Energy and Buildings 156 (2017) 258–270

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings

Da Yan[a,*], Tianzhen Hong[b,*], Bing Dong[c], Ardeshir Mahdavi[d], Simona D'Oca[b], Isabella Gaetani[e], Xiaohang Feng[a]

[a] School of Architecture, Tsinghua University, China
[b] Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, USA
[c] Department of Mechanical Engineering, University of Texas San Antonio, USA
[d] Department of Building Physics and Building Ecology, Vienna University of Technology, Austria
[e] Department of the Built Environment, Technische Universiteit Eindhoven, Netherlands

ARTICLE INFO

Article history:
Received 29 May 2017
Received in revised form
11 September 2017
Accepted 26 September 2017
Available online 28 September 2017

Keywords:
Occupant behavior
Energy modeling
Interdisciplinary approach
Energy use
IEA EBC Annex 66
Building performance

ABSTRACT

More than 30% of the total primary energy in the world is consumed in buildings. It is crucial to reduce building energy consumption in order to preserve energy resources and mitigate global climate change. Building performance simulations have been widely used for the estimation and optimization of building performance, providing reference values for the assessment of building energy consumption and the effects of energy-saving technologies. Among the various factors influencing building energy consumption, occupant behavior has drawn increasing attention. Occupant behavior includes occupant presence, movement, and interaction with building energy devices and systems. However, there are gaps in occupant behavior modeling as different energy modelers have employed varied data and tools to simulate occupant behavior, therefore producing different and incomparable results. Aiming to address these gaps, the International Energy Agency (IEA) Energy in Buildings and Community (EBC) Programme Annex 66 has established a scientific methodological framework for occupant behavior research, including data collection, behavior model representation, modeling and evaluation approaches, and the integration of behavior modeling tools with building performance simulation programs. Annex 66 also includes case studies and application guidelines to assist in building design, operation, and policymaking, using interdisciplinary approaches to reduce energy use in buildings and improve occupant comfort and productivity. This paper highlights the key research issues, methods, and outcomes pertaining to Annex 66, and offers perspectives on future research needs to integrate occupant behavior with the building life cycle.

1. Introduction

Occupant behavior (OB) has significant impacts on building energy consumption. Masoso and Grobler [1] studied the electricity consumption in an office building, claiming that 56% was consumed during non-working hours (exceeding the energy consumption during working hours), mainly due to occupants leaving on lights or other devices when they left the office. Al-Mumin [2] drew similar conclusions from a case study of a residential building, in which a high proportion of occupants left lights on even when the room was not occupied. Bahaj and James [3] found that buildings with identical geometrical location, building envelope, and shape could have differences in actual building energy use as large as 300%, mainly driven by differing home appliance use patterns. Other researchers have identified notable energy reductions through OB interventions. Wood and Newborough [4] studied the effects on real energy consumption as a result of providing feedback on energy use and energy-saving suggestions to occupants. The results showed that nearly half of the buildings had achieved an energy reduction of 10% to 20%. A similar study conducted by Ouyang and Hokao [5] on appliance use also claimed an energy reduction of about 10% by influencing OB. However, energy savings from such behavioral changes may not be sustainable due to the rebound effect and other factors.

OB is also a key factor in the evaluation of energy-saving technology. Whether an energy-saving technique performs as expected relies heavily on how occupants understand and interact with the technology while the building is in use. Zhou et al. [6] simulated the energy performance of centralized and decentralized air-conditioning systems based on a quantitative description of

* Corresponding authors.
E-mail addresses: yanda@tsinghua.edu.cn (D. Yan), thong@lbl.gov (T. Hong).

https://doi.org/10.1016/j.enbuild.2017.09.084
0378-7788/

occupant use patterns. The simulation results showed that the system type with the lowest energy consumption (between two options) was dependent on the occupant use patterns. Guo et al. [7] studied improvements on building envelope insulation and their effects on heating energy consumption in Shanghai, China. Similarly, different use patterns were set and the simulation results suggested that the energy-saving potential was related to the use patterns. In the case where the room temperature was at a low setting and occupants only activated the heating when the spaces were occupied, the energy-saving potential with improved insulation was rather small. Wei et al. [8] conducted simulation research on energy-saving potential by improving the envelope insulation in an office building. They also concluded that OB influenced the extent of energy savings.

The quantitative description and simulation of OB, as revealed from the aforementioned cases, plays a fundamental role in accurately evaluating building energy performance and energy-saving technologies. The challenge in OB modeling and simulation lies in its distinctive features: stochastics, diversity, and complexity. Stochastics refer to the fact that occupants do not strictly repeat their behavior from day to day, as their behavior is influenced by numerous factors. Peng et al. [9] produced an air-conditioning use profile in a household where the times of air-conditioning operation varied every day. A data-collection case study in office buildings from Mahdavi et al. [10] drew a similar conclusion from occupancy observations. Diversity refers to differing behaviors among occupants even when the stimuli are the same, due to different tolerances and comfort preferences. Surveys on occupant adjustment to thermal comfort issues conducted by IFMA [11] collected thousands of responses on the manner in which occupants restored comfort and found a large variety in occupant responses. Another survey in China [12] investigated the driving factors of occupant operation of air-conditioning, claiming that occupants varied in their behavior patterns. Complexity implies that OB has complicated underlying mechanisms and is influenced by multiple disciplinary factors. Fabi et al. [13] grouped factors affecting occupant window operation into different categories, namely, the physical environment and contextual, psychological, physiological, and social factors. Foster and Oreszczyn [14] suggested that occupants residing in rooms facing other buildings would lower their blinds out of consideration for privacy.

Inspired by and building upon the main outcomes and unanswered research questions of Annex 53, which studied six influencing factors of real energy use in buildings, Annex 66 was established in November 2013 and is due to be completed by December 2017. The main goals of *Annex 66: Definition and simulation of occupant behavior in buildings* are to establish a standardized OB definition platform, establish a quantitative simulation methodology to model OB in buildings, and understand the influence of OB on building energy use and the indoor environment. The ultimate target of the research in this Annex is to reduce the gap between the simulated and measured energy use in buildings by modeling OB quantitatively, integrating the models with building performance simulation programs, and demonstrating the methodology through case studies.

2. Overview of the research from Annex 66

The purpose of Annex 66 is to establish a scientific methodological framework of OB simulation in buildings, from data collection, modeling and evaluation, and software integration to applications supporting building design, operation, policymaking, and other potential areas. The key research issues with regard to OB simulation are identified in Fig. 1, and their corresponding outcomes from this Annex are highlighted.

Annex 66 generated outcomes to improve the modeling and application of OB simulation. This paper highlights the research and outcomes from five research activities within Annex 66; details and other research activities are available in the final report. A monitoring guidebook was published to guide researchers with a comprehensive review and instruction on OB data collection (Section 2.1). A comprehensive study was performed for modeling approaches and evaluation methods, including a review of existing OB modeling approaches and exploration of rigorous model evaluation practice (Section 2.2). OB simulation modules were integrated into a standardized framework to represent diverse and flexible occupant behavior in building performance simulation (BPS) programs (Section 2.3). A case study sourcebook was written to bring together examples of building OB modeling and applications from around the world (Section 2.4). Finally, an international OB survey was developed in an interdisciplinary effort to investigate building-user interactions in workspaces by combining OB modeling with studies from the psychological and sociological fields (Section 2.5).

2.1. Data collection

2.1.1. Research issues

Collecting data from building occupants is one of the critical elements during OB research. Over the previous decades, there have been numerous occupant field and in-situ studies with different methods of data collection to meet specific research goals, including modeling occupant presence [15–20], window open/closed state and related environmental parameters for window opening/closing behavior [13,21–27], curtain/blinds adjustment behavior [14,28–38], light switching behavior [34,39–41], and air-conditioner adjustment behavior [17,42–44]. Furthermore, there have been a number of laboratory studies where human subjects are put into a controlled environment with a specific scientific aim, such as identifying thermal [45] or visual comfort [34,46], or social impacts on OB [47]. Surveying, a self-reporting mechanism, is another way to collect data regarding perception and social aspects of OB [48–50].

Given the various methods available for occupant data collection, some general questions to answer before performing any OB research are which data is needed and which data collection method is most suitable for the specific research purpose. To answer these general questions, a series of research questions were posed: (1) What is the type of occupancy and OB to be monitored; (2) What are the current state-of-the-art occupant sensing (e.g., passive infrared sensors) and data acquisition technologies; (3) What are the available occupant measurement methods (e.g., laboratory-based or survey); (4) What is the best way to get ground truth data and validate them, and (5) to properly manage data; and (6) What are some potential ethics issues with the data collection process? The activities of Annex 66 were carried out with these questions in mind to provide useful outcomes for the OB research field.

2.1.2. Outcomes from Annex 66 activities

A comprehensive literature review on existing data collection methods was conducted with regards to (1) OB data category, (2) occupant sensing method, (3) OB measurement method, (4) ground truth validation, and (5) ethics issues. The purpose was to provide guidelines for future OB research activities. A summary of this work is provided in the following paragraphs.

2.1.2.1. Occupant behavior data categories. Occupants can interact with various building systems and the built environment through their presence and actions. Their behavior can be influenced by four types of factors: *physiological*, *individual*, *environmental*, and *spatial adjustments* [47]. Moreover, potential triggers and contextual fac-

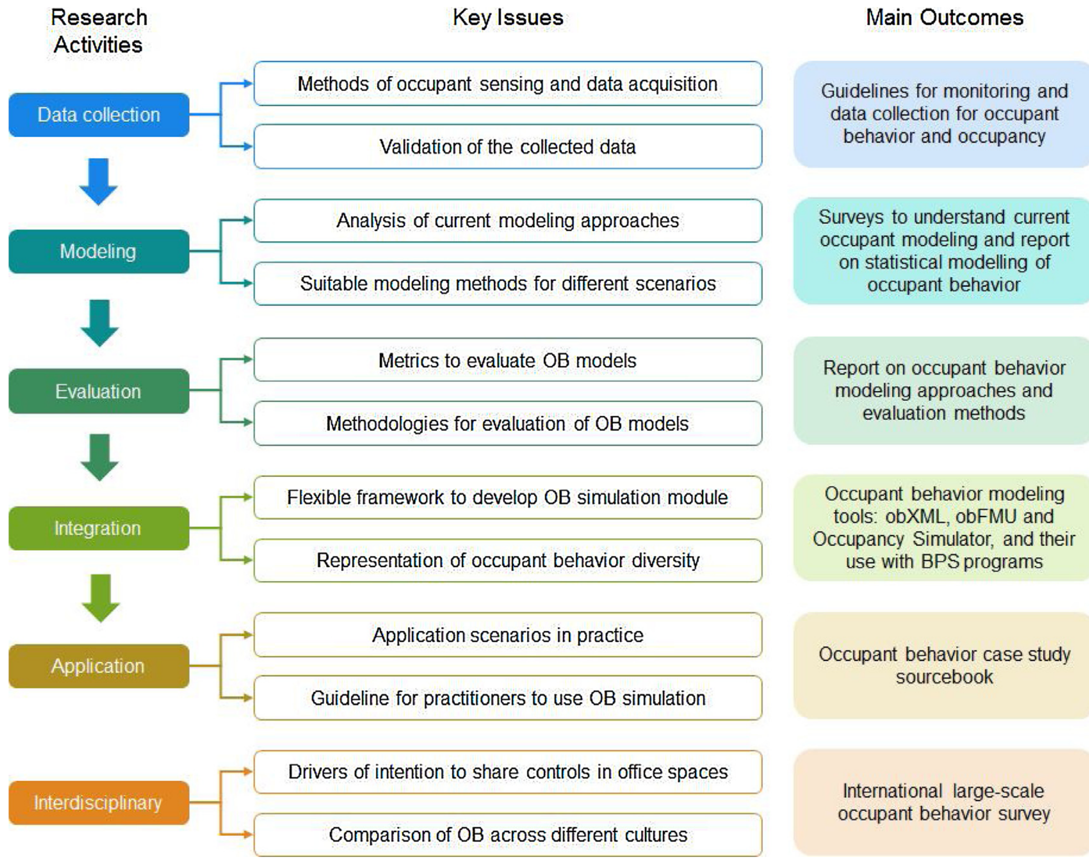

Fig. 1. Research activities, key issues, and main outcomes of the research pertaining to Annex 66.

tors influencing OB include internal (biological, psychological, and social) and external (building and building-equipment properties, physical environment, and temporal) factors [48,51,52].

2.1.2.2. Occupant sensing and data acquisition methods. Current state-of-the-art occupant sensing approaches can be grouped into six major categories: image-based, threshold and mechanical, motion sensing, radio-based environmental, human-in-the-loop, and consumption sensing. In addition, nine performance metrics have been developed to evaluate occupant sensing technologies: cost, deployment area, collection style, power type, sensing range, accuracy, data storage, data collected by sensors, and deployment level. A mixed sensing approach is often adopted in which various types of sensors are used together [17,53]. With these technologies, occupant data can be transmitted through a building automation system (BAS), a wireless sensor network, or the internet [54–57]. An ontology able to represent and incorporate multiple layers of OB data in pertinent computational applications, such as building performance simulation tools and building automation systems, has been developed and demonstrated [58].

2.1.2.3. Occupant behavior measurement method. The method of occupant measurement can be divided into three categories: in-situ, laboratory, and survey. The in-situ method collects and monitors OB in their natural environment, using existing or additional occupant sensors. In-situ studies can be performed over a long period (up to years). Privacy, ethics, participant recruitment, and ensuring informed consent are some of the challenges in using this approach [59]. A laboratory study is often performed in a well-controlled indoor environment such as an environmental chamber [60–62] or a dedicated laboratory space [45,47,63,64]. Laboratory studies have many more controls than in-situ studies, and often involve experiments using different environmental conditions to understand occupant perceptions. However, laboratory studies are often expensive compared to in-situ studies and only last for a short time. In addition, OB may be impacted by the Hawthorne effect (where individuals alter their behavior under observation). Surveys are a self-reporting mechanism for personal behavior. Most of the time, surveys provide a large sample size in a cost-effective way. In the context of this Annex, researchers reviewed projects from the energy-related OB research literature that employed cross-country surveys [65] or interview methods for data collection (such as transverse [66] and longitudinal surveys [67]), including quantitative and qualitative methods. Research praxis highlighted the cross-country questionnaire survey as one of the most useful methods to gain insights on behavioral patterns, drivers, causes, and perceived effects of behavior and to find connections between human, social, and local comfort parameters [65]. Emerging methods include mixed-design methods [68] and virtual reality-based immersive environments [69]. Sample size and survey data storage and management are all critical aspects to consider in questionnaire design to avoid bias in results. Response rates can be kept high by providing respondents with some incentives that motivate them to fill in the questionnaire, such as monetary awards [70] and gift certificates [71]. Ethics protocols, privacy issues, and informed consent must always be approved before handling human subject research [72].

2.1.2.4. Ground truth validation. The concept of ground truth has been adopted in other fields, such as computer vision and biometrics, to refer to the underlying absolute state of information or to express the notion of data that is understood to be correct [9]. Ground truth data in OB research often comes from sensors, particularly cameras, and survey data [73]. There are no existing guidelines on how to validate occupant measurements. However, a calculation of measurement uncertainty is often adopted to quantify data quality. The measurement uncertainty is defined as the dispersion of the quantity values being attributed to a measurand, which can be calculated by summing the contributions of each component of variation in the measurement procedure.

2.1.2.5. Ethics. To conduct OB research studies, it is necessary to involve human subjects. Ethical conduct is achieved by ensuring scientific validity and minimum potential harm to participants during the study. Various countries have ethical committees and procedures such as the Institutional Review Board (IRB) and the European Network of Research Ethics Committees (EUREC), while the World Health Organization (WHO) has a Research Ethics Review Committee. Ethics should be considered with regards to participant recruitment and risks. Informed consent is often used to address privacy and confidentiality issues.

2.1.3. Key findings

Occupant data collection is not a trivial process and often leads to new research paradigms. Due to costs, privacy concerns, and other socioeconomic factors, small-scale data collection is often conducted for a specific OB study. Key findings from Annex 66 are described below.

- Previous studies indicate that OB is influenced by various complex factors, including physical, social, and psychological factors. Additionally, all previous studies focus only on one or two factors correlating with a specific OB. No comprehensive study including all possible factors and their interdependencies has yet been explored.
- The application of current sensing technologies to OB research includes occupant presence, people counting, human-building interactions (such as turning lights on or off and adjusting thermostats and window blinds), energy consumption impacts of miscellaneous loads, and movement tracking. Occupant sensing is costly and requires heavy maintenance efforts. The future occupant sensor should be peel and stick, require minimal maintenance, and use an extremely low power supply. Innovation should focus on new sensing elements, intelligent power consumption management, smart processing, and minimum communication demands.
- In-situ data collection is often used for long-term OB monitoring, with limited controls over participant numbers, sample size, system, and space configurations. Laboratory studies have flexible controls over the indoor environment and sensing equipment; however, they often only focus on one or two environmental factors. The survey approach is used to explore a specific OB (such as turning air-conditioning on or off), includes various physiological, social, and psychological factors, and allows for a large sample size; however, it has suffered from issues with uncertainty and data quality.
- When collecting data through a questionnaire survey, although generally a low-cost option for obtaining large-scale OB data in a short period of time, the data quality as well as inconsistencies between what people indicate on the survey and what they actually do remains a challenge.

2.2. Modeling approaches and model evaluation

2.2.1. Research issues

Some factors responsible for the paucity of general procedures and guidelines for the evaluation of OB models have been identified. Firstly, the development of an occupant-related behavioral model represents a relatively recent domain of inquiry, and even though there is a considerably longer tradition of thermal-comfort research, it still faces similar challenges [47]. Secondly, a critical problem for model evaluation lies in the limited availability of observational data. As data are hard to come by, models are often developed and deployed with insufficient empirical justification, underlining the importance of broad building monitoring efforts. Thirdly, behavioral models require the consideration of multiple physiological, psychological, and sociocultural parameters. Many potential influencing factors have not yet been identified, due to the weak signals of factors suspected to lead to behavioral manifestations.

2.2.2. Outcomes from Annex 66

A critical evaluation of the existing occupant modeling approaches has been performed based on a literature review. The reviewed cases mainly focused on office buildings. Based on the literature review and previous related studies [74], occupant models were grouped into three types: adaptive behavior models, non-adaptive behavior models, and occupancy models. Four different forms of behavior models were found: (1) schedules, (2) Bernoulli models, (3) discrete-time Markov models, and (4) discrete-event Markov models. In the reviewed literature, adaptive behavior models were typically developed as weekly schedules, Bernoulli models, and discrete-time or discrete-event Markov models. Bernoulli models predict the likelihood of a building component with which occupants frequently interact at a given state (e.g., the percentage of lights switched on at a given outdoor illuminance). Markov models predict the likelihood of an adaptive action as a function of explanatory variables (e.g., the probability of a light switching on in the next time step in a discrete-time Markov model, or at the next arrival in a discrete-event Markov model). Non-adaptive behavior models include weekly schedules, survival models, or occupancy schedules from a similar building. Survival models for non-adaptive behaviors predict the lifetime of an occupant action or the state of a building component with which occupants interact (e.g., the lifetime of blind positions before they are changed). Occupancy models can take the form of weekly schedules, discrete-time Markov models predicting the timing and frequency of arrivals and departures, and survival models predicting the duration of an uninterrupted occupancy/vacancy period.

To improve the quality of model validation practices in behavioral modeling, some key conceptual issues and implications were clarified [58].

- Performance simulation (dynamic computational representation of building behavior) should not be confused with prediction. The main utility of building performance simulation lies in complex systems analysis, rather than in accurate long-term predictions. The mismatch often observed between simulation-based predictions and respective observations (the performance gap) can be the result of multiple sources of uncertainty, pertaining not only to internal (occupancy-related) processes, but also to external (weather) conditions, building fabric, and building systems.
- The term deterministic, which has substantial philosophical baggage, is often used in a potentially misleading manner to characterize fixed diversity profiles (e.g., assumed fixed schedules of occupant presence) and rule-based behavioral models. Although the use of probabilistic methods can improve the accuracy of simulation results, compared with homogeneous deterministic diversity profiles and rule-based models (see for example D'Oca et al. [75]), it has not been conclusively demonstrated that specific modeling methods automatically result in more accurate simulation results. Section 2.4 Applications further illustrates what types of OB models are appropriate for various application types (i.e., problems to solve).

2.2.3. Key findings

The strengths and weaknesses of the various model forms were identified. As a general conclusion, it was found that switching on lights, closing blinds, and opening/closing windows by occupants are most accurately modeled with discrete-time or discrete-event Markov models. On the other hand, survival models adequately characterize occupant plug-in equipment use, blind opening, and light switch-off behaviors.

With regard to the model evaluation challenge, Annex 66 found the following insights:

- Data-driven probabilistic methods of occupant control actions can be very useful. This, however, does not remove the need for fundamental studies of the motivational field shaped by physiological, psychological, and social factors. Despite not yet being a common practice, the inclusion of contextual and behavioral variables in building energy models can increase the accuracy of predictive models for the human–building interaction in office spaces, thus supporting optimized building design and operation and human-centered energy policies, as well as enhancing occupant comfort and the usability of building technologies.
- The validity of specific behavioral models can only be assessed via careful and transparent documentation of the model development and evaluation processes. In this manner, independent instances could require reappraisal of such procedures. Furthermore, behavioral models cannot be deemed to be validated based on a limited set of observational data. Specifically, datasets for model development and model evaluation should not be conflated. Likewise, one should not extrapolate from a single behavioral study to all kinds of populations, building types, locations, and climates.
- As in other scientific research areas, the model evaluation process must be guarded against bias. Internal evaluation by model developers is insufficient to establish the validity of a model. External evaluation procedures, double-blind studies (e.g., Schweiker et al. [76]), and round-robin tests can provide more convincing evidence for the reliability of a model.
- To demonstrate the general validity of developed behavioral models, further study is required to test the hypothesis that the intention to behave in a certain way is factually influenced by individual motivational drivers, together with socio-physical factors such as attitudes, subjective norms, and perceived behavioral control of the building technologies.

Given these observations, it is essential to exercise substantial care when integrating insufficiently documented and tested behavioral models in broadly used simulation applications, lest tool users are misled into assuming such models necessarily capture the reality of occupant presence and behavior in buildings.

2.3. Occupant behavior modeling tools and their integration with building performance simulation programs

2.3.1. Research issues

Building performance simulation (BPS) programs have been widely applied to evaluate the performance of building energy systems and technologies [68,77]. However, OB—a key driver of building performance—is usually represented in BPS models with oversimplified and predefined static schedules or fixed settings and rules, leading to deterministic and homogeneous simulation results that ignore the stochastic nature, dynamics, and diversity of OB [78]. For example, shading devices are turned off if a space has too much solar heat gain (causing thermal discomfort) or too much glare (causing visual discomfort), windows are opened if the indoor temperature is high and outdoor temperature is lower than the indoor temperature, and the electrical lighting is dimmed or completely turned off if a space has adequate daylight to meet the occupant visual comfort needs. However, occupants may interact with a control system (e.g., open windows) for a variety of reasons, including: (1) feeling hot, as a thermal comfort response, (2) feeling stuffy, as an indoor air quality consequence, or (3) arriving in a space, as an event-driven situational driver [79].

Field measurement data and large-scale surveys have confirmed that stochastic occupant presence and adaptive behaviors could be represented as probabilistic models of behavior [30], with independent variables of indoor and outdoor environmental conditions (e.g., air temperature, relative humidity, illuminance, and CO_2 concentration), occupant presence and movement, and the operational conditions of the building system (e.g., windows, lighting, plug loads, thermostat, heating/ventilation/air conditioning (HVAC), shades, and blinds). Through the machine learning process, correlations can be established between some observed–physical or situational–environmental conditions and the observed human-building interaction [80].

Quantifying OB influence on building performance requires the integration of energy-related OB models with BPS programs [81]. Popular BPS programs, including EnergyPlus, IDA ICE, ESP-r, DeST, TRNSYS, and DOE-2, use various approaches at various levels of fidelity to represent occupant-related input and to implement OB models for simulation. Typically, OB models are developed based on independent variables and metrics. The selection of different drivers for similar OB models makes it difficult to compare the models and incorporate them into BPS programs. OB models also tend to be located in multiple locations of BPS program code, making any changes difficult to implement. A recent review of modeling and simulation approaches for OB in buildings [82] discussed the problem of transferring occupant models that have been developed based on selected observation studies to different building models. Additionally, one of the key takeaways drawn from previous studies [83–85] has been the lack of a standardized method to represent and implement energy-related OB models in BPS programs.

The non-trivial environment of common simulation engines, which typically have unfriendly interfaces and require programming knowledge and specific code validation procedures to incorporate custom behavioral models, exacerbates the limited diffusion of OB models in current BPS programs.

2.3.2. Outcomes from Annex 66

Annex 66 developed quantitative representations of OB models and integrated them with BPS programs to improve the analysis and evaluation of the impacts of OB on building performance. A comprehensive review was conducted to identify and compare approaches to representing and implementing OB models in eight of the most widespread BPS programs in the engineering and simulation community [85,86]. BPS programs use varying and non-standardized input syntaxes to represent OB models. For OB model implementation in BPS programs, four approaches were used: (1) direct user input or control using BPS input syntax (all eight BPS programs), (2) user functions or custom code (EnergyPlus, DOE-2, and IDA-ICE), (3) built-in OB models (DeST and ESP-r), and (4) co-simulation with dedicated OB software tools such as obFMU (EnergyPlus and ESP-r).

A suite of new OB modeling tools has been developed by Annex 66 to capture the diversity, stochastic nature, and complexity of OB in buildings. They thus improve the simulation and evaluation of behavioral measures, as well as of the impact of OB on technology performance and energy use in buildings.

The ***obXML*** is an XML schema to standardize the representation and exchange of OB models for building performance simulation [84]. The obXML builds upon the drivers-needs-actions-systems (DNAS) ontology [87]. Drivers are the environmental factors that stimulate occupants to fulfill a physical, physiological, or psycho-

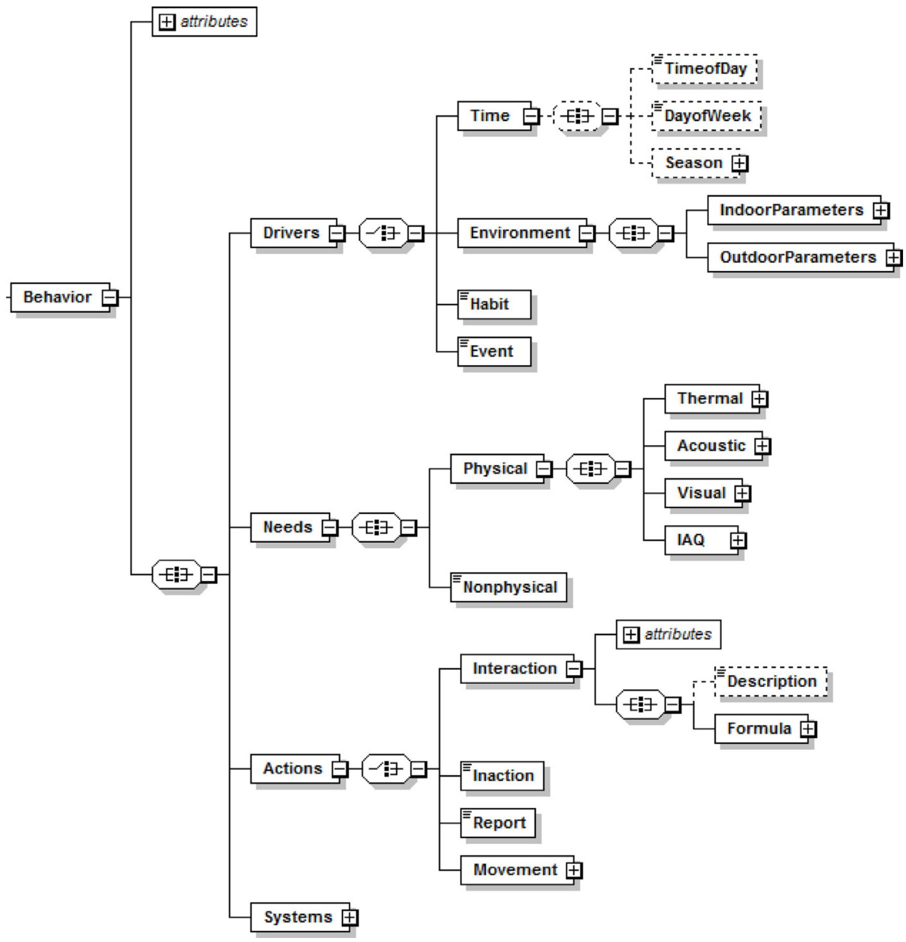

Fig. 2. Overview of the obXML schema.

logical need. Needs are the physical and non-physical requirements of the occupant that must be met to ensure their satisfaction with their environment. Actions are the interactions with systems or activities that occupants can perform to achieve environmental comfort. Systems are the equipment or mechanisms within the building with which occupants may interact to restore or maintain their environmental comfort. A library of obXML files [88], representing 52 typical energy-related OB in buildings, has been developed based on the literature. These obXML files can be exchanged between different BPS programs, applications, and users. Fig. 2 shows the four key elements and sub-elements of the obXML schema.

The ***obFMU*** [83] is a modular software component represented in the form of a functional mockup unit, enabling its use via co-simulation with BPS programs through the standard functional mockup interface. The obFMU reads OB models represented in obXML, functioning as a solver. A variety of OB models are supported by obFMU, including (1) lighting control based on occupant visual comfort need and daylight availability, (2) comfort temperature set-points, (3) HVAC system control based on occupant thermal comfort needs, (4) plug-load control based on occupancy, and (5) window opening and closing based on indoor and outdoor environmental parameters. The obFMU has been used with EnergyPlus and ESP-r via co-simulation to improve OB modeling. Fig. 3 shows the key components and workflow of an obFMU co-simulation with EnergyPlus.

It should be noted that other OB co-simulation platforms are also available, for example, the BCVTB [89], and the Matlab-based MLE+ [90].

The ***Occupancy Simulator*** [91] is a web-based application that can run on multiple platforms and devices to simulate occupant presence and movement in buildings, generating sub-hourly occupant schedules for each space and individual occupant as CSV files and EnergyPlus IDF files. The Occupancy Simulator uses a homogeneous Markov Chain model [18] and performs an agent-based simulation for each occupant. A hierarchical input structure is adopted, building on the input blocks of building type, space type, and occupant type, to simplify the input process while allowing flexibility for detailed information that captures the diversity of space use and individual OB. Users can select an individual space or the entire building to receive the simulated occupancy results.

Applications of these modeling tools are demonstrated by three case studies to (1) simulate and quantify the energy-saving potential of OB measures in office buildings [92], (2) simulate and quantify the impacts of OB on energy savings from building technologies [93], and (3) demonstrate an integrated approach and workflow to simulate and visualize OB in office buildings [94]. The Occupancy Simulator was verified by Luo et al. [95].

2.3.3. Key findings

Current BPS programs use diverse approaches to represent and implement OB models, which hinder the exchange, reuse, and comparative analysis of OB models. There is a significant need for:

- a common ontology (data dictionary) and data model to standardize the representation of OB models and enable their flexibility and exchange; and

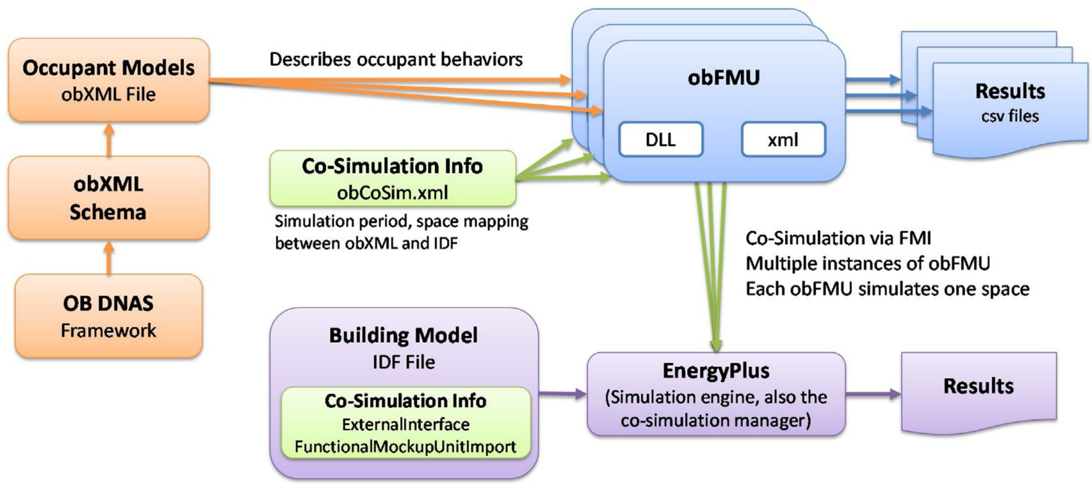

Fig. 3. Key components and workflow of obFMU.

- a modular software implementation of OB models adopting the common data model and enabling a robust and an interoperable integration with multiple BPS programs.

To address these needs, three new OB modeling and simulation tools were developed.

- The obXML provides a standardized method to represent OB models; enables their exchange and use between BPS programs, applications, and users; and improves the consistency and comparability of simulation results.
- The obFMU enables the reuse of an OB model solver for all BPS programs through the FMI co-simulation interface.
- The Occupancy Simulator generates realistic occupant schedules for BPS, capturing the diversity and stochastic nature of occupancy in buildings.

These tools help standardize the input structures for OB models, enable the collaborative development of a shared library of OB models, and allow for a rapid and widespread integration of OB models in various BPS programs. This ultimately improves the simulation of OB and the quantification of its impact on building performance.

2.4. Applications

2.4.1. Research issues

The main issue regarding the application of OB models in BPS is the choice of the appropriate models for a specific case [96]. Even when assuming that OB modeling standardization, evaluation, validation, and implementation in BPS has been solved, there is still a lack of decision-support guidelines for selecting which available model to use for a particular application [97]. Such guidance is an essential step towards the practical implementation of OB models and is a significant need for practitioners [53].

The existing OB models can be grouped according to their complexity [97,98], from time-based schedules, to rule-based schedules, to data-driven non-probabilistic models, to stochastic/probabilistic models, to agent-based models. Agent-based models are the most complex, as they employ the probabilistic methods depicted in Section 2.2.2 but add granularity in respect to occupant diversity. As a general rule, a fit-for-purpose model is the simplest available model that meets the required accuracy in performance predictions. In other words, a fit-for-purpose model enables efficient and reliable decision making. Indeed, complex models should not be used if a simpler model would be adequate for a specific application. Aside from fit-for-purpose modeling in terms of complexity, it is essential to deploy OB models within their validity range, which should be made explicit [99]. Different buildings and performance indicators are affected by various aspects of OB in different ways [100,101]. The adoption of different model types for each OB aspect should depend on its influence on the results and on its ease of prediction (Fig. 4). Other issues concerning the application of OB models relate to the appropriate use of higher complexity models [102] and the presentation and utilization of stochastic results [59]. A framework to investigate OB influence on building performance is necessary from the initial stages of building design [103], when the information about actual OB is still limited.

2.4.2. Outcomes from Annex 66

Most research efforts of the Applications Subtask of Annex 66 concern three topics: (1) a framework for considering the influence and relevance of OB, (2) decision support in different building phases, and (3) decision support through modeling and simulation.

In determining an appropriate framework, a literature review regarding the influence of OB on building performance was conducted. Then, the factors determining the influence of various OB aspects on chosen performance indicators were identified [96,97] with the aim of achieving a rigorous framework to identify the importance of OB for BPS. Various case studies have provided examples of when OB proved to be influential or trivial for building performance (e.g., [92,93]).

To develop decision support, building project phases were reviewed according to the standards of different countries and were harmonized with a focus on design and operation. The required OB inputs were identified for each design phase. A list of simple indices was proposed as a first guideline for the potential influence of various OB aspects. In this case, the collected case studies provided examples of decision-making processes in different phases (along with the desired model inputs), with a focus on behavior change during operation. A strategy for selecting the appropriate model complexity for BPS, i.e., the fit-for-purpose OB modeling (FFP-OBm) strategy [104], is currently under development.

The available OB models were initially classified with regards to their complexity and other key characteristics (type of behavior, building typology, and location, among others). Then, comparative studies, which identified best performing models across the complexity categories for a range of purposes and buildings, were reviewed. The results confirmed the initial hypothesis that there is no one-size-fits-all model type that proves superior in all cases, but

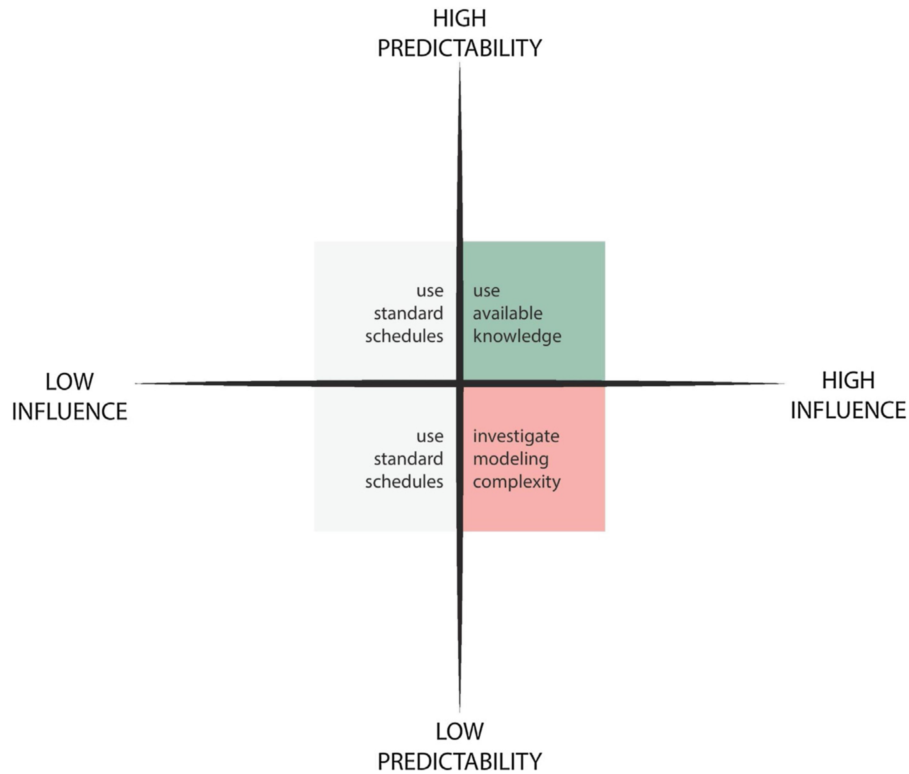

Fig. 4. OB model selection according to the influence and predictability of OB aspects.

rather that the various model types differ in efficiency and predictive ability according to their application case [97,103]. Ultimately, the FFP-OBm strategy itself was developed. The strategy is based on two concepts: (1) the trade-off between abstraction error (the error due to modeling abstractions, i.e., using an incomplete model of a physical system [105]) and input uncertainty when increasing modeling complexity, and (2) the varying influence of different OB aspects on a given performance indicator [106]. Moreover, the specific purpose dictates whether OB diversity and stochasticity must be taken into account (e.g., fixed schedules cannot be applied in a control optimization study). Case studies were used to demonstrate how different aspects of OB have a dissimilar influence on various performance indicators and how there is no benefit to increasing modeling complexity for non-influential OB aspects. In particular, standard schedules provided an adequate representation of non-influential aspects. The FFP-OBm strategy led to meaningful results for the investigated case studies and is currently being implemented in other applications, such as in policymaking; research and development of various technologies; and building design, operation, and maintenance. Studies have been carried out to discuss the appropriate presentation and deployment of stochastic results [59,94].

2.4.3. Key findings

Annex 66 has made significant steps towards the standardization of OB models, their evaluation, and their integration into BPS programs. However, the issue remains of how to apply these models in practice, that is, which model to use for a particular case. To provide a solution to this problem, a framework was introduced that can evaluate OB based on its influence on building performance. A list of simple indices is currently under development to provide a first estimate of the sensitivity of various performance indicators to different aspects of OB as a necessary step towards appropriate and efficient decision support starting at the initial phases of a building design project. The FFP-OBm strategy was developed to guide OB model selection in BPS. This strategy has been tested on a variety of case studies, which have demonstrated its validity. Further work will cover the application of the FFP-OBm strategy to policy making in the building life cycle.

2.5. Interdisciplinary approach

2.5.1. Research issues

The issue of OB and its impact on building energy use is a highly complex problem, which is not connected solely to technology-driven measures [78]. The human dimension of building energy use cannot be studied through a single disciplinary lens when, typically, a technological-social dichotomy pertains to the human-building interaction effects on building energy use. Research in the energy and social science fields, having a cross-disciplinary nature, is crucial for understanding OB and achieving low energy buildings. Sovacool [107] reviewed the state of the art of the energy studies field and reflected on the need for more meaningful cooperation between the technical and behavioral dimensions of energy usage, a thought that has been echoed by esteemed researchers in the physical and social sciences [108]. Traditional energy modeling and simulation approaches still provide a weak representation of the compound contextual processes leading occupants to exercise their interaction with their working or living built environments [46,47]. In contrast, behavioral scientists have developed and made extensive use of human behavior models that consider contextual features of the surrounding experimental environment, as early as the beginning of the century [70,71,109–112,]. Recent advances in engineering and architectural research have demonstrated that theories from social science in tandem with data-driven knowledge from analytics and building science could unlock a deeper understanding of the human factor in building energy use.

Responding to this emergent trend in energy and social science research, Annex 66 activities have focused on unlocking an interdisciplinary understanding of the human factor in energy use.

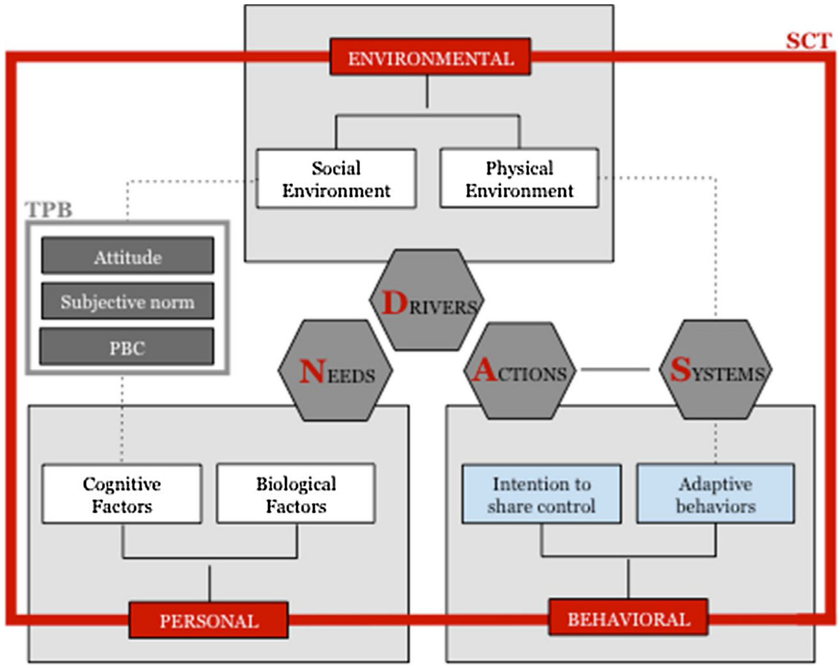

Fig. 5. Interdisciplinary framework for the questionnaire survey on OB in office buildings.

Annex 66 proposed a research agenda to integrate OB in an interdisciplinary approach that combines insights from the technical, analytical, and social dimensions of building energy use. One of the key aspects of this research vision involves focusing on the understanding of occupant behaviors, preferences, and needs in order to exploit the full energy-saving potential of innovative human-building interaction technologies. The inclusion of contextual and behavioral variables in building energy models can increase the accuracy of predictive models of the human–building interaction in office spaces, thus supporting optimized building design and operation and human-centered energy policies, as well as enhancing occupant comfort and the usability of building technologies. The research aim was to combine data-driven analysis modeling, simulation, and building physics expertise with social science insights to produce interdisciplinary solutions on human-centered energy efficiency in buildings.

2.5.2. Outcomes from Annex 66

The Annex 66 interdisciplinary activities have provided data and insights in the fields of energy research and social sciences. These outcomes are useful for the advancement of behavior-based energy-saving programs, the improvement of building energy codes and standards, and development of the next generation of control systems designed to achieve human-centered, low-capital investment, low-energy, and high-performance buildings worldwide. As an example, during the interdisciplinary cross-country survey, many questions pertaining to the energy and social science fields were answered, providing insights on advances in sensing, modeling, simulation, and regulation for enhancing future human-building interactions [65].

Scholars [111–113] have stressed that additional interdisciplinary knowledge on individual adaptive behavioral patterns and motivational drivers is especially necessary for the office environment, where interactions with building control devices to establish comfort conditions are negotiated in social networks, and because the monetary incentives for engaging in pro-environmental behaviors are negligible compared to those in residential spaces. There is also a need for cross-country studies [114] that can help isolate climatic, cultural, and socio-demographic behavioral factors, thus ensuring the validity, robustness, and efficiency of future studies. One of the key objectives for cross-country studies is to transform the knowledge discovered through large-scale survey data into behavioral-based energy efficiency solutions and insights, taking into consideration not only the energy metrics and physical properties from building physics, but also the contextual/habitual aspects of energy-related behaviors in workspaces located in different geographic and climatic areas [65]. To embrace these needs, Annex 66 has provided interdisciplinary and updated building OB data coverage by investigating the differences among countries and climates through a variety of settings (e.g., university and commercial buildings). For this specific issue, one of the Annex 66 research activities has focused on the development and deployment of an international OB framework and survey questionnaire [65] (Fig. 5). This study introduced an interdisciplinary framework based on theories and insights from energy and social sciences as a way to investigate building-user interactions in diverse office settings and cultural contexts. The framework is grounded on the integration of social cognitive theory (SCT) [115], the drivers–needs–actions–systems (DNAS) ontology [84], and the theory of planned behavior (TPB) [116].

The research framework addresses energy-related behaviors that have an impact on comfort provisions and operational costs in buildings, such as adjusting windows, blinds, shades, thermostats, and artificial lights. The work attempts to expand the state-of-the-art understanding of (1) the environmental, personal, and behavioral drivers motivating the occupants to interact with the control systems in diverse office settings and cultural contexts, (2) how the intention to share controls and the choice of adaptive actions is influenced by group negotiation dynamics, (3) the perceived ease of usage and knowledge on how to interact with building technologies, and (4) the correlation between perceived behavioral control, satisfaction, and productivity during different seasons. Based on this research framework, an online survey of 37 questions was designed to collect responses from office occupants in 14 universities and research centers in the US, Europe, China, and Australia. Data from the survey is currently being collected.

2.5.3. Key findings

The proposed interdisciplinary framework developed by Annex 66 aims to account for the psychological implications of behaviors, together with individual motivational drivers, societal norms, and group interactions, mediated by the multi-disciplinary knowledge borrowed from social sciences (i.e., for behavioral change) and data science (i.e., for human-in-the-loop technologies). By unlocking this innovative knowledge, research activities aim to provide insights into more relaxed centralized comfort requirements, allowing for reduced energy consumption and increased satisfaction and productivity, all of which result in reduced operational costs for building owners.

Undertaking interdisciplinary research remains a challenging task. Key challenges come from a lack of technical knowledge of the psychological and cultural—rather than purely physical—phenomena regulating occupant physiological adaptation in indoor environments, from energy and social science research respectively. A second related challenge is the lack of consistency in terminology between the social science and engineering disciplines when referring to motivation, habits, and behaviors in general. The design of robust models and effective control logics to achieve behavioral-based energy savings while ensuring occupant satisfaction in buildings remains an open problem. Another challenge is that simulation frameworks and schema representing OB (e.g., obXML and obFMU) are developed based on quantifiable physical parameters driving the behavioral adaptation phenomena to the indoor environment (thermal, visual, and comfort). It is challenging to quantify and integrate social variables into these frameworks, and more importantly, to convince conventional engineering practices to incorporate them into their energy simulation scenarios.

Some of the foreseen effects of further research applications include:

- Enabling a higher level of perceived personal control and comfort, allowing users to solve a personal comfort-driven task or action at the zone level, and increasing satisfaction with the indoor environmental quality without influencing the overall comfort level (centrally designed neutral/static homeostasis) and energy efficiency (avoiding over-running the system) at the building scale.
- Enabling the next generation of building technologies to negotiate comfort conditions between occupants sharing spaces and HVAC controls.
- Developing machine-learned comfort preferences and building occupancy data and implementing them in model predictive controls to provide high-level intelligence in conjunction with technologies able to deliver hierarchical zone-to-campus optimization control logics.

3. Discussion and conclusive remarks

The major product of Annex 66 consists of a methodological framework to guide OB simulation research on data collection, modeling and evaluation, modeling tools integration, application, and interdisciplinary issues. In brief, Annex 66 proposed scientific approaches to reduce the gap between the simulated and measured values for building energy performance by representing OB in a standardized quantitative way, and went further by integrating them with current building performance simulation programs, which could have important impacts on the industry from various perspectives.

During the cooperative research activities and frequent discussions, the Annex 66 community reached a consensus regarding OB research and identified some important issues that are worth thorough deliberation and further discussion. The following topics have been discussed and explored within the Annex 66 community, while their significance labels them as research topics needing further study in future work.

- Data collection is fundamental for the modeling of OB. The methods of collecting data are evolving with the rapid development of sensors and information and communication technologies (ICT). Most data collection campaigns are conducted in a typical working environment rather than in a laboratory. With precise control of the indoor environment and good reproducibility, laboratories are becoming an alternative for collecting reliable OB data. However, the Hawthorne Effect [117], which implies that the subjects may alter their behavior when they are aware they are being observed, may be an unfavorable factor during laboratory research involving occupants. New sensors for detecting occupancy and occupant actions are being developed. For example, the occupancy in a space could be measured in various ways. The indirect approach refers to the change rate of CO_2 concentration to estimate the occupancy. Infrared or ultrasonic occupancy sensors try to detect the movement of occupants around a room. Wearable sensors and smartphones can locate occupants with high resolution. Video cameras are also being used to recognize occupancy patterns, the data from which could be analyzed with image recognition algorithms at high computational capacity. New devices, such as Kinect, are being introduced to automatically detect occupancy [118]. The evolution of technology requires researchers to have a good understanding of the available data collection methods and apply them to the most appropriate situation. However, there are still uncertainties regarding the accuracy of image analysis and positioning using Wi-Fi signals, as well as correlated ethical considerations to be taken into account [119]. The development of a data collection technique further generates large-scale datasets. For instance, applications on phones can identify occupants and their movements, the data from which can reveal nationwide patterns of individual habits. Data mining methods are being introduced to efficiently analyze and extract valuable knowledge from this type of dataset.
- The modeling of OB often encompasses stochasticity. Nevertheless, related studies have suggested that stochastic models do not necessarily perform better than simplified deterministic models. The appropriate model should be determined based on the selected application scenario. Current OB models focus on the estimation of building energy consumption for a relatively long period, typically a year. The purpose of this type of model is to have the estimation as accurate as possible. In another situation, such as in model predictive control, however, the purpose of a model is to predict the specific parameters for the short-term future. Models that aim at energy consumption simulation are not good candidates in this context, as they have little predictive ability based on available historical data. Another aspect of current OB models is that they are data driven, implying that the models were built using regressions based on data collected from the environment and occupancy or occupant actions, rather than from studying the OB mechanism from a physiological or psychological perspective. The development of thermal comfort research and the combination with sociological studies can potentially shed some light on the description and modeling of OB on a mechanism-modeling basis. The combination of these studies allows for a new path for OB modeling. Evaluation of OB models, as revealed earlier, should have explicit metrics that come from the application scenarios to quantify their performance. Specifically, the evaluation of stochastic models has roots in the statistical comparison between stochastic simulation results and deterministic measurement results (i.e., using bootstrap validation, cross-validation, or random sample validation

methods [120]). New approaches adopting statistics are under development for the evaluation of model accuracy [76].

- The integration of OB models with building performance simulation tools links academic research with industrial applications. The DNAS framework and the co-simulation architecture proposed in this Annex have made progress towards integrating multiple OB models and building performance simulation tools in a flexible and robust manner. Nevertheless, significant work remains to be done to offer easy-to-use interfaces in OB simulation for industrial applications. An important issue to address is the representation of OB diversity. Behavior patterns differ among individuals, and this diversity is perplexing for researchers and engineers tasked with identifying the behavior patterns and corresponding parameters to be set in a simulation involving occupants. As a compromise between the diversity of actual OB and simplicity in building simulation, some typical occupant traits have been proposed, i.e., reconciling clusters of behavioral patterns with data-driven inputs and predictive models [121]. Efforts have been made within the Annex 66 community to address OB diversity with different approaches, such as case measurements and questionnaire surveys. The issue remains an open question that is of great significance in the application of occupant simulation and requires significant further investigation.
- During OB model application, the technical details of modeling are veiled and the engineer is provided with a friendly interface. A guidebook detailing the appropriate situations for applying each model would provide significant help to simulation users, to avoid the use of a model in scenarios dissimilar to those under which it was developed. Policy makers could benefit from the OB modeling by observing the simulated energy reduction with altered behavior patterns. This procedure facilitates the development of efficient policies for reducing energy consumption in buildings. The remaining unresolved issue is the modeling of OB evolution when incentives are provided to motivate energy-saving behavior. A similar question arises in the situation where occupants are transferred to a new environment and their behavior changes in response. The sociological and psychological aspects of occupants should be studied under these circumstances to gain clear explanations of the alternation of OB according to different incentives. Going forward, efforts to strengthen and update interdisciplinary and international relationships and networks have to be continuously nurtured, both within the IEA research arena as well as within industrial communities such as the American Society of Heating, Refrigerating, and Air-Conditioning Engineers Multidisciplinary Task Group on Occupant Behavior in Buildings (ASHRAE MTG.OBB). The ultimate objective of such research is to derive better empirical findings for the development of market actions and international codes and standards in the field of OB modeling and simulation research for the building sector. The Annex 66 community at large envisions future follow-up papers that will further present and discuss the ongoing activities of this Annex.

Acknowledgments

This paper summarizes and highlights the main research issues, outcomes, and findings from Annex 66, drawing content from the final report on Annex 66 and other publications. The authors appreciate the strong leadership and technical contribution of the subtask leaders, as well as the contributions from all of the Annex 66 participants. The IEA (International Energy Agency) Energy in Buildings and Community (EBC) Programme (iea-ebc.org) carries out research and development activities toward near-zero energy and carbon emissions in the built environment. These joint research projects are directed at energy-saving technologies and activities that support technology application in practice. The results are also used in the formulation of international and national energy conservation policies and standards. Da Yan and Tianzhen Hong, the operating agents of Annex 66, appreciate the strong support received from the IEA EBC Chair, Secretary, and Executive Committee.

This study was supported by the China Ministry of Housing and Urban-Rural Development and the Ministry of Science & Technology, under the U.S.-China Clean Energy Research Center for Building Energy Efficiency (grant no. 2016YFE0102300-04), and Innovative Research Groups of the National Natural Science Foundation of China (grant number 51521005).

Participation of Lawrence Berkeley National Laboratory in Annex 66 was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the United States Department of Energy under Contract No. DE-AC02-05CH11231.

References

[1] O.T. Masoso, L.J. Grobler, The dark side of occupants' behaviour on building energy use, Energy Build. 42 (2010) 173–177, http://dx.doi.org/10.1016/j.enbuild.2009.08.009.
[2] A. Al-Mumin, O. Khattab, G. Sridhar, Occupants' behavior and activity patterns influencing the energy consumption in the Kuwaiti residences, Energy Build. 35 (2003) 549–559, http://dx.doi.org/10.1016/S0378-7788(02)00167-6.
[3] A.S. Bahaj, P.A.B. James, Urban energy generation: the added value of photovoltaics in social housing, Renew. Sustain. Energy Rev. 11 (2007) 2121–2136, http://dx.doi.org/10.1016/j.rser.2006.03.007.
[4] G. Wood, M. Newborough, Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design, Energy Build. 35 (2003) 821–841, http://dx.doi.org/10.1016/S0378-7788(02)00241-4.
[5] J. Ouyang, K. Hokao, Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China, Energy Build. 41 (2009) 711–720, http://dx.doi.org/10.1016/j.enbuild.2009.02.003.
[6] X. Zhou, D. Yan, G. Deng, Influence of Occupant Behavior on the Efficiency of a District Cooling System, 13th Conf. Int. Build. Performance Simul. Assoc. (2013) 1739–1745, http://www.ibpsa.org/proceedings/BS2013/p_2563.pdf.
[7] X. Guo, D. Tiller, G. Henze, C. Waters, The performance of occupancy-based lighting control systems: a review, Light. Res. Technol. 42 (2010) 415–431, http://dx.doi.org/10.1177/1477153510376225.
[8] S. Wei, R. Buswell, D. Loveday, Probabilistic modelling of human adaptive behaviour in non-air-conditioned buildings Adapt. to Chang. New Think. Comf., 55, 2010, pp. 9–11 http://nceub.commoncense.info/uploads/07-01-07-Wei.pdf.
[9] C. Peng, D. Yan, R. Wu, C. Wang, X. Zhou, Y. Jiang, Quantitative description and simulation of human behavior in residential buildings, Build. Simul. 5 (2012) 85–94, http://dx.doi.org/10.1007/s12273-011-0049-0.
[10] A. Mahdavi, A. Mohammadi, E. Kabir, L. Lambeva, Occupants' operation of lighting and shading systems in office buildings, J. Build. Perform. Simul. 1 (2008) 57–65, http://dx.doi.org/10.1080/19401490801906502.
[11] International Facility Management Association (IFMA), Temperature Wars: Savings vs. Comfort, 2009.
[12] X. Feng, D. Yan, C. Wang, H. Sun, A preliminary research on the derivation of typical occupant behavior based on large-scale questionnaire surveys, Energy Build. (2015), http://dx.doi.org/10.1016/j.enbuild.2015.09.055.
[13] V. Fabi, R.V. Andersen, S.P. Corgnati, F. Venezia, Influence of User Behaviour on Indoor Environmental Quality and Heating Energy Consumptions in Danish Dwellings, Cobee, 2012.
[14] M. Foster, T. Oreszczyn, Occupant control of passive systems: the use of Venetian blinds, Build. Environ. 36 (2001) 149–155, http://dx.doi.org/10.1016/S0360-1323(99)00074-8.
[15] B. Dong, B. Andrews, Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings, Elev. Int. IBPSA Conf. (2009) 1444–1451, http://dx.doi.org/10.1016/j.buildenv.2006.10.024.
[16] B. Dong, Y. Duan, R. Liu, T. Nishimoto, The impact of occupancy behavior patterns on the energy consumption in low-income, in: CATEE Clean Air Through Energy Effic. Conf., San Antionio, Texas, 2013.
[17] B. Dong, K.P. Lam, A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting, Build. Simul. 7 (2014) 89–106, http://dx.doi.org/10.1007/s12273-013-0142-7.
[18] C. Wang, D. Yan, Y. Jiang, A novel approach for building occupancy simulation, Build. Simul. 4 (2011) 149–167, http://dx.doi.org/10.1007/s12273-011-0044-5.
[19] W.K. Chang, T. Hong, Statistical Analysis and Modeling of Occupancy Patterns in Open-Plan Offices Using Measured Lighting- Switch Data, 2014.
[20] T. Labeodan, K. Aduda, G. Boxem, W. Zeiler, On the application of multi-agent systems in buildings for improved building operations,

performance and smart grid interaction – a survey, Renew. Sustain. Energy Rev. 50 (2015) 1405–1414, http://dx.doi.org/10.1016/j.rser.2015.05.081.
[21] H.B. Rijal, P. Tuohy, M. Humphreys, J.F. Nicol, A. Samuel, J. Clarke, Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, Energy Build. 39 (2007) 823–836, http://dx.doi.org/10.1016/j.enbuild.2007.02.003.
[22] H.B. Rijal, P. Tuohy, F. Nicol, M.A. Humphreys, A. Samuel, J. Clarke, Development, Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings, J. Build. Perform. Simul. 1 (2008) 17–30, http://dx.doi.org/10.1080/19401490701868448.
[23] F. Nicol, H. Rijal, M. Humphreys, P. Tuohy, Characterising the use of windows in thermal simulation, 2nd PALENC Conf. 2 (2007) 712–717.
[24] G.Y. Yun, K. Steemers, Time-dependent occupant behaviour models of window control in summer, Build. Environ. 43 (2008) 1471–1482, http://dx.doi.org/10.1016/j.buildenv.2007.08.001.
[25] F. Haldi, D. Robinson, On the behaviour and adaptation of office occupants, Build. Environ. 43 (2008) 2163–2177, http://dx.doi.org/10.1016/j.buildenv.2008.01.003.
[26] F. Haldi, D. Robinson, Interactions with window openings by office occupants, Build. Environ. 44 (2009) 2378–2395, http://dx.doi.org/10.1016/j.buildenv.2009.03.025.
[27] R. Andersen, V. Fabi, J. Toftum, S.P. Corgnati, B.W. Olesen, Window opening behaviour modelled from measurements in Danish dwellings, Build. Environ. 69 (2013) 101–113, http://dx.doi.org/10.1016/j.buildenv.2013.07.005.
[28] F. Haldi, D. Robinson, Adaptive actions on shading devices in response to local visual stimuli, J. Build. Perform. Simul. 3 (2010) 135–153, http://dx.doi.org/10.1080/19401490903580759.
[29] P. Correia da Silva, V. Leal, M. Andersen, Occupants interaction with electric lighting and shading systems in real single-occupied offices: results from a monitoring campaign, Build. Environ. 64 (2013), http://dx.doi.org/10.1016/j.buildenv.2013.03.015.
[30] C. Wang, D. Yan, H. Sun, Y. Jiang, A generalized probabilistic formula relating occupant behavior to environmental conditions, Build. Environ. 95 (2016) 53–62, http://dx.doi.org/10.1016/j.buildenv.2015.09.004.
[31] V. Inkarojrit, Developing predictive venetian blinds control models using visual comfort predictors, 23rd Conf. Passiv. Low Energy Archit. (2006) 6–8.
[32] V. Inkarojrit, Monitoring and modelling of manually-controlled Venetian blinds in private offices: a pilot study, J. Build. Perform. Simul. 1 (2008) 75–89, http://dx.doi.org/10.1080/19401490802021012.
[33] L. Sanati, M. Utzinger, The effect of window shading design on occupant use of blinds and electric lighting, Build. Environ. 64 (2013) 67–76, http://dx.doi.org/10.1016/j.buildenv.2013.02.013.
[34] C. Reinhart, K. Voss, Monitoring manual control of electric lighting and blinds, Light. Res. Technol. 35 (2003) 243–260, http://dx.doi.org/10.1191/1365782803li064oa.
[35] V. Inkarojrit, Balancing Comfort Occupants' Control of Window Blinds in Private Offices, 2005.
[36] M. Konstantoglou, A. Tsangrassoulis, Dynamic operation of daylighting and shading systems: a literature review, Renew. Sustain. Energy Rev. 60 (2016) 268–283, http://dx.doi.org/10.1016/j.rser.2015.12.246.
[37] I. Bennet, W. O'Brien, H.B. Gunay, Effect of Window Blind Use in Residential Buildings: Observation and Simulation Study, eSim, 2014, http://www.ibpsa.org/proceedings/eSimPapers/2014/3A.3.pdf.
[38] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, S. Gilani, Development and implementation of an adaptive lighting and blinds control algorithm, Build. Environ. (2016), http://dx.doi.org/10.1016/j.buildenv.2016.08.027.
[39] T. Moore, D.J. Carter, A. Slater, Long-term patterns of use of occupant controlled office lighting, Light. Res. Technol. 35 (2003) 43–59, http://dx.doi.org/10.1191/1477153503li061oa.
[40] S. Pigg, M. Eilers, J. Reed, Behavioral aspects of lighting and occupancy sensors in privates offices: a case study of a university office building, ACEEE 1996 Summer Study Energy Effic. Build. (1996) 161–170.
[41] A. Mahdavi, A. Mohammadi, E. Kabir, L. Lambeva, Occupants' operation of lighting and shading systems in office buildings, J. Build. Perform. Simul. 1 (2008) 57–65, http://dx.doi.org/10.1080/19401490801906502.
[42] J. Tanimoto, A. Hagishima, H. Sagara, A methodology for peak energy requirement considering actual variation of occupants' behavior schedules, Build. Environ. 43 (2008) 610–619, http://dx.doi.org/10.1016/j.buildenv.2006.06.034.
[43] M. Schweiker, M. Shukuya, Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions, Build. Environ. 44 (2009) 2137–2149, http://dx.doi.org/10.1016/j.buildenv.2009.03.004.
[44] X. Ren, D. Yan, C. Wang, Air-conditioning usage conditional probability model for residential buildings, Build. Environ. 81 (2014) 172–182, http://dx.doi.org/10.1016/j.buildenv.2014.06.022.
[45] Y. Zhang, P. Barrett, Factors influencing the occupants' window opening behaviour in a naturally ventilated office building, Build. Environ. 50 (2012) 125–134, http://dx.doi.org/10.1016/j.buildenv.2011.10.018.
[46] J. Jakubiec, C. Reinhart, The adaptive zone – a concept for assessing discomfort glare throughout daylit spaces, in: Build. Simul. 2011 12th Conf. Int. Build. Perform. Simul. Assoc. Sydney, 14–16 November, Sydney, 2011, http://dx.doi.org/10.1177/1477153511420097.
[47] M. Schweiker, A. Wagner, The effect of occupancy on perceived control, neutral temperature, and behavioral patterns, Energy Build. (2015), http://dx.doi.org/10.1016/j.enbuild.2015.10.051.
[48] W. O'Brien, H.B. Gunay, The Contextual Factors Contributing to Occupants' Adaptive Comfort Behaviors in Offices–A Review and Proposed Modeling Framework, 2014.
[49] K. Zhou, S. Yang, Understanding household energy consumption behavior: the contribution of energy big data analytics, Renew. Sustain. Energy Rev. 56 (2016) 810–819, http://dx.doi.org/10.1016/j.rser.2015.12.001.
[50] X. Yu, Y. Su, Daylight availability assessment and its potential energy saving estimation – a literature review, Renew. Sustain. Energy Rev. 52 (2015) 494–503, http://dx.doi.org/10.1016/j.rser.2015.07.142.
[51] F. Stazi, F. Naspi, M. D'Orazio, A literature review on driving factors and contextual events influencing occupants' behaviours in buildings, Build. Environ. 118 (2017) 40–66, http://dx.doi.org/10.1016/j.buildenv.2017.03.021.
[52] V. Fabi, R.V. Andersen, S. Corgnati, B.W. Olesen, Occupants' window opening behaviour: a literature review of factors influencing occupant behaviour and models, Build. Environ. 58 (2012) 188–198, http://dx.doi.org/10.1016/j.buildenv.2012.07.009.
[53] W.O. Brien, I. Gaetani, S. Gilani, S. Carlucci, International survey on current occupant modelling approaches in building performance simulation, Buildi. Perform. Simul. (2016) 1–19.
[54] Q. Pu, S. Gupta, S. Gollakota, S. Patel, Whole-Home gesture recognition using wireless signals, Proc 19th Annu Int Conf Mob Comput Netw—MobiCom '13 (2013), p. 27.
[55] R. Melfi, B. Rosenblum, B. Nordman, K. Christensen, Measuring building occupancy using existing network infrastructure, BT – 2011 Int. Green Comput. Conf. IGCC 2011, July 25, 2011 – July 28, 2011 (2011).
[56] R.H. Dodier, G.P. Henze, D.K. Tiller, X. Guo, Building occupancy detection through sensor belief networks, Energy Build. 38 (2006) 1033–1043, http://dx.doi.org/10.1016/j.enbuild.2005.12.001.
[57] M.W. Ahmad, M. Mourshed, D. Mundow, M. Sisinni, Y. Rezgui, Building energy metering and environmental monitoring – a state-of-the-art review and directions for future research, Energy Build. 120 (2016), http://dx.doi.org/10.1016/j.enbuild.2016.03.059.
[58] F. Tahmasebi, S. Mostofi, A. Mahdavi, Exploring the implications of different occupancy modelling approaches for building performance simulation results, Energy Procedia 78 (2015) 567–572, http://dx.doi.org/10.1016/j.egypro.2015.11.737.
[59] S. Gilani, W. O'Brien, H.B. Gunay, J.S. Carrizo, Use of dynamic occupant behavior models in the building design and code compliance processes, Energy Build 117 (2016), http://dx.doi.org/10.1016/j.enbuild.2015.10.044.
[60] P. Ole Fanger, Thermal Comfort, Danish Tech Press, 1970.
[61] P. Ole Fanger, J. Toftum, Extension of the PMV model to non-air-conditioned buildings in warm climates, Energy Build. 34 (2002) 533–536, http://dx.doi.org/10.1016/S0378-7788(02)00003-8.
[62] S. Schiavon, K.H. Lee, Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures, Build. Environ. 59 (2013) 250–260, http://dx.doi.org/10.1016/j.buildenv.2012.08.024.
[63] G.S. Brager, G. Paliaga, R. De Dear, B. Olesen, J. Wen, F. Nicol, M. Humphreys, Operable windows, personal control, and occupant comfort, ASHRAE Trans. (2004) 17–35.
[64] S. Schiavon, A.K. Melikov, Energy-saving strategies with personalized ventilation in cold climates, Energy Build. 41 (2009) 543–550, http://dx.doi.org/10.1016/j.enbuild.2008.11.018.
[65] S. D'Oca, C. Chen, T. Hong, Z.D. Belafi, Synthesizing building physics with social psychology: an interdisciplinary framework for context and occupant behavior in office buildings, Energy Res. Soc. Sci. 34 (2017) 240–251.
[66] D.A. Leeuw, E.D. Hox, J.J. Dillman, International Handbook of Survey Methodology, Psychology Press, 2008.
[67] J. Langevin, P.L. Gurian, J. Wen, Tracking the human-building interaction: a longitudinal field study of occupant behavior in air-conditioned offices, J. Environ. Psychol. 42 (2015) 94–115, http://dx.doi.org/10.1016/j.jenvp.2015.01.007.
[68] C. Teddlie, A. Tashakkori, Foundations of Mixed Methods Research: Integrating Quantitative and Qualitative Approaches in the Social and Behavioral, SAGE, 2009.
[69] A. Heydarian, E. Pantazis, D. Gerber, B. Becerik-Gerber, Use of immersive virtual environments to understand human-building interactions and improve building design, Int. Conf. Human-Computer Interact. (2015).
[70] M. Ajzen, I. Fishbein, Attitude–behavior relations: a theoretical analysis and review of empirical research, Psychol. Bull. 84 (1977) 888–918.
[71] R.H. Bandura, A. Walters, Social Learning and Personality Development, Holt, Rinehart, & Winston, New York, 1963.
[72] B. Skinner, Science And Human Behavior, 1953, pp. 461, http://books.google.com/books?hl=en&lr=lang_en&id=Pjjknd1HREIC&pgis=1.
[73] J. Zhao, B. Lasternas, K.P. Lam, R. Yun, V. Loftness, Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining, Energy Build. 82 (2014), http://dx.doi.org/10.1016/j.enbuild.2014.07.033.
[74] D. Yan, W. O'Brien, T. Hong, X. Feng, H.B. Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: current state and future challenges, Energy Build. 107 (2015) 264–278, http://dx.doi.org/10.1016/j.enbuild.2015.08.032.

[75] S. D'Oca, V. Fabi, S.P. Corgnati, R.K. Andersen, Effect of thermostat and window opening occupant behavior models on energy use in homes, Build. Simul. 7 (2014) 683–694, http://dx.doi.org/10.1007/s12273-014-0191-6.
[76] M. Schweiker, F. Haldi, M. Shukuya, D. Robinson, Verification of stochastic models of window opening behaviour for residential buildings, J. Build. Perform. Simul. 5 (2012) 55–74, http://dx.doi.org/10.1080/19401493.2011.567422.
[77] T. Hong, S.K. Chou, T.Y. Bong, Building simulation: an overview of development and information sources, Build. Environ. 35 (2000).
[78] T. Hong, D. Yan, S. D'Oca, C. Chen, Ten questions concerning occupant behavior in buildings: the big picture, Build. Environ. (2016) 1–13, http://dx.doi.org/10.1016/j.buildenv.2016.12.006.
[79] T. Hong, S.C. Taylor-Lange, S. D'Oca, D. Yan, S.P. Corgnati, Advances in research and applications of energy-related occupant behavior in buildings, Energy Build. (2015), http://dx.doi.org/10.1016/j.enbuild.2015.11.052.
[80] X. Liang, T. Hong, G.Q. Shen, Occupancy data analytics and prediction: a case study, Build. Environ. 102 (2016), http://dx.doi.org/10.1016/j.buildenv.2016.03.027.
[81] W. Parys, D. Saelens, H. Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices – a review-based integrated methodology, J. Build. Perform. Simul. 4 (2011) 339–358, http://dx.doi.org/10.1080/19401493.2010.524711.
[82] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices, Build. Environ. 70 (2013) 31–47, http://dx.doi.org/10.1016/j.buildenv.2013.07.020.
[83] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy Build. (2015), http://dx.doi.org/10.1016/j.enbuild.2015.10.033.
[84] T. Hong, S. D'Oca, S.C. Taylor-Lange, W.J.N. Turner, Y. Chen, S.P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: implementation of the DNAS framework using an XML schema, Build. Environ. 94 (2015) 196–205, http://dx.doi.org/10.1016/j.buildenv.2015.08.006.
[85] A. Cowie, T. Hong, X. Feng, Q. Darakdjian, Usefulness of the obFMU module examined through a review of occupant modelling functionality in building performance simulation programs, in: IBPSA Build. Simul. Conf., San Francisco, 2017.
[86] T. Hong, Y. Chen, Z. Belafi, S. D'Oca, Occupant behavior models: a critical review of implementation and representation approaches in building performance simulation programs, Build. Simul. (2017) 1–14.
[87] T. Hong, S. D'Oca, W. Turner, S.C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: introduction to the DNAs framework, Build. Environ. 92 (2015) 764–777.
[88] Z. Belafi, T. Hong, A. Reith, A library of building occupant behavior models represented in a standardized schema, in: BEHAVE 2016 4th Eur. Conf. Behav. Energy Effic., Coimbra, 2016.
[89] M. Wetter, Co-simulation of building energy and control systems with the building controls virtual test bed, Build. Perform. Simul. 4 (2011) 185–203.
[90] W. Bernal, M. Behl, T.X. Nghiem, R. Mangharam, MLE+: A tool for integrated design and deployment of energy efficient building controls, in: Proceedings of the 4th ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Toronto, Canada, 2012, pp. 123–130.
[91] Y. Chen, T. Hong, X. Luo, An agent-based occupancy simulator for building performance simulation, Build. Simul. (2017) 1–13.
[92] K. Sun, T. Hong, A simulation approach to estimate energy savings potential of occupant behavior measures, Energy Build. 136 (2017) 43–62, http://dx.doi.org/10.1016/j.enbuild.2016.12.010.
[93] K. Sun, T. Hong, A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures, Energy Build. 146 (2017) 383–396.
[94] Y. Chen, X. Liang, T. Hong, X. Luo, Simulation and visualization of energy-related occupant behavior in office buildings, Build. Simul. (2017) 1–14, http://dx.doi.org/10.1007/s12273-017-0355-2.
[95] X. Luo, K.P. Lam, Y. Chen, T. Hong, Performance evaluation of an agent-based occupancy simulation model, Build. Environ. 115 (2017) 42–53.
[96] A. Mahdavi, F. Tahmasebi, The deployment-dependence of occupancy-related models in building performance simulation, Energy Build. 117 (2016) 313–320, http://dx.doi.org/10.1016/j.enbuild.2015.09.065.
[97] I. Gaetani, P.J. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: towards a fit-for-purpose modeling strategy, Energy Build. (2015), http://dx.doi.org/10.1016/j.enbuild.2016.03.038.
[98] C. Duarte, K. Van Den Wymelenberg, C. Rieger, Revealing occupancy patterns in an office building through the use of occupancy sensor data, Energy Build. 67 (2013) 587–595, http://dx.doi.org/10.1016/j.enbuild.2013.08.062.
[99] A. Mahdavi, F. Tahmasebi, On the quality evaluation of behavioural models for building performance applications, J. Build. Perform. Simul. 0 (2016) 1–11, http://dx.doi.org/10.1080/19401493.2016.1230148.
[100] G. Branco, B. Lachal, P. Gallinelli, W. Weber, Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data, Energy Build. 36 (2004) 543–555, http://dx.doi.org/10.1016/j.enbuild.2004.01.028.
[101] O.G. Santin, Behavioural patterns and user profiles related to energy consumption for heating, Energy Build. 43 (2011) 2662–2672, http://dx.doi.org/10.1016/j.enbuild.2011.06.024.
[102] X. Feng, D. Yan, C. Wang, On the simulation repetition and temporal discretization of stochastic occupant behaviour models in building performance simulation, J. Build. Perform. Simul. 0 (2016) 1–13, http://dx.doi.org/10.1080/19401493.2016.1236838.
[103] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy Build. 41 (2009) 295–302, http://dx.doi.org/10.1016/j.enbuild.2008.09.008.
[104] I. Gaetani, P. Hoes, J.L.M. Hensen, Introducing and testing a strategy for fit-for-purpose occupant behavior modeling in a simulation-aided building design process, in: Building Physics and Services, Eindhoven University of Technology, P.O. Box 5 13, 5600 MB Eindhoven, The Netherlands Abst, in: IBPSA Build. Simul. 2017, San Francisco, 2017, pp. 761–768.
[105] M. Trčka, J.L.M. Hensen, Overview of HVAC system simulation, Autom. Constr. 19 (2010) 93–99, http://dx.doi.org/10.1016/j.autcon.2009.11.019.
[106] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, On the sensitivity to different aspects of occupant behaviour for selecting the appropriate modelling complexity in building performance predictions, J. Build. Perform. Simul. 0 (2016) 1–11, http://dx.doi.org/10.1080/19401493.2016.1260159.
[107] B.K. Sovacool, What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda, Energy Res. Soc. Sci. 1 (2014) 1–29, http://dx.doi.org/10.1016/j.erss.2014.02.003.
[108] B.K. Sovacool, S.E. Ryan, P.C. Stern, K. Janda, G. Rochlin, D. Spreng, M.J. Pasqualetti, H. Wilhite, L. Lutzenhiser, Integrating social science in energy research, Energy Res. Soc. Sci. 6 (2015) 95–99, http://dx.doi.org/10.1016/j.erss.2014.12.005.
[109] P.C. Stern, What psychology knows about energy conservation, Am. Psychol. 47 (1992) 1224–1232, http://dx.doi.org/10.1037/0003-066X.47.10.1224.
[110] W. Abrahamse, L. Steg, Factors related to household energy use and intention to reduce it: the role of psychological and socio-demographic variables, Hum. Ecol. Rev. 18 (2011) 30–40.
[111] C. Chen, K. Knight, Energy at work: social psychological factors affecting energy conservation intentions within Chinese electric power companies, Energy Res. Soc. Sci. 4 (2014) 23–31, http://dx.doi.org/10.1016/j.erss.2014.08.004.
[112] S. D'Oca, S. Corgnati, A.L. Pisello, T. Hong, Introduction to an Occupant Behavior Motivation Survey Framework, Clima, 2016, pp. 2016.
[113] J.K. Day, D.E. Gunderson, Understanding high performance buildings: the link between occupant knowledge of passive design systems, corresponding behaviors, occupant comfort and environmental satisfaction, Build. Environ. 84 (2015) 114–124, http://dx.doi.org/10.1016/j.buildenv.2014.11.003.
[114] B. Mills, J. Schleich, Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: an analysis of European countries, Energy Policy 49 (2012) 616–628, http://dx.doi.org/10.1016/j.enpol.2012.07.008.
[115] A. Bandura, Social Foundations of Thought and Action: A Social Cognitive Theory. Prentice-Hall Series in Social Learning Theory, Social Fou, Prentice-Hall, Inc, Englewood Cliffs, NJ, US, 1986.
[116] I. Ajzen, The theory of planned behavior, Organ. Behav. Hum. Decis. Process. 50 (1991) 179–211, http://dx.doi.org/10.1016/0749-5978(91)90020-T.
[117] R. McCarney, J. Warner, S. Iliffe, R. van Haselen, M. Griffin, P. Fisher, The Hawthorne Effect: a randomised, controlled trial, BMC Med. Res. Methodol. 7 (2007) 30, http://dx.doi.org/10.1186/1471-2288-7-30.
[118] M.C. González, C.A. Hidalgo, A.-L. Barabási, Understanding individual human mobility patterns, Nature 453 (2008) 779–782, http://dx.doi.org/10.1038/nature07850.
[119] F. Adib, D. Katabi, See through walls with Wi-Fi!, ACM SIGCOMM, Comput. Commun. Rev. 43 (2013) 75–86, http://dx.doi.org/10.1145/2534169.2486039.
[120] V. Fabi, R.K. Andersen, S. Corgnati, Verification of stochastic behavioural models of occupants' interactions with windows in residential buildings, Build. Environ. 94 (2015) 371–383, http://dx.doi.org/10.1016/j.buildenv.2015.08.016.
[121] S. D'Oca, T. Hong, A data-mining approach to discover patterns of window opening and closing behavior in offices, Build. Environ. 82 (2014) 726–739, http://dx.doi.org/10.1016/j.buildenv.2014.10.021.