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Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs

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Abstract

Occupant behavior (OB) in buildings is a leading factor influencing energy use in buildings. Quantifying this influence requires the integration of OB models with building performance simulation (BPS). This study reviews approaches to representing and implementing OB models in today's popular BPS programs, and discusses weaknesses and strengths of these approaches and key issues in integrating of OB models with BPS programs. Two key findings are: (1) a common data model is needed to standardize the representation of OB models, enabling their flexibility and exchange among BPS programs and user applications; the data model can be implemented using a standard syntax (e.g., in the form of XML schema), and (2) a modular software implementation of OB models, such as functional mock-up units for co-simulation, adopting the common data model, has advantages in providing a robust and interoperable integration with multiple BPS programs. Such common OB model representation and implementation approaches help standardize the input structures of OB models, enable collaborative development of a shared library of OB models, and allow for rapid and widespread integration of OB models with BPS programs to improve the simulation of occupant behavior and quantification of their impact on building performance.

Keywords

Occupant behavior, data model, behavior modeling, building performance simulation, co-simulation

1. Introduction

Occupant behavior (OB) in buildings refers to occupants' presence and movement, and interactions with building systems that have an impact on building performance (thermal, visual, acoustic, and indoor air quality). The interactions include adjusting thermostat settings, opening or closing windows, dimming or turning on/off lights, pulling up or down window blinds, switching on or off plug loads, and consuming domestic hot water. Energy-related OB in buildings is one of the six influencing factors of building performance (Yoshino, 2013), including climate, building envelope, building equipment, operation and maintenance, OB, and indoor environment conditions. People spend most of their time in buildings; their daily interactions with building systems strongly influence building energy use. Occupants' expectations of desired comfort, including economic, physiological, and psychological needs, drive their actions to adjust their surrounding environment (e.g., indoor temperature, humidity level, lighting, CO_2).

Technologies alone do not necessarily guarantee low energy use in buildings. Low-cost behavioral solutions have demonstrated significant potential energy savings (Navigant Consulting, 2016). Clearly, understanding and accurately modeling OB in buildings are crucial to reducing the gap between design and actual building energy performance, especially for low-energy buildings relying more on passive design features, occupant-controlled technologies, and occupant engagement.

Building performance simulation (BPS) programs are applied extensively to appraise the performance of building energy systems and technologies. Presently, there is a significant disagreement between simulated results and actual building energy consumption (Bordass et al., 2004), which limits the application and potential impact of BPS programs. The core issues are not with deterministic factors, such as the physical characteristics of building envelope, HVAC systems, or lighting and electrical equipment, which have been investigated for the past several decades. Discrepancies mainly arise from a lack of quantitative research truthfully representing energy-related OB in buildings.

Advances in BPS over the last decades envisioned a switch from a deterministic approach to a stochastic approach in considering OB in buildings (Cowie, Hong, Feng, & Darakdjian, 2017; Parys, Saelens, & Hens, 2011). Traditionally, OB is represented as oversimplified and predefined *deterministic or static* schedules or fixed settings and rules (Cowie et al., 2017) which are input into BPS programs resulting in deterministic and homogeneous results—ignoring the stochastic nature, dynamics, and diversity of OB (Parys, Saelens, Roels, & Hens, 2011). For example, shading devices are closed 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 electrical lighting is dimmed or completely turned off if a space has adequate daylight to meet occupant visual comfort needs. However, occupants may interact with a control system—i.e., open windows—for a variety of reasons: (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 (O'Brien & Gunay, 2014).

Field-measured data and large-scale surveys confirmed that stochastic occupant presence and adaptive behaviors can be represented as probabilistic models of behavior (Wang et al., 2016). Probabilistic models of behavior can be derived from historical data of the indoor and outdoor environment conditions (e.g., air temperature and relative humidity, illuminance levels, CO_2 concentration), occupancy presence and movements, and the operating conditions of the building systems (e.g., windows, lighting, plug loads, thermostat, HVAC, shades, blinds). Through the machine learning process, the correlations can be established between some observed physical or situational environmental conditions and the observed human-building interaction. The final outputs of the behavioral models are probabilities of occupants being present in a space or performing a certain action when triggered by various environmental or situational conditions. In this view, probabilistic models provide structural solutions to organize the random and stochastic phenomena of OB in buildings. Accordingly, data-driven models have been widely developed by the research community and adopted by several BPS programs to improve simulation assumptions on occupancy presence and adaptive interactions (Hong, Taylor-Lange, D'Oca, Yan, & Corgnati, 2015).

Quantifying OB influence on building performance requires energy-related OB models to be integrated with BPS programs. Popular BPS programs, including EnergyPlus (and its various user interfaces, such as DesignBuilder), 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 as probabilistic regression equations based on independent variables and metrics. The selection of different influencing variables for similar OB models makes it difficult to compare the models and incorporate them into BPS programs. OB models also tend to be located all over the code of BPS programs, making it difficult to change. A recent review of modeling and simulation approaches for OB in buildings (Gunay, O'Brien, & Beausoleil-Morrison, 2013) discussed the problem of transferability of occupant models developed based on a selected observation study to different building models. Also, one of the key takeaways drawn from previous studies (Hong, D'Oca, Taylor-Lange et al., 2015) is the deficiency of a standardized method for representing and implementing energy-related OB models in BPS programs.

Shortcomings in the diffusion of OB models implementation in current BPS programs are exacerbated by the non-trivial environment of common simulation engines, which have unfriendly interfaces and require programming knowledge and specific code validation procedures to incorporate custom behavioral models. Further, when a behavioral model allows its embedding via source-code alteration, idiosyncratic data syntax and file format/structure issues do not permit flexibility or a standardized way to achieve transferability of behavioral models between simulation engines.

This study critically reviewed approaches to the implementation and representation of OB models in eight popular BPS programs among the engineering and simulation community. Approaches to modeling occupant behavior have been reviewed (Yan et al., 2015), such as (1) Average value models (deterministic), Bernoulli models, Survival models, and agent-based models are used to predict state, and (2) Markov models and Survival models are used to predict events (state-transitions). Therefore, OB modeling approaches are not covered in this study. The goal of this study is to provide insight into the following important questions:

(1) What approaches are employed in BPS programs to implement OB models (i.e., what will enable users to model OB)?
(2) What approaches are used in BPS programs to represent the inputs of OB models?
(3) What are the strengths and weaknesses of different implementation and representation approaches?
(4) What are the challenges of enabling the interoperability of OB models for BPS programs?

2. Implementation of OB models in BPS programs

This study identified and reviewed four approaches to implementing OB models in BPS programs. The implementation of OB models in BPS programs, in this context, refers to simulation users or energy modelers choosing certain approaches and preparing inputs for the OB models to be included as part of a building energy model using a particular BPS program. These OB models can be either deterministic/static or stochastic by nature. For example, a deterministic occupant-driven control would determine occupant actions based on indoor and/or outdoor environmental conditions using a deterministic correlation function. On the other hand, a stochastic OB model is related to occupants performing specific actions with a probability related to environmental conditions (e.g., occupants feeling hot and opening a window) or events (e.g., entering or leaving a space). This section describes each of the four approaches and categorizes them based on the BPS program supporting their implementation. The strengths and weakness of each approach are discussed.

2.1. Four implementation approaches of OB models

2.1.1. Direct input or control

The direct input or control approach defines occupant-related inputs using BPS program semantics—just as other model inputs (building geometry, constructions, internal heat gains, and HVAC systems) are defined.

In this approach, the user defines and inputs temporal schedules for thermostat settings (cooling and heating temperature set points), occupants, lighting, plug loads, and the HVAC system. Direct input is supported by almost all BPS programs. Some BPS programs also allow users to specify deterministic or static rules governing the operation of building components and systems based on indoor and outdoor environmental parameters.

The direct input or control approach requires users to pre-calculate the schedules based on the correlations between the environmental conditions and the occupant actions of the OB models, as illustrated in Figure 1. There is no runtime communication between the pre-calculation module and the BPS program. The outputs of occupant behavior pre-calculations are based on pre-defined rules or default values, or assumed environmental conditions, rather than those generated by the BPS. Users may need to manually adjust the pre-calculation assumptions based on the simulated results several times to ensure the results are reasonable. It is a challenge, especially when some dynamic indoor parameters (i.e., air temperature) are used in both sides of the correlation function (e.g., turn on or off air conditioners when feeling hot or cold). Static set points (i.e., temperature set point) are typically used as an approximate to determine the occupant actions and generate the schedules in this approach, which may reduce OB model accuracy.

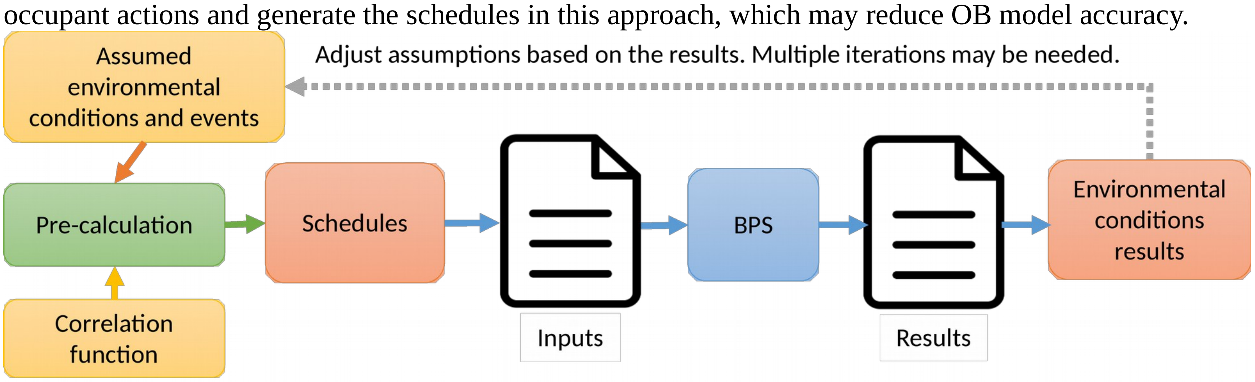

Figure 1. Workflow for the direct input or control approach

2.1.2. Built-in OB models

The second method is to use the OB models already implemented in the BPS programs (Figure 2), usually in a dedicated software module. The built-in OB models approach provides a simple way to model the specific OB models; however, currently, there are only limited built-in OB models in few BPS programs, which affects the flexibility of this approach.

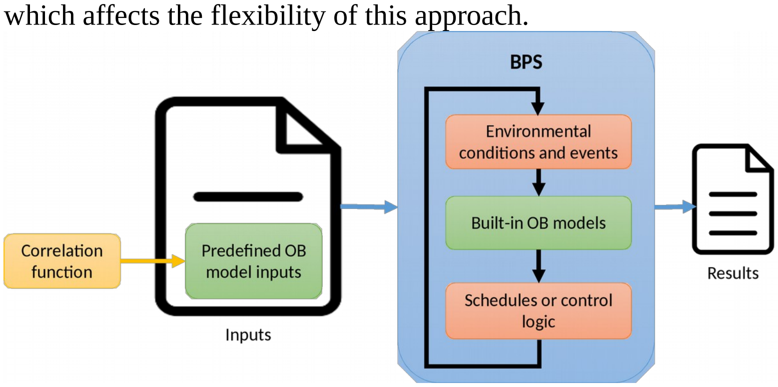

Figure 2. Workflow for the built-in OB models approach

2.1.3. User function or custom code

In the user function or custom code approach, the user can write functions or custom code, as part of a building energy model input file, to implement new building operation and supervisory controls or to overwrite existing or default ones (Figure 3). For example, EnergyPlus has the energy management system feature and DOE-2 has the user function feature that implements such functionality (Yan et al., 2015). This approach provides flexibility by enabling users to change how a BPS program simulates a building energy model without having to recompile the source code of a BPS program. This approach allows both deterministic and stochastic OB models using built-in or user-defined stochastic mathematical functions.

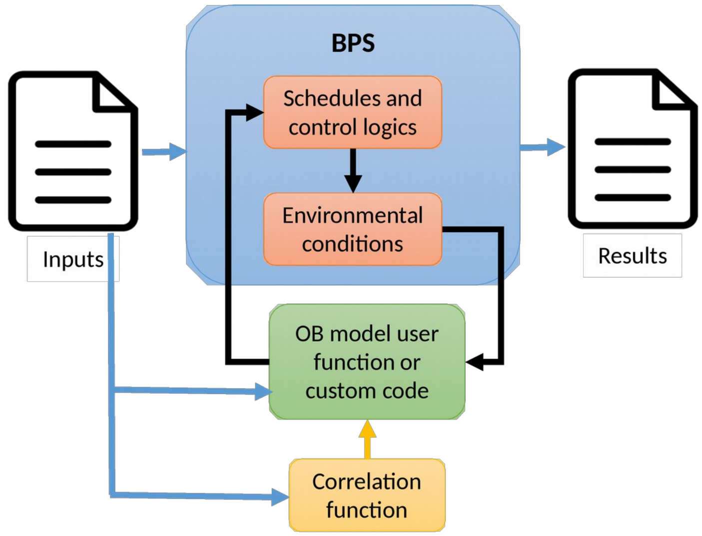

Figure 3. Workflow for the user function or custom code approach

2.1.4. Co-simulation

Co-simulation is a simulation methodology that allows distinct components to be simulated by different simulation tools running simultaneously and switching information in a combined routine (Wetter, 2011). As an example, today's most advanced visual comfort and blind control models are based on image-based annual glare analysis of multiple viewpoints in a scene using a combination of RADIANCE, DAYSIM, and EVALGLARE (Reinhart and Wienold, 2011; Gunay et al., 2014). Assuming that BPS developers do not want or do not have enough expertise to fully implement those visual comfort and blind control models, co-simulation becomes a feasible option to integrate those models with the BPS program for a fully consistent analysis. Similar examples can be described for computational fluid dynamics (CFD) based natural ventilation studies predicting the performance of natural ventilation in large-scale naturally ventilated buildings (Wang and Wong, 2008; Wang and Wong, 2009; Tan and Glicksman, 2005). Typically, current BPS programs do not implement multi-zone CFD models for large openings or atrium configurations simulation to improve natural ventilation prediction and optimize design methods. Once again, co-simulation between dedicated CFD models and BPS program emerges as one of the plausible ways to evaluate their integrated performance.

Co-simulation allows BPS to be carried out in an integrated manner, running modules developed in different programming languages or in different physical computers. Co-simulation can be performed in EnergyPlus using two methods. The first is to use the building control virtual test bed (BCVTB) as a master for the simulation, controlling the execution and exchange of data between other tools (Wetter, 2011). For example, using this method, both an indoor air quality analysis tool and EnergyPlus can be the slaves of the BCVTB, and the outdoor air flow rate in EnergyPlus can be determined based on the indoor air quality analysis at each time step of the simulation (Chen, Gu, & Zhang, 2015). This is also the case of the MLE+ toolbox (Bernal, Behl, Nghiem, & Mangharam, 2012), which provides a set of MATLAB functions and classes, as well as a Simulink library, for performing co-simulation with EnergyPlus (version 8.3). This method uses a specific interface defined by BCVTB and EnergyPlus, rather than a standardized interface, to exchange data among the tools. A tool developed to co-simulate with EnergyPlus via BCTVB cannot be reused by other BPS programs. The second method overcomes such limitations by adopting a standardized way of using the functional mock-up interface (FMI), which is a tool-independent standard for the exchange of dynamic models and for co-simulation. In this case, all models implementing FMI can be integrated with all the BPS programs adopting the FMI standards. For example, the OB functional mock-up unit (obFMU) (Hong, Sun, Chen, Taylor-Lange, & Yan, 2016) can be used by both EnergyPlus and ESP-r for co-simulation. Figure 4 illustrates a co-simulation approach using the BPS program as a master and the co-simulation module as a slave.

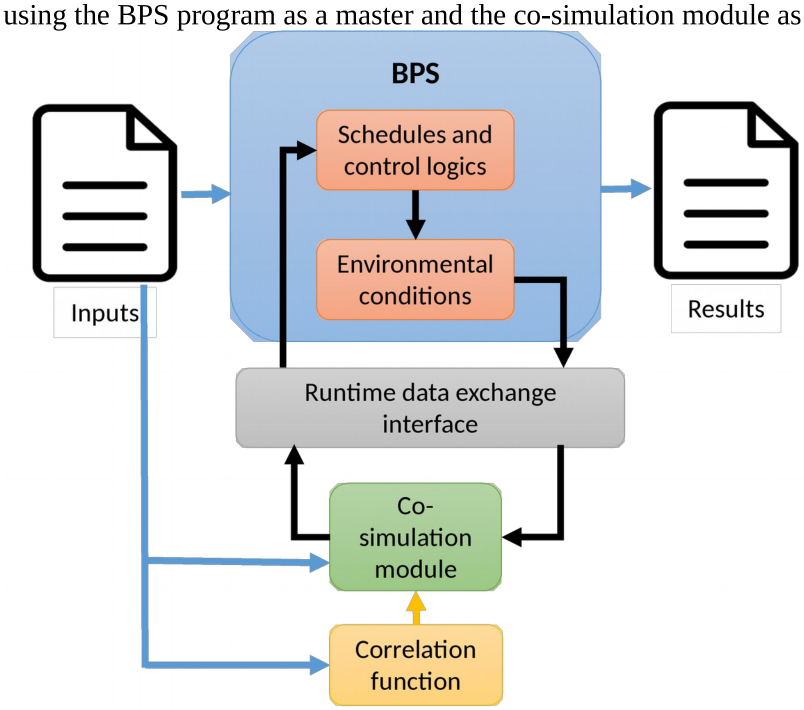

Figure 4. Workflow for the co-simulation approach

2.2. Which implementation approach to choose for different OB model types

Given these four approaches to simulating OB models in BPS programs, energy modelers (i.e., simulation users) must decide which is the most appropriate to select. Table 1 illustrates a qualitative evaluation (based on the authors' experience using various BPS programs) of ease of use of the four implementation approaches for the two types of OB models: deterministic and stochastic. Typically, direct input or control logics and built-in OB models take the form of deterministic model types. Modelers may also choose to implement a data-driven deterministic control logic or customized code for the specific purpose of the simulation study. It is inconvenient and rare for users to develop a complex co-simulation environment for the limited purpose of implementing deterministic OB rules. However, this is still one option modelers can exploit when existing co-simulation environments are already in place.

Probabilistic models typically are implemented as user functions or customized codes, or in a dedicated co-simulation environment. Interestingly, some OB models are appearing as built-in models in certain BPS programs, as described below. This enhancement enables even non-expert modelers to initiate the process of implementing advanced behavioral inputs to model and evaluate the impact of OB on building energy performance—namely energy and comfort—to the same extent of other indoor and outdoor input variables of their simulation models.

Overall the direct input or control is the approach most frequently used by most simulation users. The built-in OB models approach is limited to a few BPS programs (e.g., DeST and ESP-r). The user function approach is also limited to a few BPS programs (e.g., EnergyPlus, DOE-2, IDA ICE, and TRNSYS). The co-simulation approach is emerging as a more robust and interoperable approach to simulating OB, as more BPS programs (e.g., EnergyPlus and ESP-r) are adopting this approach.

Table 1. Qualitative evaluation of the implementation of deterministic and probabilistic OB models using four approaches in BPS programs.

Model Type	**Direct input or control**	**Built-in OB models**	**User function or custom code**	**Co-simulation**
Deterministic / static	***	**	*	*
Probabilistic / stochastic		**	*	***

Note: * applicable, but not convenient; ** commonly used; *** most often used

2.3. The implementation approaches used in the eight BPS programs

This section provides an overlook of the most common implementation approaches adopted by the state-of-the-art research and practices among the simulation community, focusing on the eight popular BPS programs. Table summarizes which of the four implementation approaches are supported in the eight

BPS programs. To compile this table, authors used their modeling experience and interviews with BPS software developers.

Table 2. OB model implementation approaches in the eight BPS programs

	DOE-2	EnergyPlus	DeST	ESP-r	IDA ICE	TRNSYS	IES VE	TRACE
Direct input or control	x	x	x	x	x	x	x	x
Built-in OB models			x	x				
User function or custom code	x	x			x	x		
Co-simulation		x		x				

The direct input or control approach is implemented in all eight BPS programs. The other three approaches show significant diversity within the BPS programs. Currently, EnergyPlus and ESP-r support co-simulation. Only DeST and ESP-r provide built-in OB models. User function or custom code is supported in EnergyPlus, DOE-2, IDA ICE, and TRNSYS.

DOE-2 v2.1E (DOE-2, 2017) uses deterministic time schedules to represent the number of occupants in spaces and the operation conditions of lighting, windows, internal gains, plug loads, and HVAC systems. Lighting and windows can be controlled based on indoor or outdoor environmental parameters. A probability can be specified to represent the likelihood of occupants operating the blinds, assuming other conditions (e.g., solar radiation, glare) are met. Also, advanced users can develop user functions to overwrite all the controls listed above.

In EnergyPlus v8.7 (U.S. DOE BTO, 2017), occupancy, internal loads, and HVAC operation is determined by deterministic schedules and set points. However, it allows windows to be opened or closed and shading to be operated based on indoor and outdoor environmental parameters (e.g., air temperatures, enthalpy, and wind velocity for windows). Also, datasets and schedules can be imported as inputs to certain controls. For example, the room-level occupancy data simulated in the Occupancy Simulator (Chen, Luo, & Hong, 2016; Luo, Lam, Chen, & Hong, 2017) using the stochastic Markov-chain processes can be exported as part of an EnergyPlus input file in input data file (IDF) format. The airflow network model allows more comprehensive ventilation controls. Lighting can be controlled by deterministic schedules and daylighting levels. EnergyPlus has a dynamic clothing model based on ASHRAE Standard 55 (Schiavon & Lee, 2013), as well as an adaptive comfort model based on US ASHRAE Standard 55 (de Dear & Brager, 1998) and EU ISO Standard 15251 (EN 15251:2008). Advanced users can use the energy management system feature to write code to implement OB models. Another possibility is to use the external interface that provides FMI to co-simulate with an external OB tool obFMU (Hong et al., 2016). A few researchers already have successfully implemented these approaches for modeling OB (Chen, Liang, Hong, & Luo, 2017; Gunay, O'Brien, & Beausoleil-Morrison, 2015; Langevin, Wen, & Gurian, 2014). In one case, OB models were implemented into EnergyPlus using an energy management system and a program written in Ruby to allow BPS users to select OB models to be used during the EnergyPlus simulation with a user-friendly graphic interface called OpenStudio (O'Brien & Gunay, 2016). This approach significantly simplifies the use of stochastic OB models since the integration with energy models are implemented automatically.

DeST v2.0 (Yan et al., 2008) users can define deterministic schedules and choose stochastic OB models already implemented for occupant movement between rooms, as well as lighting, window opening, and HVAC operation. The occupancy is simulated by a Markov chain model (Wang et al., 2011; Feng et al., 2015) which describes the transition probability for each occupant among spaces. The operation is modeled as a probabilistic variable under a generalized framework, related to both the events occupants are involved in and the environmental conditions (Ren, Yan, & Wang, 2014; C. Wang, 2014). Occupant use of appliances is currently controlled by simple schedules.

ESP-r v12.3 (EPS-r, 2017) can represent occupants both with built-in schedules and direct data import. For lighting and blind control, the Lightswitch 2002 (Reinhart, 2004); for lighting, Hunt (Hunt, 1979); and for windows and fans, Rijal et al. (2008) adaptive control algorithms are implemented. These algorithms use SHOCC (Bourgeois 2005), a sub-hourly occupancy-based control model, via a hard-coded interface for coupling with ESP-r (Cowie et al., 2017). With the same method, ESP-r can gain functionality to link equipment use (and associated small power loads) to occupant presence through advanced power management profiles. The co-simulation module is under development right now.

IDA ICE v4.7 (EQUA Simulation AB, 2017) provides flexibility for users via the input and control rule definition. Predefined default schedules can be used, or the user can build up a control macro using a user-friendly graphic interface. Here rules can be defined using various inputs, including data import, sensors output, and other environmental parameters. Also, users can access the semantics of the software to code algorithms to model OB. Some research projects have used this approach (R. V. Andersen, 2009; Buso, Fabi, Andersen, & Corgnati, 2015; D'Oca, Fabi, Corgnati, & Andersen, 2014; Fabi, Andersen, Corgnati, & Venezia, 2012).

For TRNSYS v17 (TRNSYS, 2017), stochastic models can be linked via DLL software components. Also, TRNSYS and CSTB provide a library, called TESS, which allows users to develop stochastic models (language W). TRNSYS allows environmental parameter-based controls but cannot model daylighting (can only import results from tools such as Radiance or Daysim). One study represented OB models in Modelica and connected them to TRNSYS (Baetens & Saelens, 2011). TRNSYS does not adopt FMI or other data exchange framework for users to implement co-simulation directly. However, as a component/module based tool, TRNSYS allows advanced users to develop their own middleware for exchanging data with other tools. For example, Beausoleil-Morrison et al. (Beausoleil-Morrison et al., 2012) develop a middleware to demonstrate the ESP-r and TRNSYS co-simulation for modeling solar buildings. For Integrated Environmental Solutions (IES) Virtual Environment (VE) (IES VE, 2017), custom controls can be created in the program's interface even with user-defined formulas, so it is possible to implement more advanced OB controls, but it is not integrated yet. Also, measured data can be fed in at a 1-second time step. IES VE does not allow the user access to the software code.

In Trane Air Conditioning Economics (TRACE) 700 v6.3 (Trane, 2017) users can use schedules to define times for events based on input schedules. There is no specific algorithm for opening windows, but input and schedule are available for infiltration. The user could enter the maximum air flow rate of infiltration and use a schedule to decrease or increase that number during certain hours when the window is expected to be open. This is not directly tied to occupancy. Also, the user is unable to modify the software code.

2.4. Strengths and weaknesses of the implementation approaches

Strengths and weaknesses of each of the implementation approaches are discussed as follows, using four qualitative metrics: ease of implementation, flexibility, reusability, and accuracy.

- Ease of implementation or application refers to the degree of knowledge required from the modeler to implement the OB model into the BPS environments.
- Flexibility is an indicator of the capability of the implementation approach to cover different control logics or model types.
- Reusability hinges on the capability of one implementation approach to reiterate OB models for different uses, studies, or purposes.
- Finally, accuracy invokes the extent to which the simulation outcomes derived from the OB models implementation conform to the actual measurements or benchmark.

The direct input or control approach is straightforward to *implement* and easy to use. Because of this reason, this implementation approach emerges today as the most commonly used among the engineering community. However, it is limited in terms of OB model representation, since the specific BPS program's semantics for input determine a lack of *reusability* among simulation tools. Further, direct input or control approach has low *flexibility* because it is usually not robust enough to represent complex logics or algorithms for certain OB models. This approach often associates occupant controls with building systems or components rather than the occupants themselves. For example, occupant actions (opening or closing windows) can be performed when occupants are not even present. This typically leads to low prediction *accuracy* during the validation process, contributing to significant discrepancies between simulation results and actual measured performance.

In the case of built-in models, the stochastic nature, complexity, and diversity of OB in buildings can be represented in BPS. With the built-in OB models approach, OB results more *flexibly* represented with a good degree of *ease of implementation*. However, one of the drawbacks of this implementation approach is that users cannot create new types (equation forms or new input variables) of OB models or use new algorithms for the built-in OB models. Moreover, users can only choose those OB models that are already embedded in the simulation tool—hindering *reusability* of models and *accuracy* of simulation results.

Regarding *ease of implementation*, the user-customized code and functions approach usually requires advanced user experience and deep knowledge of a particular BPS program to use such features correctly and efficiently. Another limitation—which hinders *usability* and reusability—is that most BPS programs are supporting user-written code that lacks a comprehensive debugging mechanism. Typically, modelers can call new codes and functions only at certain predefined points within a BPS program, allowing little *flexibility* for creating customized control options. Although some user-customized codes and functions have been developed and employed among the simulation community (IEA-EBS Annex 66, 2016), only very few attempts have been made to investigate the *accuracy* of this simulation approach, providing reliable validation procedures and results (Langevin et al., 2014; Schweiker et al., 2012).

The co-simulation approach provides the maximum *flexibility* regarding implementation of complex OB models in a separate software module that is independent of and interoperable with BPS programs. One unique requirement is that BPS programs have to implement FMI to support the co-simulation feature. Developing and testing OB models in FMUs for co-simulation also requires detailed knowledge of FMU and FMI, which are factors hindering the *ease of implementation* and the *usability* among modelers in the engineering and simulation community. The real-time exchange of information between BPS programs and the co-simulation modules leads to computing overhead, which can slow the simulation process. Besides the co-simulation approach using obFMU with EnergyPlus (Hong et al., 2016), there are advanced users who started to use the co-simulation approach using a different framework. For example, multi-agent simulation (MAS) is used in CitySim (Robinson et al., 2011) and MATSim (MATSim Community, 2017).

2.5. Application of OB models with BPS programs

Deterministic OB models are handled as fixed inputs of the BPS programs, to the same extent as other variables of the building energy models—i.e., thermos-physical characteristics of walls, roofs, windows, lighting system power and schedules, as well as HVAC system and equipment efficiency. For stochastic OB models in BPS programs, the simulation process consists of three main steps. First, the OB model is implemented as probabilistic inputs of the BPS programs, according to one of the four selected approaches (direct input, built-in model, user function or custom code, and co-simulation). The simulation is then run a set of times (i.e., 20 or 100 times) with the BPS programs. For each run the simulated probability of behavior is paired with a uniformly distributed set of generated random numbers to determine the actual behavior condition—i.e., a space being occupied or an adaptive action being performed. To maintain the stochastic patterns of OB, only when the simulated probability is higher than the randomly generated number is the behavior action activated and simulated.

This methodological approach for simulating probabilistic OB models needs to consider several important factors. First, the number of simulation runs necessary to ensure a statistically relevant representation of the stochastic nature of OB depends on the use cases which have been discussed (R. Andersen, Fabi, Toftum, Corgnati, & Olesen, 2013; Buso et al., 2015; D'Oca et al., 2014; Fabi, Andersen, Corgnati, & Olesen, 2012; Feng, Yan, & Wang, 2016). Second, each simulation run calculates a different value of the building performance (either energy use, peak demand, or comfort level). All simulation runs provide a probabilistic distribution of the building performance rather than single values. This reflects the nature uncertain impact of OB on the building performance in reality. Explicitly, this opens a collateral issue on how to better communicate probabilistic results of the simulations to clients.

Applications of the results of the simulated OB on building energy performance are manifold and heterogeneous. Application and impact of OB models are starting to be seen in a multidisciplinary and multiscale perspective of energy efficiency, over the entire building life cycle.

Results of OB simulations in BPS—without regard to the implementation or representation approach—find pertinence during the building and control system design phase, from the early schematic to the detailed design stages. Operating conditions of the building performance (i.e., via building management and control of the HVAC and plant systems) can be improved by enabling data-driven (i.e., from smart meter data and building automation systems) and machine-learned (i.e., by employing big data analytics and data mining techniques) OB model predictive controls. This is attained by optimizing HVAC systems and equipment sizing, precooling spaces or avoiding unnecessary conditioning in unused spaces, and predicting occupancy schedules for presence and movements (e.g., time of the first arrival and last departure, time of intermediate absences at the zone level, number of people at the building level). Also, BPS programs enabling OB models can be adopted for the evaluation of different retrofit strategies, both at the building- and city-scale level, with better assessment of the variation of retrofit benefit (e.g., energy savings, energy cost savings). On the one hand, the diverse OB model application perspectives open a broad spectrum of simulation opportunities. On the contrary, the complexity of the OB simulation process, from the selection of the most appropriate model and approach to the choice of the most suitable application into a BPS program, can lead to the dangerous possibility of misleading simulation results. These aspects need to be considered when appraising the wider diffusion of the OB simulation among current BPS programs.

3. Representation of OB models in BPS programs

OB models are currently represented using either the specific syntax of particular BPS programs or a common semantic data model, e.g., in the form of XML (eXtensible Markup Language). Section 3.1

focuses on illustrating the fragmentation in specific semantic input format adopted for BPS programs (Table 3). Section 3.2 introduces the IFC (Industry Foundation Class) based data models. Section 3.3 describes the XML-based data models, including the Green Building XML (gbXML), a de-facto industry standard used to represent buildings and systems for energy modeling, and the obXML standardized language to represent OB models in BPS programs. Finally, a graphical summary is provided to link content introduced in various sections and discuss further research development requirements.

JSON (JavaScript Object Notation) is an open-standard format that uses human-readable text to transmit data objects consisting of attribute–value pairs and array data types (wikipedia). It is easy for humans to read and write. It is easy for machines to parse and generate. YAML is a human-readable data serialization language (wikipedia). It is commonly used for configuration files, but could be used in many applications where data is being stored (e.g. debugging output) or transmitted (e.g. document headers). Although JSON and YAML are similar to XML, they have not been used yet to represent OB models in the literature.

3.1. Specific input semantics in BPS programs

The eight BPS programs use their syntax to represent OB models in either ASCII text format or binary format.

EnergyPlus supports input files written in its native IDF format. IDF files conform to the ASCII (American Standard Code for Information Interchange) text-based data format written using the Input Data Dictionary (IDD) semantics. To enhance the flexibility of EnergyPlus' OB modeling capability, Lawrence Berkeley National Laboratory (LBNL) recently developed a co-simulation software (Hong et al., 2016). Accordingly, co-simulation in EnergyPlus is performed by using an FMI to allow for direct coupling with various programs.

IDA ICE employs equation-based models based on the Modelica-like Neutral Model Format (NMF), making it straightforward to quickly expand the software with built-in models or by more complex user-customized functions. However, newly created NMF OB models can only be shared with other IDA ICE users. NMF is an ASCII text-based semantics system for IDA ICE.

DeST enables users to input parameters related to occupant behavior through a graphical user interface, where there are several typical behavior patterns for users to select from, and customized settings are also supported. The inputs are stored in a binary-based SQL database. The SQL database allows the use of multiple data tables to represent user inputs for building components and systems, as well as OB models. Different tables are linked together using unique IDs or keys. The inputs can also be imported and exported as XML files for potential communications with other tools.

The ESP-r simulation engine—namely "bps"—formulates, by default, binary results libraries in the ASCII text format. With the condition of a GNU libxml2 library available on the system, BPS can export the results directly into ASCII XML and comma-separated-value formats. If the GNU libxmlt library is available, BPS can be configured to translate the XML result file into any user-specified ASCII format. Using the BCVTB, users can link ESP-r with OB models implemented in other tools such as MATLAB, Simulink, Dymola, and Radiance.

TRNEdit, the TRNSYS Editor, allows users to create stand-alone models having the TRNSED input file (.trd extension) format and syntax. The TRNSYS simulation engine is written using the FORTRAN programming language and uses a dynamically linked library (DLL) system architecture to allow for a modular structure that can be extended around the core simulation engine called "IISiBat," by adding new DLLs to the system. This allows TRNSYS users to create quite a straightforward custom model components (e.g., to represent a new type of heating module) using a choice of DLL compiling programming languages including FORTRAN, Pascal, C, C++, etc.

DOE-2 supports the building description language (BDL) ASCII text-based input syntax, which is compatible with the conventions defined in both the C and FORTRAN programming languages. Expressions can include elements such as special BDL functions, math and logical operators, and logical structures. Manual entry of user-customized BDL expressions requires a relatively detailed knowledge of the BDL text data structure.

IES VE's input files are in the MIT/MTD native binary format. However, the IES codes are not public, and modelers cannot gain direct access to MIT/MTD files in a text editor.

TRACE supports data serialized into closed-source binary BLOBs (binary large objects). Binary data are stored as a single entity in a Sybase relational database. One of the drawbacks of binary BLOBs is that, since the data source code is not available, inputs cannot be freely improved upon by modelers, and input formats cannot be translated into different software architecture—nor can codes be adapted or modified to operate user-customized variants of the simulation software.

Table 3. Input semantics in the eight BPS programs

Simulation engine	Native input format
DOE-2	BDL (text)
EnergyPlus	IDF (text)
DeST	SQL (binary)
ESP-r	bps (text)
IDA ICE	NMF (text)
TRNSYS	TRANSED/DDL (text)
IES VE	MIT/MTD (binary)
TRACE	Sybase Database (binary)

3.2. The IFC data models

The IFC is an open and neutral ISO-certified (according to ISO 16739:2013) standard format for Building Information Modeling (BIM) data (Thein, 2011). The IFC data files use the STEP physical file structure according to ISO 10303-21, and must be validated according to the IFC-EXPRESS specification. The IFC data format has been used over the last 20 years to represent data models having different natures and domains. Currently, a limited number of software applications support, import, and or export IFC file formats to describe building and construction industry data (Hong, Zhang, & Jiang, 1997). Significantly, IFC never gained momentum among the simulation community due to its complexity and lack of human-and-machine readability. To partially overcome this drawback, since 2004, the XML-based ifcXML schema has been regulated by the international standard ISO 10303-28. The ifcXML format is an interoperability format to exchange 3-D building models among XML tools. The ifcXML language's purpose is to make data accessible to a broader audience, focusing on representing the built environment and related services. One of the ifcXML application areas is a mapping between the IFC object model and document-based representations such as schedules and quantity datasheets. Also, the ifcXML provides communication with other XML-based domains, such as the GIS object models based on the GML3 standards. The ifcXML representation is also expected to facilitate the extraction, transmission, and merging of partial building models during AEC-FM processes in parallel and collaborative design processes. Despite its enabling data transferability capacity, the ifcXML is only partially diffused in practice, due to the large size of typical ifcXML building model (an ifcXML file dimension is usually 300%–400% greater than an IFC file). At the current stage of development, IFC file format has not been used to represent any OB models.

3.3. The XML-based data models

Some data formats were considered appropriate for providing a data structure to describe OB model input into BPS programs. Similar to other markup languages such as HTML, XML uses tags to separate data items from one another (Fourer et al., 2009). Tags are nested in a tree structure, but the definition, position, and order of tags is left to the user and can be described in a schema file (which is itself an XML document).

One of the advantages of working in XML is the vast availability of tools such as parsers, visualization tools, and development environments. Originally designed to change the context of large-scale electronic publishing, in its general form, XML is a meta-markup language providing a standard data format for representing structured information. Typically, XML files take the form of human- and machine-readable documents conveying transferability characteristics (1) among applications of the same software and (2) between different software tools. Well-formed XML language follows some basic standardized syntax rules: (1) The XML language is case sensitive, (2) No spaces are allowed between content and markup, and (3) The attribute values must appear in a "value" format.

The XML language has the great advantage of being a neutral exchange language able to represent data and models in a way that can easily be integrated into a diverse software environment. In the field of building engineering, several existing standards, and data models make use of the XML data format and structure to describe data content from heterogeneous sources among applications of the same software. Among an extensive array of XML data standard protocol development, first examples are the gbXML (an industry de-facto BIM standard) and obXML (an emerging XML schema to standardize representation and exchange of energy-related OB models in buildings).

3.3.1. The gbXML

Early in 1999 the California Energy Commission's Public Interest Energy Research (PIER) Program, Pacific Gas and Electric, and Green Building Studio funded the development of gbXML. The gbXML's primary goal was to enable the transmission of building information stored in CAD building models (Ioannidis et al., 2012). By doing so, the gbXML aims to enable a two-way integrated interoperability and communication between a broad range of design and engineers' building models. The gbXML has the advantage of representing one of the most widespread standard schemas for data standardization and exchange among the BPS programs. The gbXML is now an open source schema available to everyone.

3.3.2. The obXML

Although gbXML provides an XML-based standard representation of buildings and systems, it represents occupant activities and models/controls in very simplified approaches. There is a strong need for a standardized language to represent and exchange OB models over BPS programs. A previous study developed a homogeneous semantic information model for the representation of occupant behavioral models that enables interoperability of inputs and transferability of simulation outputs (Hong, D'Oca, Taylor-Lange et al., 2015; Hong, D'Oca, Turner, & Taylor-Lange, 2015). This consistent schema and language was designed to provide enough flexibility for existing and future OB to be captured and implemented into BPS programs consistently.

A unifying format to express a broad range of behavioral models would help to optimize modeling in the building simulation community. Researchers (Hong, D'Oca, Taylor-Lange et al., 2015) selected XML as the most appropriate choice to resolve behavioral data standardization in building energy simulation. LBNL developed obXML, a standardized XML schema based on the DNAS framework for OB in buildings. . The purpose of the XML representation of OB data and models is to enable the international research community to access a unified schema that represents the OB phenomena in the built environment at a large scale.

The obXML schema is grounded on an ontology of energy-related behavior in buildings integrally embedded into a DNAS framework, described in (Hong, D'Oca, Taylor-Lange et al., 2015). The topology of the DNAS framework was implemented in the obXML schema based on the main root element

OccupantBehavior branching into five sub-elements (1) Behaviors, (2) Buildings, (3) Occupants, (4) Seasons, and (5) TimeofDay (Figure 5). The OccupantBehavior root element has an ID and version attribute, indicating a unique ID and version. For a more detailed description of the obXML structure, refer to (Hong, D'Oca, Taylor-Lange et al., 2015). Efforts have been made to build an obXML library, translating the existing OB models published over the last 30 years in international journals into the XML language (Belafi et al., 2016). When decoded into the obXML semantics, OB models developed for one tool and application can be used for any other tools and applications. When implanted into a co-simulation approach, any obXML translated model can be co-simulated with a BPS program such as EnergyPlus, enabling model validation and outcome comparison. In recent years, several studies attempted to co-simulate separate occupant behavioral software modules with BPS programs (Gunay et al., 2015; Langevin et al., 2014; Lee and Malkawi, 2014; Andrews et al., 2013).

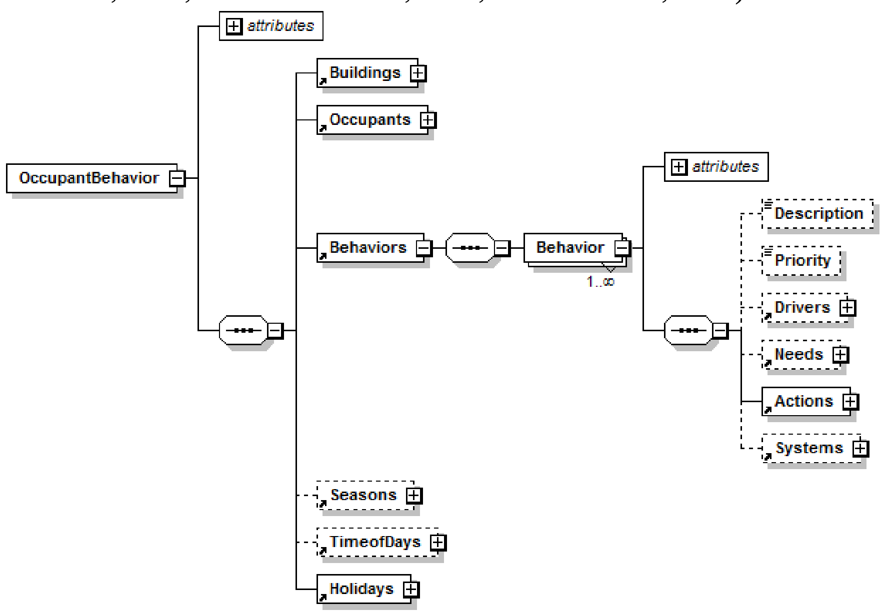

Figure 5. ***The main topology of the obXML structure, based on the Drivers, Needs, Actions, and Systems (DNAS) framework***

With the purpose of ensuring transferability of OB models among BPS programs, the obXML schema generates XML data-structured OB models that can be shared with various BPS programs. In EnergyPlus, OB models represented in obXML files are consumed by a dedicated FMU obFMU (Hong et al., 2016) which co-simulates with EnergyPlus at each simulation time step according to the FMI. The FMI is an independent standard that allows for component development and tool coupling, using a combination of XML and compiled C code. The FMI standard (Blochwitz et al., 2009) encompasses two main issues. First, it provides an explanation of how a modeling environment can generate C code and be utilized. Second, it technically describes the interface standard for coupling in a co-simulation environment (Nouidui et al., 2014). By adhering to the obXML content and syntax in representing OB models, the simulation community will benefit from an internationally established data exchange format which has been widely approved in several domains of building modeling tools. The obXML schema is designed to provide enough flexibility for existing and future OB models to be captured and implemented into the diverse BPS programs consistently (Figure 6).

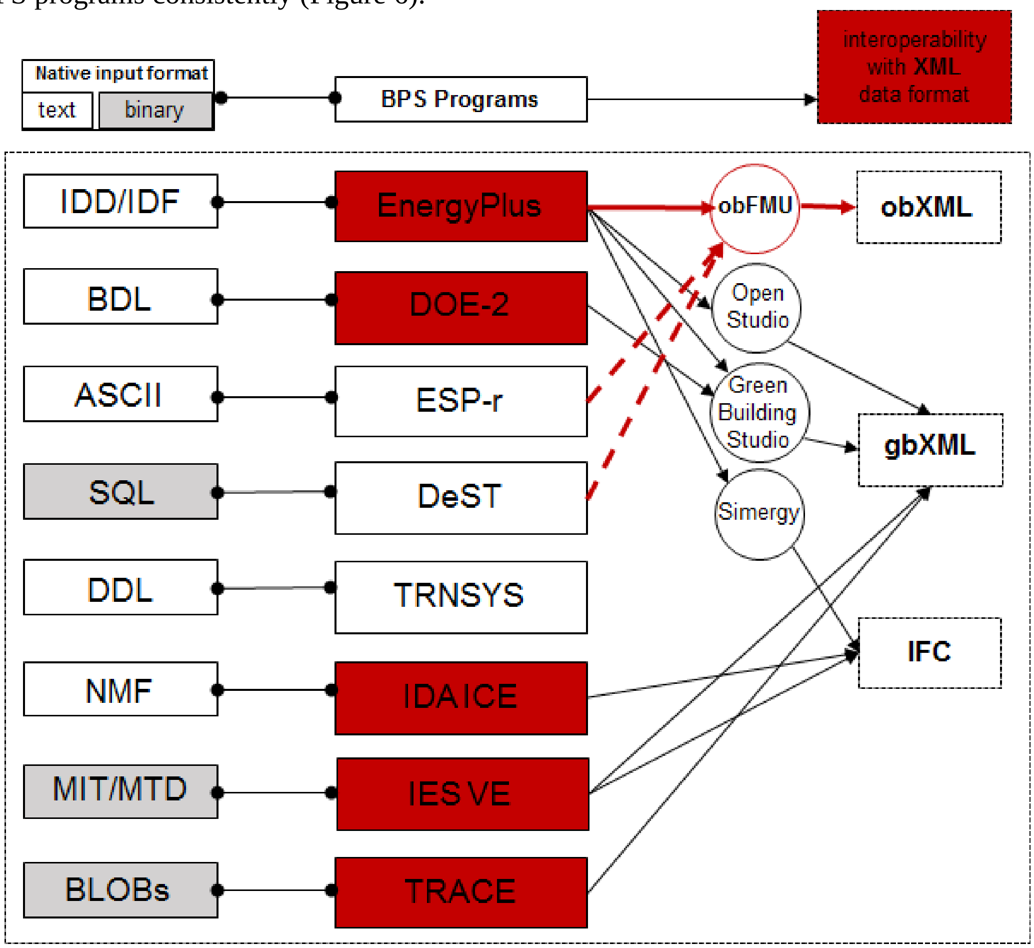

Figure 6. *Specific input format of OB models in BPS programs and interoperability with the XML data schema*

Figure 6 also shows the status of these BPS programs supporting XML-based data models. The gbXML is supported directly through import by IES VE and TRACE, and through OpenStudio and Green Building Studio for EnergyPlus. DOE-2 supports gbXML via the Green Building Studio. IFC is supported directly by IDA ICE and IES VE, and through Simergy (Haves et al., 2014) for EnergyPlus.

3.4. Strengths and weaknesses of the representation approaches

The text- or binary-based representation of OB models in BPS programs does not require separate semantics to describe OB models. However, it is subject to the limitations of inherent input semantics of each BPS program, which may not be adequate to describe complex OB models using diverse driving factors. Furthermore, OB models coded for a specific BPS program cannot be reused by other BPS programs. It is also difficult for these models to share with users of the same BPS program as they are embedded and scattered in the whole input file of a building energy model. XML-based OB model representation, although requiring the use of an XML schema, provides more flexibility for users to develop their OB models that can be shared with a wide community of users and multiple BPS programs.

4. Discussion

First, to capture the complexity of OB models and to quantify their impact on building performance, a common semantic approach to representing OB models—one that can be shared with different building performance simulation programs— is critical. The common data model must be universally machine and human readable and implemented in the common neutral syntax of XML, JSON, or YAML. The recent XML-based OB model representation obXML, although requiring knowledge of an XML schema, appeared to provide the maximum flexibility for users to develop their OB models that can be shared with a wide community of users and multiple BPS programs. In such a view, a library of 52 OB models has been developed and shared across the building simulation community (Belafi et al., 2016) using the obXML.

Second, such common OB model protocol must overcome weaknesses of actual implementation and representation approaches, as shown in Figure 6. Synthetically, it must be as *easy to implement* as direct input or control, allowing enough *flexibility* to capture several variables to be applied as model inputs. Among the various approaches to implementing OB models in BPS programs, the co-simulation approach emerges today as the one offering a wider spectrum of unique advantage under this last perspective. Moreover, it must ensure *reusability* of models among various simulation tools adopting a standardized data syntax, as well as ensure *accuracy* by avoiding the danger of implementing circumstantial models for diverse or non-appropriate simulation purposes.

Moreover, as a general remark, despite the selected approach to implementing and representing behavior models in BPS programs, researchers conducting occupant behavior studies tend to have backgrounds in engineering and architecture. Accordingly, few behavior researchers having a background in the environmental psychology and sociology are likely to be able to implement their OB models into BPS programs and understand their impact on simulation accuracy. This aspect puts a limit on the type of variables and factors already implemented or included as direct input or control in most widespread BPS programs, not directly correlated to building consumption or comfort (e.g., behavior attitudes, motivation, perceptions) and similar ways to implement and represent social, behavior models into BPS programs.

5. Conclusions

Today's building performance simulation programs use different approaches to representing and implementing OB models, making it difficult for their reuse across different BPS programs or different user applications. A common occupant behavior data model implemented in the form of XML, JSON, or YAML is needed to provide a standardized representation of OB models, enabling their exchange between different BPS programs. A modular software implementation of OB models, such as functional mock-up units for co-simulation, adopting the standardized data model of occupant behavior, has advantages in providing a robust and interoperable integration with multiple BPS programs.

The common data model representation and the co-simulation implementation approaches help standardize the input structures of OB models, enable collaborative development of a shared library of OB models, and allow for rapid and widespread integration of OB models in various BPS programs among the engineering and research community as a whole. Future studies can focus on refining the standard representation of OB models to better reflect the dynamic, stochastic, and multidisciplinary nature of energy-related OB in buildings. Also, the co-simulation interface should be supported by more BPS programs to integrate the standardized OB models in the form of functional mock-up units.

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