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Take the Right Seat: The Influence of Occupancy Schemes on Performance Indicators of Lighting in Open Plan Offices

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Abstract: Work processes and sociological structures can differ significantly between organizations. These organizational aspects determine user behavior, which in turn exerts considerable influence on the key performance indicators of artificial lighting systems. Accordingly, the use of generalized assumptions about user behavior in the building design phase can lead to large discrepancies between design and operation. In the following work, the possible influences of different occupancy schemes, an essential aspect of user behavior and shaped by the organization, on energy demand and workplace-related daylight dose are evaluated. For this purpose, calculations are made based on real measurement data of an open-plan office with zoned lighting. Multi-level calculation models are used to determine improved user distributions in the room to ensure optimization according to the desired target criteria. The results show that occupancy schemes have a significant impact on energy demand, contributing significantly to overall building performance, but only slightly to workplace-related light exposure rates in terms of total daily light dose. A correlated influence on the target criteria could not be demonstrated, but given the minor influence on daily light dose, the optimization of planning and operation can be focused on energy efficiency.

Keywords: energy efficiency; daily light dose; artificial lighting; occupancy schemes; blossom algorithm; Hungarian algorithm; assignment problems

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1. Introduction

1.1. Work Interruptions as an Organizational Cultural Aspect

Depending on the profession, the time periods associated with activities at the office workplace and activities at another work location vary greatly. One of the most common work activities that contributes to this dynamic and has received increasing attention in recent years is meetings [1–4]. It is estimated that the number of meetings that occur daily in the United States is around 11 million [5]. Meetings are firmly entrenched in most organizational cultures as a tool for problem solving [6], critical reflection [2,7,8], information sharing [9–11], and idea generation [3], among others, in order to operate profitably in competitive environments [6]. Managers invest a large part of their daily business in meetings [12,13]. The associated time use increases with the position held and can consume a quarter of the working time for project managers, half for business executives and even define three quarters of the daily business for company managers [14]. In particular, people tend to underestimate the time spent on meetings [13].

The high mobility of users, e.g., caused by the follow-up of meetings, can have a decisive impact on the operational behavior of the building systems:

Planning and simulation as well as the derived control definition are currently based on generalized parameters (e.g., generalized presence time models and generally valid user comfort criteria) and concepts (e.g., interconnection of luminaires in larger groups) in order to compensate for missing information during the building design phase and to achieve the high applicability of controls. Organization-specific processes and sociological aspects resulting from the target application can be considered as frameworks and boundaries by which user behavior, and thus presence at the workplace, is significantly determined. However, organization-specific processes and their influences on user behavior only usually reveal themselves after building commissioning and may change over time. Therefore, it is not surprising that general assumptions about user behavior can be named as a major cause of existing discrepancies between expected and actually measured values [15,16]. One basic assumption of general-purpose models fails in particular when the social structure leaves open spaces, such as the indeterminacy associated with events such as meetings (specifically in terms of frequency, temporal extent, and number of participants [13]). The following figure illustrates this using the example of three workplace-related attendance profiles over time of day (Figure 1).

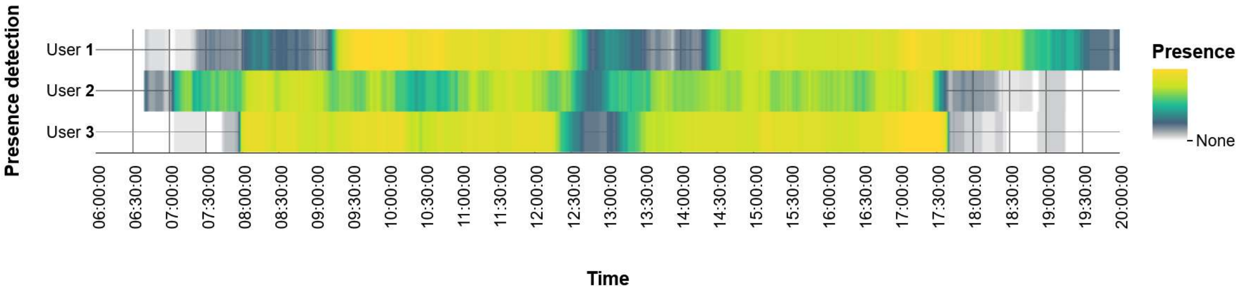

Figure 1. Representation of three exemplary presence profiles at the workplace in an open-plan office of Bartenbach, averaged in the course of the day over the period from 2 Septermber 2020–3 November 2020; The yellow-green representation represents high presence, the blue- to gray-colored representation represents low presence, and transparent areas are periods without presence; core working hours in the object of observation: Monday to Thursday 9:00–12:00 and 14:00–17:00 and Fridays 9:00–12:00.

The previous example (Figure 1) shows clear differences regarding the start and end of work, as well as with regard to the temporal characteristics of the probability of workplace occupancy. User 1 and User 3 have time windows of high presence in the morning and afternoon hours (strongly yellowish representation, Figure 1), while User 2 has consistently low attendance at the workplace (green to bluish representation, Figure 1). The more freedom the organizational structure allows and the more dynamic and complex work-specific processes are, the greater the variability in identifiable occupancy patterns.

1.2. The Influence of User Mobility on Concepts of Human-Centric Lighting

Besides the extrinsic light–dark cycle, the achieved light exposure during the day influences sleep quality, an essential part of circadian rhythmicity [17–19]. In turn, sleep quality significantly determines cognitive performance the following day. Given that humans spend about 90% of the daytime indoors [20–22], the task of controlling one of the most substantial zeitgebers of circadian rhythms falls to artificial lighting. Although artificial lighting systems offer comparatively much lower intensities than daylight, they can still produce non-visual light effects [23]. Accordingly, it is recommended to aim for higher daily light exposure to support health, especially circadian rhythmicity. In addition to illuminance, in the context of daytime sleepiness and sleep quality, the color temperature of light is also crucial [24–28]. Therefore, human-centric lighting (HCL) concepts aim to dynamically vary color temperature and intensity based on the time of day to take advantage of the non-visual effects of light. Additionally, subjective well-being also increases slightly as a result of higher light exposures [29].

However, light exposure, measured in lux hours (lxh) as the product of illuminance at the eye (E_v) and time, are highly dependent on many factors. Spatial position, the user's orientation in the room and, associated with this, the room geometry, the facade system, glazing proportion and window transmittance, as well as the reflective properties of object surfaces in the room and the outdoor situation have a decisive influence on the direct and indirect light input [30,31] and thus on the achievement of certain spectral irradiances at eye level, which are necessary as a light stimulus to generate non-visual lighting effects [32]. These criteria can be taken into account when designing an HCL concept in the workplace. It is more difficult to plan the time users spend within an HCL concept during the workday. The described mobility of users, e.g., due to an increased follow-up of meetings, can affect the effectiveness of human-centric lighting concepts. For this reason, the influence of occupancy times at the workplace must be investigated in more detail.

1.3. Energetic Significance of User Distributions in the Room

Long-term, objectively oriented control concepts can usually only insufficiently or incompletely represent such user behavior at a lower level, which leads to the user influence on the energetic system performance being correspondingly high. Analogously, user behavior and the associated distribution of users in space can have negative effects on the utilization rates of circuit concepts. For example, the field measurements and data collection initiated by Kawamoto et al. in a Japanese office show a high level of unused on-time for electrical loads [33]. Naylor et al. and Nguyen and Aiello confirm that occupant activities and behaviors of building occupants exert significant influence on the energy demand of equipment used in the heating, ventilation, air conditioning (HVAC), and lighting trades, as well as on the operating times of individual electrical loads [34–36]. In view of the fact that the building sector is responsible for around one-third of the world's energy demand and thus also for a corresponding proportion of greenhouse gas emissions [37,38], and that consideration of user behavior and occupancy patterns promises energy savings of up to 60% [39,40], it is important to give greater consideration to user behavior.

Based on this problem, the International Energy Agency (IEA) is dealing with the simulation of user behavior in buildings within the framework of Annex 66 [41]. In principle, this can reduce the gap between planning and operation, but despite more complex modulators, simulations are always based on assumptions about subsequent operating behavior. It is not forgotten that building controls have to be adjusted subsequently after initial definition. However, conceptual designs, such as the interconnection of the actuators, cannot easily be adjusted afterwards.

1.4. Derivation of the Study Objectives

While the influence of the technologies used on the energy demand and the daily light dose can be planned, the user behavior, which is determined by the corporate culture concept, is difficult to calculate [42]. Long-term data collection, as the basis of post-occupancy evaluations (POEs), offers the possibility to reflect and analyze the real building situation well. A key parameter in this context is presence at the workplace. Thus, the data collection of presence at the user level allows the identification of trends, such as periods of the day with a high probability of presence or periods of frequent user vacancy (cf. Figure 1). In this paper, the authors show the influence of occupancy behavior at the workplace on the artificial lighting energy demand and the achievable lux hours and how user distributions in the room can support or impair the effectiveness of artificial lighting installations. In this context, the ranges of the influence of the user distribution in the room on the energy demand and on the daily light dose are listed via suitable mathematical procedures. Finally, synergies between the target criteria, if they exist, are examined depending on the selected user distribution in the room.

The focus of this study is on lighting in office applications. The data basis is formed by presence data, illuminance data as well as operating times and energy consumption data of an artificial lighting system, which originate from the real operation of an open-plan office. Through this work, the energetic relevance of organization-specific aspects and post-occupancy evaluations is highlighted.

2. Materials and Methods

2.1. Study Object

The R&D office building of Bartenbach GmbH in Aldrans, Austria (Figures 2 and 3) was chosen as a case study. A workstation-zoned lighting system was installed on around 200 m^2 of office space. The office space comprises an open-plan office (28 workstations in 161.7 m^2, 24 occupied), two individual offices (head of research: 15.6 m^2; head of development: 14.7 m^2) and a meeting room (9.7 m^2), which are separated from each other by transparent glass walls (Figure 2). The focus of this study was on the occupancy pattern of the open-plan office, since the occupancy of the individual offices by the two R&D managers is fixed.

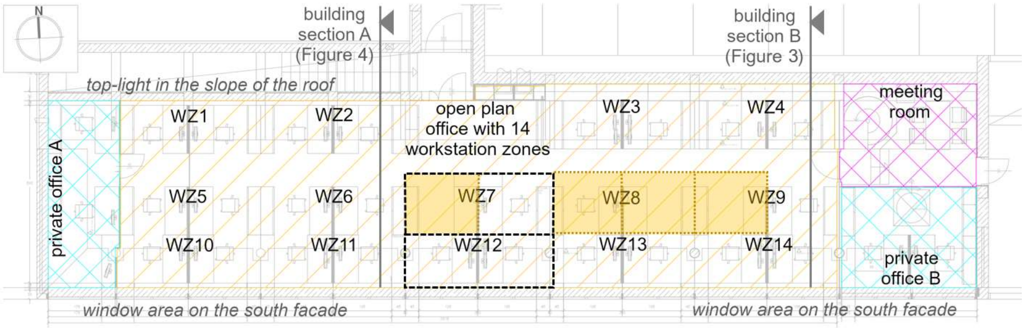

Figure 2. Floor plan of the office premises of Bartenbach GmbH with representation of the individual functional rooms (colored hatching) as well as the degree of zoning of the lighting considered for the study evaluation (black dashed border; 14 workstation zones (WZs) in the open-plan office); areas highlighted in dark yellow mark the four unoccupied workstations.

Figure 3. View through the open-plan office looking towards the west-facing individual office (cf. section B marking from the building floor plan, Figure 2); north-facing skylights on the right, south-facing facade with closed external screen on the left; photo: Bartenbach GmbH.

For this study, the 28 workstations in the open-plan office were divided with their respective adjacent workstations into separately controllable lighting zones (WZ1–WZ4: per zone: artificial light and screen of the top light; WZ5–WZ9: per zone: artificial light; WZ10–WZ14: per zone: artificial light and screen of the south facing window front; cf. Figures 2 and 4). The artificial lighting solution was implemented with ceiling-integrated LED luminaires, which are interconnected in three linear units and focused on the workstation (Figures 3 and 4). Earlier studies of the lighting concept showed that this greater user-centeredness can not only achieve a significant reduction in energy consumption, but also higher system acceptance by covering individual lighting preferences (details in [43,44]).

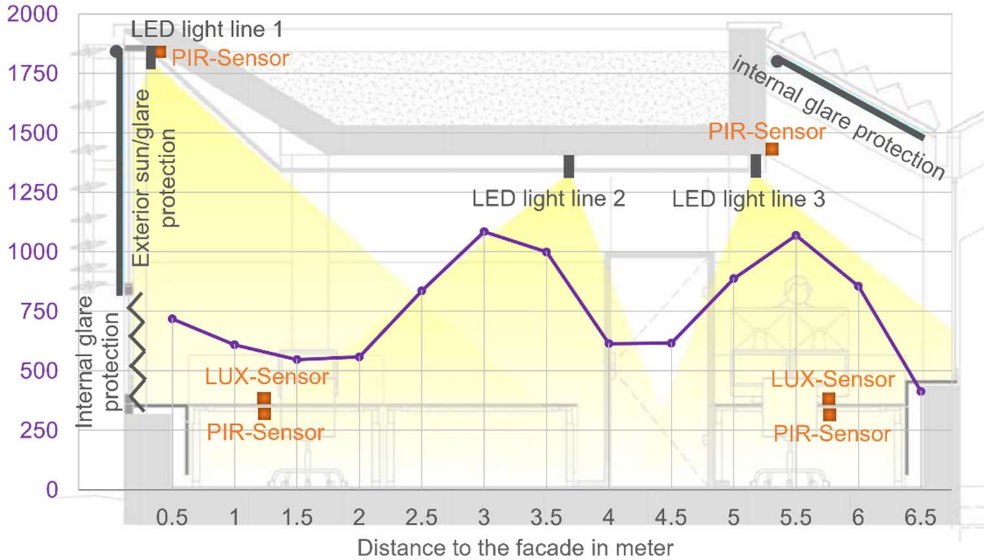

Figure 4. Overview of the sensor technology used in the building section of the study object (cf. section A marking from the building floor plan Figure 2), as well as the maximum artificial light-based illuminance levels.

The office building is characterized by high levels of daylight, which are realized by a large south-facing window front and north-facing skylights. For the study object, an average daylight autonomy $DA_{500 \cdot 8\text{-}18}$ of 81.56% could be determined with Radiance (version 5.2, http://www.radiance-online.org, accessed on 28 March 2022) (Figure 5; calculation related to the normative minimum illuminance of 500 lx according to EN 12464-1; reference time: 8:00 to 18:00, summertime not considered, calculated with necessary glare protection). To avoid glare and thermal overheating, sun-tracking screens as well as external static daylighting louvers were installed, the dimension and structure of which were specifically optimized for the geographical location of the building. The created daylight environment (with an average E_h > 1000 lx at midday) not only positively influences well-being (cf. [45]), but also shifts the need for artificial light to the edges of the day (cf. [46]). Since these ranges have high user dynamics, the use of artificial lighting control depending on presence is significant for the energy demand [46]. This was implemented in the study object with passive infrared sensors (PIR; ceiling installation: Thermokon® (Mittenaar, Germany), RDI; occupancy information at the workstation: NodOn, PIR-2-1-01, Saint Cyr en Val, France). Further energy savings are achieved in the study object through a daylight-dependent adjustment of the artificial light intensity. For this purpose, there was one illuminance sensor per workstation zone (Figure 2) on the horizontal work surface (Thermokon®, LDF 1000A). The target value in automatic mode was the normative minimum illuminance of 500 lx (EN 12464-1). The sensor positions are shown in Figure 4. In addition, a diurnally dynamically adjusted color temperature control (from 5000 K in the morning to 2200 K in the evening) was installed in the study object to support circadian rhythms (details of circadian rhythms associated with light exposure in [47]). The control system on which all this was based was a programmable logic controller (PLC; BECKHOFF, CX5140-0141, Verl, Germany).

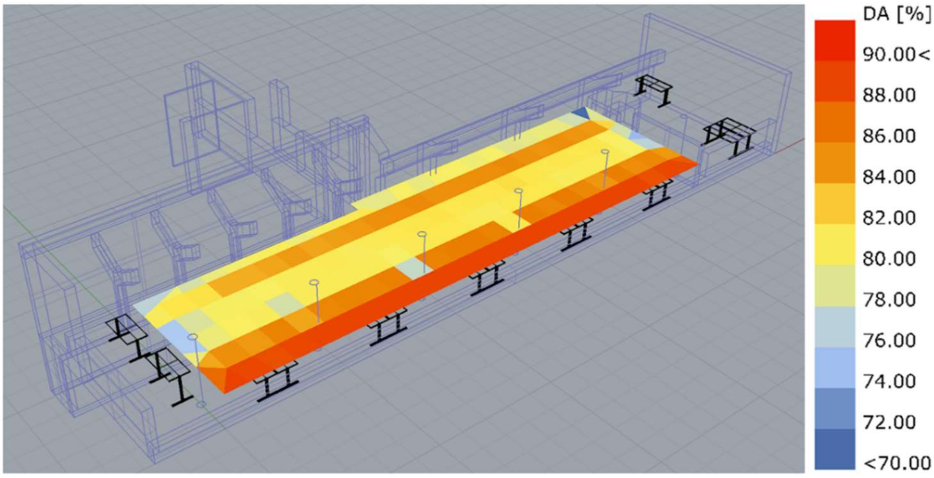

Figure 5. Daylight simulation ($DA_{500.8\text{-}18}$) of the study object, implemented with Radiance; simulation related to the normative minimum illuminance of 500 lx according to EN 12464-1; reference time: 8:00 to 18:00, daylight savings time not considered, calculated with necessary glare protection, glare protection with limit value $E_h = 2000$ lx in WZ12, (cf. Figure 2), staggered control: (1) closing of the outer screen up to half, (2) complete closing of the outer screen, (3) closing completely and closing of the hand screens.

2.2. Measurement Methodology

Since the sensitivity of a PIR sensor is greater at shorter distances [48], presence at the workstation was recorded using table-bottom mounted PIR sensors (NodOn, PIR-2-1-01; Figure 4). In addition to workplace presence data, workplace illuminance, lighting dimming level, and actuator energy consumption were also collected. The data logging was realized via the building control system (BECKHOFF-PLC) and converted into a machine-processable data format (.csv). Presence data and information from the lighting system were logged for changes in state. Illuminance was recorded cyclically per minute. An overview of the data points and sensors used is shown in Table 1.

Table 1. Overview of the sensors relevant to the study, including a list of the measurement methodology and the number of data points collected; WZ1–WZ4: one illuminance sensor per zone, WZ5–WZ14: one illuminance sensor for each two adjacent zones.

Measured Variable	Product Name	Quantity	Measurement Methodology	Data Points	Measuring Period
Presence at the workstation	NodOn, PIR-2-1-01	24	With change of state	1,661,424	1 July 2021–19 November 2021
Illuminance, horizontal	Thermokon®, LDF 1000A	9	60 s	999,189	1 July 2021–19 November 2021
Energy meter for the artificial light	Eltako, FWZ12-16A	3	60 s	569,721	1 July 2021–19 November 2021

The daily light dose refers to the vertical illuminance at the eye throughout the day. Since the horizontal illuminance at the workplace was recorded and logged by sensors in the study object, a corresponding conversion from horizontal to vertical illuminance was required. Since the required conversion factors from E_h to E_v were workplace-specific, a simulation model was used. For this purpose, the study object was remodeled in a high level of detail (exterior and interior elements) for a simulation with Rhinoceros® (version Rhino 6) (Figure 5), and one measurement point at table height for horizontal illuminance and one measurement point at eye level for vertical illuminance were provided for each workstation (cf. [49]). Honeybee [+], a Grashopper plugin in Rhinoceros® that uses

RADIANCE as a daylight simulation module, was used as the simulation platform. The daylighting simulation followed the three-phase method, based on climate data from the nearby Innsbruck site (EnergyPlus™ weather file (.epw)). Workplace-specific conversion factors (E_h to E_v) could be derived from the simulation data.

2.3. Study Execution

The occupancy pattern study started on 1 July 2021 and ended on 19 November 2021 (100 working days, holidays considered). Three measurement days in July (13–15 July 2021) were omitted due to a failure of the data logging, so the data set ultimately comprises 97 measurement days. Over the entire study period, 22 employees were continuously employed in the open-plan office (full-time: 1× female, 18× male; part-time: 1× female, 2× male). Two employees were only partially employed during the study period (9 weeks: 1× female; 18 weeks: 1× female; both as part-time workers). Absences due to vacation, sick leave and home office activities were considered, as these have an essential influence on the matching of user profiles. The core working hours during the study period were 9:00–12:00 and 14:00–17:00 from Monday to Thursday and 9:00–12:00 on Fridays. The measurement period per study day was set to 6:00–20:00 to accommodate flextime working hours. The study was conducted outside of COVID-19 influences. Accordingly, there were no occupancy constraints in this regard.

2.4. Limitations of the Current Study

Even if the detection range of the presence sensor system was limited to the image of a single workstation, it cannot be ruled out that faulty presence detections were made due to events that are difficult to calculate. These include, among others, movements of persons from one workstation zone to another, e.g., due to a meeting at the workstation. Disturbing effects of movements of persons of short duration that are difficult to calculate are intercepted by the artificial lighting switch-off delay. In this context, the adaptation of the artificial lighting switch-off delay to presence patterns and activity profiles offers the possibility of reducing the artificial lighting energy requirement [46,50,51]. However, to provide a representative baseline, the artificial switch-off delay for the study was based on the industry standard (set: 15 min; industry standard: 10–20 min [40,48,50,51]).

2.5. Methodology for Deriving User Distribution in the Room to Increase the Workplace-Related Daily Dose of Light

Since concepts of human-centric lighting are primarily designed for office applications, the following analysis of the daily light dose is limited exclusively to the lux hours that users can obtain during their time at the office workplace. Figure 6 lists the daily light dose that would result for a continuously present user during the study period. There are strong room-related differences (standard deviation 1113 lxh). Based on the logged presence profile, weighted with the workplace-related E_v-profile, it was necessary to derive user distributions that list the range of the achievable daily light dose. For the representation of the range, users were positioned in such a way that the achieved lux hours were maximized or minimized in total. In addition, a user distribution was derived that created a balanced ratio of the workplace-related daily light dose between the users. In this context, the effects of such occupancy schemes on individual users were evaluated. The daily lux hours shown were limited exclusively to the light dose received by users during their presence in the open-plan office.

Figure 6. Overview of the average daily light dose for the different workplace zones (WZs, cf. Figure 2) with permanent presence at the respective workplace (values apply exclusively to the time at the workplace), separated by viewing direction (west/east), based on the illuminance data collected in the study object during the study period (1 July 2021–19 November 2021).

From 28 seats x in the open-plan office, which are to be occupied by 28 users y (incl. 4 empty presence profiles, cf. Figure 2), there are $x!$ possibilities of a user distribution (3.05 $\times$ 10^{29} permutations). In order to highlight the influence of the user distribution on lighting design concepts, the occupancy scheme with the highest total lux hours was selected from the identified permutations, and the occupancy scheme with the lowest total lux hours was selected for comparison. Due to the number of permutations, a brute-force search to determine the solution did not appear to be expedient (9.67 $\times$ 10^{20} years with a calculation time of 0.1 s per permutation).

To make this two-dimensional assignment problem (AP2) solvable in reasonable time, the mathematical model of bipartite graphs was used. Since, according to the problem, the nodes of the graph (E_v-weighting function) can be divided into two disjoint subsets X and Y (X: space-based E_v-profile; Y: presence profile), within which there are no edges, the definition of bipartite graphs was satisfied. For each edge $\{u, v\} \in E$, the following applies: $(u \in X \wedge v \in Y) \vee (u \in X \wedge v \in Y)$. To solve in polynomial runtime weighted assignment problems on bipartite graphs, existing algorithms can be used. The best-known algorithm for an AP2 is the Hungarian algorithm (computation time in $O(n^3)$) [52–54]. The Hungarian algorithm requires a square matrix $C = (c_{ij})$. With $x = y$, the size of the matrix C to be set up is $x \times y$ (28×28). For this purpose, the normalized workplace-related daily light dose was determined from each of the 28 presence profiles (incl. 4 empty profiles) per workplace over the measurement period (corresponds to 784 individual values):

First, the individually related light dose per time point $D_i(t)$ was determined. This resulted from the product of measured presence information at the workplace $p_i(t)$ and workplace-related vertical illuminance at the eye $E_{vi}(t)$ at the same measurement time. The user-specific daily light dose D_{di} was then the sum of the individually related light dose $D_i(t)$ over the day. Since the presence profiles at the workplace differed greatly from one another (cf. Figure 1) and different illuminance levels were available over the course of the day (Figure 7), it was important to make the potentially individually achievable daily lux hours comparable. This was done by normalizing the light dose via a user-specific reference profile of the vertical illuminance, which resulted from the sum product of an average E_v-profile and the individual stamping time.

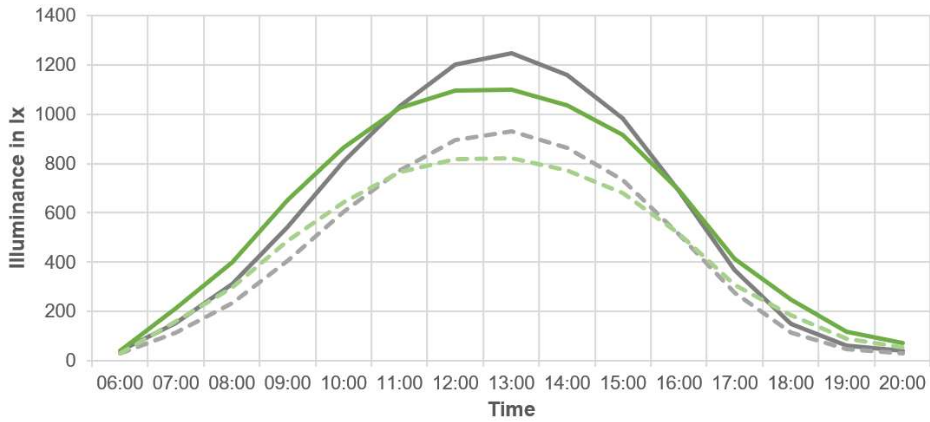

Figure 7. Overview of the average horizontal and vertical illuminance profile over the course of the day, separated by skylight side and window side, based on the illuminance data collected in the study object during the study period (1 July 2021–19 November 2021).

The calculation of the 784 single values, which are transferred into the matrix C, was carried out in an evaluation tool written in python™ (python 3.8, pandas 1.0.3, https://www.python.org/, accessed on 28 March 2022). The Hungarian method was also applied in python™ (scipy 1.7.2, [55]). The Hungarian algorithm selects the optimal solution where the assignment gives the lowest value in total [56]. To determine the association with the maximum value, the matrix is negated ($C \times (-1)$). A description of the association matrix of the Hungarian method is provided by [56].

While the Hungarian method is used to identify an assignment in which the target value is maximized or minimized overall, there is a risk that extremes are used. In order to derive a user distribution in space that provides the most uniform distribution of workplace-related daily lux hours, a different method is required. For this reason, an approximation method of logical programming was used:

For this purpose, the user-specific daily light dose was ranked from the lowest to the highest value. The same was done with the workplace-specific potentials of vertical illuminance (Figure 6). Subsequently, the rows were mirror-matched so that the person with the lowest reference of daily lux hours (normalization value, averaged over all workplaces) was positioned on the seat with the largest E_v-profile.

2.6. Methodology for Deriving a User Distribution in the Room to Reduce Energy Demand

In the energy analysis, the workplace-related presence information was combined with the workplace-related energy profile. The latter results from the artificial lighting suggest that is necessary when users are present in order to achieve the normative minimum illuminance of 500 lx for office activities (EN 12464-1). Due to the geometry of the room and the course of the sun, there were also differences in the workplace-related energy profile depending on the position of the room and the time-of-day occupancy behavior at the workplace (cf. Figure 8). Since the artificial light energy demand of a lighting zone (cf. Figure 2) is composed of the joint presence profile of two users (logical-OR-linkage of the associated individual profiles), the position-dependent energy profile of the other users must be included in energy optimization of the user distribution (Figure 8). It is shown that in terms of the total energy demand of a lighting zone, the greater the individual profiles of the same zone, the less overlapping time there is between the profiles and the greater the presence in the daytime boundary areas, i.e., the time in which artificial lighting is supplemented. For User 1 and User 2 shown in Figure 8, the overlap percentage of presence within the lighting zone is 17.9% (based on the maximum occupancy time of the lighting zone). For User 3 and User 4, the overlap percentage is 22.4%.

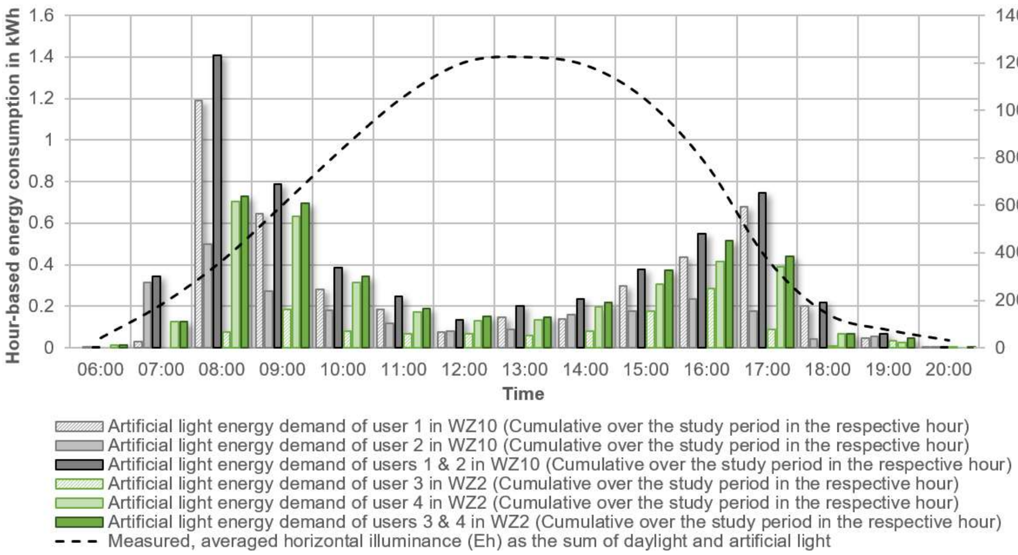

Figure 8. Time course of artificial light energy demand for different user combinations in different zones (as cumulative data) and average horizontal illuminance at the workplace (black dashed); the data set corresponds to the study period (1 July 2021–19 November 2021); core working hours in the study object: Monday–Friday 08:00–12:00, Monday–Thursday 14:00–17:00.

The derivation of user distributions in the room, which have the minimum or maximum energy demand, leads to a combinatorial assignment problem. The permutations result from the interconnection of the presence profiles of the users to each other and are energetically weighted to the room position. Based on 28 presence profiles y (incl. 4 empty profiles) and 14 lighting zones, each occupied by 2 persons (or empty) ($z = 2$; order within the zone is arbitrary), the number of possible assignments $P_{z,y}$ can be calculated as follows:

$$P_{z,y} = \prod_{i=0}^{\frac{y}{2}-1} \frac{(y-2i)!}{z!((y-2i)-z)!} \tag{1}$$

For $y = 28$ and $z = 2$, this results in 1.86×10^{25} permutations, which rules out a brute-force search for solution determination (59×10^{15} years with a computation time of 0.1 s per permutation). Moving to graph theory, it follows that AP2 can be solved efficiently in polynomial time [52,54], but not multidimensional assignment problems, such as AP3. These problems are considered NP-hard [57,58]. For this reason, it is justified to apply heuristics to find near-optimal solutions to AP3. The solution chosen by the authors for approximation relies on the ideas of Gabrovšek et al. and Huang and Lim by breaking down a k-assignment problem to a set of two-dimensional assignment problems [59,60]. While the solution to AP2 consists of one permutation q, the solution to an AP3 results from two permutations p and q. Now, if the permutation p is fixed, the optimization of q becomes an AP2 problem, and vice versa [60].

In the first step, the permutation of the presence profiles to each other is therefore optimized. The energy weighting is not done in relation to the room position, but in relation to an averaged energy profile resulting from the 14 lighting zones (Figure 2). This creates independence from the room position. Based on an averaged energy profile and the 28 presence profiles y, the number of possible user pairings results as follows, whereby the order within a user pairing is arbitrary.

$$P_y = \sum_{i=1}^{y} y - i \tag{2}$$

For the resulting 378 user pairings, the corresponding cumulative artificial light energy demand over the measurement period is then determined. The presence of the user pair results from a logical-OR-operation of the two individual profiles. The artificial switch-off delay for absence is 15 min. Edmond's Blossom algorithm is used to select the most energetically favorable combination (or, for comparison, the least energetically favorable combination) from the 378 user pairings. The Blossom algorithm is a polynomial time algorithm to find a minimum, or maximum, match in a graph [61]. By definition, in a graph, a match is a subset of edges of the graph, where no node is included more than once [61].

The artificial light energy demand of a user pairing was determined using an evaluation tool written in python™ (Python 3.8, pandas 1.0.3). The Blossom algorithm for minimum weight matching was used via a C++ implementation of [62] (based on [63]). In order to identify user pairings in the Blossom algorithm that provide the highest energy demand in total, the data basis was negated.

Once the user pairings were fixed, the optimization was performed in relation to the room position. For this purpose, the same python™ evaluation tool was used to determine the cumulative artificial lighting energy demand for each of the 14 identified user pairs, based on the real energy profile of the lighting zones. With these values, a square matrix C could be formed (14×14), for which the Hungarian algorithm provided an allocation optimized to the minimum or to the maximum [56]. The calculation was carried out analogously to the lighting improvement of the user distribution in the room.

The presented multilevel procedure for AP2 lists the influence of the user distribution in the room on the artificial light energy demand. Furthermore, an approximation method based on logical programming was applied to derive the most energy efficient user distribution. The potential of this logical programming shall be put in relation to the methods of graph theory. In logical programming, the users with the greatest presence at the workstation during the morning and evening hours, i.e., those time areas that are significant for artificial light energy demand (cf. Figure 8), are placed in the row of seats along the window area and top light, since these areas have the highest daylight autonomy (cf. Figure 5). In this case, seating is initially allocated along the window area, due to the higher $DA_{500 \cdot 8\text{-}18}$. The remaining users are positioned aisle-centered together with the empty profiles.

3. Results

3.1. Impact of the User Distribution on Light Exposure Rates

The following table (Table 2) lists the daily light dose cumulated over all users as well as the normalization values of the lux hours for better comparability. The data refer to the user distributions in the room, which the Hungarian algorithm outputs for minimization and maximization, and exclusively to the achievable lux hours for the presence in the open-plan office. The results are put in relation to the user distribution of the initial situation. From the results, it can be seen that the daily light dose cumulatively across all users is 11.1% higher than that of the initial situation due to the derived improved user distribution. The user-specific improvement in lux hours is significant in this case (t-test, one-sided; significance level $\alpha = 0.05$; $p = 0.0034$). The data set was tested for normal distribution using the Kolmogorov–Smirnov test prior to statistical analysis ($\alpha = 0.05$; max deviation of 0.1784; critical value of 0.2693). With the improved occupancy scheme, the achieved lux hours cumulatively over the full-time workers with a normal weekly working time of 40 h can be increased (9.5%), as well as for the part-time workers (23.1%). The most unfavorable user distribution results in a daily light dose, cumulated over all users, that is 13.6% lower than the initial situation. Thereby, the workplace-related daily light dose cumulatively over the full-time employees is reduced by 14.6% and cumulatively over the part-time employees by 6.08%.

Table 2. Overview of the workplace-related daily light dose over the study period for different occupancy schemes: the initial situation, the arrangement optimized for the minimum and for the maximum, derived via the Hungarian algorithm; data excluding empty presence profiles.

Occupancy Schemes			Most Unfavorable Occupancy Scheme in Terms of Lighting	Initial Situation	Improved User Distribution in Terms of Lighting	Balanced Occupancy Scheme of the Daily Light Dose
Calculation Method			**Hungarian Method for Minimization**	**Calculation from Measured Values**	**Hungarian Method for Maximization**	**Logical Programming**
Mean daily light dose, cumulated over all users			83,729.5 lxh	96,959.8 lxh	107,753.7 lxh	98,576.1 lxh
Normalization value	all users	Average ± Standard deviation	0.6237 ± 0.1612	0.7226 ± 0.3172	0.8023 ± 0.3880	0.7168 ± 0.2343
		Minimum–Maximum	0.3249–1.0937	0.3604–1.6552	0.2480–2.0096	0.3031–1.2598
	Full-time employees	Average ± Standard deviation	0.6358 ± 0.1686	0.7519 ± 0.3194	0.8188 ± 0.4066	0.7286 ± 0.2432
		Minimum–Maximum	0.3249–1.0937	0.4089–1.6552	0.2480–2.0096	0.3031–1.2598
	Part-time employees	Average ± Standard deviation	0.5629 ± 0.1149	0.5765 ± 0.3019	0.7198 ± 0.3094	0.6579 ± 0.2018
		Minimum–Maximum	0.4076–0.6821	0.3604–1.0221	0.4311–1.1546	0.4476–0.9328

To derive a user distribution in which the normalized daily light dose is distributed as equally as possible for all users, the logical programming presented was used (see Section 2.5). Logic programming results show a 1.67% improvement in cumulative daily lux hours compared to baseline, with less dispersion of values (Table 2).

Figure 9 lists how the daily light dose changes for individual users depending on the selected user distribution in the room (data as average over the study period; standard deviations: baseline: 1805.8 lxh, Hungarian method for minimization: 1061.7 lxh, Hungarian method for maximization: 2222.7 lxh, logical programming: 1324.4 lxh). Since the users are ranked according to the achievable dose, the linear slope of the light dose can be given, which can be considered as a measure of the homogeneity of the lux hours between the users.

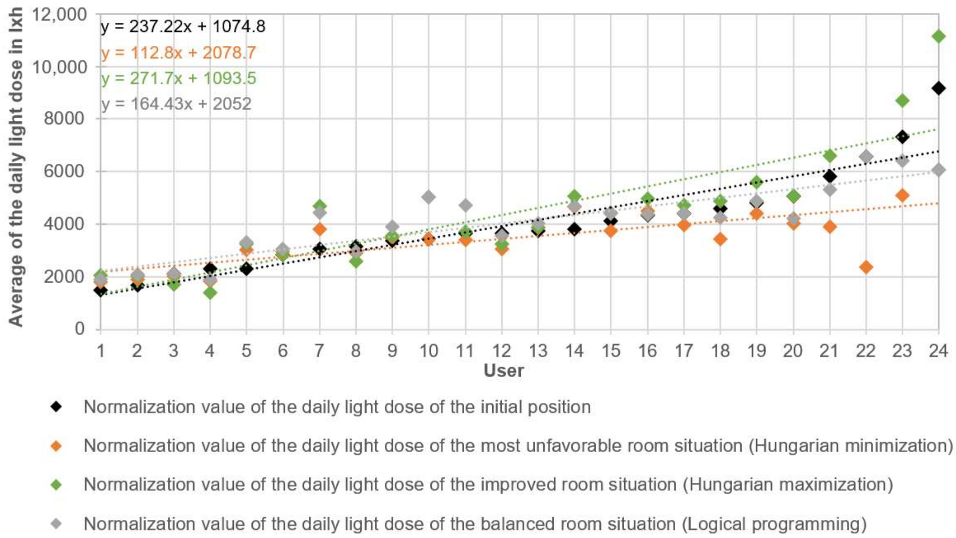

Figure 9. Overview of achievable daily lux hours (average) depending on different user distributions in the room.

The following figure (Figure 10) lists where the unoccupied workstations are located after the lighting improvement of the user distribution in the room (Hungarian method for maximization, green shaded areas, Figure 10), for the most unfavorable user distribution (Hungarian method for minimization, orange shaded areas, Figure 10), and for the lighting balanced user distribution (logical programming, gray shaded areas, Figure 10; initial situation in Figure 2).

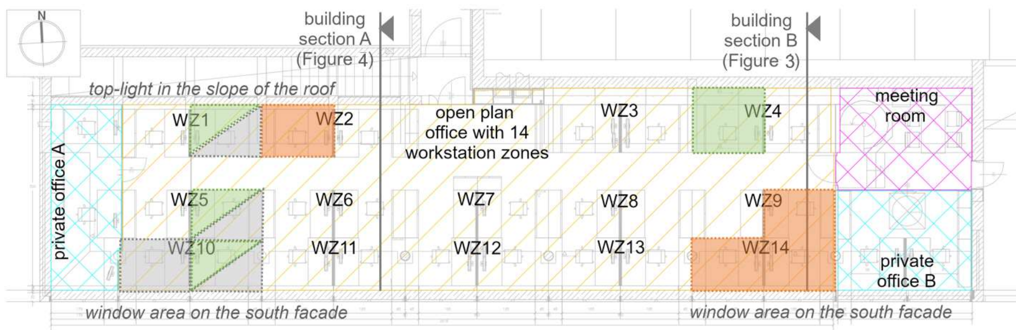

Figure 10. Floor plan of the office premises of Bartenbach GmbH with representation of the individual functional rooms (colored hatching); the position of the four free workstations is highlighted in color as an area according to the derived occupancy scheme (user distribution in the room improved according to the daily dose of light: green; most unfavorable user distribution of the lux hours: red; user distribution in the room for a balanced daily dose of light: gray); cf. initial situation in Figure 2.

3.2. Impact of the User Distribution on Energy Demand

For the user distribution according to the initial situation, the cumulative energy demand for the artificial lighting system over the study period (1 July 2021–19 November 2021) is 83.8 kWh (area of the open plan office: 161.7 m^2). The average of the energy demand across all lighting zones is 6.76 kWh $\pm$ 3.13 kWh (excl. zones with unoccupied workstations). At the lighting zone level, there are large fluctuations in terms of energy demand (minimum: 2.01 kWh; maximum: 12.3 kWh; excl. zones with one unoccupied workstation).

To list the effects of user distribution on energy demand, staged graph theory algorithms were applied (see Section 2.6). The identified energetically improved user distribution in the room leads to 30.2% energy savings compared to the initial situation (4.87 kWh $\pm$ 1.75 kWh). The derived maximum variant leads to an increase in artificial lighting energy demand of 15.3% (7.01 kWh ± 3.05 kWh). In this context, Figure 11 illustrates the effects of user pairing and user positioning in the room on artificial lighting energy demand. The corresponding values are listed in Table 3.

Table 3. Overview of the influence of the individual optimization steps on the energy demand of the artificial lighting system; energy demand of the original occupancy scheme: 83.8 kWh; study period: 1 July 2021–19 November 2021; area of the open-plan office: 161.7 m^2.

Occupancy Schemes		**Adjustment of Room Position**	
		Hungarian Method for Minimization	**Hungarian Method for Maximization**
Adjustment of the user pairing	Blossom algorithm for minimization	58.4 kWh	88.2 kWh
	Original User-combination	72.4 kWh	96.8 kWh
	Blossom algorithm for maximization	86.4 kWh	96.7 kWh

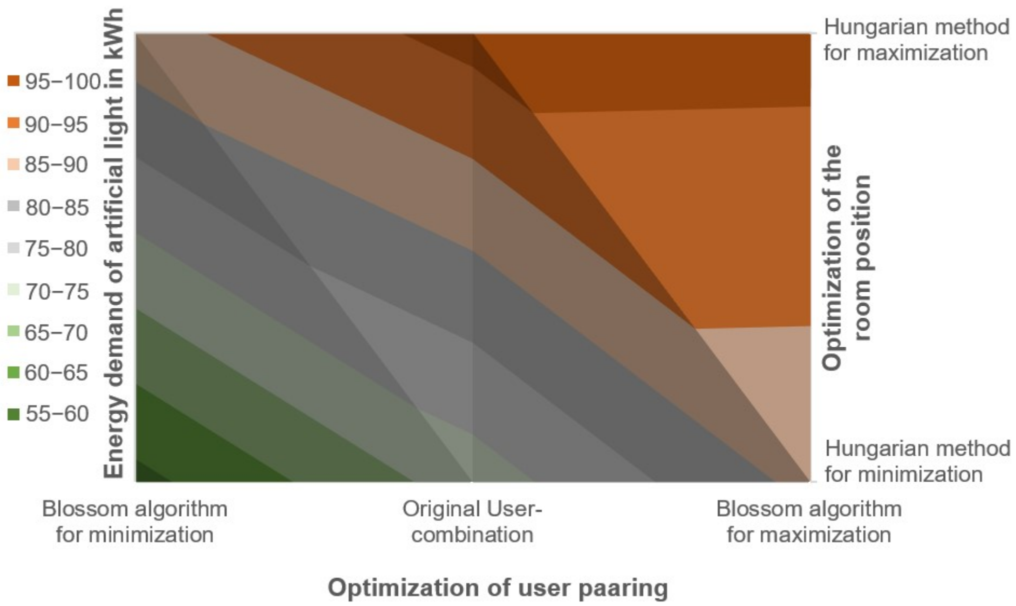

Figure 11. Overview of the influence of the individual optimization steps on the energy demand of the artificial lighting system, based on the presence, energy, and illuminance data collected in the study object, the R&D open-plan office of Bartenbach GmbH in the period from 1 July 2021–19 November 2021; energy demand of the original user distribution: 83.8 kWh; area of the open-plan office: 161.7 m^2.

The user-specific energy savings proved to be significant (*t*-test, one-sided; significance level $\alpha = 0.05$; $p = 0.0017$). The baseline data set was tested for normal distribution using the Kolmogorov–Smirnov test prior to statistical analysis ($\alpha = 0.05$; max. deviation of 0.1163; critical value of 0.2693).

As an alternative variant to graph theory methods, logical programming was used to derive the most energy-efficient user distribution in the room. The results provide a user distribution with an artificial light energy demand of 75.2 kWh. This represents savings of 10.3% over the baseline. Across all lighting zones, the average energy demand is 6.26 kWh ± 4.54 kWh.

Figure 12 lists where the unoccupied workstations are located after the energetic improvement of the user distribution based on graph theory methods (green shaded areas, Figure 12), for the energetically least favorable occupancy scheme based on graph theory methods (orange shaded areas, Figure 12), and for the energetic improvement based on logic programming (gray shaded areas, Figure 12; initial situation in Figure 2).

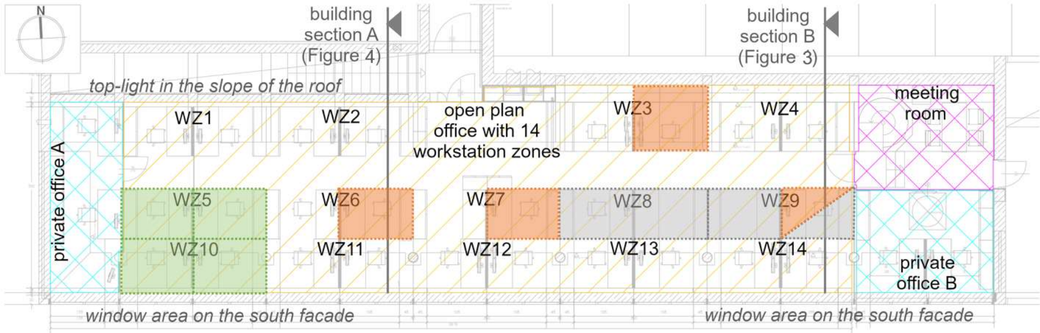

Figure 12. Floor plan of the office premises of Bartenbach GmbH with representation of the individual functional rooms (colored hatching); the position of the four free workstations is highlighted in color as an area according to the derived occupancy scheme (energetic minimization: green; energetic maximization: red; logical programming for energy reduction: gray); cf. baseline in Figure 2.

Since the overlap time of the user presences within a lighting zone is decisive for the artificial light energy demand of the corresponding zone (cf. Figure 8), Table 4 lists the overlap share of the individual user pairings in relation to the maximum occupancy time of the respective zone. From Table 4, it can be seen that the mean overlap percentage of the user pairings improves by 43.3% compared to the baseline situation for the energetically improved user distribution based on the graph theory methods. Logical programming results in a 30.1% increase in simultaneous presence within a lighting zone.

Table 4. Overview of the overlap fraction over the study period 1 July 2021–19 November 2021, for different user distributions in the room: the baseline, the minimum, and the maximum energetically optimized occupancy scheme, derived via the Hungarian and Blossom algorithm as well as the energetically improved user distribution based on logical programming; average and standard deviation data are exclusive of pairings with empty presence profiles.

Occupancy Schemes	**Energetically Most Unfavorable User Distribution**	**Initial Situation**	**Energetically Improved User Distribution I**	**Energetically Improved User Distribution II**
Calculation Method	**Blossom and Hungarian Algorithm for Maximization**	**Calculation from Measured Values**	**Blossom and Hungarian Algorithm for Minimizing**	**Logical Programming**
Average overlap time ± standard deviation, within an occupancy scheme	13.0% ± 7.1%	19.1% ± 8.8%	27.4% ± 14.2%	24.9% ± 12.9%
Deviation compared to the initial situation	−31.9%	Reference	43.3%	30.1%

3.3. *Testing for Synergies between the Impacts on Energy Demand and Light Exposure Rates*

In order to reveal possible synergies between the two target criteria as a function of the selected user distribution, the average daily light dose for each user is determined for the derived energetic user distributions. The resulting workplace-related daily lux hours are listed in Table 5 and visualized in Figure 13. A Pearson correlation indicates that an energetic improvement in user distribution is not simultaneously accompanied by an improvement in daily light dose (t-test statistic: 0.6474; $p = 0.5205$; $\alpha = 0.05$). The Pearson correlation is based on the user-specific energy consumption and lux hours of the baseline situation and the energetically optimized user distribution.

Table 5. Overview of workplace-related daily light dose for the energetically improved occupancy scheme or energetically unfavorable occupancy schemes; cumulative daily lux hours of the user distribution of the initial situation: 96 959.8 lxh.

Occupancy Schemes			**Adjustment of Room Position**	
			Hungarian Method for Minimization	**Hungarian Method for Maximization**
Adjustment of the user pairing	Blossom algorithm for minimization	Cumulated	98,201.2 lxh	96,089.7 lxh
		Average ± standard deviation, normalized	0.7324 ± 0.3070	0.7122 ± 0.3132
	Original user-combination	Cumulated	98,756.5 lxh	94,792.0 lxh
		Average ± Standard deviation, normalized	0.7362 ± 0.3024	0.7029 ± 0.3395
	Blossom algorithm for maximization	Cumulated	90,140.3 lxh	94,941.1 lxh
		Average ± standard deviation, normalized	0.6696 ± 0.2467	0.7060 ± 0.2870

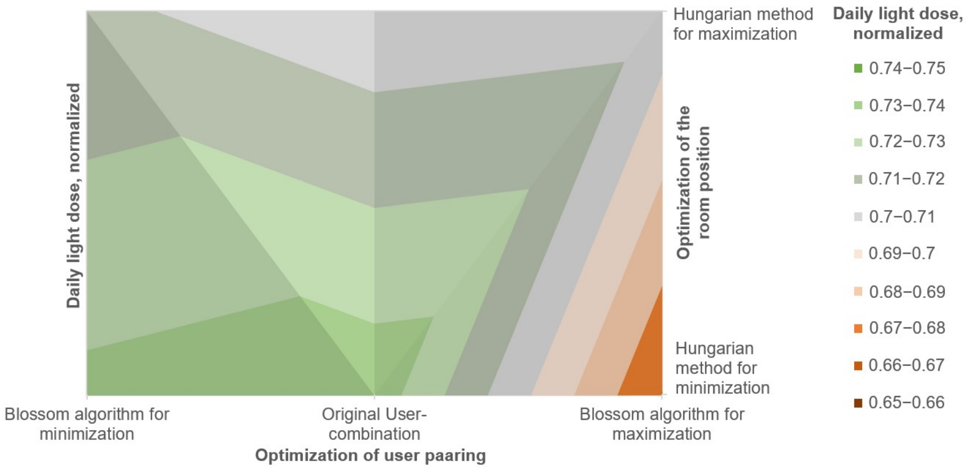

Figure 13. Overview of the daily light dose, presented as a normalization value and averaged over all users, for the different derived energetic user distributions in the room.

The energetically enhanced logical programming occupancy scheme results in a cumulative workplace-related daily light dose of 92,505.2 lxh. The result value is 4.59% lower than the baseline. The average of the normalized daily light dose is 0.6842 ± 0.2976 (excl. zones of unoccupied workplaces).

For maximizing the workplace-related daily lux hours, based on the Hungarian algorithm, the artificial light energy demand can be determined. Maximizing the lux hours results in an artificial light energy demand of 81.3 kWh (3.01% less than the baseline). Across all lighting zones, this results in an average of the energy demand of 7.41 kWh ± 3.47 kWh. The decrease is not significant (Pearson correlation, t-test statistic: 0.1209; $p = 0.9043$; $\alpha = 0.05$). Accordingly, there is no dependence between the improvement of daily light dose and the increase in energy efficiency. The performed Pearson correlation is based on the user-specific energy consumption and lux hours of the initial situation and the occupancy scheme of the daily light dose optimized to the maximum.

Under the objective of distributing the lux hours as evenly as possible, the logical programming leads to an energy demand of 82.5 kWh (1.56% less than the baseline). The average of the energy demand of the lighting zones in this case is 6.77 kWh ± 3.22 kWh.

4. Discussion

The distribution of users in the room has an influence on the effectiveness of lighting concepts. Table 2 shows a range of about 24,000 lxh between minimum and maximum. This corresponds to ±12.4% deviation around the achievable daily light dose of the initial situation (cumulated over all users). There are clear differences in the available lux hours in terms of room position and time (cf. Figures 6 and 7). These prove to be greatest along the south facade (Figure 5). Thus, the high diversity of the presence patterns (cf. Figure 1) coupled with the strong spatial differences in the availability of high illuminance levels leads to the identified ranges. It thus follows that the greater the absence at the workplace, the more the room position becomes important for individual users to take advantage of non-visual lighting effects. In addition, indoor climatic conditions (IEQ, Indoor Environmental Quality, which includes visual comfort) have a direct impact on the productivity of the building user [64].

Since the Hungarian algorithm maximizes the daily light dose of the overall situation (Table 2), individual users may experience a decrease in the achievable daily light dose. Thus, users who achieve low lux hours may end up in even less favorable seating positions (which occurred with five users, cf. Figure 9), in order to take greater advantage of the influence of users with high presence in well-lit areas of the room. Logical programming is able to close the gap between the individual users. This is clearly illustrated in Figure 9 by the comparison of achievable lux hours per user as a function of method. Logical programming does not improve the achievable lux hours of the overall situation as much as the Hungarian method (1.67% compared to 11.1%), but instead achieves a higher uniformity (spread 0.2342 compared to 0.3880). In application, this could be created by the introduction of guideline values for planning to avoid the disadvantage of individuals.

The distribution of the free seats shows that, both when maximized by the Hungarian algorithm and by logical programming, three of the four free seats are located in the lighting zones WZ5 and WZ10, those areas which, according to Figure 6, have the lowest potential in the workstation-specific E_v-profile. The low achievable lux hours in WZ10 (south facade) can be attributed to time-dependent shading caused by the outdoor situation. As expected, the minimization of the light dose by the Hungarian algorithm places the empty profiles in the best working areas in terms of light (WZ9 and WZ14; cf. Figure 6).

The distribution of users in the space also determines the effectiveness of energy objectives. Thus, the individual procedures for the strongly daylit study object (161.7 m^2, cf. Section 2.1) over the study period (1 July–19 November 2021) result in a range of 38.4 kWh. Against the background that the most unfavorable user distribution results in 96.8 kWh, the user distribution significantly determines the artificial light energy demand in the study object.

The ranges are again due, among other things, to the room position. Due to the high average illuminance over the midday period, the artificial light energy demand is determined by the time-of-day margins (Figure 8). For time periods that exhibit high user dynamics, since the real energy demand of a lighting zone results from the combined presence profile of both users of a zone (cf. Figure 8; determined via logical-OR-linking of the presence profiles), the overlapping time of the presence profiles of a lighting zone plays a major role. The greater the overlap, the more efficiently the artificial lighting can be used in a lighting zone. It is therefore important to combine those energy profiles in a zone that are as similar as possible in their temporal course (cf. Figure 1).

The optimization procedure lists an improvement of the overlapping times of the presences of 43.3% compared to the initial situation due to the derived user pairings. Logical programming leads to a 30.1% improvement in overlap times. The degree of zoning proves to be significant in this context: Due to the identified low attendances at the workplace and the simultaneous low overlap times, larger lighting zones could often be incompletely occupied. A preliminary study in the same study object lists that the artificial light energy demand decreases significantly with increasing zoning degree [43]. The reduced use of artificial lighting also indirectly results in energy savings in the area of cooling [30,65].

The study results further show that the unfavorable positioning of the original user pairing (96.8 kWh) leads to almost the same energy demand as the least favorable occupancy scheme (96.7 kWh), which can be derived via the algorithm. For the improved user pairing, an energy range of 29.7 kWh results depending on the room position. For the least favorable user distribution in the room, this amounts to 10.2 kWh. The influence of the room position therefore gains in importance with better user matching (Figure 11).

When the occupancy scheme is energetically improved, the unoccupied seats collapse (Figure 12). This creates an unused space area. The fact that this is not located in the center of the open-plan office, but rather in the peripheral area, offers the advantage of reducing the disruptive influence of faulty presences due to fewer room movements. In addition, WZ10 proves to be the most unfavorable zone in terms of lighting (cf. Figure 6).

The results further indicate that an energetic improvement in the user distribution is not simultaneously accompanied by an improvement in the workplace-related daily light dose and vice versa. This is evident from the fact that in Figure 13, high lux hours are present both for energetically improved user distributions and for energetically less favorable user distributions in the room. The fact that the derived occupancy schemes of the lighting improvement result in minor energy savings can be explained by the fact that the initial situation already shows a very energetically unfavorable user distribution (cf. Figure 11 and Table 3). A detailed analysis shows that the users who achieve the highest workplace-related lux hours (cf. Figure 9) are also the users who have high energy profiles even in optimized occupancy schemes. This is due to the fact that they list a generally high occupancy rate. Accordingly, high variability in occupancy profiles prevents the equal optimization of daily light dose and energy demand through user distribution. The lack of synergy between objectives leads to planning challenges:

In view of the fact that the building sector accounts for about one third of the energy demand [37,38] and that lighting energy in commercial buildings is a major contributor [66], it is necessary to reduce the energy demand in order to meet current climate protection targets. A current problem is the existing gap between planning and operation. Since the occupancy behavior at the workplace only becomes apparent after commissioning, user-centered mapping in the building design phase proves to be difficult or impossible to implement. This can lead to incorrect system sizing and result in inefficient building operation. The study lists a significant impact of user distribution in the space on energy demand. Occupancy times in the workplace are determined by organization-specific processes and social structures—aspects that result from the target application. In this context, a classification of organizations via relative frequency distributions of different variants of occupancy profiles could help to plan in a more targeted way and to close the gap between planning and operation. Such a classification could represent a middle ground between user-centeredness and generalized assumptions. However, this requires organizational research in the energy context. Through this research, possible factors influencing occupancy hours could be identified and made usable for planning and simulation.

The motive of the study is to show the influence of the space utilization concept on the key performance indicators energy demand and workplace-related lux hours. However, acceptance studies are required to evaluate the practicality of re-locations in operation. This study determines user distributions in the space based on zoning the lighting concept to two opposing users. For larger zoning levels, other matching methods would be required, or this case could be NP-complete.

The lux hour calculations of this study served to show the influence of the user distribution in the room on lighting planning concepts. For this reason, the daily light dose was limited to the times of presence at the workplace for the calculation. The influence of the user distribution in the room on the daily light dose proved to be significant. However, the achievement of lux hours is also determined outside of office presence and in individual cases can significantly outweigh the influence of the user distribution in the room. For the periods outside of an office presence, there are conditions that are difficult to control in terms of measurement technology, so that assumptions would have to be made. This would require corresponding specifications in the planning. Likewise, the guideline values for the health effects of light turn out to be insufficiently broken down, so that further research on this is necessary in order to realize a trade-off between the objectives. In this context, there is a high need for research concerning the suitability of the daily light dose as a parameter, concerning the benchmark of a daily light dose to be achieved and concerning the individuality of such a parameter. Energy planning is currently more explicit in the formulation of the objective and highly relevant in practice.

5. Conclusions

As the study results indicate, occupancy patterns can strongly influence the effectiveness of lighting and/or energy objectives. Due to the time-varying nature and complexity of behavior, users therefore exert decisive influence on the building energy demand [15,67,68]. A basic assumption of generally valid models fails especially when the social structure leaves a lot of freedom, e.g., flextime of working hours or high dynamics of presence at the workplace.

Monitoring and data analyses of ongoing operation (post-occupancy evaluations, POE) can serve as a basis to analyze user behavior and thus break down their impact on building energy demand [34]. Based on this, measures can be derived to better align the real-world situation with the target. Wireless sensor networks proved to be a useful tool in this context and also offer the advantage of reducing installation effort by eliminating wiring and providing flexible sensor positioning [34,69,70]. The quality of the occupancy data depends largely on the intended application [34]. The position, number, and detection range of the sensors are crucial in order to be able to map profiles sufficiently accurately [71–73]. Since the use of sensors is associated with intrinsic energy requirements for production, operation, and disposal, it is important to ensure that the resulting energy savings potential in the target application outweighs the sensors' own energy demand.

However, long-term verification is required to establish subsequent repositioning of users as a more advanced approach to POE. This is because the study presented represents the calculations for only one office example, which cannot be representative of different office concepts (cellular offices, open-plan offices, etc.) with different target applications. A generalization of the statements therefore first requires further investigations.

Crucial to deriving improved user arrangements in space is the measurement period. Since work tasks and the associated workflows change over time, it is important to mark transitions in the work processes, to recognize them at an early stage, in order to determine the most favorable time for optimizing the occupancy schemes.

The study results also indicate that methods from graph theory can be used to derive more energy-efficient occupancy schemes, or in terms of daily light dose, improved occupancy schemes. Approximation methods for multidimensional assignment problems, as in the energetic case, prove to be of high practical relevance.

6. Perspective

The article emphasizes the importance of organizational aspects on the key performance indicators. Therefore, the article should primarily be an impetus for further research in this area to close the performance gap. Due to the focus on building technology, the consideration of the flow design of work processes was deliberately left out. Communication is described as an essential aspect needed to efficiently accomplish work objectives, and thus critical to maintaining smooth operations and achieving business goals [74]. Communication in the workplace is commonplace, ubiquitous, and controllable in terms of user distribution in space. Therefore, a user arrangement can also be done in terms of reducing communication paths. In this context, those employees who are working on the same project topic or whose work focus are similar would be placed as close to each other as possible. The authors therefore recommend the identification of procedures for deriving holistically improved user distribution in space that combine building-, organization-, and user-specific aspects as an objective for future research.

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Informed Consent Statement: In this study, measurement data were collected and analyzed at the individual workstation level. To avoid conflicts with data protection regulations, a voluntary declaration of consent was requested from all users at whose workstations the occupancy profile was recorded and analyzed. The publication of measurement data and results was pseudonymized.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. As this is measurement data at the individual workstation level, the data are not publicly available.

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