A SYSTEMATIC ASSESSMENT OF THE SENSITIVITY OF BUILDING PERFORMANCE SIMULATION RESULTS WITH REGARD TO OCCUPANCY-RELATED INPUT ASSUMPTIONS

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ABSTRACT

The considerable performance implications of occupants' presence and behaviour in buildings render the inclusion of corresponding models in building performance simulation applications both necessary and critical. In this context, an important question concerns the implications of selecting a specific occupancy modelling approach for building performance simulation results. The present contribution addresses this issue by modelling an existing – continuously monitored – office building to obtain the annual and peak heating and cooling demands in a sequence of simulation runs. Thereby, different occupancy-related diversity profiles (standard-based, average and individual observation-based), random realizations of these profiles (obtained from a stochastic occupancy model), and the original full-year observational data are deployed to represent occupancy in the simulation model. The simulation results suggest that the viability of simulation results is primarily dependent on the availability of reliable estimations of actual occupancy levels. In contrast, it is of little significance whether probabilistic or non-probabilistic representations of such estimations are deployed.

INTRODUCTION

Occupants influence buildings' energy and indoor environmental performance due to their presence (via releasing sensible and latent heat) and actions (operation of devices such as windows, shades, and luminaries) (Mahdavi 2011). Occupancy models are intended to provide a representation of building users in building performance simulation models in the absence of high-resolution data in the design phase. Frequently, occupancy patterns are represented in the building models by average profiles of presence probability. In this context, a widely used set of suggested occupancy schedules for different types of buildings has been provided in ANSI/ASHRAE/IES Standard 90.1 (ASHRAE 2013). In addition, multiple efforts are being undertaken to derive more reliable building occupancy profiles (see, for example, Davis & Nutter 2010, Duarte et al. 2013).

More recently, probabilistic occupancy models have been developed and implemented to generate random non-repeating occupancy daily profiles to better capture the stochastic nature of occupants' presence. As one of the first attempts, Newsham et al. (1995) deployed the probability of first arrival and last departure as well as the probability of intermediate departures and arrivals to generate lighting profiles for a typical office. Reinhart (2001) further developed this model by using the inverse transform sampling method to generate samples of arrival and departure times, and by deploying distributions of break lengths. In a more recent effort, Page et al. (2008) proposed a generalized stochastic occupancy model using the profile of presence probability over a typical week and a parameter of mobility (defined as the ratio of state change probability to state persistence probability) as input.

In this context, an important question concerns the implications of selecting a specific occupancy modelling approach for building performance simulation results. To address this question in a systematic manner, multiple studies of a variety of simulation applications are needed, whereby different performance indicators could be obtained from simulation runs while using different occupancy models. As an example of such an application-based evaluation of occupancy models, Mahdavi & Tahmasebi (2015) examined a number of probabilistic and non-probabilistic occupancy models in view of short-term occupancy predictions for simulation-powered predictive building systems control. The present contribution, however, addresses the conventional use of simulation models for calculation of buildings' heating and cooling demand. Toward this end, we selected an office area, for which long-term occupancy data is available. Modelling the office in a performance simulation tool, conventional standard-based diversity profiles, observational aggregate and individual occupancy-related profiles, random realizations of these profiles, and the original full-year observational data were deployed to represent occupancy.

The structure of the study (sequence of simulation runs) facilitates the exploration of a number of essential questions: To which extent do the results of simulations that use conventional diversity profiles and stochastic occupancy models differ from a reference simulation model, which utilizes extensive high-resolution empirical occupancy information? Does the level of difference depend on the temporal aggregation interval of the pertinent performance indicator (e.g. annual versus hourly)? Does the use of randomly generated occupancy profiles compensate for the lack of high-resolution observational occupancy data? To address these questions, we present and discuss the results in view of their implications for occupancy modelling in building performance simulation.

METHOD

Overview

To investigate implications of different occupancy modelling approaches for building performance simulation results, we modelled an office area, for which long-term occupancy data is available. Occupants were represented in the model through following modelling alternatives:

1a) Fixed diversity profiles for weekdays, Saturdays and Sundays, using ASHRAE 90.1 schedules for office occupancy, lighting, and plug loads;

1b) Random daily occupancy profiles, generated by a stochastic occupancy model 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;

2b) Random daily occupancy profiles, generated by a 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;

3b) Random daily occupancy profiles, generated by a 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.

We obtained building annual and peak heating and cooling demands via the sequence of simulation runs. Thereby, sensitivity of simulation results to the occupancy-related input assumptions could be systematically assessed. The information regarding the above modelling options is summarized in Table 1. Further details on the assumptions associated with building model and occupancy modelling approaches can be found in the following sections.

Office area simulation model

For the purpose of the present study, we selected an office area in a university building in Vienna, Austria (see Figure 1). This office is equipped with a monitoring infrastructure, which continuously collects data, among other things, on occupants' presence (via wireless ceiling-mounted PIR motion detectors), plug loads, and state of the lights.

The building was modelled in the energy simulation tool EnergyPlus v8.1. The office floor and ceiling components are set to adiabatic in the thermal model, as the office area is a middle floor in a multi-story building. Office occupants with an activity level of 120 W/person and the electric lighting and equipment with nominal installed power were defined in the model. The diversity profiles for occupants' presence and the applicable fractions of installed lighting and equipment were defined according to modelling scenarios 1a to 4. The building was exposed to a typical metrological year weather data for Vienna, Austria. Table 2 summarizes basic information about the office building energy model.

Table 1 Key characteristics of the generated simulation models with regard to occupancy

Model	Occupancy representation	Lighting & 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 profiles – Fixed	Average empirical profile – Fixed
2b	Average empirical profiles – 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

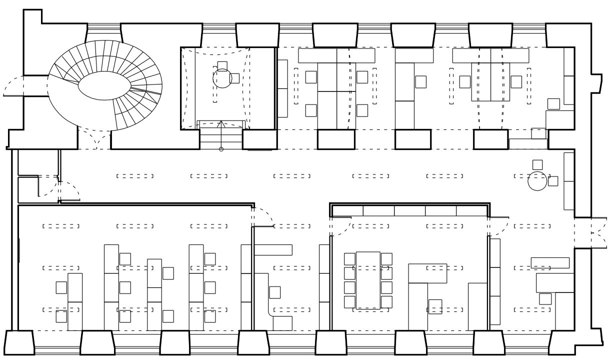

Figure 1 Office area floor plan.

Table 2
Office area data and modelling assumptions.

Building data / Model assumptions	**Value**
Net conditioned office area [m^2]	187.6
Gross wall Area [m^2]	120.1
Average window-wall ratio [%]	26.7%
Exterior walls U-value [W.m^{-2}.K]	0.65
Exterior windows U-value [W.m^{-2}.K]	2.79
Floor area per person [m^2.person^{-1}]	23.4
Lighting power density [W.m^{-2}]	4.05
Equipment power density [W.m^{-2}]	9.86
Infiltration rate [h^{-1}]	0.20
Mechanical ventilation [m^3.s^{-1}.Person^{-1}]	0.007
Heating set-point [°C]	20
Cooling set-point [°C]	25
HVAC availability on weekdays	6:00 – 22:00
HVAC availability on weekends	6:00 – 18:00

Standard-based diversity profiles

For the modelling scenario 1a, we used the diversity profiles according to ASHRAE 90.1 (ASHRAE 2013) for office buildings, i.e. weekday, Saturday, and Sunday schedules for occupancy, lighting, and plug loads (Figure 2). These schedules are assigned to all office occupants and the lights and electric equipment associated with their workspaces. Note that, Sunday profiles were used for public holidays as well.

Observation-based diversity profiles

To generate empirical diversity profiles, we used one-year 15-min interval data on occupancy, plug loads and state of the lights, obtained from the building monitoring infra-structure.

In modelling alternative 2a, the empirical data on occupants' presence, plug loads, and use of lights were averaged across all occupants. The resulting full-year data set for an average occupant was then processed to obtain a set of average profiles of presence probability, fraction of maximum lighting load, and fraction of maximum equipment load for weekdays, Saturday, as well as Sundays and public holidays (Figure 3). Neglecting diversity among occupants, the resulting average schedules were assigned to all occupants and associated lighting and equipment in the simulation model.

Model 3a was intended to consider diversity among occupants. Therefore, the weekday, Saturday, and Sunday average schedules were generated for each individual occupant, electric outlet and light switch and assigned to the corresponding objects in the simulation model. Figure 4 illustrates a sample of individual empirical diversity profiles for occupancy, lights, and plug loads. Note that, to derive the diversity profiles for models 2a and 3a, vacation days were not excluded. Therefore, the resulting profiles implicitly represent the vacations.

In modeling scenario 4, however, full-year empirical data was incorporated into the simulation model. That is, instead of using typical schedules for weekdays and weekends, occupancy states, state of the lights and the plug loads are retrieved from the original empirical data-sets at each simulation time-step. Therefore, simulation model 4 acts as a reference, as it has the highest resolution in terms of occupancy and is entirely observation-based. In other words, this option represents the reality benchmark, as far as the actual occupancy circumstances are concerned.

Random occupancy profiles and associated gains

To represent occupants' presence in models 1b, 2b and 3b in a probabilistic approach, we used the stochastic occupancy model developed by Page et al. (2008). This model inputs a profile of presence probability and parameter of mobility (defined as the ratio of state change probability to state persistence probability) and returns random non-repeating daily profiles of occupancy states (present or not present).

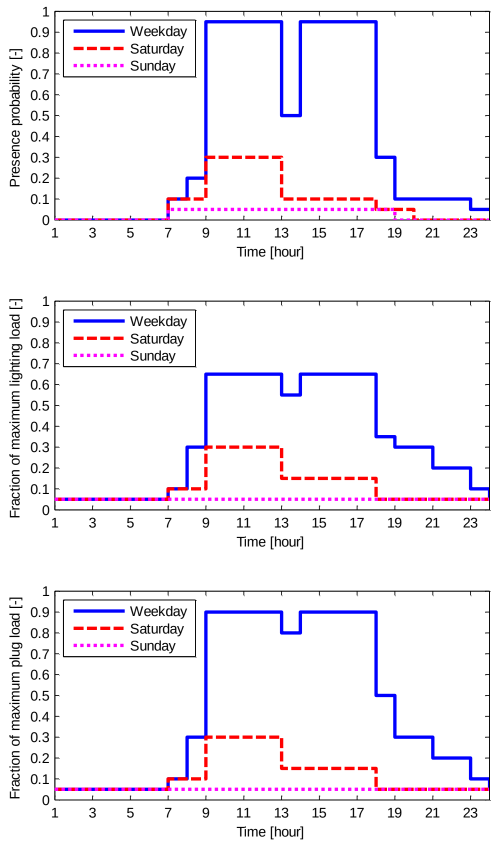

Figure 2 ASHRAE 90.1 schedules for occupancy (top), lights (middle), and plug loads (bottom).

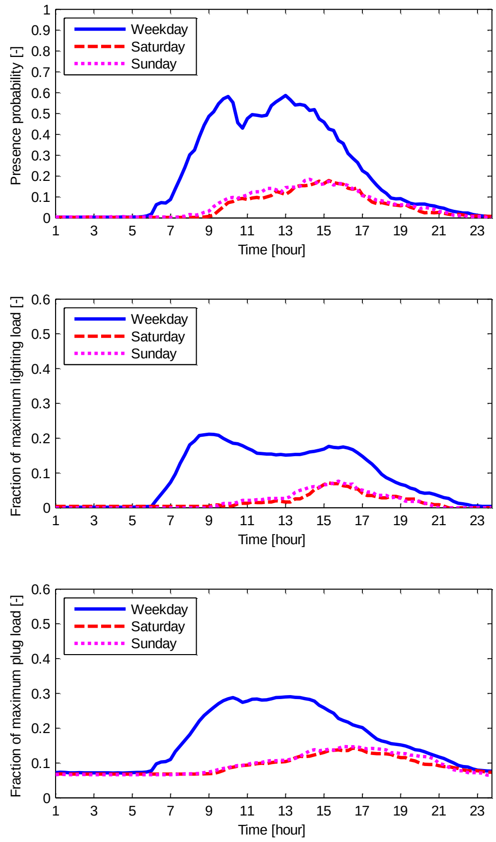

Figure 3 Average empirical profiles for occupancy (top), lights (middle), and plug loads (bottom).

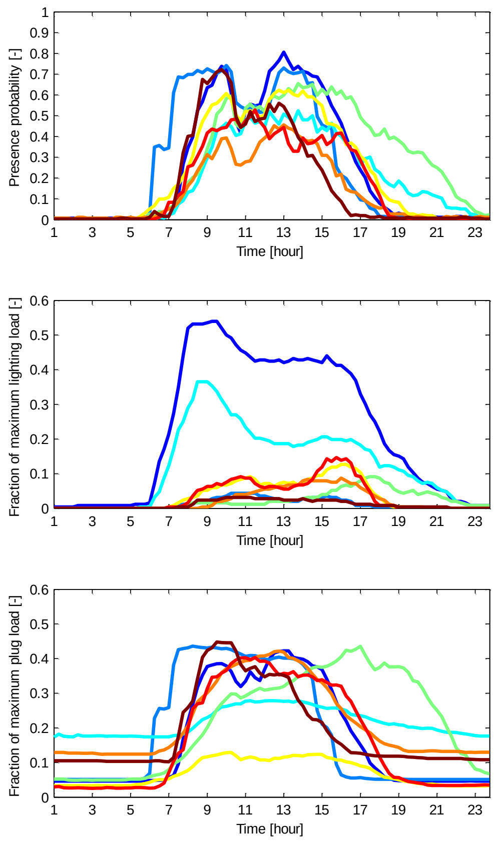

Figure 4 A sample of individual empirical profiles for weekday occupancy (top), lights (middle), and plug loads (bottom).

This model has been formulated based on the hypothesis that the value of occupancy at the each time step depends on the previous occupancy state and the probability of transition from this state to either the same state or its opposite state. To generate a daily occupancy profile, the procedure starts from the first time step of the day with a vacant state for commercial buildings. Subsequently, for each time step, a random number between 0 and 1 is generated and compared with the transition probabilities (which have been calculated using the input occupancy profile and parameter of mobility) to see if a change of occupancy state occurs. This is a simple case of using the inverse transform sampling method. Further details on this occupancy model can be found in (Page et al. 2008).

In order to generate random non-repeating profiles of occupancy states for models 1b, 2b, and 3b, the fixed occupancy profiles used in models 1a, 2a, and 3a were provided respectively as input for the stochastic model. We ran the stochastic occupancy model 365 times to obtain year-long random daily presence profiles for each occupant. The occupancy profiles for weekdays, Saturdays, Sundays, and public holidays were input to the model in the right order, such that the days of the week are consistent in models with fixed and random occupancy profiles. The resulting schedules (each a column vector of 0 and 1 with length of 35040) were incorporated into the simulation models and were referenced by People objects. Note that in models 1b and 2b same set of occupancy profiles is randomized for all occupants, whereas in model 3b the stochastic model randomizes a unique set of occupancy profiles for each occupant. The parameter of mobility was set to 0.5 for all model executions in scenarios 1b and 2b. In scenario 3b this parameter was calculated for each occupant using full-year empirical data, providing inputs for the stochastic model with the highest precision.

It should be noted that, for the purpose of current study, we did not explicitly include vacations in any of the modelling scenarios, but the average occupancy profiles implicitly represented long absences. Therefore, we also did not implement the "long absence" component of the above-mentioned stochastic occupancy model.

To generate lighting and plug load schedules according to the randomly generated occupancy states, it was required to determine the applicable fraction of installed lighting and electric equipment, when each occupant is present. In addition, the electric loads, which were not dependent on the occupants' presence, had to be considered. Therefore, in simulation models 1b, 2b, and 3b, lighting and plug loads were defined in two parts: base load and occupancy-dependent load. The base loads' fractions were identified from the fixed light and plug loads schedules used in each modelling scenario as the constant fraction of loads during the night. The remaining lighting and plug loads' fractions were assumed to be proportional to occupancy level. In detail, the applicable fractions of lighting and plug loads for each occupant were defined as the ratio of occupancy-dependent lighting or equipment loads' diversity factors to the presence probability at each time step, both obtained from the fixed schedules used for that occupant.

Metrics for evaluating occupancy realizations

Before exploring the implications of different occupancy modelling options for building performance simulation results, we briefly compared the occupancy model outputs to the actual occupancy levels (represented in Model 4), so that the implications of these scenarios for simulation results could be better understood.

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 3 metrics, namely Mean Error, Root Mean Squared Error (RMSE), and Jensen-Shannon Distance.

Mean Error and RMSE were used to track time-step differences between the predicted and measured occupancy levels. These metrics were obtained using the following equations:

$$Mean\ Error = \frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)^2}{n}} \quad (2)$$

Where $BOF_p(t)$ is the predicted building-level occupancy fraction at time-step t, $BOF_r(t)$ is the reference building-level occupancy fraction at time step t (obtained from model 4), and n is the number of simulation time-steps in a year, which equals 35040.

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. This metric is used to compute distances between two probability distributions. For discrete probability distributions P and Q, Jensen-Shannon divergence (JSD) is calculated based on Kullback–Leibler divergence (KLD), as follows:

$$JSD(P,Q) = \frac{1}{2}KLD(P,M) + \frac{1}{2}KLD(Q,M) \quad (3)$$

Where,

$$M = \frac{1}{2}(P+Q) \quad (4)$$

$$KLD(P,Q) = \sum_i P(i)\ln\frac{P(i)}{Q(i)} \quad (5)$$

Jensen-Shannon divergence is bounded between 0 and ln(2). The square root of Jensen–Shannon divergence is referred to as Jensen-Shannon distance metric, which is used to quantify the distance between two probability distributions.

RESULTS

Comparison of modelling options in view of occupancy predictions

Figure 5 shows the probability distribution of occupancy levels in the modelled building (expressed as the percentage of maximum occupancy) obtained from different modelling scenarios. Note that model 4, which is based on the original full year occupancy data acts as our reference.

Table 3 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, as the reference case.

Building performance Simulation results

Table 4 provides the obtained values for annual and peak heating and cooling demands per conditioned floor area from the simulation models. Relative errors of simulation results of models 1a to 3b (with reference to model 4) are given in Table 5. Figures 6 and 7 illustrate the cumulative distribution of heating and cooling demand values for models 1a, 1b, 3a, 3b, and 4. Note that, as the results obtained from models 2a and 2b are very close to models 3a and 3b respectively, they have not been plotted in the figures, so that the data series can be better recognized.

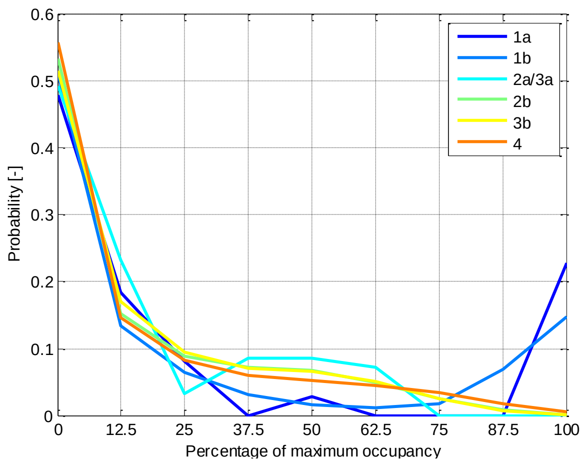

Figure 5 Probability distribution of occupancy level in the modelled building, obtained from different occupancy modelling scenarios

Table 3
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 4
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	67.1	18.0	50.0	39.8
2a	79.9	9.7	58.5	30.0
2b	78.2	10.6	58.5	31.7
3a	79.5	9.9	58.6	30.2
3b	78.5	10.5	59.0	33.3
4	78.2	9.4	57.1	27.9

Table 5
Relative error of simulation results of models 1a to 3b with reference to model 4

Models	**Relative error** [%]			
	Annual heating demand	**Annual cooling demand**	**Peak heating demand**	**Peak cooling demand**
1a	-15.7%	97.1%	-13.5%	41.3%
1b	-14.3%	91.6%	-12.4%	42.7%
2a	2.1%	3.4%	2.5%	7.7%
2b	0.0%	12.5%	2.4%	13.8%
3a	1.6%	5.6%	2.5%	8.4%
3b	0.4%	11.8%	3.4%	19.3%

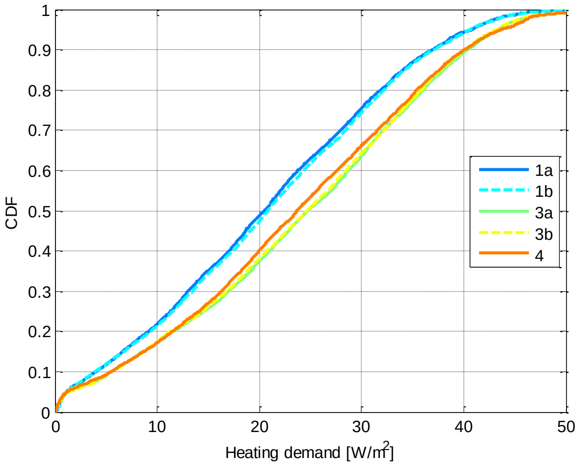

Figure 6 Cumulative distribution of simulated heating demands models 1a, 1b, 3a, 3b, and 4

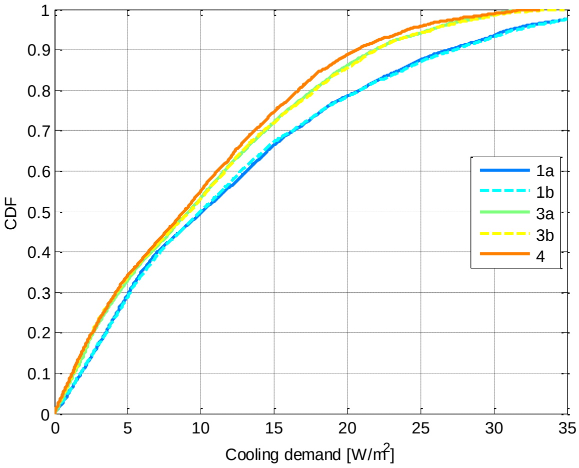

Figure 7 Cumulative distribution of simulated cooling demands for models 1a, 1b, 3a, 3b, and 4

As mentioned before, the stochastic occupancy model was executed 365 times to obtain each occupant's random daily presence profiles for annual simulations. Presumably, the obtained values of performance indicators could be at least slightly different, if such annual simulations would be repeated multiple times. We did not conduct a full-fledged Monte Carlo model execution to address this issue in detail. We did, however, conduct multiple random tests to ensure that potential slight undulations of the performance indicator results due to repeated annual simulations do not influence the credibility of our results and their interpretation.

DISCUSSION

A careful examination of the result leads to a number of interesting observations. Firstly, as illustrated in Figure 5 and considering the values for Square root of Jensen-Shannon divergence in Table 3, the distribution of probabilistic predictions of occupancy levels appears to be closer to the actual occupancy level distribution. This, however, does not necessarily translate into a better predictive performance concerning indicators such as annual and peak heating and cooling demands (see Table 5).

Second and foremost, divergence of the simulation results of different models is not mainly 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. 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 3), resulting in systematically lower heating loads (see Figure 6) and systematically higher cooling loads (see Figure 7).

What these results suggest is very clear. Randomization of occupancy patterns does appear to reduce the distance between the predicted and actual distributions of occupancy levels. However, randomization per se does not guarantee that simulation results pertaining to typical performance indicators (e.g., annual and peak heating and cooling demands) are any closer to reality than simulations based on non-probabilistic occupancy assumptions. To achieve high-fidelity simulation results (at least with regard to basic performance indicators such as annual heating and cooling demands) it is thus much more important to possess reliable estimations of actual occupancy levels than whether probabilistic or non-probabilistic representations of such estimations are deployed.

CONCLUSION

To explore the implications of different occupants' presence assumptions for a number of standard building performance simulation results, the annual and peak heating and cooling demands of an office building were computed using a dynamic energy simulation tool. Thereby, conventional standard-based diversity profiles, observational aggregate and individual occupancy-related profiles, random realizations of these profiles, and the original full-year observational data were deployed to represent occupancy in the simulation model.

The results suggest that, the probabilistic approach to model occupants’ presence does not necessarily lead to more reliable simulation results. Moreover, the divergence of the results of the different models is not mainly due to the probabilistic versus non-probabilistic nature of the occupancy models. The significant difference is between generic (standard-based) assumptions and assumptions that rely on actual occupancy information.

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