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THE IMPACT OF SEASONAL OCCUPANCY PATTERNS ON ENERGY-RELATED LIGHTING OBJECTIVES

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Abstract

A greater reduction in artificial lighting energy demand in buildings is necessary to achieve climate targets. The control of artificial lighting depending on presence plays a central role in this. To optimise the energy consumption of switch-off times coupled with passive infrared sensor technology without affecting disruptive false-off rates, there are probabilistic approaches that adapt the switch-off times to real occupancy patterns. The identification of individual attendance patterns and their consideration in the control system is essential for the optimisation process. Work processes and sociological structures have a significant influence on occupancy behaviour and can prove to be time-variant. It is therefore necessary to examine whether one-off or cyclical applications of the optimisation algorithm are required. This study uses a high-resolution data set from an open-plan office to investigate the effect of temporal variability on switch-off time optimisation. The results show that there are no significant seasonal effects.

Keywords: Energy efficiency, Switch-off time, Occupancy behaviour, Optimisation algorithms

1 Introduction

1.1 User-centred lighting control

Occupants in buildings are involved in various activities that lead to movement between rooms in particular. Due to subjective preferences or professional requirements, the behaviour of occupants can vary greatly. For example, a manager may spend less time in their own office than their assigned employees due to frequent meetings. In fact, the occupancy of a building is stochastic in terms of both time and space, as both random and planned events, such as meetings, influence behaviour (Feng et al., 2015). Occupancy behaviour, especially the attendance pattern at the workplace, is thus largely determined by organizational aspects (such as home office regulations and flexitime regulations) and work-specific processes (e.g., the follow-up to meetings (Hammes et al., 2021a; Panko and Kinney, 1995)), i.e., the framework conditions of a target application. These influences can vary greatly from organisation to organisation and thus also influence the occupancy behaviour.

The formative influences and thus the picture of the occupancy dynamics in the room usually only emerge completely after commissioning. It is therefore not surprising that occupancy behaviour is complex and difficult to predict due to its stochastic nature and is one of the most important factors influencing building energy demand (D'Oca and Hong, 2015; Yoshino et al., 2017). As building occupancy has a high impact on energy demand, understanding it and taking it into account in control systems and simulations is crucial to avoid inefficient system operation (D'Oca and Hong, 2015). In order to overcome the associated uncertainties, assumptions about occupancy behaviour that are as generally valid as possible are usually made in the building design phase in order to achieve a high level of applicability. Building occupancy plans are therefore often based on static models, e.g., sia (Schweizerischer Ingenieur- und Architektenverein (sia), 2006) and ASHRAE Standard 90.1-2004 (American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), 2004; D'Oca and Hong, 2015). However, discrepancies between real occupancy behaviour and generally valid assumptions can lead to incorrect system dimensioning and result in inefficient system operation (Chang and Hong, 2013; Duarte et al., 2013).

One example of this is generalised switch-off times (Guo et al., 2010), which are used in the context of presence-based artificial lighting control via passive infrared sensors (PIR) in order to keep disruptive false-off rates low. Such generalised switch-off times are typically used in the range of 10-20 minutes (min). (Garg and Bansal, 2000). Although PIR-based presence control of artificial lighting is one of the most important approaches to improve energy efficiency due to low installation costs and easy commissioning (Galasiu et al., 2007; Guo et al., 2010), artificial lighting operating times could be further reduced by adapting the switch-off time to individual presence patterns at the workplace without compromising comfort due to increased false-off rates. (Hammes et al., 2021b). Optimisation approaches for this are carried out in the context of extended commissioning, as a data-supported evaluation of real occupancy data is necessary. This is done in so-called post-occupancy evaluations (POE).

The reduction of switch-off time is valid for optimising after-use and is also highly necessary in view of the fact that lighting is one of the most significant energy consumers in the building sector (Chow et al., 2013).

1.2 Problem definition

The adjustment of the switch-off time to individual presence patterns has so far mostly only been used as a one-off optimisation after commissioning over a fixed period of time. There are currently no evaluations of their validity over time. This is because occupancy behaviour can be subject to temporal variability, as work processes, particularly in the context of project-related work activities, as well as the degrees of freedom that a social structure allows, can change over time.

The trend towards providing employees with flexible working conditions has gained momentum, not least due to the COVID-19 pandemic. Time-based working dynamics are also increasingly required in the context of unpredictable social or technological changes. In addition, the physical workspace is increasingly being supplemented by a digital space. To follow this trend, the New Ways of Working approach is being introduced in many organisations around the world. This is geared towards flexible work organisation and is made possible by information and communication technologies (Blok et al., 2011). In addition to spatial flexibility, working arrangements are often characterised by temporal freedom (Voll et al., 2022) (Allen et al., 2013). This can result in a high degree of variability. The study by Duarte et al. analysed 23 months of occupancy sensor data from a large office building to establish occupancy diversity factors and investigate their influence on energy simulation models. The results show that occupancy diversity factors vary significantly with days of the week and seasons (Duarte et al., 2013). Chang and Hong confirm in their research that occupancy can be strongly dependent on the time of day, season, weather, habits and personality of the users (2013).

This study therefore addresses the research question of the extent to which attendance patterns after commissioning are so variable over time that this has an influence on the temporal validity of the optimisation algorithm for the switch-off time. In doing so, it is specifically analysed how this is reflected in the energy demand.

1.3 Structure of this paper

While the importance of precise consideration of the occupancy pattern at the workplace and its temporal variability for ensuring energy targets was emphasised at the beginning, existing approaches from the literature that optimise occupancy models in order to minimise the risks of inefficient system operation are listed below. Based on this, our own methodology is presented. This is based on real high-resolution attendance data from an open-plan office. These are segmented into suitable time series for the analysis and used to apply the optimisation methods for switch-off time and redistribution of users in the room. The variability of the results is checked using suitable statistical analysis methods. This is to determine whether seasonal effects significantly influence the results of the switch-off time optimisation. After a discussion on the practical relevance and possible implementation approaches, a final conclusion is drawn and an outlook for future investigations based on this is given.

2 Related Work

Precise occupancy profiles prove to be important in order to be able to estimate the actual energy demand and to define control concepts accordingly (Yang and Becerik-Gerber, 2014). For this reason, numerous studies have already been carried out in the past.

The study by Chang and Hong uses light switch data to analyse the occupancy status of 200 office cubicles in an open-plan office and identifies five typical occupancy patterns. They develop a stochastic occupancy model based on probability distributions of absence frequency and duration, which enables more realistic occupancy schedules for building simulations. The results show that short occupant vacancies can significantly influence the accuracy of simulated building energy data (Chang and Hong, 2013).

The work of Yan et al. deals with the evaluation of stochastic occupancy behaviour models from an application-oriented perspective and uses the lighting behaviour in an office space as a basis. Five classic lighting behaviour models were evaluated using different application scenarios. The results show that no model is universally valid and that scenario-dependent validation is crucial for reliable use (Yan et al., 2018).

Model-based control systems have low generalisation capability, as they require building and occupancy models that are complex to develop. These significantly increase the complexity of system development and represent a major obstacle to broad and flexible application in the construction sector (Esrafilian-Najafabadi and Haghighat, 2022).

In the study by Esrafilian-Najafabadi and Haghighat, a self-learning, model-free controller based on a double deep Q-networks algorithm was developed that independently learns occupancy profiles, energy consumption patterns and delay times of heating, ventilation, and air-conditioning (HVAC) systems through interaction with the environment. It uses a reinforcement learning method that does not require the creation of explicit building or occupancy models (Esrafilian-Najafabadi and Haghighat, 2022). This provides an alternative approach to generalised assumptions, such as those used in sia and ASHRAE standards. Real occupancy patterns are taken directly from the environment. In principle, learning approaches enable temporal variance in occupancy behaviour to be taken into account. For example, genetic programming was used to model the behaviour of a single office occupant based on attendance data (prediction accuracies of around 80 %) (Yu, 2010).

This research also helps to create a basic understanding of occupancy behaviour and its formative influences. Seasonal effects can be lost in models if time series are regarded as coherent. The generalisation of historical data can thus make it more difficult to validate the reliability of the underlying truth. Statistical results are easily distorted by irregular and atypical occupancy patterns. Averaging occupancy over longer periods of time can lead to considerable deviations and thus impair the validity of the models (Duarte et al., 2013; Yang and Becerik-Gerber, 2014). For this reason, a review of seasonal effects and the impact of temporal variance on energy efficiency is required.

3 Methodology

3.1 Study object

In order to test the seasonal influences on the optimisation of the switch-off time, an open-plan office in Austria is used, which regularly provides space for 18 people on 160 m² (Figure 1). Two people are assigned to each separately controllable lighting zone or workstation zone. Zoned lighting concepts also promise advantages for energy requirements in the context of open-plan offices (Hammes et al., 2020; Koo et al., 2010). Four of these workstation zones are located along a north-facing skylight and five workstation zones along a predominantly glazed south-facing façade. The latter ensures a high level of daylight autonomy (DA_{500}=81,56 %), which means that the use of artificial lighting to achieve standardised minimum illuminance levels of 500 lx is limited to the morning and evening hours. In order to avoid glare and overheating due to the high daylight input, there are static external daylight louvres and automatically controllable textile screens. To reduce energy consumption, each zone has

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presence control via PIR sensors and daylight control via illuminance sensors (target value 500 lx). Like the artificial lighting systems, the daylight systems can be overridden manually. The user is generally given the option of overriding such automated logics, as this has proven to be another essential system acceptance criterion (Despenic et al., 2017).

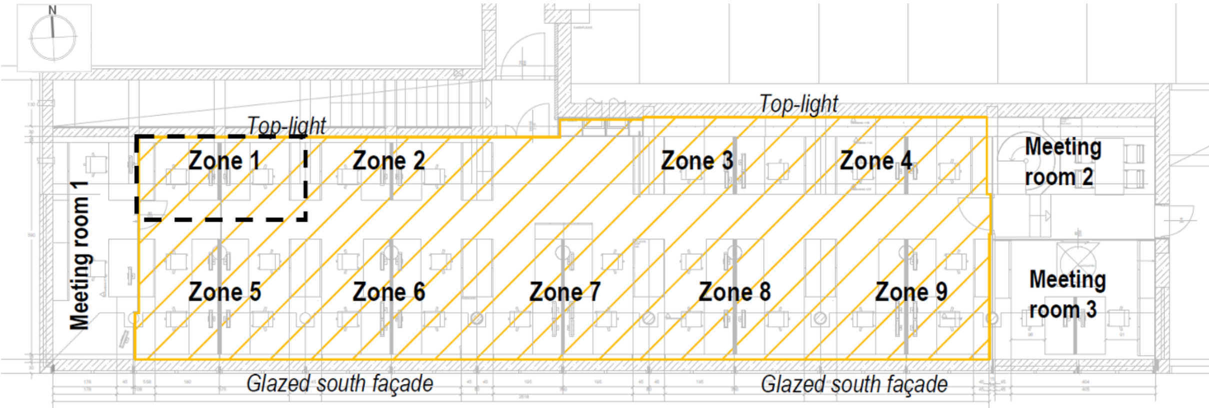

Figure 1 – Floor plan of the study building, open-plan office with nine lighting zones

The calculations are based on the presence data at individual workstation level. These are logged for changes in status and offset against the artificial light energy profile of a lighting zone. There is a complete data set from the period Jan. 2022 to Jul. 2024, i.e., the measurement data was collected outside the influence of COVID-19. To derive the necessary use of artificial lighting, there is a minute-by-minute resolution of the illuminance data at lighting zone level and logging of the status of the dimming level for status changes. In combination with electrical power values per dimming level, the artificial lighting energy requirement can be determined via the time series.

All data collection was carried out in compliance with data protection aspects. The employees in the study object are project managers in research and development. This work task involves regular follow-up meetings that take place both at the workplace and in meeting rooms. Project-specific work activities can vary greatly between individual days and project activities, e.g., longer working hours at the workstation for software development, absence from the open-plan office due to the follow-up of longer measurement work in the laboratory. There is also a flexitime system. This results in highly dynamic workplace utilisation, which can also exhibit seasonal differences.

3.2 Adaptation of the switch-off time to the individual occupancy behaviour

For the reference situation, i.e., the initial user distribution in the room and 15 min switch-off time, the artificial lighting energy requirement for the study period (Jan. 2022 to Jul. 2024) is 409,3 kWh. As two people are assigned to each separately controllable lighting zone, the logical-or-linked presence profile of a zone is always used. The switch-off time is optimised by applying POE of the occupancy pattern and probabilistic methods based on this. In this way, the individual probabilities of the minimum absence durations can be derived, i.e., the time when a return of the users to the workplace zone is less likely than a permanent absence. This can increase energy efficiency without compromising user comfort (Hammes et al., 2021b). By optimising the switch-off time, the artificial lighting energy requirement can be reduced to 323,2 kWh (i.e., 21 % reduction; assessed over the entire study period).

3.3 Segmentation

As the switch-off time optimisation according to Hammes et al. already takes comfort assurance into account (2021b), significantly shorter sequences can be selected. Shorter evaluation periods are recommended to minimise the risk of false-off rates and thus the risk of comfort restrictions. The occupancy profile is formatted as a binary time series. The Hamming distance is used to generate a corresponding segmentation of the occupancy pattern at the workplace. This involves segmenting the time-resolved attendance status into contiguous time series with similar patterns (Bookstein et al., 2002; Minsky and Papert, 1990). A tolerance level of one third is selected, i.e., if more than one third of the data deviates, the sequence is broken. The advantages of the Hamming distance are short calculation times. On average, 130 ± 65,9 sequences per workstation were identified over the study period using the Hamming distance. Figure 2 illustrates the dynamics of the switch-off times.

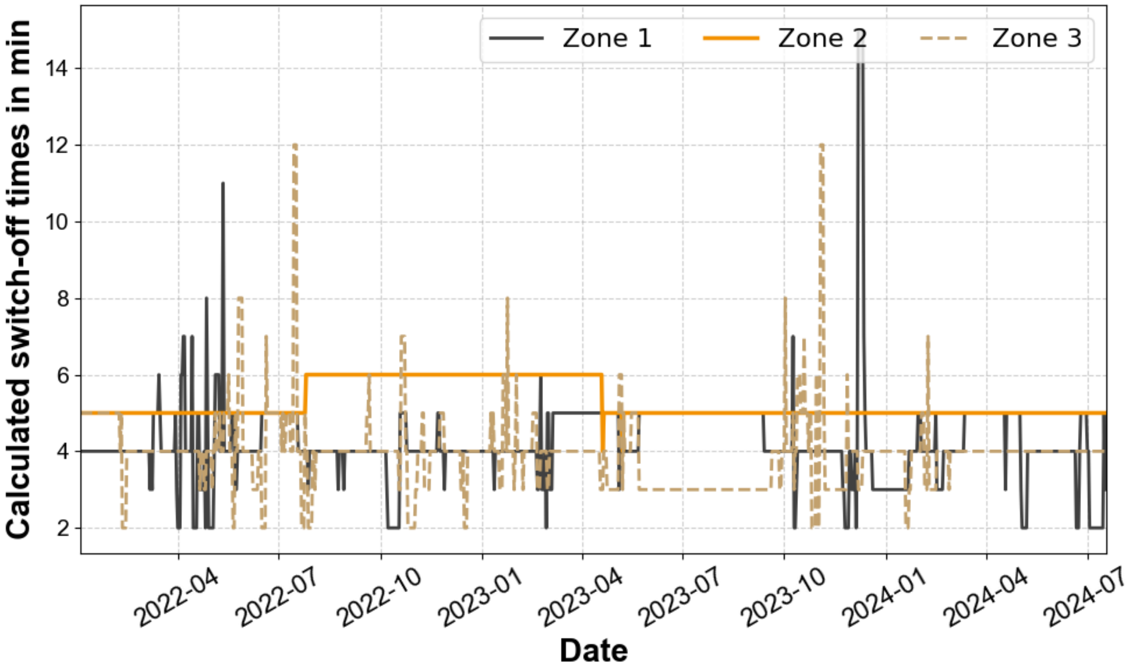

Figure 2 – Switch-off times for three lighting zones for segmentation by Hamming distance

3.4 Statistical evaluation

It is statistically checked whether there are significant differences between the individual sequences and therefore whether a cyclical application of the optimisation algorithm is necessary. Both significant correlations between the combined attendance profiles and time-dependent effects are analysed. The temporal analysis takes into account the factors month, quarter, summer-winter period and calendar year. The Shapiro-Wilk test is used to test the normal distribution. If the assumption of normal distribution is not fulfilled, non-parametric methods such as the Kruskal-Wallis test are used. Dunn's post-hoc test is used as a supplement to identify specific differences. In the case of significant effects, the medians with the corresponding 25 % and 75 % quartiles are shown in parentheses. All analyses were performed at a significance level of 0,05 (two-sided) using JASP (version 0.19.1.0).

4 Results

The Shapiro-Wilk test and Kolmogorov-Smirnov showed a significant deviation from normal distribution ($p<0,05$). Figure 3 illustrates the spread of the optimised switch-off time based on individual occupancy behaviour. Averaged across all zones, the median of the switch-off time is 4 min with an interquartile range from the 25th to the 75th percentile of 4 min to 5 min. It can be seen that some zones exhibit strong outliers with low frequency. For example, the range between minima and maxima in zone 1 and zone 6 is between 2 min and 15 min (median (IQR25-IQR75), 4 min (4-5) in each case), while this is only minimal for other zones, e.g., zone 2 between 4 min and 6 min (5 min (5-6)).

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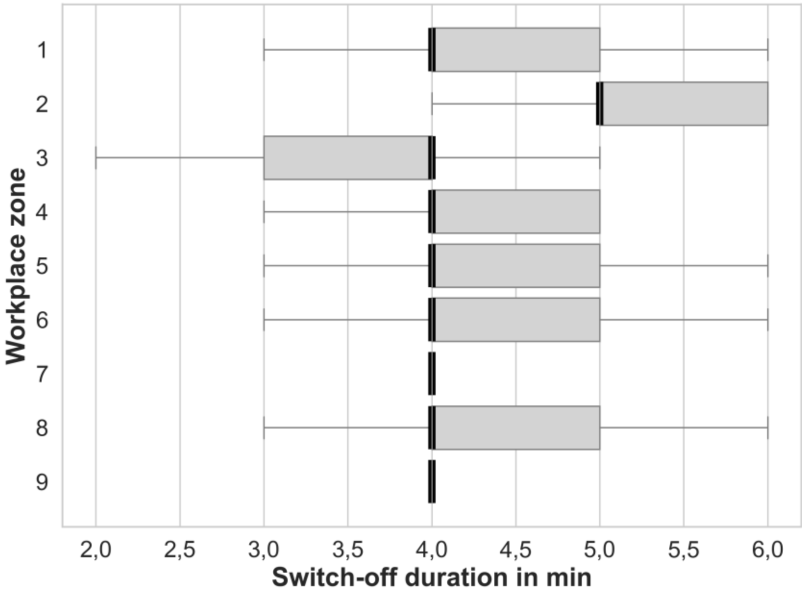

Figure 3 – Scattering of the derived optimized switch-off times per zone under segmentation according to the Hamming distance

The Kruskal-Wallis test showed that there are significant differences between the resulting switch-off times of the various workplace zones ($p<0,05$). In order to further break down seasonal effects, Figure 4 shows the test using the Kruskal-Wallis test of switch-off time per zone as a function of different time periods. However, it can be seen that for most occupancy profiles per zone there are no significant differences between months, quarters, summer and winter periods or years (grey, with $p>0,05$). Individual significant seasonal effects could be identified for workplace zones 7 and 9 in particular, which occur over the years (orange, $p<0,05$). Subsequent Dunn's post hoc tests show that significant deviations occurred for zone 7 between the first year of the measurement period (2022) and the second year (2023). For zone 9 between 2022 and 2023 and between 2022 and 2024. For zone 8, there are significant differences between Q1 and Q4 ($p<0,05$). The effect size is moderately low for all significant deviations ($0,01<p<0,06$, tested using Kendall's ε^2).

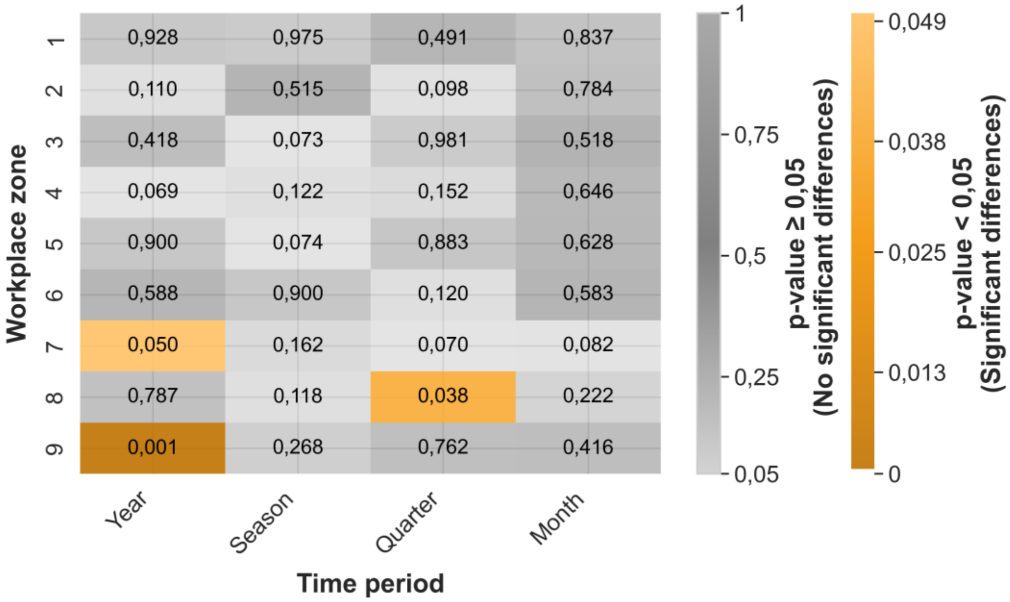

Figure 4 – Testing the derived optimized switch-off times per zone for significant differences over different time periods

It can be seen that the derived switch-off times between the individual periods, e.g., per quarter (Fig. 5a), change only insignificantly. This effect also means that the resulting energy savings between a one-off optimised switch-off time on the individual occupancy behaviour (323,2 kWh, total across all zones, evaluated over the entire study period) and a continuous adaptation after segmentation via the Hamming distance differ only insignificantly (327,7 kWh, total across all zones, evaluated over the entire study period). With regard to the energy effects, there are no significant differences due to the use of segmentation (Fig. 5b). With energy savings of around 20 % compared to the generally recommended switch-off times of 15 min, their one-off application is necessary in order to contribute to make a contribution to securing the climate targets.

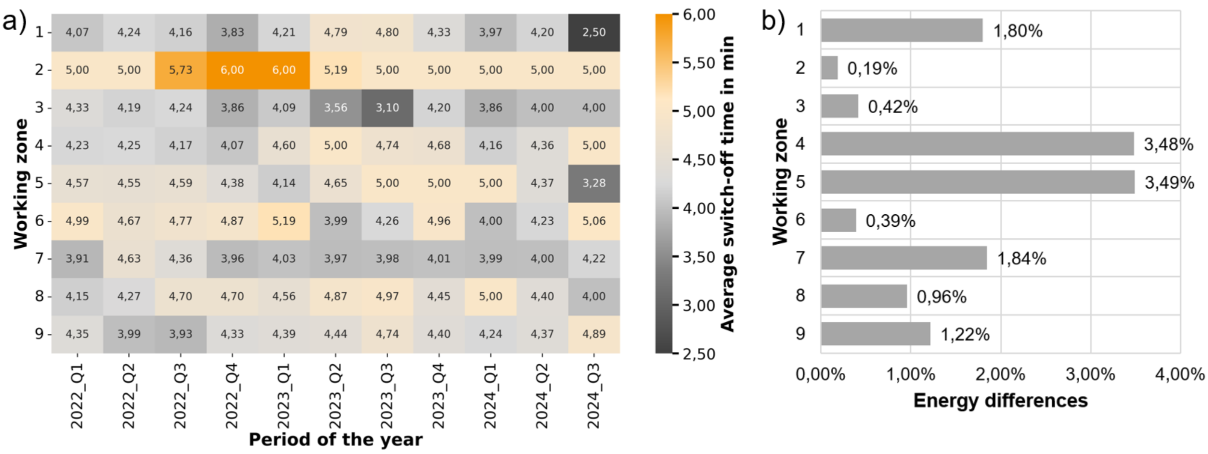

Figure 5 – a) Variation of switch-off times over different quarters and b) Energy differences between continuous optimization with segmentation via Hamming distance and one-off optimization

5 Discussion

The results show that when the run time optimisation is applied cyclically and segmented by Hamming distance, there are almost no significant changes in the switch-off times within a working zone over time (months, quarters, seasons, years), suggesting that the switch-off times remain relatively stable over these periods. This may be due to the fact that the variability within the data is too low for the given study setting. In order to generalise the conclusion about the absence of seasonal effects, it would be necessary to examine further data collection from other application areas, especially cases where, for example, the work content is more dynamic and therefore the periods of presence and absence at the workplace vary more from period to period.

However, even small changes in the switch-off time have different effects on the energy demand for artificial lighting due to seasonal variations in daylight availability and occupancy. This means that isolated outliers at individual time intervals can be avoided. In addition, setting a single switch-off time over an extended period of time carries the risk of failure rates exceeding a critical level and negatively impacting user comfort. In the future, the use of machine learning methods may help to automatically take into account the dynamics of individuality without the need for facility managers to actively adjust the control system (e.g., the method of (Hammes et al., 2024)).

5.1 Limitations

Although the switch-off optimisation procedure was tested for acceptance, this was only during a single implementation. Users may subconsciously adjust their evaluation of the switch-off time, e.g., through repeated (positive or negative) experiences, even when they are not actively aware of the lighting control. What is initially accepted may be evaluated differently in the long term (Greenwald and Banaji, 1995). A cyclical review therefore seems necessary to systematically capture such dynamic changes in user acceptance.

As the study object is characterised by high daylight autonomy (DA_{500}=81,56 %, (Hammes et al., 2021a)) and thus the artificial lighting energy demand is limited to the morning and evening hours, the influence of occupant behaviour could be overestimated. Therefore, further studies under different organisational conditions and for other building types are needed to make general statements.

6 Conclusion

Deviations from planned occupancy profiles, e.g., due to flexible working hours or working from home, can lead to incorrect load calculations and inefficient systems. The results show that POUs can help to understand occupancy behaviour, identify its impact on energy demand and initiate appropriate countermeasures. One such measure is the optimisation of switch-off times. Even if no relevant seasonal effects of the switch-off times can be identified, there are regular, small fluctuations in the switch-off time adapted to individual occupancy behaviour. A dynamic adjustment of the switch-off time therefore appears to be less necessary for energy efficiency, but more important for keeping disruptive false switch-off rates low. This needs to be investigated in long-term studies.

7 Outlook

In addition to examining other application areas, future analyses will also include additional segmentation methods such as dynamic time warping. Furthermore, social and organizational science influence criteria on segmentation will be investigated and their effect size quantified.

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References

ALLEN, T.D., JOHNSON, R.C., KIBURZ, K.M. and SHOCKLEY, K.M. 2013. Work–Family Conflict and Flexible Work Arrangements: Deconstructing Flexibility. *Personnel Psychology,* 66, 345–376. https://doi.org/10.1111/peps.12012

AMERICAN SOCIETY OF HEATING, REFRIGERATING AND AIR-CONDITIONING ENGINEERS (ASHRAE). 2004. ASHRAE Standard 90.1-2004, Energy Standard for Buildings except Low-Rise Residential Buildings.

BLOK, M., GROENESTEIJN, L., VAN DEN BERG, C. and VINK, P. 2011. New Ways of Working: A Proposed Framework and Literature Review, in: Robertson, M.M. (Ed.), *Ergonomics and Health Aspects of Work with Computers, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Berlin, Heidelberg*, 3–12. https://doi.org/10.1007/978-3-642-21716-6_1

BOOKSTEIN, A., KULYUKIN, V.A. and RAITA, T. 2002. Generalized Hamming Distance. *Information Retrieval,* 5, 353–375. https://doi.org/10.1023/A:1020499411651

CHANG, W.-K. and HONG, T. 2013. Statistical analysis and modeling of occupancy patterns in open-plan offices using measured lighting-switch data. *Building Simulation,* 6, 23–32. https://doi.org/10.1007/s12273-013-0106-y

CHOW, S.K.H., LI, D.H.W., LEE, E.W.M. and LAM, J.C. 2013. Analysis and prediction of daylighting and energy performance in atrium spaces using daylight-linked lighting controls. *Applied Energy*, 112, 1016–1024. https://doi.org/10.1016/j.apenergy.2012.12.033

DESPENIC, M., CHRAIBI, S., LASHINA, T. and ROSEMANN, A. 2017. Lighting preference profiles of users in an open office environment. *Building and Environment,* 116, 89–107. https://doi.org/10.1016/j.buildenv.2017.01.033

D'OCA, S. and HONG, T. 2015. Occupancy schedules learning process through a data mining framework. *Energy and Buildings,* 88, 395–408. https://doi.org/10.1016/j.enbuild.2014.11.065

DUARTE, C., VAN DEN WYMELENBERG, K. and RIEGER, C. 2013. Revealing occupancy patterns in an office building through the use of occupancy sensor data. *Energy and Buildings,* 67, 587–595. https://doi.org/10.1016/j.enbuild.2013.08.062

ESRAFILIAN-NAJAFABADI, M. and HAGHIGHAT, F. 2022. Towards self-learning control of HVAC systems with the consideration of dynamic occupancy patterns: Application of model-free deep reinforcement learning. *Building and Environment*, 226, 109747. https://doi.org/10.1016/j.buildenv.2022.109747

FENG, X., YAN, D. and HONG, T. 2015. Simulation of occupancy in buildings. *Energy and Buildings,* 87, 348–359. https://doi.org/10.1016/j.enbuild.2014.11.067

GALASIU, A.D., NEWSHAM, G.R., SUVAGAU, C. and SANDER, D.M. 2007. Energy Saving Lighting Control Systems for Open-Plan Offices: A Field Study. *LEUKOS,* 4, 7–29. https://doi.org/10.1582/LEUKOS.2007.04.01.001

GARG, V. and BANSAL, N.K. 2000. Smart occupancy sensors to reduce energy consumption. *Energy and Buildings,* 32, 81–87. https://doi.org/10.1016/S0378-7788(99)00040-7

GREENWALD, A.G. and BANAJI, M.R. 1995. Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, 102, 4–27. https://doi.org/10.1037/0033-295X.102.1.4

GUO, X., TILLER, D., HENZE, G. and WATERS, C. 2010. The performance of occupancy-based lighting control systems: A review. *Lighting Research & Technology,* 42, 415–431. https://doi.org/10.1177/1477153510376225

HAMMES, S., HAUER, M., GEISLER-MORODER, D., WENINGER, J., PFLUGER, R. and POHL, W. 2021a. The impact of occupancy patterns on artificial light energy demand - simulation and post-occupancy-evaluation. In: *Proceedings of Building Simulation 2021: 17th Conference of IBPSA, Sept. 1-3, 2021, Bruges, Belgium.* 3536-3543. https://doi.org/10.26868/25222708.2021.30508

HAMMES, S., WENINGER, J., CANAZEI, M., PFLUGER, R. and POHL, W. 2020. Die Bedeutung von Nutzerzentrierung in automatisierten Beleuchtungssystemen. *Bauphysik*, 42, 209–217. https://doi.org/10.1002/bapi.202000010

HAMMES, S., WENINGER, J., GEISLER-MORODER, D., PFLUGER, R. and POHL, W. 2021b. Reduzierung des Kunstlichteinsatzes durch Anpassung der Nachlaufzeit an individuelle Anwesenheitsmuster. *Bauphysik*, 43, 50–64. https://doi.org/10.1002/bapi.202000039

HAMMES, S., WENINGER, J. and ZECH, P. 2024. Closer to Realtime: A Comparison of Machine Learning Methods to Reduce Artificial Switch-Off Times. In: *Proceedings of the 2024 IEEE Sustainable Smart Lighting World Conference & Expo (LS24)., Nov. 12-14, 2024, Eindhoven, Netherlands*, 1–4. https://doi.org/10.1109/LS2463127.2024.10881955

KOO, S.Y., YEO, M.S. and KIM, K.W. 2010. Automated blind control to maximize the benefits of daylight in buildings. *Building and Environment,* 45, 1508–1520. https://doi.org/10.1016/j.buildenv.2009.12.014

MINSKY, M.L. and PAPERT, S.A. 1990. Perceptrons: an introduction to computational geometry, 5th, expanded ed. MIT Press, Cambridge, Mass.

PANKO, R.R. and KINNEY, S.T. 1995. Meeting profiles: size, duration, and location. In: *Proceedings of the Twenty-Eighth Annual Hawaii International Conference on System Sciences, Wailea, HI, USA, 1995*, 1002–1011. https://doi.org/10.1109/HICSS.1995.375647

SCHWEIZERISCHER INGENIEUR- UND ARCHITEKTENVEREIN (sia). 2006. Standard-Nutzungsbedingungen für die Energie- und Gebäudetechnik.

VOLL, K., GAUGER, F. and PFNÜR, A. 2022. CREM perspective on home office—a consideration of the workplace and its mechanisms of action. *Zeitschrift für Immobilienökonomie,* 8, 139–171. https://doi.org/10.1365/s41056-022-00060-4

YAN, D., FENG, X., JIN, Y. and WANG, C. 2018. The evaluation of stochastic occupant behavior models from an application-oriented perspective: Using the lighting behavior model as a case study. *Energy and Buildings*, 176, 151–162. https://doi.org/10.1016/j.enbuild.2018.07.037

YANG, Z. and BECERIK-GERBER, B. 2014. The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use. *Energy and Buildings*, 78, 113–122. https://doi.org/10.1016/j.enbuild.2014.04.002

YOSHINO, H., HONG, T. and NORD, N. 2017. IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods. *Energy and Buildings*, 152, 124–136. https://doi.org/10.1016/j.enbuild.2017.07.038

YU, T. 2010. Modeling Occupancy Behavior for Energy Efficiency and Occupants Comfort Management in Intelligent Buildings, in: *Proceedings of the Ninth International Conference on Machine Learning and Applications (ICMLA), 2010, IEEE, Washington, DC, USA*, 726–731. https://doi.org/10.1109/ICMLA.2010.111