DOI: 10.1016/B978-0-12-818567-4.00012-0

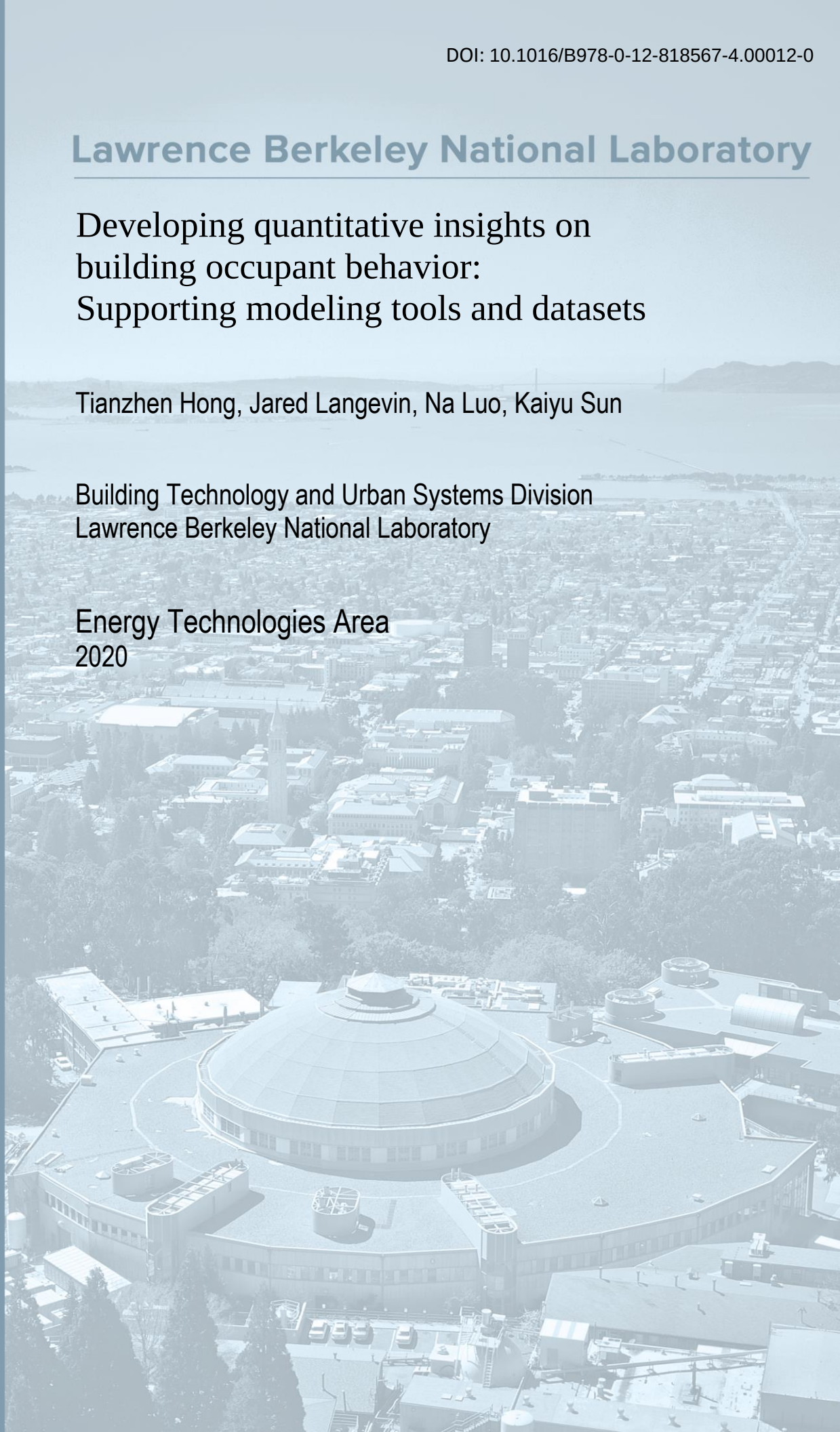
Lawrence Berkeley National Laboratory

Developing quantitative insights on building occupant behavior: Supporting modeling tools and datasets

Tianzhen Hong, Jared Langevin, Na Luo, Kaiyu Sun

Building Technology and Urban Systems Division
Lawrence Berkeley National Laboratory

Energy Technologies Area
2020



Disclaimer:

This document was prepared as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor the Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or the Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof or the Regents of the University of California.

Chapter 13

Developing quantitative insights on building occupant behavior: Supporting modeling tools and datasets

Tianzhen Hong, Jared Langevin, Na Luo, Kaiyu Sun
Building Technology and Urban Systems Division
Lawrence Berkeley National Laboratory

Abstract (150 words)

Energy-related occupant behavior is crucial to the design and operation of low-energy buildings. This chapter introduces state-of-the-art methods, tools, and datasets for quantifying occupant impacts on building energy use and occupant comfort. The chapter begins with an overview of how occupants can influence building environments and energy performance, and highlights gaps in the abilities of building energy simulation programs to represent these influences. Next, state-of-the-art methods and modeling tools that enable more sophisticated occupant behavior simulation are reviewed, along with the most prominent datasets available to support quantitative behavior model development. Then, an overview of application areas for occupant behavior modeling tools and datasets across the building life cycle is presented, and example applications are demonstrated through three case studies. The chapter concludes by identifying emerging opportunities and challenges surrounding the use of occupant behavior simulation to support the design and operation of low-energy buildings that foster greater occupant satisfaction.

Keywords (5-10 words)

Occupant behavior, energy behavior, energy use, energy efficiency, energy modeling, behavioral insights, interdisciplinary, low energy buildings, building performance simulation

13.0 Introduction

The energy-related behaviors of building occupants constitute a key factor influencing building performance; accordingly, realistic representation of occupant behavior in building performance simulations is essential to ensuring that such simulations yield accurate guidance for building design and operation decisions. For the purpose of this chapter, building occupant behavior (OB) refers to (1) occupant presence in spaces and movement between spaces, (2) occupant interactions with building systems, and (3) occupant adaptations (e.g., changing clothing, having hot/cold drinks).

Occupant behaviors such as adjusting a thermostat for comfort, switching lights on/off, using appliances, opening/closing windows, pulling window blinds up/down, and moving between spaces can have a significant impact on energy use and occupant comfort in buildings. Depending on the building type, climate, and degree of automation in operation and controls, existing studies have found that occupant behavior may increase or decrease energy use by a factor of up to three for residential buildings (Andersen 2012), and increase energy use by up to 80% or reduce energy use by up to 50% for single-occupancy offices (Hong & Lin 2013); another study (Sun & Hong 2017a) estimates that occupant behavior measures have a 41% energy savings potential for office buildings. Developing a deeper understanding of occupant behavior and further quantifying its impact on the use of building technologies, occupant satisfaction and building performance using simulation tools is crucial to the design and operation of low-energy buildings with high indoor environmental quality (IEQ).

Nevertheless, in most building design, construction, operation, and retrofit practices, the influence of occupant behavior remains under-recognized and over-simplified. In the most widely used building performance simulation programs, for example, the representation of occupant behavior is limited to pre-defined static schedules or fixed settings and rules (Cowie et al. 2017), leading to deterministic and homogeneous simulation results that fail to capture the stochasticity, dynamics, and diversity of occupants' energy behavior in buildings. Meanwhile, available models of occupant behavior have been developed across different researchers and have showed inconsistencies, precluding arrival at a consensus within the research community on how to approach experimental design and modeling methodologies. Given the above issues, a strong need has emerged in recent years for researchers to work together on devising a consistent research framework for occupant behavior definition and simulation.

Whole-building performance simulation (BPS) programs such as EnergyPlus (BTO 2017), ESP-r (Hand 2015), IDA-ICE (Equa 2017), DeST (Yan et al. 2008), and TRNSYS (2012) have recently been applied to quantitatively evaluate the effects of occupant behaviors on the performance of building technologies and energy systems, with the aim of reducing energy use in buildings and associated greenhouse gas emissions. Half of current BPS programs include built-in stochastic occupant behavior modeling capabilities; however, this functionality is far from consistent across

different BPS tools and generally lacks flexibility for user customization (Cowie et al. 2017). In these programs, prescribed schedules and rule-based control are frequently used to represent building occupants and their energy-related behaviors. Overall, the stochastic representation of occupants within BPS programs is much less ubiquitous than deterministic modeling capabilities (Cowie et al. 2017).

A recent study (Hong et al. 2017) provides a thorough overview of OB implementation approaches in the current BPS tools, which are: (1) *Direct input or control* - refers to the case when occupant-related inputs are defined using the semantics of BPS programs – just as other model inputs are defined (building geometry, construction, internal heat gains and HVAC systems); (2) *Built-in OB models* - users can choose deterministic or stochastic OB models already implemented in the BPS program, which are originally data-driven and use functions and models such as linear or logit regression functions. These models typically include occupant movement models, window operation models, and lights switching on/off models; (3) *User function or custom code* - users can write functions or custom code to implement new or overwrite existing or default building operation and supervisory controls; and (4) *Co-simulation approach* - allows simulations to be carried out in an integrated manner, running modules developed by different programming languages or in different physical computers. For a building energy modeler, the choice of which implementation approach to select is a difficult one. All of these approaches have their advantages and disadvantages, such as precision, calculation time, and input model development time.

There is a strong need to homogenize and stimulate wider uptake of stochastic occupant modeling capabilities in BPS programs. The development of a BPS program-independent co-simulation platform could address the gaps by centralizing functionality, allowing models to be implemented within the platform and then applied in a consistent way among different BPS tools. There is also a significant need for developing a suite of new occupant behavior modeling tools to improve the building performance simulation by: (1) providing a standard representation of occupant behavior models, enabling the exchange and use of occupant behavior models between BPS programs, applications, and users to improve the consistency and comparability of simulation results, and (2) generating realistic occupancy schedules. These tools capture the diversity, stochastics, and complexity of occupant behavior in buildings to improve the simulation and evaluation of behavioral measures, as well as of the impact of occupant behavior on technology performance and energy use in buildings.

In this chapter, state-of-the art methods and tools that enable more sophisticated occupant behavior simulation in BPS programs are reviewed, along with the most prominent datasets available to support quantitative behavior model development. A particular focus is placed on the OB tools yielded by the recently concluded International Energy Agency (IEA) Annex 66: Definition and Simulation of Occupant Behavior in Buildings. Four advanced occupant behavior

modeling tools which allow for a rapid and widespread integration of OB models in various BPS programs are introduced: (1) obXML – an XML schema representing OB models using the DNAS (Drivers-Needs-Actions-Systems) ontology; (2) obFMU – an OB model solver using the functional mockup unit; (3) Occupancy Simulator – an agent-based Markov chain model of occupant presence and movement in buildings; and (4) Buildings.Occupants – an open-source package of occupant behavior models implemented in Modelica, an equation-based, object-oriented language. Next, an overview of application areas for OB modeling tools and datasets across the building life cycle is presented, and example applications are demonstrated through three case studies. The chapter concludes by identifying emerging opportunities and challenges surrounding the use of occupant behavior simulation to support the design and operation of low-energy buildings that foster greater occupant satisfaction.

13.1 Occupant behavior modeling methods, datasets, and simulation tools

This section reviews the state-of-the art methods and tools that enable more sophisticated occupant behavior simulation, along with the data collection approaches and the most prominent datasets available to support quantitative behavior model development.

13.1.1 State-of-the-art occupant behavior modeling approaches

Various mathematical methodologies have been used in occupant behavior modeling. Classical statistical models such as general and generalized linear models have been applied extensively, while for time-dependent data, Markov and Hidden Markov chains (Dong & Lam 2014; Liisberg et al. 2016; Andersen et al. 2014; Richardson et al. 2008) have proved to be useful tools. Mixed-effects and agent-based models have been applied to capture the diversity among occupants (Haldi 2013; Langevin, Wen, et al. 2015), and machine learning and data mining techniques such as clustering (Pan et al. 2017; Ren et al. 2015) and decision trees have followed from the improved availability of large occupant behavior datasets (Hong, D'Oca, Turner, et al. 2015). In this section, the use of different modeling approaches in the literature is described, with the models organized by the different behavior types for which they were developed. As aforementioned, the occupant behaviors referred to in this chapter are: (1) occupant presence/absence in spaces and movement between spaces, (2) occupant interactions with building systems (e.g., opening the windows, operating the HVAC system), and (3) occupant personal adaptations (e.g., changing clothing, having hot/cold drinks). This section mainly focuses on the first two occupant behavior types, as few existing modeling studies cover occupants' personal adaptations.

Representative modeling approaches

Markov chains assume that future system states (e.g., of occupancy, or of a building control) are dependent only on the current system state together with the probabilities of the state changing. A Markov chain consists of a set of transition probability matrices that describe the transition between states in each time step. The matrix entries can be estimated from the source data using

maximum likelihood estimation. A hidden Markov model (HMM) consists of a Markov chain whose states are not directly observed, and information is derived about the unobserved entity from a series of related observations. For a detailed description of Markov chains, refer to Zucchini et al. (2016). Time series in which quantities take a finite number of states can be modeled using Markov chains. In practice, Markov chains are employed to model (1) occupancy (presence, absence, people count); (2) window states over time (open, closed); (3) blind usage (open, closed, fraction of opening); and (4) activity level (working, sleeping, resting, laundry, cooking, absent).

The ***general linear model*** (classical GLM) is a classical statistical model that assumes normally distributed response variables and a linear relationship between the explanatory variables and the response variable. For example, ordinary linear regression and the analysis of variance (ANOVA), and mixtures thereof, are classical examples of GLM. Let $Y = (Y_1, \dots, Y_n)$ be a vector of n observations of a response variable. We assume that Y follows a multivariate normal distribution $N(\mu, \Sigma)$. In the classical GLM, it is assumed that the vector of mean values $\mu = (\mu_1, \dots, \mu_n)$ can be expressed as a linear combination of some explanatory variables expressed by column vectors $X_1, \dots, X_k$.

Generalized linear models (GLM) relax the assumption of normally distributed errors, relating a linear predictor $X\beta$ to the expected response $E(Y)$ via a link function g where $g\big(E(Y)\big) = X\beta$. In a binary logistic regression modeling a dichotomous response variable, for example, the link is defined as $\ln\left(\frac{\pi}{1-\pi}\right) = X\beta$, where π is the expected probability of a response $Y = 1$ and model errors are assumed to follow a logistic distribution. A further generalization of the linear model adds random effects U to the fixed effects of predictor variables X, or in the case of the binary logistic regression: $\ln\left(\frac{\pi}{1-\pi}\right) = X\beta + ZU$; random effects account for unobserved heterogeneity in the data. This class of approaches is termed generalized linear mixed models (GLMM).

Bayesian network models (BNs) are directed acyclic graphs or belief networks that are used to represent the relationships among a predefined group of discrete and continuous variables (*Xi*). BNs consist of a graphical model and an underlying conditional probability distribution. The nodes of the graph represent the variables, and the dependencies between variables are depicted as directional links corresponding to conditional probabilities. Hence, the construction of a BN consists of determining the structure and the probability distribution associated with these relations. The relationships between nodes can be explained by employing a family metaphor: a node is a parent of a child if there is an arc from the former to the latter. For instance, if there is an arc from X_1 to X_3, then node X_1 is a parent of node X_3. The Markov property of the BNs implies that all probabilistic dependencies are identified via arcs and that child nodes only depend on the parent nodes.

Agent-based models (ABMs) represent systems from the bottom-up, simulating individual actors or 'agents' with personal attributes and behavioral possibilities, as well as rules for interacting with other agents and their surrounding environment; macro- or group-level behaviors emerge from the micro-level behaviors of individual agents. For more guidance on the agent-based modeling approach, refer to (Macal & North 2010), as well as the chapter in this book titled "Agent-Based Modelling of the Social Dynamics of Energy End-Use" by Chappin et al.

Modeling studies of building occupancy

Occupancy is defined in existing studies as either the presence or absence of an occupant or the occupant count (the number of occupants) in a given space. One of the most typical occupancy modeling approaches is Markov chains. The occupancy models of Richardson et al. (2008) and Page et al. (2008) are the earliest published examples of first-order Markov chains being used to generate stochastic synthetic occupancy patterns. This first-order Markov chain technique has since been widely adopted in the development of occupancy models in office buildings (Wang et al. 2011; Liao et al. 2012; Andersen et al. 2014). In certain studies, presence/absence at the space level is modeled alongside the number of occupants – for example, in (Hong et al. 2013), which uses the occupancy models to determine the lighting and heating requirements of a building. More recently, Wilke (2013) used first- and higher-order homogeneous Markov processes to represent building occupancy, where a higher-order Markov process extends the first-order Markov case by including multiple past values of occupancy state. This approach is coupled with a survival analysis method, in which a Weibull distribution is used to estimate occupant presence durations at greater time lags before the present simulation step. Hence, information about the next time step is not only based on current occupancy state, but also on past occupancy values through the survival function that also captures the durations of occupant presence and absence coherently.

Modeling studies of occupant interactions with building systems

In naturally ventilated buildings, window opening and closing behavior is an important control mechanism used by building occupants to regulate the indoor thermal environment and air quality. It is crucial to have window operation models that create realistic patterns for use in building performance simulations. Accordingly, models of window use are particularly prevalent within the existing behavior literature.

The most common modeling approach for window operations is logistic regression as a special case of GLMs. In some cases, interaction terms between several predictors are considered. Time dependencies are modeled by Markov chains (Fabi et al. 2014; Calì et al. 2016), and survival analysis has been applied to model opening durations (Haldi & Robinson 2009).

More recently, GLMMs have been used to model the diversity in window opening behavior across occupants (Schweiker et al. 2012); this application of GLMMs has also been suggested by

Haldi (2013). Here, the inclusion of random effects in the GLMM approaches allows inter-individual variability to be described - i.e., the diversity in behavior among different occupants, where fixed effect models only capture an average occupant's behavioral tendencies. Hence, the GLMMs separate the variability in the data corresponding to occupants' diversity from other sources of uncertainty. These kinds of models are especially useful for Monte-Carlo simulations, because an occupant is randomly drawn from a population in every simulation run, resulting in a spread of behavior that reflects reality.

In another recent study, Barthelmes et al. (2017) used a Bayesian Network (BN) to model window control behavior in the residential sector. Their study addressed five key research questions related to modeling window control behavior: (1) variable selection for identifying the key drivers of window control behavior, (2) correlations between key variables for structuring a statistical model, (3) target definition for finding the most suitable target variable (window control actions rather than window states), (4) development of a BN model with the ability to treat mixed data, and (5) validation and demonstration of the high predictive power of stochastic BN models.

In addition to the window opening and closing behavior, light switching behavior is also considered as a major factor influencing the electricity use in domestic homes and office buildings. Studies on the modeling of lighting switch behavior have mostly focused on small office and residential buildings, with the research findings greatly dependent on building layout and daylight control systems. The first report of a stochastic approach to manual lighting control was by Newsham et al. (1995), who developed a regression model called Lightswitch that simulated user activities of turning lights on/off in the workplace based on measured field data from an office building in Ottawa, Canada. The probability of turning on lights has also been modeled as dependent on natural/daylight level and occupant movement (Widén et al. 2009).

A small number of studies attempt to integrate prediction of multiple types of human-building interactions in a single modeling package. For example, the agent-based modeling approach reported by Langevin et al. (2015) predicts the probability of several inter-dependent behaviors, including window opening and closing, adjustment of thermostats, use of personal heating and cooling devices, and the adjustment of personal clothing levels. In this framework, each agent represents an individual office occupant that acts adaptively based on the simulated distance between current thermal sensation and a thermal acceptability range, where both are modeled probabilistically based on occupant comfort field data from the ASHRAE RP-884 database (*https://sydney.edu.au/architecture/staff/homepage/richard_de_dear/ashrae_rp-884.shtml*).

13.1.2 Occupant behavior datasets

Data collection approaches

The collection of datasets for developing and validating behavior models is an essential driver of improved understanding and representation of behavior in BPS. To capture occupants' energy-related behaviors in buildings, researchers may collect two types of information: (1) reported information using surveys and/or (2) monitored information from sensing and data acquisition technologies.

Surveys are a cost-effective means of achieving a large sample size and can measure phenomena that would be difficult or impossible to measure with sensors (e.g., thermal comfort sensation and clothing level, social interactions and attitudes). Several recent studies (Becerik-Gerber et al. 2011; Konis 2013; Haldi & Robinson 2008) have relied on custom technological survey solutions for polling occupants more frequently than a telephone, paper, or online survey would allow. Surveys have also been used to develop models (e.g., Haldi and Robinson, 2009; Langevin, Wen and Gurian, 2015). Despite the aforementioned benefits to using surveys in occupant research, a number of established psychological biases, including the Hawthorne effect and social desirability bias, suggest that self-reported behavior may not always match observed behavior (McCambridge et al. 2014). In addition, a lack of understanding of different building services systems or the misinterpretation of questions may cause occupants to unknowingly report certain variable states incorrectly. Relative to other in-situ and laboratory monitoring approaches, surveys typically do not lend themselves to frequent sampling because they rely on occupants' active input; therefore, their use in longitudinal studies may be limited to targeted periods of study, with the goal of limiting occupant fatigue (Langevin, Gurian, et al. 2015).

Outside of surveying techniques for behavior data collection, previous studies have used sensing and data acquisition technologies to yield more granular occupant information (including both occupancy and activities). Sensor data collection may be conducted either *in-situ* (e.g., in a field setting) or in a laboratory condition. Data are typically acquired passively through sensors that feed into the building automation system (BAS). Such sensors measure variables that include: occupants' presence, adaptive actions (e.g., changing window or door state, turning on/off personal heating and cooling devices), energy use (through sub-metering), and environmental variables such as temperature, humidity, air velocity, lumen level, and CO_2 concentration (Haldi & Robinson 2010; Duarte et al. 2013). For *in-situ* studies, the measurement sample size may be constrained by the small number of willing participants in a given building, though frequent measurement intervals (1-5 minutes) may still yield large amounts of data for a small occupant sample. Additionally, lack of flexibility in sensor placement to avoid interfering with occupants' activities or to prevent the measurements being disturbed by the occupants can reduce the accuracy of measurements (Reinhart & Voss 2003; Andersen et al. 2013).

On the other hand, laboratory facilities for occupant research are typically costly to build and operate, and experiments are often significantly more expensive than *in-situ* studies because of the human resources required. Another downside to laboratory studies is that the short-term and potentially unnatural characteristics of laboratory environments may yield occupant response data that is unrepresentative of a field setting; new experimental techniques propose using augmented reality technologies to allow laboratory settings for occupant behavior research to more closely mimic occupants' experiences in real buildings over long time periods (Saeidi et al. 2017).

To summarize, occupant behavior data collected through survey instruments may reveal important insights on the rationales and motivations for behavior and cover variables that would be difficult to measure using sensor and data acquisition instruments; yet, survey techniques can prompt occupant response fatigue and they often rely on occupant recall of behavior, which may be inaccurate. Meanwhile, data collected by sensing instruments may yield richer and more granular insights on variables such as occupant presence, certain actions, and environmental conditions across long time periods; yet, measurement sample size may be constrained by the number of occupants who are willing to be monitored and suboptimal sensor placement in the field can compromise the accuracy of collected data.

Ultimately, the most favorable behavior data approaches are likely to involve some combination of both survey and sensor measurements, enabling one data source to be cross-referenced with the other and supporting the compilation of a comprehensive set of information on the physiological, psychological, and social aspects of occupant behavior.

Existing dataset resources

An increasing number of datasets on building occupant behavior are being developed and shared through a growing variety of channels.[1] Here we list a few of the most prominent existing datasets concerning occupant behavior.

- *ASHRAE Global Thermal Comfort Database I and II*
  The ASHRAE Global Thermal Comfort Database project (Földváry Ličina et al. 2018) was launched in 2014 under the leadership of University of California at Berkeley's Center for the Built Environment and The University of Sydney's Indoor Environmental Quality (IEQ) Laboratory. The exercise began with a systematic collection and harmonization of raw data from the last two decades of thermal comfort field studies around the world. The final database is comprised of field studies conducted between 1995 and 2015 from around the world, with contributors releasing their raw data to the project for wider dissemination to the thermal comfort research community. After the quality-assurance process, there was a total of 81,846 rows of data of paired subjective

[1] Google recently developed a database search tool (https://toolbox.google.com/datasetsearch), which includes occupant behavior related datasets.

comfort votes and objective instrumental measurements of thermal comfort parameters. An additional 25,617 rows of data from the original ASHRAE RP-884 database are included, bringing the total number of entries to 107,463.
The database is intended to support diverse inquiries about thermal comfort in field settings. To achieve this goal, two web-based tools were developed to accompany the database:

a. Interactive visualization tool (https://cbe-berkeley.shinyapps.io/comfortdatabase/): provides a user-friendly interface for researchers and practitioners to explore and navigate their way around the large volume of data in ASHRAE Global Thermal Comfort Database II.
b. Query builder tool (http://www.comfortdatabase.com/): allows users to filter the database according to a set of selection criteria, and then download the results of that query in a generic comma-separated-values (.csv) file.

- *Library of occupant behavior models*
  Within the effort of Annex 66, energy-related OB literatures have been reviewed to identify and compile a list of 127 commonly-used OB models in the field that cover the following categories: (1) *behavior types* - occupant movement and different types of occupant interactions with windows, doors, shading, blinds, lighting systems, thermostats, fans, HVAC systems, plug-loads; making hot/cold beverages and adjusting clothing levels. (2) *building types* - office, residential and school buildings. In this list, those models with clear documentation were considered for library inclusion, and were processed and implemented using the DNAS (Drivers, Needs, Actions, Systems) framework, presented in a standardized way called obXML (occupant behavior eXtensible Markup Language, see below).

  In addition to the obXML library (Belafi et al. 2016), a library of occupant behavior models in another language - Modelica was also recently developed (Wang et al. 2018). This Modelica package of occupant behavior models could be more conveniently integrated into other Modelica-based building system models.

- *Surveys on building simulation practices and human-building interactions*
  As aforementioned, surveys are a cost-effective means of achieving a large sample size and can measure phenomena that would be difficult or impossible to measure with sensors. Two surveys were conducted under Annex 66 (https://annex66.org/).

  The first survey seeks to understand the current practices and attitudes of current building simulation users towards occupant modeling (O'Brien and Cowie, 2017). In total, 274 valid responses were collected from BPS users (practitioners, educators, and researchers) from 37 countries. The results of this 36-question international survey indicate that

occupant assumptions made by simulation users vary widely and are considerably simpler than what has been observed in reality. Most participants cited lack of time or understanding as their primary reason for not delving deeply into occupant modeling, but responded that they are receptive to further training.

The second survey is a cross-country questionnaire based on theories and insights from building physics and social psychology. This survey aims to investigate the building-user interaction in the workspace, as well as the degree to which this interaction impacts comfort provision, energy use, and operating costs in diverse office settings and cultural contexts worldwide (D'Oca et al. 2015). A total of 37 questions were devised by an interdisciplinary team having architecture, engineering and social science backgrounds, and responses were collected from administrative staff and faculties at 14 universities and research centers across six countries spanning the U.S., Europe, China and Australia. The outcomes highlight the correlation between perceived behavioral control and perceived comfort, satisfaction and productivity in office spaces.

- *OpenEI.org*
  OpenEI provides a free platform for sharing datasets specifically in the area of renewable energy and energy efficiency. Currently, there are several datasets available on this platform that relate to occupant behavior. For instance, Langevin et al. (2015) published a one-year longitudinal dataset (15-minute interval) on local thermal conditions, related occupant behaviors, and comfort of twenty-four occupants of a medium-sized office building between July 2012 and August 2013 in Philadelphia, PA. The long-term data were collected via online daily surveys and data logger measurements of the local thermal environment and behavior.

- *Zenodo*
  Zenodo (Zenodo.org) is a web platform that promotes open data for open science. Datasets, software and other materials can be deposited and shared through the Zenodo platform, which includes datasets related to occupant behavior. For instance, a recently published dataset on Zenodo contains movement behavior (head, eye, torso) and electroencephalogram (EEG) signals (a recording of the electrical activity of the brain from the scalp) of 21 young normal-hearing (11 males, 11 females, mean age 25 +/- 3.6 years) and 19 elderly normal-hearing subjects (9 males, 12 females, mean age 69 +/- 5.4 years) measured in virtual audiovisual environments in the laboratory. The virtual audiovisual environments that were used are: a living room, a lecture hall, a cafeteria, a street and a train station. The video and audio material for the environments is also available on the website (Hendrikse et al. 2018).

- *Nature Scientific Data*

Nature Scientific Data is a peer-reviewed, open-access journal for descriptions of scientifically valuable datasets and research that advances the sharing and reuse of scientific data. The journal was launched by Nature Research to enable the discoverability, reproducibility and reuse of valuable data. Scientific Data primarily publishes Data Descriptors, a new type of publication that combines the narrative content characteristic of traditional journal articles with structured, curated metadata that outline experimental workflows and point to publicly archived data records. Currently, there are around 20 datasets in this resource that relate to occupant behavior or energy consumption measurements. For instance, Makonin et al. (2016) collected long-term measurements of electric and water consumption, energy use behavior, and HVAC operational parameters for a residential house in Canada between 2012 to 2014.

Advanced occupant behavior simulation tools

A suite of computational tools has been developed to standardize the representation of OB models and enable their use via co-simulation with BPS programs.

obXML: An occupant behavior XML schema

obXML (Hong, D'Oca, Turner, *et al.*, 2015; Hong, D'Oca, Taylor-Lange, *et al.*, 2015) is an XML schema that standardizes the representation and exchange of occupant behavior models for building performance simulation. obXML builds upon the Drivers–Needs–Actions–Systems (DNAS) ontology to represent energy-related occupant behavior in buildings. Drivers represent the environmental and other context factors that stimulate occupants to fulfill a physical, physiological, or psychological need. Needs represent the physical and non-physical requirements of occupants that must be met to ensure satisfaction with their environment. Actions are the interactions with systems or activities that occupants can perform to achieve environmental comfort. Systems refer to the equipment or mechanisms within the building that occupants may interact with to restore or maintain environmental comfort. A library of obXML files, representing typical occupant behavior in buildings, was developed from the literature (Belafi et al. 2016). These obXML files can be exchanged between different BPS programs, different applications, and different users. Figure 1 shows the four key elements of the obXML schema and their sub-elements.

*** Insert Figure 13.1 ***

Caption: Overview of the obXML schema showing the DNAS ontology.

Credit: *Hong et al., 2016*

obFMU: An occupant behavior functional mockup unit

obFMU (Hong et al. 2016) is a modular software component represented in the form of functional mockup units (FMUs), enabling its application via co-simulation with BPS programs using the standard functional mockup interface (FMI). FMU is a file (with extension .fmu) that contains a

simulation model that adheres to the FMI standard. obFMU reads the occupant behavior models represented in obXML and functions as a solver. A variety of occupant behavior models are supported by obFMU, including (1) lighting control based on occupants' visual comfort needs and availability of daylight, (2) comfort temperature set-points, (3) HVAC system control based on occupants' thermal comfort needs, (4) plug load control based on occupancy, and (5) window opening and closing based on indoor and outdoor environmental parameters. obFMU has been used with EnergyPlus and ESP-r via co-simulation to improve the modeling of occupant behavior. Figure 2 shows the workflow of co-simulation using obFMU and EnergyPlus.

*** Insert Figure 13.2 ***

Caption: Co-simulation workflow of obFMU with EnergyPlus.

Credit: Yan and Hong, 2018

Occupancy Simulator: A web-based occupancy app

Occupancy Simulator (Chen et al. 2018; Luo et al. 2017) is a web-based application running on multiple platforms to simulate occupant presence and movement in buildings. The application can also generate sub-hourly occupant schedules for each space and individual occupants in the form of CSV files and EnergyPlus IDF files for building performance simulations. Occupancy Simulator uses a homogeneous Markov chain model (Wang et al. 2011; Feng et al. 2015) and performs agent-based simulations for each occupant. A hierarchical input structure is adopted, building upon the input blocks of building type, space type, and occupant type to simplify the input process while allowing flexibility for detailed information capturing the diversity of space use and individual occupant behavior. Users can choose an individual space or the whole building to see the simulated occupancy results.

Buildings.Occupants: An occupant behavior model package in Modelica

To simulate the continuous and dynamic interaction between occupants and building systems, Buildings.Occupants (Wang et al. 2018) can be used. The Buildings.Occupants package, as part of the Modelica Buildings Library (Wetter et al. 2014), supports fast prototyping by seamlessly integrating occupant behavior models with Modelica models from existing libraries for building dynamics. Additionally, the structure of the package has been designed to allow for the flexible implementation of user-defined models by tuning the parameters and calling functions defined in the BaseClasses package. The Buildings.Occupants package includes reported occupant behavior models in the literature that are more commonly used and well documented in terms of the data source, mathematical equation, independent variables, parameter values etc. The models are categorized into sub-packages based on the building types and systems. There are 34 occupant behavior models for office and residential buildings that are included in the first release of the Buildings.Occupants package. The office building models include eight models on windows

operation, six models on window blind operation, four models on lighting operation, and one model on occupancy.

13.2 Application of occupant behavior models across the building life cycle

This section brings an overview of application areas for occupant behavior modeling tools and datasets across the building life cycle. It summarizes Annex 66's 32 case studies of building occupant behavior modeling applications from around the world, and then introduces three example applications through case studies focusing on the building design-stage, operation and control-stage, as well as the retrofit-stage.

13.2.1 Fit-for-purpose occupant behavior modeling in the building life cycle

As suggested earlier in this chapter, occupant behavior is an important source of uncertainty when dealing with BPS (Clevenger & Haymaker 2006; Hoes et al. 2009), and an increasing number of models has accordingly attempted to represent occupant behavior in a more realistic manner within BPS. Such models can be classified according to their complexity – here defined as the amount of detail in a model, which in turn results from its size and resolution (Zeigler & Oren 1979).

At the lowest spectrum of complexity are the diversity factors, or schedules: hourly fractions from 0 to 1 which are multiplied for a maximum amount of e.g. heat gains due to people, equipment, lighting, etc. Schedules are commonly employed to represent occupant presence and occupant behavior in current BPS tools, due to their ease of use and to the incentives from the building code (Yan et al. 2015). However, it is argued that simple schedules are not representative of actual occupant behavior, which is typically stochastic and influenced by a high number of variables. Moreover, schedules neglect occupants' diversity (O'Brien et al. 2017).

For this reason, researchers have developed non-probabilistic, probabilistic, and agent-based models, which give a more accurate representation of people's behavior (Gaetani et al. 2016; Gunay et al. 2013). Here, it is important to note that the required confidence in the building performance prediction depends on the purpose of the simulation. For example, Gaetani et al. (2016) argue that a more complex behavior model is needed when energy usage for a single building is assessed (design/retrofit), but such complexity may not be necessary or feasible when aggregating predictions across the scale of a district with a collection of buildings. Furthermore, different buildings and performance metrics may be affected in a diverse way by the various aspects of occupant behavior: some cases are extremely sensitive to the way a particular aspect is modeled, while others may be little affected.

In practice, BPS users may not understand the details of available behavior models and may not use them as intended. Above all else, the modeler must justify the chosen behavior modeling approach on a case-by-case basis to ensure that it is fit-for-purpose. Figure 3 illustrated the fit-

for-purpose framework for occupant behavior model selection and application (Gaetani et al. 2016). First, there is a need to select an appropriate tool for the given system design complexity. Then, information on the design parameters should be commensurate with the level of detail of the model. The characteristics of BPS tools that incorporate occupant behavior should therefore vary according to application context. Highly complex behavior modeling software may not be of much use when simple energy use estimations are required. In contrast, for a building design phase that calls for detailed modeling, additional behavior modeling sophistication may be warranted.

*** Insert Figure 13.3 ***

Caption: A fit-for-purpose framework for occupant behavior model selection and application.

Credit: *Gaetani et al., 2016*

13.2.2 Summary of 32 case studies for occupant behavior models and data in Annex 66

IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings (Yan et al. 2017), an international collaborative project involving more than 120 researchers from 20 countries working together from November 2013 to May 2018, collected a set of 32 case studies (Clinton et al. 2017) of modeling occupant behavior in buildings using various computational decision support tools.

Motivation to accurately represent occupant behavior in these case studies comes from BPS practitioner beliefs that occupant behavior is a major source of discrepancy between simulated and measured building energy performance and that current modeling practice with regards to occupant behavior is overly simplistic (O'Brien & Gunay 2016). Indeed, the previously cited review of nine current BPS programs by Cowie et al. (2017) identified "a widening gap between knowledge and implementation in the field of occupant behavior modeling."

Accordingly, the purpose of the case study review was to illustrate the range and types of occupant behavior modeling applications, to contribute to a framework for classifying these applications, and to explore which behavior modeling approaches are most appropriate for which contexts. Essential elements of this framework answer the canonical journalistic questions about any story: who, what, why, when, and where. To determine which model is most fit for which context, three dimensions emerge as being particularly important: the stakeholder and their problem (who and why); the building type, services and provisions (what); as well as the process stage and relevant tools (when).

The most innovative cases of occupant behavior modeling provide a "demand-pull" view, as seen by the users of such tools, to counterbalance the "supply-push" perspective that many who create such models bring to the subject (Godin 2017). The case studies collectively provide a

framework for thinking about: (1) when occupant behavior becomes important for making decisions about buildings, (2) which tools are most appropriate for specific applications, and (3) what insights emerge from practical experience with these tools.

13.2.3 Three representative case studies: design-stage application, operation and control-stage application, and retrofit-stage application

Case study 1 - the impact of occupant behavior modeling assumptions on energy efficiency measure performance

To improve energy efficiency—during new building design and building retrofit—evaluating the energy saving potentials of energy conservation measures (ECMs) is critical. ECMs refer to building technologies (e.g., LED lights), control strategies (e.g., daylighting and dimming control of lights), and behavior changes (e.g., occupants turning off lights when leaving an office) that improve upon the per-unit energy use of comparable incumbent or "business-as-usual" technologies or approaches. Occupant behaviors significantly impact building energy use and raise uncertainty when estimating the effectiveness of ECMs. This case study presents a simulation framework of quantifying the impact of occupant behavior on ECM savings.

Methodology

The ECM savings are influenced by many factors such as the building type, weather data, building operation, and occupant behaviors. The estimated ECM savings would vary with different model input assumptions. Traditional ECM evaluation methods adopt deterministic inputs and generate a static single result of energy savings, which neglects the uncertainty of the ECM savings. However, estimating the uncertainties of the ECM savings is critical, especially during risk analysis and decision making for ECM investment (Heo et al. 2011). Decision makers should be aware of the potential risks of implementing ECMs before selecting the most appropriate ECMs for a specific building.

In this case study, a simulation framework was proposed to evaluate ECM savings considering the variations of occupant-related inputs and their influence on the ECM energy savings (Figure 4). This proposed framework includes the following steps: (1) defining the three occupant behavior styles representing people with different levels of energy consciousness (austerity, normal, and wasteful), using quantitative occupant behavior models; (2) developing three baseline models using each of the predefined three occupant behavior styles and other same model inputs such as weather data, internal heat gains and energy system efficiencies; (3) calculating the energy uses of the three baseline models; (4) applying the ECMs to each baseline model to create the alternate models for each ECM, and (5) simulating the ECM energy models to calculate their energy use.

The simulated ECM saving results using the proposed framework are a range of values instead of a single fixed value, which reflects the possible variations of the ECM savings due to different

occupant behaviors in the building. Therefore, the framework can be adopted to evaluate ECM savings in a more comprehensive and robust way, giving decision makers the information they need to recognize and assess the potential risks of investing in ECMs in buildings with different occupant behaviors. ECMs with consistent large energy savings can be prioritized for investment compared to those ECMs with savings that are sensitive to occupant behavior style.

*** Insert Figure 13.4 ***

Caption: A framework to quantify the impact of occupant behavior on performance of ECMs.

Credit: *Sun and Hong, 2017*

This framework was demonstrated in a real office building to quantify the influence of occupant behaviors on ECM savings. Figure 5 shows the overall workflow of the pilot study. Field investigation was conducted in the building to gather information for creating the baseline energy model, including the geometry, zoning, number of occupants in each zone, and occupant schedules. Three occupant behavior styles, representing the proactive energy savers, average (norm) occupants, and the energy spenders, respectively, were adopted to represent different levels of energy consciousness and the boundaries of either extreme (as in energy savers and spenders). Occupant schedules, generated by the Occupancy Simulator with inputs from the site survey of the case building, were used in the energy models.

Seven individual ECMs and one packaged ECM were evaluated in this study, including reducing lighting power density (LPD), reducing plug-in electric equipment power density (EPD), improving envelope performance, improving HVAC system efficiency, daylighting control, variable refrigerant flow system, and natural ventilation coupled with the variable refrigerant flow (VRF) system. These ECMs were chosen considering their application to a 15-year-old building designed to comply with ASHRAE Standard 90.1-2001 standards, which were adopted in the baseline models to represent existing buildings. The efficiencies of the ECMs in this study were obtained from the more recent ASHRAE 90.1-2013 standards. The impact of occupant behavior on ECM energy savings was evaluated in four different climates—Chicago, Fairbanks, Miami, and San Francisco—so that the potential sensitivity to climate could be studied as another dimension. The selected cities represent the four typical climate types in the United States: humid continental, subarctic, tropical (subtropical), and Mediterranean, respectively.

Whole-building simulation using EnergyPlus was used to evaluate the impact of occupant behaviors on the ECM savings. Baseline models were developed in EnergyPlus to represent the investigated office building. EnergyPlus is an open-source program that models heating, ventilation, cooling, lighting, water use, renewable energy generation, and other building energy flows (Crawley et al. 2001) and is the flagship building simulation engine supported by the Department of Energy. It includes innovative simulation capabilities (e.g., sub-hourly time-steps,

natural ventilation, thermal comfort, co-simulation with external interfaces, renewable energy systems, and user customizable energy management systems). Some of the innovative capabilities, such as natural ventilation, daylighting, external schedules, and energy management systems, were used in this pilot study.

*** Insert Figure 13.5 ***

Caption: The workflow of the pilot study.

Credit: *Sun and Hong, 2017*

Results

Figure 6 shows an example of the pilot study results, which illustrates the ECM energy saving percentages compared to the baseline models under the three behavior styles in Chicago. The simulation results indicate that the saving percentages of LPD, EPD, envelope, system efficiency, and daylighting control are minimally affected by occupant behavior styles. This is because they are all purely technology-driven ECMs, which don't rely on the interactions with the occupants to save energy. On the other hand, the saving percentages of the VRF system, natural ventilation, and integrated ECM are significantly affected by occupant behavior styles, because the energy performance in these ECMs is closely related to how the occupants interact with the ECM. For example, once the VRF system is installed, which allows zonal control, the occupants have decisions to make on how to control their indoor units: the austerity occupants only turn on the indoor units when they feel hot, normal occupants turn on the indoor units as long as they are in the room, while the wasteful occupants keep the indoor units on during the entire working hours. Also, cooling and heating setpoints are different among the behavior styles. Therefore, the energy performance of such ECMs heavily depends on how the occupants behave.

*** Insert Figure 13.6 ***

Caption: ECM saving percentages compared to the baseline models with different behavior styles in Chicago.

Credit: *Sun and Hong, 2017*

Conclusion

The main findings from this study are:

(1) The occupant behavior style has significant influence on building energy use. Buildings occupied by energy spenders could consume more than twice the energy of the energy savers.

(2) For occupant-independent ECMs, which are purely technology-driven and have little interaction with the occupants, such as reducing LPD, reducing EPD, improving envelope properties, and improving HVAC system efficiency and daylighting control, energy saving percentages are minimally (less than 2%) affected by occupant behavior styles. For occupant-dependent ECMs, which have strong interaction with the occupants, such as the VRF system and natural ventilation, energy saving percentages are significantly (up to 20%) affected by occupant behavior styles.

(3) The wasteful behavior style generally achieves the greatest absolute energy savings while its saving percentages are close to or even lower than those of the austerity and normal behavior. This is important information for decision makers in retrofit planning.

(4) The occupant schedule has certain impacts on the simulated results of ECM savings, especially for the occupant-dependent ECMs coupled with the austerity behavior style. Adopting realistic occupant schedules rather than normalized ones would help improve the accuracy of ECM saving evaluation.

The zero-net energy (ZNE) technologies are successful and growing today as energy performance requirements are becoming more and more stringent. ZNE technologies, such as natural ventilation, HVAC control, and demand response, tend to need more interaction with occupants. They are more sensitive to occupant behaviors and reactions to stimulations, which makes occupant behavior a significant uncertainty factor for the technology's performance. In other words, occupant behavior may significantly change the way technologies are designed and expected to perform. The proposed framework provides a novel simulation approach enabling energy modelers to calculate the ECM savings as a range rather than a single fixed value considering the variations of occupant behaviors in buildings, which provides a critical input to the risk analysis of ECM investments.

Case study 2 - Simulating the dynamic feedbacks between individual-level behavioral adaptations and building operations

Real office building occupants interact with and adapt to their surrounding environments in deliberate and meaningful ways that affect both energy consumption and indoor environmental quality. As suggested throughout this chapter, numerous studies have estimated the magnitude of these effects, establishing the high degree of influence that occupant behavior exerts on building energy use and thermal comfort relative to other potentially significant factors (Hong & Lin 2013; Haldi & Robinson 2011; Bourgeois et al. 2006).

Given the importance of occupants' environmental adaptations to building energy and comfort outcomes, this case study presents a Human and Building Interaction Toolkit (HABIT) that co-simulates building energy and office occupant behavior. The toolkit uses a field-validated, agent-

based model that estimates both individual and group-level comfort/behavior outcomes; accommodates whole building-level analyses; and yields comprehensive outputs on energy, behavior, and indoor environmental quality (IEQ) that can guide the design and operation of low-energy, high quality office building environments.

The case study begins by describing the HABIT co-simulation exchange and its underlying agent-based model of thermally adaptive behaviors. The usefulness of the toolkit is then demonstrated through a series of case study simulations that explore a range of occupant behavior scenarios, including multiple cases where wider thermostat set point ranges are paired with the provision of efficient local heating and cooling options for occupants. The relative merits of each scenario are assessed by comparing resulting energy use intensities alongside occupant thermal unacceptability and productivity outcomes.

Methodology

Co-simulation overview

HABIT pairs a previously published ABM of office occupants' thermal comfort and adaptive behaviors (Langevin et al. 2016) in MATLAB with whole building energy simulations of office buildings in EnergyPlus (BTO 2017) using the Building Controls Virtual Test Bed (BCVTB) co-simulation program (LBNL, 2018).

The EnergyPlus/MATLAB information exchange runs as follows: EnergyPlus simulates zone-level thermal conditions and passes these as inputs to the MATLAB comfort/behavior model; the MATLAB model predicts thermal comfort and related behavior outcomes for each occupant (i.e., fan on; window open, etc.) and aggregates these outcomes across all agents in the zone; the aggregated behavior outcomes are passed back to EnergyPlus and used to adjust appropriate zone schedules (i.e., heater/fan equipment gains; thermostat set points) for the next time step; the process repeats until a simulation end time is reached.

The BCVTB negotiates single runs of the above MATLAB/EnergyPlus exchange. However, the MATLAB comfort/behavior model contains probabilistic elements. Thus, the exchange must be re-run multiple times to assess a range of possible outcomes.

Agent-based behavior model overview

In the default HABIT setup, each office occupant is represented in the MATLAB comfort/behavior model as a simulated agent that acts adaptively based on the scheme described in Langevin et al (2015). Under this scheme, behavior is considered to be the by-product of a negative feedback loop in which an agent acts to bring its current thermal perception into line with a reference range of seasonally acceptable ASHRAE thermal sensations, despite environmental disturbances.

An agent's current thermal sensation and seasonally acceptable thermal sensation range are both modeled probabilistically using the distributions developed in Langevin et al (2013); daily occupant arrival/lunch/departure times are also sampled from a normal distribution around user-defined means. Agent behavior choices may be constrained by the building management or by other agents in the space that share a given control. The reader is referred to Langevin et al (2015) for full details on the HABIT ABM and its validation.

Table 1 presents the full set of behavioral adaptations simulated by the HABIT ABM and shows how their feedback on the thermal environment/comfort is represented on both the MATLAB and EnergyPlus sides of the BCVTB co-simulation.

Case study simulations

To demonstrate the usefulness of the above simulation framework, case study simulations were performed for a medium-sized office building. The simulated building has three stories with 5600 m^2 of total floor space and one core/four perimeter thermal zones per floor; masonry construction with 20% glazing; variable-air-volume air-handling units with hot water reheat; an occupant density of 0.05 person/m^2; and a baseline occupied infiltration rate of 2.4 CFM/m^2 applied to perimeter zones (see Hendricken et al. (2012) for more details).

*** Insert Table 13.1 ***

Caption: Behaviors simulated in the HABIT framework and their default local/zone-level

feedbacks in BCVTB co-simulation.

Credit: Langevin et al., 2016

Case study simulations are performed on all zones of the case study building for the months of January and July in the Philadelphia climate.[2] These simulations each cover 15 zones (3 core; 12 perimeter) and 297 occupants. These case study simulations are ultimately intended to yield a complete picture of the link between behavior, energy, and IEQ across multiple thermal zones with different orientations and locations within the general building geometry.

In each of the simulations, multiple behavior scenarios are run to test the influence of behavior modeling assumptions on energy and IEQ outcomes. As shown in Table 2, behavior scenarios range from a "Baseline" case (B) where no thermally adaptive actions are possible, to a "Fully Unrestricted" (UR) case where a full range of actions is possible, and finally to a series of "Wider Set Points" (WSP) cases where zone thermostat set point ranges are progressively

[2] Refer to Langevin et al (2016) for additional case study simulations that explore the sensitivity of outcomes to climate and location.

widened and occupants are provided with more efficient local heating/cooling options at their desks. The "Wider Set Points" scenarios are of particular interest in testing the degree to which localized heating/cooling devices can save energy while maintaining or improving occupant thermal comfort levels (as proposed, for example, in Hoyt et al (2014)).

*** Insert Table 13.2 ***

Caption: Behavior scenarios for case study simulations. Note: cell values indicate EnergyPlus settings associated with each behavior.

Credit: *Langevin et al., 2016*

Simulation outcomes are evaluated from both the energy and IEQ perspectives. For energy, an energy use intensity is calculated; for IEQ, the percentage of occupants that the behavioral model indicates are outside their acceptable thermal sensation range without any behavioral remedy is recorded at each time step and averaged across the entire simulation period, yielding an overall percentage thermally unacceptable outcome (a thermal comfort indicator). Relative work underperformance percentage (a productivity indicator) is also evaluated using the polynomial relationship presented in Jensen et al. (2009), which describes relative performance in terms of thermal sensation:

$$\text{Relative work performance} = -0.0069tsv^2 - 0.0123tsv + 0.9945 \quad (1)$$

where *tsv* is an occupant's thermal sensation vote on the ASHRAE sensation scale. Relative underperformance is then simply 1 − relative work performance.

Results

*** Insert Figure 13.7 ***

Caption: (a) Summed electric/gas energy use intensity, (b) thermal unacceptability %, and (c) work underperformance %, for whole building, Philadelphia. Note: whiskers are 95% prediction interval on mean result.

Credit: *Langevin et al., 2016*

Key results for the case study simulations are summarized through Fig. 7a–c. Figure 7a shows that HVAC energy use intensity increases slightly in both January and July from the "Baseline" behavior scenario through the "Fully Unrestricted Behavior" scenario; the energy use intensity then moves back down across the "Wider Set Points" scenarios, which range from an initial ±1◦ C widening of the set point range ("Wider Set Points") to a ±4◦C widening of this range ("Wider Set Points (Aggressive)").

Energy end use breakdowns in Fig. 7a allow a more specific examination of these trends. In January, for example, significant reductions in HVAC energy use for the "Wider Set Points (Aggressive)" scenario (∼24%) result from a decrease in gas space heating consumption that more than offsets an associated increase in electrical equipment energy from more frequent use of personal heaters. Similarly, in July, significant reductions in HVAC energy use by the "Wider Set Points (Aggressive)" scenario (∼37%) result from a decrease in electric space cooling consumption that more than offsets a small associated increase in electrical equipment energy from more frequent use of personal fans.

Regarding IEQ, Fig. 7b shows a significant decrease in percentage of time thermally unacceptable relative to the baseline through the "Wider Set Points (Aggressive)" scenario in January, and through the "Wider Set Points (Moderate)" scenario in July, with the lowest thermally unacceptable percentage occurring as in the zone-level simulations for the "Fully Unrestricted Behavior" scenario in both months. In July, however, the "Wider Set Points (Aggressive)" scenario yields a thermally unacceptable percentage for July that is close to that of the baseline, with the prediction intervals for the two overlapping. This result also violates the 10% thermally unacceptable threshold used in thermal comfort standards, suggesting that a "Wider Set Points (Aggressive)" strategy for a Philadelphia office in the summer will yield substantial warm discomfort amongst occupants. Work underperformance results for this scenario in Fig. 7c reinforce this conclusion, moving up to 3% underperformance as a result of the high cooling set point. Ultimately, a "Wider Set Points (Moderate)" strategy is the better option for achieving significant HVAC energy savings (∼28%) while maintaining good IEQ in the Philadelphia summer months.

Conclusion

Taken together, the results from this case study suggest that building managers can pair the use of more efficient local heating and cooling options with strategic thermostat set point adjustments as a simple way of saving substantial amounts of energy (up to 24/28% in heating/cooling months, respectively) while also improving occupant thermal acceptability. Care must be taken to consider additional outcome metrics, however: managers who value occupant productivity above all else, for example, may view the small productivity decrements predicted from raising cooling set points as unacceptable. Moreover, in the heating cases, the potential

disadvantages of trading natural gas for electric heating fuel in terms of energy costs and greenhouse gas emissions must also be taken into consideration.[3]

Case study 3 - Modeling and evaluating the energy savings potential of behavior-focused retrofit measures

Occupant behavior in buildings is a leading factor influencing building energy use. Low-cost behavioral solutions have demonstrated significant potential energy savings. Estimating the behavioral savings potential is important for a more effective design of behavior change interventions, which in turn will support more effective energy-efficiency policies. This case study introduces a simulation approach to quantify the energy saving potentials of occupant behavior measures.

Methodology

This case study investigated the energy saving potentials of occupant behavior measures by (1) conducting field investigation on a real office building (including the geometry, zoning, occupancy schedule, lighting schedule, as well as plug load power density and schedule), (2) developing the baseline models based on the above information, (3) defining five occupant behavior measures, including lighting, plug load, thermal comfort criteria, HVAC control and window control, and (4) running simulation to calculate the energy saving potentials of the occupant behavior measures across four typical U.S. climates (Chicago, Fairbanks, Miami, and San Francisco) and two vintages (1989 and 2010). Overall methodology is illustrated in Figure 8.

*** Insert Figure 13.8 ***

Caption: Overall methodology.

Credit: *Sun and Hong, 2017b*

The case building has two above-ground stories with a total conditioned floor area of 1,723 m^2. Main room functions include office, conference room, classroom, and lounge (corridor). Smaller corridors are merged into office zones for simplification. The perimeter zones have operable windows, which allow the occupants to open windows for cooling or ventilation. The total number of occupants in the case building is 63. Figures 9 and 10 show the floor plan of the first and second floors, indicating the room functions. Baseline models representing the case building were developed in EnergyPlus.

*** Insert Figure 13.9 ***

Caption: The 1st floor plan.

[3] These cost tradeoffs are further quantified in Langevin et al (2016).

Credit: *Sun and Hong, 2017b*

*** Insert Figure 13.10 ***

Caption: The 2nd floor plan.

Credit: *Sun and Hong, 2017b*

Five occupant behavior measures implemented in this case study are: (1) Lighting control – lights are only on if a space is occupied and occupants feel too dark. The conditional probability of turning on/off the lights follows a three-parameter Weibull distribution, defined in Wang's paper (Wang et al. 2015). In this study, we referred to the parameters' values in Wang's paper; (2) Plug load control – 30% of power is turned off if unoccupied; (3) Thermal comfort criteria – two thermal comfort criteria were considered, one is the ASHRAE standard 55 comfort zone limits (ANSI/ASHRAE 2013), where the upper temperature limit of the ASHRAE 55 comfort zone was taken as the cooling setpoint in the simulation while the lower limit was taken as the heating setpoint. The other one is the adaptive comfort model (Brager & De Dear 2001) with 80% acceptability limits to calculate a dynamic comfort range based on ambient temperature, which was then used as dynamic cooling/heating setpoints in simulation; (4) HVAC control – HVAC is turned on if a space is occupied and occupants feel hot (in cooling mode) or cold (in heating mode). Ren's model (Ren et al. 2014) was adopted to estimate the time-step HVAC control status in our study, which used a three-parameter Weibull distribution function to describe different air conditioning usage patterns; and (5) Window control – the control logic is illustrated in Figure 11. The Weibull distribution functions describing the conditional probability of turning on/off the lights and HVAC, which were defined by Wang (Wang et al. 2015) and Ren (Ren et al. 2014), were adopted in this study. Other than the individual measures, all the five measures were integrated as well and their integral energy savings were simulated.

*** Insert Figure 13.11 ***

Caption: Control logic of window Measure.

Credit: *Sun and Hong, 2017b*

The stochastic occupant schedules were generated by the Occupancy Simulator. Compared with the normalized identical occupant schedule in all spaces, the generated schedules can reflect the variation, diversity, and stochastic characteristic of the realistic occupant movements. To make it consistent for all the studied measures, the same set of generated schedules is applied to both the baseline model and the five occupant measures.

Results

Figure 12 shows an example of the breakdown end uses of the baseline model, the five individual measures, and the integrated measure. Each measure has its different impact on energy consumption: (1) the lighting measure and the plug load measure reduce the internal heat gains, which cut the cooling load but raise the heating load; (2) the comfort criteria measure reduces the heating/cooling load by enlarging the comfort boundary; (3) the HVAC measure and the window measure reduce the energy consumption by decreasing the HVAC operation time. When they are integrated, the effect of (3) is relatively weakened due to a lower cooling load level resulting from (1) and (2), and due to the higher heating load resulting from (1).

*** Insert Figure 13.12 ***

Caption: End-use energy savings of all five individual measures and integrated measure in

Chicago and San Francisco for the baseline model of vintage 2010.

Credit: *Sun and Hong, 2017b*

Based on the simulation results, the occupant behavior measures can achieve considerable energy savings as high as 22.9% for individual measures and up to 41.0% for the integrated measures. The main energy savings captured by the occupant behavior measures come from the avoidance of energy waste in unoccupied rooms especially for their lighting, plug load, and HVAC systems.

It should be noted that if the static occupant schedules in ASHRAE standard 90.1 were used, the behavioral measures savings will be significantly reduced by up to 50%. The occupant schedule makes a significant difference on the energy savings of occupant-based measures. Therefore, when estimating the potential energy savings of occupant-related measures, it is crucial to apply realistic occupant schedules that reflect occupancy variations in each room.

Although energy savings of behavior measures would vary depending upon many factors, the presented simulation approach in this case study is robust and can be adopted for other studies aiming to quantify occupant behavior impact on building performance.

13.3 Future perspectives on data and computational tools for occupant behavior modeling

Although significant progress on occupant behavior modeling and simulation has been made through international collaboration under IEA EBC Annex 53 (Yoshino et al. 2017) and Annex 66, as well as the associated development of an occupant behavior research community, future work will be challenged to leverage the interdisciplinary nature of occupant behavior research, communicate its contribution to a building industry that is moving towards zero-net energy or zero-net emissions, and embrace the adoption of supporting technologies for behavior research

like Internet of Things (IoT), big data, machine learning, and exascale computing. A few of the most pressing needs for future occupant behavior research are enumerated below.

Data: (1) develop low-cost and reliable methods and tools to collect large-scale, high-quality occupant data covering all behavior types (i.e., presence and movement, adaptive behavior, comfort preference), occupant types, building types (commercial and residential), cultures, and climates, through in-situ smart sensing and online surveys and/or lab settings that can better mimic field settings through innovative use of virtual reality technologies, (2) employ machine learning algorithms and stochastic modeling techniques to extract knowledge and establish mathematical models of occupant behavior from the collected data, and (3) develop or adopt data sharing protocols that standardize variable types and response formats and substantively address behavioral data privacy and security concerns.

Modeling and simulation: (1) develop representation of complex occupant effects and interactions at various scales (e.g., group behavior, social dynamics, inter-occupant behavior diversity, multiple behavior choice hierarchies, aggregation to the whole-building or grid-level), (2) establish a global open-source repository of occupant behavior models using standardized representation schema to enable interoperability between tools, users and applications, (3) implement a rigorous and transparent process of model creation, evaluation and verification to ensure model validity and applicability, (4) integrate occupant modeling with building information modeling in the building design and operation workflow, and (5) develop a synthetic population of building occupants with representative behavior types to support agent-based modeling and simulation.

Application: (1) develop guidelines and tools for fit-for-purpose application of an occupant behavior model suite in commonly-used building energy simulation tools, (2) improve occupant-related assumptions and increase the use of occupant behavior models in critical decision points of the building life cycle including load calculation, evaluation of energy conservation measures, selection of equipment and system types, code compliance, performance rating, and occupant-responsive model predictive control, (3) quantify key building performance uncertainties related to occupant behavior and choose design strategies that are robust to these uncertainties in fostering energy-positive human-building interactions, and (4) establish clear communications with customers or stakeholders regarding the influence that the diversity and stochasticity of occupant behavior has in determining a range of possible outcomes for key building performance metrics.

Interdisciplinary collaboration: occupant behavior is diverse and stochastic, requiring an interdisciplinary approach to gain a deeper understanding that spans building science, environmental engineering, social and behavioral science, data science, and computer science. Through several IEA EBC annexes (i.e., Annex 53, 66 and 79), social scientists and

psychologists contributed to the design of surveys that explore the link between social and contextual factors, such as culture, gender, age, and habits, and occupants' energy use behaviors. This contribution is important and complementary to the engineering approach of using measured variables, such as indoor and outdoor environmental parameters, to formulate mathematical algorithms that yield accurate probabilities of occupants' behavioral actions. Fostering an interdisciplinary approach that engages building designers and operators is also crucial to the practical integration of occupant behavior insights (e.g., occupant needs, human-building interactions) across the building life cycle (design, construction, operation and retrofit), supporting the achievement of building performance goals through leveraging both the technological and human dimensions (D'Oca et al. 2018).

To address the aforementioned research needs, it is crucial to foster and sustain an occupant behavior research community through continuous international collaboration such as the on-going effort of IEA EBC Annex 79 (*http://annex79.iea-ebc.org/*), IEA Task 24 Phase II: Behavior Change in DSM (*http://www.ieadsm.org/task/task-24-phase-2/*), and professional organizations such as ASHRAE Multidisciplinary Task Group on occupant behavior in buildings (MTG.OBB). Dedicated conferences such as BECC – Behavior, Energy and Climate Change (*beccconference.org*), and Behave - European Conference on Behaviour and Energy Efficiency (information on the 2018's edition is available at *https://www.zhaw.ch/en/about-us/news/events/behave/*) also provide excellent venues for researchers and practitioners to exchange and share knowledge, experience, success stories and important lessons learned about the growing field of occupant behavior research.

References

Andersen, P.D. et al., 2014. Dynamic modeling of presence of occupants using inhomogeneous Markov chains. *Energy and buildings*, 69, pp.213–223.

Andersen, R., 2012. The influence of occupants' behaviour on energy consumption investigated in 290 identical dwellings and in 35 apartments. In *Proceedings of healthy buildings*. Brisbane, Australia.

Andersen, R. et al., 2013. Window opening behaviour modelled from measurements in Danish dwellings. *Building and Environment*, 69, pp.101–113.

ANSI/ASHRAE, 2013. Thermal environmental conditions for human occupancy. *Standard 55-2013*, 2013.

Barthelmes, V.M. et al., 2017. Exploration of the Bayesian Network framework for modelling window control behaviour. *Building and Environment*, 126, pp.318–330.

Becerik-Gerber, B. et al., 2011. Application areas and data requirements for BIM-enabled facilities management. *Journal of construction engineering and management*, 138(3), pp.431–442.

Behavior, O., 2017. *Technical Report: Surveys to understand current needs, practice and capabilities of occupant modeling in building simulation*,

Belafi, Z.D., Hong, T. & Reith, A., 2016. A library of building occupant behaviour models represented in a standardised schema. *Energy Efficiency*, pp.1–15.

Bourgeois, D., Reinhart, C. & Macdonal, I., 2006. Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control. *Energy and Buildings*, pp.814–823.

Brager, G.S. & De Dear, R., 2001. Climate, comfort, & natural ventilation: a new adaptive comfort standard for ASHRAE standard 55.

BTO, U., 2017. EnergyPlus.

Calì, D. et al., 2016. Analysis of occupants' behavior related to the use of windows in German households. *Building and Environment*, 103, pp.54–69.

Chen, Y., Hong, T. & Luo, X., 2018. An agent-based stochastic Occupancy Simulator. In *Building simulation*. Springer, pp. 37–49.

Clevenger, C.M. & Haymaker, J., 2006. The impact of the building occupant on energy modeling simulations. In *Joint International Conference on Computing and Decision Making in Civil and Building Engineering, Montreal, Canada*. Citeseer, pp. 1–10.

Clinton, A. et al., 2017. *Annex 66: Definition and Simulation of Occupant behavior i buildings. Technical Report : Occupant Behavior Case Study Sourcebook*,

Cowie, A. et al., 2017. Usefulness of the obFMU module examined through a review of occupant modelling functionality in building performance simulation programs. In *IBPSA Building Simulation Conference*.

Crawley, D.B. et al., 2001. EnergyPlus: creating a new-generation building energy simulation program. *Energy and buildings*, 33(4), pp.319–331.

D'Oca, S. et al., 2015. Annex 66, Definition and simulation of occupant behavior in buildings. Technical Report: An International Survey of Occupant behavior in workspaces. , (November). Available at: http://www.annex66.org/.

D'Oca, S., Hong, T., & Langevin, J., 2018. The human dimensions of energy use in buildings: a review. *Renewable and Sustainable Energy Reviews*, 81, pp. 731-742.

Dong, B. & Lam, K.P., 2014. A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting. In *Building Simulation*. Springer, pp. 89–106.

Duarte, C., Van Den Wymelenberg, K. & Rieger, C., 2013. Revealing occupancy patterns in an office building through the use of occupancy sensor data. *Energy and Buildings*, 67, pp.587–595.

Equa, A.B., 2017. IDA indoor climate and energy.

Fabi, V. et al., 2014. Occupants' behaviour in office building: stochastic models for window opening. In *8th windsor conference*. Network for Comfort and Energy Use in Buildings.

Feng, X., Yan, D. & Hong, T., 2015. Simulation of occupancy in buildings. *Energy and Buildings*, 87, pp.348–359.
Földváry Ličina, V. et al., 2018. Development of the ASHRAE Global Thermal Comfort Database II. *Building and Environment*.
Gaetani, I., Hoes, P.-J. & Hensen, J.L.M., 2016. Occupant behavior in building energy simulation: towards a fit-for-purpose modeling strategy. *Energy and Buildings*, 121, pp.188–204.
Godin, B., 2017. *Models of innovation: The history of an idea*, MIT Press.
Gunay, H.B., O'Brien, W. & Beausoleil-Morrison, I., 2013. A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices. *Building and Environment*, 70, pp.31–47.
Haldi, F., 2013. A probabilistic model to predict building occupants' diversity towards their interactions with the building envelope. In *Proceedings of the international IBPSA conference, Chambery, France*. p. 147.
Haldi, F. & Robinson, D., 2009. A comprehensive stochastic model of blind usage: theory and validation. In *Proceedings of the Eleventh International IBPSA Conference*. pp. 529–536.
Haldi, F. & Robinson, D., 2010. Adaptive actions on shading devices in response to local visual stimuli. *Journal of Building Performance Simulation*, 3(2), pp.135–153.
Haldi, F. & Robinson, D., 2008. On the behaviour and adaptation of office occupants. *Building and environment*, 43(12), pp.2163–2177.
Haldi, F. & Robinson, D., 2011. The impact of occupants' behaviour on building energy demand. *Journal of Building Performance Simulation*.
Hendricken, L. et al., 2012. Capital Costs and Energy Savings Achieved by Energy Conservation Measures for Office Buildings in the Greater Philadelphia Region. In *SimBuild 2012*. Madison, WI: International Building Performance Simulation Association. Available at: https://www.researchgate.net/publication/266553922.
Hendrikse, M.M.E. et al., 2018. Database of movement behavior and EEG in virtual audiovisual everyday-life environments for hearing aid research. Available at: https://doi.org/10.5281/zenodo.1470805#.W_3MOboHRG0.mendeley [Accessed November 27, 2018].
Heo, Y., Augenbroe, G. & Choudhary, R., 2011. Risk analysis of energy-efficiency projects based on Bayesian calibration of building energy models. In *Building simulation*. pp. 2579–2586.
Hoes, P. et al., 2009. User behavior in whole building simulation. *Energy and buildings*, 41(3), pp.295–302.
Hong, T. et al., 2016. An occupant behavior modeling tool for co-simulation. *Energy and Buildings*, 117, pp.272–281.
Hong, T., D'Oca, S., Turner, W.J.N., et al., 2015. An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. *Building and Environment*, 92, pp.764–777.
Hong, T., D'Oca, S., Taylor-Lange, S.C., et al., 2015. An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema. *Building and Environment*, 94, pp.196–205.
Hong, T. et al., 2017. Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs. In *Building Simulation*. Springer, pp. 1–14.
Hong, T., Chang, W.-K. & Lin, H.-W., 2013. A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data. *Applied Energy*, 111, pp.333–350.
Hong, T. & Lin, H.-W., 2013. *Occupant Behavior: Impact on Energy Use of Private Offices*, Berkeley, CA. Available at: https://www.researchgate.net/publication/258246691.
Hoyt, T., Arens, E. & Zhang, H., 2014. Extending air temperature setpoints: Simulated energy savings and design considerations for new and retrofit buildings. *Building and Environment*.
Jensen, K.L., Toftum, J. & Friis-Hansen, P., 2009. A Bayesian Network approach to the evaluation of

building design and its consequences for employee performance and operational costs. *Building and Environment*.
Konis, K., 2013. Evaluating daylighting effectiveness and occupant visual comfort in a side-lit open-plan office building in San Francisco, California. *Building and Environment*, 59, pp.662–677.
Langevin, J., Gurian, P.L. & Wen, J., 2015. Tracking the human-building interaction: a longitudinal field study of occupant behavior in air-conditioned offices. *Journal of Environmental Psychology*, 42, pp.94–115.
Langevin, J., Wen, J. & Gurian, P.L., 2013. Modeling thermal comfort holistically: Bayesian estimation of thermal sensation, acceptability, and preference distributions for office building occupants. *Building and Environment*.
Langevin, J., Wen, J. & Gurian, P.L., 2016. Quantifying the human-building interaction: Considering the active, adaptive occupant in building performance simulation. *Energy and Buildings*.
Langevin, J., Wen, J. & Gurian, P.L., 2015. Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors. *Building and Environment*.
Liao, C., Lin, Y. & Barooah, P., 2012. Agent-based and graphical modelling of building occupancy. *Journal of Building Performance Simulation*, 5(1), pp.5–25.
Liisberg, J. et al., 2016. Hidden Markov Models for indirect classification of occupant behaviour. *Sustainable Cities and Society*, 27, pp.83–98.
Luo, X. et al., 2017. Performance evaluation of an agent-based occupancy simulation model. *Building and Environment*, 115, pp.42–53.
Macal, C.M. & North, M.J., 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4, pp.151–162.
Makonin, S. et al., 2016. Electricity, water, and natural gas consumption of a residential house in Canada from 2012 to 2014. *Scientific data*, 3, p.160037.
McCambridge, J., Kypri, K. & Elbourne, D., 2014. Research participation effects: a skeleton in the methodological cupboard. *Journal of clinical epidemiology*, 67(8), pp.845–849.
Newsham, G.R., Mahdavi, A. & Beausoleil-Morrison, I., 1995. Lightswitch: a stochastic model for predicting office lighting energy consumption. In *Proceedings of right light three, the third european conference on energy efficient lighting, Newcastle-upon-Tyne*. pp. 60–66.
O'Brien, W. et al., 2017. A preliminary study of representing the inter-occupant diversity in occupant modelling. *Journal of Building Performance Simulation*, 10(5–6), pp.509–526.
O'Brien, W. & Gunay, H.B., 2016. Implementation of the occupant behaviour and presence models in OpenStudio. *Final Report Submitted to Natural Resources Canada. Carleton University. Google Scholar*.
Page, J. et al., 2008. A generalised stochastic model for the simulation of occupant presence. *Energy and buildings*, 40(2), pp.83–98.
Pan, S. et al., 2017. Cluster analysis for occupant-behavior based electricity load patterns in buildings: A case study in Shanghai residences. In *Building Simulation*. Springer, pp. 889–898.
Reinhart, C.F. & Voss, K., 2003. Monitoring manual control of electric lighting and blinds. *Lighting research & technology*, 35(3), pp.243–258.
Ren, X., Yan, D. & Hong, T., 2015. Data mining of space heating system performance in affordable housing. *Building and Environment*, 89, pp.1–13.
Ren, X., Yan, D. & Wang, C., 2014. Air-conditioning usage conditional probability model for residential buildings. *Building and Environment*, 81, pp.172–182. Available at: http://dx.doi.org/10.1016/j.buildenv.2014.06.022.
Richardson, I., Thomson, M. & Infield, D., 2008. A high-resolution domestic building occupancy model for energy demand simulations. *Energy and buildings*, 40(8), pp.1560–1566.
Saeidi, S. et al., 2017. Application of Immersive Virtual Environment (IVE) in Occupant Energy-Use Behavior Studies Using Physiological Responses. In *Computing in Civil Engineering 2017*.
Schweiker, M. et al., 2012. Verification of stochastic models of window opening behaviour for residential buildings. *Journal of Building Performance Simulation*, 5(1), pp.55–74.

Sun, K. & Hong, T., 2017a. A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures. *Energy and Buildings*, 146, pp.383–396.
Sun, K. & Hong, T., 2017b. A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures. *Energy & Buildings*, 146, pp.383–396. Available at: http://dx.doi.org/10.1016/j.enbuild.2017.04.065.
Sun, K. & Hong, T., 2017c. A simulation approach to estimate energy savings potential of occupant behavior measures. *Energy and Buildings*, 136, pp.43–62.
Wang, C., Yan, D. & Jiang, Y., 2011. A novel approach for building occupancy simulation. In *Building simulation*. Springer, pp. 149–167.
Wang, C., Yan, D. & Ren, X., 2015. Modeling individual's light switching behavior to understand lighting energy use of office building. In *CUE National Conference*. pp. 1–14.
Wang, Z., Hong, T. & Jia, R., 2018. Buildings. Occupants: a Modelica package for modelling occupant behaviour in buildings. *Journal of Building Performance Simulation*, pp.1–12.
Widén, J., Nilsson, A.M. & Wäckelgård, E., 2009. A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand. *Energy and Buildings*, 41(10), pp.1001–1012.
Wilke, U. et al., 2013. A bottom-up stochastic model to predict building occupants' time-dependent activities. *Building and Environment*, 60, pp.254–264.
Yan, D. et al., 2008. DeST—An integrated building simulation toolkit Part I: Fundamentals. In *Building Simulation*. Springer, pp. 95–110.
Yan, D. et al., 2017. IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings. *Energy and Buildings*, 156(April 2018), pp.258–270.
Yan, D. et al., 2015. Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy and Buildings*, 107, pp.264–278.
Yan, D. & Hong, T. , 2018. Fina Report of IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings, May 2018.
Yoshino, H., Hong, T. & Nord, N., 2017. IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods. *Energy and Buildings*, 152(March 2013), pp.124–136. Available at: http://dx.doi.org/10.1016/j.enbuild.2017.07.038.
Zeigler, B.P. & Oren, T.I., 1979. Theory of modelling and simulation. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), p.69.
Zucchini, W., MacDonald, I.L. & Langrock, R., 2016. *Hidden Markov models for time series: an introduction using R*, Chapman and Hall/CRC.