 https://doi.org/10.1051/e3sconf/202236207001

Agent-based modelling and energy performance assessment: a co-simulation case study

Christiane Berger[1*], Florian Regnath[2], Ardeshir Mahdavi[2]
[1]Department of Architecture, Design and Media Technology, Aalborg University, Aalborg, Denmark
[2]Department of Building Physics and Building Ecology, TU Wien, Vienna, Austria
** corresponding author: chbe@create.aau.dk*

Abstract

A number of recent research efforts focus on the inclusion of more detailed models of occupants in building performance computing. Thereby, agent-based modelling (ABM) has the theoretical potential to capture the dynamic and complex patterns of occupants' presence and behaviour in buildings. This paper starts with a brief reference to recent reviews of the state of the art concerning the deployment of ABM in building energy simulation. Subsequently, an illustrative case study is used to explore the potential and current challenges of ABM in building performance simulation. The case study involves the coupling of ABM with a building simulation model to evaluate the influence of occupants' energy consciousness and thermal comfort preferences on buildings' energy performance.

Introduction

In recent years, a number of research efforts have addressed the integration of occupants' behaviour in general, and their interaction with control systems in particular, in building performance computing (O'Brien et al., 2020). Thereby, it has been suggested that, as compared to more conventional occupant representation methods (e.g., fix schedules or simple rule-based systems), agent-based modelling has a richer potential to capture the dynamic and complex presence and behaviour patterns of building users.

In this context, the present paper provides a two-fold contribution. First, a brief reference to recent reviews of the state of the art concerning the deployment of ABM in building energy simulation is critically reviewed. Second, to illustrate the potential and current challenges of ABM in this field, the experiences with a specific illustrative case study are presented and discussed. This case study pertains to an effort to couple an agent-based model with a dynamic building simulation model to evaluate the influence of building users' behaviour on buildings' energy performance. To this end, four different occupant types are included in the modelling environment via a well-known ABM application (NetLogo) (Wilensky, 2022). Thereby, the occupant types are differentiated in terms of their energy consumption intensity and their preferences and tolerance levels regarding indoor (thermal) conditions. The impact of the respective building user scenarios on the energy performance is simulated for six single-occupancy offices in the case study building located in Vienna, Austria. In order to couple the ABM with the energy simulation model (EnergyPlus), the BCVTB (Building Control Virtual Test Bed) and Python are used (EnergyPlus, 2022; Python, 2022; Wetter et al., 2022).

As expected, the simulation results point to the impact of the occupants' energy consciousness level and their thermal comfort preferences on the computed energy use. More importantly, the case study allows to highlight a number of prevailing co-simulation challenges involved in the coupling of agent-based modelling with dynamic building performance simulation. These include, among others, required computational tools and resources as well as empirically-based knowledge on occupants' actual indoor-environmentally relevant preferences as well as their behavioural traits. The paper concludes with reflections on the aforementioned case study. Thereby, thoughts are offered on both the potential and current challenges of ABM applications in building performance simulation.

Background

As stated in the outset, ABM techniques are proposed to adequately represent the dynamic and complex patterns of building users' behaviour and presence. A number of recent research efforts address and critically review the deployment of ABM in building energy simulation. As for example, Berger and Mahdavi (2020) performed a systematic review and analysis of several ABM research efforts that specifically focus on modelling building occupants for energy and indoor-environmental performance analysis. Thereby, the potential of ABM application is highlighted, but also several challenges are identified. Another recent research contribution focuses on ten questions and answers concerning ABM research and application of occupant behaviour in the context of building performance simulation (Malik et al., 2022).

An illustrative ABM case study

The case study involves the coupling of an ABM platform with a dynamic building simulation application. The elements of this case study are briefly described in the following. First, the three elements of the research design (occupant behaviour assumptions, case study building, computational setup) are described, followed by the presentation and discussion of the case study results.

Occupant behaviour assumptions

In order to explore the influence of occupants on buildings' energy performance, four different occupant types are defined. Thereby, differentiations among levels of energy awareness as well as tolerance levels of indoor (thermal) conditions are considered. Table 1 illustrates the different occupant types and respective assumptions of their energy consumption intensity as well as tolerance levels regarding indoor (thermal) environmental conditions.

According to these assumptions, the idea is that building users with a high energy awareness level (Type I and II respectively) have a tendency to perform adaptive actions, such as adapting their clothing, to reach their thermally-preferred indoor conditions. Whereas, building users with a low level of awareness in terms of their energy consumption (Type III and IV respectively) tend to change the heating or cooling setpoint to enhance their thermal comfort.

Furthermore, the building user types differentiate in terms of tolerance levels of the indoor (thermal) comfort condition. Users with a low tolerance level (Type II and IV respectively) tend to change their thermal condition more likely as users with a high tolerance level (Type I and III respectively). The levels of tolerance are expressed according to functions that are based on the concept of Predicted Mean Vote (PMV) (Fanger, 1970; Regnath, 2021). Figure 1 illustrates the defined functions for high and low tolerance levels and the respective formulae are shown in Equations (1) and (2). Moreover, the occupants' operation of shading elements is assumed to depend on the energy awareness level and the contextual conditions.

To further evaluate the impact of the various occupant types, four scenarios with different compositions of occupant types are considered (see Figure 2). Thereby, Scenarios II and III consist of a combination of different occupant types. Scenario I solely includes high energy aware occupants with a high tolerance level, Scenario IV exclusively considers low energy aware occupants with a low tolerance level.

Table 1: Assumptions of occupant types (Regnath et al., 2022).

	Energy awareness	Tolerance level
Type I	high	high
Type II	high	low
Type III	low	high
Type IV	low	low

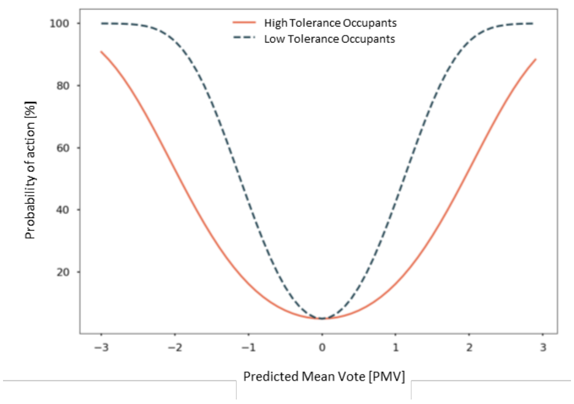

Figure 1: Assumed PMV functions corresponding to occupants' high and low tolerance levels regarding thermal conditions (Regnath et al., 2022).

$$\mathit{High\ Tolerance\ Occupant}\ [\%] = 100 - 95 * exp^{(-0.03353*PMV^4 - 0.2179*PMV^2)*0.5} \quad (1)$$

$$\mathit{Low\ Tolerance\ Occupant}\ [\%] = 100 - 95 * exp^{(-0.03353*PMV^4 - 0.2179*PMV^2)*2} \quad (2)$$

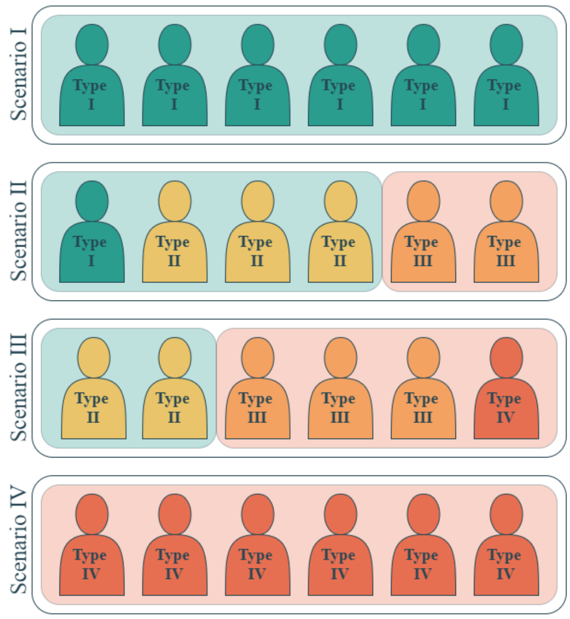

Figure 2: Four scenarios with a mix of different occupant types (Regnath et al., 2022).

Case study building

The influence of the assumed occupant type scenarios on the energy performance is simulated for six single-occupancy offices in a case study building, located in Vienna, Austria. Figure 3 illustrates the office spaces that have a total floor area of 72m^2. The respective building elements are assumed to meet the minimum requirements of the national building norm (OIB-Richtlinie 6, 2019). An overview of the case study building assumptions with regard to geometry as well as construction is given in Table 2. Note that each window is operable and equipped with an internal shading element.

In order to establish a basis for comparison, a first "Base Case (BC)" simulation of the case study building is performed using fixed pre-defined schedules. Thereby, a metabolic rate of 1.0 (corresponding to seated office work) as well as a standard heating and cooling system (HVAC Ideal Loads Air System) is assumed (see Regnath, 2021 for further information).

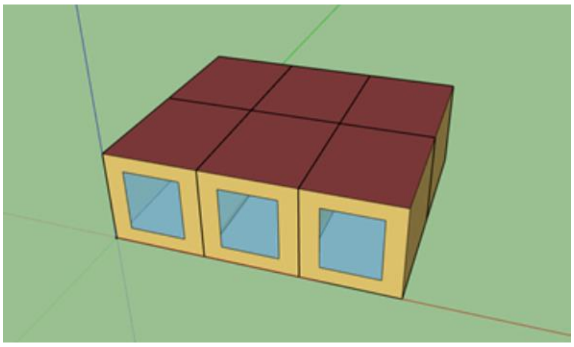

Figure 3: Case study building model (Regnath et al., 2022).

Table 2: Case study building assumptions. (A_w: zone window area; A_{zone}: zone floor area; V_g: gross volume; WWR: window to wall ratio; U-values of roof (U_{roof}), floor (U_{floor}), window (U_{window}), and external wall ($U_{ext. wall}$)) (Regnath et al., 2022).

	Variable	Unit	Value
Geometry	A_w	m^2	3.6
	A_{zone}	m^2	12
	V_g	m^3	216
	WWR	-	0.4
Construction	U_{roof}	W.m^{-2}.K^{-1}	0.15
	U_{floor}		0.11
	U_{window}		0.11
	$U_{ext. wall}$		0.20

Computational setup

As already referred to above, the well-known ABM application NetLogo (Wilensky, 2022) is used to generate the occupant behaviour model. The dynamic energy simulation is performed using the tool EnergyPlus (2022). Moreover, the BCVTB (Wetter et al., 2022) and Python language (2022) are used to couple the occupant behaviour model with the dynamic energy simulation model. A 30-min timestep duration is selected to perform the simulation in a reasonable degree of resolution. Furthermore, the simulations are performed for one illustrative week per season (i.e., in total a four-week period). Figure 4 shows the computational configuration and data exchange concept (the occupancy schedule referred to in this figure is based on Mahdavi et al., 2018). Thereby, EnergyPlus simulates the buildings' state at each timestep by considering energy consumption, temperature, illuminance, and PMV. Thereafter, the data is transferred via BCVTB and Python to NetLogo. The tool NetLogo then further simulates the respective occupant actions and gives this information via Python and BCVTB back to EnergyPlus. In the EnergyPlus environment, the updated indoor-environmental condition is simulated in the subsequent timestep.

Within this data exchange process, a decision-making routine is included in the occupant behaviour model. In this routine, a number of different possible actions that could be performed by an agent to enhance thermal discomfort at each timestep are defined and listed in the following:

- Revoke the preceding action that might have led to a thermal discomfortable condition
- Change the clothing
- Change the heating or cooling setpoint
- Open or close the window

Depending on the building user type, the likeliness to perform certain actions changes. Moreover, a limited range for certain actions is assumed (e.g., the clothing value is limited between 0.6 and 1.4.). Figure 5 shows such an illustrative decision-making routine for building users with a low energy awareness (i.e., Type III and IV) that perceive the indoor-environmental conditions as too hot. In this graph, the likeliness to perform a specific action is included. As in this example, the low energy-aware agent has a tendency to first change the heating or cooling setpoint (70%), before opening the window (20%) or changing the clothing (10%). In contrast to that, a high energy-aware agent has a higher likeliness to first change the clothing (70%), before opening the window (20%) or changing the heating or cooling setpoint (10%). Considering the probabilistic character of building users' actions, a set of multiple simulation runs is performed per each scenario. The data analysis is conducted in Python (2022) and the results presented and discussed in the subsequent section show average values for each scenario.

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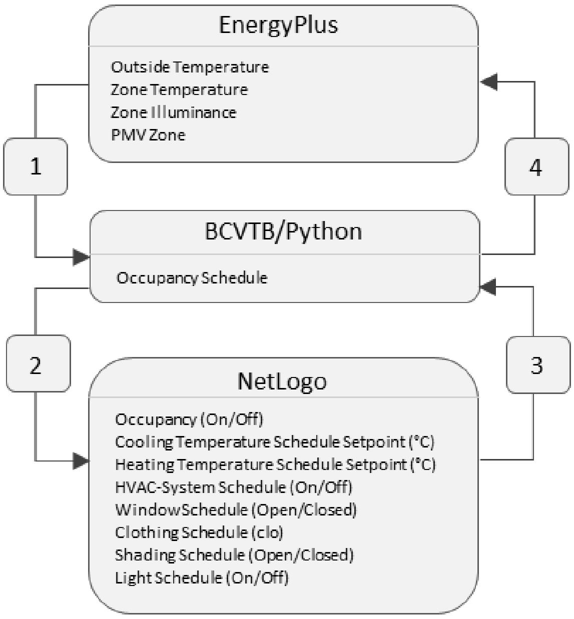

Figure 4: Diagram of the computational configuration and data exchange (Regnath et al., 2022).

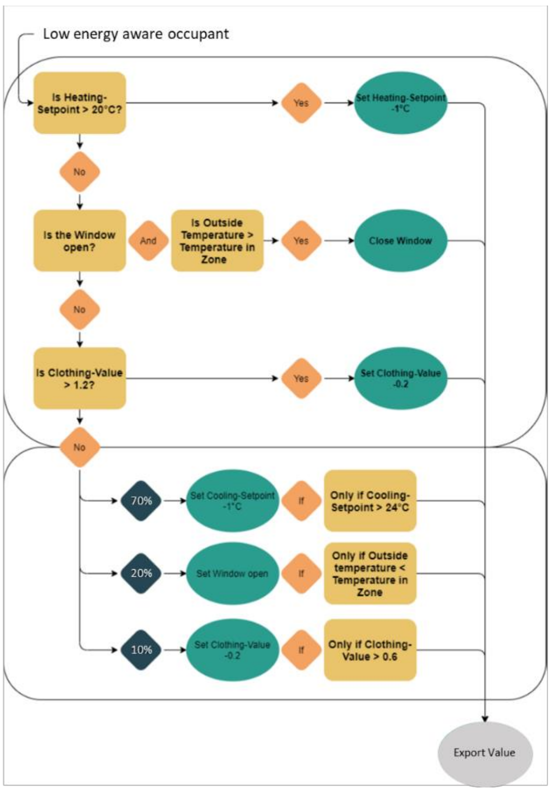

Figure 5: Illustrative decision graph for low energy aware users (Type III and IV) (Regnath et al., 2022).

Results and discussion

The simulation results (summarized in Figures 6 to 12, adopted from Regnath et al., 2022) display the impact of the occupants' energy consciousness level and their thermal comfort preferences on the computed energy use.

As expected, Figure 6 displays the tendency that actions performed by low energy aware occupants result in higher heating and cooling loads (note that this figure displays annual energy loads obtained based on extrapolation of the simulation results for the aforementioned four representative weeks). A similar trend can be seen in Figures 7 and 8 that show the hourly energy loads for each scenario in the spring season compared to the Base Case scenario.

However, the results also propose that the energy awareness level can impact and reduce the buildings' overall energy loads. For instance, Figure 9 illustrates the energy loads for each user type (in spring). The resulting median and distribution are influenced by the control actions performed by the occupants. The results of Type I and II (i.e., both high energy aware user types) show rather low medians whereas the results of Type III (i.e., low energy awareness, high tolerance level) denote the highest energy load. This might seem paradoxical at first sight; however, this can be explained by the reduced number of control (corrective) actions that result from the occupants' high tolerance level. This building user type might be oblivious to the fact that extremely low indoor thermal conditions are unfavourable in the summer season or extremely hot indoor thermal conditions in the winter season are unfavourable from an energy saving point of view.

Figures 10 to 12 denote a similar tendency by displaying the energy loads for each user type in the summer, autumn, and winter season.

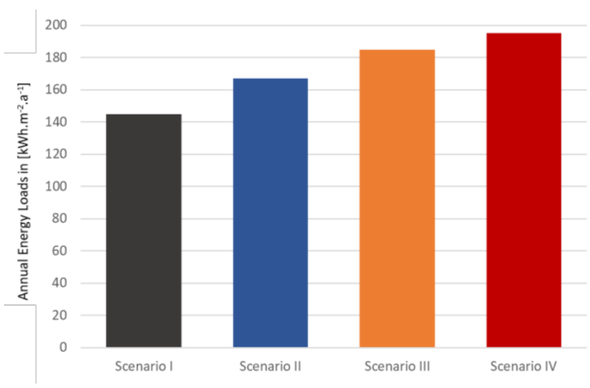

Figure 6: Annual energy load per scenario.

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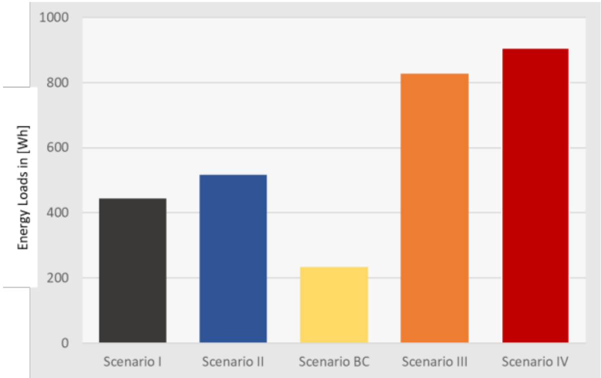

Figure 7: Total energy loads per scenario in spring.

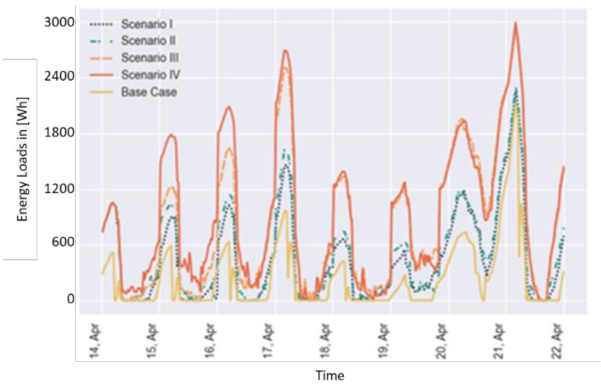

Figure 8: Hourly energy loads for the Base Case and the four scenarios in the course of a representative week in spring.

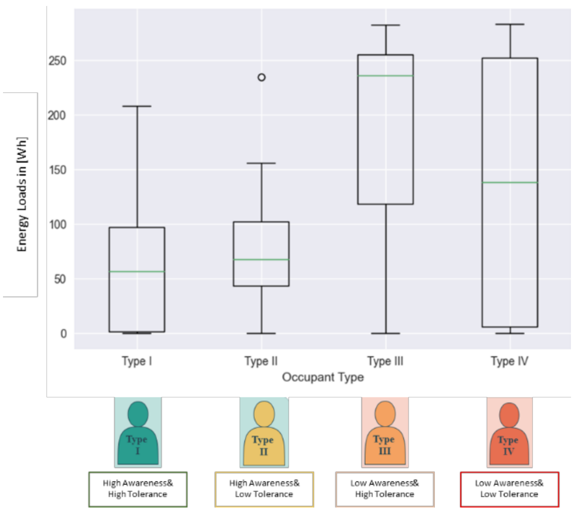

Figure 9: Distribution of energy loads (per single office during spring) occupied by different occupant types.

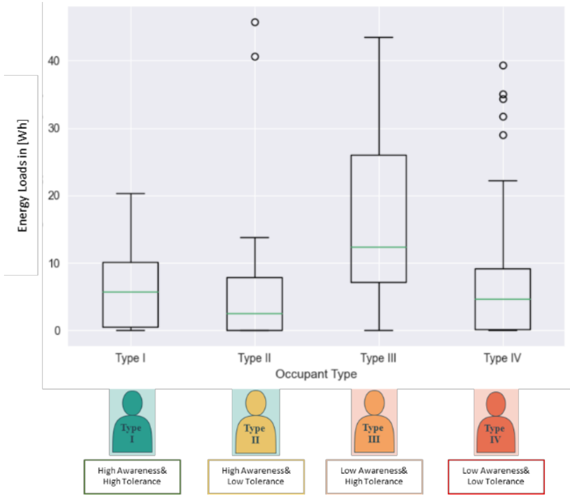

Figure 10: Distribution of energy loads (per single office during summer) occupied by different occupant types.

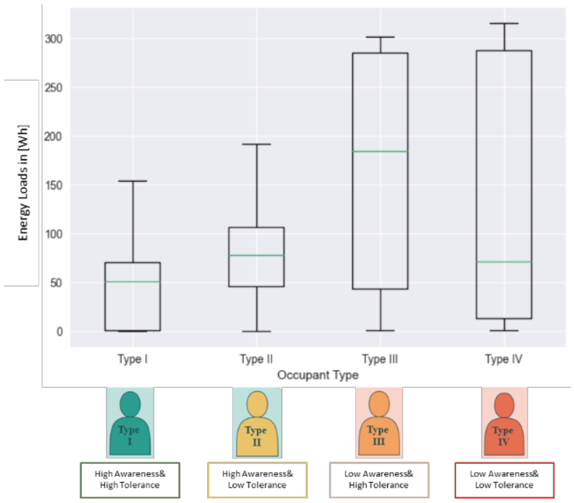

Figure 11: Distribution of energy loads (per single office during autumn) occupied by different occupant types.

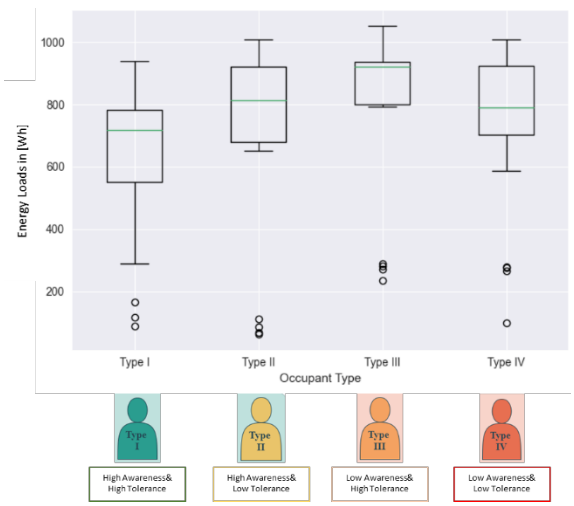

Figure 12: Distribution of energy loads (per single office during winter) occupied by different occupant types.

Conclusion

As mentioned at the outset of this contribution, there has been a recent increase in efforts to develop more detailed models of building users in building performance simulation applications. Specifically, the potential of high-resolution occupant models via ABM deployment has been highlighted in a number of recent and ongoing research and development efforts. The simple case study discussed in this paper facilitates the discussion of two basic classes of related challenges.

The first class of challenges are of a more technical nature. ABM requires considerable computational resources. The implementation entailed in the case study faced major difficulties in the process of co-simulation. As such, setting up a co-simulation framework in the field of building performance simulation is still far from a seamless process. Execution of co-simulation and data exchange management procedures cannot rely on well-rounded off-the-shelve environments and require thus considerable programming expertise. Data input, model specification, and the processing and visualization of results still require the application of non-standardized measures and techniques.

Last but not least, current co-simulation solutions are also not especially efficient in view of data handling and simulation duration. However, it can be reasonably expected that many of the predominantly technical challenges will be addressed and resolved in the near future, assuming the interest in ABM-based strategies in building performance simulation will be sustained into the future. Experiences in other building-related fields where ABM is widely used (e.g., building security, evacuation modelling, fire safety) appear to confirm this optimism. Moreover, ongoing efforts in development of occupant-centric ontologies (Mahdavi et al., 2021) are expected to support the implementation of more robust and comprehensive ABM applications.

The affairs concerning a second class of challenges may be, however, more complex. This class pertains to the actual content of the occupant representations in ABM. These representations require a considerable range of detailed data concerning occupants' attributes and behavioural tendencies. The illustrative case study discussed in the present paper clearly underlines a number of related problems. In the case study, the significant diversity of real populations was radically reduced to just a few high-level types.

The utility of ABM arguably lies in its theoretical potential to represent building users at the individual level. However, such high-resolution information is rarely available. In many cases, rather coarse demographic information is broken down into group or individual patterns not based on empirically obtained attribute distributions, but based on the appearance of plausibility. In other words, whereas ABM, as a formalism, offers the theoretical possibility of highly individualized representations of occupants, the possibility is either not used or used without firm empirical underpinnings (Mahdavi, 2021). There are other limitations in the case study that exemplify a number of further challenges. The behaviour of real individuals may change over time due to multiple reasons (e.g., health-related issues, learning processes, economic pressures). These dynamic circumstances are difficult to capture due to reasons related to both technical complexity and lack of empirical data. Last but not least, the case study was carried out based on the assumption of agents in single-occupancy settings. Again, a key theoretical strength of ABM lies in the capacity to model agents' interactions and how they lead to emergent behaviour. ABM applications in some of the other, previously mentioned, building domains such as fire safety have been probably more successful given the fact that behavioural rules in such specific situations could be perhaps more readily formulated and tested.

Note the preceding observations regarding the limitations of the current state of ABM applications are not meant to discourage efforts in this area. Rather, they are meant to contribute to the clarification of discourse. There are many application scenarios of building performance simulation that could be soundly pursued with simplified occupant representations. But there are also scenarios where detailed occupant models in general and ABM in particular may be appropriate and useful. However, the pursuit of these latter scenarios via a purely formalistic ABM (i.e., one that is not based on detailed empirical data) is unlikely to result in more expressive and reliable results.

Acknowledgement

In the writing of this paper, the authors benefited from participation and related discussions in the IEA EBC Annex 79 activities.

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