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ORIGINAL ARTICLE

A library of building occupant behaviour models represented in a standardised schema

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Abstract Over the past four decades, a substantial body of literature has explored the impacts of occupant behaviour (OB) on building technologies, operation, and energy consumption. A large number of data-driven behavioural models have been developed based on field data. These models lack standardisation and consistency, leading to difficulties in applications and comparison. To address this problem, an ontology was developed using the drivers-needs-actions-systems (DNAS) framework. Recent work has been carried out to implement the theoretical DNAS framework into an eXtensible Markup Language (XML) schema, titled 'occupant behaviour XML' (obXML) which is a practical implementation of OB models that can be integrated into building performance simulation (BPS) programs. This paper presents a newly developed library of OB models represented in the standardised obXML schema format. This library provides ready-to-use examples for BPS users to employ more accurate occupant representation in their energy models. The library, which contains an initial effort of 52 OB models, was made publicly available for the BPS community. As part of the library development process, limitations of the obXML schema were identified and addressed, and future improvements were proposed. Authors hope that by compiling this library building, energy modellers from all over the world can enhance their BPS models by integrating more accurate and robust OB patterns.

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Introduction

The concept of energy-related occupant behaviour in buildings can be defined as occupants' behavioural responses to discomfort, presence and movement, and interactions with building systems that have an impact on the performance (energy, thermal, visual, and IAQ) of buildings (D'Oca et al. 2017a). The interactions under investigation in this paper include adjusting thermostat settings, opening or closing windows, dimming or turning lights on/off, pulling window blinds up or down, and switching plug loads on or off (Hong et al. 2015a). Energy-related occupant behaviour in buildings is one of the six influencing factors of building performance (Yoshino et al. 2017; Polinder et al. 2013; Yan et al. 2017), which also includes climate, building envelope, building equipment, operation and maintenance, and indoor environmental conditions. Occupants can influence the indoor thermal and air condition directly by their mere presence (emitting heat, moisture, and CO_2), or indirectly through their interactions with building systems.

Overview of building performance simulation

The use of computer simulation for solving complex engineering problems or modelling complicated systems has been widespread for many decades now (Nguyen et al. 2014; Hong et al. 2000). With this method, scientists or practitioners were able to speed up calculation processes and handle complex systems such as buildings through a single interface in a more precise way than before.

For building analysis, designers frequently use dynamic thermal simulation programs to calculate the indoor thermal and energy behaviour of a building (Garber 2009; Hong et al. 2000). Building performance simulation (BPS) software tools can evaluate a wide range of thermal or human behavioural response to stimuli (Clark 2001). These simulations make it possible to compare different design or retrofitting scenarios from the perspective of annual energy consumption and indoor comfort in a very time- and resource-efficient way. Using these analysis techniques, optimal energy savings can be achieved, and thus greenhouse gas emissions from buildings can be reduced. In many cases, the goal of design and simulations is to optimise indoor comfort levels and building energy consumption. Practitioners would use BPS tools for predicting overheating, calculating heating and cooling loads, sizing equipment, evaluating alternative technologies (energy efficiency and renewable energy), regulatory compliance, or more recently, integrated performance design or rating (Crawley 2008). In several design methodologies, BPS serves as an integrated, well-performing support tool for optimising the entire design process (Anderson et al. 2006; Ferrara et al. 2014; Gabbar et al. 2014; Griego et al. 2015; Kanagaraj and Mahalingam 2011; Pacheco et al. 2012; Saari et al. 2012; Tibi et al. 2013).

BPS is widely used in different phases in the life cycle of a building project. In the early design stage, energy consumption estimates and comparisons are crucial as feedback to the design team and to support decision-making. Later on, in the design development phase, simulation can show code compliance and help designers determine the cooling and heating capacity of heating, ventilation and air-conditioning (HVAC) systems. After a building is completed, BPS models can be used for performance diagnostics and integration with real-time building energy system controls. In retrofitting projects, BPS can evaluate the impact of different intervention options to maximise energy savings and emissions reduction.

In fact, the energy consumption of a building is a function of a large number of parameters in regard to:

- building characteristics,
- the characteristics, control and maintenance of energy systems,
- weather conditions,
- occupants' behaviour,
- other sociological parameters (Fumo 2014).

Therefore, energy consumption predictions always contain a degree of uncertainty depending on the level of confidence in each of these input parameters (Hopfe and Hensen 2011; Lin and Hong 2013).

There has been a huge effort from the scientific community, governments, and industry to collect multiple approaches and methods, as well as numerous tools for estimating building energy performance. The Building Energy Software Tools Directory (U.S. Department of Energy. n.d.) is a comprehensive list of tools grouped in four subjects: whole building analysis; codes and standards; materials, components, equipment, and systems; and other applications. These categories show another dimension of these simulations: scale. Simulations can range from a specific component affecting energy use, such as equipment (e.g. heat pump condenser) to an analysis of the entire building (Nguyen et al. 2014), or even to investigations at the urban level.

The 2009 ASHRAE Handbook (ASHRAE handbook 2009) has broader categories for building energy simulation approaches:

- *Forward (classical) approach:* in this approach, the equations describing the physical behaviour of systems and their inputs are known, and the objective is to predict the output. The ASHRAE handbook states that generally accuracy increases as models become more complex and as more details of the building are known. However, it should be noted that as model complexity increases, models typically require more input variables. These variables all have associated uncertainties and as a result, the overall uncertainty of the model may increase (Trčka and Hensen 2010). This physics-based approach is often referred to as the white-box approach.
- *Data-driven (inverse) approach:* in this approach, input and output variables governing the performance of the systems have been measured. The known data is used to define a mathematical description of the system (Nguyen et al. 2014). This approach is also referred to as the black-box approach.

The models in both approaches can be steady-state or dynamic. Steady-state modelling does not consider the transient effect of variables and is good for analysis in timesteps equal to or greater than 1 day. Dynamic models are able to track and identify peak loads and capture thermal inertia effects (Nguyen et al. 2014).

Nguyen et al. (2014) summarised the importance and true role of BPS in the current construction industry with three quotes from well-known researchers:

- Simulation is commonly held to be the best practice approach to performance analysis in the building industry (Raftery et al. 2011);
- Energy simulation models play a key role in computing potential energy savings from retrofits (Heo et al. 2012);
- Simulation provides a mechanism to determine where savings opportunities exist or energy inefficiency occurs in a building (Ahmad and Culp 2006).

Occupant behaviour modelling approaches

As highlighted above, occupant behaviour (OB) is one of the most important driving factors of building performance and energy savings. At the same time, among other input variables, they contribute to significant discrepancies between simulated and actual (measured) energy use in buildings (Hong et al. 2015a).

Traditionally, in BPS programs, OB inputs are simplified, static and less indicative of real world scenarios. As these inputs represent a non-realistic assumption of OB, they contribute greatly to the variations in building simulation results. One of the keys to solving this problem is a better representation of energy-related OB in building energy models (Mahdavi and Pröglhöf 2009; Yan et al. 2015). BPS programs use various methods to represent OB models. The key drawback is that most implementations are complicated, difficult to reproduce, and OB models cannot be reused for other energy models, other users, or other tools. A recent study (Hong et al. 2018) provides a thorough overview of OB implementation approaches in BPS tools.

Direct input or control

The direct input or control approach refers to the case when occupant-related inputs are defined using the semantics of BPS programs—just as other model inputs are defined (building geometry, construction, internal heat gains, and HVAC systems). These OB inputs can be temporal schedules for thermostat settings (cooling and heating temperature set points), occupant presence and lighting, plug load, and HVAC system schedules or static rules governing the operation of building components.

Built-in OB models

The second method uses advanced, deterministic, or stochastic OB models already implemented in the BPS program. These models are originally data-driven and use functions and models such as linear or logit regression functions.

User function or custom code

In the user function or custom code approach, the user can write functions or custom code to implement new or overwrite existing or default building operation and supervisory controls. For example, EnergyPlus has an energy management system feature, and DOE-2 (LBNL) has a user function feature that implements such functionality (Yan et al. 2015).

Co-simulation

Co-simulation is a simulation methodology that allows distinct components and systems to be simulated by different simulation tools running simultaneously and exchanging information in a combined routine (Wetter 2011). During time integration, the simulation is performed independently for all subsystems in each timestep, restricting the data exchange between subsystems to discrete communication points (Yan et al. 2015). This approach allows simulations to be carried out in an integrated manner, running modules developed by different programming languages or in different physical computers.

For a building energy modeller, it is a tough choice which implementation approach to select. All of these approaches have their advantages and disadvantages, such as precision, calculation time, and input model development time.

Another important issue is how these advanced OB models can be represented in a specific BPS tool. Currently, most of the models available for BPS use are represented in either the native syntax of a given BPS program or a common semantic data model in the form of XML (eXtensible Markup Language) (Hong et al. 2018).

Advanced energy-related OB models developed in recent decades were built on measurement and questionnaire data taken from monitored buildings. Researchers identified predictor variables that drive occupant decisions, and behavioural models were then developed to predict the probability of an occupant acting in a certain way or interacting with a building system.

Recently published work (Hong et al. 2015c) contains a review of model types from this field of research. The authors established three categories of models: implicit, explicit, and data mining-based models.

Implicit models are used to understand the driving forces behind the behaviour itself or to predict the state of a building system or the occurrence of an occupant's action based on the predictor variable. Models used include linear regression, logistic regression models with a single or multivariate variables, simple probability equations, sub-hourly occupancy-based and complex control models (SHOCC), and Bayesian estimations.

Explicit models are used to provide a personalised description or prediction of the state of a building system or the actions of an occupant. In this case, statistical and data-mining methods can be used to obtain information on repetitive patterns of occupant behaviours and human-building interactions, and provide insights into a building system's user profiles. These models provide a probability distribution of a certain event using Monte Carlo methods, discrete and semi-hidden Markov chain models, and state transition analysis.

Data-mining methodologies (cluster analysis, association rules mining, decision tree, and rule induction) have been tested to identify and improve occupant behaviour modelling in buildings. The knowledge discovered through data-mining techniques aims to overcome the shortcomings of more traditional techniques, specifically when dealing with big data streams, by providing reliable models of energy-related behaviours with fast legibility and high replication potential (Hong et al. 2015c).

A standardised OB representation

As outlined above, over the past four decades, a substantial body of literature has explored the impacts of human behaviour on building technologies, operation, and energy consumption. A large number of data-driven behavioural models have been developed based on field monitoring and surveying the human-building-system interaction. Often, need-action-event cognitive theoretical frameworks have been used to represent human interactions within a building (Yan et al. 2015).

Studies from various parts of the world have emerged, but lack standardisation and consistency, thus leading to difficulties when compared to one another. Based on a thorough review of these models (see the "Methodology" section for review description), the authors can state that the documentation and description of methods used to develop such models has not been published consistently, meaning that authors of the papers introducing a novel model included the crucial aspects that were considered when developing the models. However, in many cases, model developers followed different logic when creating new models thus detailing different aspects of the process in the papers (e.g. more focus on sample or solely focus on environmental measurements or statistical techniques). Moreover, the use of different data processing, statistical methods, and model development techniques makes it challenging to evaluate, employ, and compare these models. To use these models for building energy performance evaluation, it is essential to clearly document and standardise them. In summary, the lack of standardisation for OB models leads to (1) inconsistency in documenting OB models in sufficient detail to define their applicability (e.g. population, building type, location); (2) difficulty in reusing the OB models, as they are represented in the BPS input files with varying syntaxes or formats; and (3) the inability of the BPS community to co-develop and share a common resource of OB models.

To address this problem, an ontology was developed to represent energy-related OB in buildings. Different aspects of a given type of human interaction is represented in elements of a standardised framework. The technical DNAS framework is developed based on four key components: (i) the drivers of behaviour, (ii) the needs of the occupants, (iii) the actions carried out by the occupants, and (iv) the building systems acted upon by the occupants. This DNAS framework is intended to support the international research community in standardising a semantic representation of energy-related OB in buildings (Hong et al. 2015c). Separate from other social behaviour theories, e.g. the Theory of Planned Behaviour (Ajzen 1991), the DNAS framework provides quantitative representation of occupant behaviour models for use with BPS programs to quantify their impacts on building performance. The DNAS framework is robust enough that it can be expanded to cover new types of occupant behaviour models in various building types and locations.

Recent work has been carried out to implement the theoretical DNAS framework into an XML (eXtensible Markup Language) schema titled 'occupant behaviour XML' (obXML). The obXML schema allows relationships to be formed and defined between different drivers and the eventual action in a standardised way. obXML is designed to provide enough flexibility for both existing and future occupant behaviour, building energy, and system models to be captured in a consistent way (Hong et al. 2015c).

The obXML schema is used for the practical implementation of the DNAS framework into BPS programs (Hong et al. 2015c). In obXML, drivers, needs, actions, and systems are implemented, and child elements of a root element are called behaviour. The schema itself was chosen because of its easy interoperability with BPS tools, and also because of the flexibility, it provides for users. Any additional information can be added to a model implemented to make it understandable and applicable for end-users.

The implementation of the DNAS framework into the obXML schema facilitates the development of occupant information modelling by providing interoperability between OB models and building energy modelling programs.

In addition, a new OB modelling tool, obFMU, has been developed as a functional mock-up unit enabling co-simulation with BPS programs (e.g. EnergyPlus and ESP-r) that implement the functional mock-up interface (Hong et al. 2015b).

Although a whole chain of OB modelling tools has been created and is now available, based on the authors' experience, its use is limited to scattered research groups. This paper presents a newly developed library of OB models represented in the standardised obXML schema format. This library provides ready-to-use examples for BPS users to employ more accurate OB representation in their energy models.

The remaining part of the paper will present the methodology used to develop the library of OB models as well as its potential applications and limitations.

Methodology

As a first step, energy-related OB literature was reviewed (for further references see Annex 66 literature database (IEA EBC - Annex66 n.d.)) to identify and compile a list of commonly used OB models in the field that cover the following categories:

- *Behaviour types*:

occupant movement and different types of occupant interactions with windows, doors, shading, blinds, lighting systems, thermostats, fans, HVAC systems, plug-loads; making hot/cold beverages and adjusting clothing levels

- *Building types*:

office, residential and school buildings

- *Model publication date*:

1970–2015.

This list contained 127 OB models in total.

Secondly, all models were processed and implemented using the DNAS framework by identifying the drivers, needs, actions, and systems. The obXML schema was then used to represent these models in a standardised way. Elements of DNAS were implemented into their respective obXML schema elements. Both implementation tasks were followed by logging the limitations of the framework and schema, and future improvements were also proposed. During the encoding of these models, two coders worked simultaneously to avoid inter-coder bias. One coder wrote the code while the other double-checked the implementation.

During the obXML implementation process, meta-data attribute fields were used to indicate the basic information of each model for categorisation and sorting purposes. These fields include information on the building, action and system types, reference information on the paper where the model was published, the region of data collection, data types, and the sample size of the database that served as a basis for the model.

Each OB model is represented in a separate XML file, but multiple OB models can be combined into a single XML file if needed.

After implementation, the validity of the XML files was checked with the most recent version of the obXML schema through the software tool XMLSpy. The model implementation was also manually double-checked for each item in the library. In the future, a script can be written to extract and check information on OB models in the library to ensure their integrity. After all the models were checked and revised, they were included in the final library and made available for public download at behavior.lbl.gov. Figure 1 illustrates the process of building the obXML library.

Results

As a result, an initial library of 52 occupant behaviour models (Table 1) was compiled and uploaded to the website behavior.lbl.gov, thus making it publicly available for the building performance simulation community. Among the 127 *initial* OB models to start with, the first version of the library tried to include at least one model for each OB category. Only the models with clear documentation were considered for library inclusion. Also, only those models that can be represented in the current version of the obXML schema were included in the library. Models included in the library were not reviewed or evaluated from the quality or accuracy point of view due to lack of data.

Twenty-three window opening/closing, ten blind lowering/opening, 11 light switch on/off, three heating, and five air-conditioning (AC) models were included, mostly for office building types and some for residential. One model is applicable in both office buildings and classrooms.

Data collection regions are also included in Table 1 to indicate the origin of data collected for the OB models. Most of the OB models are from Europe (36), one is from the USA, two are from Canada, one is from Pakistan, and five are from China. Seven models used data from multiple countries.

The categorisation of models was challenging as they used different approaches to represent types of behaviours abstracted from one dataset. For example, some researchers created different models driven by different indoor environmental parameters, some models were based on the time of day or occupant movement events, and some were for different types of spaces, building orientation, or ventilation features. These were

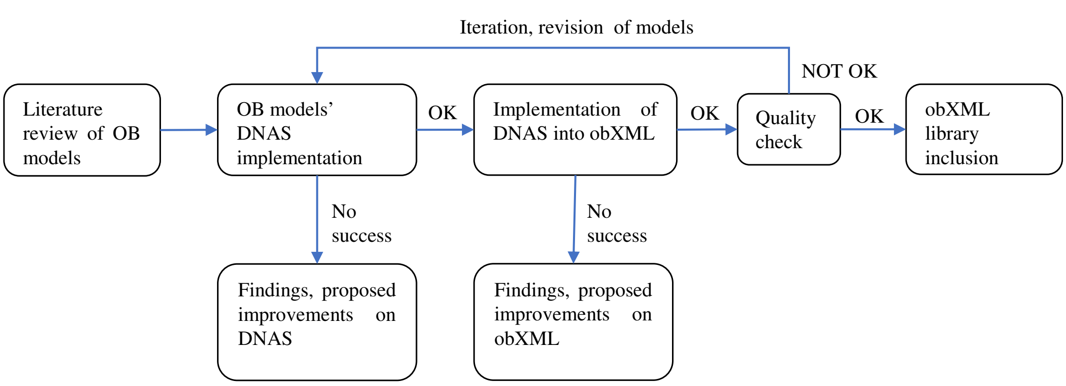

Fig. 1 The process to develop the OB models library

Table 1 List of occupant behaviour models included in the initial library

System	Action[1]	Bldg. type	Region	Other info	Ref
Blind	Close (ON)	Office	Switzerland	Based on indoor temp.	(Haldi and Robinson 2008)
Blind	Close (ON)	Office	Switzerland	Based on outdoor temp.	(Haldi and Robinson 2008)
Window	Open (ON)	Office	Switzerland	Based on indoor temp.	(Haldi and Robinson 2008)
Window	Open (ON)	Office	Switzerland	Based on outdoor temp.	(Haldi and Robinson 2008)
Window	Close (OFF)	Office	Switzerland	Arrival	(Haldi and Robinson 2009)
Window	Close (OFF)	Office	Switzerland	During the day	(Haldi and Robinson 2009)
Light	ON	Office	5 countries[2]	Arrival	(Gunay et al. 2015)
Light	ON	Office	UK	Arrival lunch	(Gunay et al. 2015)
Light	ON	Office	5 countries[2]	During the day	(Gunay et al. 2015)
Window	Close (OFF)	Office	Switzerland	Arrival	(Gunay et al. 2015)
Window	Close (OFF)	Office	UK	Cooling room	(Gunay et al. 2015)
Window	Close (OFF)	Office	Switzerland	During the day	(Gunay et al. 2015)
Window	Open (ON)	Office	Switzerland	Based on outdoor temp.	(Gunay et al. 2015)
Window	Open (ON)	Office	UK	Arrival	(Gunay et al. 2015)
Window	Open (ON)	Office	UK	During the day	(Gunay et al. 2015)
Light	ON	Office	UK	Classrooms also	(Hunt 1980)
Blind	Close (ON)	Office	USA, CA	Private office	(Inkarojrit 2008), M2
Light	ON	Office	Canada, AB	Private office 1	(Love 1998)
Light	ON	Office	Canada, AB	Private office 2	(Love 1998)
Blind	Close (ON)	Office	Austria		(Mahdavi et al. 2008)
Blind	Close (ON)	Office	Multiple regions[3]	Based on solar intensity	(Newsham 1994)
Blind	Open (OFF)	Office	Multiple regions[3]	Morning	(Newsham 1994)
Light	OFF	Office	Multiple regions[3]	Afternoon	(Newsham 1994)
Light	OFF	Office	Multiple regions[3]	Morning	(Newsham 1994)
Light	ON	Office	Multiple regions[3]	Morning	(Newsham 1994)
Heating	ON	Office	EU		(Nicol 2001)
Heating	ON	Office	Pakistan		(Nicol 2001)
Heating	ON	Office	UK		(Nicol 2001)
Light	ON	Office	Germany	Arrival	(Reinhart and Voss 2003)
Light	ON	Office	Germany	During the day	(Nicol 2001)
AC	OFF	Res.	China	Bedroom	(Ren et al. 2014)
AC	OFF	Res.	China	Living room	(Ren et al. 2014)
AC	ON	Res.	China	Bedroom	(Ren et al. 2014)
AC	ON	Res.	China	Living room	(Ren et al. 2014)
AC	ON	Res.	China	Living room	(Ren et al. 2014)
Window	Open (ON)	Office	UK	With night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	With night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	With night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	No night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	No night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	No night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	No night ventilation	(Yun and Steemers 2008)
Window	Open (ON)	Office	UK	No night ventilation	(Yun and Steemers 2008)

Table 1 (continued)

System	Action[1]	Bldg. type	Region	Other info	Ref
Window	Open (ON)	Office	UK	All orientations	(Zhang and Barrett 2012b)
Window	Open (ON)	Office	UK	East	(Zhang and Barrett 2012b)
Window	Open (ON)	Office	UK	North	(Zhang and Barrett 2012b)
Window	Open (ON)	Office	UK	South	(Zhang and Barrett 2012b)
Window	Open (ON)	Office	UK	West	(Zhang and Barrett 2012b)
Blind	Close (ON)	Office	UK	Based on solar altitude	(Zhang and Barrett 2012a)
Blind	Close (ON)	Office	UK	Based on solar radiation	(Zhang and Barrett 2012a)
Blind	Open (OFF)	Office	UK	Based on solar altitude	(Zhang and Barrett 2012a)
Blind	Open (OFF)	Office	UK	Based on solar radiation	(Zhang and Barrett 2012a)

[1] obXML has control options called 'on' and 'off' that represent 1 or 0

[2] Canada, Japan, Germany, the UK, and the USA

[3] Newsham used previously developed models from different regions (Japan and the UK), and combined them for simulation purposes

addressed using the meta-data of OB models in the obXML files.

For example, ten blind usage models included in the library, chosen from well-cited OB literature, are based on different types of drivers.

Haldi and Robinsons' models (Haldi and Robinson 2008) have two input variables to inform the logistic regression model. The probability distribution itself is given by a logit function. The way it is expressed in the model, blind closing behaviour is driven by indoor and outdoor air temperature.

Inkarojrit's (Inkarojrit 2008) results showed that the frequency of window blind closing events increased as the luminance and vertical solar radiation levels (direct normal radiation) increased. He built multiple models based on longitudinal logistic regression using one to four input variables.

Mahdavi et al.'s model (Mahdavi et al. 2008) gives a normalised relative frequency of window blind closing events and uses global vertical irradiance (direct normal radiation) as a driving variable.

Newsham identified overheating, glare, sunlight penetration depth as well as time of arrival and lunch as determining factors for blind use actions. He built a model (Newsham 1994), implemented into the obXML library, in which blinds have an opening probability based on morning arrival time and a closing action that is driven by solar intensity.

Zhang and Barrett (2012a) found that solar altitude or radiation (direct normal radiation) are the determinant parameters for blind closing probability. They used logit analysis to investigate curves of measurement data that follow a similar pattern. Their proposed models are logistic regression type.

Other types of occupant actions included in the obXML library include window opening behaviour. For example, Yun and Steemers (2008) concluded that window use actions are highly time-dependent (time of arrival and departure and intermittent periods), and identified indoor temperature as a driving variable. In this case, both probit and ordinary linear analyses were used to construct the models.

Zhang and Barrett introduced window opening models (Zhang and Barrett 2012b) driven by outdoor temperature. Different models were built for office spaces with different orientations. The models were built using the probit function.

Haldi and Robinson's window opening and closing models were included in the library as well (Haldi and Robinson 2008, 2009). In these models, window use behaviour is driven by indoor air temperature. Longitudinal survey answers and measured environmental parameters were collected in this study with a sample size of 60 office occupants.

Hunt's light switch algorithm was published in 1980 (Hunt 1980) as a very first reference model that is widely used in the literature. This model uses a probit curve with the minimum daylight illuminance level as an input variable measured in the working area.

Love's light use models (Love 1998) are based on experiments conducted in private offices. Switching probability functions were determined for two participants and logit 1D models were constructed using daylight illuminance levels as an input variable measured on desks.

Whereas Newsham's models (Newsham 1994) assumed that the switching on of artificial lighting is largely predictable based on both the time of day (morning or afternoon) and work-plane illuminance levels. Instead of applying probability functions, Newsham proposed to have a simple two-level decision-tree type of model in this case.

Reinhart and Voss's electric lighting use model for arrival (Reinhart and Voss 2003) used a 1D quadratic logit function based on minimum workplace illuminance levels. This model was built on data from ten private and two-person offices.

A light switch model from Nicol (2001) was also integrated into the library. In this case, Nicol used a longitudinal survey database, conducted in the UK, Europe, and Pakistan, to build a 1D logit regression model. As an input variable, mean outdoor temperature was used.

As mentioned above, many types of commonly used occupant behaviour action types were implemented into the library. Besides lighting, window and blind use models, heating and cooling (air conditioning—AC) use behaviour models were processed too.

In the same study introduced above, Nicol published a heating use model (Nicol 2001), where the proportion of heating systems that are switched on can be determined based on mean outdoor air temperature levels.

Air-conditioning models implemented into the library were published by Ren et al. (2014). These models assume that the switching of air-conditioning units on or off in residential buildings can be predicted based on environmental triggers (sensations of hot or cold). To describe the relationship, a Weibull distribution function was used.

Gunay et al. (2015) conducted a study in which several existing OB models were compared as well as implemented into the same modelling framework. Many models were implemented to the obXML library, including a light switch model. In these models, workplane illuminance is the primary driving factor of actions, i.e. the darker the workplane gets, the larger the probability that the lights will be switched on.

The Appendix shows a code snippet of an OB model included in the obXML library. In the first lines, metadata information can be found referring to the specific model (such as building types, reference to the paper where the model was published, data collection region, data collection methods and sample size), and then the drivers, needs, actions, and systems parts of the schema can be seen. In case of this model, the environmental driver of behaviour is outdoor air dry-bulb temperature, needs are thermal comfort not explicitly defined. The formula describing the probabilistic relationship is a 1D (i.e. one predictor parameter) logit formula and the system is shading. The model represents a certain probability that blinds/shades will be deployed depending on the outdoor air temperature.

Application of the library

The initial obXML repository of 52 OB models enables easier and more robust representation of human behaviour in building energy simulation. This section discusses the practical application of the library. One of the most powerful tool-chains was recently developed at LBNL (Hong et al. 2015b) for application purposes. The core part of this new OB modelling tool chain is an occupant behaviour functional mock-up unit (obFMU) that enables co-simulation with BPS programs that implement the functional interface (FMI).

FMI is an independent standard that allows for component development and tool coupling using a combination of XML and compiled C-code. The standard contains two main parts: (1) an explanation of how a modelling environment can generate C-code and be utilised and (2) the interface standard for coupling in a co-simulation environment. The component or simulation model that implements the FMI framework is called the functional mock-up unit (FMU).

The obXML schema contains the definition and description of all variables for the obFMU and provides a basis for the xml output file. obFMU contains four main components, including the co-simulation interface, the interface description file in XML format, the data model, and solvers (Hong et al. 2015b). In Fig. 2, the entire tool chain is introduced, where obFMU co-simulates with commonly used BPS program EnergyPlus as an example (EnergyPlus (accessed: 01.03.16) n.d.).

In Fig. 2, the orange-coloured branch shows how OB is described in the framework (using DNAS and obXML). This information is then fed to the obFMU that connects to the simulation engine, for example EnergyPlus. In this scenario, EnergyPlus acts as the co-simulation manager and transmits the calculated physical parameters of the building simulated in a given

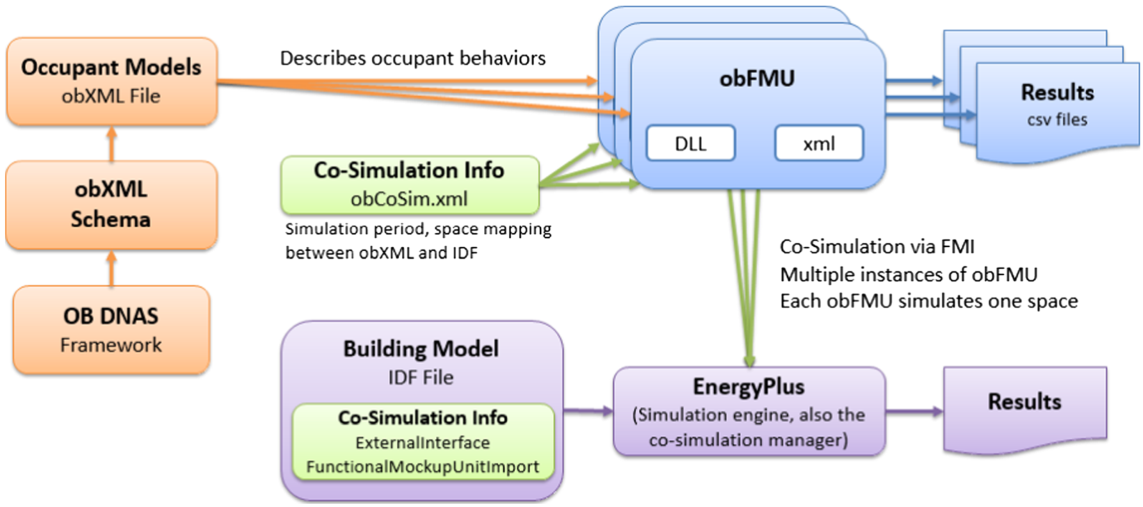

Fig. 2 Schematic of occupant behaviour modelling tool chain (Hong et al. 2015b)

timestep. obFMU then decides on occupant actions based on the input, calculated physical parameters, and OB models from obXML. The impact of these decisions (in the format of window opening or shading schedules) are then fed back to EnergyPlus, which moves to the next timestep, and so on.

Other software developers, e.g. ESP-r and IDA ICE, are working on the implementation of obXML and obFMU for co-simulation as well. There are other ways to use obXML files. The goal would be to allow the use of generic XML format in building energy simulation. For example, BSim (BSim n.d.) is implementing an interface to import obXML files that represent occupant behaviour in buildings.

Furthermore, there is a tendency in design procedures to use a common platform for representing a building under design which is readable and editable by all subcontractors and disciplines of a project. The most popular platform appears to be building information modelling (BIM).

BIM tools currently offer representation of key building systems to help the design process (NIBS 2009). Available products can currently analyze structural needs, wind loading and microclimate impacts, massing, shading and shadows, lighting needs, HVAC needs, energy use, acoustics, quantity take-offs, and costing, among others (Institution of Structural Engineers 2013). Emerging tools are capable of construction phasing, emergency evacuation, and a few other simulations of dynamic phenomena (Liu et al. 2015). Andrews et al. states that a meaningful representation of human agency is missing from most models. Richer representations of the human side of human–technology interactions in buildings are needed for usability analysis (Andrews et al. 2011).

More and more file formats using the XML language have been made compatible with BIM, such as gbXML or CityGML. Therefore, the authors hope that in the future, obXML can be linked to BIM to integrate and represent occupant behaviour on this common platform as well, which is an effort pursued by the ASHRAE Multidisciplinary Task Group on occupant behaviour in buildings.

Discussion

As another result of the project, the limitations of the DNAS framework and the obXML schema were identified and addressed. Future improvements were also proposed to make the schema more flexible for broader use (Table 2).

Meta-data representation should be refined and more information tags should be added. To be able to represent more OB models in the schema, more drivers and systems should be added, and the definition of needs should be broader to accept more types of models. Some researchers used mathematical formulas that have not yet been implemented in obXML, such as the logit function with four independent variables used by the M1 model of Inkarojrit (2008). Therefore, an equation editor should be developed to provide freedom for users. Furthermore, definable logical connections would be needed in the actions section in order to include models

Table 2 Future improvements proposed for the obXML schema

Topic	obXML v1.2	Proposed improvements
Possible meta-data categories of models	Name, IfcGuid, BuildingTypeComment, PaperAuthors, PaperYear, PaperTitle, PaperDOI, DataCollectionRegion, TypesDataCollectedOther, SampleSize	Add modelling approach, applicable season/time of day. Add to TypesDataCollected list: EnergyConsumption, FieldVisit, Interview, Occupancy, SubjectObservation, WindowStateLog, BlindStateLog
Drivers of a certain action	*Time*—TimeofDay, DayofWeek, SeasonType *Environment*—RoomAirTemperature, RoomCO2Concentration, RoomWorkPlaneDaylightIlluminance, RoomLightsPowerDensity, OutdoorDryBulbTemperature, OutdoorRainIndicator	Add attitude towards actions, brightness sensitivity, duration of absence, unshaded window fraction, rain, indoor solar intensity (W/m^2)
Needs	Comfort envelope definition (min-max values of comfort parameters)	Add free text to describe needs if applicable.
Actions—default functions	Mathematical formulas implemented as a default: ConstantValue Linear1D, 2D, 3D Quadratic1D Logit1D, 2D, 3D Weibull1D Logit1DQuadratic	Add logit 4D. Add equation editor to enable free style representation on mathematical equations.
Actions—logic	No editable logic.	Definable logical connections, e.g. if-then-else-endif
Building systems	HVAC, lights, windows, plug loads, thermostats, shades, and blinds	Add fan, door, cold drink, and clothing

using different logical structure such as decision-tree (Hailemariam et al. 2011) or fuzzy logic (Guillemin and Molteni 2002) types of models for example.

The authors would like to note that special attention should be paid to the usability of different models from different locations and sources. Readers are advised to use with caution when implementing an OB model into their BPS model as authors' intention with this work was not to evaluate the validity or quality of the models included in the obXML library, but rather to improve the tool chain and modelling resources. Usage of an OB model in simulation that was developed for a different building type, OB type or climate might lead to inaccurate or unrealistic results.

The energy-related OB research field presently lacks data on differences in OB between different countries, cultures, and climates. Therefore, the authors would advise caution in generalising these models for different locations or scenarios. Further research is ongoing on this topic within the framework of the ANNEX 66 project (Yan et al. 2017). The quantification of differences in OB between different countries is expected to be published in the upcoming year based on results from an international OB survey project.

These models not only differ in terms of geographical location applicability, but also in terms of their practical applicability. At the same time, the level of details and applicable design project phases should be considered. Designers might not need the same accuracy level of OB representation for the early, schematic phase of a small, new-construction residential building project or for the construction design phase of a major retrofitting project. A research project is currently ongoing regarding fit-for-purpose modelling where OB models are categorised by use cases to support BPS users in model selection (Gaetani et al. 2016).

Another topic to be addressed here is the prediction capability of these models in different thermal and visual comfort requirement scenarios. Most of the models use an environmental parameter (e.g. indoor or outdoor temperature or solar radiation level) as a driver of behaviour. For example, Haldi and Robinson's blind closing model from 2008 (see also the Appendix) provides a probability of closing the blind based on outdoor temperature. The warmer it gets outside, the higher the possibility that an occupant will close the blind (described with a 1D logit function). Therefore, the prediction capability does not depend on the comfort envelope of the indoor environment. This is equally true for models where the driver is an indoor parameter, as the driving variable in most cases does not have a limitation for the comfort envelope, defined in standards. If there is a limitation on the driving variable, it is described in the needs section of the obXML.

While more OB models still to be added to the library are being worked on, we would like to encourage BPS users to extend the library as well. In addition to the model library, a template file was created for OB model developers that enables them to implement new models into the library. The authors would suggest using an XML schema editing tool for implementation such as XMLSpy (XML Spy n.d.). Additionally, proposed changes, improvements, or any kind of feedback on new model implementations are welcome.

It must be mentioned at this point that many aspects of a person's behaviour cannot be represented through the DNAS framework or used in building performance simulation at present. These aspects are the non-physical variables of a building occupant setting and would require knowledge of separate disciplines such as social science and psychology. Currently, the obXML schema is adopted by certain energy modelers that use EnergyPlus ESP-r and IDA ICE. With its expected broader use, more limitations would need to be identified and addressed. An ongoing challenge is to balance the complexity, robustness, extensibility, and ease of use.

It was shown in recent studies that it is beneficial for energy-related occupant behaviour research to apply an interdisciplinary approach (Pellegrino and Musy 2017; Hong et al. 2016; D'Oca et al. 2017b). At present, specialists with behavioural and social science backgrounds are underrepresented in the field, which is partly due to the lack of specialised graduate programs, common interests, and collaboration by research institutes, as summarised by Lutzenhiser (1993). In addition, a panel discussion concluded that education and the employment of interdisciplinary environmental social scientists should be promoted (Stem et al. 1991). This can be extrapolated to the field of energy-related building occupant behaviour research as well (Deme Belafi et al. A review on energy-related occupant behaviour questionnaire surveys: under publication).

Conclusions

Data-driven occupant behaviour models lack standardisation and consistency, leading to difficulties in applications and inter-model comparisons. To address this problem, a DNAS framework was recently developed. Recent work has been carried out to implement the theoretical DNAS framework into an XML schema, the 'occupant behaviour XML' (obXML), which is a practical implementation of occupant behaviour models that can be integrated into building performance simulation programs.

This paper presents a newly developed library of 52 occupant behaviour models represented in the standardised obXML schema format. This library provides ready-to-use examples for BPS users to employ a more robust occupant representation in their models.

The library is made available at the web sites annex66.org and behavior.lbl.gov. This is an initial library; additional models are being worked on by the IEA EBC Annex 66 project as an ongoing activity. Contributions and further library extensions are welcome.

The authors hope that by compiling this library and making it publicly available, building energy modellers from all over the world can enhance their building simulation models by integrating more robust occupant behaviour models in order to capture their complexity and impact on building performance.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Example code-snippet about Haldi and Robinson's 2008 blind closing model driven by outdoor air temperature (Haldi and Robinson 2008).

```xml
<Behaviors>
    <Behavior ID="B_Blind_Haldi_Robinson_2008_Office_Tout" AppliedBuildingType="Office" SystemType="ShadesAndBlinds" ActionType="TurnOn"
    PaperAuthors="Haldi, Frédéric; Robinson, Darren" PaperYear="2008" PaperTitle="On the behaviour and adaptation of office occupants" PaperDOI=
    "10.1016/j.buildenv.2008.01.003" DataCollectionRegion="Switzerland" SampleSize="60_participants_Many_buildings" TypesDataCollected1=
    "IEQmeasurements" TypesDataCollected1="LongitudinalSurvey" TypesDataCollectedOther="weather">
        <Description>Predicting closing the shades during the day based on Tout.</Description>
        <Drivers>
            <Time>
                <DayofWeek>Workdays</DayofWeek>
            </Time>
            <Environment>
                <Parameter ID="HaldiRobinson_outdoortemp" Name="OutdoorDryBulbTemperature">
                    <Type>OutdoorDryBulbTemperature</Type>
                </Parameter>
            </Environment>
        </Drivers>
        <Needs>
            <Physical>
                <Thermal>

                </Thermal>
            </Physical>
        </Needs>
        <Actions>
            <Interaction>
                <Type>TurnOn</Type>
                <Formula>
                    <Logit1D>
                        <Description> p = exp(A*P1+B) / ( exp(A*P1+B) + 1)</Description>
                        <CoefficientA>0.139</CoefficientA>
                        <CoefficientB>-3.54</CoefficientB>
                        <Parameter1ID>HaldiRobinson_outdoortemp</Parameter1ID>
                    </Logit1D>
                </Formula>
            </Interaction>
        </Actions>
        <Systems>
            <ShadesAndBlinds>
                <ShadeAndBlindType>Operable</ShadeAndBlindType>
            </ShadesAndBlinds>
        </Systems>
    </Behavior>
</Behaviors>
```

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