EDITORIAL

On the simulation of occupant-centric control for building operations

Over the past decade, the Journal of Building Performance Simulation published two main Special Issues on modelling occupants. The first was a two-part issue that introduced the concept of modelling occupants’ presence and behaviour stochastically to improve simulation accuracy as well as building design (Robinson and Haldi 2011; Robinson and Haldi 2012). The second focused more on the fundamentals of occupant behaviour research, including the development of occupant behaviour models from various data sources and their integration in building simulations (O’Brien et al. 2017). One of the main outcomes of this line of research was using the developed models to improve the operations of buildings and their control systems. This led to introducing Occupant-Centric Control (OCC), which represents a novel approach for indoor climate control in which occupant-related information is directly measured or indirectly inferred from a variety of sensors, control interfaces, or mobile and wearable devices (Naylor, Gillott, and Lau 2018; Park et al. 2019). This concept has been demonstrated in various forms in the literature since the early 2000s with pioneering work on small-scale OCC experiments and feasibility studies (Dounis and Caraiscos 2009; Guillemin and Morel 2002).

However, technical limitations in building automation systems (BAS), technological infrastructure, as well as the general reluctance of the building industry, prevented large-scale adoption of OCC. On the other hand, recent advances in computing along with the significant increase in data availability from newer building systems renewed interest in OCC. For example, researchers introduced methods in which machine learning algorithms such as reinforcement learning, neural networks or logistic regression models were leveraged in OCC development (Peng, Nagy, and Schlüter 2019; Park et al. 2019). This led to dedicating a sub-task to OCC research within the International Energy Agency (IEA), Energy in Buildings and Communities Programme (EBC) Annex 79 on “Occupant-Centric Building Design and Operation” (O’Brien et al. 2020); by which the need for this Special Issue was identified.

Motivation for this Special Issue

Although recent studies suggest that OCC can reduce energy consumption in buildings by up to 60% while maintaining or improving occupant comfort, they also indicate its performance is subject to several sources of uncertainty (Park et al. 2019). These sources of uncertainty include typical culprits such as weather fluctuations and HVAC configurations. However, occupant preferences and OCC configurational settings, especially the selection of hyperparameter values if machine learning models are used, were found to have a more significant effect on OCC performance. Therefore, the development of OCCs in real-life can be a lengthy and challenging process. OCC hyperparameter tuning has been traditionally done through trial-and-error at the expense of occupant comfort and energy savings potential, leading to loss of stakeholder confidence in OCC solutions (Gunay et al. 2018). This phase of fine-tuning can also be constrained by other logistical challenges, such as the number of similar rooms in which OCC can be tested. Furthermore, inadequately short test periods and, sometimes, the lack of adequate submetering prevent reliable measurement and verification of the effectiveness of OCC solutions (Park et al. 2019). To this end, building simulation offers a flexible environment to rapidly study many OCC formulations and assess their impact on energy performance and indoor environmental quality (Pang et al. 2020; Ouf, Park, and Gunay 2019). In this Special Issue, different approaches to integrate OCC into building simulations are presented. The authors explored how occupancy and occupant behaviour patterns can be represented in building simulation, and finally, how these simulation studies can quantify the benefits of OCC implementation.

Before we delve into the content of this Special Issue, it is
pertinent to explain OCC strategies in more detail, including its methodological approaches and implementation challenges.

**What is Occupant-Centric Control (OCC) and how does it work?**

OCC can be sub-categorized into 1) occupancy-centric controls and 2) occupant behaviour-centric controls. Occupancy-centric rather than occupant behaviour-centric control focuses on the presence/absence of occupants; typical examples include vacancy-based light switch off and modulation of outdoor airflow rate based on occupant counts. Other occupancy-centric variables such as earliest/latest expected arrival and departure time can also be used to dynamically alter fan start and stop times as well as setback schedules, especially in rooms with frequent vacancies. On the other hand, occupant behaviour-centric controls focuses on occupant preferences that are inferred from occupants’ interactions with building systems (e.g., adjusting setpoints based on analyzing thermostat setpoint adjustments or light switches). To date, the building industry still uses the conventional assumptions, which naively consider constant occupant preferences and neglect their impact on perceived comfort and energy efficiency (Park and Nagy 2017). This is mainly due to the simplicity of representing human-building interactions in the current building design and operation practices (Park et al. 2019). For example, one of the largest post-occupancy evaluation studies reported that more than 50% of occupants were dissatisfied with their indoor environment from 351 office buildings (Frontczak et al. 2012).

OCC can be a viable approach to mitigate the challenges of the deficiency of occupant behaviour in building controls. Although OCC is relatively new and there is no formal definition, a recent review study of OCC identified its general procedure (Park et al. 2019). Essentially, the control agent gathers two data types from both occupants and the indoor space. The first data type characterizes the indoor environments (i.e., illuminance, temperature, humidity, and air quality) as well as its relationship with occupant satisfaction and productivity. The second type includes the interaction between the occupant and building systems (i.e., presence and usage of light switches, window blinds, and thermostats), which is a proxy for occupant comfort (or discomfort). By combining the two, the OCC agent can adapt to unique occupant preferences and indoor environments of the space then calculate adaptive and personalized control actions (i.e., updating set-points, moving shades or turning lights on/off) to balance occupant comfort and energy efficiency of various building system components.

**What are the current challenges of OCC?**

One of the main challenges facing OCC adoption is the lack of protocols for OCC experiments and implementation; While there are several metrics to evaluate the effect of OCC on energy performance using various M&V techniques, the assessments of occupant comfort are less emphasized (Ouf, O’Brien, and Gunay 2019). Simplifications of occupant comfort measurement (e.g., temperature range) are also naively used in various OCC studies. Moreover, there is no metric to simultaneously consider both comfort and energy perspectives at the same time. Another challenge is related to the building industry itself. Despite the paradigm shift that OCC represents, there are only a few OCC field implementations. This is mainly due to the reluctance of facility managers to install new control systems for their existing building systems; thus, facility managers limit the functionalities of building operations for potential OCC developments.

**What can you find in this Special Issue?**

Building simulation can address many of the challenges related to field implementations of OCC. However, the integration of OCC in building simulations is not a straightforward process. While typical building simulation inputs with regards to building design parameters are relatively straightforward, the way in which occupancy, occupant behaviour and OCC is represented in building simulation is not simple. Each of the studies presented in this Special Issue used a slightly different approach to represent occupants, depending on their objectives and the nature of the OCC strategies they simulated.

Cetin et al. use 14 years of the American Time Use Survey and Current Population Survey data to identify common occupancy profiles in residential buildings with various absence durations on weekdays and weekends. By leveraging cluster analysis, the distribution of these profiles across age groups and income levels is presented. The authors also provide the results of a survey that investigated the impact of the COVID-19 pandemic on occupancy profiles, which is expected to represent a paradigm shift given the rapid adoption of remote working. The authors then integrate the results of their analysis in a prototype residential building energy model to demonstrate potential energy savings due to OCC, especially when more representative occupancy schedules are used in the simulation. Their results show that energy savings due to OCC implementation in residential buildings can reach up to 17%, depending on occupancy patterns which
were found to significantly change based on household income.

Hong et al. focus on generating synthetic occupant populations for use in building simulations based on real demographic data. The authors use Bayesian Networks structural learning to synthesize populations of occupants in multi-family housing. It draws upon the Drivers-Needs-Actions-Systems framework (Hong et al. 2015) to guide the selection of variables and data imputation. The resulting synthetic occupant data show relatively high accuracy when comparing their joint distributions with actual data from the National Household Travel Survey, the Public Use Microdata Survey, as well as the ASHRAE Global Thermal Comfort Database. The authors note that the size of the target populations is one factor that determines the quality of the synthetic version, which tends to decrease if the target population is relatively small. Synthetic occupant data sets can particularly serve as an input to occupant behaviour co-simulation platforms, whereby occupants are treated as agent-based models. The outputs of this work can then be used to demonstrate the performance of OCC under various occupancy and occupant behaviour scenarios.

To provide a practical approach for implementing OCCs in building simulations, Hobson et al. introduce a library of OCC functions in R, which leverage building sensor data to prepare simulation inputs. Their approach can be divided into two main phases; the first phase focuses on offline learning in which five different occupancy- and occupant behaviour-centric control metrics (e.g., presence/absence times at the building and zone levels) are extracted from measured BAS data. The second phase focuses on simulation in which the extracted metrics are integrated into building simulations. The authors demonstrate their approach by applying the first phase using BAS data collected from 29 private offices, then integrating the calculated OCC metrics into EnergyPlus simulation models. They use these models to test several OCC strategies, showing that the energy use and thermal discomfort could be reduced by up to 37% and 65%, respectively, when OCCs are implemented.

A slightly different approach for OCC simulation is then presented by Pang et al., who quantify potential nationwide energy savings due to OCC implementation in large hotels. Their simulation presents three different scenarios, which are meant to reflect the different levels of occupant sensing capabilities. To demonstrate the effectiveness of these OCC scenarios, the authors modify occupancy schedules in building simulations based on data from multiple previous reports on hotel occupancy patterns to provide a more realistic representation of hotel occupancy. A large-scale parametric simulation is then conducted in 19 different climate zones to investigate the impacts of implementing OCCs in hotel buildings. The simulation results show that HVAC energy savings vary between 24–58%, with occupant presence sensing, which could increase by an additional 5–15% when using occupant counting sensors.

De Vries et al. focus on simulating comfort-driven solar shading controls, which represent a subset of OCCs. Their approach relies on mapping predicted occupant comfort to sensor measurements. In doing so, they define a set of performance indicators that the control strategy should optimize, which are then used to inform sensor selection. A simulation model is developed to test various control modes and evaluate their effect on occupant-centric performance targets such as daylight glare discomfort. The authors then use statistical classification to facilitate the selection of sensor deployment strategies and to identify control algorithms that optimize comfort conditions using non-ideal sensors. The authors test their method in a simulation case study in which they use a sun-tracking control strategy for indoor roller blinds, which demonstrates that the proposed method can identify high-performance shading control solutions.

For data-driven modelling in high-rise residential buildings, Stopps and Touchie investigate different regression and machine learning-based modelling approaches to compare and assess their capability to predict the performance of commercially available connected thermostats featuring occupancy-centric control features. To this end, they used connected thermostat data from 54 suites in two high-rise residential buildings to evaluate the accuracy of thermostat reported suite condition, HVAC runtime, as well as the relationship between suite HVAC runtime and thermal energy demand. In order to perform these evaluations, the authors compare thermostat measured indoor temperature and relative humidity values with those recorded by installed sensors. They also compare thermostat-reported runtime with measured runtime using current transducers. The authors then present random forest regression models to predict suite-level HVAC runtimes, which are trained using data collected from all suites for all seasonal periods.

Given the importance of building performance indicators, Li et al. identify occupant-centric key performance indicators (KPIs) in line with the general theme of this Special Issue. They first analyze the diverse factors that should be considered when formulating occupant-centric KPIs, which include temporal, spatial, normalization factors as well as general attributes of quantifiability and actionability. This is followed by synthesizing existing occupant-related performance metrics and proposing new KPIs that represent the occupant’s perspective on three integrative aspects of building performance, namely resource use (including energy and water), indoor...
environmental quality, and human–building interactions. The authors finally present a simulation-based case study to demonstrate how occupant-centric KPIs can be used to quantify the impacts of building operation changes from the occupants’ point of view. More specifically, they simulate two power outage scenarios in the winter and summer to investigate their effect on occupant-centric KPIs.

We would like to conclude this editorial by thanking the journal editors Drs. Jan Hensen and Ian Beausoleil-Morrison for promoting the field of OCC by providing a forum to demonstrate its simulation approaches in this Special Issue.

References

Dounis, A. I., and C. Caraiscos. 2009. “Advanced Control Systems Engineering for Energy and Comfort Management in a Building Environment—A Review.” Renewable and Sustainable Energy Reviews 13 (6): 1246–1261.

Frontczak, M., S. Schiavon, J. Goins, E. Arens, H. Zhang, and P. Wargocki. 2012. “Quantitative Relationships Between Occupant Satisfaction and Satisfaction Aspects of Indoor Environmental Quality and Building Design.” Indoor Air 22: 119–131.

Guillemin, A., and N. Morel. 2002. “Experimental Results of a Self-Adaptive Integrated Control System in Buildings: A Pilot Study.” Solar Energy 72 (5): 397–403.

Gunay, H. B., W. O’Brien, I. Beausoleil-Morrison, and J. Bursill. 2018. “Development and Implementation of a Thermostat Learning Algorithm.” Science and Technology for the Built Environment 24 (1): 43–56.

Hong, T., S. D’Oca, S. C. Taylor-Lange, W. J. N. Turner, Y. Chen, and S. P. Corgnati. 2015. “An Ontology to Represent Energy-Related Occupant Behavior in Buildings. Part I: Introduction to the DNAs Framework.” Building and Environment 94 (P1): 196–205.

Naylor, S., M. Gillott, and T. Lau. 2018. “A Review of Occupant-Centric Building Control Strategies to Reduce Building Energy Use.” Renewable and Sustainable Energy Reviews 96 (July): 1–10.

O’Brien, W., A. Wagner, M. Schweiker, A. Mahdavi, J. Day, M. B. Kjærgaard, S. Carlucci, et al. 2020. “Introducing IEA EBC Annex 79: Key Challenges and Opportunities in the Field of Occupant-Centric Building Design and Operation.” Building and Environment 178 (December 2019): 106738. doi:10.1016/j.buildenv.2020.106738.

O’Brien, W., B. Gunay, F. Tahmassebi, and A. Mahdavi. 2017. “Special Issue on the Fundamentals of Occupant Behaviour Research.” Journal of Building Performance Simulation 10 (5–6): 439–443.

Ouf, M. M., W. O’Brien, and B. Gunay. 2019. “On Quantifying Building Performance Adaptability to Variable Occupancy.” Building and Environment 155: 257–267.

Ouf, M. M., J. Y. Park, and H. B. Gunay. 2019. “A Simulation-Based Method to Investigate Occupant-Centric Controls.” Building Simulation 1:1–14.

Pang, Z., Y. Chen, J. Zhang, Z. O’Neill, H. Cheng, and B. Dong. 2020. “Nationwide HVAC Energy-Saving Potential Quantification for Office Buildings with Occupant-Centric Controls in Various Climates.” Applied Energy 279 (September): 115727. doi:10.1016/j.apenergy.2020.115727.

Park, J. Y., M. M. Ouf, B. Gunay, Y. Peng, W. O’Brien, M. B. Kjærgaard, and Z. Nagy. 2019. “A Critical Review of Field Implementations of Occupant-centric Building Controls.” Building and Environment 165 (May): 106351. doi:10.1016/j.buildenv.2019.106351.

Park, J. Y., T. Dougherty, H. Fritz, and Z. Nagy. 2019. “LightLearn: An Adaptive and Occupant Centered Controller for Lighting Based on Reinforcement Learning.” Building and Environment 147 (October 2018): 397–414.

Park, J. Y., and Z. Nagy. 2017. “Comprehensive Analysis of the Relationship between Thermal Comfort and Building Control Research - A Data-Driven Literature Review.” Renewable and Sustainable Energy Reviews 82 (September 2017): 2664–2679.

Peng, Y., Z. Nagy, and A. Schlüter. 2019. “Temperature-Preference Learning with Neural Networks for Occupant-Centric Building Indoor Climate Controls.” Building and Environment 154: 296–308.

Robinson, D., and F. Haldi. 2011. “Modelling Occupants’ Presence and Behaviour - Part I.” Journal of Building Performance Simulation 4 (4): 301–302.

Robinson, D., and F. Haldi. 2012. “Modelling Occupants’ Presence and Behaviour - Part II.” Journal of Building Performance Simulation 5 (1): 1–3.

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