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Revealing Occupancy Diversity Factors in Buildings Using Sensor Data

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ABSTRACT

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. Occupants' locations within a building vary throughout the day and this distribution can be valuable information when evaluating demand control strategies. Occupancy diversity factors have not been studied as extensively as for example lighting and plug loads diversity factors. Some reasons for fewer studies of occupancy is limitations accessing existing occupancy datasets and challenges interpreting the data. In a research building at UC Berkeley, we were able to add sets of passive infrared (PIR) or motion sensing for occupancy and carbon dioxide sensors in 67 private offices and 2 conference rooms, as well as in multiple open offices. In this work we study deterministic and stochastic building occupancy models based on data from the deployed sets of sensors.

Data is analyzed to show major variations of occupancy diversity factors in private offices and conference rooms for time of day, day of the week, holidays, and month of the year. The impact on the building electrical load is highlighted: 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. The diversity factors presented in this study can differ as much as 40% from those published in the literature or in the latest ASHRAE energy cost method guidelines, a document commonly used by energy modelers for building simulations. This may result in misleading simulation results and may introduce inefficiencies in the systems design and control. Therefore we argue that building occupancy is a basic and key factor in energy simulations. Occupancy sensors can certainly help in calculating better diversity factors, but what is the optimum number and distribution of sensors to improve performance and justify the cost?

Keywords: diversity factor, building occupancy, demand control strategy, building energy consumption

Introduction

Background

Due to rising energy demand and diminishing energy resources, sustainability and energy conservation is becoming an increasingly important topic. In the U.S., buildings account for 38% of total energy consumption (EIA 2013), and 46% of the primary energy use is associated with commercial buildings (DOE 2011). Energy in buildings is mostly used to maintain comfortable and healthy indoor environment, and provide building-based services. In commercial buildings, HVAC (Heating, Ventilation, and Air Conditioning) systems represent the largest share of building energy consumption, sometimes more than 40% (IEA 2007). Moreover, given the fact that in the U.S., new construction represents only less than three percent of the existing building stock in any given year and that buildings are generally in operation for 30 to 50 years, there is great potential of energy savings through improving the operations of HVAC systems in existing buildings (IEA 2007). This has attracted considerable attention in academia and the construction industry.

Occupancy is a key factor in controlling an indoor environment and deciding the load for HVAC systems (Tabak 2010), especially for central HVAC systems with local variable-air volume controls. Buildings are zoned into particular areas where temperature and ventilation can be individually controlled. When a zone is occupied, the temperature has to be maintained at an acceptable range while the occupants of that zone continuously generate heat and interact with building systems and appliances, impacting the indoor thermal environment (Rea 1984, Fritsch 1990). When a zone is unoccupied and static HVAC control strategies are used, an excess of energy may be consumed in order to maintain the designed set-points and provide disproportionate amounts of ventilation air. As much as 90% of HVAC building control systems are operated inefficiently (Carbon 2012) and up to 30% of HVAC-related energy can be potentially saved by implementing occupancy-driven control strategies (ABB 2010). Consequently, extensive research has been carried out to explore various ways for driving building control strategies based on actual or representative occupancy patterns.

Occupancy diversity factors

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 (Virote 2012). Occupants in buildings arrive and leave every day at different times and constantly move within the facilities.

The occupancy distribution can be valuable information when testing and designing demand control strategies in a building (Yang 2011). For occupied facilities, researchers can obtain estimated occupancy schedules from tenants and make adjustments in the energy control strategies. However, the most common method for considering occupancy – especially in simulation and design tools - is to use fixed design profiles (Davis 2010) that are defined by organizations such as ASHRAE and based on analyses of large-scale occupant surveys (ASHRAE 2004). Researchers and designers commonly 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. Occupancy diversity factors are hourly fractions for a 24-h day, the profiles having a range from zero to one. The diversity factors for each workweek are often treated identically with weekend days having a different profile. Alternatively each day of the week, but also each zone type, can be differentiated. In the case of HVAC systems, the occupancy diversity factor is used to multiply the design heating/cooling load in an energy simulation because occupancy will not always be at the maximum design level. This provides a way to account for the variable heat gains throughout the day.

Figure 1 illustrates the diversity factors recommended by ASHRAE Standard 90.1-2004 for use with office occupancy. The published diversity factor does not differentiate for private offices or open floor plan offices. The graph shows the factor for weekday hours reaches a value close to 100%, with an approximate drop of 50% during the noon hour. Due to the stochastic nature of human behavior, this type of deterministic schedule is broadly used, where standard workday and weekend profiles are set with no change in occupancy schedules throughout the year. In more complex and sophisticated stochastic occupancy models, schedules for one week are not the same as the next. Occupancy diversity factors have not been studied as extensively as, for instance, lighting and plug loads diversity factors (Acker 2013). The main reasons are limitations accessing existing occupancy datasets and challenges interpreting the data.

Purpose and Methodology

Purpose of the study

Studies of building energy control strategies based on original design regularly report to have substantial errors when compared to potential building performance (Scofield 2009). While errors in the energy control strategies can be attributed to several factors, reducing error by using reasonable occupancy profiles is desirable. This work aims to contribute to the research on occupancy diversity factors for research buildings by providing detailed statistical analysis of private offices and conference rooms.

This paper introduces personalized deterministic diversity factors for common university building space types using motion sensor data from a large research building at UC Berkeley. The next subsection "Methodology" describes the research building and sensors used to obtain the occupancy data, how the data were preprocessed and analyzed, as well as the methods chosen to obtain the diversity factor graphs, inspired by (Duarte 2013). The section "Results and Discussions" summarizes key findings and suggests directions for further research.

Methodology

Occupancy sensor data were collected from a 141,000 ft^2, 7-story research building in Berkeley, California. The living laboratory Sutardja Dai Hall at UC Berkeley has its own nanofabrication laboratory, many private and open plan offices as well as a café, an auditorium, classrooms, and light laboratories. The tenants of the private and open plan offices are mostly researchers, students and UC Berkeley staff, and the total office portion is about 81,000 assignable square feet (ASF).

A total of 519 sensors were deployed throughout Sutardja Dai Hall, in three packages: temperature (C), light (lux), relative humidity (%), Passive InfraRed (PIR) or motion sensor (1-3 meters) and carbon dioxide. The majority of occupancy sensors are located in private offices, followed by open plan offices. In this work we focused on 67 private offices and 2 conference rooms, all equipped with a set of sensors, throughout the fourth, fifth, sixth, and seventh floors of the building. *Figure 2* and *Figure 3* show two representative floors of the building color-coded by space type. The floor plans are equal in square footage but the 4th floor, with a larger number of private offices, has substantially more occupancy sensors. Data collection spanned approximately 18 months (June 2013-November 2014).

In this study, we focus on the data collected from the 69 installed Passive InfraRed (PIR) sensors in the private and conference rooms. It is more complex and involves more uncertainty to use occupancy sensors in open office areas to derive diversity factors. The motion sensors report change of state at a sampling rate of 10 seconds. It is important to note that occupancy sensors do not count people; rather they report time-stamped changes of state. An occupied state is recorded as soon as a PIR sensor detects the presence of a single occupant and records an unoccupied state as soon as it does not detect presence. The overall state of the space was aggregated to a time series with a 5-min time step, with each 5-min time slot being assigned a value of zero for unoccupied and one for occupied. The dominant state was assigned to the entire time step, i.e. the state was set as occupied when the sensors detected presence for longer than 2.5 min of each time step.

Data were filtered to remove US federal holidays. Any part of a single PIR sensor's data that registered as continuously occupied for 12 hours or more was replaced with the corresponding ASHRAE values from the standards. This was done to reduce the likelihood of including faulty sensors' data or data from periods of sensor malfunction. The opposite failure (sensors fault-off rather than fault-on) is more complex to detect. Indeed, it is reasonable for a space to correctly register long unoccupied periods (e.g. weekends, vacations, or research/business trips). We used the full set of sensors in each room to limit this eventuality. For any part of a single PIR sensor's data that registered as continuously unoccupied for 1 week or more, the PIR sensor's data were compared to the full set of sensors' data (including CO_2, light, temperature) and processed according to three options: (i) other sensors' signals were flat, then the full set of sensors might have been disconnected and the corresponding part of the PIR sensor's data were replaced by ASHRAE standard values; (ii) other sensors' data revealed no notable evolution (constant average value for CO_2 levels, flat signal for light detection), therefore it was considered that the room was indeed unoccupied and the data were left unchanged; (iii) CO_2, light and temperature sensors' data revealed some occupancy, the PIR sensor only malfunctioned and the corresponding part of the PIR sensor's data were replaced by ASHRAE standard values. A representative set of sensors' data (PIR, CO_2, light) in a private office of the 4th floor on Monday, October 20, 2014 are shown in *Figure 4*. It reveals how the combination of various ambient sensors can be used to detect occupancy patterns. There were a total of 38,847 days of sensor-data for private and conference rooms. The equivalent of 4,150 sensor-days (10.6%) was replaced by ASHRAE standard values due to filtering out the fault-on sensor data.

The occupancy diversity factor was obtained by adding all the private office and conference room sensors in an occupied state for a given 5-min time slot and dividing by the total number of sensors taken into account (n=69). For example, if 21 sensors registered an occupied state between 9:00 am and 9:05 am, then the diversity factor was this time slot is 21/69 or 0.3. The occupancy diversity factor is essentially the percentage of sensors that registered an occupied state for a particular space type at a particular time. In our work the occupancy diversity factor profile accumulates 5 min-by-5 min data for longer time periods.

We then used on the data set *t-test* statistic methods (95% confidence interval) to determine if there were statistically significant differences between each month of the year, day of the week and hour of the day. Monthly and day type profiles are reported including individual weekdays. Within the weekday profiles, the critical features examined were the start and end of a workday, lunch and break periods as well as peaks. These features were compared with other occupancy patterns including the ASHRAE standards to show how findings compare with each other.

Results and Discussion

Results

Figures 5 to 8 show weekdays data only, excluding Saturdays, Sundays, and US holidays. *Figure 5* shows the average diversity factor by hour for each month. The months cluster at three different diversity factor profile levels. A calculation of *t-tests* and their resulting *p-values* suggests that the months of February-June and September-October cluster together to form the high profile. December, January and July cluster to form the medium profile level, and November and August form the low profile level. *Figure 6* shows the mean for each of these three clusters along with the mean for all the months combined.

Mondays have the highest-level of occupancy of all weekdays, Fridays have the lowest, with Tuesday, Wednesday and Thursday profiles being very close to each other. The diversity factors for weekday types are shown in *Figure 7*. The graph illustrates 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 15%. The weekdays average peak is between 0.59 and 0.8 for the studied private and conference rooms. The averaged data are smooth; however the month-to-month variability for each weekday is important. The variability of the diversity factor peaks for weekdays is between 0.46 and 0.82.

Measured data shows as much as 40% reduction in average day profile peaks for private office occupancy compared to the ASHRAE model (refer for example to *Figure 8*, which represents the total weekday average versus the AHSRAE model for weekdays).

Discussion

By comparing ASHRAE standard curves for private offices to the data collected in the 69 studied office and conference rooms, one can see that both profiles have the same important characteristics in occupancy diversity factors (*Figure 8*). That is, the diversity factor starts to increase around 7:00 AM, decreases after noon, rises again at the beginning of the afternoon and drops near the end of the workday. However, there are important differences between the two profiles. According to ASHRAE standards, the diversity factor decreases at about 5:00 PM, whereas the measured data reaches a peak value at 3:00 PM and then drops quickly. Most importantly, the measured diversity factors almost never reached the 95% occupancy level as recommended in the standards; rather they peak between 60% and 80%.

It was hypothesized that summertime occupancy diversity factors may shift and start to increase and decrease earlier in the day. This does not seem to be the case as shown in *Figure 5*. These data suggest that people generally have an average work schedule independent of season. *Figure 7* shows that weekday profiles show more significant differences with the middle of the week having a similar pattern but statistically higher occupancy on Mondays and early departure on Fridays. It is interesting to note that October has the highest diversity factor profile of all months, with November and August having the lowest. These results match our expectations, with these months being popular vacation times in summer or near Thanksgiving.

Results show that measured occupancy data have a significantly lower diversity factor than the ASHRAE standards. Looking at the mean weekday profile compared to ASHRAE standards (refer to *Figure 8*), we estimated that real occupancy data at the building scale can save in average 22% of daily energy consumption. Taking into account the cost of the sensors, their installation as well as the cost of running the whole system, the return on investment for the building manager is inferior to 2.5 months.

Conclusion

This paper provides occupancy diversity factors for 69 private offices and conference rooms based upon an 18-month dataset from a research building in Berkeley, California. It shows that there are statistically significant differences to suggest three families of diversity factors for day of the week (Monday, Tuesday-Thursday, Friday) and three families of diversity factors for month of the year. Results also show that measured occupancy data have a significantly lower diversity factor than the ASHRAE standards. Measured data shows as much as 40% reduction in average day profile peaks for private office occupancy compared to the 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. The results of this study should also guide expectations of stochastic models with regard to weekdays, holidays, and time of day diversity factors. In any case, more research is necessary in order to develop a larger sample of buildings spanning geographic regions, office types, and other critical factors. It would be interesting to investigate other types of buildings to determine how occupant diversity factors differ.

Figures

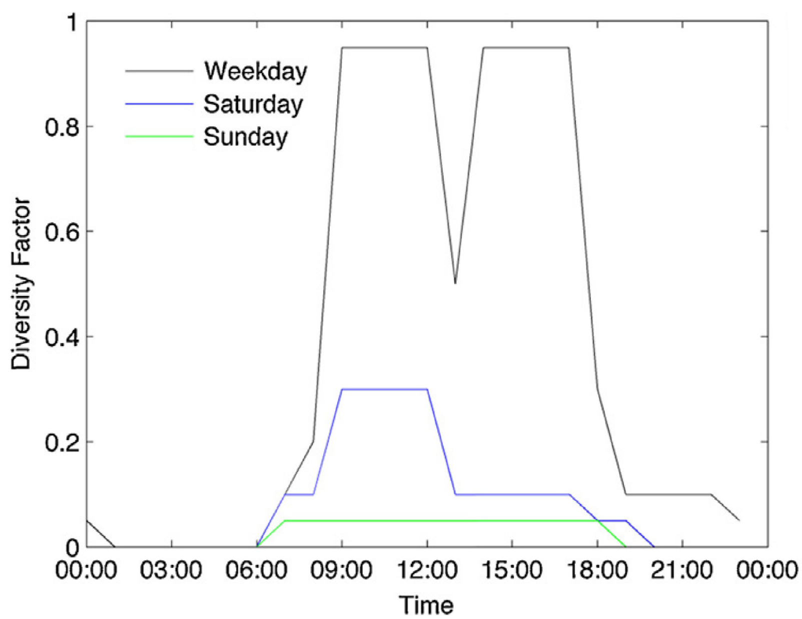

Figure 1. ASHRAE 90.1-2004 recommended occupancy diversity factor by day type

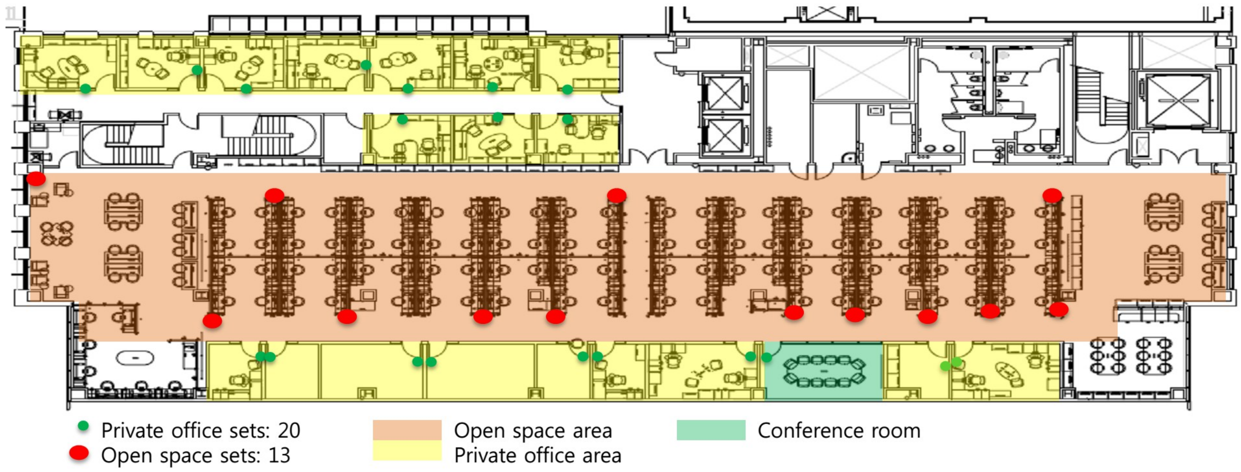

Figure 2. 4th floor representative Sutardja Dai Hall research building

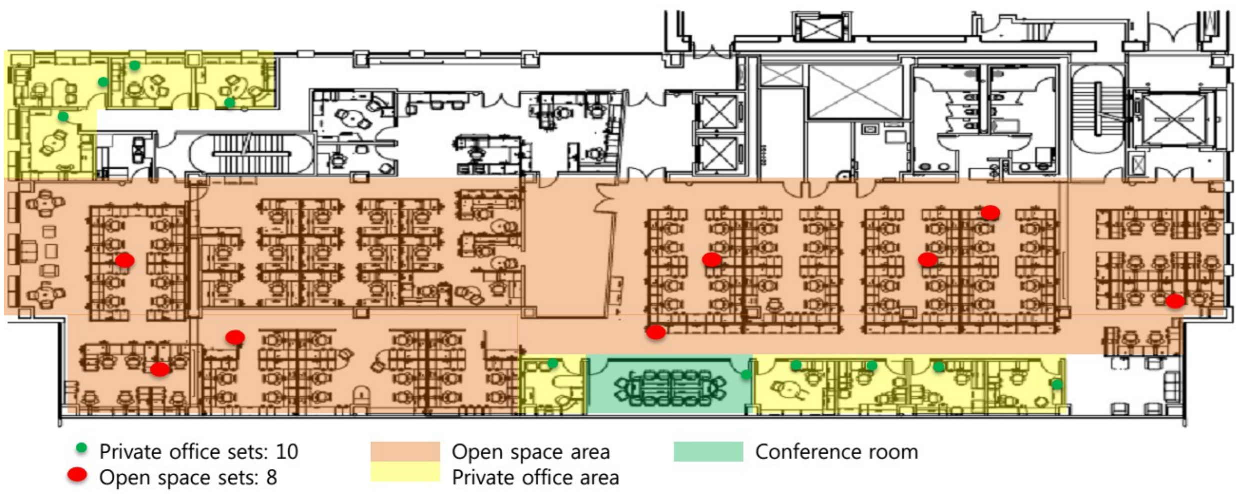

Figure 3. 5th floor representative Sutardja Dai Hall research building

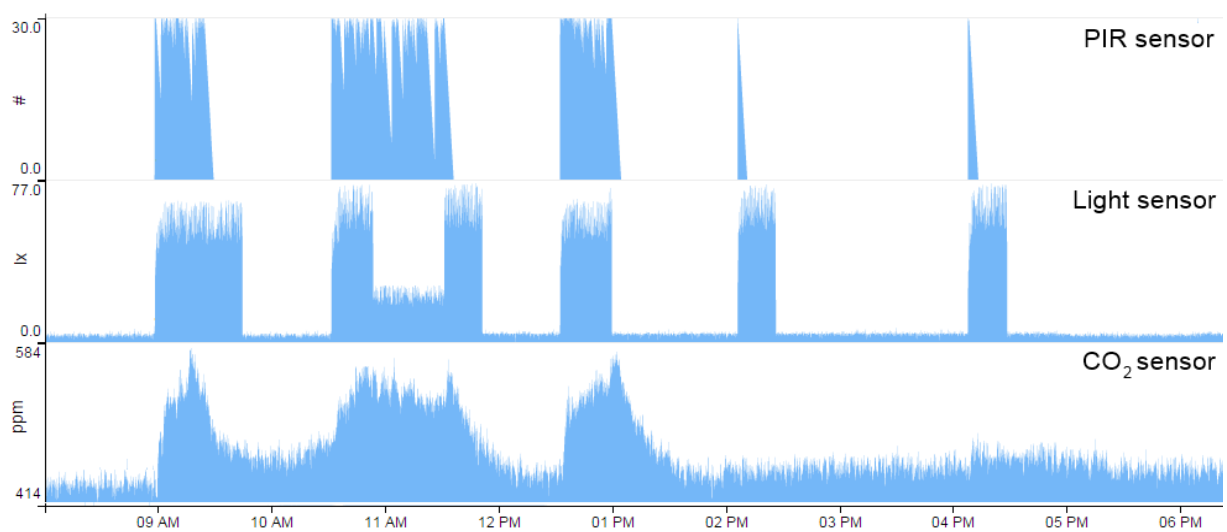

Figure 4. CO2, light and PIR sensors' data in a private office on Monday, October 20, 2014

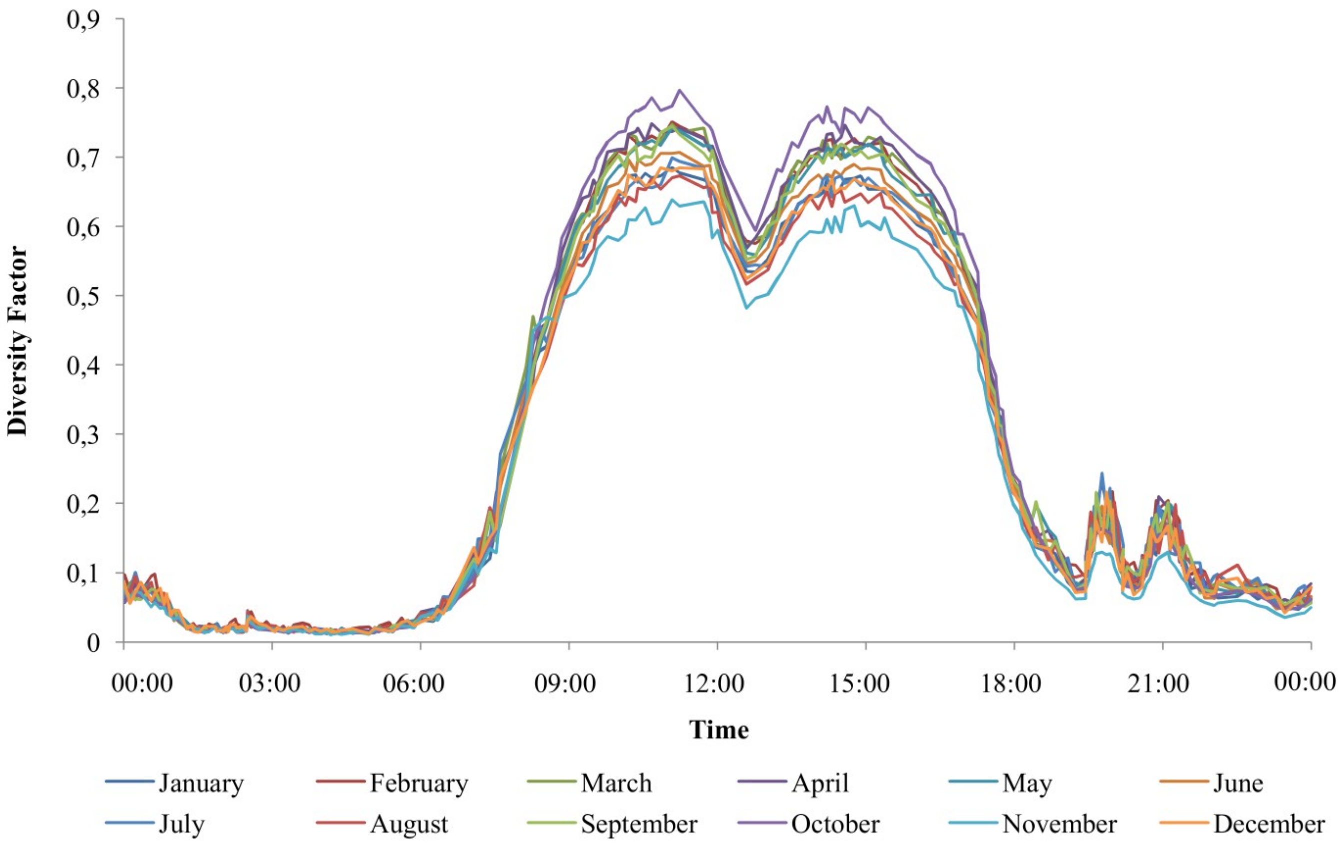

Figure 5. Average occupancy diversity factor for each month

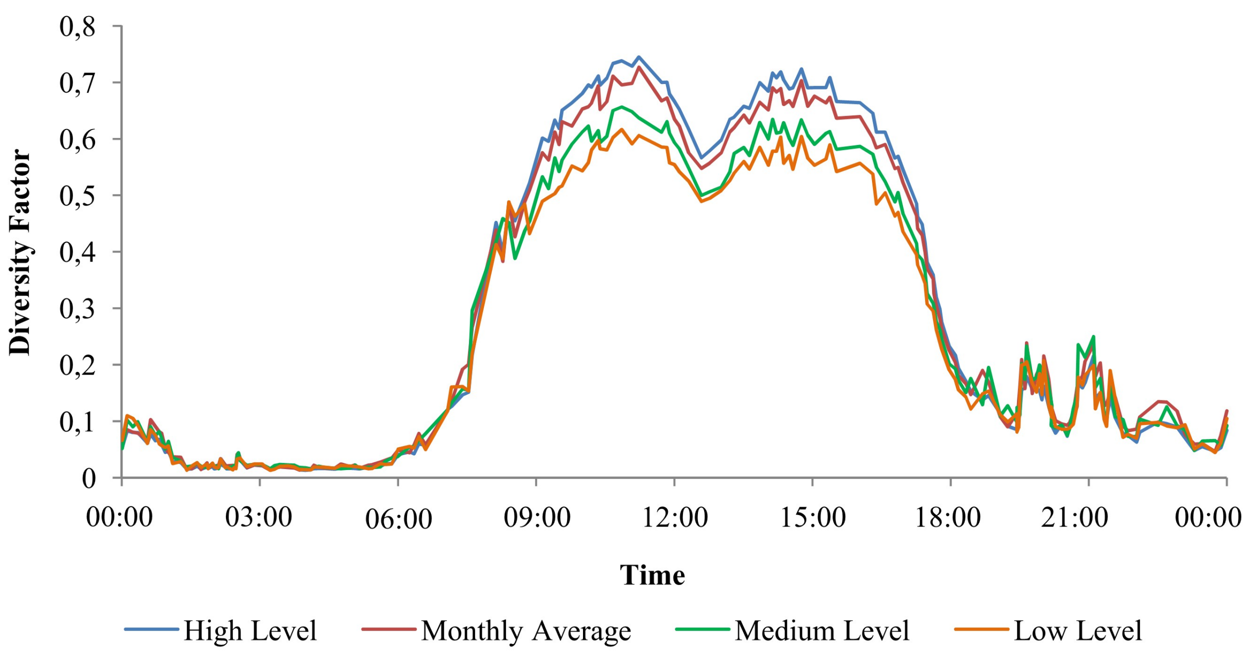

Figure 6. Diversity factors obtained for the average over all months and for the average over high-, medium-, and low-level months

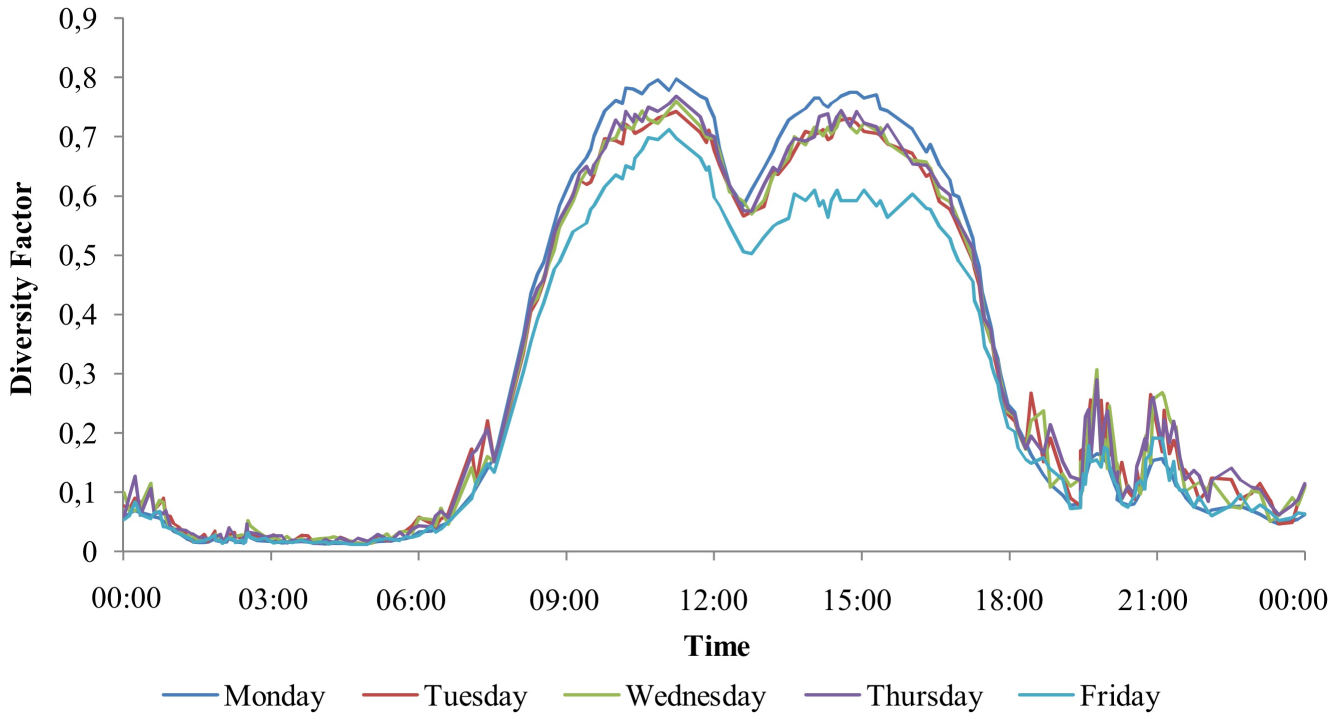

Figure 7. Average occupancy diversity factor profile for weekdays

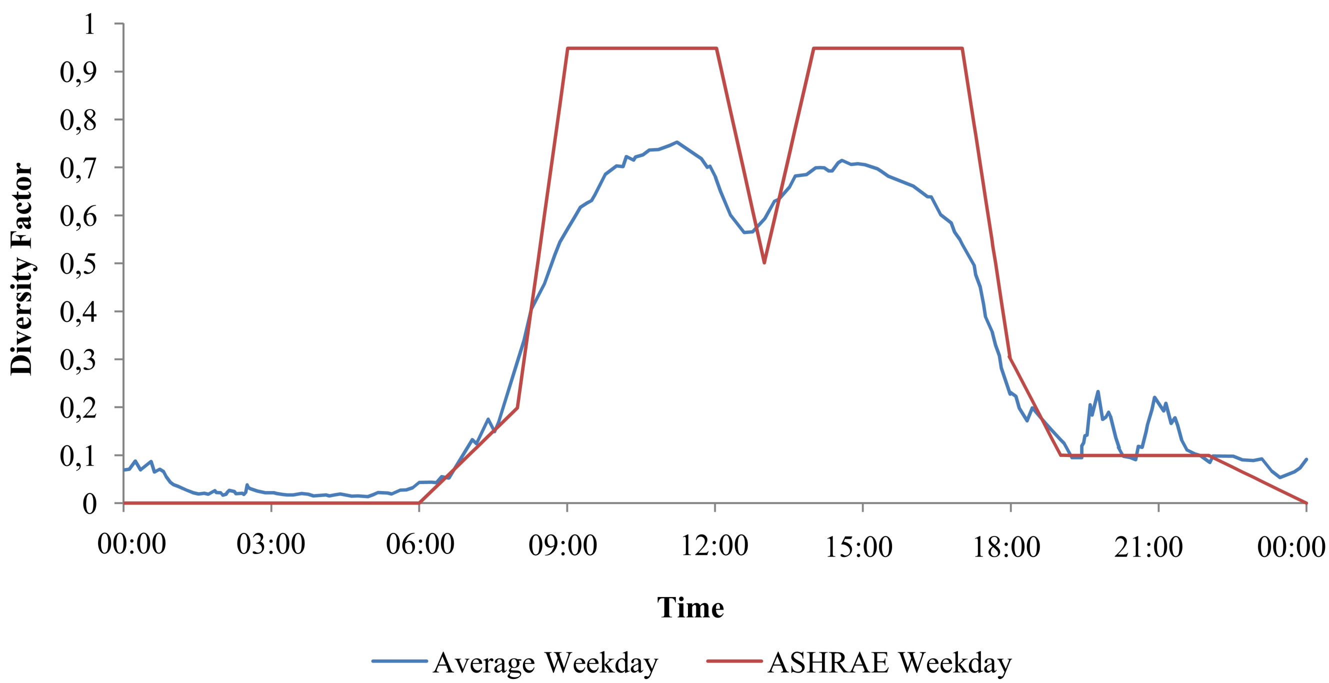

Figure 8. Comparing diversity factors from ASHRAE 90.1 2004 references to current study

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