The Diversity Challenge in Models of Occupants' Presence in Buildings

Ardeshir Mahdavi – TU Wien – amahdavi@tuwien.ac.at
Farhang Tahmasebi – TU Wien – farhang.tahmasebi@tuwien.ac.at
William O'Brien – Carleton University – liam.obrien@carleton.ca
H. Burak Gunay – Carleton University – burak.gunay@carleton.ca

Abstract

This contribution is concerned with a number of basic questions regarding inhabitants' presence in buildings: How diverse are office inhabitants' presence patterns? Aside from the differences in the absolute values of the defining markers of such patterns (e.g. arrival and departure times), to which extent do the respective distributions of the marker values differ from inhabitant to inhabitant? Are tendencies regarding presence patterns in one location transferrable to other locations? Can the diversity of presence patterns among the inhabitants be reproduced via the randomisation of the markers' mean values? To explore these questions, we use monitored presence data from two offices in two different locations. The findings point to considerable differences amongst inhabitants and locations. Moreover, an empirically observable diversity of the office workers' presence patterns cannot be simply reproduced based on the randomisation of generic presence patterns.

1. Introduction

Multiple efforts in the past have pursued the development of advanced mathematical models of people's presence in buildings (e.g. Page et al., 2008; Richardson et al., 2008; Mahdavi and Tahmasebi, 2015a; Wang et al., 2016). The effectiveness of such models depends arguably on the representativeness of the underlying empirical data. This pertains also to the existence of inter-individual differences in patterns of inhabitants' presence and behaviour in buildings (O'Brien et al., 2016; Tahmasebi and Mahdavi, 2016; Feng et al., 2015).

In a previous study, we used data from an office building in Vienna, Austria, to analyse the presence patterns of a small but diverse number of inhabitants (Mahdavi and Tahmasebi, 2015b). Thereby, differences in general long-term characteristics of individual presence profiles were studied to determine the statistical variance of the defining markers of such profiles, including arrival and departure times, presence and absence durations. We hypothesised that, even if the tendency of the specific values of these markers could be different for different occupants, the respective data distribution shapes could be comparable. If so, randomisation of general schedules could be conducted without any consideration of the occupants' diversity.

Given the limitation of this study (just one office building and a small number of inhabitants), the results were not deemed to be conclusive. The present contribution thus incorporated additional data from an office building in Canada. The respective data was similarly treated to identify central tendencies and dispersion of the marker values for inhabitants' presence patterns.

2. Approach

2.1 Selected Offices

For the Vienna study, we used one-year-long data obtained from an office area (including a single-occupancy closed office, two single-occupancy semi-closed offices, and an open plan office zone) in a university building. The collected data included indoor environmental conditions, state of devices (luminaires, radiators, windows and doors), and specifically presence patterns of eight inhabitants (academic and administrative staff).

In case of the Ottawa office, data was obtained from 16 private offices located in an academic building. The building's automation system monitors the inhabitants' presence using passive infrared (PIR)

Part of
Pernigotto, G., Patuzzi, F., Prada, A., Corrado, V., & Gasparella, A. (Eds.). 2018. Building simulation applications BSA 2017. bu,press.
https://doi.org/10.13124/9788860461360

sensors. The duration of observations varies from 19 days to 264 days across the offices.

2.2 The Occupancy Markers

We considered a number of markers (parameters) to capture presence patterns as follows:

- First arrival time (AT);
- Last departure time (DT);
- Presence duration (PD);
- Number of transitions (NT);
- Working hours (WH);
- Absence duration (AD);
- Mean break duration (MBD);
- Fraction of presence (FOP).

First arrival time (FA) and last departure time (LD) are derived by detecting the first and last occupied interval in a day (in the present study, data was structured in terms of 15-min intervals). The occupancy duration (OD) is calculated by counting the number of occupied intervals in a day. Number of transitions (NT) denotes the number of daily occupied-to-vacant transitions. Working hours (WH) are calculated by subtracting arrival time from departure time. Absence duration (AD) equals working hours (WH) minus presence duration (PD). Mean Break Duration (MBD) is obtained by dividing Absence duration (AD) by the number of transitions (NT). Fraction of presence is derived by dividing presence duration (PD) by working hours (WH).

2.3 Statistics

Presence data was processed in terms of four statistics, namely mean, median, standard deviation (SD), and coefficient of variation (CV). In addition, the values of the eight markers for all inhabitants were displayed (in aggregate and individually) in terms of probability distribution plots. This was done based on the original marker values as well as their normalized variation (i.e. difference between the marker value and the mean value of that marker).

Data analysis and interpretation targeted the following questions:

1) Considering both within-group and between-group standpoints, are the absolute values of inhabitants' presence markers similar across different inhabitants?
2) Does the between-group view of the tendencies in the two locations reveal similar overall tendencies in the absolute values of the presence markers?
3) Considering both within-group and between-group standpoints, is the statistical shape of distributions (dispersions) of the inhabitants' presence marker values comparable across different inhabitants?

3. Findings

The cumulative probability distributions of individual occupants' presence markers obtained from the offices in Austria and Canada are given in Fig. 1. Fig. 2 shows the probability distributions of normalized markers (representing the deviations from the average marker values) for aggregate data obtained from two office areas. Fig. 3 illustrates the distribution of CV values of the presence pattern markers across different occupants for the two locations. These results provide a number of insights regarding the previously stated research questions:

i. There are obviously significant differences amongst the inhabitants with regard to absolute values of the presence markers (see Fig. 1). This is true for both populations.
ii. Likewise, the between-group comparison of the tendencies in the two locations reveals significant differences with regard to the distribution of the inhabitants' presence markers (Fig. 2).

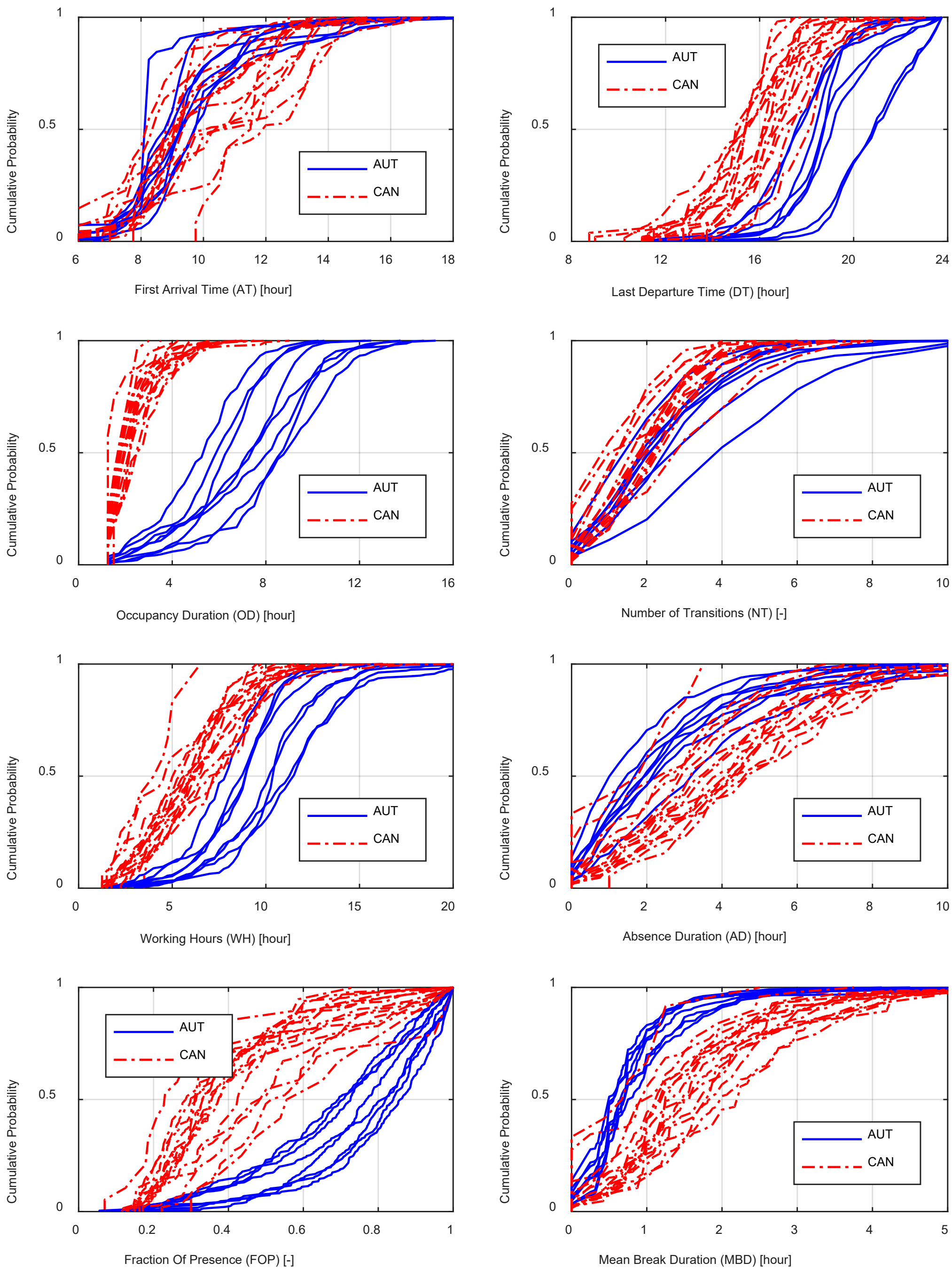

Fig. 1 – Cumulative distributions of individual occupants' presence markers obtained from the office areas in Vienna, Austria (AUT) and Ottawa, Canada (CAN)

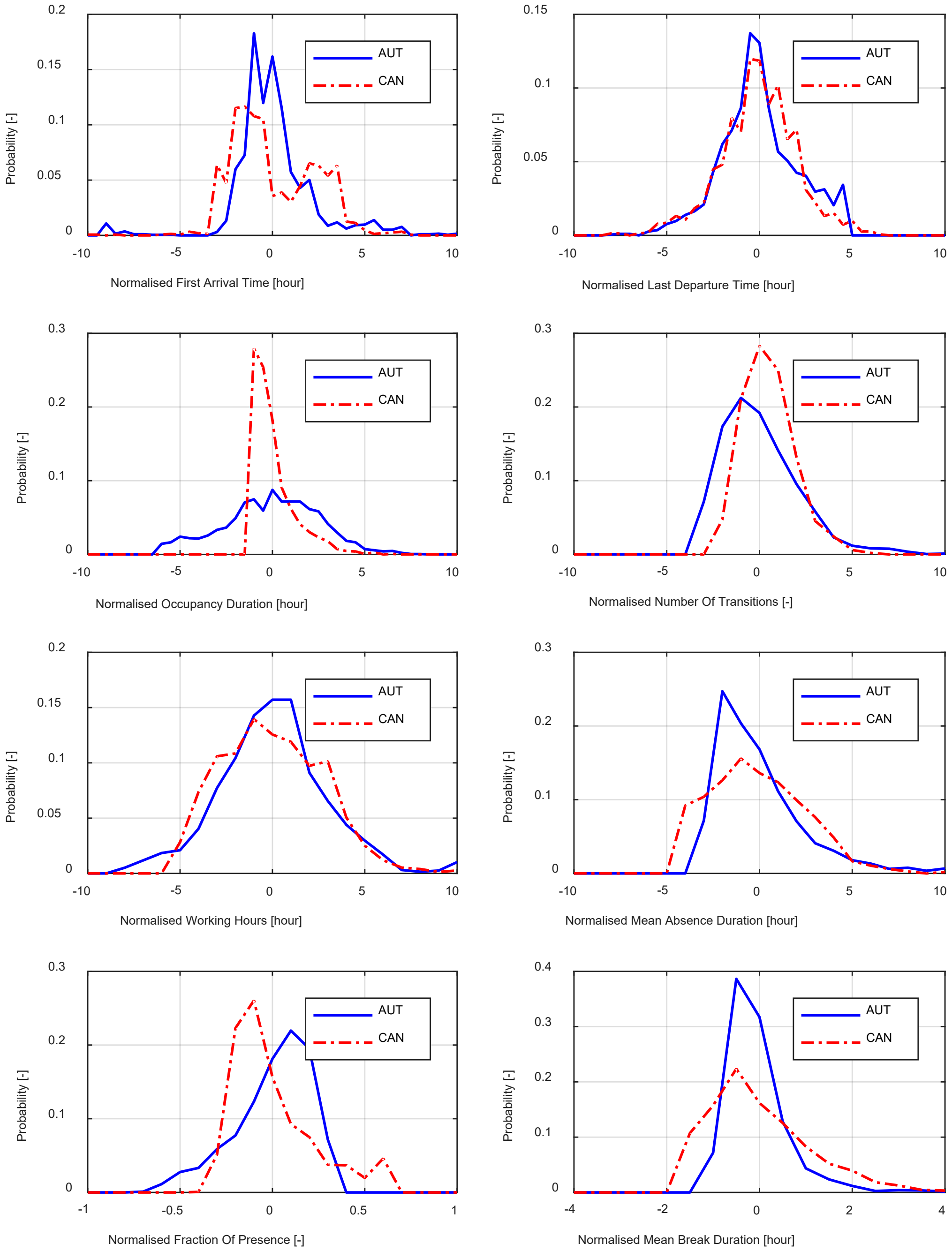

Fig. 2 – Distributions of aggregated normalized occupants' presence markers obtained from the office areas in Vienna (AUT) and Ottawa (CAN)

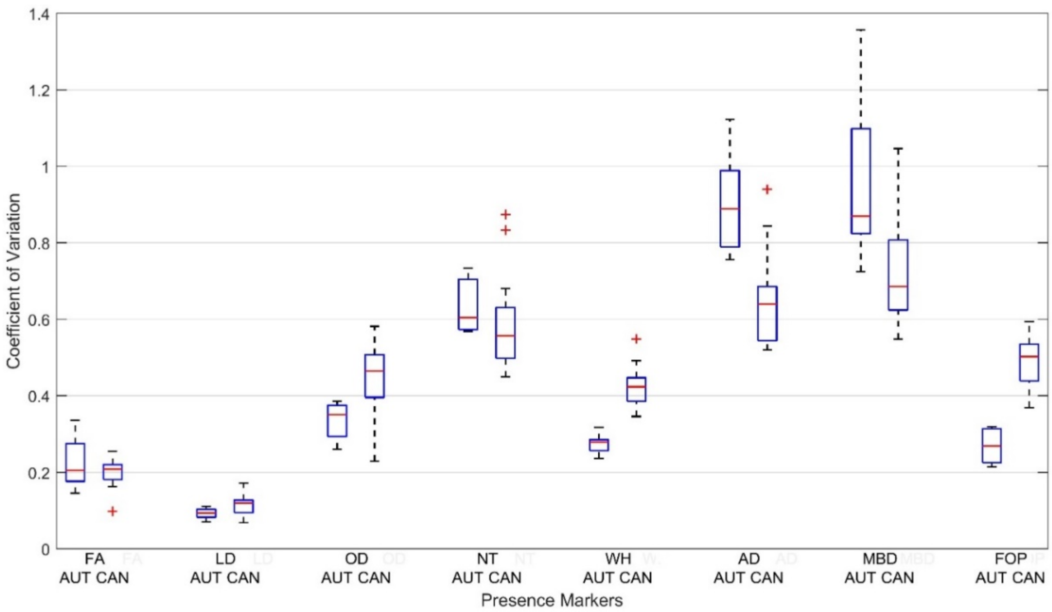

Fig. 3 – Boxplot of the coefficient of variation of the presence markers

iii. Moreover, the spread of the marker values (as expressed in terms of CV) is not small (see Fig. 3). Hence, the reproduction of the inhabitants' diversity via randomisation requires not only empirical information on the diversity of the mean marker values, but also on the diversity of respective distributions' spread and shape. As such, the generation of stochastic presence patterns would have been easy, if the statistical distributions of the marker values were similar, thus resistant to diversity. Inter-inhabitant diversity could have been thus reduced to the mean marker values. The presented data clearly suggests that this is not the case. Moreover, distributions are not only different in view of the spread, but also between the two locations.

iv. Even if we could ignore the diversity of the data distribution ranges, there would be still the problem of distribution morphologies. The two locations differ not only significantly in terms of the spread of the data (see Fig. 3), but also in terms of the distribution shapes. For instance, in the Ottawa office, AT displays a markedly bi-modal distribution. Likewise, FOP markers in the two locations display a distinct morphological asymmetry.

4. Concluding Remarks

This contribution empirically addressed the diversity of the inhabitants' presence patterns based on the inhabitants' monitored presence patterns in two office buildings in Vienna and Ottawa. The results suggest that the inhabitants' presence patterns can be significantly different and not reducible to just a few standard ones. Moreover, diversity amongst the inhabitants applies not only to the absolute values of the presence patterns' markers, but also to the spread and shape of the individual marker values' distributions.

Moreover, even if certain patterns could be suggested to apply to a specific building or location (for instance, LD and WH indicators display a very narrow range of CV values for the Vienna office), they cannot be suggested to apply to other locations. As such, without reliable empirical information regarding mean values and distributions of the marker values of inhabitants' presence patterns, simple randomisation of occupancy schedules cannot be expected to reproduce reliable representations of diversity. Seen from this specific viewpoint, the diversity of inhabitants' presence patterns in office buildings may be suggested to be irreducible.

Acknowledgements

The research presented in this paper benefited from the authors’ participation in the ongoing efforts of the IEA-EBC Annex 66 (Definition and Simulation of Occupant Behaviour in Buildings) and the associated discussions.

References

Feng, X., D. Yan, T. Hong. 2015. “Simulation of occupancy in buildings”. *Energy and Buildings* 87: 348–359. doi: 10.1016/j.enbuild.2014.11.067.

Mahdavi, A., F. Tahmasebi. 2015a. “Predicting people's presence in buildings: An empirically based model performance analysis”. *Energy and Buildings* 86: 349–355. doi: 10.1016/j.enbuild.2014.10.027.

Mahdavi, A., F. Tahmasebi. 2015b. “The inter-individual variance of the defining markers of occupancy patterns in office buildings: a case study”. In: *Proceedings of BS2015*. Hyderabad, India: IBPSA.

O'Brien, W., H.B. Gunay, F. Tahmasebi, A. Mahdavi. 2016. “A preliminary study of representing the inter-occupant diversity in occupant modelling”. *Journal of Building Performance Simulation* 10: 509-526. doi:10.1080/19401493.2016.1261943.

Page, J., D. Robinson, N. Morel, J.L. Scartezzini. 2008. “A generalized stochastic model for the simulation of occupant presence”. *Energy and Buildings* 40(2): 83–98. doi: 10.1016/j.enbuild.2007.01.018.

Richardson, I., M. Thomson, D. Infield. 2008. “A high-resolution domestic building occupancy model for energy demand simulations”. *Energy and Buildings* 40: 1560–1566. doi: 10.1016/j.enbuild.2008.02.006.

Tahmasebi, F., A. Mahdavi. 2016. “An inquiry into the reliability of window operation models in building performance simulation”. *Building and Environment* 105: 343-357. doi: 10.1016/j.buildenv.2016.06.013.

Wang, Q., G. Augenbroe, J.H. Kim, L. Gu. 2016. “Meta-modeling of occupancy variables and analysis of their impact on energy outcomes of office buildings”. *Applied Energy* 174: 166–180. doi: 10.1016/j.apenergy.2016.04.062.