Consideration of Inhabitants' Diversity in Building Performance Simulation: Does It Matter?

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Abstract

Buildings' energy and indoor environmental performance is influenced by people's presence, activities, and actions. Hence, building performance simulation needs to include representations of occupants and their interactions with buildings. Many efforts were undertaken to integrate occupants' presence and behaviour models in building performance simulation tools. However, uncertainty associated with occupancy-related assumptions remains a key challenge in building performance simulation. In this context, a major source of uncertainty is related to the inter-individual differences (diversity) in inhabitants' patterns of presence and actions. In the present contribution, we explore the degree to which the consideration of diversity can affect the results of standard simulation-based building performance queries.

Introduction

The interest for integration of occupancy-related behavioural models in building simulation is steadily increasing (Mahdavi 2011). This is explained, in part, by the recognition of inhabitants' influence on buildings' energy use (Shipworth 2013, Andersen et al. 2007). In contrast, the share of building envelope in buildings' overall energy is rather decreasing, given buildings shells' continuous thermal quality improvement (Santin et al. 2009). Recently, many efforts have been undertaken to integrate occupants' presence and behaviour models in building performance simulation. Typically, representation of inhabitants in building performance simulations relies on libraries of standardized schedules. These profiles are derived from long-term monitored data from different building types. However, such models do not properly represent the highly dynamic nature of inhabitants' control-oriented actions (Yan et al. 2015). More recently, there have been efforts to develop more realistic – typically probabilistic – models of building occupants' presence and control actions (e.g. see Andersen et al. 2013; Rijal et al. 2007; Borgeson and Brager 2008; Page et al. 2008; Schweiker et al. 2011). However, uncertainty associated with occupancy-related assumptions remains a key challenge in building performance simulation (Mahdavi et al. 2016, Mahdavi and Tahmasebi 2016, Tahmasebi and Mahdavi 2016a and 2016b; Wang et al. 2016).

In this context, the research community has been making efforts to study the existence and level of the inter-individual differences (diversity) in inhabitants' patterns of presence and actions in buildings, as a potential major source of the uncertainty (e.g. Mahdavi and Tahmasebi 2015; O'Brien et al. 2016). Inhabitants have different sensitivities and preferences regarding comfort condition and may respond differently to the same environmental condition.

It has been argued that inter-individual differences between occupants must be addressed in respective behavioural models. Multiple factors have been suggested to constitute the grounds for this diversity, including physiological, psychological, and social (e.g., cultural) parameters (e.g. see Liao and Chang 2002, Peffer et al. 2011). Arguably, the representation of inhabitants' presence and behavioural diversity is insufficiently reflected in existing models. Hence, multiple research efforts are undertaken internationally to advance the sophistication of occupancy-related models in view of the diversity issue. Thereby, a central question pertains to the implications of inclusion or exclusion of diversity aspects in building performance simulation.

Accordingly, in the present contribution, we explore the degree to which the consideration of diversity can affect the results of standard simulation-based building performance queries. Toward this end, an existing office building is selected as a case study of inter-occupant diversity in building performance simulation. Thereby, we focus on diversity as relevant to inhabitants': *i)* presence patterns; *ii)* operation of windows for natural ventilation.

Approach

Case study

For the purpose of the present study, an existing office space is selected in a university building (TU Wien) in Vienna, Austria. The office area includes an open space with multiple workstations and a single-occupancy closed office. The occupants include academic and administrative staff. Figure 1 provides a schematic plan of the office. We focus here on seven workstations marked on Figure 1 (i.e., P1 to P7). Each of the selected occupants have access to a manually operable casement window (i.e. W1 to W7).

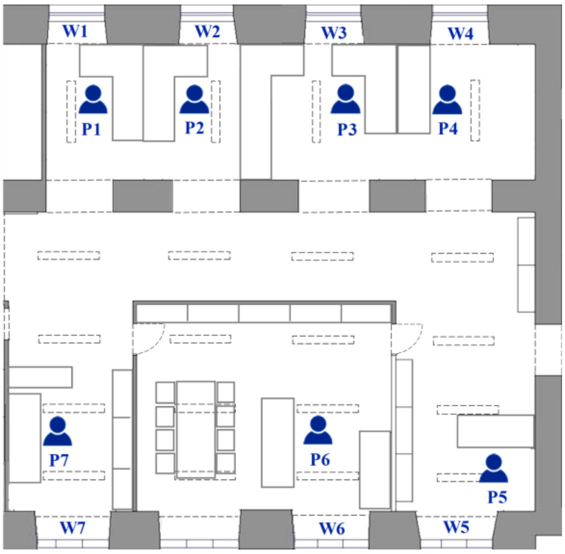

Figure 1: Schematic illustration of the office space.

Monitored data

This office is equipped with a monitoring infrastructure and a number of variables are monitored on a continuous basis, including, users' presence, indoor air temperature, relative humidity, carbon dioxide concentration, plug loads, state of the lights as well as state of the windows (open/close). Moreover, for a detailed recording of the outdoor conditions a weather station is also installed in close proximity of the building.

Simulation model

The office area was modelled in the building energy simulation tool EnergyPlus 8.6 (EnergyPlus 2016). The appropriate office model was generated and fed with the required input data (e.g., construction details and associated thermal properties, internal loads, HVAC system, weather data). The office building is naturally ventilated and uses a hydronic heating system in the cold season. In the model, the heating period (from September 26 to April 21) and free-running period (from April 22 to September 25) were set based on monitored data from the year 2013. For the simulation of the heating season, the ASHRAE 90.1 HVAC schedule with a heating set point of 20°C was incorporated in the model.

Modelling approaches

To investigate the importance of inter-occupant diversity in building performance simulation, we focus on diversity as relevant to:

- inhabitants' presence patterns
- operation of windows for natural ventilation.

Moreover, we consider, for each of these two items, two different modelling approaches:

- A conventional approach involves the use of fixed schedules (or diversity profiles) in case of presence patterns and the use of simple rules in case of window operation.
- A more detailed approach, which involves the use of stochastic modelling techniques.

Given the modelled processes (occupancy, window operation) and the modelling techniques (schedule or rule-based versus stochastic), the eight fundamental scenarios of Table 1 emerge. Note that this Table also includes a scenario involving simulation results based on observed presence and window operation data. A more extend description of these scenarios is as follows:

1. Fixed aggregated profiles using available standard occupancy schedules and rule-based window operation (without diversity representation, i.e. identical profiles for different occupants and identical rules for the operation of the windows);
2. Fixed observation-based average profiles of occupancy and rule-based window operation as described above (see 1);
3. Fixed observation-based individual profiles of each occupant and rule-based window operation (diverse profiles for different occupants, but identical rules for the operation of the windows);
4. Fixed observation-based individual profiles of each occupant together with individual rule-based window operations (diverse profiles for different occupants and diverse rules for the operation of the windows);

2*. Random daily observation-based average profiles of occupancy together with stochastic window operation model using scenario 2 as input;

3*. Random daily observation-based individual profiles of each occupant together with stochastic window operation model using scenario 3 as input;

4*. Random daily observation-based individual profiles of each occupant together with diversified-stochastic window operation model using scenario 4 as input;

5. Original year-long observational data for each occupant and window. This model is the benchmark having the highest resolution.

For the modelling scenario 1, we used ASHRAE 90.1 diversity profiles for office buildings (Figure 2), which offers weekday, Saturday, and Sunday schedules for occupancy as an example of typical input data when the actual schedules are not known (ASHRAE 2013). Moreover, for window operation control ASHRAE Standard 55 adaptive comfort model was used. In this case the windows are assumed to be open if the zone temperature is out of the 90% acceptability limits (i.e. comfort temperature ±3.5 K) of the adaptive comfort in ASHRAE Standard 55. Moreover, venting availability schedule were also added to the office model which allowed window operation only for the occupied hours.

Table 1: Modelling scenarios with regard to occupancy and window operation

Scenario	Presence patterns	Operation of windows
1	ASHRAE 90.1 Fixed	Fixed
2	Observed Average-Fixed	Fixed
3	Observed Diverse-Fixed	Fixed
4	Observed Diverse-Fixed	Diverse-Fixed
2*	Observed Average-Randomized	Randomized
3*	Observed Diverse-Randomized	Randomized
4*	Observed Diverse-Randomized	Diverse-Randomized
5	Observed original	Observed original

To generate observation-based occupancy profiles, we used one-year 15-min interval data on occupancy, obtained from the building monitoring infrastructure. For modelling scenario 2, the observational data on occupants' presence were averaged across all occupants. The resulting year-long data set for an average occupant was then processed to obtain a set of average profiles of presence probability for weekdays, Saturday, and Sundays (Figure 3). The resulting average schedules were assigned to all occupants, neglecting the diversity among occupants. Note that the rule-based window operation in scenario 2 was the same as defined in scenario 1.

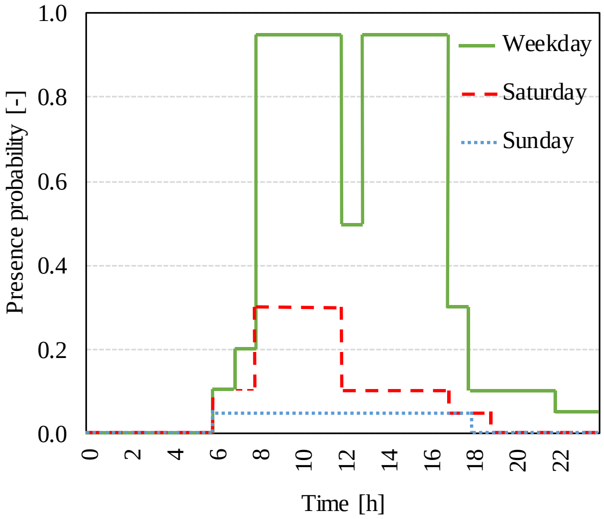

Figure 2: ASHRAE 90.1 profiles for weekday, Saturday, and Sunday occupancy, used in scenario 1.

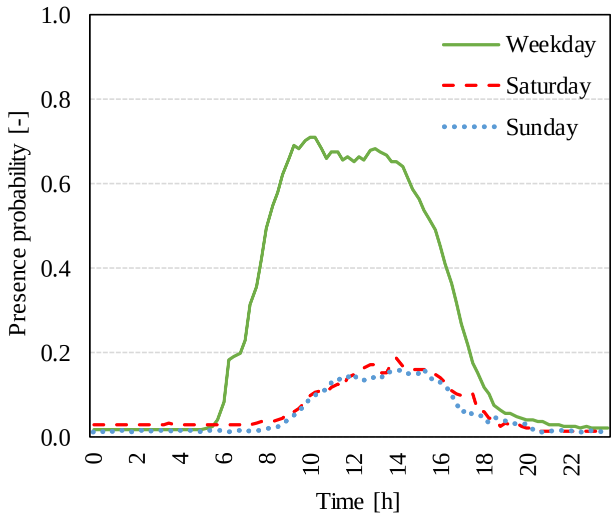

Figure 3: Observed average profiles for weekday, Saturday, and Sunday occupancy, used in scenario 2.

In order to consider occupants' diversity in modelling scenario 3, fixed observation-based individual diversity profiles are generated for each individual occupant separately. Figure 4 illustrates the observed individual occupancy profiles for weekday, Saturday and Sunday. The window operation in scenario 3 was modelled with identical rules for the operation of different windows, as defined in scenario 1 and 2.

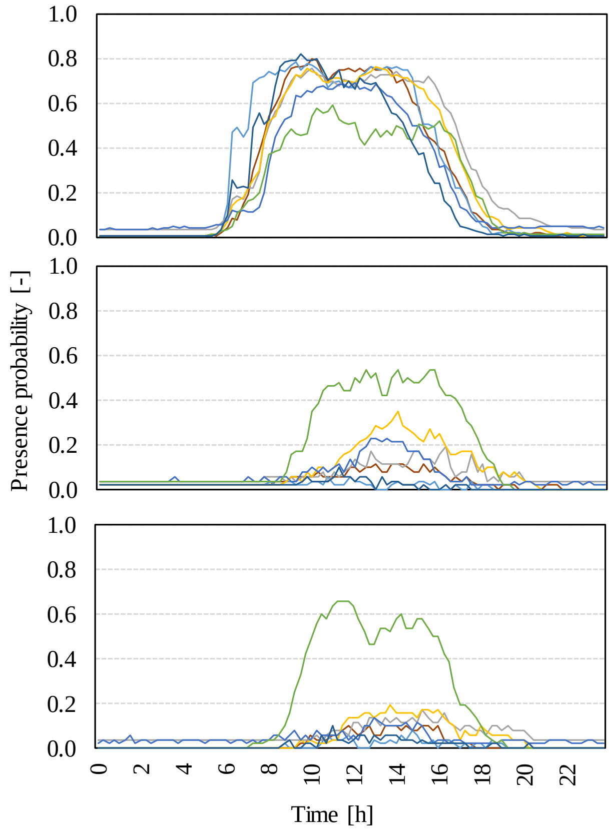

Figure 4: Observed individual diversity profiles for weekday (top), Saturday (middle), and Sunday (bottom) occupancy used in scenario 3 and 4.

For representation of the diversity in window opening actions, in scenario 4 window operation rule was diversified. As mentioned before, each of the seven occupants have access to one manually operable casement window. Basically seven individual window operation rules were defined with respect to different zone temperature acceptability limits among different occupants. Thereby, acceptability ranges around the comfort temperature was assumed to vary amongst individual occupants from ±2K to ±5K in steps of 0.5K.

In order to probabilistically represent the occupants' presence and window operation action in scenarios 2*, 3*, and 4*, we used previously published stochastic occupancy and window operation models. These models return random nonrepeating daily profiles of occupancy states and window operations. For the probabilistic representation of the occupants' presence, we used stochastic occupancy model developed by Page et al. (2008). This model uses as input a profile of presence probability and parameter of mobility and returns random non-repeating daily profiles of occupancy states (present or not present). In order to generate random profiles of occupancy states for scenario 2*, 3*, and 4*, the fixed occupancy profiles of scenario 2, 3, and 4 were used as input for the stochastic model, respectively.

For probabilistic representation of the window operation actions in scenario 2*, 3*, and 4*, a stochastic window operation model developed by Rijal et al. (2007) was deployed. This model estimates the probability of opening and closing windows based on outdoor and operative temperature, when operative temperature is outside a dead-band (Comfort temperature ± 2°C). In the current study, the original dead-band of the model was modified as follow:

- Model 2* and 3*: Comfort temperature ± 3.5°C
- Model 4*: Different dead-band values of comfort temperature varying from ±2 K to ±5 K assigned to different inhabitants.

Moreover, to better account for the local circumstances, the model was modified in the sense that windows were assumed to be closed when the office was not occupied. The profiles for the applicable fractions of installed lighting and equipment were defined according to each modelling scenarios. Specifically, for modelling scenario 1, the weekday, Saturday, and Sunday schedules for lighting together with plug loads of ASHRAE 90.1 were used. In modelling scenario 2, fixed observed average, and in scenarios 3, and 4 fixed observed individual lighting and plug load schedules were used. For probabilistic models (scenarios 2*, 3*, and 4*) lighting and plug loads were defined proportional to the occupancy profiles.

Implications of the occupants' presence and window opening behaviour

To study the implications of the occupants' presence and window opening behaviour for building performance simulation results, we considered different building performance indicators in heating and free-running periods. Considering the heating period two basic building performance indicators, namely annual heating demands per unit floor area and peak heating loads per unit floor area were computed. For the free-running period, the indoor temperature distribution was considered. Performance indicators in different models were compared to the benchmark, i.e. scenario 5.

Results and discussions

Annual heating demand predictions

Figure 5 illustrates the annual heating demand obtained from different scenarios. In comparison with the benchmark, i.e. scenario 5, model 1 (representing ASHRAE 90.1 standard occupancy profile together with rule-based window operation model) considerably underestimates the annual heating demand. In models 2, 3, and 4, observation-based occupancy profiles together with rule-based window operation were used. These three models provide good approximations of the annual heating demand as given by the benchmark. However, the consideration of diversity in scenarios 3 (occupancy) and 4 (occupancy and window operation) does not appear to have a noticeable impact. The same trend can be seen from the results of stochastic models 2*, 3*, and 4*, in which diversification did not noticeably affect the outcomes. Note that the use of stochastic models as such provided slightly better estimations of annual heating demand.

The annual heating demand simulation results can be further explained via consideration of mean (annual) internal heat gains (in $kWh.m^{-2}$) (Table 2). The overestimation of these gains in case of scenario 1 explains the corresponding considerably lower annual heating demand as compared to the other scenarios and benchmark. Likewise, we explored the indoor-outdoor temperature difference during intervals when windows were assumed to be open. As data in Table 2 suggests, for probabilistic models (scenarios 2*, 3*, and 4*) the prevailing indoor-outdoor temperature difference happened to be closer to the benchmark as compared to the non-probabilistic models in scenarios 2, 3, and 4.

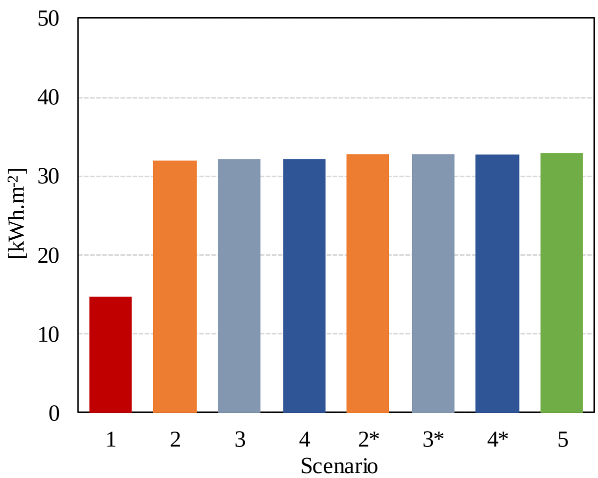

Figure 5: The annual heating demands.

Table 2: Mean (annual) internal heat gains as well as mean indoor-outdoor temperature differences during the periods when windows were assumed to be open

Scenario	Internal heat gains [kWh.m^{-2}]	Mean indoor-outdoor temperature differences (θ_{in}-θ_{out}) for open window state intervals [K]
1	62.2	4.9
2	11.9	2.3
3	11.9	2.5
4	11.9	3.0
2*	10.5	3.6
3*	10.4	3.6
4*	10.4	4.0
5	12.0	4.6

Peak heating demand predictions

A number of observations can be made based on the peak heating demand values provided in Table 3 and Figure 6:

First, as it could be expected, use of real data (in case of non-probabilistic scenarios 2, 3, and 4) yields results that are closer to the benchmark values (scenario 5) than those based on the standard schedule (scenario 1). Note that, similar to the case of the annual heating demand, the standard-based scenario also underestimates the peak heating load.

Second, consideration of diversity in representing the occupants does not appear to improve the predictive performance of the models. As such, the results of scenarios 3 and 4 are practically identical with those of scenario 2. Likewise, consideration of diversity in the case of probabilistic models (scenarios 3* and 4*) did not bring the results any closer to the benchmark values.

Third, in the present case, both the probabilistic and non-probabilistic models provide reasonable predictions of peak heating loads with regard to either the magnitude or the time of occurrence.

Table 3: Magnitude and time of peak heating demand

Scenario	Peak heating demand [W.m^{-2}]	Time of peak
1	80.9	28. Jan. 06:15
2	88.2	28. Jan. 06:15
3	88.2	28. Jan. 06:15
4	88.2	28. Jan. 06:15
2*	89.0	28. Jan. 06:15
3*	87.8	28. Jan. 06:15
4*	87.8	28. Jan. 06:15
5	89.6	28. Jan. 06:15

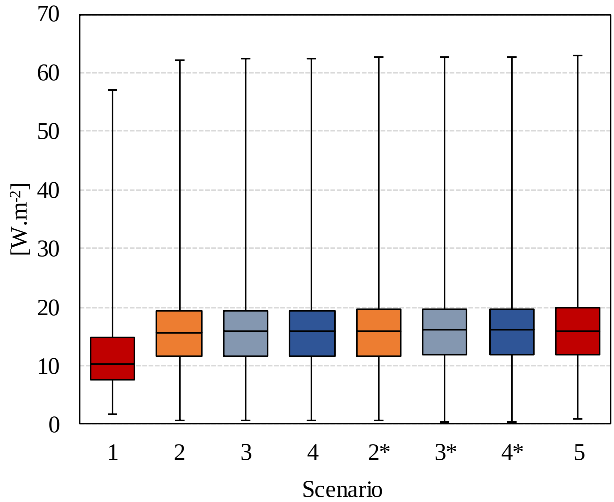

Figure 6: Box plot of hourly heating demand for all scenarios.

Free-running season assessment

Figures 7 and 8 demonstrate the cumulative distribution and box plot of the indoor temperature in the free-running mode. Consistent with the previously discussed results, scenario 1 involves, as compared to the benchmark, an overestimation of indoor temperatures due to assumed higher internal gains. Inclusion of diversity appears to improve the performance of both probabilistic and non-probabilistic methods in this case, but only insignificantly. Note that also in the case of predicted indoor temperatures, the deployment of stochastic models does not lead to an overall improvement of the results. As such, the difference between the predictions based on the two approaches (probabilistic and non-probabilistic) is rather small.

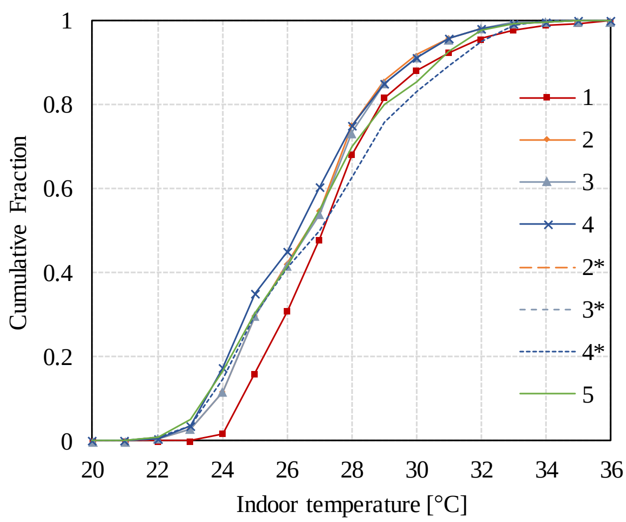

Figure 7: Cumulative distribution of indoor temperature in the free-running mode.

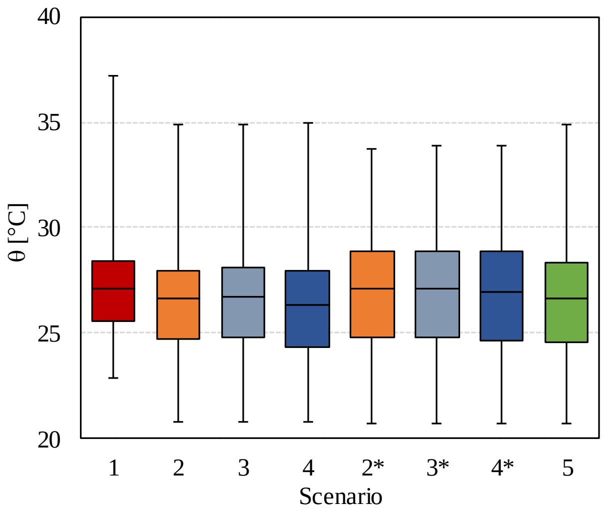

Figure 8: Box plot of indoor temperature in the free-running mode.

Conclusion

We conducted a study to address the implications of inclusion or exclusion of inter-occupant diversity aspects in building performance simulation. An existing office building was selected as a related case study. We dealt with diversity as relevant to inhabitants' presence patterns and operation of windows for natural ventilation. Given the modelled processes (occupancy, window operation) and the modelling techniques (diversified versus non-diversified, stochastic versus non-stochastic), eight scenarios were defined and the sensitivity of simulation results to the occupancy-related input assumptions were systematically assessed. Basic building performance indicators were considered addressing both heating and free-running periods. These were annual and peak heating demand per floor area for the heating period and indoor temperature for the free-running period.

The results did not reveal major changes in the predicted indicator values (annual and peak heating demands, indoor air temperatures) as a consequence of inclusion of diversity. This observation was made for both non-probabilistic and probabilistic modelling scenarios. Rather, availability of reliable basic information (as opposed to standard-based assumptions) appears to be more essential for the predictive performance of the models than both inclusions of diversity and deployment of probabilistic modelling techniques. However, reliable basic monitored information typically becomes available in the building operation phase. It rarely is available in the early stages of building design. Consequently, it can be argued that the primary role of occupancy-related standardized profiles and behavioural models may be the provision of clear and transparent information to the designer to explore if-then scenarios and to understand the ramifications of occupants' control-oriented behaviour via building performance simulation. Moreover, the clarity and transparency of the occupancy-related simulation assumptions makes it easier to interpret the simulation results.

Needless to say, the presented results represent only a snapshot in a highly complex research domain. Given the small range of available data as well as a rather limited representation of behavioural diversity, we do not intend to make any claims toward the general validity of the conclusions. Rather, it is clear to us that the above conclusions need to be further examined in future studies involving a much broader empirical data set, multiple locations, multiple building typologies, and a larger number of occupants. Nonetheless, the results do suggest that one needs to be careful with *a priori* claims concerning the critical importance of diversity inclusion in view of typical simulation-supported building performance queries. The credibility of such claims would require likewise large-scale cross-section validation studies.

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