ON MODELLING AND SIMULATION OF OCCUPANT MODELS

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ABSTRACT

The selection of modelling and simulation methodologies plays an unprecedented role over the predictive accuracy of the data-driven occupant behaviour and presence models. In this study, different modelling and simulation formalisms emerging from the literature were introduced to represent occupant's presence and lighting use in building performance simulation (BPS) tools. Lighting use and occupancy models were developed and simulated in these formalisms by employing six months worth of observational data gathered in five private offices in an academic building. The modelling and simulation formalisms' ability to regenerate the patterns of the observational dataset were contrasted. When a discrete-event agent-based lighting use model was coupled with an agent-based occupancy model — whereby the events were defined as an arrival or a decrease in the indoor light intensity —, both the mean weekday lighting load and the frequency/timing of the light switch-on actions could be predicted more accurately.

INTRODUCTION

In many office buildings, the zone level building systems — window blinds, electric lighting, operable windows, terminal heating and cooling — can be controlled by occupants. The way these systems are used accounts for great uncertainty over a building's energy use and occupants' comfort (Reinhart 2004; Reinhart, Mardaljevic et al. 2006; Haldi and Robinson 2011). Therefore, without realistically representing occupant interacting components in BPS, it is less likely that we make meaningful performance predictions and appropriate design or control decisions.

Problem definition: Occupant interacting components in BPS tools are typically represented in terms of static schedules — meaning that these schedules do not change from design to design nor do they vary from individual to individual (Hoes, Hensen et al. 2009). For example, a BPS model with a poor fenestration design would input the identical electrical lighting and blinds schedules as any other fenestration design (Deru, Field et al. 2011). This implies that occupants are merely passive recipients of the indoor climate chosen for them. As illustrated in Figure 1, there should be a dynamic interaction between a building and its occupants. Occupants often can adapt their indoor climate by interacting with lights, blinds, windows, and thermostats or they can adapt to the indoor climate by changing their clothing assembly or the type of activity (Haldi and Robinson 2008; Gunay, O'Brien et al. 2013; D'Oca, Fabi et al. 2014). In other words, different design and control alternatives studied in BPS models should result in unique schedules for lighting, blinds, window, thermostat, clothing and activity schedules. Evidently, the use of static schedules to represent occupant interacting components in BPS models fails to reflect this dynamic interaction between the users and a building's design; and therefore it does not necessarily promote better design alternatives.

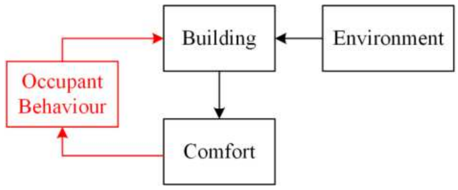

Figure 1 The dynamic interaction between a building and its occupants.

Background on occupant modelling: Occupant behaviour and presence models mimic the interactions of occupants with zone level building systems (e.g., lights) and with themselves (e.g., clothing insulation) (Clarke, Macdonald et al. 2006). They are developed upon long-term observational studies. There are several broad categories of modelling and simulation methods that exist in the literature. The majority of the models input explanatory variables to predict the likelihood of a state change. For example, Reinhart (2004)'s light switch model inputs the workplane illuminance to predict the likelihood of a light switch-on action. Page, Robinson et al. (2008)'s occupancy model predicts the likelihood of an arrival or departure event. Because occupants in an office (as individuals or collective entities) are modelled as autonomous agents undertaking actions, these models are also known as agent-based models.

In general, the agent-based occupant models have been derived from a Markovian perspective; meaning that the state-transition probability depends on the current state only (Parys, Saelens et al. 2011). When a Markov occupant model is simulated as a discrete-time random process, it inputs the explanatory variables to provide the likelihood of a state-transition in the next time-step. For example, Haldi and Robinson (2010)'s blinds use model predicts the likelihood of a blinds closing action in the next five minutes by looking at the workplane illuminance and unshaded window fraction. However, limitations may arise due to the fact that this simulation approach requires a fixed and prescribed time-step (Gunay, O'Brien et al. 2014). Because a time-step is prescribed for each model, the time-step cannot change between simulations. Consequently, occupant models can become incompatible with each other or with building and HVAC component models, which require different temporal discretizations.

Alternatively, when a Markovian occupant model is simulated as a discrete-event random process, it inputs explanatory variables to provide the likelihood of a state-transition in the next event-step. Commonly, occupant models can be tied to a state change in occupancy (Newsham 1994; Rijal, Tuohy et al. 2008; Haldi and Robinson 2011); i.e., time-step after arrival or time-step prior to departure. For example, Reinhart (2004)'s light switch model inputs workplane illuminance to predict the likelihood of a light switch-on action upon arrival. The next event time can also be sampled from a survival function (Haldi and Robinson 2011). For example, Wang, Federspiel et al. (2005) computed the duration of an intermediate vacancy period (e.g., lunch break) from an exponential distribution. Similarly, Haldi and Robinson (2009) determined the duration windows remain open based on a survival analysis. Another promising method to simulate a Markovian occupant behaviour model in a discrete-event formalism is to tie the events to the change in the environmental conditions (Gunay, O'Brien et al. 2014). For example, a simulated-occupant decides whether or not to undertake a light switch-on action, when the workplane illuminance changes by the event-step since the last decision-making instance — not at every simulation time-step or at each arrival.

As an alternative for the agent-based models, in some models occupant behaviour and presence were represented as Bernoulli random processes. These models input explanatory variables to predict the probability of finding a zone level building component at a certain position. For example, Haldi and Robinson (2008)'s models provide the probability of finding a window open by looking at the indoor temperature. Mahdavi and Tahmasebi (2015)'s occupancy model inputs the time of the day to predict the likelihood of finding a space occupied. Unlike the agent-based models, occupants' actions were not explicitly predicted; instead the state (e.g., lighting state, occupancy state) was predicted.

<u>Motivation:</u> The selection of modelling and simulation methodologies plays an unprecedented role over the predictive accuracy of an occupant behaviour and presence model. So far, only a few studies attempted contrasting different modelling and simulation methodologies (Haldi 2010; Haldi and Robinson 2011; Parys, Saelens et al. 2011; Mahdavi and Tahmasebi 2015). This study presents a comparison between these modelling and simulation methodologies by using an independent dataset. Six months worth of observations were gathered in five private offices through motion sensors, building automation system (BAS) integrated light switches, and indoor light intensity sensors. These observations were first used to develop two lighting use models. One of them was a Bernouilli model predicting the electric lighting state, and the other one was an agent-based model predicting the light switch-on actions. The agent-based light switch-on model was simulated by employing three different simulation methodologies: (a) in discrete-time formalism whereby the likelihood of a light switch-on action was predicted at all occupied time-steps when the lights were off, (b) in discrete-event formalism whereby the event was defined as an occupant's arrival, (c) in discrete-event formalism whereby the event was defined as a change in environmental conditions or an occupant's arrival. The model accuracy were assessed in making predictions for the mean weekday lighting state and the light switch-on patterns at hourly intervals. The observations were also used to develop two occupancy models. Of these, one was a Bernouilli model predicting the likelihood of presence, and the other one was an agent-based model predicting the likelihood of arrival or departure events. It should be noted that there can be many other modelling and simulation formalisms (e.g., different event definitions). Here, only those emerging from the literature were studied.

It should be noted that the main motivation of this paper is to better understand how modelling and simulation formalism choices influence the predictive accuracy of an occupant model. Developing a new transferable occupant behaviour or presence model is not within the scope of this work. Models developed in this study are contextually restricted to the building they were derived from.

METHODOLOGY

This section first presents the characteristics of the monitored building (e.g., sensor types and positions, office layouts) and the observational dataset (e.g., mean hourly occupancy and lighting load profiles, arrival/departure times of the days, light switch-on action times). Then, different lighting and occupancy use models are developed by employing the dataset. The simulation formalisms used for these models are introduced.

<u>The characteristics of monitored building and the observational dataset:</u> The occupancy, indoor light intensity and BAS-integrated light switches in five private office spaces in an academic building were monitored for six months. The occupancy in each office space was inferred from movements detected by motion sensors. In a time frame of thirty minutes, if a movement was detected, the room was assumed occupied. This time delay value was selected in line with prior research (Page, Robinson et al. 2008; Dong, Andrews et al. 2010; O'Brien and Gunay 2014). Note that the motion sensor based occupancy detections can lead to false absence detection, if an

occupant is immobile more than 30 min. Exclusively the occupants could switch on the lights, whereas the lights were automated to switch-off when the space was unoccupied. Hobo U12 data loggers were used to measure the photodiode-based indoor light intensity at fifteen minute intervals. In order to eliminate the risk that occupants cover the surface of light intensity sensors during the data acquisition, the sensors were placed to measure the vertical illuminance (1.5 m above the floor) — instead of the workplane illuminance. Figure 2 illustrates the office layouts, and the sensors' positions.

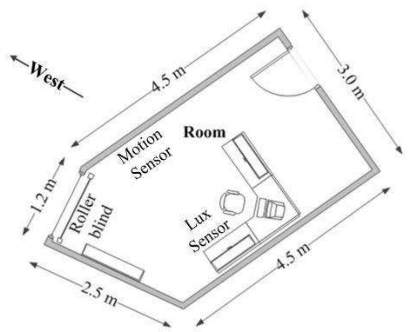

Figure 2 An illustration of the office layouts and sensor positions.

During the monitoring period, the offices were occupied for 1184 h. There were 1184 occupancy state transition events (592 arrivals and 592 departures). In the same time period, 332 light switch-on actions were captured through the building automation system. Figure 3 presents the mean weekday occupancy and electric lighting loads. These observations point out that occupancy profiles first peak (occupied 25% of the times) at around 10h00. This was followed by a local minimum (occupied 12% of the times) at noon and a peak (occupied 30% of the times) at 15h00. The lighting load followed a similar pattern albeit at a lesser value.

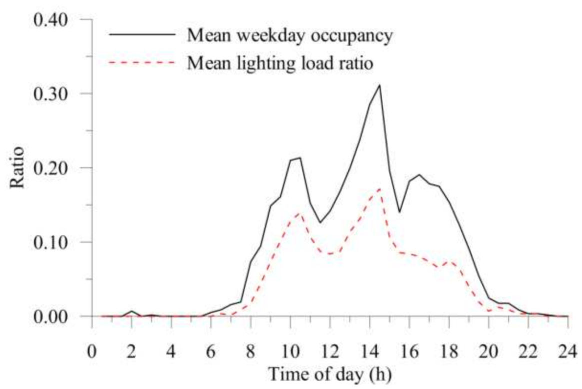

Figure 3 Mean weekday occupancy and lighting load ratios.

Figures 4 and 5 present the distribution of the arrival and departure times, respectively. The distribution of the arrival events (including the intermediate arrivals) indicates that arrivals concentrate between 8h00 to 10h00 or between 12h00 to 14h00 or between 16h00 to 18h00. The departure events (including the intermediate departures) peak at 11h30 and at 15h30, albeit continues at a declining rate until about 22h00. Figure 6 presents a histogram plot representing the distribution of the times of light switch-on actions. Observations indicate that the light switch-on actions coincide with the same time periods where majority of the arrival events take place. This is in line with previous observational studies, which reported occupants tend to switch on their lights as they arrive (Reinhart and Voss 2003; Boyce, Veitch et al. 2006; Haldi 2010).

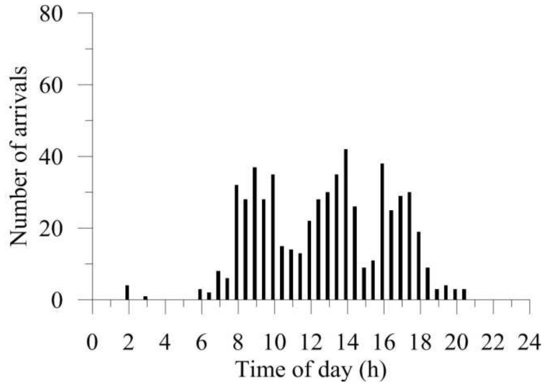

Figure 4 The distribution of the arrival event times in 30 min bins.

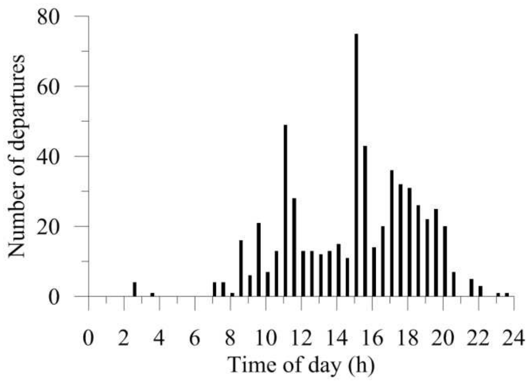

Figure 5 The distribution of the departure event times in 30 min bins.

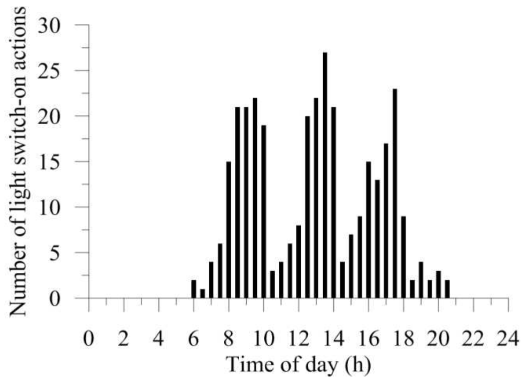

Figure 6 The distribution of the light-switch event times in 30 min bins.

Modelling formalisms: By employing the observational dataset, four different occupant models were developed. Two of these mimic the lighting use behaviour, while the other two mimic the occupancy patterns. The Bernoulli lighting use model (see Figure 7) predicts the likelihood of finding electric lighting as a function of the indoor illuminance reading. It computes the probability of finding the lights on, as follows:

$$p\left(on \middle| E_{lux}\right) = \frac{e^{0.3027\text{-}0.0003 E_{lux}}}{1+e^{0.3027\text{-}0.0003 E_{lux}}} \qquad (1)$$

where E_{lux} (lux) indoor light intensity reading.

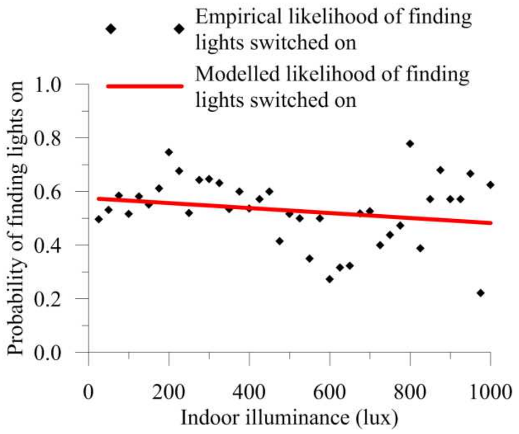

Figure 7 The Bernoulli lighting use model

The agent-based lighting use model (see Figure 8) predicts the likelihood of observing a light switch-on action in the next time-step (30 min) as a function of the indoor illuminance reading. It computes the probability of a light switch-on action, as follows:

$$p\left(on \middle| off, E_{lux}\right) = \frac{e^{0.1328-0.0040 E_{lux}}}{1+e^{0.1328-0.0040 E_{lux}}} \qquad (2)$$

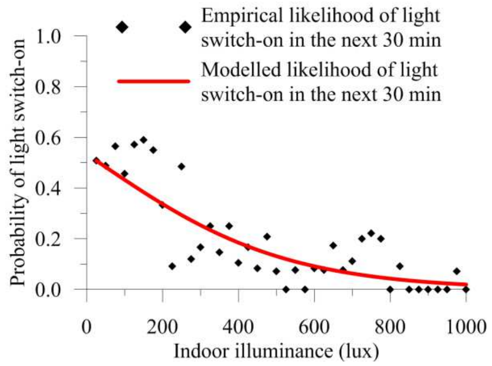

Figure 8 The agent-based lighting use model

The Bernoulli lighting use model (see Figure 7) exhibits a weaker correlation to indoor illuminance reading than the agent-based lighting use model (see Figure 8). This can be interpreted with the fact that occupants switch on lights when it gets dark, yet they do not necessarily switch them off even if the daylight becomes sufficient later during the day. In fact, there were only three manual light switch-off actions captured during 1184 occupied hours. The motion sensors triggered nearly all of the light switch-off actions. This is in line with Pigg, Eilers et al. (1996) that occupants are less likely to undertake light switch-off actions in presence of motion sensor activated light switches.

For the observational dataset, it was found that using unimodal probability distributions (e.g., Poisson's distribution (Wang, Federspiel et al. 2005; Page, Robinson et al. 2008) or a Gaussian distribution (Reinhart 2004)) were inappropriate for modelling occupancy. Instead, occupancy models were developed by employing the Gaussian mixture models (Dong and Lam 2011; Kamthe, Erickson et al. 2011). It is worth recalling that this study merely aims to compare modelling (i.e., Agent-based vs. Bernoulli) and simulation formalisms (i.e., Discrete time vs. Discrete event) with the given dataset; it does not aim to compare different models (i.e., Poisson's vs. Mixture models) as this can be limited due to dataset specific nuances.

The Bernoulli occupancy model (see Figure 9) predicts the likelihood of finding an office occupied as a function of the time of day. The probability of presence $p(pre)$ was represented as follows:

$$p(pre|t) = 0.12\left(e^{-\left(\frac{t-10}{1.5}\right)^2} + e^{-\left(\frac{t-14}{4.5}\right)^2} + 1.25e^{-\left(\frac{t-16}{3.5}\right)^2} \right) \qquad (3)$$

where t (h) is the time of day.

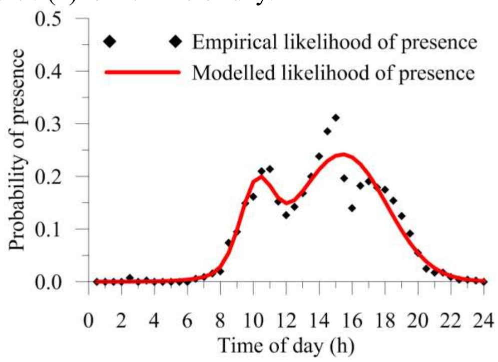

Figure 9 The Bernoulli occupancy model

The agent-based occupancy model provides the likelihood of observing an arrival event in the next 30 min when the space is unoccupied (see Figure 10), and the likelihood of observing a departure event in the next 30 min when the space is occupied (see Figure 11). The probability of arrival $p(pre|abs)$ in the next 30 min can be computed as follows:

$$p(pre|t, abs) = 0.02\left(5e^{-\left(\frac{t-9}{1.3}\right)^2} + e^{-\left(\frac{t-11}{5.4}\right)^2} + 5e^{-\left(\frac{t-15}{3.4}\right)^2} \right) \qquad (4)$$

The probability of departure $p(abs|pre)$ in the next 30 min can be computed as follows:

$$p(abs|t, pre) = 0.06\left(e^{-\left(\frac{t-16}{2.2}\right)^2} + 2e^{-\left(\frac{t-20}{1.3}\right)^2} + 5e^{-\left(\frac{t-23}{0.2}\right)^2} \right) \qquad (5)$$

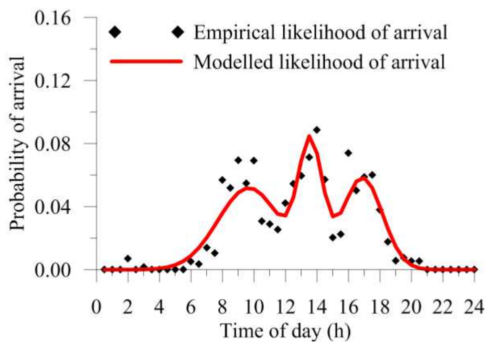

Figure 10 The agent-based arrival model

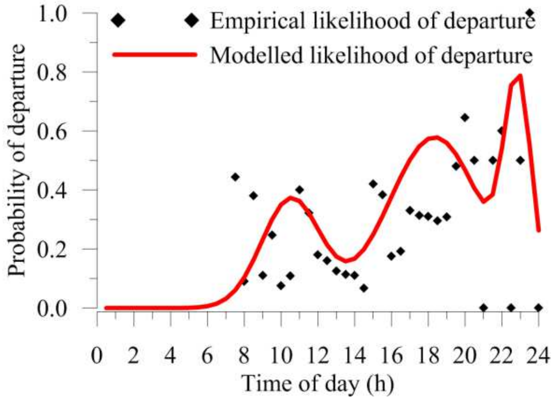

Figure 11 The agent-based departure model

Simulation formalisms: The models attempt to predict a state (e.g., presence) or a state-transition (e.g., arrival), whereas the simulation formalisms decide when these models should be invoked during the building simulation.

The flowchart shown in Figure 12 presents the simulation of the Bernoulli occupancy model in tandem with the Bernoulli lighting use model as a Bernoulli random processes. In a Bernoulli random process, each observation is assumed independent from previous state (e.g., a coin toss). The mean occupancy rate and mean lighting load ratio computations as a Bernoulli random process are independent from the simulation time-step size (Δt); yet the number of arrival or departure events or the light switch-on actions will increase as Δt decreases.

Figure 13 presents the simulation of the agent-based occupancy and lighting use models in the discrete-time formalism. When the occupant is absent, the agent-based arrival model (Figure 10) is invoked at each time-step. When the occupant is present, the agent-based departure model (Figure 11) is invoked in every time-step. If the lights are off when the occupant is present, the agent-based light switch model (see Figure 8) is invoked at each time-step. The mean occupancy rate and mean lighting load ratio computations as a discrete-time random process depends on the simulation time-step size (Δt). The BPS tool users must stick to the time-step size prescribed for the model — herein 30 min.

Figure 14 presents the simulation of the agent-based occupancy and lighting use models in the discrete-event formalism. In discrete-event formalism, the probability of undertaking the light switch-on behaviour is accumulated until an external event triggering the adaptive behaviour occurs. When the event occurs, the accumulated likelihood of undertaking the adaptive behaviour (1-*P* in Figure 14) is compared with a random number [0,1]. The external events triggering occupant's behaviour can be defined differently. In this paper, two different event definitions were adopted: (a) an occupant's arrival and (b) an occupant's arrival or a change in the light intensity level.

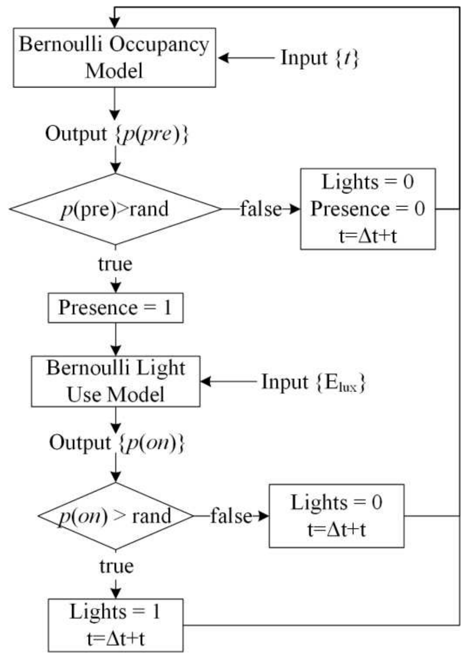

Figure 12: Simulating the Bernoulli occupancy and lighting models as Bernoulli random processes.

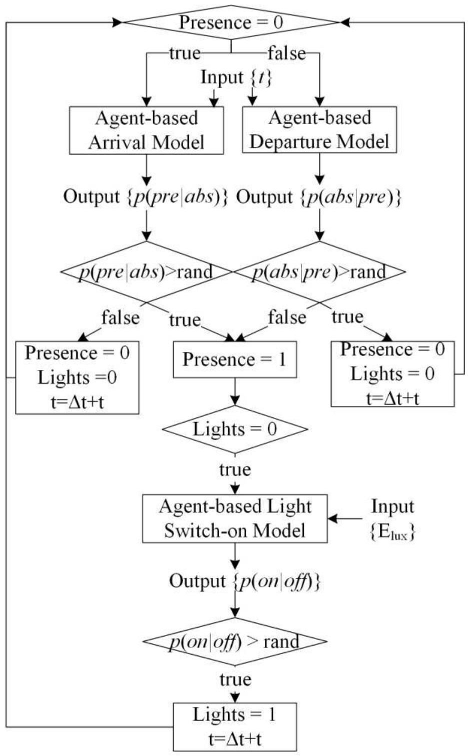

Figure 13: Simulating the agent-based occupancy and lighting models in discrete-time formalism.

The first event definition relies on the fact that, occupants tend to undertake light switch-on actions upon their arrival (Reinhart 2004; Boyce, Veitch et al. 2006) — perhaps due to their ease of access or the change in visual stimuli between indoors and outdoors. However if the daylight availability diminishes during intermediate occupancy or the occupancy model fails to generate the frequency of intermediate arrivals reasonably, the first event definition may become misleading as well. The second event definition acknowledges that occupants tend to undertake a light switch-on action upon arrival. However, it also recognizes that occupants tend to switch on lights during intermediate occupancy, if the indoor light intensity decreases substantially.

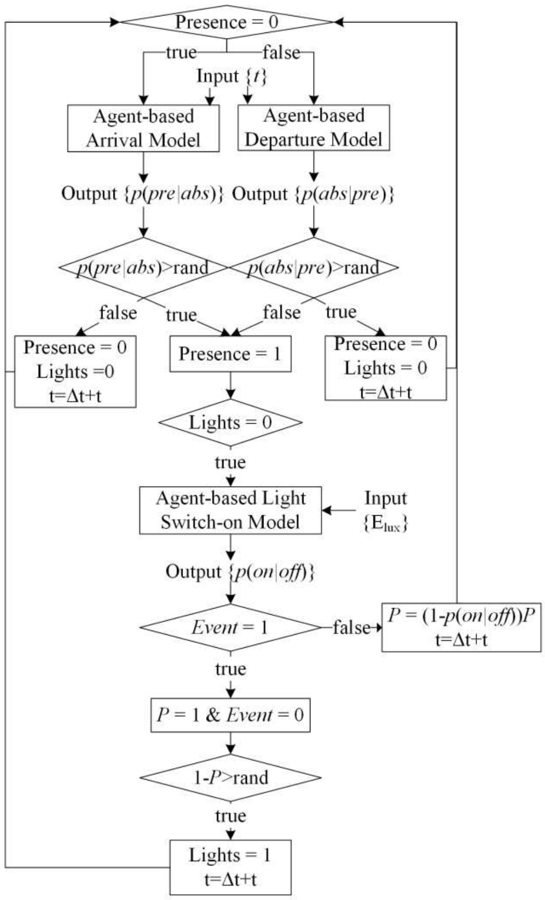

Figure 14: Simulating the agent-based occupancy and lighting models in discrete-event formalism.

RESULTS AND DISCUSSION

The modelling and simulation formalisms' ability in regenerating the patterns of the observational dataset was contrasted. It is important to recall that this study does not intend to assess the predictive accuracy of the models. In fact, the formalisms were not intended to represent performance predictions for the studied office spaces. Therefore, the observational data were not partitioned into a training set (upon which the models are developed), and a test set (with which the models' predictive accuracy is tested). Doing so could bias the comparison of the formalism, as the datasets are non-stationary and occupants' behaviour and occupancy patterns may evolve in time.

The modelling and simulation formalisms were contrasted through their ability to replicate the mean weekday occupancy rate and the lighting load ratio. Furthermore, their ability in describing the frequency and timing of the light switch-on actions, arrival and departure events was discussed. Representing the frequency and timing of the adaptive actions realistically is important, because they can provide inferences about the user's comfort (Gunay, O'Brien et al. 2014). For example, if a simulated-occupant frequently overrides the automated blinds closing action, this may indicate that the blinds closing set point is too low for the office space. Moreover, since the stochastic nature of human behaviour, simulations were repeated over a population of 100 simulated-occupants.

Figure 15 presents a comparison of different occupancy models' predictions with the observed occupancy. Results indicate that the multimodal nature of occupant models was not fully captured by the models. The Bernoulli occupancy model — which predicts occupancy directly but not the state transitions — appears to perform slightly better than the agent-based occupancy model in capturing mean weekday occupancy patterns. The Pearson correlation coefficients (ρ) between the modelled and observed mean occupancy rate were 0.93 for the Bernoulli occupancy model and 0.87 for the agent-based occupancy model. However, the weakness of the Bernoulli occupancy model was that it exaggerated the number of occupancy state-transitions (see Figure 15.b and c). Despite overestimating the number of arrivals and departures by about 20%, the agent-based occupancy model appeared to capture the timing and frequency of the occupancy state-transitions significantly better than the Bernoulli occupancy model.

Figure 16 presents a comparison of the lighting use models' predictions with the observed lighting use. When the simulation algorithm shown in Figure 12 is employed (the Bernoulli lighting use model coupled with the Bernoulli occupancy model), the mean electric lighting use was estimated 10.5 h/week — while the dataset indicates 8.1 h/week. Because it predicts the state of occupant interacting components directly — instead of modelling occupants' behaviours individually —, it is computationally efficient, and thus it can be more appropriate for whole-building energy simulation than agent-based models. However, the frequency and timing of state-transitions are not meaningful, thus it is inappropriate to infer occupants' comfort from their adaptive actions. In case, a modeller is primarily interested in energy use — accepting traditional comfort metrics, a Bernoulli behaviour model coupled with a Bernoulli occupancy model can be an appropriate choice. However, a Bernoulli occupancy model should not be coupled with an agent-based behaviour model.

When the discrete-time agent-based lighting model coupled with the agent-agent based occupancy model algorithm as shown in Figure 13, the lighting use was overestimated by 25% (10.1 h/week instead of 8.1 h/week). Both of the event-driven simulation approaches estimated the lighting use duration with less than 0.3 h/week errors. However, the discrete-event simulation which accepts the events as the occupants' arrival or a decrease in the indoor light intensity reading achieves better resemblance (ρ=0.91) to the observational dataset than the discrete-event simulation which accepts the events merely as the occupants' arrival (ρ=0.84). This can be interpreted as the occupants' light switch-on actions occur either at arrival or after a significant change in the indoor climate during intermediate occupancy. Although lumping the likelihood of adaptive actions to the time-step following arrivals can be appropriate in cases where occupants tend to leave/enter the space frequently, it fails to explain the intermediate light switch actions.

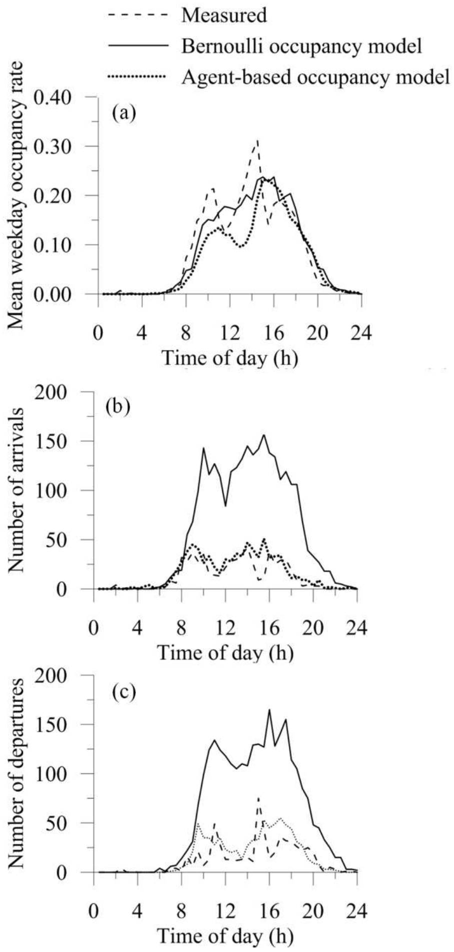

Figure 15: Comparison of the occupancy models' predictions with the observed occupancy.

CONCLUSIONS

Different modelling and simulation formalisms emerging from the literature were introduced to represent occupant's presence and lighting use in BPS tools. Lighting use and occupancy models were developed and simulated in these formalisms by employing six months worth of motion sensor, light intensity sensor, and electric lighting state data gathered in five private offices in an academic building.

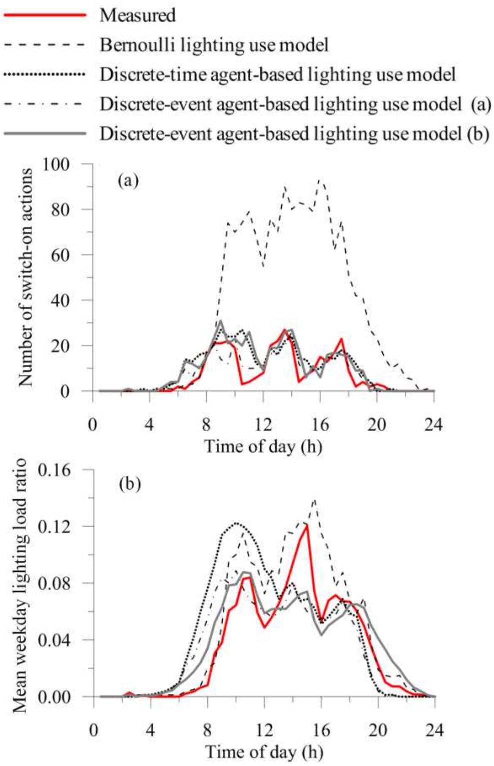

Figure 16: Comparison of the lighting use models' predictions with the observed lighting use.

The modelling and simulation formalisms' ability to regenerate the patterns of the observational dataset were contrasted. Results indicated that the choice of modelling and simulation formalisms can play a significant role over predicted lighting load and the frequency and timing of the light switch behaviour patterns. When a Bernoulli lighting use model is coupled with a Bernoulli occupancy use model, it can result in accurate mean lighting load predictions. However, it fails to generate a representative daily profile for the frequency and timing of state-transitions.

When an agent-based lighting use model is simulated as a discrete-event simulation — whereby the event is defined as an arrival or a decrease in the indoor light intensity, accurate mean lighting load predictions as well as more accurate predictions for the frequency and timing of light switch-on actions can be made.

For future work, current study should be extended to a wider number of modelling and simulation methodologies by taking into account for other adaptive behaviours — such as opening windows and operating fans, heating and cooling systems.

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