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

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ABSTRACT

Occupants account for a significant impact on building performance through their interactions with zone level building components. Empirically-derived occupant models, despite their potential to represent occupants' impact in building performance simulation (BPS), have minimal penetration in design and code compliance processes. Instead, occupants are represented with static schedules or simple deterministic triggers. The objective of this paper is to better understand the influence of assumptions made in representing occupant interactions with building components over a BPS model's energy use and comfort predictions, as well as their ability to promote better design decisions. To this end, the energy and daylight performance of a generic perimeter office space in Ottawa, Canada were evaluated using a set of comprehensive performance metrics. Results indicate that representing dynamic occupant–building interactions lead to different energy predictions from the static schedules. The maximum difference in the total electricity use was for window-to-wall area ratios (WWR) of 20%, which was about 30% higher with the stochastic cases than the blind-open static cases. WWR 60% and 40% generally yielded the lowest lighting electricity use with the static and stochastic cases, respectively. This paper emphasizes the importance of incorporating empirically-derived dynamic occupant models for simulation-aided design and code compliance.

1. Introduction

Occupants have a significant impact on energy performance of buildings due to their operation of windows, use of shading devices, lighting control, and thermostat adjustment (e.g. [1–4]). Despite the active role of occupants on building performance, designers usually treat occupants as passive agents in the design process by implementing simplistic schedules in building performance simulation (BPS) tools. However, occupants behave differently from what designers indicate through modeling assumptions (e.g. [5,6]). Occupants frequently respond to discomfort to restore comfort in the easiest way, rather than an energy-efficient way. They are often not as knowledgeable or conscious of building's energy performance as designers expect from them (e.g. [7]). In addition, some building systems are difficult for users to understand and/or operate. Therefore, a gap between the real and the predicted building performance arises.

Increasingly, design practice and code compliance are relying on BPS tools to predict energy performance and comfort [8,9]. For code compliance, the model is often expected to predict performance relative to a reference scenario. However, the amount of energy savings relative to the reference building may be inaccurate since current simulation tools report occupants' discomfort without considering occupants' adaptiveness and reactions to discomfort situations [10]. This places little incentive for simulation-aided designers to design for comfort. To account for the important role of occupants on building performance, dynamic interactions between a building and its occupants should be considered using appropriate occupant behavior (OB) models in the design process. These OB models can be empirically-based and developed from long-term field studies to represent the dynamic interactions between occupants and buildings. There are two possible risks associated with the use of inappropriate OB models and assumptions: (1) energy and other predicted performance results can be inaccurate, but perhaps more critically, (2) the results could mislead designers to make sub-optimal design decisions.

Bonte et al. [4] investigated the impact of occupants' actions on building energy performance and thermal comfort in two different climates by defining two extreme conditions for each of the occupants' actions. They concluded that conventional modeling assumptions underestimate building energy use and overestimate occupants' comfort. Parys et al. [3] implemented stochastic OB

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models in building energy simulations to optimize multiple offices in a commercial building and concluded that energy consumption predicted using the conventional assumptions is higher than that of the stochastic occupant models. However, Parys et al. [1] drew an important conclusion in a similar study that the uncertainty of single office performance reported by other research may exaggerate total uncertainty because of the diversifying effect of multiple offices at building scale.

Hoes et al. [11] analyzed the effect of occupant models in the building design process and performed a sensitivity analysis of different design parameters to OB modeling. They concluded that optimization of a building design is achievable by incorporating improved OB modeling in building energy simulation during the design process. Detailed simulation analysis by Tzempelikos and Athienitis [12] on optimal window size in single-person offices in Montreal showed that without movable shading, the improvement in daylight autonomy was significant for up to window-to-wall area ratios (WWR) of 30% and 50%. Beyond mid-sized windows, there was little improvement to daylighting. Shen and Tzempelikos [13] found the same optimal WWR as Tzempelikos and Athienitis's [12] study with automated shading control, for Los Angeles and Chicago. However, it remains unclear how manual blind use affects optimal WWR. In previous research (e.g. [13–18]), the effect of manual blind use on the predicted building energy use and thermal comfort has been studied. More recent developments such as the blind modeling efforts of Haldi and Robinson [19] and the research by Reinhart and Wienold [20] for a combined analysis of daylighting and thermal performance, demonstrate how different manual blind control strategies affect energy use, visual comfort, and view to the outdoors.

Balancing adequate daylight with minimized visual discomfort is a non-trivial task because ensuring adequate daylight levels during overcast period requires larger windows than during sunny periods. But large windows may cause chronic daylight glare and can have major energy use implications [21,22]. Thus, a considerable number of studies (e.g. [12,20]) have focused on assessing façade and controls design using holistic annual performance metrics – considering both comfort and energy – instead of instantaneous daylight analysis under just a handful of sky conditions.

Despite the previous studies, even simplistic consideration of blinds to assess views and daylight availability is not commonplace for simulation-based design. Current modeling guidelines, codes, standards, and rating schemes and metrics regarding daylight and views, all too often focus on potential for daylighting rather than real performance. As eloquently stated by Reinhart et al. [18], simplistic metrics can lead to designers using "the more the better" rationale for large windows. Clearly, inclusion of blinds would not improve views or daylight availability; though they could mitigate against daylight glare and reduce cooling energy use. Since Reinhart et al.'s [18] paper, newer versions of the Leadership in Energy and Environmental Design (LEED) have adopted more representative metrics, including spatial daylight autonomy and annual sunlight exposure [23]. However, previous efforts (e.g. [18,20]) have used mostly deterministic occupant models and therefore, questions over real OB control of blinds and diversity modeling remain. For instance, Van Den Wymelenberg [24] and O'Brien et al. [25] reported that in reality mean shade occlusions of the numerous studies that have been performed range from 10% to 90% and that while some occupants move their shades more than once per day, frequencies of weekly or less are not uncommon. This is in significant contrast to the more common, optimistic modeling assumptions. Due to the rare implementation of stochastic occupant models in design practice, research about the effect of these models on comfort and building energy performance still has a great potential.

This paper attempts to identify how different OB modeling approaches affect predicted energy use and comfort; and, how these approaches may influence design decisions. The next section discusses the methodology used to develop a case study in Ottawa and provides an overview of modeling and simulation practice with regards to occupants. Then, the daylight performance and energy results are analyzed using a comprehensive set of existing and developed metrics. Afterwards, the limitations of the study are discussed and the recommendations for future simulation practice are outlined. This paper concludes that representing occupant interactions with building components using dynamic occupant models is imperative for simulation-supported design and code compliance to provide more accurate predicted building performance and near-optimal design solutions.

2. Methodology

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

2.1. Occupant behavior models

To study the impact of stochastic occupant behaviors on building design, three empirically-driven probabilistic occupant models were implemented in the EMS feature of EnergyPlus using the scripts available in Gunay et al. [26]. These models are as follows: (a) Wang et al.'s [27] presence model, (b) Reinhart's [28] light switch model, and (c) Haldi and Robinson's [19] blinds use model. Wang et al.'s [27] presence model allows for an approximation of the vacancy periods instead of assuming constant values for the breaks and lunch periods. Reinhart's [28] light switch model permits light switch-on actions at any time of the occupied period. Haldi and Robinson's [19] blind use model allows for partial or full opening or closing blind events at any time of the occupied period.

Because the models are stochastic, a Monte Carlo analysis was conducted over a synthetic occupant population. Note that stochastic modeling of the occupancy was necessary for this study, because lighting and blind use depend on the arrival and departure times and the intermediate vacancy durations. Each of occupant models used in this study is briefly explained below.

Based on Wang et al.'s [27] model for occupancy, the arrival, departure, break times, and the duration of breaks were randomly generated for each day. In this study, the mean arrival and departure times were assumed 9:00 and 17:00, with a standard deviation of 15 min. Mean lunchtime and two breaks times were assumed to start at 12:00, 10:30, and 15:00, respectively, with a standard deviation of 15 min. The mean vacancy period for two breaks and lunchtime were assumed 15 min and 1 h, respectively. The vacancy periods were generated randomly for each day using an exponential probability distribution as described in Wang et al.'s [27] model.

According to Reinhart's [28] Lightswitch-2002 model for lighting, the probability of light switch-on events was modeled as a function of the workplane illuminance. Based on this model, observing a light switch-on action upon arrival was modeled to be more likely than it was during intermediate occupancy periods. The light switch-off events are permitted to occur only in the time step at departure (including intermediate departures). The chances a simulated occupant turns off the lights were modeled to increase as a function of the duration of absence following a departure event [29].

Haldi and Robinson's [19] blind use model provides a series of logistic regression models as a function of the workplane illuminance and initial blind position to predict the probability of the occupant's action for changing the blind position at arrival and during the intermediate period. If the model predicts that the occupant changes the blind position, it determines whether the occupant will fully open or close the blind based on a series of logistic regression models that depend on outdoor global horizontal illuminance and current blind position. But, if the model predicts a partial blind movement, the magnitude of the movement is sampled from a Weibull distribution. The equations and the regression parameters for Haldi and Robinson's [19] blind use model are presented in Appendix A.

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

2.2. Energy and daylight simulation

Simulations performed for this study included creating a typical office model in EnergyPlus and DAYSIM 3.1 [30]. EnergyPlus was used to evaluate the energy performance of the simulated office space. It should be noted that EnergyPlus also provides the illuminance map for the daylighting analysis in a zone with hourly time steps. However, in this study, DAYSIM was used as a more accurate daylighting analysis tool [31]. The stochastic occupant models were implemented in EnergyPlus, with 5-min time steps. For simulating partially-open blind using Haldi and Robinson's [19] blind use model in EnergyPlus, the blind positions were discretized into five positions: fully open, 1/4, 1/2, and 3/4 closed, and fully closed. This compromises between accuracy and computational cost. Since EnergyPlus is limited to just two blind positions (i.e. open/closed), the window was modeled with four identical vertically stacked pieces. It is worth noting that the properties of window assembly required in EnergyPlus were calculated using WINDOW 7.3 [32] (described in Section 2.4).

To analyze the indoor daylight illuminance, annual simulations were performed in DAYSIM 3.1 [30], with hourly time steps as per IES LM-83-12 [23]. In DAYSIM, to calculate the diffuse sky illuminance, the celestial hemisphere is divided into 145 rectangular sky segments that completely cover the celestial hemisphere without any overlap. DAYSIM calculates the direct daylight coefficients for 65 representative sun positions based on the latitude for when the sun is up throughout the year. The direct daylight coefficients for other sun positions are interpolated using the 4 representative sun positions that circumscribe the sun position at other times of the year [33].

The daylighting and energy simulations were coupled using MATLAB. The indoor illuminance was calculated for the five blind positions for the studied WWRs and for the three design options (explained in Section 2.4) using the static shading device in DAYSIM. With knowledge of the blind position from EnergyPlus for each design case at each hour, the indoor illuminance was extracted from the output files generated for that blind position at that hour using DAYSIM. For the blind-closing trigger as per IES LM-83-12 [23] (explained in Section 2.3), the indoor illuminance from direct sunlight obtained using DAYSIM for the 64 points (explained in Section 2.3), were defined as schedules for blind-open and closed positions in EnergyPlus. Based on a script in the EMS feature of EnergyPlus, the blind was closed whenever more than one analysis point of the 64 points received at least 1000 lx direct sunlight.

2.3. Performance metrics

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

- Annual lighting, heating, and cooling energy use intensity (kW h/m^2).
- Annual electricity use intensity (kW h/m^2) assuming a coefficient of performance (COP) of 3. This assumption was made to approximate the electricity use for heating and cooling.
- Useful daylight illuminance ($UDI_{100-2000}$); $UDI_{100-2000}$ is the percent of occupied times when the workplane illuminance is between 100 and 2000 lx [34]. It is calculated based on the following equation:

$$UDI_{100-2000} = 100 \times \frac{\sum_{time=1}^{n} \begin{cases} 1 & \text{if } 100 \le E_{in} \le 2000, \quad \text{presence} \\ 0 & \text{otherwise} \end{cases}}{\sum_{time=1}^{n} \begin{cases} 1 & \text{if presence} \\ 0 & \text{otherwise} \end{cases}} \quad (1)$$

where E_{in} is the indoor illuminance (lx) and presence is when there is an occupant in the office.In this paper, $UDI_{100-2000}$ was evaluated on the illuminance map which had 8×8 cells, each cell with dimensions 0.5×0.5 m, at a height of 0.8 m. The illuminance sensors were located at the center of each cell. First, for each cell of the illuminance map, the $UDI_{100-2000}$ was calculated using Eq. (1) and then, the median of $UDI_{100-2000}$ on all cells (% of occupied period) was computed.
- $UDI_{<100}$ and $UDI_{>2000}$; $UDI_{<100}$ is the percent of occupied times when the workplane illuminance is less than 100 lx (i.e. the space is dark). $UDI_{>2000}$ is the percent of occupied times when the workplane illuminance is higher than 2000 lx (i.e. the space is too bright).
- Daylight Autonomy (DA); the percent of occupied period when the workplane illuminance is sufficient [18]. In this study, the required minimum workplane illuminance for the office space was assumed 300 lx which represented a useful indicator of annual daylight illuminance performance in IES LM-83-12 [23].
- Spatial Daylight Autonomy ($sDA_{300,50\%}$); the percent of floor area that receives at least 300 lx for at least 50% of occupied hours. For this metric, if the Annual Sunlight Exposure (explained next) is not below the required threshold, blinds are controlled hourly to prevent direct sunlight penetration into the space. This daylight metric is approved by IES LM-83-12 [23] and is required in LEED Version 4.0 [35] to receive the daylight credits. Spatial daylight autonomy must meet at least 55 and 75% of floor area for a 'nominally acceptable' and 'favorably/preferred' space, respectively. Based on IES LM-83-12 [23], for an analysis area smaller than 200 ft^2 (18.6 m^2), the hourly blind-closing trigger occurs whenever more than one analysis point on a 2×2 ft (0.6×0.6 m) grid receives at least 1000 lx direct sunlight. In this study, $sDA_{300,50\%}$ was applied to the static occupant modeling with the blind trigger as per IES LM-83-12 [23]. Also, it was applied to the blind-open/closed static and stochastic cases (as explained in Section 2.4) to investigate the daylight performance of these manual blind controls based on $sDA_{300,50\%}$. In the current study, $sDA_{300,50\%}$ was evaluated for the illuminance map (as described for $UDI_{100-2000}$). For the calculation of spatial daylight autonomy, first the daylight autonomy at the center of each cell was calculated based on Eq.

(2). Then, the spatial daylight autonomy was calculated based on Eq. (3) as follows:

$$\mathrm{DA_{cell}} = 100 \times \frac{\sum_{\mathrm{time}=1}^{n} \begin{cases} 1 & \text{if } E_{in} \geq 300, \text{ presence} \\ 0 & \text{otherwise} \end{cases}}{\sum_{\mathrm{time}=1}^{n} \begin{cases} 1 & \text{if presence} \\ 0 & \text{otherwise} \end{cases}} \quad (2)$$

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

$$\mathrm{sDA_{300,50\%}} = 100 \times \frac{A_{\mathrm{cell}}}{A_{\mathrm{floor}}} \times \sum_{\mathrm{cell}=1}^{n} \begin{cases} 1 & \text{if } \mathrm{DA_{cell}} \geq 50\% \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

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

- Annual Sunlight Exposure ($\mathrm{ASE_{1000,\,250\,h}}$); the percent of floor area that receives higher than 1000 lx direct solar radiation for at least 250 occupied hours. This daylight metric is also approved by IES LM-83-12 [23] and is required in LEED Version 4.0 [35] for the evaluation of daylight performance and only applicable to blind open position. In the current study, this metric was applied to the stochastic and static cases with blind open position and the blind trigger as per IES LM-83-12 [23]. According to IES LM-83-12 [23], $\mathrm{ASE_{1000,\,250\,h}}$ must be less than 10% of floor area. In this study, the evaluation of $\mathrm{ASE_{1000,\,250\,h}}$ was performed for the illuminance map (as explained for $\mathrm{UDI_{100-2000}}$). It should be noted that for calculating direct sunlight in DAYSIM, the indoor illuminance was simulated using a zero-bounce method (to eliminate the reflection from other surfaces) with only the direct irradiance in the weather file (to exclude the diffuse sky component). For the calculation of annual sunlight exposure for the whole illuminance map, first the annual sunlight exposure at the center of each cell was calculated according to Eq. (4). Then, the annual sunlight exposure ($\mathrm{ASE_{1000,\,250\,h}}$) (% of floor area) for the whole space was calculated based on Eq. (5) as follows:

$$\mathrm{ASE_{cell}} = \sum_{\mathrm{time}=1}^{n} \begin{cases} 1 & \text{if } E_{\mathrm{in,\ dir}} > 1000, \text{ presence} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

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

$$\mathrm{ASE_{1000,250\,h}} = 100 \times \frac{A_{\mathrm{cell}}}{A_{\mathrm{floor}}} \times \sum_{\mathrm{cell}=1}^{n} \begin{cases} 1 & \text{if } \mathrm{ASE_{cell}} \geq 250 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

2.4. Description of models

For evaluating comfort and energy use under the different occupant models, a parametric study was performed. The parameters that were determined for this study were: WWR (design option 1), window type (design option 2), and blind transmittance (design option 3) (Table 1). To this end, the baseline model for EnergyPlus simulation was developed in OpenStudio using the template for office spaces in the climate zone 6A based on ANSI/ASHRAE/USGBC/IES Standard 189.1 [36]. The model's location was assumed Ottawa, Canada where winters are cold, summers are warm and humid, and it is generally sunny year round. The heating and cooling degree days (with balance temperature 18 °C) for Ottawa are about 4200 °C day and 300 °C day, respectively. The annual horizontal solar radiation for Ottawa is about 1300 kW h/$\mathrm{m^2}$.

The office room had dimensions $W \times L \times H = 4.0 \times 4.0 \times 3.0$ m, with a south-facing window of different window-to-wall area ratios (WWR), including the window frame, which was between 20% and 60% in increments of 10%. The window's sill height was 0.8 m for all the analyzed WWRs (Fig. 1) as a typical window height from the floor. This study was conducted for just south-facing facades since most existing OB models were developed from observations for this orientation. The south wall was exposed to the outdoor environment, while all the other surfaces of the room were adjacent to spaces with the same thermal conditions. The visible reflectance of the interior surface of the floor, walls, and ceiling were assumed to be 0.2, 0.5, and 0.8, respectively. The window was assumed to be fixed with thermally-broken aluminum framing with a U-factor of 5.79 W/$\mathrm{m^2}$ K [37] and profile width of 6 cm, regardless of WWR. The window frame was assumed to be just around the whole area of the window, without any dividers. Two glazing systems were considered; where the glazing systems for design options 1 and 3 were the same and modeled on the basis of ANSI/ASHRAE/IES Standard 90.1 [38] (Table 1). The properties of the glazing systems and different WWRs were calculated using WINDOW 7.3 [32].

Two kinds of interior blind were modeled in the parametric study, where the blind types for design options 1 and 2 were identical (Table 1). It is worth noting that Tzempelikos and Athienitis [12] concluded that a transmittance of 20% presented the optimal daylight and energy performance, though this value should be 5% if glare is to be kept at a minimum. Therefore, the current work considered 20% transmittance as the second blind alternative.

The office was assumed to be occupied by one person during the occupied period. For the static schedules, the occupied periods were 9:00 to 12:00 and 13:00 to 17:00. Note that a daylight savings period, starting on the 2nd Sunday in March and ending on the 1st Sunday in November, was applied to the annual run period. The internal heat gains from the occupant, lighting, and electric equipment were assumed to be 120 W, 8.8 W/$\mathrm{m^2}$, and 10 W/$\mathrm{m^2}$, respectively, during the occupied period. Lighting heat gain is based on the lighting power density provided in ANSI/ASHRAE/IES Standard 90.1 [38] for an office space. To control lighting for the static occupant modeling, it was assumed that lighting was on whenever daylight illuminance on workplane (E_{wp}) was less than 300 lx during the occupied period. Accordingly, daylight autonomy exactly corresponds with lighting electricity use. In this study, lights were controlled according to the illuminance at the center of the 0.8 m-high workplane. For the static occupant modeling, two blind settings, including fully open and fully closed, were considered. However, for the performance metrics $\mathrm{sDA_{300,50\%}}$ and $\mathrm{ASE_{1000,\,250\,h}}$ another blind setting based on IES LM-83-12 [23] with the static cases was also investigated. A summary of the occupancy schedule, and lighting and blind control for the static and stochastic OB modeling approaches are presented in Table 2.

Fresh air was supplied into the office room at a rate of 7.3 L/s based on ANSI/ASHRAE Standard 62.1 [39] during the occupied period. To reduce unnecessary mechanical cooling, outdoor air was introduced into the office space at a rate of 100 L/s when the minimum and maximum indoor temperature, minimum and maximum outdoor temperature, and the minimum difference between the indoor and outdoor temperature were 20 °C, 24 °C, 15 °C, 22 °C, and 2 °C, respectively. The infiltration rate into the office was assumed 0.3 air changes per hour (ACH) which is a common infiltration rate

Table 1
Fenestration system design parameters.

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

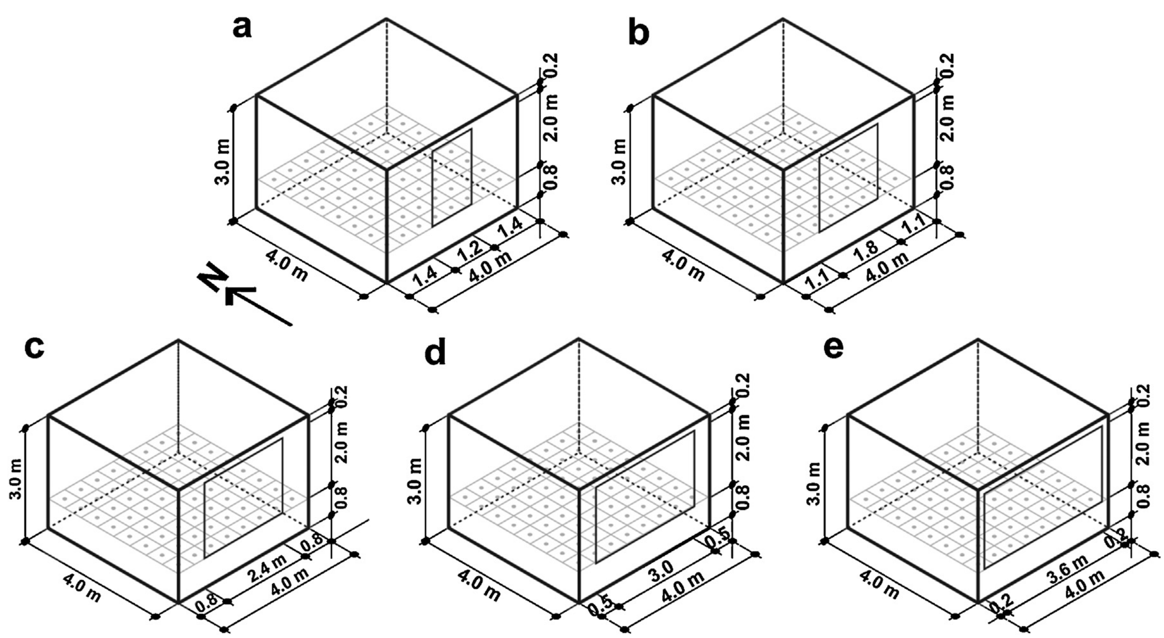

Fig. 1. Geometry of a generic office room with different window-to-wall area ratios (WWR): (a) WWR 20%, (b) WWR 30%, (c) WWR 40%, (d) WWR 50%, and (e) WWR 60%.

Table 2
Occupant presence and actions models for stochastic and static occupant modeling.

	OB model		
OB approach	Occupancy	Lighting control	Blind control
Stochastic	Wang et al. [27]	Reinhart [28]	Haldi and Robinson [19]
Static: blind open Static: blind closed Static: IES blind trigger	Weekdays: 9:00–12:00, 13:00–17:00	On if E_{wp} < 300 lx in occupied period; otherwise off	Always open Always closed Closed whenever more than 1 daylight analysis point receives at least 1000 lx direct sunlight

for office buildings (e.g. [40]). The HVAC equipment of the office was modeled as an air-based ideal load system with heating and cooling capacity of 1500 W as the focus of this paper is modeling occupants for early stage design. This heating and cooling capacity was chosen based on a preliminary sizing run. Heating and cooling setpoints were assumed to be: 21 °C and 24 °C during occupied hours, 15.6 °C and 26.7 °C during unoccupied hours. These setpoints were based on the template developed for office spaces in OpenStudio according to ANSI/ASHRAE/USGBC/IES Standard 189.1 [36].

3. Results

In this section, the annual daylight and energy performance of the three design options for five different window sizes (as explained in the previous section) are presented. The results include several performance metrics to evaluate how different OB modeling approaches affect the daylight and energy performance. Meanwhile, daylight metrics specified in IES LM-83-12 [23] are also computed, and the design strategies are compared to determine the effect of OB modeling approaches on simulation-supported design.

3.1. Daylight performance

Fig. 2 shows the distribution of $UDI_{100–2000}$ for the baseline design (design option 1) with different window sizes under the static and stochastic modeling approaches. This figure shows that for the blind-open static cases, a larger area near the window is affected by the window (i.e. lower $UDI_{100–2000}$ and higher $UDI_{>2000}$), especially for larger windows, compared to the stochastic cases. This is because occupants are more likely to close blinds if the window is larger. Fig. 2 also shows that for the blind-closed static cases, the regions of higher $UDI_{100–2000}$ is concentrated in the front zone of the space. On the contrary, for the stochastic and blind-open static cases, it is concentrated in the back zone of the space because the front of the space is often too bright (higher $UDI_{>2000}$).

The median of $UDI_{100–2000}$ on the 64 cells of the illuminance map is displayed in Fig. 3. Note that in all the graphs presented the results from stochastic cases, the error bars indicate the standard deviation of the 50 simulated occupants. For the stochastic and blind-open static cases, generally the larger the window, the less the median of $UDI_{100–2000}$. For the stochastic cases, this is due to the higher blind occlusion rates for larger windows as shown in Fig. 4 (i.e. higher $UDI_{<100}$), which is more noticeable with a glazing system with a higher VT (design option 2). However, for the static cases, this is due to higher $UDI_{>2000}$. Using a glazing system or a blind with a higher VT leads to lower $UDI_{100–2000}$ for larger windows with the stochastic and blind-open static cases and higher $UDI_{100–2000}$ with the blind-closed static cases. The stochastic cases predict a worse performance for smaller windows than the blind-open static cases, in contrary to larger windows. This is due to the blind closing actions with the stochastic modeling, which can reduce daylight performance for smaller windows, but helps improve daylight performance for larger windows.

The median DA on the 64 cells in the illuminance map is shown in Fig. 5. This figure indicates that the trends for DA for the stochastic and blind-open static cases are similar, with the exception of design option 2. The blind-open static cases significantly overestimate both the DA and the benefit of larger windows compared to the stochastic cases.

Fig. 6 displays the daylight performance of the studied design alternatives based on $sDA_{300,50\%}$. In this figure, in addition to the blind-open and closed static cases, another blind closing trigger for the static cases is shown, based on IES LM-83-12 [23]. It shows that the IES blind trigger cases will not deliver the required threshold for a nominally-acceptable space for WWR 20% with design options 1 and 3. The required credit for a favorably/preferred space is achievable with WWR 40%, 50%, and 60% under the IES blind trigger. Fig. 6 also shows that the blind-open static cases yields $sDA_{300,50\%}$ for more than 80% of the floor area for all the considered window sizes. However, the stochastic cases will not deliver the threshold for a nominally acceptable and favorably/preferred space for WWR 20% of design options 1 and 3, respectively. The stochastic cases predict favorably/preferred-daylit spaces for all the design alternatives with WWR 30–60%, which receive the most LEED points for new construction [35].

Fig. 7 shows the $ASE_{1000,\,250\,h}$ for the studied design alternatives. It shows that larger windows lead to higher values of $ASE_{1000,\,250\,h}$ for the stochastic and static cases. Generally, $ASE_{1000,\,250\,h}$ exceeds the maximum allowable threshold based on IES LM-83-12 [23] with the static and stochastic cases. The deviation between $ASE_{1000,\,250\,h}$ with the static and stochastic cases increases for larger windows due to higher blind occlusion rates. In this figure, the $ASE_{1000,\,250\,h}$ for static cases with blind closing trigger as per IES LM-83-12 [23] shows that WWR 20% with design options 1 and 2 deliver the require threshold. Furthermore, Fig. 7 shows that the stochastic cases predict better daylight performance than the blind-open static cases based on the $ASE_{1000,\,250\,h}$ metric because the occupants tend to close their blinds when daylight conditions are bright.

3.2. Energy performance

Figs. 8 and 9 display the annual heating/cooling and lighting energy use. The results indicate that heating and cooling loads generally increase with larger windows. However, using a glazing system with a higher SHGC and lower *U*-factor results in lower heating load and significantly higher cooling load for larger windows, especially for the blind-open static cases. Fig. 8 shows that the stochastic cases predict higher heating loads than that the blind-open static cases. Moreover, the blind-open static cases over-predict the cooling loads relative to the stochastic cases. The deviation between the stochastic and static cases generally increases with larger windows due to the higher blind occlusion rates. Fig. 8 also shows that the maximum standard deviation in the heating/cooling loads with the stochastic cases are 1 kW h/m^2, 3 kW h/m^2, and 1 kW h/m^2 for design options 1, 2, and 3, respectively. The low standard deviation in the heating and cooling loads is due to the fact that the annual mean blind occlusion levels were almost the same for each occupant and that the annual lighting only plays a small role in heating and cooling loads regarding the assumed internal heat gains from lighting and the annual lighting use in the current study. Thus, the annual level of resolution does not fully exhibit the stochastic nature of occupants. In addition, the mean annual blind occlusion for the 50 simulated occupants was generally a low value (i.e. about 0.2–0.3) and therefore, the effect of blind on the heating/cooling loads is minor. Moreover, other ways that occupants affect the heating and cooling loads, such as thermostat adjustment, window operation, and plug loads, were not modeled as stochastic in the current study.

As shown in Fig. 9, for the static cases, the larger the window, the lower the lighting electricity use. Therefore, the near-optimal window size with the blind-open static approach is WWR 60% from the perspective of lighting electricity use. However, the stochastic cases, where the dynamic occupant–building interaction is taken into account, yield different optimal window size. For design options 2 and 3, WWR 40% is the near-optimal design due to more frequent occupants' blind closing with larger windows. Fig. 9 also shows that using a glazing system or a blind with a higher VT leads to lower lighting electricity use for each corresponding window size with respect to the baseline design with the static cases. However, with the stochastic cases, using a glazing system with a higher VT leads to generally higher lighting use for larger windows, which is due to higher blind occlusion rates for larger windows relative to the baseline design. Using a blind with a higher VT results in lower lighting use.

Fig. 10 displays the annual total electricity use, including heating, cooling, and lighting. Note that this graph is based on a COP of 3 for providing heating and cooling loads. It shows that the energy use predicted by the static and stochastic cases diverges for smaller windows with design option 1 and 3. However, for design option 2, their predictions diverge for both the smaller and larger windows. This figure also indicates that WWR 20% is the near-optimal window size from an energy perspective for the blind-open static cases. However, with the stochastic cases, WWR 30%, of the considered window sizes is the near-optimal designs for design option 1 and 3. Furthermore, using a window with a higher SHGC and VT increases the annual total electricity use significantly for larger windows with the stochastic and blind-open static cases. In this case, closing the blind helps decrease the electricity use.

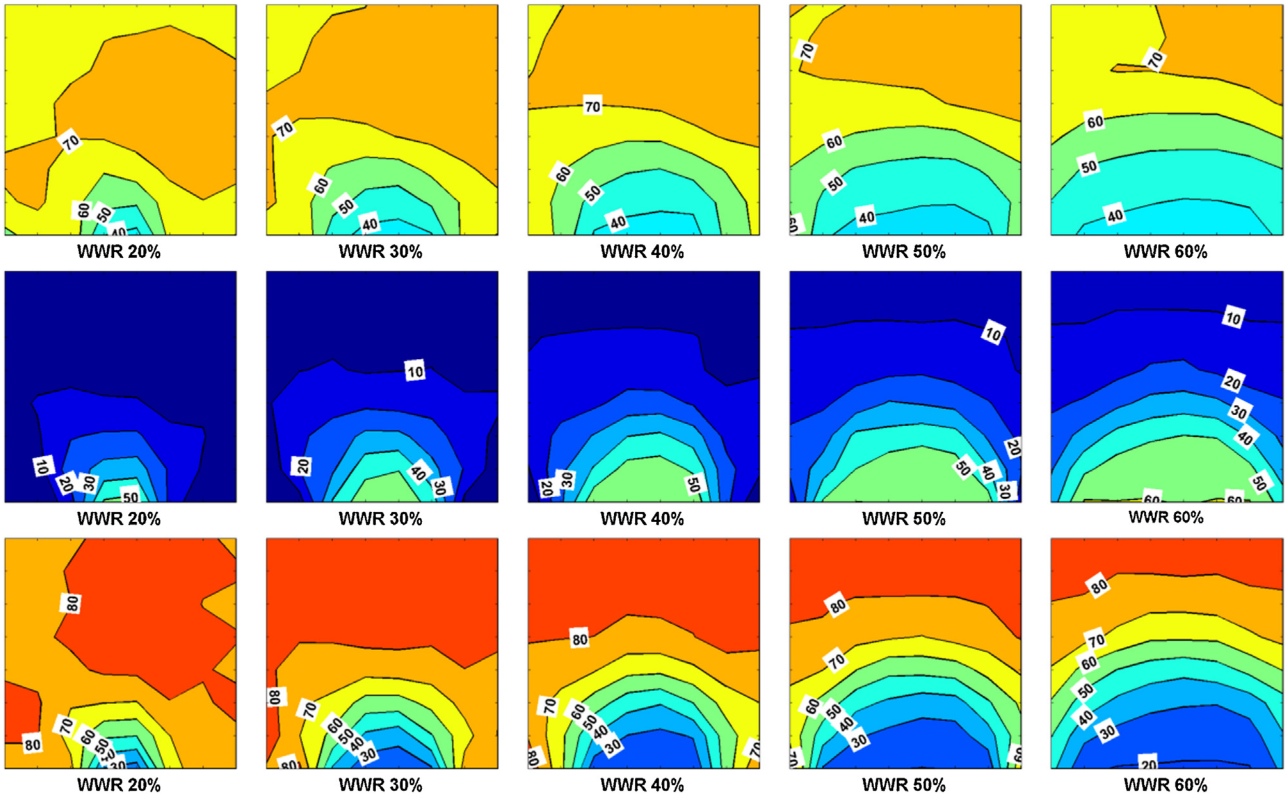

Fig. 2. Distribution of $UDI_{100–2000}$ (% of occupied period) for the baseline design under: stochastic OB modeling (top row), blind-closed static OB modeling (middle row), and blind-open static OB modeling (bottom row). (North is up and window is on the south side).

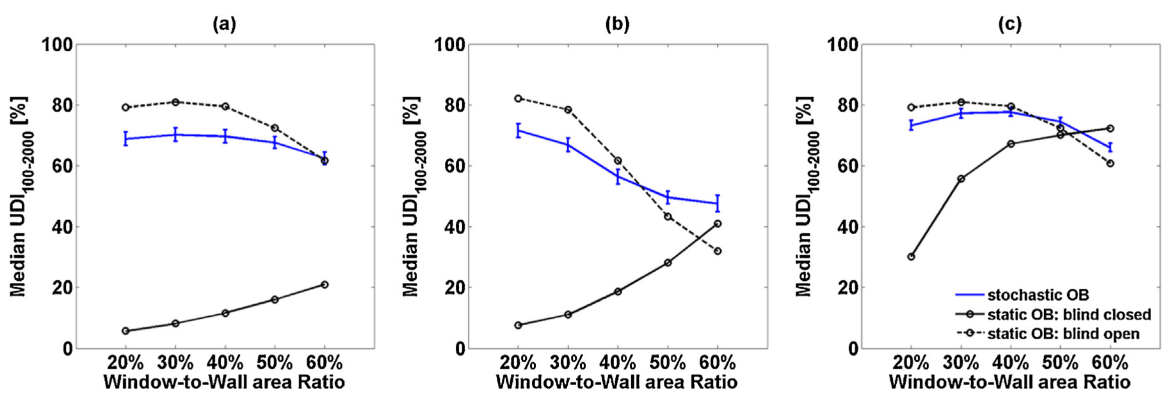

Fig. 3. Median of $UDI_{100–2000}$ (% of occupied period) under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

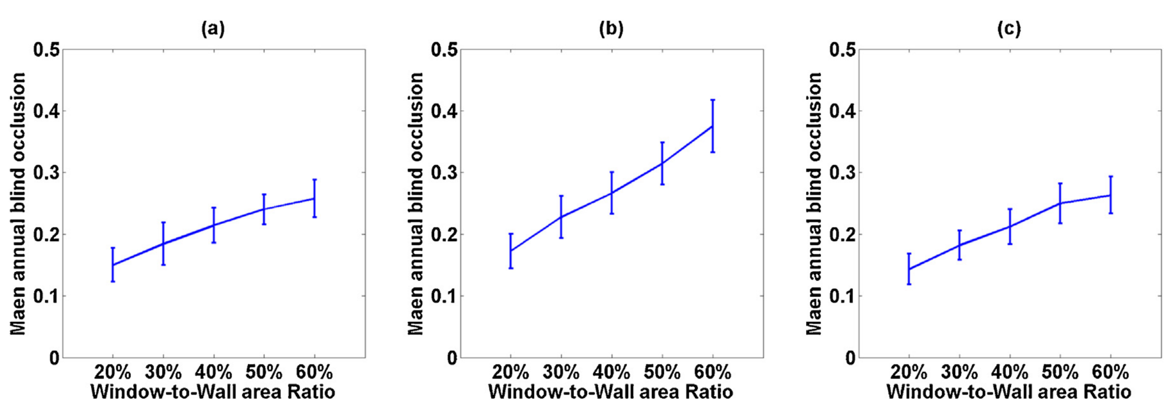

Fig. 4. Mean annual blind occlusion rate under stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

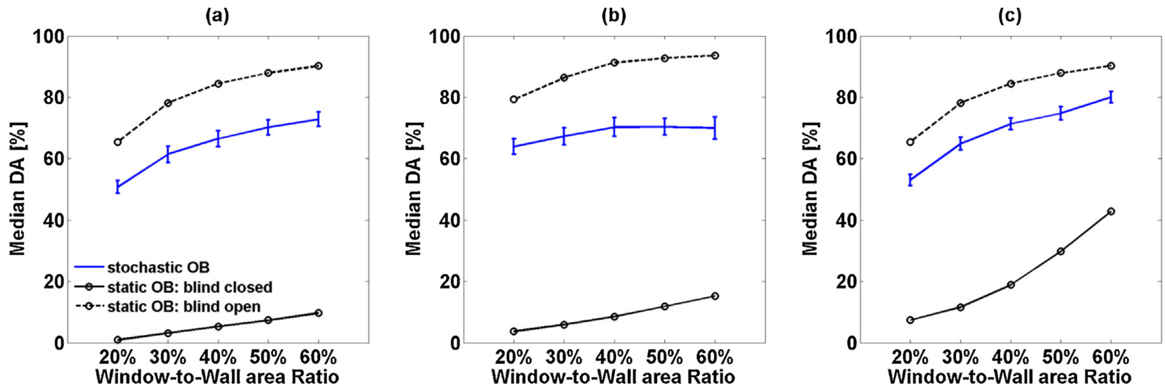

Fig. 5. Median of DA (% of occupied period) under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

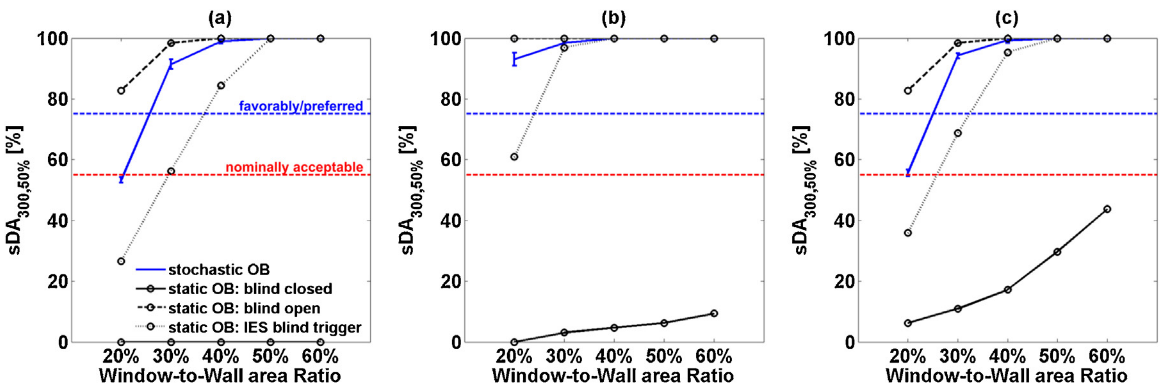

Fig. 6. $sDA_{300,50\%}$ (% of floor area) under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

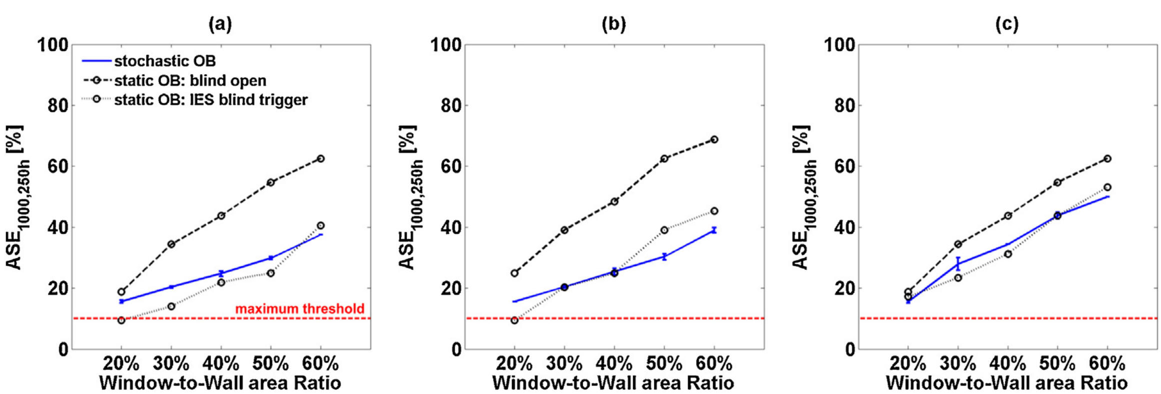

Fig. 7. $ASE_{1000,250\,h}$ (% of floor area) under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

4. Discussion

The results of this study indicate that there is a deviation between the conventional and stochastic OB modeling approaches in predicting the energy and daylight performance. Conventional occupant modeling failed to capture the influence of building design over occupants' behavior, and vice versa. The static and stochastic OB modeling approaches yielded different optimal design regarding energy consumption. However, they generally led to similar near-optimal designs from daylight perspective based on the set of daylight metrics used in this study. The results of this study necessitate more advanced OB models as requirements for code compliance modeling to prevent the two risks associated with the use of conventional occupant models: inaccurately predicted building performance and sub-optimal designs. Accordingly, the authors recommend that code and standards development committees, as well as simulationists, begin to examine stochastic and adaptive behavior models. While the research community has not yet converged on a set of specific models for each occupant action [6] (and it is not clear if they will or should), it is important for designers and simulationists to begin to think more carefully about the complex occupant–building interaction dynamics.

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

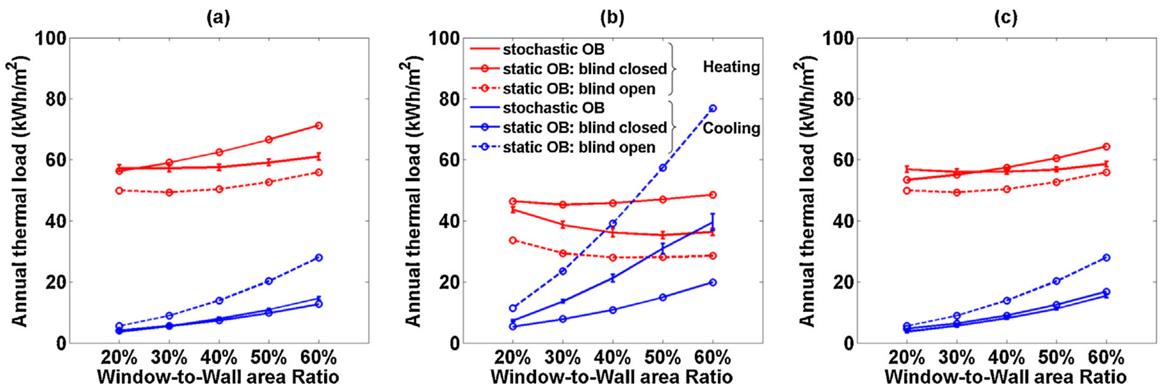

Fig. 8. Annual heating and cooling loads under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

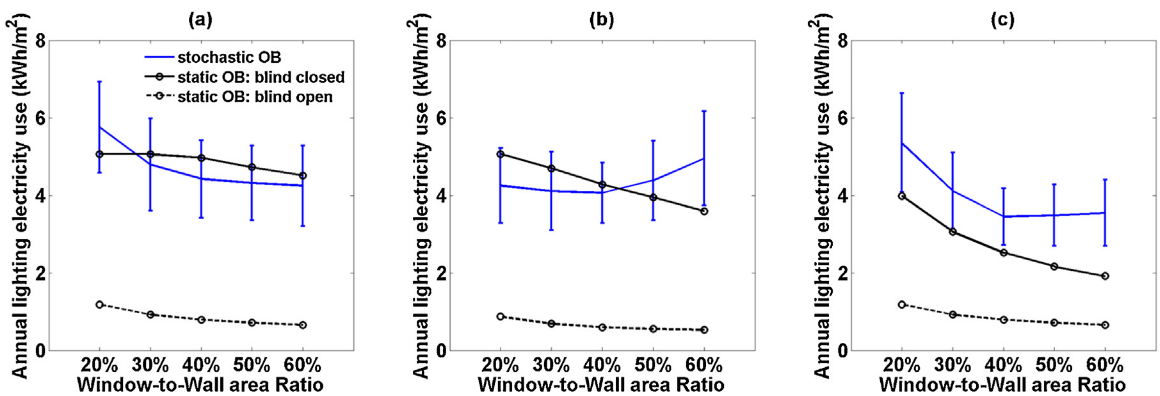

Fig. 9. Annual lighting electricity use under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

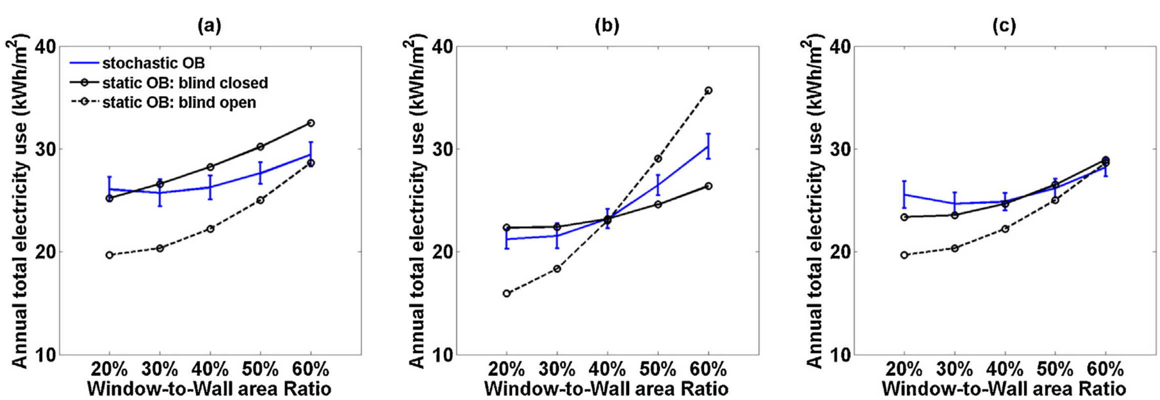

Fig. 10. Annual total electricity use under static and stochastic OB modeling for: (a) design option 1 (baseline design), (b) design option 2 (window type), and (c) design option 3 (blind transmittance).

4.1. Methodology limitation

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

- The threshold of 1000 lx for direct solar radiation in $ASE_{1000,250h}$ in IES LM-83-12 [23] may significantly over-predict glare compared to how occupants have been observed to react to daylight conditions. Reinhart and Voss [41] reported that in their study all the occupants closed their blinds to avoid direct solar radiation above 50 W/m^2 (~5000 lx). Haldi and Robinson's [19] blind use model indicates that the probability of closing the blind in the next 5 min for the indoor illuminance of 1000 lx is quite low (~1%). However, in Haldi and Robinson's [19] blind use model, the provided indoor illuminance included the diffuse and direct solar radiation (in contrast to $\mathrm{ASE}_{1000,\,250\,h}$, which includes only direct solar radiation). Also, the motivation for blind closing actions and positioning remains unclear, whether it was due to glare, thermal discomfort, effort to close the blind, privacy, and social constraints in shared office. Furthermore, if occupants are given some freedom over closing blind, their position, and orientation of their desk, daylight illuminance of 1000 lx is not necessarily a concern—particularly if it only occurs in a small portion of the space. It remains unclear whether it is appropriate to develop illuminance thresholds from blind closing observations, since some occupants may psychologically cope with daylight glare without acting. Therefore, it would be valuable to conduct laboratory and survey-based research on the direct solar radiation threshold that occupants find acceptable, with recognition of adaptive opportunities, such as relocating or reorienting.

- This study was performed on a model of a 4 by 4 m private office space with a single window. The results using $sDA_{300,50\%}$ for the static cases with the blind trigger as per IES LM 83-12 [23] indicate that daylight is generally adequate for WWR 40-60% to replace electric lighting for more than 50% of occupied hours in more than 50% of the office area. However, the $ASE_{1000,\ 250\,h}$ metric predicts daylight glare in more than 20% of floor area. In future studies, the same analysis should be performed for deeper spaces or on the whole building scale to investigate the effect of the space depth on the mentioned daylight metrics. Most existing stochastic OB models are limited in scope to small offices and not open-plan offices, therefore developing OB models for such spaces is a critical future research topic.
- This study was conducted for an interior blind and the low blind occlusion rates did not significantly affect the heating and cooling loads. It is necessary to investigate the impact of exterior blinds on the heating and cooling loads using stochastic occupant behavior models.
- In this study, a workflow between EnergyPlus and the indoor illuminance obtained from DAYSIM was developed in MATLAB. The whole simulation process in EnergyPlus, which included in total 795 annual run periods, was computationally heavy and time-consuming. More efficient tools workflows should be developed in the future so that design feedback can be provided quickly (e.g. at design charrettes). In addition, a user-friendly interface should be developed for the workflow between daylighting and building energy simulation engines and the OB models. Standard methods for visualizing stochastic performance predictions are also required, given that industry is accustomed to single and deterministic predicted performance results.

4.2. Occupant model limitation

In this study, three different models based on different monitoring contexts were incorporated. However, it is not clear whether the existing occupant models are applicable beyond their monitoring contexts (e.g. [42]), such as climate, building geometry, occupants, control systems, and interior layout. Future research should assess the predictive accuracy of the OB models in different contexts. The feasibility of combining different occupants models from different contexts for one space should also be evaluated in future studies. Each of the occupant models used in this study also imposed the following limitations on modeling occupant behaviors:

- Wang et al.'s [27] model for occupancy requires a certain number of prescribed break intervals. However, in reality the number of intermediate breaks should be modeled as stochastic.
- Haldi and Robinson's [19] blind use model was developed in peculiar cellular offices with motorized blinds for which the button was easily accessible. Also, there were internal vertical slat blinds and two external blind sets: upper and lower, where the upper one covered with an anidolic system to reflect external radiation. These characteristics may have increased the blind movement actions, especially the upper blind which did not obstruct the view to the outdoors.
- Reinhart's [28] Lightswitch-2002 model is dependent on the occupancy model's ability to predict the number and timing of the arrival events.
- Reinhart's [28] Lightswitch-2002 model and Haldi and Robinson [19]'s blind use model are based on illuminance at a single point. This assumption neglects daylight variations within the office and the occupant's ability to rotate or move as an adaptive measure to avoid glare or obtain more daylight.
- Reinhart's [28] Lightswitch-2002 model and Haldi and Robinson [19]'s blind use model were developed based on field surveys in offices with near-south facing windows. However, light and blind use models are affected significantly by window orientation (e.g. [43]). Therefore, the current study was limited to south-facing space. Development of light and blind use models for other orientations is necessary to perform dynamic OB simulation in design process for other orientations as well.

5. Conclusion

In this paper, the effect of conventional and stochastic OB modeling approaches on the energy and daylight performance in a simulation-based design was evaluated. The evaluation was conducted by employing EnergyPlus and DAYSIM models of a south-facing perimeter office space in Ottawa, Canada. The EnergyPlus models were used to represent the energy performance and the DAYSIM models were used to represent the daylight performance. The impact of several design parameters were compared using a set of comprehensive performance metrics. The results show the deviation between the conventional and advanced OB modeling approaches in the predicted energy and daylight performance. The stochastic OB modeling approach – by capturing the influence of design alterations over the occupant behavior and vice versa – can realistically predict energy and daylight performance. Therefore, this paper emphasizes the importance of incorporating more advanced OB models as requirements for code compliance modeling to prevent inaccurate predicted building performance and sub-optimal design decisions in the simulated-based design.

Specifically the following conclusions are drawn based on the parametric study performed:

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

Table A1
Regression parameters in Haldi and Robinson's blind model for action and fully closing/opening probabilities.

Occupant behavior		a	b_1	b_2	x_1	x_2
Upon arrival	Closing blind	-7.41 ± 0.16	$(10.35 \pm 0.19) \times 10^{-4}$	2.17 ± 0.16	Indoor horizontal illuminance	Unshaded fraction
	Opening blind	-1.520 ± 0.051	$(-6.54 \pm 0.46) \times 10^{-4}$	-3.139 ± 0.068	Indoor horizontal illuminance	Unshaded fraction
During presence	Closing blind	-8.013 ± 0.086	$(8.41 \pm 0.13) \times 10^{-4}$	1.270 ± 0.086	Indoor horizontal illuminance	Unshaded fraction
	Opening blind	-3.625 ± 0.030	$(-2.76 \pm 0.22) \times 10^{-4}$	-2.683 ± 0.040	Indoor horizontal illuminance	Unshaded fraction
Fully closing blind		-0.27 ± 0.14	-2.23 ± 0.16	–	Unshaded fraction	–
Fully opening blind		0.435 ± 0.062	$(0.91 \pm 1.33) \times 10^{-6}$	1.95 ± 0.11	Outdoor global horizontal illuminance	Unshaded fraction

stochastic cases generally suggest WWR 30% as the near-optimal window size.

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Appendix A.

Haldi and Robinson's [19] blind use model provides logistic regression models in the form of Eq. (1) to calculate the probability of occupants' action and fully blind closing/opening.

$$p = \frac{e^{a+\sum_{i=1}^{n} b_i x_i}}{1 + e^{a+\sum_{i=1}^{n} b_i x_i}} \tag{1}$$

where p is the probability, x_i is the predictor and a and b_i are the regression parameters as summarized in Table A1. If a fully closing/opening action is not taken place, the shaded fraction is determined from a Weibull distribution with a shape parameter ($\propto$) of 1.708 and scale parameter (λ) that depends on the current shaded fraction ($B_{L,\,\mathrm{init}}$) using the following equation:

$$\lambda = e^{-2.294+1.522 B_{L,\mathrm{init}}} \tag{2}$$

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