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## Exploring occupants' impact at different spatial scales

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### ABSTRACT

Buildings' users have widely been accepted as a source of uncertainty in building energy performance predictions. However, it is not evident that the diversity of occupants' presence and behavior at the building level is as important as at the room level. The questions are: How should occupants be modeled at different spatial scales? At the various scales of interest, how much difference does it make if: (1) industry standard assumptions or a dynamic occupant modeling approach is used in a simulation-based analysis, and (2) probabilistic or deterministic models are used for the dynamic modeling of occupants? This paper explores the reliability of building energy predictions and the ability to quantify uncertainty associated with occupant modeling at different scales. To this end, the impacts of occupancy and occupants' use of lighting and window shades on the predicted building lighting energy performance at the room and building level are studied. The simulation results showed that the inter-occupant variation at larger scales is not as important as at the room level. At larger scales (about 100 offices), the rule-based model, custom schedule model, and stochastic lighting use model compared closely for predicting mean annual lighting energy use.

### KEYWORDS

Occupant modeling approaches; Spatial resolution; Custom schedules; Rule-based models; Building performance simulation.

### INTRODUCTION

Occupants have widely been considered as a source of the gap between the predicted and measured energy performance of buildings (Menezes et al., 2012; de Wilde, 2014). Likewise, previous studies indicated that occupants' impact on the energy performance of buildings varies between occupants (Haldi and Robinson, 2011; Saldanha and Beausoleil-Morrison, 2012; Clevenger et al., 2014). This variation in occupants' presence and behavior may begin to cancel out their impacts on the energy use for larger buildings. Therefore, the stochastic nature of occupants' presence and behavior at the building level may not be as important as at smaller scales. A few studies challenged the notion of simulating the whole building's energy performance using the probabilistic modeling approach (Parys et al., 2011; Evins et al., 2016). This modeling approach has been widely used in studying occupants in a simulation-based analysis. However, it is not evident whether using this modeling approach at larger scales yields the wide range of occupants' impacts on the energy performance of a building as that at the room level. To address the gaps in the literature, the main objective of this paper is to systematically assess the impact of occupants on the energy performance of buildings at different spatial scales. The focus of this paper is on the domain of lighting use, though the general conclusions are expected to apply to other occupant-related domains. The methodology of this paper is to implement four occupant model forms for the lighting use in a simulation-based analysis, while occupancy and window shade use domains are simulated using the probabilistic modeling approach. Simulation-based analysis of the impact of

occupant modeling approaches for occupancy and window shade use domains at different spatial scales has been previously presented (Gilani et al., 2018).

## OCCUPANT MODELING

For the analysis of the impact of occupants at different spatial scales, a simulation-based analysis methodology was implemented. As there is little consensus on which occupant modeling approach best represents occupants' impacts on the energy performance of buildings in a simulation-based analysis (Mahdavi and Tahmasebi, 2015), four modeling approaches have been used in the current study for the domain of lighting use. Occupant modeling approaches can be categorized as: (1) static versus dynamic, and (2) deterministic versus probabilistic. Dynamic models represent the two-way impact that occupants and building can have on each other, whereas static models neglect this impact. Parameters of probabilistic models and generated numbers in Monte Carlo simulation method (Gilks et al., 1996) are chosen randomly for each simulated occupant and/or at each timestep. Therefore, outputs of probabilistic models may alter at each simulation run while results of deterministic models do not change every time they are simulated. The resulting four model types are shown in Figure 1. In this paper, both static/dynamic and deterministic/probabilistic approaches were implemented in simulation for the lighting use domain, however occupancy was modeled with the static-probabilistic modeling approach and window shade use was modeled using the dynamic-probabilistic modeling approach. For the static modeling of lighting use, standard and custom schedules were incorporated; whereas for the dynamic modeling of lighting use, stochastic and rule-based models were used. A brief description of the model forms which were implemented in simulation in this paper is provided in the following sections.

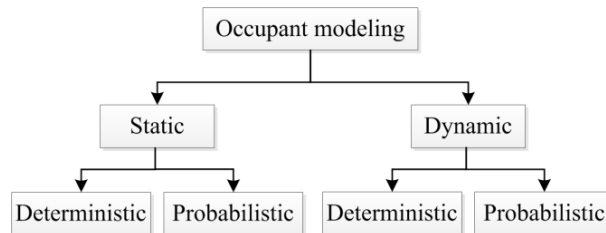


Figure 1. General categories of occupant modeling approaches.

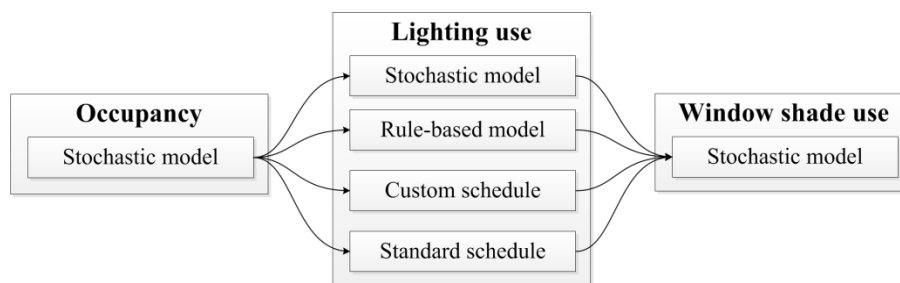


Figure 2. Four combinations of occupant model forms for occupancy and lighting and window shade use domains.

### Standard schedule

For the static-deterministic modeling of lighting use, the standard schedule from National Energy Code of Canada for Buildings (NECB) (National Research Council Canada, 2015), was used (Figure 3). NECB's (2015) lighting schedule is almost identical to the lighting schedule in ANSI/ASHRAE/USGBC/IES Standard 189.1 (2014).

### Custom schedule

Custom schedule was the other model form that was used for the static-deterministic modeling of lighting use. To develop custom lighting use schedules, 100 annual run periods of the stochastic models (as described later) were simulated using the Monte Carlo simulation method (Gilks et al., 1996). The hourly ratio profiles of lights-on during occupied or unoccupied periods on weekdays were generated based on the outputs of the 100 simulation run periods. To this end, the hourly lights-on ratios during occupied or unoccupied periods were calculated for each of the 100 annual run periods. The mean hourly lights-on ratios during occupied or unoccupied periods were computed using the weighting method based on the total occupied or unoccupied hours of each simulated office (Figure 3).

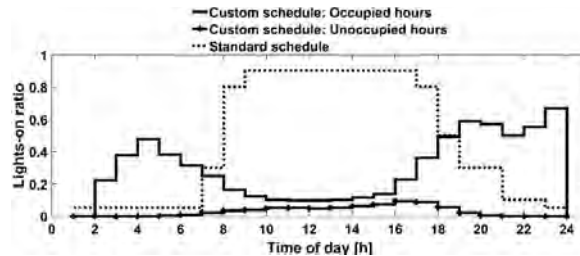


Figure 3. Hourly custom schedules for lights-on ratio during occupied and unoccupied hours and standard schedule.

### Rule-based model

A rule-based model, which consists of thresholds to trigger occupants' manual light switch-on actions, was developed for the dynamic-deterministic modeling of light switch-on actions. Lights were set to be turned off automatically with a 30-minute time delay. The workplane illuminance ( $E_{in}$ ) was considered as the predictor for the light switch-on actions (Hunt, 1979; Reinhart and Voss, 2003; Haldi and Robinson, 2010; Gunay et al., 2017). The thresholds for light switch-on actions were calculated based on the outputs of the 100 annual run periods of the stochastic models (as described next). To this end, a wide range of plausible values were systematically set for thresholds until the annual lighting energy use of 100 annual simulations were almost identical to the results of 100 simulations using the stochastic models.  $E_{in}$  was obtained 500 and 950 lx for light switch-on actions upon arrival and during intermediate periods, respectively.

### Stochastic model

For the probabilistic modeling of the considered domains in this paper, three existing stochastic models were implemented: (1) Page et al.'s (2008) occupancy algorithm, (2) Gunay et al.'s (2017) light switch-on model, and (3) Haldi et al.'s (2016) window shade use model. For the occupancy domain, daily presence profiles and mobility parameters, which are required inputs for Page et al.'s (2008) occupancy algorithm, were generated using 17 months' worth of data collected in 24 offices in an academic building. Similar to O'Brien et al.'s (2016) study, a three-mode Gaussian mixture model (GMM) was fit to the profiles of daily occupied ratio for each monitored office. The probabilities of turning on lights and opening or closing window shades were estimated using the generalized linear model (GLM). Lights were assumed to be turned off automatically with a 30-minute time delay.

## SIMULATION

For each of the four combinations of the model forms (see Figure 2), 150 annual run periods were simulated. This number was determined as the results of a sensitivity analysis of 1000 annual simulation runs showed that the coefficient of variation of the lighting electricity use

on the sample sizes of larger than 150 offices was less than 10%. The parameters of the occupancy and light switch-on models were generated randomly from the normal distribution of the required variables with the mean value and the covariance of the variables. The diversity approach proposed by O'Brien et al. (2016), which is based on keeping the joint variability between each pair of parameters, was used to address the variations in occupants' presence and lighting use. To consider the diversity in window shade use, Haldi et al.'s (2016) approach on using generalized linear mixed model (GLMM), was implemented.

A typical office space located in Ottawa, Canada, was simulated in RADIANCE-based daylighting tool DAYSIM (Reinhart, 2001) to calculate the workplane and ceiling illuminance in the simulated office for a typical year. To simulate indoor illuminance at partial shade movements using Haldi et al.'s (2016) window shade use model, five shade positions were simulated: fully open, quarter closed, half open, quarter open, and fully closed. Occupant models were implemented in MATLAB, where the DAYSIM daylighting simulation outputs were used as inputs. The timestep for the simulation in DAYSIM and MATLAB was set as 5 minutes. The office space had the dimensions of  $W \times L \times H = 4.0 \times 4.0 \times 3.0$  m. The exterior south-facing window of the office had the width of 2.4 m and the height of 2.0 m with the sill height of 0.8 m. The reflectance of the floor, walls, and ceiling were set as 0.2, 0.5, and 0.8, respectively. The window glazing was assumed to have the visible transmittance of 0.44 and the visible transmittance of the window shade was assumed to be 0.2.

## RESULTS AND DISCUSSION

Figure 4 shows the mean of the annual lighting electricity use for when the stochastic models were implemented for occupancy and window shade use, whereas four light switch-on models were implemented for lighting use (see Figure 2). Figure 4 also shows the coefficient of variation ( $CV$ ) of the annual lighting electricity use, which is the ratio of the standard deviation to the mean annual lighting electricity use. For each of the considered number of offices, samples of offices were chosen randomly with replacement and with the size equal to the corresponding number of offices from the 150 offices. Figure 4 indicates that the annual lighting energy use averaged across the 150 simulated offices was predicted to be about 2.3 kWh/m<sup>2</sup> when the stochastic and rule-based models and custom schedule were used for light switch-on events. With the standard lighting schedule, which does not give credit for daylight, the lighting use was predicted to be about three times as much as the stochastic light switch-on model. Figure 4 shows that the average annual lighting energy use in random sampling of different numbers of offices gives similar values after a given number of offices. The standard deviation of the annual lighting energy use did not change significantly after a given number of offices as well. These observations follow the *Central Limit Theorem*. Note that since the stochastic occupancy model was used, the lighting energy use varied when the static-deterministic lighting use models were used.

To find the number of offices at which the mean annual lighting energy use approached a consistent value, the  $CV$  was calculated. The obtained  $CV$  indicated that the occupant modeling approach highly influences the office building size at which the standard deviation fell below 10% of the mean lighting energy use. The rule-based model and custom schedule for lighting use provided a similar prediction of the annual lighting energy use to the stochastic model. However, they require a smaller number of offices to provide a good approximation of the lighting use of a larger office building (Table 1).

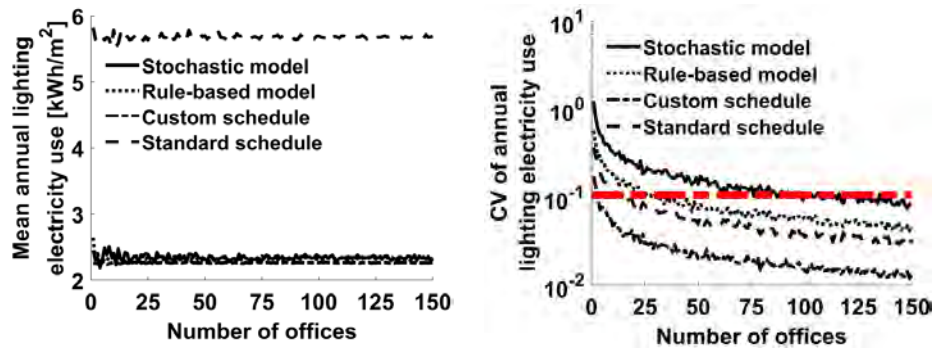


Figure 4. Annual lighting electricity use of samples with different sizes based on the simulation results of 150 annual run periods. Red dashed line represents  $CV$  of 10%.

Table 1. Number of offices at which lighting electricity use approached a consistent value with different modeling approaches for occupants' lighting use.

Lighting use model	Number of offices	Mean lighting electricity use of 150 offices (kWh/m <sup>2</sup> )
Stochastic model	87	2.3
Rule-based model	30	2.3
Custom schedule	3	2.3
Standard schedule	17	5.7

## CONCLUSION AND FUTURE WORK

This paper evaluated how the variations in occupants' presence and behavior can affect the predicted lighting electricity use at different spatial scales under different occupant modeling approaches for lighting use.

The results indicated that while occupants have been considered as an uncertainty source in the prediction of building energy performance, the inter-occupant variations at larger scales is not as important as at the room level. Therefore, building engineers may not need to be concerned about inter-occupant diversity in large office buildings if their objective of simulating buildings is to reliably predict the average annual lighting energy use of buildings. However, stochastic models still play an important role in a simulation-based design, such as evaluation of the robustness of a particular design. The results of this paper indicated that rule-based lighting use model and custom lighting use schedules can reasonably represent occupants' impact on the energy performance of buildings at larger scales. For an office building which is comprised of more than 100 private offices, rule-based lighting use model and custom lighting use schedules can be used instead of stochastic models to provide a good approximation of the lighting electricity use of the office building.

This research assumed that the lighting use of each office was controlled independently. However, one control system may be used for a group of offices. Future research on the impact of the number of offices which are controlled together is necessary. Impact of variation in occupants' characteristics, such as occupants' age, gender, and profession, at different spatial scales should also be studied.

## ACKNOWLEDGEMENT

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