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Exploring the implications of different occupancy modelling approaches for building performance simulation results

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Abstract

Occupancy patterns in building performance simulation are typically represented via fixed diversity profiles. More recently, stochastic models have been developed to generate random non-repeating occupancy profiles. In this context, an important question concerns the implications of occupancy modelling approaches for simulation results. The present contribution involves a virtual office building for which annual and peak heating and cooling demands are simulated. Thereby, both conventional and random profiles are deployed and different levels of occupants' interaction with building systems are modelled. For the specific case considered here, the results do not show a noticeable difference between conventional and stochastic occupancy models.

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Keywords: Stochastic occupancy models, typical fixed schedules, annual and peak heating and cooling demand

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1. 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, luminaries, radiators, and fans) [1]. 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 occupancy schedules for different types of buildings has been provided in ANSI/ASHRAE/IES Standard 90.1-2013 [2]. In

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addition, multiple efforts are being undertaken to derive more reliable building occupancy profiles (see for example [3,4]).

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. [5] considered the probabilistic nature of occupancy while developing a stochastic model to predict lighting profiles for a typical office. Their model deployed the probability of first arrival and last departure as well as the probability of intermediate departures from and returning back to the workstations. Reinhart [6] 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 another effort, Page et al. [7] proposed a generalized stochastic model for the occupancy simulation using the presence probability over a typical week and a parameter of mobility (defined as the ratio of state change probability to state persistence probability).

In this context, an important question concerns the implications of selecting a specific occupancy modelling approach on 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 et al. [8] 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. For the purpose of this work, we deploy a virtual reference office building, for which the annual, monthly, and peak heating and cooling loads are computed using a widely used numeric energy simulation tool. Thereby, both conventional fixed diversity profiles and the random non-repeating occupancy profiles are deployed. 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 stochastic occupancy models differ from those using conventional diversity profiles? Does the level of difference depend on the temporal aggregation interval of the pertinent performance indicator (e.g. annual, versus monthly, versus hourly)? What are the additional effects of user-based actions (i.e., operation of shades and mechanical ventilation) on the discrepancy between conventional and stochastic approaches? To address these questions, we present and discuss the results in view of their implications for occupancy modelling in building performance simulation.

2. Method

2.1. Overview

In order to investigate the implications of different occupancy modelling approaches for building performance simulation results, we considered two different approaches:

1) Fixed profiles for weekdays and weekends, using ASHRAE 90.1-2013 [9] schedules for office occupancy, lighting, and plug loads;
2) Random daily occupancy profiles, generated by a stochastic occupancy model [7] using the same schedules from ASHRAE 90.1-2013 as input, together with associated lighting and plug loads.

To explore the implications of selecting a specific occupancy modelling approach for the simulation results and the additional effects of user-based actions in a systematic manner, we used a reference virtual office building to generate a set of simulation models with different occupancy-related assumptions (see Table 1 for an overview).

From each simulation run, we obtained the building annual and peak hourly heating and cooling demands per conditioned floor area. Further details on the occupancy modelling approaches, the assumptions associated with each building model, and the results and discussion can be found in the following sections.

Table 1. Key characteristics of developed simulation models with regard to occupancy.

Model	Occupancy	Lighting & plug loads	Mechanical ventilation	Shading devices
1a	Fixed profiles	Fixed profiles	Constant air flow	-
1b	Random profiles	Proportional to occupancy profiles	Constant air flow	-
2a	Fixed profiles	Fixed profiles	Occupancy-dependent	-
2b	Random profiles	Proportional to occupancy profiles	Occupancy-dependent	-
3a	Fixed profiles	Fixed profiles	Occupancy-dependent	Operable exterior blinds
3b	Random profiles	Proportional to occupancy profiles	Occupancy-dependent	Operable exterior blinds

2.2. Reference office model

For the purpose of this study, we used the “small office” reference building model developed by the U.S. Department of Energy [10]. The building was modelled in the building energy simulation tool EnergyPlus v8.1 [11] and consists of one core and four perimeter thermal zones (see Fig. 1). We assumed that the office area is a middle floor in a multi-story building. Therefore the office floor and ceiling components are set to adiabatic in the thermal model. The buildings were exposed to a typical metrological year weather data for Vienna, Austria. Table 2 summarizes basic information about the reference office building energy model.

2.3. Typical profiles of occupancy and internal gains

For the modelling scenarios with fixed occupancy profiles (models 1a, 2a, 3a), we used the schedules offered by ASHRAE 90.1-2013 [9] for office buildings, i.e. weekday, Saturday, and Sunday schedules for occupancy, lighting, and plug loads (Fig. 2).

Table 2. Reference office building data and modelling assumptions.

Building data / model input parameters		Value	Unit
Total building area		511.2	m^2
Net conditioned building area		511.2	m^2
Gross wall Area		281.5	m^2
Gross window-wall ratio (all façades)		19.8	%
Exterior walls U-value		0.36	$W.m^{-2}.K$
Exterior windows U-value		2.79	$W.m^{-2}.K$
Infiltration rate		0.2	h^{-1}
Mechanical ventilation		0.007	$m^3.s^{-1}.Person^{-1}$
Heating set-point		20	°C
Cooling set-point		26	°C
HVAC availability schedule	Weekdays	6:00 – 22:00	-
	Saturdays	6:00 – 18:00	-
Maximum number of people	Total	31	-
	North zone	7	-
	East zone	4	-
	South zone	7	-
	West zone	4	-
	Core zone	9	-
Occupants’ activity level		120	$W.Person^{-1}$
Maximum lighting power density		8.8	$W.m^{-2}$
Maximum equipment power density		8.1	$W.m^{-2}$

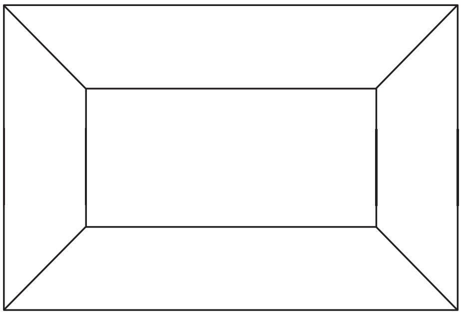

Fig. 1. Building thermal zoning scheme.

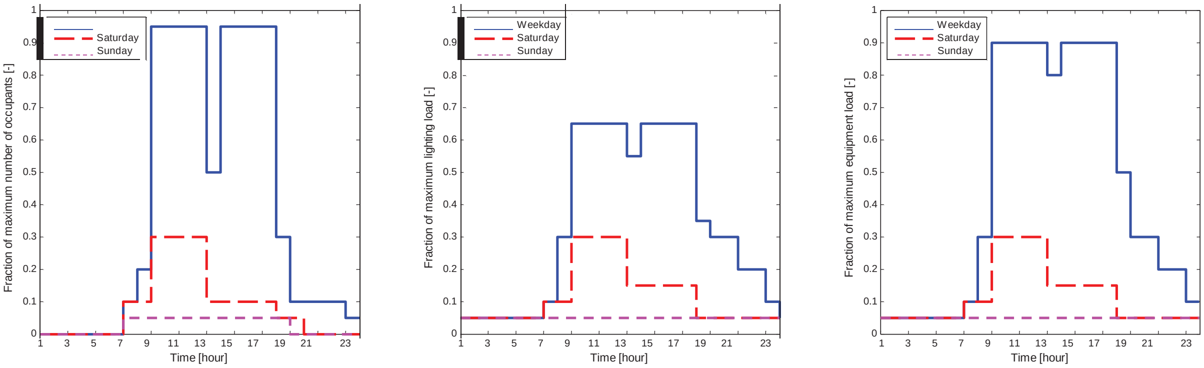

Fig. 2. Fixed schedules for occupancy (left), lights (middle), and plug loads (right) used for models 1a, 2a, and 3a.

2.4. Random occupancy profiles and associated internal gains

To represent occupants' presence in models 1b, 2b and 3b, we used the stochastic occupancy model developed by Page et al. [7]. 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 occupancy profiles. The model has been formulated based on the hypothesis that the value of occupancy at 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 [12]. Further details on this occupancy model can be found in [7].

We provided the same occupancy schedules from ASHRAE 90.1-2013 (with time steps of 15 minutes) to the above-mentioned model and executed the model 365 times to obtain year-long random daily presence profiles for each occupant in models 1b, 2b, and 3b. The parameter of mobility was set to 0.5 for all model executions. The occupancy profiles for weekday, Saturday, and Sunday 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 31 schedules (each a column vector of 0 and 1 with length of 35040) were incorporated in the simulation models and were referenced by People objects in the models. Note that we did not include any holiday in the models with fixed occupancy schedules. Therefore, we also did not implement the "long absence" component of the above-mentioned stochastic occupancy model.

The lighting and plug loads in models with random occupancy profiles were defined in two parts: Base load and occupancy dependent load. From the fixed schedules for lights and plug loads (see Fig. 2), we set a fraction of 0.05 of the lighting load as the base load. In case of the plug loads, the base load fractions were set to 0.4 and 0.3 for the weekdays and weekends respectively. The remaining lighting and plug loads were assumed to be proportional to occupancy level. The loads associated with each occupant are derived based on ASHRAE 90.1 schedules for office occupancy, lighting, and plug loads, using Eq. 1:

$$L_{\text{!""\#\$\%\&'}}(t) = \frac{LF_{\text{!"}}(t)}{OF(t)\times O_{\text{!"\#\$}}} \times L_{\text{!"\#\$}} \tag{1}$$

Where $L_{\text{!""\#\$\%\&'}}(t)$ is the lighting or plug loads associated with each occupant at time step t, $LF_{\text{!"}}(t)$ is the occupancy dependent fraction of lighting or plug loads at time step t, $OF(t)$ is the fraction of occupancy at time step t, $O_{\text{!"\#\$}}$ is the maximum number of occupants in the zone, and $L_{\text{!!"\#}}$ is the zone maximum lighting or plug loads.

2.5. Mechanical ventilation

As opposed to models 1a and 1b, where the mechanical ventilation rate is assumed to be constant during the working hours (0.007 m^3/s per person for maximal occupancy), in models 2a, 2b, 3a, and 3b, the mechanical ventilation was divided into a base part and an occupancy dependent part. In these models, regardless of occupants' presence, the zone is provided with a base fresh air flow rate of 0.001 m^3/s per person for maximal occupancy. However, the presence of each occupant adds 0.006 m^3/s to the fresh air flow rate.

2.6. Shading devices

In models 3a and 3b, we added exterior venetian blinds to all building windows. The blind slats were assumed to have a beam solar reflectance of 0.5 and fixed angles of 30 degree. Each window blind is deployed if the occupant associated with that window is present and if solar irradiance on the window exceeds 150 W/m^2. In model 3b each blind is coupled with one occupant, whereas in model 3a, the number of blinds that may be operated are determined based on the occupancy fraction obtained from the fixed schedule.

3. Results and discussion

Table 3 provides the obtained values for annual and peak hourly heating and cooling demands per conditioned floor area from the simulation models.

The results clearly show that in the case of the selected sample office, the deployment of the stochastic model to generate random occupancy profiles does not have a noticeable impact on computed values of the annual and peak heating and cooling demand. One could argue that in comparison case 1a versus 1b, only the "passive" impact of occupants' presence is considered. However, a significant difference in results are not observed, even if we couple certain operational processes (ventilation, shading) to occupants' presence, as it is the case in models 2a, 2b, 3a, and 3b. Specifically, in case of models 3a and 3b, the occupants' level of presence determines the magnitude of ventilation rates and the state of the blinds. Nonetheless, even with regard to peak demands, simplified versus stochastic occupancy modeling alternatives do not result in noteworthy differences (only 0.7% difference for peak heating load and 1.8% for peak cooling load). Therefore, as long as there is no reliable empirically-based and detailed (and diverse) occupancy data available, the mere randomization of average occupancy profiles does not appear to add any value to the building performance simulation effort.

It should be noted that in current study only one typical occupancy schedule was used. In other words, by using an average presence profile, the diversity among occupants was neglected. To address this issue, we are currently conducting a similar study involving a real office building for which high-resolution monitored occupancy data is available.

Table 3. Annual and peak hourly heating and cooling demands per conditioned floor area obtained from simulation models.

Model	Occupancy modelling characteristics	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	Fixed schedules for occupancy, lighting & plug loads	20.4	24.4	58.6	45.2
1b	Random schedules for occupancy, lighting & plug loads	20.5	24.4	58.8	45.3
2a	Fixed occupancy schedules, occupancy dependent ventilation	13.3	27.3	58.2	44.7
2b	Random occupancy schedules, occupancy dependent ventilation	13.3	27.4	58.3	45.0
3a	Fixed occupancy schedules, occupancy dependent ventilation, operable blinds	14.5	22.5	58.4	38.8
3b	Random occupancy schedules, occupancy dependent ventilation, operable blinds	14.5	22.7	58.8	39.5

4. Conclusion

To explore the implications of different occupants' presence assumptions on a number of standard building performance simulation results, the annual and peak heating and cooling demands of a virtual reference office building were computed using a dynamic energy simulation tool. Thereby, both conventional diversity profiles and stochastic models of occupancy were deployed and different levels of occupants’ interaction with building systems were modelled. The results showed that deployment of the stochastic occupants' presence model, which is solely based on average occupancy profiles does not have a noticeable impact on the annual and peak heating and cooling demand evaluations.

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