Achieving a Deeper Understanding of User-Related Influences on Artificial Lighting Energy Demand Using High-Performance Computing

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Abstract

Occupancy behaviour, including presence at the workplace, has a significant influence on a building's energy requirements. However, modelling occupancy behaviour is complex, multidisciplinary, and stochastic rather than deterministic. As little information about the intended use is available during the building planning phase, general assumptions about occupancy behaviour are made during building simulation and system planning, based on empirical and standardised models. However, these are formulated as generally as possible to achieve the broadest possible applicability. For example, despite improved simulation techniques, assumptions about occupant behaviour in the workplace often lead to deviations from the real situation, i.e. energy performance gaps. A better understanding of the factors that influence occupant behaviour, their weighting, and the improved models derived from them are proving to be crucial for eliminating performance gaps. Using advanced statistical methods and High-Performance Computing, representative samples of potential scenarios were created in this study to fully quantify the impact on energy performance. This was based on minute-by-minute occupancy and energy data from a one-year series of measurements in an open-plan office of Bartenbach, Austria. This research, based on High-Performance Computing, presents a breakdown of organisational and individual factors influencing energy-related occupancy behaviour. The results provide a promising basis for future research and pave the way for more targeted and energy-efficient building planning.

1. Introduction

1.1 The Influence of User Behaviour

The deviations between predicted and actual energy requirements are known as energy performance gaps (EPG). The real energy demand is usually greater than the assumptions on energy demand from planning and simulation. Furthermore, performance gaps can exist not only in terms of energy demand but also, for example, in relation to the performance indicators of comfort and health. In the context of the building design phase, uncertainties in building modelling (such as insufficient geometric and material properties, and environmental data) as well as institutional restrictions and technical limitations of existing modelling tools can be identified in the literature as causes of EPGs (Lee & Selkowitz, 2006; Van Dronkelaar et al., 2016). In the context of the construction phase, the main causes include suboptimal installations and system calibrations (and thus inefficient system operation) as well as qualitative deviations in construction specifications (Menezes, 2012). However, the greatest cause of performance gaps can be identified as uncertainty regarding user behaviour while planning and the associated system designs (Calì et al., 2016), especially deviations resulting from the occupancy models used (Niu et al., 2016; de Wilde, 2014). These are currently mostly based on generally applicable models to bridge information gaps in the building design phase about subsequent room utilisation (cf. models in sia, 2006). It has been shown that these models fail when occupancy behaviour is very dynamic, e.g. strongly varying presence at the workplace due to frequent follow-up meetings (Hammes

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et al., 2021), which can account for around a quarter of managers' working time (Panko, 1992). In addition, organisational and social factors can influence occupancy dynamics, for example through flexitime arrangements. This information usually only becomes apparent after commissioning. With such uncertainties, it is not surprising that, depending on the actual occupancy dynamics, there are large ranges in terms of system-related energy requirements (cf. Hammes et al., 2021). In addition to occupancy patterns, uncertainty also includes user preferences. Preferences, e.g. regarding visual comfort, can differ greatly between individuals (Despenic et al., 2017).

The negative consequence of energy performance gaps is usually a higher energy requirement and therefore higher operating costs, as well as the risk of incorrect system dimensioning. The latter can result in inefficient operation, which in turn can be reflected in energy requirements and can also be to the detriment of user comfort. For these reasons, the improvement of planning and simulation methods is currently one of the most important challenges facing the construction industry (Menezes et al., 2012). Above all, it is important to create a better user mapping through improved occupancy models to reduce deviations between planning and operation. The need for this has already been recognised by the scientific community and several papers have been written on the subject. In addition, the energy-related influence of user behaviour and its mapping has been included in international research efforts (IEA EBC Annex 66 & IEA EBC Annex 79).

1.2 Related Work

Zou and Alam (2020) use a post-utilisation evaluation to identify causes of the EPG using content analysis and statistical analysis methods using the example of a multi-storey office building and to develop a stakeholder-oriented methodological framework to close the EPG. Manual override of automatic systems and inaccurate predictions of energy demand outside general business hours were identified as user-related causes (Zou & Alam, 2020). Here, too, user behaviour is determined by more influencing factors than by framework conditions set by the organisational structure.

Using support vector regression based on operational data from an office building, significant improvements in the prediction of individual user profiles were achieved for the case study compared to existing models (Weninger & Hammes, 2023).

Menezes et al. (2012) provide a general overview of the causes that can lead to performance gaps. The authors also show how the findings from post-occupancy evaluation (POE - the system evaluation after commissioning) can be used to create more accurate energy performance models. Their results show that by combining measurement data with predictive energy modelling, the accuracy of energy forecasts can be improved (Menezes et al., 2012).

The role of POE in the breakdown of performance gaps and their closure via improved planning and simulation methods becomes clear via the thematic literature. The comparison of measured data and simulation results proves to be essential to ensure the validity of models (Fabi, 2013). To break down the energy-relevant user behaviour, this study is therefore also based on post-occupancy data.

1.3 Objective

The negative consequences of EPGs currently pose a significant challenge, particularly those EPGs that arise due to the indeterminacy of user behaviour. A precise measurement of their extent and a breakdown of relevant influencing factors can counteract this. This study therefore aims to use post-occupancy data and High-Performance Computing (HPC) to break down the user-related energy demand regarding the influencing factors and, based on this, to derive recommendations for improved planning and simulation techniques.

As artificial lighting is one of the largest consumers of electrical energy in commercial buildings, accounting for around one third (Chow et al., 2013), the study focusses on this trade. Furthermore, office buildings are the most common type of building in most countries in terms of floor space and energy requirements (Labeodan, 2015). The study is therefore further focused on office buildings.

2. Methodology

2.1 Study Object and Data Base

The post-occupancy data on which this study is based result from the 160 m² open-plan office of Bartenbach GmbH, which was converted into a LivingLab in 2019 (Fig. 1). Since commissioning, over 100 sensors have been used to record the indoor and outdoor climate and energy consumption of the lighting system components as well as user-related variables such as occupancy patterns and interaction behaviour with the lighting systems in high resolution. In addition to the latter, all system states of the integral artificial and daylight lighting system are also logged. The recording of user-related variables is carried out in compliance with data protection aspects. The Bartenbach LivingLab has already been able to derive several improvement measures for energy efficiency and comfort from post-occupancy evaluations.

A special feature of the open-plan office relevant to the study is a high daylight input (daylight autonomy (DA) of 81.56%, based on the normative workplace lighting of 500 lx and reference time of 08:00-18:00, excluding summertime, see (Hammes et al., 2021)), which means that the use of artificial light is primarily limited to the morning and evening hours. Furthermore, daylight and artificial light can be controlled zonally per desk group (cf. Fig. 1), which offers advantages for energy efficiency and especially comfort, as individual lighting preferences can be better mapped (Hammes et al., 2020). There are a total of nine lighting zones (=workplace zones), four along the skylight and five along the south façade (Fig. 1). The study includes 18 people, two people per zone. The activity profile of the employees involved in the study object corresponds to that of project managers, which is associated with a corresponding occupancy dynamic (cf. time study for managers by Panko & Kinney, 1992). The core working hours in the study period from Mon-Fri are 09:00-12:00 and Mon-Thu 14:00-17:00. The employees have the option of flexitime and working from home. Accordingly, there is a high degree of dynamism among residents regarding occupancy times at the workplace. To reduce energy-unfavourable artificial lighting operating times during absences, there is a passive infrared presence control system for each workplace. In addition, there is daylight control of the artificial light to the standardised 500 lx per zone.

Fig. 1 – Interior of the LivingLab at Bartenbach GmbH in Aldrans, Austria - south façade with half-closed sun protection on the right, skylight on the left (image source: Bartenbach GmbH)

The artificial light energy requirement of a zone results from the logical OR linking of the presence profiles of all persons in this zone. To realise presence detection in the best possible way, the detection range of the passive infrared sensors used is limited to the workplace.

For the study setting described above, the data basis for the study is formed by attendance data per individual workstation (pseudonymisation was used to ensure data protection), illuminance values and the dimming level of the artificial light for each zone. The latter two pieces of information were used to break down the illuminance value per zone according to the proportion of daylight and artificial light. The data covers a period from February 2022 to January 2023. The resolution is per minute or change of state.

2.2 Variant Creation via High-Performance Computing

The lighting zones are utilised more or less efficiently depending on the respective user combination and the associated occupancy dynamics at the workplace. This means that with increasing overlap of working times in the energy-relevant morning and evening hours, the zone is utilised more efficiently in terms of energy if the joint absences are high during these times. Furthermore, the position of the workplace is also relevant, as there are different daylight potentials per zone.

There are two people per table group, i.e. for each of the 9 controllable lighting zones. Varying the combination of presence profiles and the assigned workplace zone results in a total of $1.25*10^{13}$ combinations (all possible combinations for 9 different pairs distributed over nine different workstation zones). Considering that individual users can have very individual behavioural patterns, it can be assumed that, depending on the combination of different user characteristics, significant differences may occur in the influences on the key performance indicators. In addition, previous studies have already shown that the relevance of the position increases with improved user pairing (Hammes et al., 2022). Therefore, expanding the understanding of the underlying profile properties proves to be necessary to make them usable for planning and simulation as well as to reduce performance gaps.

To gain an understanding of formative user characteristics, a representative sample size of potential occupancy scenarios was created using HPC. 10.24 million samples were generated using Monte Carlo simulation. A sample represents a completely randomised variation of user pairings and their position in the room. Repetitions of identical user distributions in the room were avoided. In addition, the HPC was used to determine the specific artificial lighting energy requirement for each sample, based on the measured illuminance of the daylight input per zone, the artificial lighting energy required to achieve the 500 lx and the combined presence profiles. The calculations were carried out on the VSC-5 of the Vienna Scientific Cluster (Austrian National Supercomputing Centre). Several batches were used, distributed across multiple nodes with each batch parallelized to be evaluated on 128 CPU cores. The calculation of the samples took approximately 60,000 hours of core time.

2.3 Characteristics of the Generated Data

The real artificial lighting energy requirement is 237 kWh (based on the lighting zones in the study object over the observation period Feb 2022 - Jan 2023). For a direct comparison of the measured value-based data with simulation-based data, the occupancy models according to (sia, 2006) were matched with the measured illuminance levels or the derived demand values for artificial lighting energy per zone (172 kWh). The results show significant deviations from the real energy demand (38%).

The representation of the 10.24 million different samples generated by HPC as a histogram, with the energy demand as the abscissa, shows an approximately normal distribution (see Fig. 2). All user pairings (regardless of their position in space) occur almost equally frequently. The identified mean value of the artificial lighting energy demand with standard deviation is 239 kWh ± 12. The most unfavourable combination of the generated samples in terms of energy results in an artificial lighting energy demand of 285 kWh. The minimum identified is 183 kWh, i.e. there is a range between the minimum and maximum value of 102 kWh. The range between the minimum and maximum values of the samples and the deviation from the simulation highlights the need for a better understanding of the defining characteristics of user-related performance gaps and a quantification of possible ranges of energy demand. Fig. 2 also shows 247 kWh for the upper quantile (Q3), 230 kWh for the lower quantile (Q1) and correspondingly 17 kWh for the interquartile range (IQR). The median is 239 kWh. The upper whisker is 273 kWh, and the lower whisker is 205 kWh.

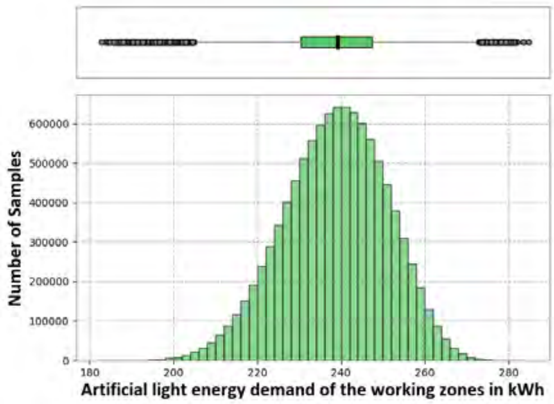


Fig. 2 – Artificial light energy requirement for the 10.24 million samples generated via HPC as a frequency distribution

2.4 Data Evaluation and Limitations

In a first step, the data generated using HPC was analysed to determine which presence profiles and combinations are responsible for particularly low or particularly high energy consumption. Advanced statistical methods, such as variance analysis

(ANOVA), are primarily used for this purpose. In addition, their diurnal and seasonal influence is evaluated as well as the influence of the room position. The post-processing analyses were carried out in Python (version Python 3.10, primary libraries used: pandas 2.0.0, scipy 1.11.1, scikit-learn 1.3.0). Supplementary statistical analyses were carried out with JASP (version 0.18.3.0).

As meetings often take place at the workplace, there is a risk of incorrect detections due to people moving between zones. In addition to this sensor-related limitation of the study, there was no gender-specific evaluation. Furthermore, two data logging system failures totalling 11 days should be mentioned.

3. Results and Discussion

An examination of the frequencies of individual user combinations in the border areas of the histogram, i.e. the minimum and maximum energy ranges, shows that certain user combinations occur more frequently than other user combinations. For both low energy values and the very high energy range, 10,240 samples each were considered, which corresponds to 0.1% of the entire data set of 10.24 million. This is associated with nine user combinations per sample. Fig. 3 shows the frequency combinations of individual user combinations as an example for the minimum range (the same was done for the maximum range). Based on this distribution, the most important user combinations were analysed to list the special features that have a positive or negative impact on energy requirements and therefore possibly influence the extent of performance gaps.

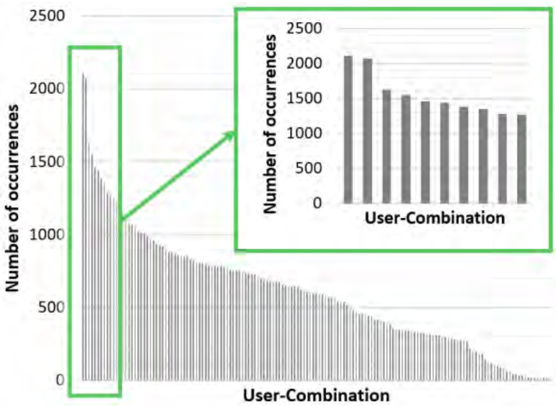


Fig. 3 – Frequency distribution of all 153 possible user combinations for the low energy demand area according to Fig. 2

The attendance data at the workplace was recorded in high resolution. This means that measurement data is available at time intervals of less than 1 min over the study period. The arithmetic mean over the time of day of the five profile combinations that occur most frequently in the minimum ranges compared with the five profile combinations that occur most frequently in the maximum ranges shows clear differences, particularly in the morning and evening hours (cf. Fig. 4a and 4b). These are the times that have the greatest influence on energy demand due to the study setting (see Hammes et al., 2022). While the most frequent user combinations for high energy demand are characterised by high presence in the morning hours (in Fig. 4b, yellow-green area), the most frequent user combinations from the low energy range show almost no presence here. It can also generally be seen that the attendance probability is higher for the identified user combinations from the maximum range (more yellow). This results in a higher probability of artificial lighting during the day, especially when the sky is overcast.

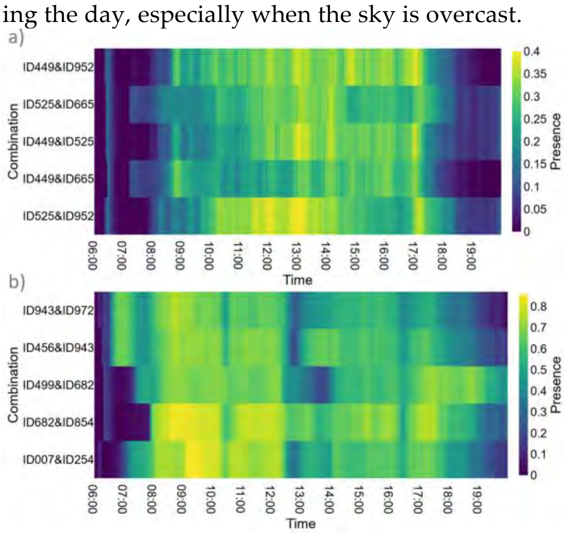
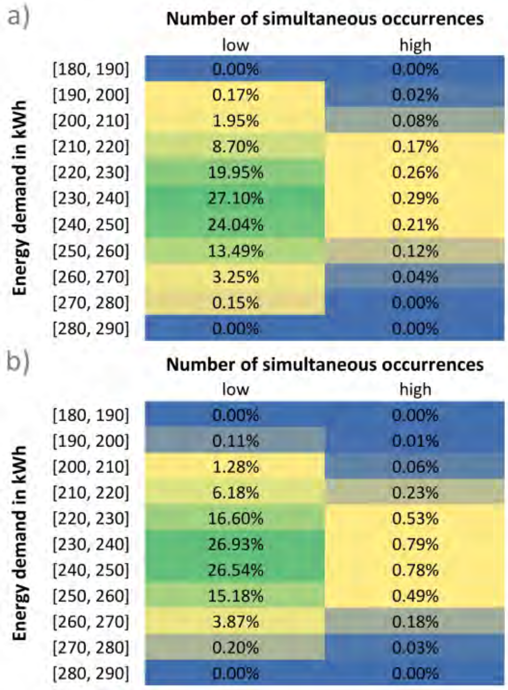


Fig. 4 – Averaged presence over the time of day for the five most frequent user combinations that occur in the area of a) minimal energy demand and b) maximal energy demand. Users pseudonymized. Higher probability of presence if the color is yellow, lower probability of presence if the color is blue

These differences are also supported by the statistical analyses. A two-way ANOVA was conducted to determine if there was an interaction between the factors profile type and hour of the day on energy demand. Prescence times were normally distributed within all groups, with skewness and kurtosis statistics between -2 and +2. There was no homogeneity of variances, as assessed by the Levene's test for equality of variances ($p < 0.05$); however, because the assumption of normal distribution was satisfied with an equal number of datapoints in each group, the two-way ANOVA is considered robust to this violation (Maxwell et al., 2017).

The results show significant main effects in both factors (both $p < 0.001$), with generally higher attendance times in higher energy requirement profiles (M_{high} = 5,036 min, M_{low} = 2,485 min). More interestingly, there was also a statistically significant interaction between profile type and hour of the day, $F(14, 120) = 1.98$, $p < 0.05$, $\omega^2 = 0.03$. Bonferroni-corrected post-hoc tests show that the differences are primarily due to the edge of the day in the morning. Significant differences (both $p < 0.05$) between both profile types can be demonstrated in the morning between 08:00 and 09:00 and between 09:00 and 10:00. There were no significant differences for the remaining time periods. It turns out that the option of flexitime regulation is perceived very differently by each person, which is reflected in the energy profiles.

An examination of the frequencies of relevant combinations for the entire data set, i.e. for all 10.24 million samples, shows that the relevant profile combinations for a lower energy requirement also tend towards the lower energy level, while relevant profile combinations for a higher energy requirement are shifted to the maximum (Fig. 5a and 5b). The mean value of the distribution of the data for Fig. 5a is 237 kWh, for Fig. 5b 239 kWh, for comparison across all samples the mean value is 239 kWh. Less favorable combinations occur slightly more frequently. A Chi-Square Goodness of Fit Test for an adjusted sample size of 5,000 samples was performed to determine whether the frequencies of lower and higher energy requirement profiles were equally distributed over the different energy levels. The frequencies did significantly differ between the two profile types, $X^2(8, N = 5{,}000) = 135.87$, $p = < 0.001$, supporting the assumption that the profile types can be assigned to the respective lower or higher areas of the distribution. As the user combinations generated via HPC occur equally frequently per zone, this emphasizes that with zoned lighting concepts it is essential how the zones are occupied.



a)

Energy demand in kWh	Number of simultaneous occurrences: low	high
[180, 190]	0.00%	0.00%
[190, 200]	0.17%	0.02%
[200, 210]	1.95%	0.08%
[210, 220]	8.70%	0.17%
[220, 230]	19.95%	0.26%
[230, 240]	27.10%	0.29%
[240, 250]	24.04%	0.21%
[250, 260]	13.49%	0.12%
[260, 270]	3.25%	0.04%
[270, 280]	0.15%	0.00%
[280, 290]	0.00%	0.00%

b)

Energy demand in kWh	Number of simultaneous occurrences: low	high
[180, 190]	0.00%	0.00%
[190, 200]	0.11%	0.01%
[200, 210]	1.28%	0.06%
[210, 220]	6.18%	0.23%
[220, 230]	16.60%	0.53%
[230, 240]	26.93%	0.79%
[240, 250]	26.54%	0.78%
[250, 260]	15.18%	0.49%
[260, 270]	3.87%	0.18%
[270, 280]	0.20%	0.03%
[280, 290]	0.00%	0.00%

Fig. 5 – Percentage distribution of those samples containing the 10 most relevant profile combinations for a) low energy demand and b) high energy demand; Each applied to all samples

A final check of the energy deviations between relevant combinations of minimum and maximum ranges over the time of day and month shows a continuous difference in the morning hours over the year (Fig. 6). Deviations in the evening hours occur primarily in the first half of the year.

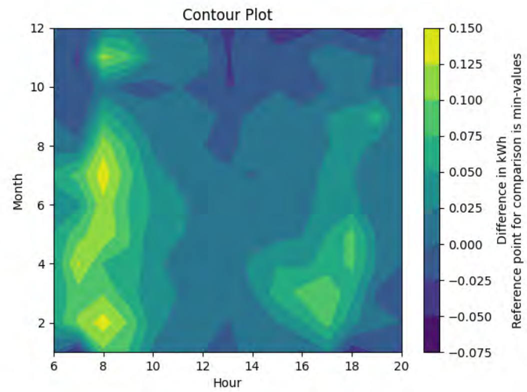


Fig. 6 – Deviation between the average daily and monthly resolved energy profiles from the identified minimum and maximum range, applied to the 10 most relevant profiles in each case

5. Conclusion

The results of this study help to decipher the causes of the EPG, especially in the lighting area, and to identify dependent variables. For this study, a high occupancy time in the morning and evening hours was identified as a particularly influential factor on the EPGs. Statistically significant interactions were found between profile type and the morning hours of 08:00-10:00. While the energy significance of zoned lighting concepts and their advantages for user comfort have already been demonstrated several times (i.e. in Hammes et al., 2020), the combination of profiles is essential for the energy requirements of dynamic occupancy. The study results also show a very wide variation in the probability of presence at the workplace, which in the study object is due to flexitime arrangements and the high number of follow-up meetings. Such dynamic processes are difficult to depict in simulations, which can lead to generally valid models usually resulting in energy-inefficient operation, which in turn becomes visible in EPGs.

The results of the study show that existing planning models can only incompletely depict dynamics in the morning and evening hours, which calls into question their suitability for application. However, the development of an applicable model requires a significantly larger data set and further research in the areas of user individuality and work processes. For more accurate building planning and simulation and thus a lower risk of performance gaps, it would therefore be advisable to classify the results for different organisational and building typologies. In this sense, the approach presented in this paper can be seen as a first step towards improved user modelling in simulation processes. Further research activities can also be carried out to quantify the influence of occupancy behaviour and other factors, such as weather and user position in the room, on total energy consumption and thus make it easier to plan by deriving improved models for the simulation.

The presented work also emphasises the importance of POEs to gain insights for improving planning and simulation after commissioning and thus reducing EPGs. POEs also allow measures to be derived after commissioning to improve energy requirements. Accordingly, optimisation algorithms could derive improved user distributions in the room and thus reduce EPGs.

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