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The deployment-dependence of occupancy-related models in building performance simulation

Ardeshir Mahdavi, Farhang Tahmasebi*

Department of Building Physics and Building Ecology, TU Wien, Karlsplatz 13, 1040 Vienna, Austria

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ABSTRACT

The relationship between the proper choice of occupancy-related models for building performance simulation and the pertinent purpose of the simulation-based query is not well understood. We thus address the necessary conditions for a better understanding of the context-dependence of occupancy-related model use in building performance simulation. First, given the multitude of application scenarios (involving different users, different phases of the building delivery process, different queries, etc.) in which building performance simulation can be deployed, we propose a conceptual framework in terms of a multi-dimensional simulation deployment space. To demonstrate the desirability and usability of such a framework, we provide two specific case studies, involving deployment instances of probabilistic and non-probabilistic occupancy models. One case study focuses on occupancy model deployment options in the context of simulation-based predictive building systems control. The second case study explores the implications of occupancy model selection in the context of simulation-based building design support.

1. Introduction

Performance simulation models can be generated with different levels of resolution with regard to the representation of the underlying (physical) phenomena, required (input) information, and produced results (output). Generally speaking, the choice of a specific level of resolution in these aspects is not independent of the types of queries, which the simulation model is expected to provide answers for. Most professionals are familiar with the query-dependence of modeling choices regarding representational methods of physical phenomena such as heat transfer. For example, it is generally understood that queries regarding buildings' dynamic behavior (e.g. their thermal inertia) cannot be supported using steady-state heat transfer models. However, such familiarity cannot be taken for granted in all aspects of model generation.

In this context, an important case in point pertains to possible choices in the type and resolution of representations of people's presence and behavior in building performance simulation models. The relationship between these choices and the purpose of the simulation-assisted analyses is not well understood. This, however, represents a practical problem, as it implies that adopted methods in capturing people's presence and behavior in a simulation process may in fact be inappropriate with regard to specific simulation use scenario at hand. Likewise, it can be argued that the criteria for the evaluation of the representational fidelity of people's presence and behavior in buildings are not independent of the types of the studies undertaken in the course of simulation tool deployment.

As such, there are a considerable number of scientific efforts toward quantifying the impact of occupants on building performance. For instance, Azar and Menassa [1] observed that energy models of office buildings' in different climatic zones in USA are highly sensitive to occupancy-related behavioral parameters. More specifically, Yang and Becerik-Gerber [2] showed that application of HVAC schedules that use observation-based personalized occupancy profiles in a three-story office building test bed could save up to 9% energy compared to the conventional (default) schedules. More recently, researchers have tried to classify and critically review different modeling approaches (see, for example, [3] with regard to presence models and [4], which addresses the adaptive occupant behaviors). General criteria for the evaluation of the fidelity and fitness of occupancy-related models were outlined as part of a recent review paper [5].

Many more instances of studies on occupants' behavior in buildings and respective modeling techniques could be mentioned. However, there are arguably very few studies that have explicitly addressed the fitness of occupancy-related models with regard to different simulation queries. Gupta and Mahdavi [6] first proposed

* Corresponding author.
E-mail address: farhang.tahmasebi@tuwien.ac.at (F. Tahmasebi).

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– in a different context – a perspective to view and structure the performance queries in terms of a multidimensional query space. The classification of the queries was intended to render them more suitable for analysis, resulting in enhanced responses through selection and execution of appropriate computational tools and techniques. Specific to the deployment of occupancy models, Hoes et al. [7] used sensitivity analysis to arrive at the minimal required user model resolution with regard to a number of building performance indicators and design parameters. That is, when for example a performance indicator is determined to be more sensitive to the occupancy-related assumptions, the simulation effort should start with a more sophisticated model of occupancy (and if the performance indicator still does not fall within the required target value range, a higher resolution level should be applied). However, the focus of the study is on the design stage and it does not involve empirical data to confirm the conjecture that using more sophisticated models would necessarily provide more accurate results.

Given this background, we must conclude that the relationship between the proper choice of occupancy-related input data models for building performance simulation and the pertinent purpose of the simulation-based query is still not well understood. Hence, the need for further explorations in this area was recognized, amongst other instances, by the IEA Annex 66 [8], an international forum working on the advancement of the state of the art in the area of occupancy-related model development and evaluation.

Specifically, the present contribution addresses the necessary conditions for a better understanding of the context-dependence of occupancy-related model use in building performance simulation. Given the multitude of scenarios (i.e., use cases involving different users, different phases of the building delivery process, different queries, etc.) in which building performance simulation can be deployed, a respective well-structured conceptual framework in terms of a multi-dimensional simulation deployment space is of utmost importance. Such a framework is not only a prerequisite for establishing a solid basis for the suitability evaluation of alternative modeling techniques and resolutions with regard to people's presence and behavior in buildings, but also contributes to substantiating the evaluation process of such modeling techniques.

To demonstrate and elaborate on the desirability and usability of such a framework, we provide two specific case studies, involving probabilistic and non-probabilistic occupancy models. One case study focuses on occupancy model deployment options in the context of simulation-based predictive building systems control. The second case study explores the implications of occupancy model selection in the context of simulation-based building design support.

Note that the purpose of these case studies is not to argue for the superiority of any specific modeling approaches, be those probabilistic or non-probabilistic. In our view, it is of fundamental importance that research in developing occupancy-related models is not hampered by a priori or arbitrary fixation on specific techniques or tools. Rather, our objective is to emphasize that models cannot be meaningfully evaluated without a backdrop of the deployment scenarios.

2. The conceptual space of simulation-based deployment scenarios

In order to discuss the relationship between performance simulation deployment scenarios and the corresponding occupancy-related models, a structured overview of the former is needed. As a possible vehicle for such a structured overview, a multi-dimensional simulation deployment space can be highly expedient (see [6], as an instance of early work in this area). The idea is to locate a specific simulation-based analysis activity concerning building design and operation in a conceptual space of all theoretically possible simulation deployment scenarios.

Table 1
Dimensions of the proposed simulation deployment space.

	Dimension	Remarks/examples
i	Phase in the building delivery process	Early design, detail design, HVAC systems design, building operation
ii	Purpose (or nature) of the study	Parametric study of design options, generation of energy compliance documents, HVAC system sizing, HVAC controls
iii	Domain (discipline)	Energy, thermal comfort, lighting, acoustics, fire safety
iv	Building type	Dominant function of the building (residential, commercial, educational, mixed use)
v	Indoor climate control strategy	Passive, hybrid (mixed mode), fully air-conditioned
vi	Physical destination	Building details, whole buildings, campus, district, urban
vii	Zonal destination (resolution)	Whole building, individual floors, orientations, micro-zoning
viii	Performance indicator (results)	Annual heating/cooling demand, peak heating/cooling loads, PMV
ix	Temporal resolution (horizon)	Entire life-cycle, annual, monthly, daily, hourly, sub-hourly

A first step toward establishing such a framework would be the specification of the multiple dimensions of such a simulation tool deployment scenarios. In the following, we briefly outline nine such dimensions (see Table 1) that may be considered to be directly relevant for the selection of appropriate occupancy-related models. These dimensions specifically address: (i) relevant phase in the building delivery process; (ii) purpose (or nature) of the simulation-based study; (iii) disciplinary domain of the study; (iv) building type; (v) indoor climate control approach; (vi) physical destination (object) of the study; (vii) zone-level destination of the study; (viii) relevant building performance indicator; (ix) relevant time-resolution (or time horizon) of performance results.

From a broader perspective that is not specifically targeted at occupancy-related models, further considerations pertaining to users' professional background, users' experience, and the client type may also play a role in the identification of desirable tool attributes with respect to various simulation use scenarios. For instance, the proper and robust use of any kind of an analysis tool requires that the user can cope with the complexity of the modeled phenomena. Proper compilation of model input data, correct selection of simulation settings, and sensible interpretation of the results are parts of that process. It is thus not unreasonable to require that in general the sophistication of modeling tools and processes are commensurate with the user's professional background. Moreover, depending on their experience, even users with similar backgrounds may still display very different levels of comprehension and skills regarding constructing building models and conducting simulation-based performance analyses. Finally, the addressees of the outcome of simulation studies have implications not only for the scope and resolution of the analyses, but also for the way they are processed and presented: The clients' concerns can thus influence the choices regarding the representation of internal processes in building modeling.

2.1. Phase in the building delivery process

A simulation-based study can be conducted at different stages of the building delivery process. The implications for occupancy-related model selection is evident, as the resolution of available information may constrain the meaningful deployment of highly complex representations of building occupants.

2.2. Purpose (or nature) of study

The purpose and scope of a simulation study have arguably implications for occupancy-related representations. Simulation-based assessment of code compliance or generation of benchmarking documents with regard to basic building fabric properties is typically conducted in the context of reference boundary conditions (external climate, internal processes). However, HVAC (heating, ventilating, air-conditioning) system sizing for as specific zone of a specific building may require a much higher resolution in depiction of use patterns.

2.3. Domain of application

The depth and kinds of people representation in simulation-based building performance studies obviously depend on the applicable technical domain. Simulation can support, amongst other things, energy performance assessment, thermal comfort studies, exploration of visual conditions, queries concerning building and room acoustics, and examination of fire safety requirements. However, the nature of occupants' influences (specifically, the scope of passive versus active impact) and the corresponding proper representational schemes can be very different in each domain.

2.4. Building type

Different functional destinations of buildings (residential, office, school, hospital, etc.) correspond to substantially different occupancy-related patterns. Some functional patterns (e.g., schools) may be more amenable to schedule-based representation of occupancy-related processes than others (e.g. residential buildings).

2.5. Indoor climate control strategy

From the deployed indoor climate strategy in a building inferences can be made to the degrees of freedom occupants have in interacting with building control devices. The scope of possible interactions is in a centrally controlled fully air-conditioned building much more limited than a free-running building with natural ventilation and manual shading opportunities. Hence, in the latter case, it may be more critical to include probabilistic behavioral models while simulating thermal performance.

2.6. Physical destination (object)

The targeted objects of Simulation studies may be very different in nature and extension. For instance, behavioral factors may be entirely irrelevant to certain technical simulation-aided investigations of heat transfer phenomena in thermal bridges or wind-driven rain's impact on building facades.

2.7. Zonal destination

Differences in alternative representations of occupancy-related phenomena may be more or less consequential depending on the zonal resolution of building performance simulation models. For instance, when modeling large thermal zones that accommodate multiple occupants, the deployment of probabilistic versus non-probabilistic representations of individual office users in a simulation model does not result in significant differences in the computed values of typical thermal performance indicators (such as heating and cooling loads).

2.8. Performance indicators

It could be plausibly argued that spatio-temporally aggregated performance indicators such as a building's annual total heating demand may be less prone to random occupancy-related fluctuations than those indicators with a more limited spatial and temporal scope (e.g., peak hourly cooling load of an office space). This in turn may have consequences for the proper selection of the occupancy model.

2.9. Temporal horizon

Consider inquiries pertaining to the entire life cycle of a building. In such a case, aggregated annual energy use data may be accumulated for time horizons consisting of multiple decades. Comparison of alternative design options in such a scenario need to rely on highly transparent representations of both external boundary conditions and internal (occupancy-dependent) processes. Hence, appropriate behavioral models for such a case need to be transparent and display consistency in repeated parametric deployment scenarios.

3. Two case studies

The proposed conceptual application space of building performance simulation does not of course answer as such specific questions about what type of occupancy-related model should be used for which type of application scenarios. But it provides a systematic framework for reflecting on such questions. To underline the relevance and importance of this point, and to facilitate the discussion of occupancy-related model adequacy in building performance simulation, we present in the following two illustrative case studies. Specifically, these case studies involve the use of probabilistic and non-probabilistic occupancy models in two very distinct simulation-aided building performance assessment scenarios. The first case study concerns simulation-based predictive building systems control. The simulation deployment pertains thus in this case to the building's operation phase and primarily addresses the problem of short-term predictions of people's presence in an office building. These predictions are then subsequently used to assess indoor conditions in view of overheating risk. The second study deals with the more common instance of simulation-aided annual energy use estimation in the building design phase.

To illustrate the situatedness of these two case studies within the previously discussed conceptual simulation deployment space, Table 2 provides a condensed description of the relevant attributes of each case study with respect to the aforementioned nine dimensions.

3.1. A comparison of occupancy models in the context of predictive building systems control

In a previous publication [9], we deployed three occupancy models to generate predictions of daily occupancy profiles using the past monitoring occupancy data obtained from a number of (individually monitored) workplaces in an office area. Two of these models, referred here to as RE [10] and PA [11] are probabilistic, whereas the third one (MT) is an original non-probabilistic model of occupants' presence [9].

Short-term predictions of occupancy patterns are critical in run-time use of simulation models in the building operation phase, as practiced in simulation-based predictive building systems control approaches [12–14]. Thereby, short-term predictions of

Table 2
Illustrative specification of the positions of the case studies (see text) within the proposed conceptual simulation deployment space.

	Dimension	Case study 1	Case study 2
i	Phase in the building delivery process	Operation phase	Design phase
ii	Purpose (or nature) of the study	Predictive simulation-based HVAC control	Parametric study of design options
iii	Domain (discipline)	Energy/Thermal comfort	Energy
iv	Building type	Office	
v	Indoor climate control strategy	Hybrid (Winter: conditioned, Summer: free-running)	Fully air-conditioned
vi	Physical destination	Whole-building	
vii	Zonal destination (resolution)	Multiple zones in a single floor	
viii	Performance indicator (results)	Overheating rate	Peak and annual heating and cooling demands
ix	Temporal resolution (horizon)	Daily	Annual

occupancy and weather are incorporated in the simulation model to predict the near-future performance of the building toward optimizing its operational regime (e.g., schedules of windows, luminaires, and blinds operation, or temperature set-points and dead bands for space heating and cooling). Thus, the level of achievable day-to-day agreement between the predicted and real occupancy profiles is of utmost importance. The main objective of the respective case study was to discern how well these three models performed toward predicting daily occupancy profiles for the aforementioned workplaces.

We used two separate data sets for model training and model evaluation. Once trained, the models were used to predict the daily occupancy profiles of eight workplaces in the aforementioned office for 90 working days. To evaluate the two probabilistic methods, multiple predictions were generated via a 100-run Monte Carlo execution. As the process of model comparison and evaluation in the occupancy domain has not been systematically codified, we decided to select and adopt a set of five statistics for this purpose. We suggest that these statistics can help quantifying the magnitude of the models' errors with regard to the following questions:

- What is the temporal distance between the predicted and actual time of the first arrival of an occupant in the office? (FA)
- What is the temporal distance between the predicted and actual time of the last departure of an occupant from the office? (LD)
- What is the difference between the predicted and actual total presence time (daily occupancy duration) – in a specific day – of an occupant in the office? (OD)
- What is the fraction of time during a standard working day for which the presence state of an office occupant is wrongly predicted (i.e., there is a mismatch between the predicted and actual state of occupancy)? (SM)
- How many times, during a standard working day, the occupancy state of an occupant changes from present to absent (or vice versa)? (NT)

The three models' (RE, PA, MT) predictions were compared with the corresponding monitored values. A summary of the results in terms of the above five error categories (FA, LD, OD, SM, and NT) are provided in Tables 3 and 4. Table 3 presents the 80th percentile of the errors. Table 4 shows the percentage of errors below five corresponding specific threshold values.

Table 3
The 80th percentile of the errors for three occupancy models (RE, PA, MT) used for short-term predictions.

Evaluation statistics	Models		
	RE	PA	MT
FA (h)	1.2	1.4	1.0
LD (h)	2.4	2.4	2.4
OD (h)	2.3	2.2	1.6
SM (–)	0.48	0.48	0.45
NT (–)	3.3	3.6	2.9

Table 4
Percentage of predictions with errors below specific thresholds for three occupancy models.

Evaluation statistics	Error threshold	Models		
		RE	PA	MT
FA	1 (h)	74.2	70.0	78.5
LD	1 (h)	46.9	46.7	46.0
OD	1 (h)	45.3	46.1	58.1
SM	0.4 (–)	46.8	48.9	61.0
NT	2.0 (–)	61.5	56.8	63.5

These results suggest that, with the exception of Last Departure errors, where all three models practically display the same performance, the MT model performs best. In other words, in this specific deployment scenario, stochastic models do not necessarily display a better short-term predictive performance. The following thought may throw light upon this circumstance: The probabilistic models aim to reflect the random diversity in the occupancy patterns. This could be highly important in applications (such as the design and sizing of building systems) where the consideration of diversity is critical. However, in the case at hand (short-term occupancy prediction based on historical data), the non-probabilistic model remains close to the overall tendency of the past occupancy patterns, yielding thus a better predictive performance.

3.2. A comparison of occupancy models in the context of simulation-based building design support

Typical energy performance simulation queries involve the computation of indicators such as the annual and peak heating and cooling demands of buildings. In the present case study, we investigated the implications of different occupancy modeling approaches for the results of such simulations. Toward this end, we selected an office space, for which long-term occupancy data is available. We generated a detailed simulation model of this office space and populated it with different occupancy data options as follows:

1a	Fixed diversity profiles for weekdays, Saturdays and Sundays, using ASHRAE 90.1 [15] schedules for office occupancy, lighting, and plug loads (Fig. 1)
1b	Random daily occupancy profiles, generated by a stochastic occupancy model [11] using Model 1a occupancy schedules as input, together with associated lighting and plug loads
2a	Fixed observation-based average diversity profiles of occupancy, lights, and equipment for weekdays, Saturdays, and Sundays (Fig. 2)
2b	Random daily occupancy profiles, generated by the stochastic occupancy model using Model 2a occupancy schedules as input, together with associated lighting and plug loads
3a	Fixed observation-based individual diversity profiles of each occupant and the associated lights and equipment for weekdays, Saturdays, and Sundays (Fig. 3)
3b	Random daily occupancy profiles, generated by the stochastic occupancy model using Model 3a occupancy schedules as input, together with associated lighting and plug loads
4	Original full-year empirical data for each occupant, light, and electrical equipment. This model has the highest resolution in terms of occupancy and acts as a reality benchmark as far as the actual occupancy circumstances are concerned

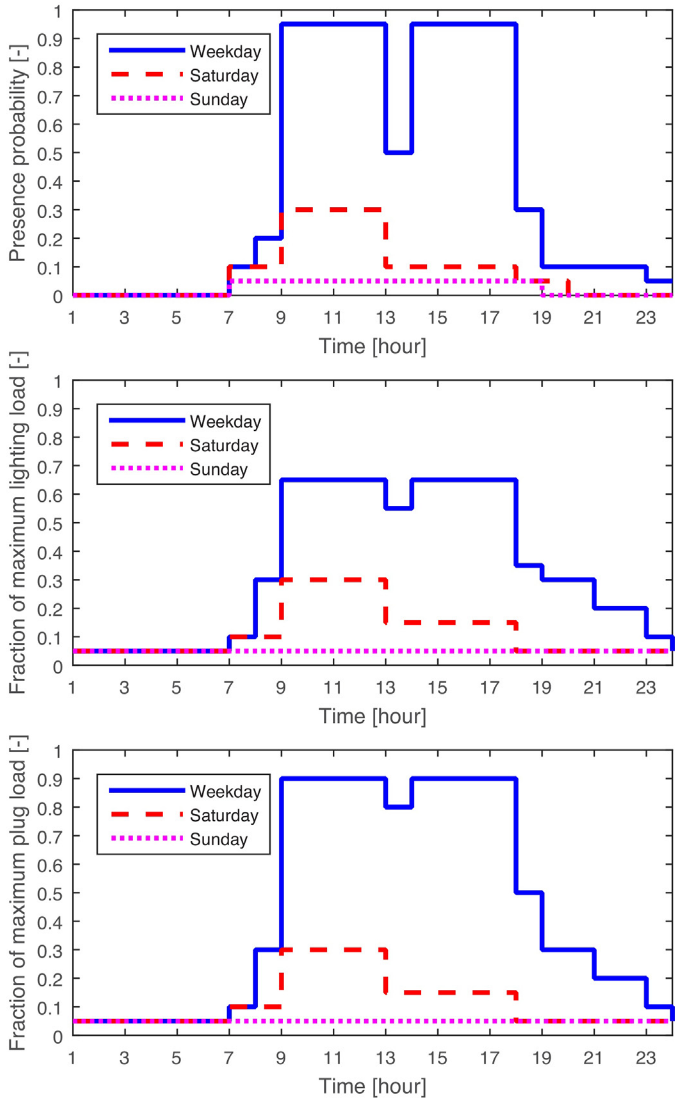

Fig. 1. Schedules for occupancy (top), lights (middle), and plug loads (bottom) according to ASHRAE 90.1.

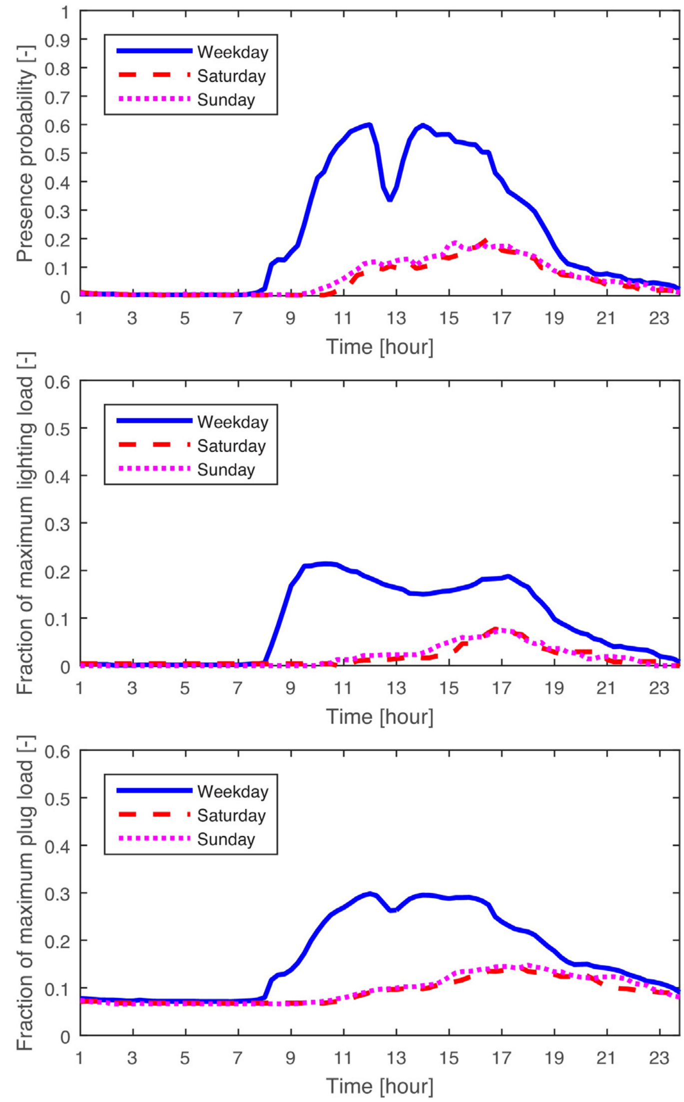

Fig. 2. Average empirical profiles for occupancy (top), lights (middle), and plug loads (bottom).

The information regarding the above options is summarized in Table 5 (see [16], for additional detailed information). Note that the randomization of the underlying average data in the applicable options (1b, 2b, and 3b) was conducted using the method described in [11].

Before exploring the implications of different occupancy modeling options for building performance simulation results, we briefly compared the occupancy model outputs to the actual occupancy levels (represented in Model 4). Toward this end, we examined, at the building level, the predicted fractions of maximum occupancy by each model throughout the year, which have been resulted from the incorporated fixed or random occupancy profiles.

To conduct a quantitative evaluation, we considered three statistics. Mean error and root mean squared error (RMSE) were used to track differences between the predicted and measured occupancy levels. In addition, to compare the distribution of predicted occupancy levels with the distribution of occupancy levels obtained from the reference case, we utilized the square root of Jensen–Shannon divergence (known as Jensen–Shannon distance). This metric is typically used to compute distances between two probability distributions [17].

Fig. 4 shows the cumulative distribution of occupancy levels in the modeled building (expressed as the percentage of maximum occupancy) obtained from modeling scenarios 1a, 1b, 3a, 3b, and 4. Note that Model 4, which is based on the original full year occupancy data, serves as our benchmark. Table 6 gives the mean error, RMSD, and Jensen–Shannon distance values, obtained via contrasting occupancy results of models 1a, 1b, 2a, 2b, 3a, and 3b with that of Model 4 (the reference case).

Table 7 provides the obtained values for annual and peak heating and cooling demands per conditioned floor area from the simulation models. As mentioned before, in case of Models 1b, 2b, and 3b (Table 5) the stochastic occupancy model must be executed 365 times to obtain each occupant's random daily presence profiles for annual simulations. However, the random nature of daily occupancy patterns implies that slight differences could emerge, if the process would be repeated. Consequently, the obtained values of performance indicators could be also at least slightly different, if such annual simulations would be repeated multiple times. To address this concern, we conducted a full-fledged Monte Carlo model execution involving 500 runs for each model. The resulting variations in the values of the performance indicators (annual and peak heating and cooling loads) were, however, very small. Thus,

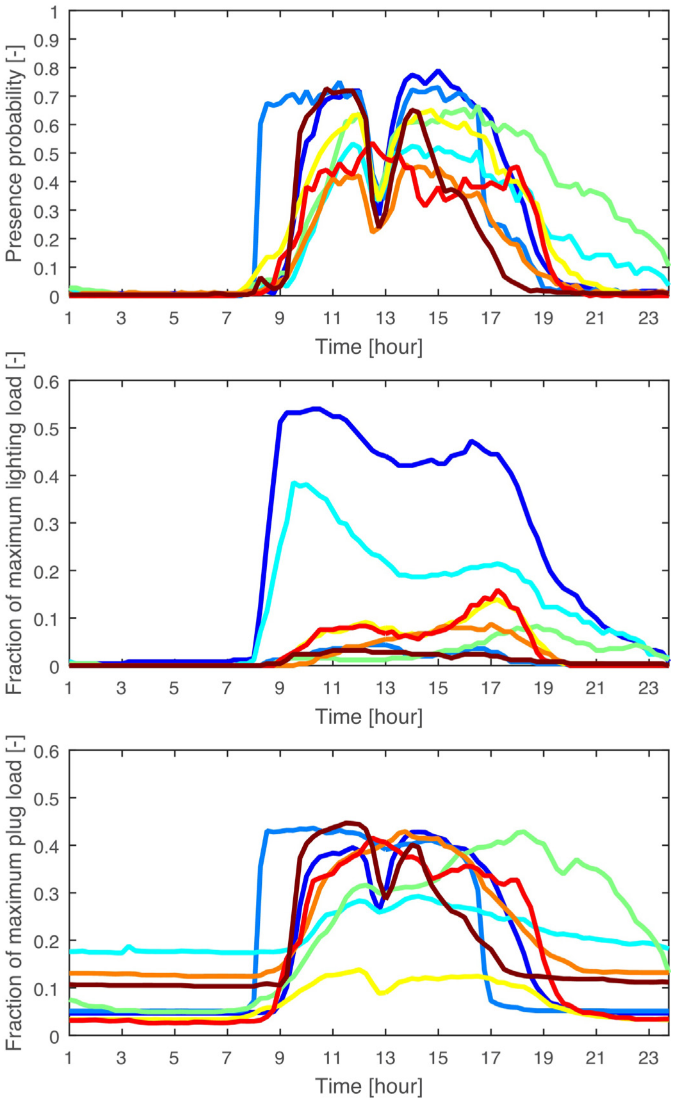

Fig. 3. A sample of individual empirical profiles for weekday occupancy (top), lights (middle), and plug loads (bottom).

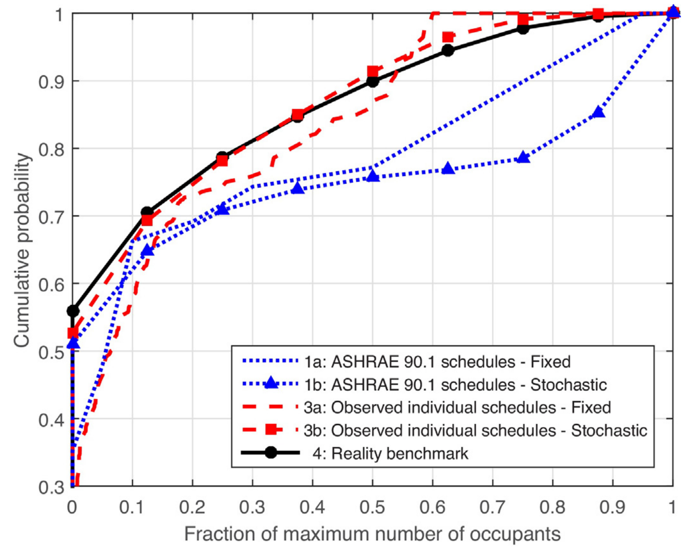

Fig. 4. Cumulative distribution of occupancy level in the modeled building, obtained from different occupancy modeling scenarios.

these slight undulations of the performance indicator results due to repeated annual simulations do not influence the credibility of our results and their interpretation. Nonetheless, to explicitly clarify this point, Table 7 includes, for Models 1b, 2b, and 3b both the mean values and the standard deviations resulting from the 500-run Monte Carlo analysis. Figs. 5 and 6 illustrate the cumulative distribution of heating and cooling demand values for Models 1a, 1b, 3a, 3b, and 4.

A careful examination of the result facilitates the formulation of a number of observations. Firstly, as illustrated in Fig. 4 and considering the values for square root of Jensen–Shannon divergence in Table 6, the distribution of probabilistic predictions of occupancy levels represents a closer approximation of the actual occupancy level distribution. As such, this advantage could be of importance in cases involving, for instance, occupant-driven control actions. However, in the present case (e.g., estimation of aggregated – i.e. annual – performance indicators such as cooling and heating loads), this advantage does not necessarily translate into a better predictive performance (see Table 7).

Second, the divergence of the simulation results of different models is not necessarily due to the nature of occupancy models (i.e., probabilistic versus non-probabilistic). Options 1a and 1b yield fairly comparable results, as do options 2a and 2b, and options 3a and 3b. Rather, the significant difference is between generic (standard-based) assumptions (options 1a, 1b) and assumptions that rely on actual occupancy information (2a, 2b, 3a, 3b, 4). In the present case, standard-based assumptions (options 1a and 1b) obviously overestimate the actual occupancy (see mean error values in Table 6), resulting in systematically lower heating loads (see Fig. 5) and systematically higher cooling loads (see Fig. 6).

The results of this case study have further implications. Randomization of occupancy patterns can reduce the distance between the predicted and actual distributions of occupancy levels. However, randomization of presence profiles per se does not guarantee that simulation results pertaining to typical performance

Table 5
Key characteristics of the generated simulation models with regard to occupancy.

Models	Occupancy representation	Lighting and plug loads
1a	ASHRAE 90.1 profiles – fixed	ASHRAE 90.1 profiles – fixed
1b	ASHRAE 90.1 profiles – randomized	Proportional to occupancy profiles
2a	Average empirical profile – fixed	Average empirical profile – fixed
2b	Average empirical profile – randomized	Proportional to occupancy profiles
3a	Individual empirical profiles – fixed	Individual empirical profiles – fixed
3b	Individual empirical profiles – randomized	Proportional to occupancy profiles
4	Original full-year empirical data	Original full-year empirical data

Table 6
Mean Error, RMSE, and Jensen-Shannon distance values for models 1a to 3b (compared with model 4).

Models	Mean error (%)	RMSE (%)	Square root of Jensen–Shannon divergence (–)
1a	11.7	27.9	0.36
1b	11.9	29.5	0.26
2a	0.0	15.6	0.19
2b	0.0	20.7	0.04
3a	0.0	15.6	0.19
3b	0.0	19.9	0.05

Table 7
Annual and peak heating and cooling demands per conditioned floor area obtained from simulations.

Models	Annual heating demand (kWh/m^2)	Annual cooling demand (kWh/m^2)	Peak heating demand (W/m^2)	Peak cooling demand (W/m^2)
1a	65.9	18.5	49.4	39.4
1b	67.0 ± 0.06	17.9 ± 0.05	49.4 ± 0.61	39.6 ± 0.30
2a	79.9	9.7	58.5	30.0
2b	78.2 ± 0.05	10.6 ± 0.03	58.1 ± 0.43	31.8 ± 0.73
3a	79.5	9.9	58.6	30.2
3b	78.4 ± 0.09	10.5 ± 0.06	58.7 ± 0.36	32.0 ± 1.14
4	78.2	9.4	57.1	27.9

indicators (e.g., annual and peak heating and cooling demands) are closer to reality than simulations based on non-probabilistic occupancy assumptions. Thus, to achieve high-fidelity simulation results (particularly with regard to basic performance indicators such as annual heating and cooling demands), it is more important to possess reliable estimations of actual occupancy levels than whether probabilistic or non-probabilistic representations of such estimations are deployed.

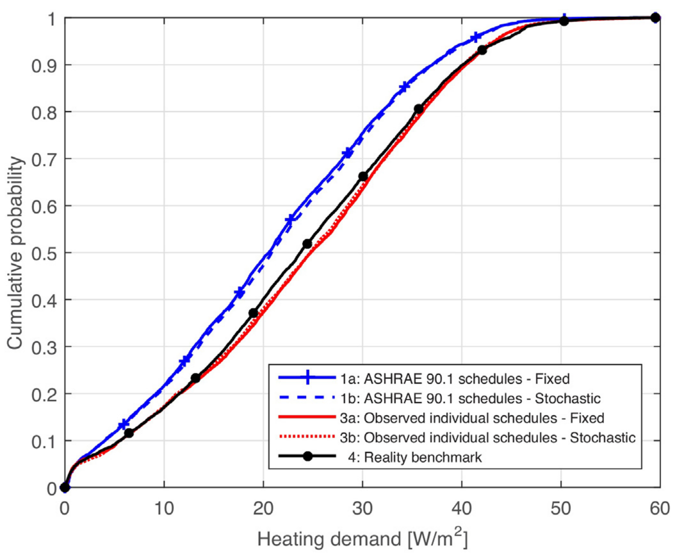

Fig. 5. Cumulative distribution of simulated heating demands models 1a, 1b, 3a, 3b, and 4.

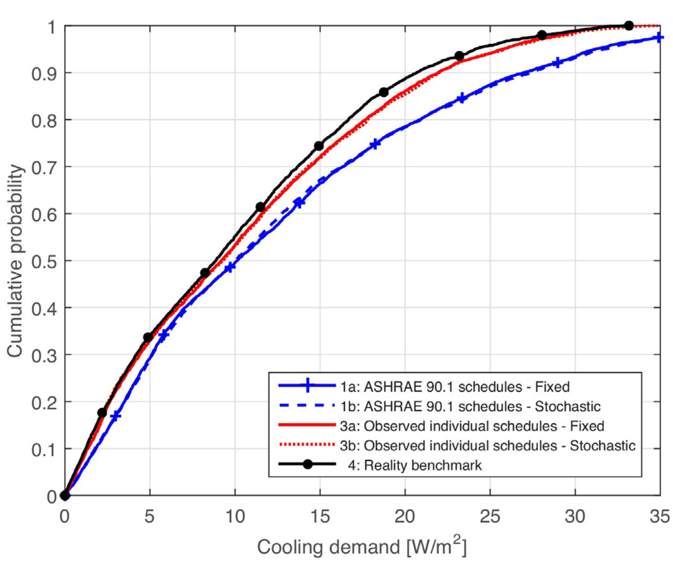

Fig. 6. Cumulative distribution of simulated cooling demands for models 1a, 1b, 3a, 3b, and 4.

4. Conclusion

In this paper, we argued that the criteria for the development, evaluation, comparison, and specific deployment of different occupancy-related modeling approaches and options must consider the deployment context of simulation-based building performance queries. To contribute to a systematic and productive discussion of this matter, we proposed a conceptual multi-dimensional simulation deployment space. Specific criteria for the selection and evaluation of alternative occupancy-related models could be assessed with regard to the position of simulation-based queries in this multi-dimensional application space.

To underline the relevance and utility of this conceptual framework, we presented the results of two illustrative case studies. Specifically, these case studies compared different occupancy models in two distinct application scenarios. The findings suggest that we cannot simply declare a priori that a particular modeling technique for generation of occupancy-related input information for performance simulation is superior to others. Rather, we must carefully consider the circumstances pertaining to the nature of application scenario such as time horizon of predictions or granularity of performance indicators. In other words, we have good reasons to suggest that the choice of an appropriate occupancy model and the criteria for evaluating its performance depends on the position of the relevant simulation-based query within the proposed application space.

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