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THE INTER-INDIVIDUAL VARIANCE OF THE DEFINING MARKERS OF OCCUPANCY PATTERNS IN OFFICE BUILDINGS: A CASE STUDY

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ABSTRACT

Recently, increased efforts have been invested to enhance the sophistication of occupancy modelling approaches in building performance simulation. However, the effectiveness of such approaches depends on the robustness of the underlying empirical information. Thereby, an important question pertains to the existence and level of inter-individual differences in occupancy patterns. In the present contribution, we use a repository of monitored occupancy data in an office building to address this problem empirically. While this repository does not include a large enough number of occupants to warrant a statistically significant treatment, it does allow for initiating a discussion of the diversity in observed occupancy profiles and the implications for relevant occupancy models in building performance simulation.

INTRODUCTION

Given the impact of occupants on building performance, modelling occupant's presence and behaviour is one of critical topics in the studies pertaining to building performance simulation (Mahdavi 2011). Specifically, numerous libraries of typical occupancy profiles (see, for example, ASHRAE 2013, Davis et al. 2010, Duarte et al. 2013) and a number of probabilistic and non-probabilistic models (e.g., Reinhart 2001, Page et al. 2008, Richardson et al. 2008, Mahdavi et al. 2015) have been proposed to represent the complex nature of occupancy patterns in building performance simulation tools.

In this context, occupancy modelling in terms of stochastically behaving individual agents represents a potentially promising approach. However, the effectiveness of such an approach depends on the robustness of the underlying empirical information. Thereby, an important question pertains to the existence and level of inter-individual differences in occupancy patterns. In other words, independent of the characteristics of the proposed and applied occupancy models, the diversity of occupants and its implications must be dealt with.

While detailed occupancy information is rarely available for model development purposes, systematic statistical analyses of existing data can improve the state of art in consideration of occupancy diversity in respective modelling efforts. Knowledge of the diversity among the occupants and corresponding models also could help to bring about a proper balance between simulation resolution and computational costs by selecting the optimum sample size and targeting for the suitable complexity level in occupancy-related models.

Given this background, we address a number of relevant questions using a repository of monitored data in an office building regarding the presence patterns of eight occupants. One question relates to the scope of differences in general long-term characteristics of individual occupancy profiles. A second – highly critical – question relates to the statistical variance of the defining markers of such patterns. Occupants' presence patterns in an office building provide a case in point for the latter question. An occupancy presence pattern may be defined in terms of markers such as arrival times, intermediate absence intervals, and departure times. Relevant empirical data could facilitate the examination of two specific null-hypotheses as follows:

i) Individual long-term occupancy patterns of office workers are insignificantly diverse.
ii) The statistical variance of the defining markers of the office workers' occupancy patterns does not display significant inter-individual differences.

In this paper, we illustrate the process by which the analyses of data on occupants' presence can contribute to a rigorous examination of these hypotheses.

METHOD

For the purpose of the present study, we use data obtained from an office area in a university building in Vienna, Austria. This office area is equipped with a monitoring infrastructure to continuously collect data on indoor environmental conditions, state of devices (luminaires, radiators, windows and doors), and occupancy (presence). Specifically, we focus here on data regarding the presence of eight occupants who work in this area. The occupants include both academic and administrative staff, and both faculty members and graduate students. The area layout includes a single-occupancy closed office, two single-occupancy semi-closed offices, and an open plan office area.

The occupancy data has been obtained via wireless ceiling-mounted PIR motion detectors. The internal microprocessors of the sensors are activated within a time interval of 1.6 minutes to detect movements. The resulting data log entails a sequence of time-stamped occupied to vacant (values of 0) or vacant to occupied (values of 1) events. To facilitate data analysis, the event-based data streams were processed to generate 15-minute interval data. This procedure derives the duration of occupancy states (occupied / vacant) from the stored events and returns the dominant occupancy state of each interval. Occupancy periods before 8:00 and after 19:45 were not included in the study to exclude, amongst other things, the presence of janitorial staff at the offices. Occupancy data for a 35-month period (April 2011 to February 2014) were used to conduct the current study.

Data was analysed via basic means of visualisation and descriptive statistics. The results are expressed in terms of the following markers:

- 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)

The first four markers are obtained directly from the empirical data. The first arrival time (FA) and last departure time (LD) are derived by detecting the first and last occupied 15-min intervals in a day. The occupancy duration (OD) is calculated by counting the number of occupied intervals in a day. Number of transitions (NT) represents the number of daily occupied-to-vacant transitions.

The next four markers are derived from the previous ones. Working hours (WH) is calculated by subtracting arrival time from departure time, whereas absence duration (AD) equals working hours (WH) minus presence duration (PD). Dividing Absence duration (AD) by the number of transitions (NT) yields the Mean break Duration (MBD). Fraction of presence is calculated by dividing presence duration (PD) by working hours (WH).

We would like to stress again that, given the small number of occupants, the present analysis is merely of exploratory nature. The idea is to obtain a first impression of the critical issues and examine the structure of the research conducted as a starting framework for future – more expansive – studies.

RESULTS AND DISCUSSION

Table 1 summarizes the eight occupants' observed presence data in terms of six basic statistics, namely mean, standard deviation, coefficient of variation (CV), median, mode, and interquartile range for the aforementioned markers. Despite the small number of occupants, the values of the eight markers for all occupants were displayed in terms of probability distribution box plots. Figures 1 to 5 provide instances of such box plots (for FA, NT, WH, MBD, and FOP). The monitoring results and the associated statistics support a number of observations:

1. Already a cursory look at Table 1 reveals the significant differences with regard to the presence patterns of the observed occupants. For instance, differences between occupants with regard to the mean values of FA, LD, and WH can be one and a half hours or more.
2. Statistically speaking, some indicators (OD, NT, FOP) appear to display a normal (symmetrical) distribution pattern, whereas others (FA, LD, WH, MBD) are non-symmetric (see Figures 1 to 5). Specifically, as one could expect, FA is left skewed (most arrivals occur before noon) and LD is right skewed (most departures occur after noon). Likewise, WH is plausibly right skewed, as the probability of shorter than normal working hours is higher than extremely long ones.
3. The skewedness of FA, LD, WH, and MBD may not be pronounced in the statistical mean, but the position of median (and mode) with regard to mean provides pertinent information. For instance, in case of FA and MBD, median and mode values are smaller than mean, whereas in case of LD and WH median and mode values are consistently larger than mean.
4. The values of CV point to a larger spread of data in case of the OD, NT, and MBD.
5. Certain markers (FOP, NT) show a somewhat higher level of consistency across multiple occupants (as expressed in the values of almost all statistics considered). Provided future studies would point in the same direction, it could be suggested that the values of such markers might be less prone to occupants' diversity.
6. Let us consider CV as a classical statistical dispersion measure applied to the distribution of the markers' values. As the results summarized in Table 1 imply, CV values do no vary much across different occupants. Again, if confirmed by future, more extensive studies, this finding could be of critical importance: While the absolute averaged long-term values of occupancy pattern markers could be very different from one occupant to another, the extent of variance (or dispersion) of the values could be statistically similar, consistent, and resistant to occupants' diversity.

Table 1 Summary of the statistical analysis results

Indicators	Statistical measures	Occupants							
		P1	P2	P3	P4	P5	P6	P7	P8
FA	mean	11.1	8.7	9.7	9.8	9.6	10.0	10.0	9.4
	median	10.8	8.3	9.3	9.3	9.3	9.5	9.5	9.3
	standard deviation	1.2	1.1	1.2	1.2	1.4	1.3	1.4	0.7
	mode	10.8	8.3	8.8	9.3	9.3	9.3	9.0	9.3
	CV	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	IQR	0.8	0.8	1.0	1.0	1.0	1.5	1.8	0.5
LD	mean	18.0	16.7	18.2	18.0	17.7	17.6	18.3	16.2
	median	18.3	17.0	18.5	18.5	18.3	17.8	18.5	16.5
	standard deviation	1.4	0.8	1.6	1.7	1.8	1.6	1.2	1.1
	mode	18.5	17.3	20.0	19.3	19.0	17.8	18.8	17.3
	CV	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1
	IQR	1.8	0.8	2.0	2.0	2.3	2.0	1.3	1.3
OD	mean	3.3	4.4	4.0	3.9	3.7	3.4	3.9	3.2
	median	3.3	4.5	4.0	3.8	3.8	3.3	3.8	3.3
	standard deviation	1.3	1.4	1.4	1.4	1.4	1.3	1.2	1.0
	mode	3.0	4.8	4.3	3.3	3.8	3.3	3.5	2.5
	CV	0.4	0.3	0.4	0.4	0.4	0.4	0.3	0.3
	IQR	2.0	1.8	2.0	2.0	1.8	1.8	1.8	1.3
NT	mean	4.7	5.4	5.6	5.0	5.0	4.8	5.6	5.0
	median	5.0	6.0	6.0	5.0	5.0	5.0	6.0	5.0
	standard deviation	1.9	1.8	2.2	2.1	2.1	2.0	1.9	1.6
	mode	4.0	6.0	5.0	5.0	6.0	4.0	6.0	5.0
	CV	0.4	0.3	0.4	0.4	0.4	0.4	0.3	0.3
	IQR	3.0	3.0	3.0	3.8	2.0	3.0	3.0	2.0
WH	mean	6.9	8.0	8.6	8.3	8.1	7.6	8.3	6.8
	median	7.0	8.5	9.0	8.8	8.5	8.0	8.8	7.3
	standard deviation	1.8	1.4	1.9	1.9	2.1	2.0	1.8	1.3
	mode	8.3	9.0	9.8	9.5	9.8	8.5	9.3	7.8
	CV	0.3	0.2	0.2	0.2	0.3	0.3	0.2	0.2
	IQR	2.5	1.3	2.3	2.5	2.8	2.5	2.5	1.8
AD	mean	3.6	3.6	4.5	4.3	4.5	4.2	4.4	3.6
	median	3.5	3.5	4.8	4.3	4.5	4.3	4.5	3.5
	standard deviation	1.5	1.3	1.7	1.7	1.8	1.7	1.6	1.2
	mode	3.5	3.5	5.5	3.8	4.8	4.5	4.5	4.0
	CV	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3
	IQR	2.3	1.8	2.3	2.3	2.8	2.0	2.3	1.6
MBD	mean	0.8	0.7	0.9	1.0	1.0	1.0	0.9	0.8
	median	0.7	0.6	0.8	0.9	0.9	0.8	0.8	0.7
	standard deviation	0.5	0.5	0.6	0.7	0.7	0.6	0.5	0.4
	mode	0.5	0.5	0.5	0.8	0.8	0.8	0.8	0.5
	CV	0.6	0.6	0.7	0.6	0.7	0.6	0.5	0.5
	IQR	0.5	0.4	0.5	0.6	0.6	0.5	0.4	0.4
FOP	mean	0.49	0.55	0.48	0.48	0.47	0.46	0.48	0.48
	median	0.47	0.56	0.47	0.47	0.45	0.45	0.46	0.47
	standard deviation	0.16	0.14	0.16	0.15	0.15	0.15	0.13	0.13
	mode	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
	CV	0.33	0.26	0.33	0.32	0.33	0.34	0.28	0.28
	IQR	0.23	0.20	0.19	0.21	0.21	0.19	0.18	0.18

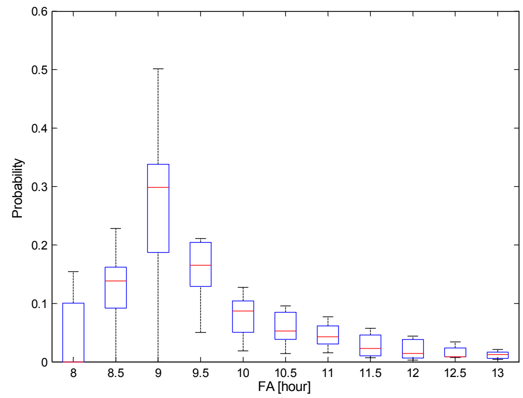

Figure 1 First arrival time boxplot

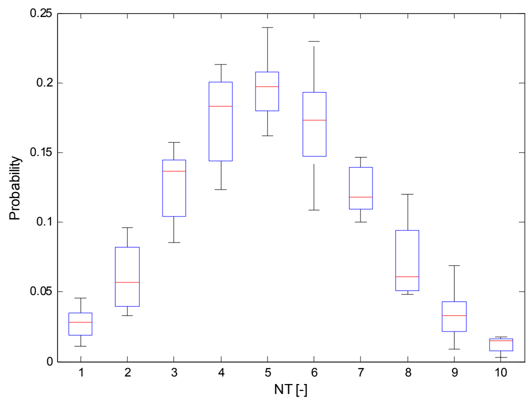

Figure 2 Number of transitions boxplot

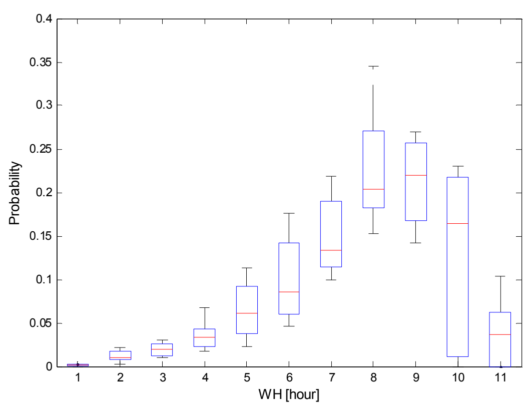

Figure 3 Working hours boxplot

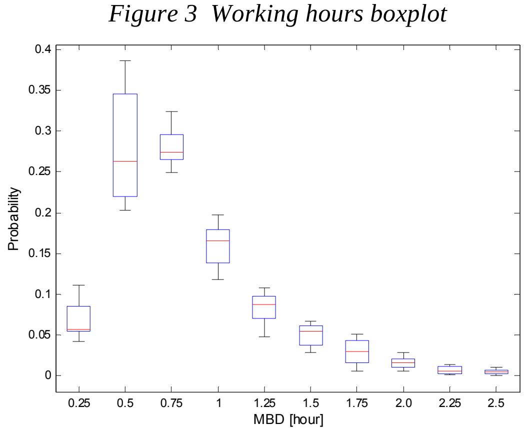

Figure 4 Mean break duration boxplot

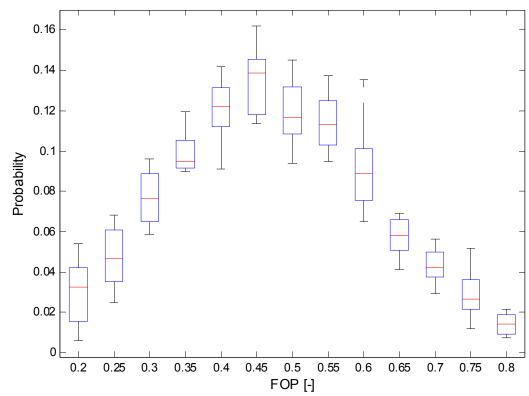

Figure 5 Fraction of presence boxplot

CONCLUSION

Using limited but high-fidelity empirical data on occupants' presence patterns in an office building, we conducted a study of a number of numerical markers of such patterns. Framed in terms of the previously formulated hypotheses, the study's results appear to suggest the following:

i) Individual long-term presence patterns of office workers as expressed in terms of mean marker values can be indeed highly different amongst different occupants. Hence, approaches geared toward detailed modelling of occupants' presence in buildings cannot ignore such inter-individual differences.

ii) The statistical dispersion of the defining markers of the office workers' occupancy patterns (as expressed in terms of CV values) does not indeed display significant inter-individual differences. Consequently, basic information about the shape of distribution (normal, skewed, etc.) together with the dispersion information can provide a reliable basis for the randomisation of typical occupancy schedules. This in turn can provide the basis for stochastic occupancy models suitable for deployment in building performance simulation applications.

As mentioned before repeatedly, the credence of the above conclusions needs to be carefully examined in future studies involving a much broader empirical data set and a larger number of occupants. Nonetheless, the results to date represent a highly promising line of inquiry. In a nutshell, they suggest that empirically grounded knowledge of individual presence patterns (schedules) is indispensable, if highly realistic and highly detailed representations are needed. However, stochastic implementations of such patterns via randomisation of the respective schedules may not necessarily require detailed knowledge of occupants' diversity. In other words, the statistical dispersion of the marker values may not be decisively affected by occupants' diversity (as represented by the mean values of such markers).

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REFERENCES

ASHRAE, 2013. ASHRAE 90.1-2013 Appendix G. Building Performance Rating Method, ASHRAE.

Davis, J.A., Nutter, D.W., 2010. Occupancy diversity factors for common university building types, Energy and Buildings 42 (2010) 1543–1551.

Duarte, C., Wymelenberg, K.V.D., Rieger, C., 2013. Revealing occupancy patterns in an office building through the use of occupancy sensor data, Energy and Buildings 67 (2013) 587–595.

Mahdavi, A., 2011. People in building performance simulation, in J. Hensen, R. Lamberts (Eds.), Building Performance Simulation for Design and Operation, Taylor & Francis, New York, ISBN: 9780415474146, pp. 56-83.

Mahdavi, A., Tahmasebi F., 2015. Predicting people's presence in buildings: An empirically based model performance analysis, Energy and Buildings 86 (2015), pp. 349–355.

Page, J., Robinson, D., Morel, N., Scartezzini, J. L., 2008. A generalized stochastic model for the simulation of occupant presence, Energy and Buildings 40 (2008), pp. 83–98.

Reinhart, C.F., 2001. Daylight availability and manual lighting control in office buildings simulation studies and analysis of measurements, Ph.D. thesis, Technical University of Karlsruhe, Germany.

Richardson I., Thomson, M., Infield, D., 2008. A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (2008), pp. 1560–1566.