A simulation-based approach to test and fine-tune occupant-centric lighting control strategies

Mohamed M. Ouf[1], Erik Bowden[1], June Young Park[2], Burak Gunay[3]
[1]Concordia University, Montreal, QC Canada
[2]University of Texas at Arlington, Arlington, TX USA
[3]Carleton University, Ottawa, ON Canada

Abstract

Occupant-centric control (OCC) strategies aim to optimize building operations by learning and predicting occupancy patterns and occupant preferences. However, testing OCCs and adjusting their configuration in real buildings can be a lengthy process. To this end, we present an approach for testing OCCs in a simulation environment. The workflow entails coupling synthetic occupant behaviour models with OCCs that learn their preferences. The proposed method was applied in a case-study to simulate OCCs for lighting while modifying their settings and occupant behaviour assumptions. Results enabled comparing their performance for minimizing energy use and improving comfort under different scenarios. Using this method, building designers and operators can identify potential issues with OCCs and fine-tune their configurational parameters prior to field implementation.

Introduction

Indoor climate control in buildings (for heating, cooling, ventilation, and lighting) represents about 15% of the worldwide energy use and CO_2 emissions (Hobson et al., 2019; Pang et al., 2017). In modern buildings, a set of fixed setpoints and schedules are typically used to control different systems to achieve the desired indoor climate conditions. These setpoints and schedules are rarely changed during building operations unless major retro-commissioning work takes place (Gunay, 2016). Because exact occupancy patterns and occupants' preferences are rarely known, operators tend to make conservative assumptions with regards to building control setpoints and schedules. This conservative approach can often lead to wasteful energy use (e.g., heating empty spaces, or providing ventilation rates that exceed indoor air quality requirements) (Gunay et al., 2019) and may trigger occupant discomfort (Cho and Liu, 2009) especially if the programmed setpoints do not meet occupant satisfactions.

To this end, OCC presents a mode of indoor climate control in which occupancy and occupant preferences are either directly measured or indirectly inferred from a variety of sensors, control interfaces, or mobile and wearable devices (Barbour et al., 2019). OCC aims to deliver building services only when and where they are needed in the amount that they are needed (Shen et al., 2017). It can be broadly categorized as occupancy- or occupant behaviour- centric, based on the type of occupant-related information used by an OCC algorithm (Park et al. 2019). Occupancy-centric controls rely on measured presence/absence or occupant count data using different methods (e.g., motion detectors, CO_2 monitors, people counting cameras) at different spatial and temporal scales to adjust control setpoints or schedules. In contrast, occupant behaviour-centric controls learn occupants' temperature and illuminance preferences using direct feedback (e.g., using surveys) or indirect methods (e.g., recording occupant interactions with building systems) to adjust indoor temperature and illuminance setpoints accordingly.

Despite the potential benefits of OCCs, technical limitations in buildings and sensing infrastructure typically prevented their large-scale deployment. Only a small number of studies investigated their effect on energy savings and occupant comfort through simulations. However, these studies focused on occupancy-centric rather than occupant behaviour-centric controls (e.g., Erickson et al., 2009; Pang et al., 2017). To address some of these limitations, we present a method for simulation-based testing of both occupancy-centric and occupant behaviour-centric controls prior to field implementation. The method entails integrating stochastic and dynamic occupant behaviour models into building simulations, then adding OCC algorithms that learn their occupancy patterns and/or preferences to adapt building controls and operations accordingly. The objectives of this paper are to 1) provide a proof-of-concept of the proposed method and 2) demonstrate its benefits for quick and holistic evaluation of OCC performance using different metrics. A case-study is then presented in which a single office was modelled under various scenarios that entail different combinations of OCC configurations and occupant behaviour types.

Background

Over the past decade, OCC research has grown significantly (O'Brien et al., 2018) and new control agents for OCCs have been developed that 1) acquire data from occupants and indoor environments, 2) utilize this collected information to understand occupant behaviour (i.e., occupancy patterns, thermal/visual preferences) and the system performance, and 3) ultimately calculate the optimal control setpoints for building systems (e.g., HVAC system, lighting fixtures) to balance between occupant comfort and energy efficiency.

A recent review by Park et al. (2019) indicated that OCC studies in the literature mainly entailed concept papers and small-scale experiments that lasted for only short periods (typically a few days to three months), while only few studies entailed field implementations. This is mainly because, it is difficult to generalize the performance of OCC for energy savings and occupant comfort. To quantify the performance level of OCCs for both objectives using a simulation-based approach, researchers typically modelled the target buildings, simulated the building energy consumption, and compared the results with baseline cases (de Bakker et al., 2017; Jung and Jazizadeh, 2019). Similarly, occupant comfort was measured based on simulation results (e.g., indoor air temperature) with naïve assumptions of comfortable temperature range (Naylor et al., 2018; Park and Nagy, 2017).

To evaluate OCCs holistically using a simulation-based approach, proper simulation inputs are required for measurement and verification. As OCCs depend on human-building interactions, simulation-based OCC studies should be verified with a comprehensive occupant behaviour model, which consists of both passive and dynamic behaviour types (Zhao et al., 2016). The passive behaviour type is mainly related to schedule factors, e.g., occupancy (absence/presence), light, equipment, and miscellaneous usage. On the other hand, the dynamic behaviour is defined as actual responses of internal or external stimuli. For example, occupants are adaptive in their indoor environments (e.g., they may adjust their thermostats, switch on or off their lights, and open or close their windows). These actions have impacts on the building energy performance as well (Gunay et al., 2016). Hong et al. (2015) identified adaptive behaviour types and developed an ontology to represent them in building simulation; which was later incorporated in EnergyPlus. These studies indicate that robust occupant behaviour models were extensively developed and implemented for building design research studies (Hong et al., 2017) rather than the evaluation of building control research to the authors' knowledge.

Method

The main feature of the proposed method is integrating the simulation of stochastic and dynamic occupant behaviour to ensure the simulation testbed of OCCs mimics real-life scenarios. The proposed workflow, which is shown in Figure 1, enables adjusting occupant-related assumptions and OCC configurations to represent the diversity of occupant behaviour and test their interactions with different OCCs.

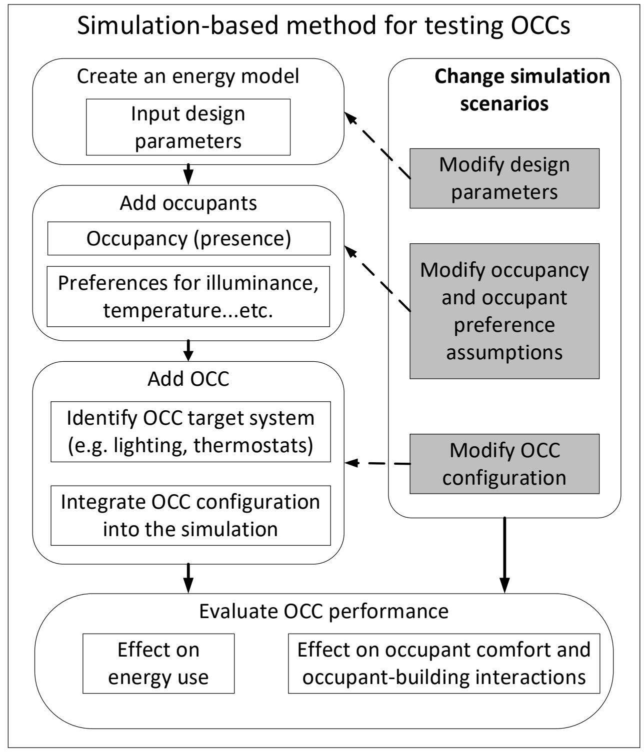

Figure 1: Overview of the proposed method for simulation-based testing of OCCs

Different approaches can be used to simulate stochastic and dynamic occupant behaviour as well as an OCC algorithm simultaneously. In this paper, we focused on writing custom scripts using Energy Management System (EMS) application of EnergyPlus following the approach outlined by Gunay et al. (2016). Note that other simulation tools and workflows including co-simulation can be used to implement the proposed method.

Case study

A case study was developed to demonstrate the proposed method by modelling a single office (4m x 4m x 3m) using EnergyPlus V9.1, as shown in Figure 2. The Canadian Weather for Energy Calculations (CWEC) annual weather data file for Ottawa, ON Canada was used for simulations, which is based on average weather data measured between 1998 to 2014. The south-facing wall of this office was exposed to the outdoor environment, while all other surfaces of the room were assumed to be adjacent to spaces with the same thermal conditions (i.e. adiabatic). A window with dimensions 2.2m x 1.6m was placed on the south-facing wall (i.e., 30% WWR), with an insulation U-value of 1.62 $W/m^2{\cdot}K$ and a solar heat gain coefficient of 0.25. The outside wall insulation U-value was specified as 0.325

W/m^2.K which exceeds the requirements of ASHRAE Standard 90.1 (ASHRAE, 2019) for climate zone 6A

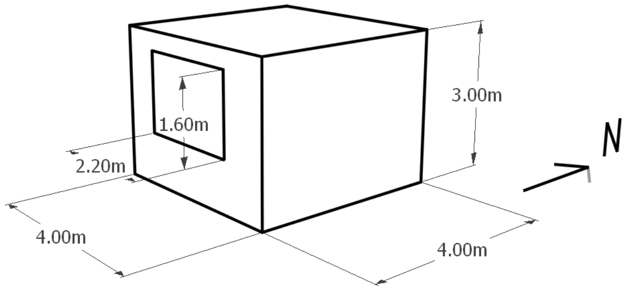

Figure 2: Dimensions of the single office model used in the case-study

Internal heat gains from occupants were assumed to be 130 W/person. Lighting, and electric equipment power densities were assumed to be 8.5 W/m^2, and 8.1 W/m^2, respectively, as specified in ASHRAE Standard 90.1. The infiltration rate into the office was set to 0.3 air changes per hour (ACH), which is the default used in EnergyPlus simulation and drops to 0.075 ACH during the daytime, when the ventilation system is operational. The HVAC system was modelled as an air-based ideal load system with heating and cooling capacity of 1500 W. This heating and cooling capacity was chosen based on a preliminary sizing run, while COP was assumed to be 3 for both heating and cooling. The heating and cooling set-points were assumed to be 22°C and 23°C for winter and summertime, respectively. However, the system could only provide heating or cooling at a given time. The switchover date from heating to cooling was set to May 1st, while switch over to heating was set to October 1st.

Occupant behaviour was integrated into the simulated office using probabilistic models, which were implemented with custom scripts in the EMS Object of EnergyPlus. These scripts changed the schedule values for occupancy, lighting, and thermostat setpoints at each time step. Readers can refer to Gunay et al., (2016) for more details on this implementation workflow. In addition to simulating occupant preferences, OCCs were added into the simulation using a similar workflow. Generally, when OCCs were implemented, occupant behaviour programs preceded their execution at every time-step to ensure their parameters are adjusted based on the simulated occupant preferences, as shown in Figure 3. By allowing OCC parameters to change after each time-step based on the simulated occupant preferences, the "learning rate" of OCCs could also be evaluated by observing the duration it took these parameters to converge to constant values. More details on the implemented occupant behaviour models and OCCs, including their parameters are described below.

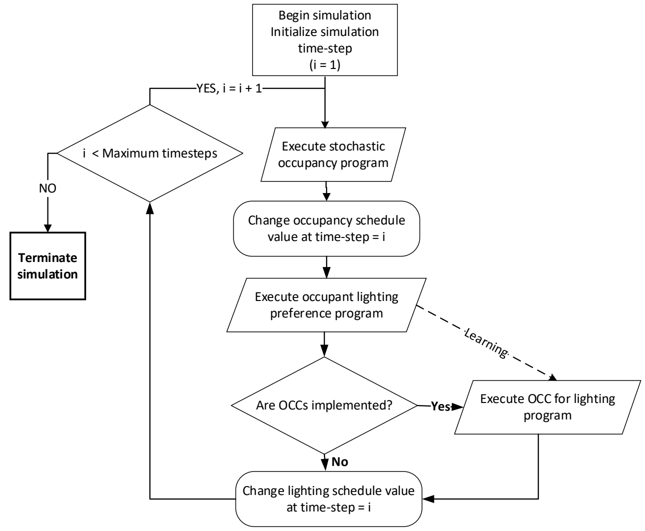

Figure 3: Overview of the simulation workflow involving occupant behaviour and OCC modelling

Occupant-related parameters

Occupancy (i.e., occupant presence) was simulated based on the model proposed by Wang et al. (2005) without any major adjustments. Occupancy was assumed to be zero on weekends and holidays. At the beginning of each weekday, five different event times were randomly sampled for each occupant from pre-defined normal distributions. These arrival and departure events were as follows (1) arrival time at 9am ± 15 min, (2) a coffee break at 10:30am ± 15 min, (3) a lunch break at 12pm ± 15 min, (4) a second coffee break at 3pm ± 15 min, and (5) departure time at 5pm ± 15 min. The duration of coffee breaks and lunch breaks was drawn from an exponential probability distribution of time constants 15 min and 60 min, respectively.

To represent occupant lighting preferences, a probabilistic logistic regression model of modifiable coefficients was implemented in the simulation. It predicted the probability of switching lights on based on indoor illuminance. The coefficients of this logistic regression model were modified to represent sensitive and tolerant occupant behavioural tendencies, in which the former had a higher probability of switching lights on than the latter, given the same indoor illuminance as shown in Figure 4. A constant probability of 50% for light switch-off events was used for short-term departures (e.g., for coffee breaks and lunch) and 90% for long-term departures at the end of the day. All of these assumptions can be modified upon further implementation of the proposed method to test additional case studies.

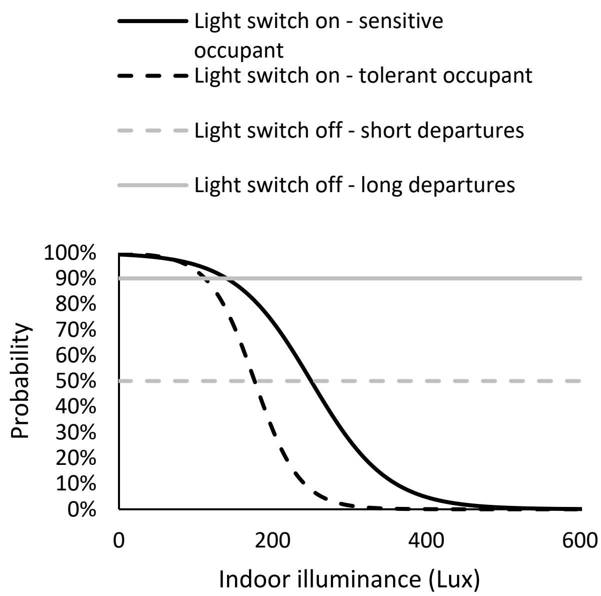

Figure 4: Probability of light switches under sensitive and tolerant occupant behaviour assumptions

Occupant-centric controls

Two different OCCs for lighting were implemented. Lighting OCC #1 was based on the work presented by Gunay et al. (2017). This control strategy automatically switched lights off during vacancy or when indoor workplane illuminance exceeded a certain threshold, which was specified as one of its parameters. This illuminance threshold decreased slowly as the occupied time elapsed without a light switch-on action. The decrease was interrupted by light switch-on actions, upon which the illuminance threshold slightly increased (i.e., learning from occupant actions). Irrespective of the decrease or increase in illuminance threshold for switching lights off, the original configuration of this OCC stipulated minimum and maximum threshold values of 200 and 500 lux, respectively. In other words, the light switch-off threshold could only decrease down to 200 lux after which it becomes constant. To simulate an alternative modified configuration of this OCC, these threshold maximum and minimum limits were removed.

Lighting OCC #2 was implemented based on the work presented by Nagy et al. (2015). This control approach entailed identifying a minimum illuminance threshold, below which the control system switched lights on, in case of occupancy. This threshold was determined by registering indoor illuminance at each time the occupant manually switches the lights on (i.e., learning from occupant actions), then taking their average over a specific period (originally set to 4 weeks). Another setpoint for switching lights off is evaluated if indoor illuminance exceeded a certain threshold. This maximum illuminance threshold was determined as the simple addition of the artificial lighting illuminance to the minimum illuminance threshold value. To simulate an alternative configuration of this OCC, the minimum illuminance threshold value was set to be updated once a week instead of every 4 weeks.

Simulations were conducted to evaluate the performance of these OCCs using modified and original configurations under sensitive as well as tolerant occupant behaviour assumptions. Results are presented and analysed in the following section.

Reproducibility

As previously explained, implementation of this simulation approach was achieved using EnergyPlus' ErL language. To implement probabilistic occupant behaviour models for lighting, the probability of each occupant light switch was calculated at each simulation timestep based on the models shown in Figure 4. A random number between 0 -1 was then generated and compared to this probability to determine whether an action will take place and change the status of lighting accordingly. For example, if the probability of switching lights on was higher than the random number, light status will be changed to 1 (i.e., on) in the next timestep. The lighting OCCs were then implemented using a similar approach. For example, for OCC #1, logistic regression model coefficients were updated every timestep depending on light switch actions or lack thereof (predicted using the occupant behaviour model). These coefficients were then used to update the thresholds for switching lights off based on indoor illuminance and the model would automatically switch lights off in this case. Overall, these simulations took approximately one minute to simulate a full year of light use within the single office model shown in Figure 2.

Results

This section presents the results of simulating OCC performance in the developed single office model under various combinations of OCC configurations and occupant behaviour assumptions. The first sub-section focuses on the effect of OCCs on electricity use, while the second sub-section focuses on their effect on occupant comfort and interactions with lighting systems. Finally, alternative metrics to evaluate OCC performance are presented.

Evaluating the effect of OCCs on electricity use

One of the main (and more traditional) approaches to evaluate OCC performance is to investigate their effect on minimizing energy use per floor area. The analysis presented in this sub-section demonstrated that the effect of implementing OCCs on specific energy end-uses is highly susceptible to occupant behaviour assumptions as well as OCC configurations. Simulation results of the different scenarios showed large variations in electricity use for lighting which ranged between 4 kWh/m^2 and 21 kWh/m^2 (i.e., >400% difference), as shown in Figure 5. The lowest electricity use for lighting was observed under the assumption of tolerant occupant behaviour after implementing OCC #2 without modifying its configurations.

Relative to scenarios without OCC implementation, a decrease in electricity use for lighting was always observed under tolerant occupant behaviour assumptions regardless of the implemented OCC or its configuration. However, implementing lighting OCCs under sensitive occupant behaviour assumptions was found to increase electricity use for lighting except when OCC #2 was implemented, and its configuration was modified. In this case, since the sensitive occupant was assumed to be much more likely to switch lights on under low illuminance conditions, the impact of implementing OCCs (which automatically switched lights off) increased the frequency of occupant overrides and resulted in an overall increase in electricity use for lighting. Electricity use for lighting only decreased when the frequency of updating OCC #2 thresholds increased to weekly basis instead of every 4 weeks as shown in Figure 5.

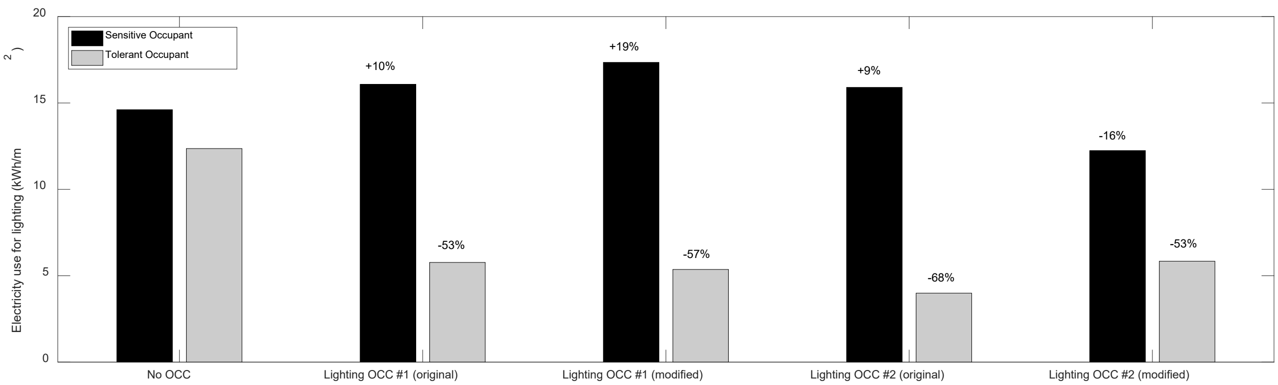

Figure 5: The effect of implementing lighting OCCs on electricity use for lighting under different scenarios

Evaluating the effect of OCCs on adaptive behaviour

Another objective of the proposed approach is to evaluate the effect of OCCs on occupant comfort. Although several approaches can be used to evaluate comfort, the proposed workflow enables the evaluation of occupant-building interactions (i.e., adaptive behaviours), which were previously proposed as a proxy for comfort (Gunay et al., 2018). This analysis indicated that implementing OCC #1 under tolerant occupant behaviour assumptions would result in the minimum number of light switches per year, as shown in Figure 6. However, OCC #2 resulted in increasing the frequency of light switches per year irrespective of its configuration. Unlike OCC #1 which only switched lights off automatically given a maximum illuminance setpoint, OCC #2 additionally switched lights on based on a minimum illuminance setpoint. This led the simulated occupant to switch lights off more frequently which increased the total frequency of light switches per year.

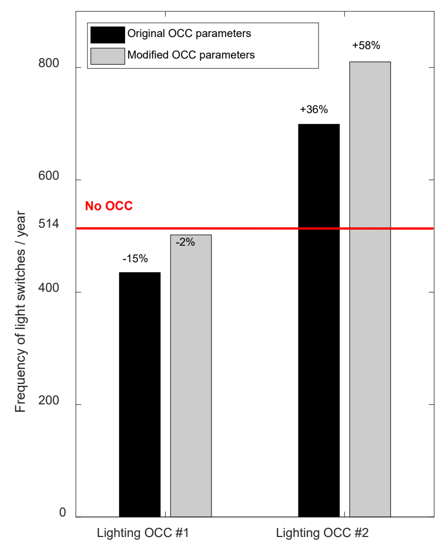

Figure 6: Frequency of light switches under different OCC configurations and tolerant occupant behaviour assumptions

To further evaluate the effect of modifying OCC configurations (e.g., setpoint thresholds), the change in lighting switch off setpoint over three years was investigated under tolerant occupant behaviour assumptions. This setpoint represents the maximum indoor illuminance value which would lead the OCC to automatically switch lighting off if it is exceeded. A three-year period was selected to observe the changes in lighting switch off setpoint over a longer period and ensure no more significant changes to it will occur. As shown in Figure 7, OCC #1 generally had a lower light switch off setpoint, which continuously decreased to 200 lux under the original configuration.

By removing this minimum threshold, the modified version of this OCC suggested that the light switch off setpoint could be further decreased to approximately 100 lux under tolerant occupant behaviour assumptions. This led to increasing the frequency of automatically switching lights off in the space, which decreased electricity use for lighting by 57% relative to the scenario without OCC implementation. For OCC #2, modifying the frequency of updating the light switch off setpoint from monthly to weekly was not found to significantly change the light switch off setpoint which converged to a range between 350 – 450 lux. However, as shown earlier, changing the threshold value on a weekly basis led to increasing electricity use for lighting and the frequency of occupant overrides which suggests that the original configuration, in which the setpoint is updated monthly, performed better for energy efficiency and comfort.

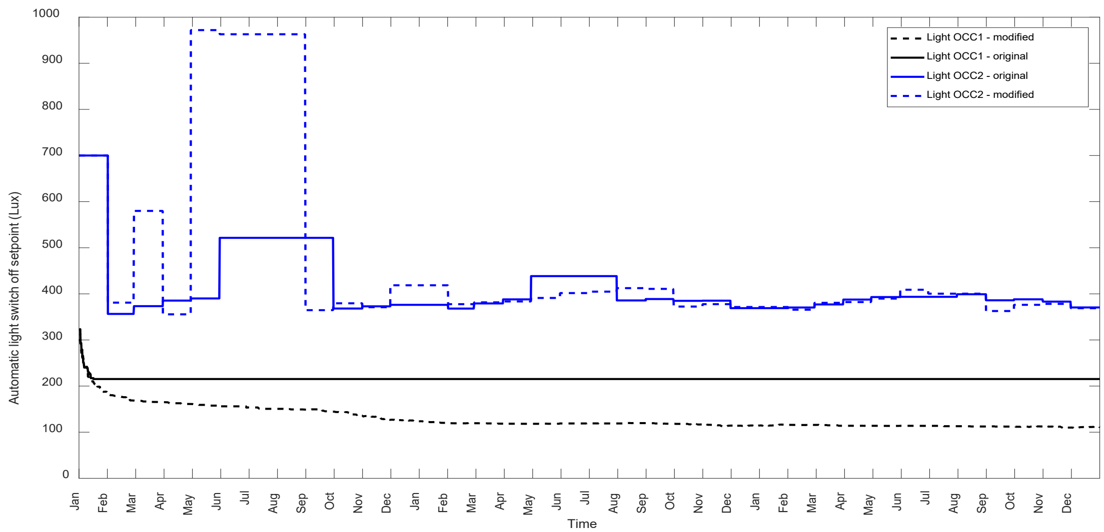

Figure 7: Change in lighting switch off setpoint over the year under both lighting OCCs with different configurations and tolerant occupant behaviour assumptions

Discussion

The previous results represent a proof-of-concept of the proposed method for simulation-based testing of OCCs. Findings indicated that assumptions regarding occupant behaviour tendencies can significantly influence OCC performance, although they are rarely accounted for in the literature. Results of the case-study also suggested that OCCs which were previously implemented in real buildings under specific conditions of building design and occupancy patterns (e.g., Nagy et al., 2015, Gunay et al., 2017), can show similar trends of improving energy efficiency in different simulation scenarios. However, under sensitive occupant behaviour assumptions, some OCCs may lead to increasing energy use and the frequency of occupant overrides. This may have resulted from configurations that were not suitable for sensitive occupants, such as relatively slower learning rates. Modifying some of these configurations (e.g., changing the frequency of updating light switch thresholds from monthly to weekly) resulted in a substantial reduction in energy use under sensitive occupant behaviour assumptions as shown in Figure 5.

The proposed method enabled taking a more holistic approach to evaluate OCC performance by integrating occupant behaviour in simulations. Using this approach results quantified the frequency of occupant-building interactions, which can be used as a proxy for occupant comfort. However, using these multiple metrics to evaluate OCC performance can make it challenging to select the most suitable OCC for specific scenarios. For example, the case study findings indicated that OCC #2 under tolerant occupant behaviour assumptions would result in the lowest electricity use for lighting (out of the investigated 64 scenarios). However, OCC #1 under tolerant occupant behaviour assumptions resulted in the lowest number of light switches per year. Without standardization and prioritization of performance objectives, these somewhat conflicting results may make it difficult to identify the most suitable OCC configurations for a given building prior to field implementation.

One of the main benefits of the proposed method is providing a virtual testing environment to expedite the process of configuring OCC parameters. Fine-tuning OCC configurations can be a lengthy process in field implementations to ensure they perform well under site-specific conditions, requiring at least a few days or weeks of testing. In the proposed simulation-based method, these parameters can be quickly changed in conjunction with occupant-related assumptions, to evaluate their effect on OCC performance and inform field implementation. Therefore, the proposed method could also be expanded to automate the process of identifying optimal OCC configurations for different scenarios using parametric analyses or optimization search algorithms.

The proposed method also enabled quick comparisons between different OCC algorithms under similar conditions. Doing these comparisons in real buildings may be constrained by logistical challenges (e.g., the number of similar rooms in which OCC experiments can be implemented) which would make it difficult to implement various OCC algorithms. The proposed method can address this issue by enabling quick implementations of different

OCC algorithms. However, the integration of more complex OCC algorithms into simulations should be investigated, especially given the limited capabilities of the EnergyPlus Runtime Language which is used for creating the EMS scripts in EnergyPlus. Future research should focus on identifying new workflows (e.g. co-simulation or using other simulation tools) for implementing advanced OCC strategies in simulations while representing stochastic and dynamic occupant behaviour.

Conclusion

The proposed method enables quick evaluation of different OCC algorithms and fine-tuning their configurational settings to improve performance under various operational scenarios. The presented case-study provided a proof-of-concept of the proposed method and demonstrated that significant variations in OCC performance would be observed based on occupant behaviour assumptions. Findings suggested that configurational settings of OCC algorithms may need to be adjusted to achieve energy savings for some occupant types. Future research will focus on developing a comprehensive library of OCC algorithms for a simulation testbed, which can then be used to identify the suitable OCCs for specific site conditions (building and occupant types, building design parameters, types of building systems available, etc.). This can be used by designers or building operators who are interested in implementing OCCs in their buildings by testing different OCC strategies prior to field implementation.

It should be noted that some limitations exist for the proposed method. Although the implemented occupant behaviour models were based on previously published studies, the assumptions of tolerant and sensitive behaviour tendencies were arbitrarily assigned to represent extreme scenarios. Future research should explore integrating other behaviour models (e.g., for blinds use) and investigate a wider range of occupant behaviour assumptions and OCC strategies. Simulating occupant behaviour and preferences using stochastic models may also not be representative of actual occupant behaviour in real buildings, especially as some contextual factors that influence occupant behaviour are not captured in these models (O'Brien and Gunay, 2014). The effect of these factors on occupant behaviour and consequently on OCC performance would not be observed except in field implementations. One of the next steps for this research is developing a standardized approach for holistic evaluations of OCC performance using a defined set of comparable and reproducible metrics. This would enable benchmarking and comparing different algorithms and configurational settings under various scenarios to identify suitable OCCs prior to field implementation. Combining the proposed method with optimization search algorithms would enable automating the process of identifying optimal OCC configurational parameters and developing algorithms that would effectively optimize comfort and energy performance for a wide large range of occupant and building types. This approach could also be used in future work to investigate if building design optimization would be influenced by the implementation of OCCs.

Acknowledgement

This research was supported by Concordia University's Dean of the Faculty of Engineering and Computer Science Start-up funds program and Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant Program. This work was also developed thanks to the excellent research networking provided by IEA EBC Annex 79 "Occupant-Centric Building Design and Operation".

References

ASHRAE, 2019. ANSI/ASHRAE Standard 90.1-2019 Energy Standard for Buildings Except Low-Rise Residential Buildings.

Barbour, E., Davila, C.C., Gupta, S., Reinhart, C., Kaur, J., González, M.C., 2019. Planning for sustainable cities by estimating building occupancy with mobile phones. Nat. Commun. doi:10.1038/s41467-019-11685-w

Cho, Y., Liu, M., 2009. Minimum airflow reset of single duct VAV terminal boxes. Build. Environ. 44, 1876–1885. doi:10.1016/j.buildenv.2009.01.001

de Bakker, C., Aries, M., Kort, H., Rosemann, A., 2017. Occupancy-based lighting control in open-plan office spaces: A state-of-the-art review. Build. Environ. 112, 308–321. doi:10.1016/j.buildenv.2016.11.042

Erickson, V.L., Lin, Y., Kamthe, A., Brahme, R., Surana, A., Cerpa, A.E., Sohn, M.D., Narayanan, S., 2009. Energy efficient building environment control strategies using real-time occupancy measurements. ACM Work. Embed. Sens. Syst. Energy-Efficiency Build. 19. doi:10.1145/1810279.1810284

Gunay, B., 2016. Improving energy efficiency in office buildings through adaptive control of the indoor climate. Carleton University, Ottawa.

Gunay, H.B., O'Brien, W., Beausoleil-Morrison, I., 2016. Implementation and comparison of existing occupant behaviour models in EnergyPlus. J. Build. Perform. Simul. 9, 567–588. doi:10.1080/19401493.2015.1102969

Gunay, H.B., O'Brien, W., Beausoleil-Morrison, I., Gilani, S., 2017. Development and implementation of an adaptive lighting and blinds control algorithm. Build. Environ. 113, 185–199. doi:10.1016/j.buildenv.2016.08.027

Gunay, H.B., Ouf, M., Newsham, G., Brien, W.O., 2019. Sensitivity analysis and optimization of building operations. Energy Build. 199, 164–175. doi:10.1016/j.enbuild.2019.06.048

Gunay, Shen, W., Newsham, G., Ashouri, A., 2018. Modelling and analysis of unsolicited temperature setpoint change requests in office buildings. Build. Environ. 133, 203–212. doi:10.1016/j.buildenv.2018.02.025

Hobson, B.W., Lowcay, D., Gunay, H.B., Ashouri, A., Newsham, G.R., 2019. Opportunistic occupancy-count estimation using sensor fusion: A case study. Build. Environ. 159, 106154. doi:10.1016/j.buildenv.2019.05.032

Hong, T., D'Oca, S., Taylor-Lange, S.C., Turner, W.J.N., Chen, Y., Corgnati, S.P., 2015. An ontology to represent energy-related occupant behaviour in buildings. Part I: Introduction to the DNAs framework. Build. Environ. 94, 196–205. doi:10.1016/j.buildenv.2015.08.006

Hong, T., Yan, D., D'Oca, S., Chen, C. fei, 2017. Ten questions concerning occupant behaviour in buildings: The big picture. Build. Environ. 114, 518–530. doi:10.1016/j.buildenv.2016.12.006

Jung, W., Jazizadeh, F., 2019. Human-in-the-loop HVAC operations : A quantitative review on occupancy , comfort , and energy-efficiency dimensions. Appl. Energy 239, 1471–1508. doi:10.1016/j.apenergy.2019.01.070

Nagy, Z., Yong, F.Y., Frei, M., Schlueter, A., 2015. Occupant centered lighting control for comfort and energy efficient building operation. Energy Build. 94, 100–108. doi:10.1016/j.enbuild.2015.02.053

Naylor, S., Gillott, M., Lau, T., 2018. A review of occupant-centric building control strategies to reduce building energy use. Renew. Sustain. Energy Rev. 96, 1–10. doi:10.1016/j.rser.2018.07.019

O'Brien, L., Hong, T., Gilani, S., Ouf, M., Gaetani, I., Gunay, B., Yan, D., Wagner, A., 2018. From IEA EBC Annex 66 to 79: Key outcomes and challenges in building occupant modelling and simulation. IBPSA NEWS 23.

O'Brien, W., Gunay, H.B., 2014. The contextual factors contributing to occupants' adaptive comfort behaviours in offices - A review and proposed modeling framework. Build. Environ. 77, 77–88. doi:10.1016/j.buildenv.2014.03.024

Pang, X., Piette, M.A., Zhou, N., 2017. Characterizing variations in variable air volume system controls. Energy Build. 135, 166–175. doi:10.1016/j.enbuild.2016.11.031

Park, J.Y., Nagy, Z., 2017. Comprehensive analysis of the relationship between thermal comfort and building control research - A data-driven literature review. Renew. Sustain. Energy Rev. 82, 2664–2679. doi:10.1016/j.rser.2017.09.102

Park, J.Y., Ouf, M.M., Gunay, B., Peng, Y., O'Brien, W., Kjærgaard, M.B., Nagy, Z., 2019. A critical review of field implementations of occupant-centric building controls. Build. Environ. 165, 106351. doi:10.1016/j.buildenv.2019.106351

Shen, W., Newsham, G., Gunay, B., 2017. Leveraging existing occupancy-related data for optimal control of commercial office buildings : A review. Adv. Eng. Informatics 33, 230–242. doi:10.1016/j.aei.2016.12.008

Wang, D., Federspiel, C.C., Rubinstein, F., 2005. Modeling occupancy in single person offices. Energy Build. 37, 121–126. doi:10.1016/j.enbuild.2004.06.015

Zhao, J., Poh, K., Ydstie, B.E., Loftness, V., 2016. Occupant-oriented mixed-mode EnergyPlus predictive control simulation. Energy Build. 117, 362–371. doi:10.1016/j.enbuild.2015.09.02