent activity. For example, there is only one pair of bathrooms on each floor and it only takes one occupant to activate the sensor. Therefore, the data suggest, somewhat surprisingly, that there is at least one person in these space types for most of the workday.

Furthermore, one can notice that bathrooms, open office areas, hallways, workrooms, and conference rooms have similar profile shape characteristics as private office spaces, but lower peak values. They all tend to decrease at the same time during the lunch hour and rise again afterwards. A noticeable difference is the time when lobbies start to increase and decrease as compared to open office spaces and private office spaces. Lobbies begin to increase in occupancy as much as an hour before offices while private offices begin to decrease as much as 2 h before lobbies decrease and open offices decrease as much as an hour before lobbies decrease.

Note that it is not possible to describe occupancy with confidence due to the limitations of the occupancy sensors in large spaces that are likely to have multiple occupants such as conference rooms, and open plan offices. Future research is planed to incorporate additional measurement techniques to better describe occupancy profiles in such spaces.

4.4. Stochastic comparison

As mentioned in the literature review, other researchers have developed stochastic occupancy models intended for use with energy simulation. Fig. 8 shows a comparison of measured occupancy data from this study with the stochastic model developed by Page et al. In this figure, a typical week with high occupancy and a typical week with low occupancy from our study building are plotted with the stochastic model by Page et al. The profiles show similar characteristics; occupancy begins to increase and decline at about the same time. However, one major discrepancy stands out when comparing the measured data to is the stochastic model; the occupancy profile for the model has substantial variation throughout the day. This is likely due to the small data set (10 private offices) used to calibrate the stochastic model [5]. The erratic occupancy from 1 h to the next are not typical in large commercial office building studied likely due to the fact that it had 223 private offices

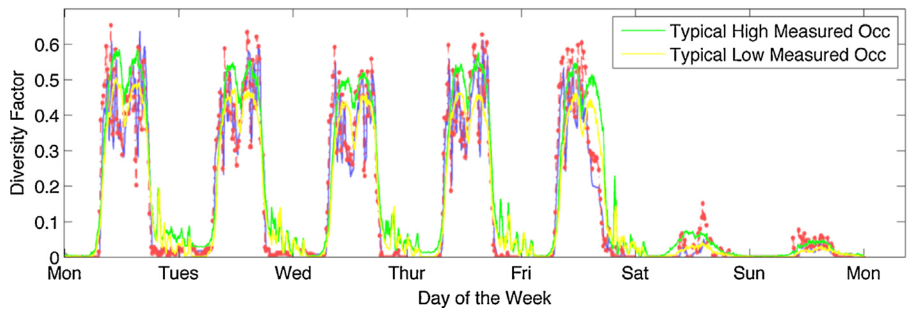

Fig. 8. Comparison of measured occupancy data with Page et al. [5] measured occupancy (solid blue line) and occupancy model (dotted red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

effectively smoothing the behavior. Finally, it is understandable that developers of stochastic models want to model the random behavior of people in buildings but it is arguable that energy modelers don't want to complicate inputs unnecessarily. An alternative approach would be for modelers, especially those working on a large building, to conduct two simulations, one with a typical low occupancy and a second with typical high occupancy in the building. In this way, the modeler can report a range of expected energy consumption in the building instead of having one number that will most likely change during the lifetime of the building.

5. Conclusion

This paper provides occupancy diversity factors for multiple space types based upon a 23-month dataset from a large multi-tenant commercial office building. It shows that there are statistically significant differences to suggest four unique diversity factors for day of the week (Monday, Tuesday–Thursday, Friday, and three unique diversity factors for month of the year (shown in Fig. 3b), and for three holiday groups (as shown in Fig. 5a).

It has been shown that measured occupancy data have a significantly lower diversity factor than the ASHRAE 90.1 2004 recommended practice. Measured data shows as much as a 46% reduction in average day profile peaks for private office occupancy and about a 12% reduction for open plan office spaces when compared to the ASHRAE model. However, additional research is needed to accurately describe occupancy in open areas such as open plan offices. Given that the results presented herein support and extend previous research [1,17,40] energy modelers would be wise to base assumptions regarding occupancy diversity factors on measured data in addition to the recommended ASHRAE 90.1 2004 model. Given these findings, future research, examining a data set large enough to support a new ASHRAE recommended practice seems warranted. Until then, energy modelers may want to use high and low typical conditions from the measured data presented here or other similar data.

Stochastic model developers can use the information presented in this paper to improve their algorithms and thus improve their models' ability to simulate random human behavior in commercial office buildings for use with energy simulation software. The presented information should guide expectations of stochastic models with regard to weekdays, holidays, and time of day diversity factors.

Even though there is a large number of private offices in the study building, ($n = 223$), more research is warranted in order to develop a larger sample of buildings spanning geographic regions, office types, and other critical factors. While speculative office buildings provide useful differences in office tenant types (law, financial, software etc) and are a good choice for future research, it would also be interesting to investigate owner-occupied buildings, and government buildings to determine how occupant diversity factors differ.

Acknowledgments

Work supported by the U.S. Department of Energy under DOE Idaho Operations Office Contract DE-AC07-05ID14517.

The authors also acknowledge the cooperation of Professor Ralph Budwig, Ery Djunaedy, Brad Acker, and Professor Milos Manic for their guidance as well as the Christensen Corporation, Guy Newsham and Encelium Technologies for their support in procurement of the data.

References

[1] J.A. Davis III, D.W. Nutter, Occupancy diversity factors for common university building types, Energy and Buildings 42 (9) (2010) 1543–1551.
[2] B. Abushakra, A. Sreshthaputra, J.S. Haberl, D.E. Claridge, Compilation of diversity factors and schedules for energy and cooling load calculations, ASHRAE research project, Final Report 1093-RP, Sept. 2001.
[3] D. Robinson, Some trends and research needs in energy and comfort prediction, in: Comfort and Energy Use in Buildings, Windsor, United Kingdom, 2006.
[4] C. Wang, D. Yan, Y. Jiang, A novel approach for building occupancy simulation, Building Simulation 4 (2011) 149–167.
[5] J. Page, D. Robinson, N. Morel, J.-L. Scartezzini, A generalised stochastic model for the simulation of occupant presence, Energy and Buildings 40 (2) (2008) 83–98.
[6] D. Wang, C.C. Federspiel, F. Rubinstein, Modeling occupancy in single person offices, Energy and Buildings 37 (2) (2005) 121–126.
[7] Y. Yamaguchi, Y. Shimoda, M. Mizuno, Development of district energy system simulation model based on detailed energy demand model, in: Proceedings of the Eighth International IBPSA Conference, Eindhoven, The Netherlands, 2003.
[8] J. Virote, R. Neves-Silva, Stochastic models for building energy prediction based on occupant behavior assessment, Energy and Buildings 53 (0) (2012) 183–193.
[9] X.-B. Yang, X.-Q. Jin, Z.-M. Du, B. Fan, X.-F. Chai, Evaluation of four control strategies for building VAV air-conditioning systems, Energy and Buildings 3 (2011) 414–422.
[10] N. Nassif, A robust CO_2-based demand-controlled ventilation control strategy for multi-zone HVAC systems, Energy and Buildings 45 (2012) 72–81.
[11] C.Y.H. Chao, J.S. Hu, Development of a dual-mode demand control ventilation strategy for indoor air quality control and energy saving, Building and Environment 39 (4) (2004) 385–397.
[12] M. Mysen, J.P. Rydock, P.O. Tjelflaat, Demand controlled ventilation for office cubicles—can it be profitable? Energy and Buildings 35 (7) (2003) 657–662.
[13] ASHRAE, ASHRAE 90.1 Section 11 Energy Cost Budget Method, ASHRAE, 2007.
[14] ASHRAE, ASHRAE 90.1 Appendix G. Building Performance Rating Method, ASHRAE, 2004.
[15] X. Zhang, J. Xia, Z. Jiang, J. Huang, R. Qin, Y. Zhang, Y. Liu, Y. Jiang, DeST—an integrated building simulation toolkit Part II: Applications, Building Simulation 1 (3) (2008) 193–209.
[16] S. Attia, E. Gratia, A. De Herde, J.L.M. Hensen, Simulation-based decision support tool for early stages of zero-energy building design, Energy and Buildings 49 (0) (2012) 2–15, Jun.
[17] A. Mahdavi, Patterns and implications of user control actions in buildings, Indoor and Built Environment 18 (5) (2009) 440–446.
[18] G. Young Yun, H. Joo Kong, J. Tai Kim, A field survey of occupancy and air-conditioner use patterns in open plan offices, Indoor and Built Environment 20 (1) (2011) 137–147.
[19] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy and Buildings 41 (3) (2009) 295–302.
[20] Y.S. Lee, Y.K. Yi, A. Malkawi, Simulating human behaviour and its impact on energy uses, in: Presented at the 12th Conference of International Building Performance Simulation Association, Sydney, Australia, 2011.

[21] D.E. Claridge, B. Haberl, A. Sreshthaputra, Electricity diversity profiles for energy simulation of office buildings, ASHRAE Transactions 110 (1) (2004) 365–377.
[22] K. Opdal, B. Brekke, Energy saving in lighting by utilization of daylight, in: Proceedings of the Third European Conference on Energy-Efficient Lighting, 2013, pp. 67–74.
[23] J. Jennings, F.M. Rubinstein, D. DiBartolomeo, S. Blanc, Comparison of control options in private offices in an advanced lightihng control testbed, in: IESNA 1999 Annual Conference, New Orleans, LA, 1999.
[24] J.A. Love, Manual switching patterns in private offices, Lighting Research and Technology 30 (1) (1998) 45–50.
[25] D. Maniccia, B. Rutledge, M.S. Rea, W. Morrow, Occupant use of manual lighting controls in private offices, Journal of the Illuminating Engineering Society 28 (2) (1999) 42–56.
[26] B. Acker, C. Duarte, K. Van Den Wymelenberg, Office Plug Load Profiles, in: Technical Report 20100312-01, Integrated Design Lab, University of Idaho, Idaho, 2013.
[27] L. Moorefield, B. Frazer, P. Bendt, Office Plug Load Field Monitoring Report, Ecos, Durango, CO, 2008.
[28] L. Moorefield, C. Mercier, Commercial Office Plug Load Savings Assessment, in: PIER Program: Evidence-based Design and Operations CEC #500-09-049, Ecos, Durango, CO, 2011.
[29] J.A. Roberson, C.A. Webber, M.C. McWhinney, R.E. Brown, M.J. Pinckard, J.F. Busch, After-hours Power Status of Office Equipment and Energy Use of Miscellaneous Plug-Load Equipment, Lawrence Berkeley National Laboratory, Berkley, CA, 2004, LBNL-53729-Revised.
[30] M. Sanchez, C. Webber, R. Brown, J. Busch, M. Pinckard, J. Roberson, Space Heaters, Computers, Cell Phones Chargers: How Plugged In Are Commercial Buildings, Lawrence Berkeley National Laboratory, Berkley, CA, 2007, LBNL-62397.
[31] C. Webber, J.A. Roberson, R.E. Brown, C.T. Payne, B. Nordman, J.G. Koomey, Field Surveys of Office Equipment Operating Patterns, Lawrence Berkeley National Laboratory, Berkley, CA, 2001, LBNL-46930.
[32] Y. Benezeth, H. Laurent, B. Emile, C. Rosenberger, Towards a sensor for detecting human presence and characterizing activity, Energy and Buildings 3 (2011) 305–314.
[33] B. Dong, B. Andrews, K.P. Lam, M. Höynck, R. Zhang, Y.-S. Chiou, D. Benitez, An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network, Energy and Buildings 42 (7) (2010) 1038–1046.
[34] N. Li, G. Calis, B. Becerik-Gerber, Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations, Automation in Construction 24 (2012) 89–99.
[35] B. Dong, B. Andrews, Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings, in: Building Simulation, Glasgow, Scotland, 2009.
[36] Improving Building Energy Efficiency with a Network of Sensing, Learning and Prediction Agents. Association for the Advancement of Artificial Intelligence, 2011.
[37] G.R. Newsham, S. Mancini, B.J. Birt, Do LEED-certified buildings save energy? Yes, but. . ., Energy and Buildings 41 (8) (2009) 897–905.
[38] J.H. Scofield, Do LEED-certified buildings save energy? Not really. . ., Energy and Buildings 41 (12) (2009) 1386–1390.
[39] W. Stopper, Occupancy Sensor: Design and Application Guide, http://images3.cableorganizer.com/watt-stopper/uw-100/application-guides.pdf
[40] B. Abushakra, D. Claridge, Accounting for the occupancy variable in inverse building energy baselining models, in: First International Conference for Enhanced Building Operations, Austin, TX, 2001.