Representations of people in Urban Building Energy Models

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Abstract

Occupant behaviour is commonly acknowledged as a key driver for variation in building energy performance (Gaetani et al., 2016). ASHRAE (2009) notes it as an important factor in the significant discrepancy between proposed building performance and actual energy consumption. A large body of literature exists dedicated to exploring energy behaviours and the need for more holistic considerations of energy behaviours, but this has not been connected to occupant modelling in Urban Building Energy Models (UBEMs). This paper develops a framework to identify and classify representations of people in UBEMs by reviewing and connecting the behaviour change and UBEM literatures. Combined with the classification of the approaches of people's representation, we show that schedule-based models perform better although it cannot provide a full explanation of energy practices. While agent-based approaches offer the potential to incorporate the more holistic approaches called for by Kierstead (2006) the computational burdens which result may be excessive at the urban scale. The main framework developed can provide simulation practitioners with insights into energy behaviours.

Key Innovations

- Integrate behaviour change models and occupancy models of UBEMs;
- Develop a Technology-Activity-Aspiration (TAA) framework to identify people's behaviour represented in UBEMs;
- Classify UBEMs by the approaches to representing occupants
- Evaluate the effectiveness of UBEMs in addressing the behavioural responses.

Practical Implications

This paper can be a reference for simulation practitioners when they use or develop UBEMs, with an insight to the behaviour interpretation. People's behaviour is one of the keys to a precise building energy simulation but is often overlooked. An improved approach to behaviour simulation should be developed to mitigate the error caused by this lack of attention.

Introduction

The fundamental driver of energy consumption in the urban environment is people and their need for the services that energy provides. These services include thermal comfort, entertainment, cooking and lighting. However, representations of people in Urban Building Energy Models (UBEMs) are typically limited to a set of rules for interaction with buildings and systems.

UBEMs model the building-related energy demand of a neighbourhood, a city or a region. They can be classified as top-down or bottom-up according to whether the starting point is stock level energy consumption, which must be broken down into its constituent parts, or energy consumption of individual units, which must be aggregated to determine stock level demand (e.g. Swan and Ugursal, 2009). Bottom-up models can further be broken down into: statistical models which use historical data and assess the relationships between building information and energy use data; and building physics-based models (Lim and Zhai, 2017).

As Yan and Hong (2018) concluded from 32 case studies, occupant behaviour significantly affects energy use and occupant comfort or convenience levels in buildings. A review by Salim et al. (2020) examined how occupant behaviour is modelled in UBEMs. The authors found that the rules, or ways in which people interacted with buildings, could either be deterministic or applied stochastically. In both cases these engineering approaches are part of the physical-technical-economic model of energy consumption which has been criticised for failing to incorporate behavioural responses to technological improvements (2006).

In response, this paper considers a range of behavioural frameworks and develops an over-arching framework for assessing the completeness of models of occupancy behaviour within UBEMs. A range of UBEMs are assessed using this framework to consider their abilities to address the diversity of occupant behaviour in an urban setting.

Methods

This paper addresses two research questions:

- Can behaviour change models be integrated with occupancy models within UBEMs?

- How effectively do UBEMs currently address the behavioural responses?

To address these questions, we begin with a literature review of behaviour change models. The models reviewed mainly cover the individual energy behaviour models, social-oriented models, and culture-based models. A composite framework was developed based on this review which incorporates elements of the reviewed models and provides a tool for classification of existing UBEMs.

A review of existing UBEMs was then undertaken to classify their approach to occupant modelling. Six commonly used UBEMs (EnergyPlus, SUNtool, CitySim, FlexiGIS, IDEAS , IDEAS +StROBe and HOMER) were selected. The purposes, inputs, sub-models and datasets related to each model were reviewed. The extracted elements of how people were represented were integrated using the composite framework, which links behaviour change models and occupancy models.

The approaches to occupant representation were classified according to how the model inputs realize the energy use simulation through occupant behaviour modelling. The classification focussed on the contents of people's representation, the importance of people (the extent to which the simulation of people's role determines the results of models) and complexity (difficulty of behaviour simulation).

Results

Behaviour Change Models

This paper reviews eight Energy Behaviour Change Models, summarizing how they explain energy behaviour, and leading to a framework named Technology-Activity-Aspiration (TAA), which is used to classify the sample of UBEMs.

The basic structure to analyse the rationale of individual behaviour is the *Attitude Behaviour Choice (ABC)*, where people are assumed to be rational (Chatterton, 2011). People form an intention leaning in their behaviour based on their own attitudes or preferences (Attitude-Intention-Behaviour). On the basis of ABC, *Triandis' Theory of Interpersonal Behaviour*, states that behaviour is motivated by intention and habits, constrained by facilitating conditions(Chatterton, 2011; Martiskainen, 2007). It also includes several factors leading to Intention and Habits, together with some underlying factors, such as social norms and roles. This framework assumes people make energy decisions rationally, based on mainly economic and psychological motivations, under the constraint (or enablement) of facilitating conditions.

Similar frameworks include *MINDSPACE*, which sets out nine elements that should be considered when making policy (Dolan et al., 2010). In addition to norms, affect, ego (similar to self-concept in Triandis' model) and incentives (similar to attitude in Triandis' model), it assumes people will respond to others with different roles (messenger), 'go with the flow' (defaults), pay more attention to the novel (salience), respond to sub-conscious clues (priming), and keep their public promises (commitments).

In contrast to the ABC and Mindspace models, the *Three-element model* is a socially-orientated model which focuses on energy habits and practice, analysing why specific habits are common among people (Chatterton, 2011). The three elements are materials, image and skills (Shove and Pantzar, 2007; Shove and Panzar, 2005). In this framework: materials denote physical objects and equipment used; images denote the interpretations of activities, determining the way people may perform; and skills denote the knowledge about certain ways of doing things or activities. The practices are generated from the interaction and reproduction of these three elements.

The *Energy Culture Framework* is based on the 'culture' concept, which interprets the integrated system of knowledge, belief and behaviour, as reinforced by physical materials (Stephenson et al., 2010). It contains cognitive norms (e.g., beliefs), material culture (e.g., technologies) and energy practices (e.g., activities). Cognitive norms determine the technology and practice choices. Material culture change or upgradation can lead to changes in norms and practices. Energy practices affect how technologies are chosen and used, and also partly affect people's beliefs. This framework is therefore useful to understand why people use energy according to their current practices (Stephenson et al., 2010)

Other frameworks include *Comfort-Cleanliness-Convenience* (Shove, 2003) which focuses on: the initiatives of people's energy behaviours; a *multi-factorial model* of interactions between values, situational and psychological variables by (Barr and Gilg, 2007), focusing on people's attitudes and the gap between intention and behaviour; an agent-based integrated *domestic energy consumption (DEC) framework* by (Keirstead, 2006)focusing on energy consumption by and via different agents.

The frameworks above offer diverse ways to conceptualise and analyse energy behaviours, ranging from the individual to the societal scale. They illustrate that energy behaviours can be analysed from economic, sociological, psychological, educational and technological perspectives (Geels, 2004; OFGEM, 2011; Wilson and Dowlatabadi, 2007). The relevant frameworks have different focuses, ranging from physical materials and technology, intention and beliefs, norms and culture, actors, and so forth. A summary is presented in Table 1.

Some of the frameworks analyse behaviour from the features and categories of behaviour, while others focus on the underlying motivations. Most of them stress the interactions between motivations and behaviours and combine of actors and technologies. Three of the eight frameworks are composed of technology (physical materials), activity (energy practice) and aspiration (the underlying driver for the energy practice, e.g., the achievement of thermal comfort). This synthesis of the existing frameworks can be conceptualised actions undertaken (activities) using equipment (technology), in order to achieve a particular goal (aspiration). The distinction between activities and aspirations is important since multiple alternative actions and technologies may be employed to achieve the aspiration. The framework is illustrated conceptually in Figure 1.

Table 1: Summary of energy behaviour frameworks reviewed

Framework	Content	Focus/Aspects
Attitude Behavior Choice (ABC) (Chatterton, 2011)	Attitude-Intention-Behavior	Economic and psychological theories on individuals
Triandis' Theory of Interpersonal Behavior (Martiskainen, 2007)	Intention; Habits; Facilitating conditions; other detailed elements underneath	Economic, psychological, sociological theories on individuals; technology as constraint
MINDSPACE (Dolan et al., 2010)	norms, affect, ego, incentives, messenger, defaults, salience, priming, commitments	sociological and psychological theories on individuals
"Three-element" model (Shove et al., 2012)	materials, image and skills	Mainly sociological theory; energy habit and practice
Energy Culture Framework (Stephenson et al., 2010)	cognitive norms, material culture; energy practices	Economic, sociological and technological theories
Agent-based integrated domestic energy DEC framework (Keirstead, 2006)	Consumption by different agents and relevant factors according to agents	Emphasis on technology and economic incentives; agent-based
Comfort-Cleanliness-Convenience (Shove, 2003)	Energy demand enforced by incentives towards comfort, cleanliness and convenience	Psychological and sociological incentives of individuals
A multi-factorial model (Barr and Gilg, 2007)	interactions between values, situational and psychological variables	Economic, sociological, psychological intention; emphasis on the gap between intention and behavior

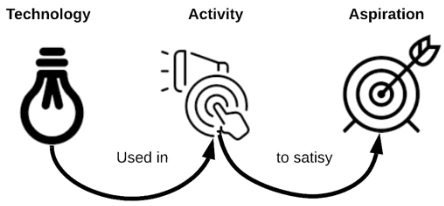

Figure 1: The TAA framework

The mapping of the existing frameworks to the TAA framework is shown in Table 2.

Table 2: Elements covered in eight energy behaviour frameworks

Framework	Technology	Activity	Aspiration
ABC		✓	✓
Triandis'	✓	✓	✓
MINDSPACE			✓
Three-element	✓	✓	✓
Energy Culture	✓	✓	✓
DEC	✓		✓
Comfort-Cleanliness-Convenience			✓
Multi-factorial		✓	✓

This review reveals three elements which are used to describe energy behaviours – technology, activity and aspiration (TAA). We use this TAA framework to describe how people are represented in energy planning models. In this framework, '**Technology**' includes the physical material, tools or energy generating technologies used in energy consumption habits, which is the necessary physical foundation of people's behaviour. **'Activity'** refers to energy practices, which could be reflective (rational) or automatic (routine) in theory. '**Aspiration'** denotes the driver of the practice i.e., the underlying reasons why people behaviour in particular ways or what they hope to achieve.

Classifying existing UBEMs

In order to classify UBEMs, each was analysed focusing on the interpretation of occupant behaviour, following the TAA framework. This paper analyses seven UBEMs: EnergyPlus (Crawley et al., 2001), SUNtool (Robinson et al., 2007), CitySim (Robinson et al., 2009), FlexiGIS (Alhamwi et al., 2018, 2017), IDEAS (Baetens et al., 2012), IDEAS + StROBe (Baetens and Saelens, 2016) and HOMER (Lambert et al., 2005). The following sections give a brief overview of each of the UBEMs and how occupant behaviour is addressed in each:

EnergyPlus is a tool for generating solutions of thermal zone conditions and radiant balance and energy consumption modelling(Crawley et al., 2001). A number of UBEMs have been developed which use EnergyPlus as the underlying simulation engine including MIT's Urban Modelling interface (UMI) (Reinhart et al., 2013), and UCL's SimStock (Coffey et al., 2015). Inputs include location-climate-weather file, schedules, surface construction elements, thermal zone description, internal gains etc. In addition to being indirectly modelled through schedules for use of building systems and equipment, people are one of the components in internal gains, requiring information on number of people, activity level schedule, mean radiant temperature, work efficiency schedule etc. It assumes the motivation of using energy is comfort, which is affected by people's activities, radiant temperature and air velocity, and surface material. Each factor has a specific calculation code, which, while deterministic, provides flexibility on defining activities and relevant. The amount of energy consumption is determined based on assumptions about thermal comfort. The demand simulation is based on the balance between thermal comfort and surrounding climate (radiance).

SUNtool is a model solving the complexity of radiant exchanges and optimising the lay-out planning and design of buildings so as to fully utilise the technology choices and minimise energy demand (Robinson et al., 2007). The only class of the solvers behind is stochastic occupancy-related models. SUNtool assumes people are intrinsically unpredictable and the energy consumption is based on the presence (arrival, departure and breaks) of people(Robinson et al., 2007). It uses quarter-hourly profiles of the probability of presence to simulate light, shade and appliance use (Page et al., 2008). This model therefore deterministically assumes people's presence by using a fixed and repeated time schedule. Energy aspirations are not limited to a specific purpose, but rather are determined by people's instinctive needs. Further, window opening is determined by the micro-climate and comfort standards, which means people also act to seek thermal comfort.

CitySim, (Robinson et al., 2009). CitySim builds on SUNtool adding a thermal model, plant and equipment models and behavioural models which model heat gains and pollutants due to occupants, infiltration rates due to window opening, irradiance due to blind operation, heat gain and power demand due to lights and electrical appliances and the production of combustible and recyclable solid waste. The behavioural models are driven by a stochastic occupant presence model in which all occupants act independently and actions depend only upon the state in the previous timestep.

FlexiGIS is a GIS-based tool, which aims to integrate information on spatial relationships. It also processes and displays energy data for better urban building planning (Alhamwi et al., 2018, 2017). The model analyses energy demand based on previous data (time series), and incorporates energy system costs. It seeks to optimize cost and balance energy supply and demand. The urban microclimate and heating and cooling load data are integrated into the dataset. Energy consumption is calculated using mathematical models of indoor heat load and heat transmission, which can be ascertained from the building exterior. People's behaviour is overlooked, because the energy consumption/ demand prediction is simulated based on previous integrated information and consumption data. There seems to be no specific technology and activity assumed, while the model assumes people will behave according to their previous or instinctive energy habits related to the microclimate.

The Integrated District Energy Assessment by Simulation (IDEAS) tool targets the evolution to zero-energy neighbourhood and buildings. It allows for the simulation of thermal and electrical processes at the neighbourhood scale and assessment of the electrical challenges at feeder level of the building (Baetens et al., 2012). It integrates information on architectural types, technology choices and occupant behaviour. IDEAS adopts a stochastic model to represent people's behaviour. Energy practices are based on the use of appliances, which refers to individual domestic load (Richardson et al., 2010). The time-correlated data on people's daily activities is based on data from a Time Use Survey (TUS), and the stochastic modelling uses an inhomogeneous Markov chain. To link the activities and appliances, activity profiles are created and assigned to each appliance with the varying likelihood of usage to generate a stochastic simulation. Sharing and correlated use of appliances is also considered via active occupancy. The final outputs are presence, activity, use of appliance and lighting (depending on household size), time and global irradiances (Baetens et al., 2012). Therefore, the model assumes people behave according to their true needs in daily life, affected by the characteristics of dwellings, time and climate.

IDEAS has also been coupled with the *StROBe* stochastic occupant behaviour model ,developed for district energy simulations (Baetens and Saelens, 2016). It draws on the 2005 Belgian Time-Use Survey and Household budget survey to establish probabilities of performing different activities and correlation with demographic parameters.

The HOMER Micropower Optimisation Model is targeted at the micropower systems design to compare ranges of power generation technologies (Lambert et al., 2005). It mainly models the physical behaviour of a power system and the life-cycle cost. This enables the identification of the system with the lowest life-cycle cost, while simultaneously satisfying technical requirements. It determines whether the system can feasibly serve the electric and thermal loads. The simulation of power systems is based on statistical data about the system only, without considering climate or any other variables as other models do. Therefore, the energy consumption simulation in HOMER is unrelated to people, while it treats the consumption statistics and system cost as a function of the micropower system.

Table 3 shows a summary of how people are represented in UBEMs following the TAA framework.

How people and their behaviour are incorporated into UBEMs may be stochastic (i.e., people's behaviour is determined by sampling from a probability distribution of responses; these can be random or can represent complex changes of drivers) or deterministic (i.e., people's behaviour is determined through fixed model assumptions). Furthermore, the approaches taken by the different UBEMs can be categorized as detailed below:

1) *Schedule-based approach*: assumes people act according to time or their daily routine;

2) *Standard-based approach*: assumes people's characteristics and roles are determined by fixed standards of acting or patterns of feeling and incorporates particular standards e.g., comfort standards defined through a temperature set point;

3) *Appliance-based approach*: interprets energy demand based on the need of appliances and equipment;

4) *Statistic-based approach*: simulates energy consumption based on historical consumption data for a time period or cumulative historical data, namely assuming people act according to their existing habits while no other information can be interpreted;

5) No interpretation – the model does not contain and consideration of occupant behaviour.

Having categorised the models, the complexity of behavioural simulation and the importance of people, this section reflects upon how people are included in the analysed UBEMs.

Table 3: Summary of people's representation under TAA framework

Model	Dominant approach type	Activity	Aspiration	Technology
FlexiGIS	Statistic-based (Deterministic)	People act according to their previous habits	-	-
EnergyPlus	Standard-based (Deterministic)	Energy consumption correlated with thermal comfort	Thermal comfort	Flexible set
SUNtool	Schedule-based (Stochastic)	Presence generates energy consumption, based on appliance and feelings of comfort	Instinctive need; daily routine	Solar-related technology; Lights, shading, electric and water appliance
CitySim	Schedule- based (Stochastic)	Presence generates energy consumption, based on appliance and feelings of comfort	Instinctive need; daily routine	Lights, shading, electric and water appliance
IDEAS	Appliance-based (Stochastic)	Activity performed is affected by time, dwelling, climate etc.	Instinctive need; daily routine	Appliances and lighting
IDEAS + StROBe	Statistic-based (Stochastic)	Activity occurs based on previous probabilities	-	Appliances, lighting, space heating, hot water, ventilation and solar shading control
HOMER	No interpretation: simulation of power system only according to system data, regardless of people use information			

FlexiGIS simulates people's energy demand based only on statistics and mathematical regression, according to load, climatic data, building types and other such variables. This explains why these models are statistic-based types when interpreting behaviour, containing no specific assumptions of people's behaviour and few contents related to people. The importance of people's role in the models and behaviour simulation complexity are comparatively low.

Energy demand in EnergyPlus is assigned to 'standard-based' and 'schedule-based', which is based on people's thermal comfort standard and schedule profile. This determines how people may use energy based on data on climate, building and so on. Here, standard is chosen as more dominant as the energy consumption simulation depends on the comfort standard and surrounding climate only. The aspiration represented is thermal comfort and the schedule profile actually serves the comfort modelling.

As the comfort standard simulates people's behavioural patterns and is combined with schedule and other sub-models in EnergyPlus, the complexity is higher than in other models. This indicates the relative importance of how people are represented within the model.

SUNtool and CitySim interpret people's role using a schedule-based stochastic model, which focuses on the presence of people. However, behaviour also depends on the appliances and comfort, so the complementary approaches are appliance and standard based.

By contrast, the stochastic model used in IDEAS is based on random use of appliance according to schedule and daily routines of people. As a result, means they are both appliance-base and schedule-based. Amongst these models, the types of approaches have tight correlations: the appliance use is always associated with time and the daily routine activity also depends on the energy equipment. The stochastic models try to simulate people's real energy practices with assumptions about the unpredictability of people, leading to high levels of complexity in the simulation. This is indicative of the importance of people as a variable, which requires sufficient and detailed data, as well as the design of the stochastic scheme.

In contrast to all other models, HOMER has no interpretation of people. It regards energy consumption values as a function of the building's characteristics and focuses on the operation of power systems. As a result, it neglects people's roles in energy consumption.

In general, the interpretation complexity of stochastic models is higher than that of deterministic models – the more complex the simulation of behaviour, the higher importance of people in the model. Figure 1 illustrates how the analysed UBEMs interpret people. 'Schedule-based' and 'appliance-based' models assign people higher importance. As a result, they perform comparatively better than other models in terms of how people are represented, thus ensuring more complete simulation of energy behaviours. The 'standard-based' does not interpret people as well as stochastic models, which have assumptions regarding people's behaviour, although they tend to be static. The 'statistic-based' category has the least interpretation of people except for the no interpretation type, as no specific assumptions of behaviour are contained but only some simple default logics related to people are assumed.

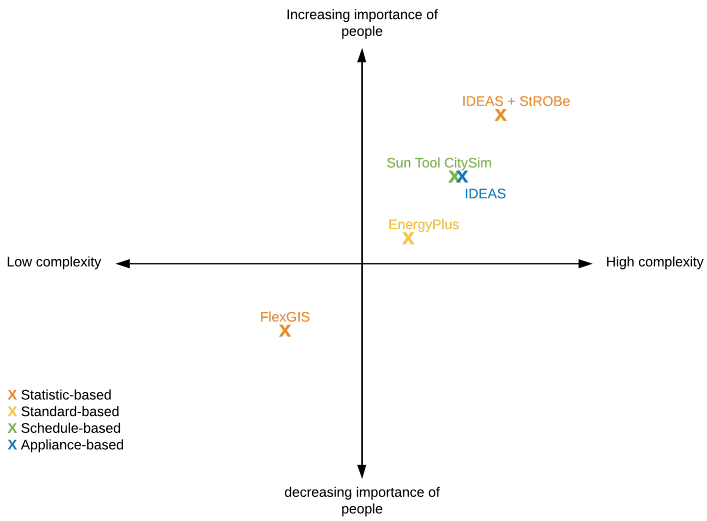

Figure 2 Classification of UBEMs

Discussion

Except for HOMER, all UBEMs analysed here take people's behaviour into consideration to some extent. However, the technologies and activities they involve are limited. Commonly considered technologies include lighting and appliances, but the electricity used may not be limited to them. Similarly, the activities considered are limited. While presence might be appropriate for judging the use of lighting, it may be poorly correlated when talking about windows, shades and other appliances. Time schedule may be the best approach for building energy simulation among those reviewed here, but how to narrow the error range is an important consideration for future work.

However, one of the key challenges relates to the incorporation of energy aspirations. Aspirations currently considered are limited to thermal comfort and routine needs, while the heterogeneity of people is rarely considered. According to the behaviour change models reviewed, belief, social factors or even emotions can all significantly affect energy use, which may lead to discrepancy between simulation results and observed consumption. Put another way, the failure to consider aspirations means that, at present, UBEMs mainly start from the endpoint (technologies) or the halfway (activity). None of them questions why energy is needed, and the services it provides. This is particularly important given the use of UBEMs in assessing competing retrofit options. Models which incorporate changes in technology resulting from a retrofit, but which fail to consider the underlying aspirations driving behaviour, make the assumption that activities will remain unchanged after retrofit. In so doing, they can significantly over- or under-estimate the impact of the retrofit measure. An example is the case of comfort-taking, where more efficient heating systems may be used for longer hours than previous inefficient ones since they are cheaper to operate. As a result, the opportunity to achieve the aspiration for thermal comfort is within reach.

Some commonly-used UBEMs, such as FlexiGIS and HOMER, neglect parts or all of TAA. If "people" are missing, the simulation would be a calculation of data based on physical items alone. In some cases, it may provide a general view on energy use, especially for assembly lines or factories with a comparatively fixed workload. However, when we simulate households' energy demand, errors may be significant.

One way to better interpret people, their behaviours and aspirations is to adopt an activity-based approach e.g., StROBe. This interprets energy demand according to the stochastic activity of people. However, this model relies on historic data and without consideration of the motivations (aspirations) for activities, may not be able to predict responses to new situations. SynCity (Sivakumar, 2013), a modelling platform for urban energy system, uses an activity-based approach to understand lifestyle and individual motivations This approach is anchored in energy behaviour aspirations, and forms an energy use network starting from people's aspirations. This may be closer to reality in terms of how energy use is rationalised. However, collecting data on activity profiles and the subsequent calculations will likely represent an addition challenge. The greater the complexity of a model is also likely to increase the risk of error. In other words, computational burden is a key challenge for improving UBEMs.

An alternative use of the TAA framework is as an assessment tool for data screening prior to modelling. Documenting the technologies, activities and aspirations, which are implicit in the occupancy datasets, and reviewing for consistency is a simple but powerful step towards more holistic representations of people in UBEMs.

Conclusion

This paper reviewed the literature on models of energy behaviour change, as well as that on seven UBEMs. The first research question this study aimed to explore was how behaviour change models could be reconciled with occupancy models. To address this the TAA framework was developed which allowed the identification and classification of approaches to modelling occupant behaviour into 'schedule-based', 'statistic-based', 'standard-based', 'appliance-based' and 'no interpretation'.

To address the second research question, the representation of people's behaviour in seven UBEMs was assessed using the TAA framework. We found that HOMER had no interpretation of people's behaviour. FlexiGIS, a statistic-based model, contains little information about people's roles. Rather, it is based on consumption data and simple mathematical regression, with limited interpretation about people's aspirations and technologies used. The 'standard-based' type uses static assumptions on energy consumption and thermal comfort standards to incorporate people in the model. While people are important in these models, in reality comfort is not the only required energy service, which limits the interpretation. The 'schedule-based' and 'appliance-based' models have more complex interpretations of behaviour. These simulate energy consumption with stochastic behavioural sub-models based on the real activities and instinctive needs of people.

This paper can be a reference for model developers and researchers when they choose or develop models, with an insight to the behaviour interpretation. It builds a bridge between UBEMs and energy behaviour frameworks. Most of the models reviewed here consider people's behaviour when they simulate energy demand or energy consumption. In some models, such as EnergyPlus, the people's roles are contained in several sub-models (e.g., schedule, thermal comfort, internal gains). The TAA framework may support the identification of key factors that shape why and how people use energy, and how these may be incorporated into UBEMs.

This study reviewed a limited number of models, and further research will need to expand this scope. In particular, more models will need to be reviewed to build confidence in each of the model categories identified here. Meanwhile, the TAA framework provides a valuable high-level framework to understand energy behaviours and integrate these into models. People's activities can be categorized into detailed groups with sufficient models and activities. Future research will need to examine additional models to generate more detailed understandings of how people are incorporated into UBEMs and how these representations may be improved. Such a study would provide important insights for model developers, as well as those who seek to use the insights generated from UBEMs.

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