The impact of occupants' energy awareness and thermal preferences on buildings' performance

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Abstract. Recent research efforts in building performance simulation increasingly focus on the representation of people's behaviour (specifically, their interactions with buildings' control systems). In this context, the use of agent-based modelling (ABM) is suggested to be a promising approach, as it can capture, in principle, the complexity and dynamics of the patterns of individual occupants' presence and behaviour in buildings. The present contribution describes a related effort, whereby an agent-based model (generated using the NetLogo application) was coupled with a dynamic building simulation model to examine the impact of occupants' energy-related behaviour on buildings' energy performance. To this end, four user types were defined in the agent-based modelling environment. These occupant types were assumed to correspond to different energy awareness levels as well as different tolerance levels with regard to indoor-environmental conditions that are deemed to be desirable. The behavioural model is linked to the dynamic energy simulation tool EnergyPlus via co-simulation using the Building Control Virtual Test Bed tool and Python programming language. A case study object (specifically, six single-occupancy office spaces in an office building) was selected to simulate the impact of different occupant types on the building energy performance. The simulation results suggest that the awareness level of occupants regarding energy conservation issues can have significant influence on the computed energy performance of the case study building. Moreover, occupants' level of tolerance regarding deviations of indoor-environmental conditions from "optimal" settings, was likewise shown to influence energy use. Finally, the case study highlights existing usability challenges concerning co-simulation processes involving both ABM and performance simulation.

Keywords. Occupant behaviour, agent-based modelling, indoor environment.
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1. Introduction

A number of past and ongoing research contributions address occupants' behaviour representation in building simulation tools [1-5]. Specifically, much focus has been recently laid on understanding occupants' interaction with buildings' control systems and other building occupants. In this context, different occupant modelling approaches and techniques have been considered [6,7]. Thereby, the agent-based modelling (ABM) approach is proposed to be a promising approach, as it can capture, in principle, the complexity and dynamics of the patterns of individual occupants' presence and behaviour in buildings [8,9]. Within a recent review effort, several ABM research efforts were systematically analysed and discussed [10]. This effort highlighted the potential of ABM to provide a flexible way of representing the dynamic and complex behaviour of occupants' presence and behaviour in buildings. However, a number of limitations and challenges were identified in the reviewed ABM studies.

One main limitation pertains to co-simulation challenges, when coupling a behavioural (agent-based) model with a dynamic energy simulation model. The issue is of relevance to the present contribution, as it involves the coupling of an agent-based model (generated using the NetLogo application) with a building simulation model. Thereby, the main objective is to explore the implications of occupants' energy awareness and thermal preferences for occupants' behaviour in buildings and how this influences buildings' energy performance. Toward this end, a case study building (including six single-occupancy office spaces in an office building) was selected to simulate the impact of different occupant-related configurations on the building energy performance. The paper presents and discusses the simulation results.

2. Research method

2.1 Case study building

In order to simulate the influence of building users' behaviour on the energy performance, a case study building that is assumed to be located in Vienna (Austria) is selected. The building includes six single-occupied office spaces and comprises a total floor area of 72 m^2 (see Figure 1). Each office space has an operable window with a window to wall ratio of 0.4. The building components are defined in a way to meet the minimum requirements of the Austrian building guideline (OIB Guideline 6 [11]). Table 1 gives an overview of the case study building assumptions, including geometry-related variables (A_w: zone window area; A_{zone}: zone floor area; V_g: gross volume) and construction-related variables (U-values of roof (U_{roof}), floor (U_{floor}), window (U_{window}), and external wall ($U_{ext.wall}$)). Each window is equipped with an internal shading system.

2.2 Occupant behaviour

As alluded to before, the main focus of this research effort is to explore the impact of occupants' energy awareness and thermal preferences on buildings' energy performance. In this context, four different occupant types were defined (see Table 2). The defined occupant types differ in terms of two different levels of energy awareness (low/high) and two different tolerance levels with regard to indoor-environmental conditions (low/high). The assumption is that occupants, who have a higher level of awareness concerning their energy consumption (i.e., Type I and II), tend to carry out a number of adaptive actions (as for example changing their clothing) to enhance their thermal comfort. In contrast, occupants who are less energy-conscious (i.e., Type III and IV), are assumed to be more likely to adapt the heating or cooling setpoint to maintain their preferred thermal condition.

Moreover, the occupant types are assumed to differ in view of their thermally relevant levels of tolerance. As such, occupants with a low tolerance level (i.e., Type II and IV) are more likely to change their indoor-environmental conditions to reach an optimal thermal comfort condition as compared to occupants with a high tolerance level (i.e., Type I and III). The tolerance levels assumed in the model are defined in terms of a function that is based on the PMV (Predicted Mean Vote) concept by Fanger [13]. Figure 2 shows the assumed PMV functions for high and low tolerance levels (in percentage). The respective formulae are given in equation (1) (high tolerance level) and equation (2) (low tolerance level).

Furthermore, it was assumed that the occupant operates the shading elements depending on the level of their energy awareness as well as the contextual circumstances (for additional details see [12]).

$$PMV = 100 - 95 \cdot exp^{(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2) \cdot 0.5} \quad (1)$$

$$PMV = 100 - 95 \cdot exp^{(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2) \cdot 2} \quad (2)$$

In order to explore the influence of different occupant types, four scenarios including a composition of varying occupant types were defined. Figure 3 shows the composition of these four scenarios. Whereas Scenario I exclusively consists of high energy awareness occupants with a high tolerance level, Scenario IV includes only low energy awareness occupants with a low tolerance level. Scenarios II and III include a mix of different occupant types.

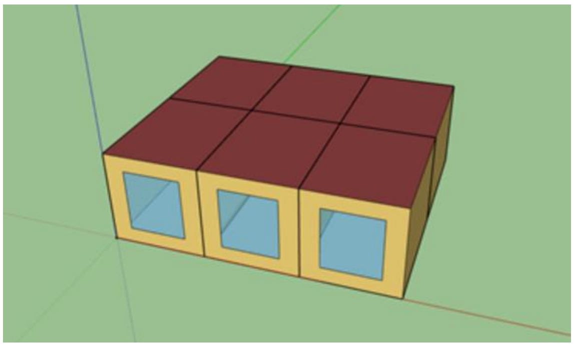

Fig. 1 – Building model in SketchUp [12].

Tab. 1 – Case study building assumptions.

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

Tab. 2 – Occupant type assumptions.

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

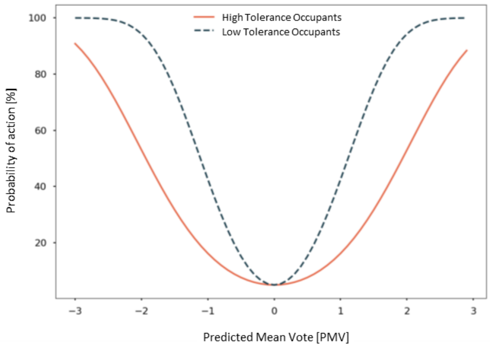

Fig. 2 – Assumed PMV functions corresponding to occupants' high and low thermal tolerance levels regarding thermal conditions [12].

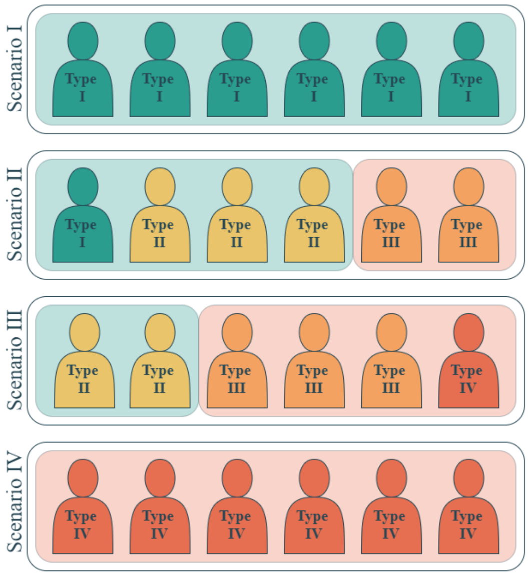

Fig. 3 – Four scenarios with different compositions of occupant types [12].

2.3 Computational configuration

The occupant behaviour model is generated in NetLogo [14], whereas the thermal model is generated in the energy simulation application EnergyPlus [15]. In order to couple the dynamic energy simulation model with the occupant behaviour model, the BCVTB (Building Control Virtual Test Bed) and the Python language were used [16,17]. To obtain the simulation results in a reasonable degree of resolution, the time step duration was set to 30 minutes. Simulations were conducted for a period of four weeks (one representative week per season).

The diagram of the computational configuration and data information exchange is shown in Figure 4. The data exchange process is as follows. At each time step, EnergyPlus simulates the buildings' state (including energy consumption, temperature, illuminance, PMV). The simulated data is communicated via BCVTB and Python to NetLogo. As such, BCVTB is used as a link between NetLogo and EnergyPlus. NetLogo further simulates the building users' actions and communicates this information back to EnergyPlus via Python and BCVTB. EnergyPlus simulates, for the subsequent time step, the updated environmental condition.

Note that a decision-making routine is included in the agent-based model. Thereby, the agent decides, depending on the indoor-environmental condition and the related agents' preferences and tolerance levels, which action will be performed at each time step in order to achieve thermal comfort. In this model, the following possible set of actions is included: *i)* reverse previous action that could have caused thermal discomfort (i.e., close opened window), *ii)* opening or closing the window, *iii)* changing the clothing, and *iv)* changing the heating or cooling setpoint. The likeliness to perform a certain action depends on the user type. Furthermore, limitations for each action are defined (i.e., clothing value limits between 0.6 and 1.4).

An illustrative example of a decision graph is given in Figure 5. This graph depicts a decision routine that pertains to an occupant with a low energy awareness level (i.e., Type III and IV) who perceives the thermal conditions as too warm. As such, the graph shows the relative likelihood of opting for one of these options (alternative control actions) in case of the specific occupant. As alluded to before, the decision routines vary among the different occupant types. Specifically, the likelihood to perform an action is dependent on the energy awareness level of the individual occupants. For instance, a low energy aware occupant (see Figure 5) has a higher likelihood to first change the heating/cooling setpoint (70%) before opening the window (20%) or changing the clothing (10%). Whereas a high energy aware occupant has a higher likeliness to first adapt the clothing (70%) before opening the window (20%) or changing the heating/cooling setpoint (10%).

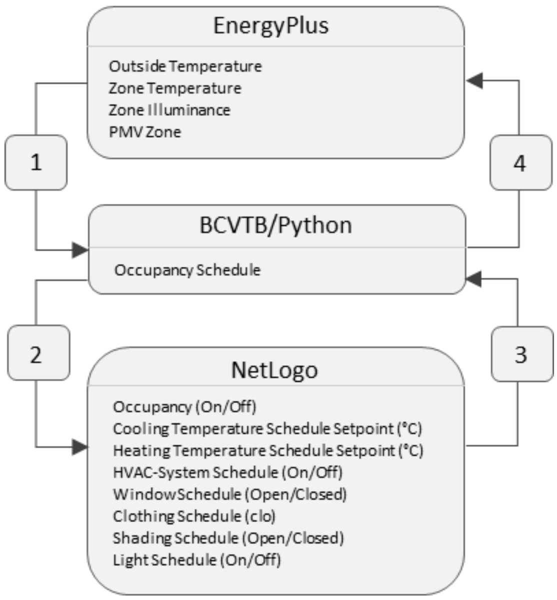

Fig. 4 – Diagram of the computational configuration and data exchange [12].

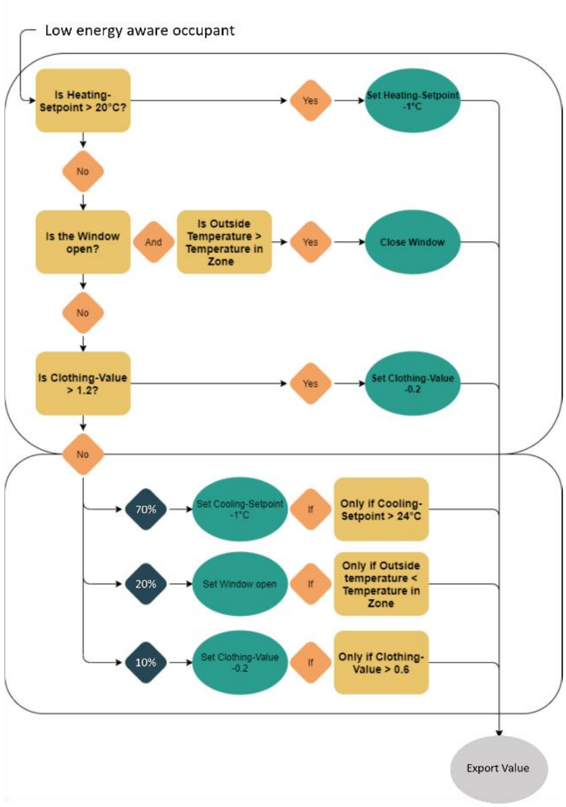

Fig. 5 – Illustrative decision graph for low energy aware users (Type III and IV) [12].

Given the probabilistic aspect of the study, multiple simulation runs were conducted for each scenario. As such, the results illustrated in the following section represent average values over each scenario. The data analysis was performed using Python [17].

3. Results and discussion

The results display, in principle, the significant impact of assumptions regarding occupants' attitudes and behaviour on the buildings' energy loads. Specifically, actions of occupants with low energy awareness result, as it could be expected, in higher heating and cooling loads (see Figure 6). A similar tendency is visible also in Figure 7 and 8, which depicts mean energy loads per scenario (for spring season) in comparison to the Base Case (BC).

The results also suggest that occupants' energy awareness level can contribute to reducing the buildings' overall energy consumption. The results displayed in Figure 9 show the mean energy loads per each occupant type (for the spring season). Note that both the median and the distribution of the results are influenced by the occupants' behaviour. The medians of Type I and II occupants are relatively low. The highest mean energy load corresponds to Type III, which denotes low energy awareness and high tolerance level. This result may appear paradoxical at first but can be explained due to the reduced number of corrective actions resulting from this occupant type's high tolerance level. For instance, an occupant of this type may be oblivious to the fact that very low indoor temperatures in the summer (or very high indoor temperatures in winter) time are detrimental from the energy saving view. A similar trend can be seen in Figures 10 to 12 illustrating the mean energy loads per each occupant type in summer, autumn, and winter.

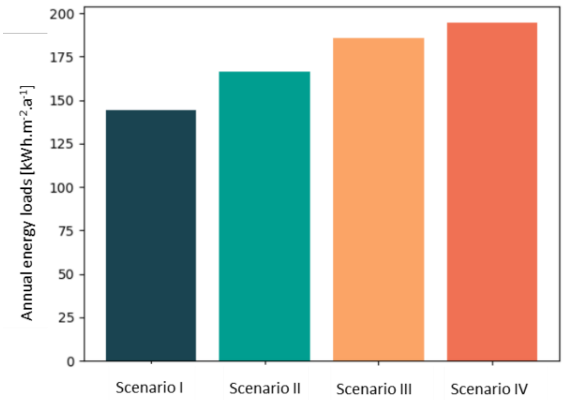

Fig. 6 – Annual energy load per scenario [12].

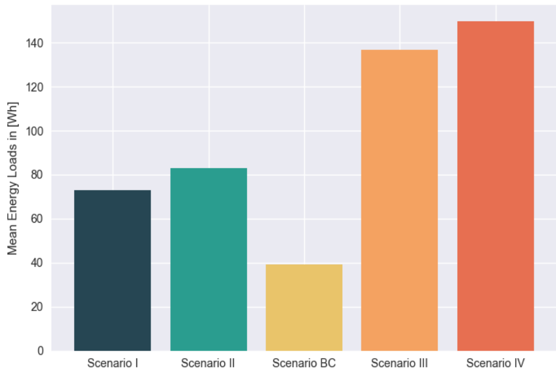

Fig. 7 – Mean energy loads per scenario in spring [12].

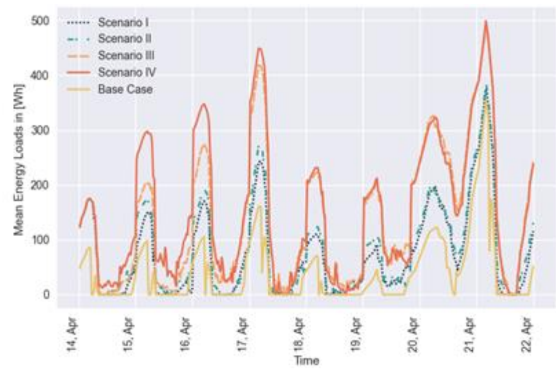

Fig. 8 – Mean energy loads for the Base Case and the four scenarios in spring [12].

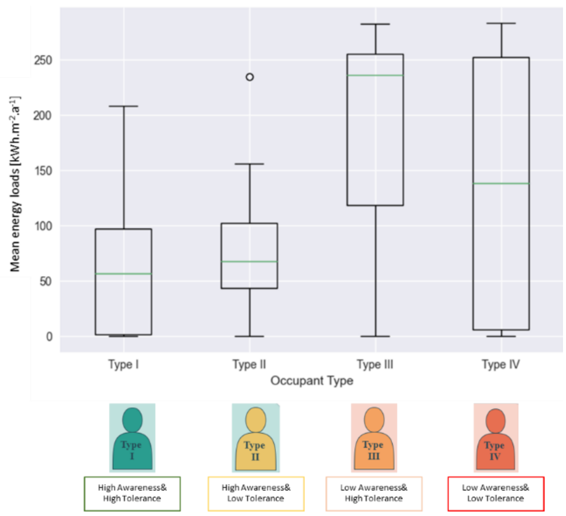

Fig. 9 – Mean energy loads per each occupant type in spring [12].

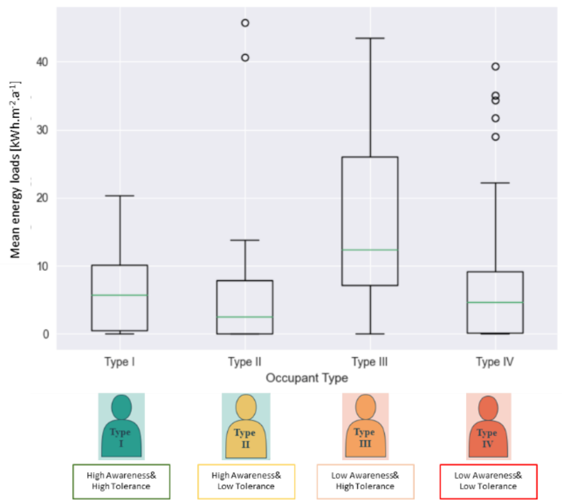

Fig. 10 – Mean energy loads per each occupant type in summer [12].

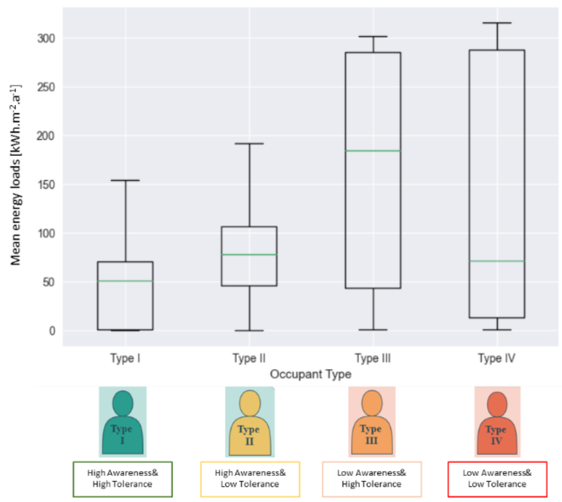

Fig. 11 – Mean energy loads per each occupant type in autumn [12].

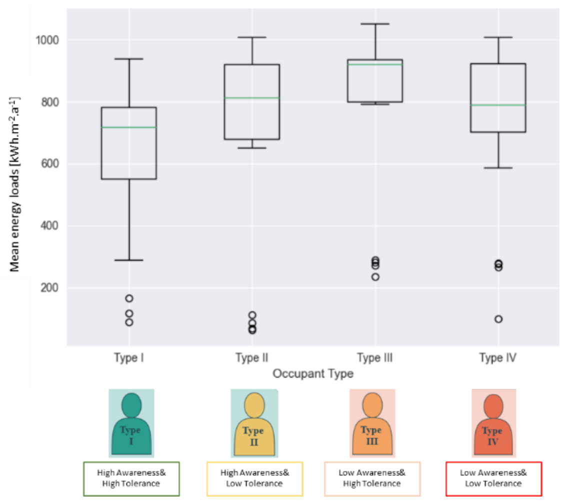

Fig. 12 – Mean energy loads per each occupant type in winter [12].

4. Concluding remarks and future outlook

The study presented in this paper represents an effort to illustrate the potential of ABM integration in energy simulation in order to better capture occupants' attitudes and behaviour. Thereby, several limitations must be acknowledged. For instance, the case study included only single-occupied office spaces. Hence, interactions among multiple occupants, whose modelling could benefit from ABM capabilities, were not taken into consideration. Likewise, the study considered only a limited number of actions that occupants could perform. Future studies could not only address multiple building types and locations, but also include a richer repertoire of occupant types (and associated preferences and behavioural tendencies). It is also important to mention that the ABM implementation presented in this paper, could not be tested against empirical information. As such, the authors would not suggest that the deployed model was validated.

Despite the above limitations, the study presented in this contribution clearly highlights the considerable relevance and importance of occupant-related model assumptions in building performance simulation. The results suggest that computational estimates of buildings' energy consumption are considerably influenced by assumptions pertaining the attitudes (e.g., energy awareness level) or habitual preferences (e.g., thermal conditions in indoor spaces). Specifically, occupants' level of tolerance regarding deviations of indoor-environmental settings from "optimal" thermal conditions could be shown to significantly influence buildings' energy performance.

Aside from the study's main topical concern, a concluding remark regarding the existing usability challenges in ABM applications must be mentioned. These challenges pertain specifically to the necessary co-simulation processes involving both agent-based modeling and building performance simulation. The currently existing complexity of establishing a co-simulation between ABM tools (in this case, NetLogo) and the performance simulation tool (in this case EnergyPlus) requires a considerable level of programming knowledge, which arguably inhibits a broad-scale usage. Advances in this area (including applications for efficient generation and operation of co-simulation environments) could facilitate a richer representational stance regarding the nature and diversity of building occupants' needs, expectations, and actions. As such, a broader understanding of occupants' impact on buildings cannot only facilitate more reliable predictions of building energy use and environmental emissions, but can also contribute to improving occupants' comfort, health, and well-being in the built environment.

5. Acknowledgement

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6. References

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