Quantification of Effective Temporal Exposure to Daylight Illuminance Levels in Healthcare Settings

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Abstract. The purpose of this study is the quantification of the exposure of occupants to daylight illuminance levels. The case study is the typical floor of a patient tower occupied by nurses in twelve hours shifts, from 7 am to 7 pm. Significant evidence exists regarding the positive impact of access to daylight on staff outcomes in healthcare facilities in terms of reduction of stress, absenteeism, medication errors, and burn outs. However, the standard daylight simulation methods evaluate the building and do not capture the dynamic nature of people's behavior while moving through the space. The proposed approach combines agent-based simulation and daylight performance analysis to compute the occupants' exposure to daylight levels throughout the year. The results show the discrepancies between building-centric and human-centric types of analysis and the contribution of dynamic simulation methods to design occupancy schedules to warranty equitable access to daylight to building occupants.

Keywords: Agent-based simulation, Performance-based design, Spatial occupancy, Human-centric analysis

1 Introduction

A multitude of research has been done on analyzing the building performance achieving high levels of resolution and reliable results. Unlike energy analysis, which is based on thermal zones, most of the environmental analyses are grid-based. These analyses define an analysis plane, at a certain height, a grid of points, evaluate the intensity levels for a given metric per sensor point, and visualize results through heatmaps. Even though grid-based analyses effectively characterize performance, they are building-centric and do not necessarily capture occupants' exposure to the environmental conditions they measure. Occupants behave like moving sensors, constantly changing positions and orientations through space and time. Consequently, occupant's comfort cannot be accurately calculated solely relying on these grid-based analyses. The characterization of the spatiotemporal occupancy of the space remains an active area of research (Gomez Zamora, 2017).

On the other hand, several efforts have been made to simulate realistic user occupation of buildings through a combination of Discrete Event and Agent-based systems (Heath, et al. 2011). This approach represents variations in position and orientation of each occupant through time, which has been tested in usability and accuracy to represent human behavior (Luo, et al. 2017). These simulations rely on agents representing different occupant roles and interactions and schedules embedding the expected sequence of actions they are supposed to perform along with a specific time frame such as daily shifts, weeks, or even the entire year. These simulation models can be based either on predefined schedules or data based on real measurements of people's behavior. They provide valuable information to predict the actual use of the space. Several implementations have been made with increasing levels of complexity across different fields. Initially, in highly abstracted proofs of concepts to optimize space planning (Shen, et al, 2010). They were later developed together with pedestrian simulation as a tool to improve designer-client communication (Shen, et al. 2013) and evaluate occupancy performance indicators such as path lengths and density (Schaumann, et al, 2019). And finally, allowing designers to assess behavioral consequences of design decisions (Schaumann, et al. 2020).

We can find examples of Pre-Occupancy Evaluations (PrOE) in the field of energy analysis (Hong, et al. 2015), mainly to evaluate more realistic building energy consumption (Chen, et al. 2017), or in small-scale user-space interactions (Shin, et al., 2016). Gomez-Zamora et al. (2019) also demonstrated the radical influence of the caregivers' circulation paths and schedules on the accumulated time of unplanned surveillance patients receive, affecting patient outcomes. However, there is still ground to cover to dynamically evaluate the occupant's comfort levels in other areas such as Daylight, Glare, Thermal Comfort, or Views of the Outdoors.

To measure occupants' exposure to environmental conditions, specifically Daylight Illuminance, this proposed approach merges both building performance analysis and occupant's behavior simulations in an integrated process. We tried our approach in a healthcare facility for Critical and Medical-Surgical Care Units to quantify the exposure to the daylight of healthcare providers during working hours. Unlike inpatients that spend a fair amount of time in bed in a fixed location in these units, healthcare providers are constantly moving from one location to another during the long twelve-hour seven-to-seven shifts.

The relevance of accurately tracking the actual exposure of caregivers to daylight is due to the significant influence on staff outcomes and, subsequently, on the patients' direct benefits. For example, Alimogli & Donmez (2005) surveyed the positive effect of exposure to sunlight for more than three hours on reducing nurses' work-related levels of stress and increasing job satisfaction. Ulrich et al. (2008) published an extensive review of evidence-based design in healthcare literature that shows the correlations, not necessarily causality, between environmental factors and staff and patient outcomes. They classified the results of several research efforts and reported the impact of illuminance levels on different areas. The results show medication errors rate reductions from 3.8% to 2.6% while increasing daylight intensity from 450 to 1500 lux (Buchanan et al.,1991). In the same report, Lepparmaki et al. (2003) show the impact of repeated brief exposure (4x20 minutes) to bright light over 5000 lux on self-reported well-being of night shift nurses, and Partonen & Lonnqvist (1998) found that treatment with bight over light 2500 lux has a positive impact on distress associated with night shifts and even mood in healthy people. In terms of visual tasks, Figueiro et al. (2006) measured the performance benefits at the working plane starting at 600 lux, and Zadeh et al. (2014) documented the benefits of the presence of sunlight on physiological responses, improved communication, and even on the overall mood of the healthcare providers while comparing the performance of nurses assigned to windowed versus windowless locations.

More recently, assuming the positive impact of access to daylight on the staff outcomes. Hadi and Pewzer (2018) quantified the duration of the exposure to daylight by comparing the annual average illuminance levels per space and the amount of time the caregivers stayed in each room. For this purpose, they implemented a Discrete Event Simulation model based on schedules and data collected on-site to simulate staff behavior in a module of twelve exam rooms. The results showed the staff experiencing far less than three hours of daylight exposure, compromising their overall performance. They also pointed out the need to increase the accuracy of the analysis at higher levels of granularity to create a more realistic evaluation of such a critical aspect. In this regard, the purpose of this study is to measure the caregiver's exposure to daylight at the resolution of two-by-two square feet every hour throughout the entire year. The aim is to capture the slightest variation in daylight intensity in space and time.

The proposed methodology also integrates both behavioral and environmental simulations in a single process. This approach executes two types of simulations: a performance analysis to characterize the space's environmental conditions and a multi-agent narrative model to represent the space occupancy. While we simulate the occupant's movement across space, we link the position and orientation to the environmental information to calculate the accumulated exposure and plot the fluctuations along the year at the grid level. The results show significant variations in daylight exposure of caregivers assigned to the same floor, performing a similar task, but in different building orientations.

2 Methodology

The methodology to estimate the exposure to the daylight of caregivers in Critical and Medical-Surgical Care Units is composed of three models: The multi-agent narrative approach by Schaumann that simulates user occupancy through a set of scheduled and unscheduled narratives composed by actors, activities, and spaces; the Theta* pathfinding algorithm by Nash & Koenig (2010) that can generate human-like angle-free paths by improving on A* algorithm by adding line-of-sight to the calculation; and the environmental analysis that simulates the annual daylight building performance.

2.1 Case Study

The case study is the typical floor of a patient tower located in climate zone 3 in the United States (Fig. 1). It has two wings and a central core with shared programs such as the break room. The East wing corresponds to the Medical-Surgical Care Unit, and the West to the Critical Care area. The design proposes documentation stations every two rooms from where nurses directly view the inpatients to minimize walking distances and maximize the time spent with inpatients and safety.

2.2 Nurse Narrative

Even though the patient related tasks are regularly divided between the nurse and the techs in most of the facilities, in this study, a generic nurse executes all the tasks. This study only evaluates the annual exposure to illuminance during the day shift from 7 am to 7 pm. During shifts, they need to visit the patients every hour according to the schedule represented as the activity diagram in Figure 2. While the number of patients per nurse in Medical-Surgical Care is four, in Critical Care, it decreases to two. On average, they visit one inpatient every fifteen and thirty minutes, respectively.

Between patients, they need to prepare medication in the medication room, pick supplies from another room, visit the nutrition room if necessary, and update the records in the computer located in the documentation station. Once or twice per shift, they have a fifteen-minute break for lunch or go a few minutes to the restroom. The time spent in each room varies from two minutes to four depending on if it is to check vital signs or if the patient needs medication. The visits could be longer if the patient needs assistance to the restroom, help with dressing, cleaning wounds, or any other special treatment. But still, the nurses need to manage to visit them every hour.

We excluded a few tasks for this study, such as attending a short meeting at the beginning of the shift at the nurse stations in the center or sending exams through the tubes located in the same station.

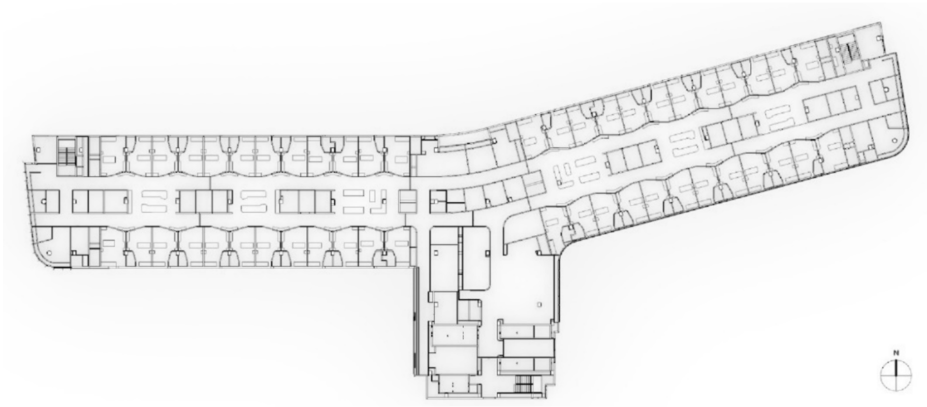

Figure 1. Critical Care Units to the left and Medical-Surgical Care Units to the right.

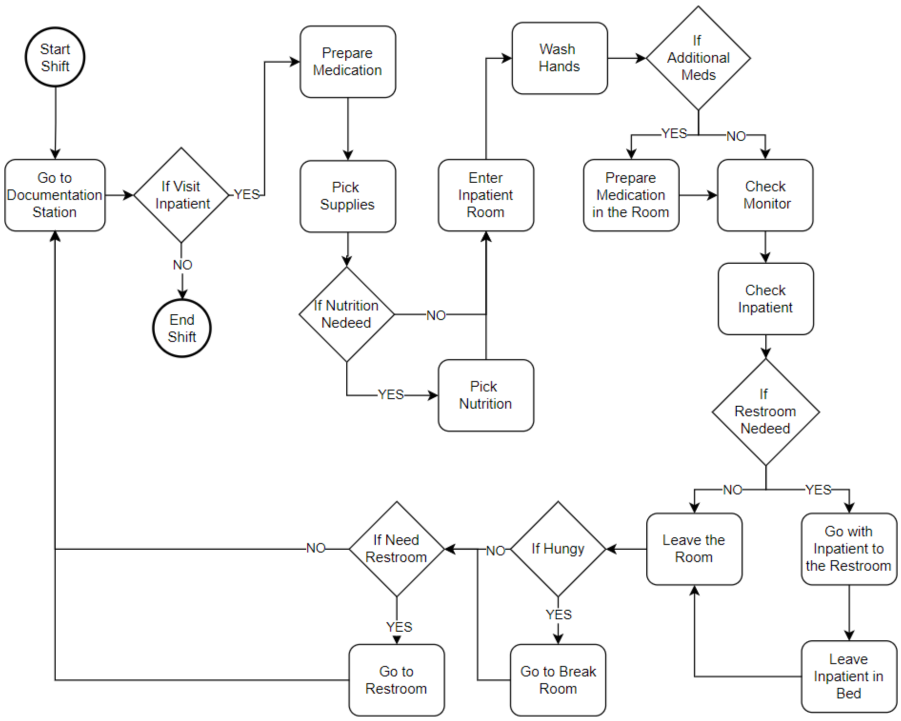

Figure 2. Activity diagram representing the sequence of actions and decisions nurses make every time they visit inpatients during twelve hours shifts.

2.3 Circulation Paths

We use a pathfinding algorithm to simulate user movement inside the building to generate the closest path between the current user position and the desired destinations. A path grid is generated at the beginning of the simulation process, considering obstacles, such as walls and furniture. Paths are generated during the occupancy simulation (Fig. 3) through an implementation of the open-source Theta* algorithm (Naderpour, et al. 2019). Right after the path generation, we simulate the user movement by evaluating the resulting polyline according to human velocity and desired resolution allowing different levels of accuracy. In contrast to a pedestrian agent-based approach (Wang, 2019), this allows us to execute faster simulations regardless of user-to-user collision. A stochastic component varies the destination and length of stay of the agents in each room since the actual occupancy of the space randomly changes depending on patient needs. The agents representing nurses are classified into four groups, Critical Care North and South, and Medical-Surgical Care Northwest and Southeast, to facilitate post-processing (Fig.4).

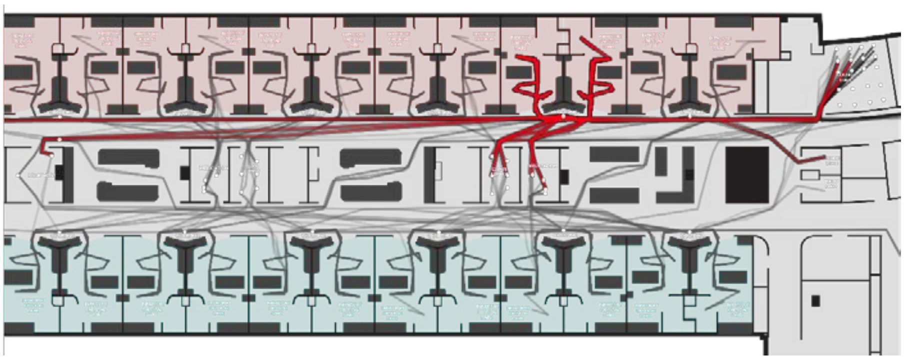

Figure 3. Highlighted in red is the circulation path of Nurse N° 4 in Critical Care.

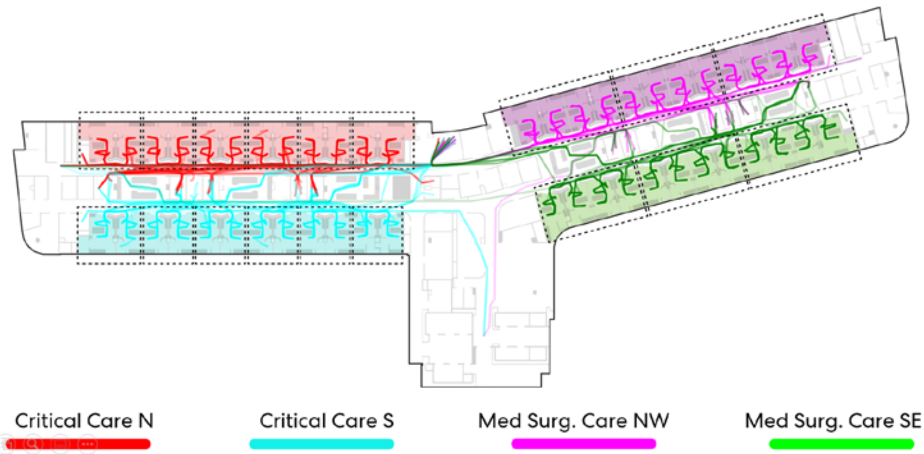

Figure 4. Circulation path at floor level

2.4 Daylight Exposure

To calculate nurses' exposure to daylight illuminance levels larger than 300, 600, and 1500 lux, firstly, we use Climate Studio (Solemma, 2020) to run the annual daylight simulations with a grid of sensor points two-by-two feet at the working plane (Fig.5). The data contains values for each sensor every hour of the entire year (Fig.6). A second post-process calculates the intersection in space and time with the agents representing nurses to compute their hourly exposure. To do so, we record the agents' positions in the grid each second during the twelve-hour shift together with their corresponding timestamps, resulting in 43,200 total locations for each agent every day. Later, we identify the closest hour and grid point to each agent position to obtain the illuminance value. This process is executed for the 365 days of the year. To plot the results, we average the exposure of all the nurses per zone.

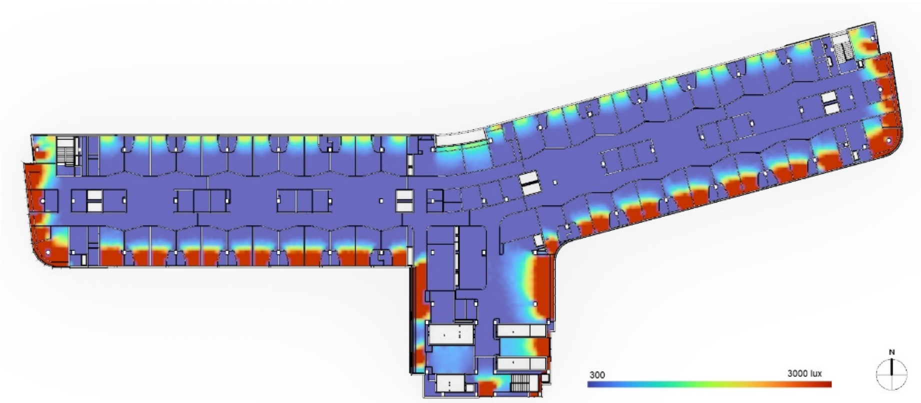

Figure 5. Annual illuminance average. Below 300lux blue, above 3000lux red.

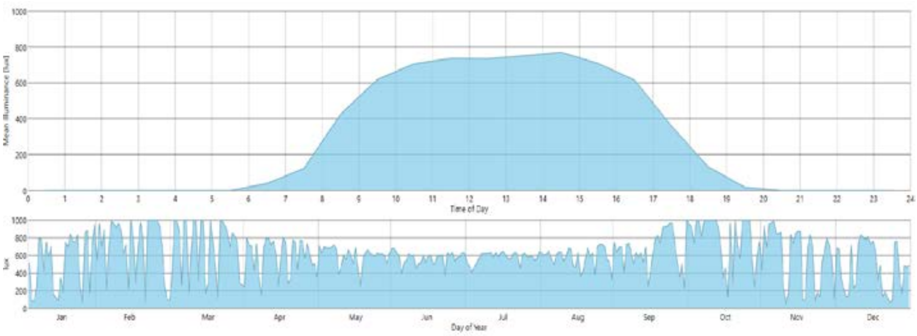

Figure 6. Overall daily mean illuminance above, mean illuminance for 365 days below.

3 Results

We implemented narratives for nurses that constantly navigate through the space. We record each movement and link their position and direction with the results of the adjacent sensor points. Once the simulation is complete, we obtain each occupant's accumulated temporal exposure to different thresholds of 300, 600, and 1500 lux during shifts (Fig.7) throughout the entire year.

Stress reduction and job satisfaction occurs when the accumulated daylight exposure is more than three hours a day. The minimum threshold we can associate with the presence of daylight is 300lux. The 300lux threshold (Fig.8) shows that nurses in the Medical-Surgical Care East wing are exposed most days above the three-hour threshold in both orientations. The illuminance levels in the Medical-Surgical Care wing are higher than in the Critical Care due to the slight rotation of the floor plan on the Eastside. Nevertheless, the West wing seems close to the desired threshold for the two groups in that area.

The 600lux threshold (Fig.9) that correlates with visual tasks shows Critical Care South around 1.5 hours per day and Medical-Surgical Care Southeast 2.4 hours per day most of the year, which is remarkable. However, Critical Care North and Medical-Surgical Care Northwest show an uneven distribution concentrating the higher exposure in the center half of the year reaching 0.6 and 1.2 hours per day, respectively, exposing the need for artificial lighting to support visual tasks the rest of the year.

The 1500lux threshold (Fig.10), which correlates with reducing medication errors, shows lower durations in the four groups. While the Critical Care North and Medical-Surgical Care Northwest groups achieve no time within the threshold, the Critical Care South and the Medical-Surgical Care Southeast achieve almost half an hour in the beginning and end of the year.

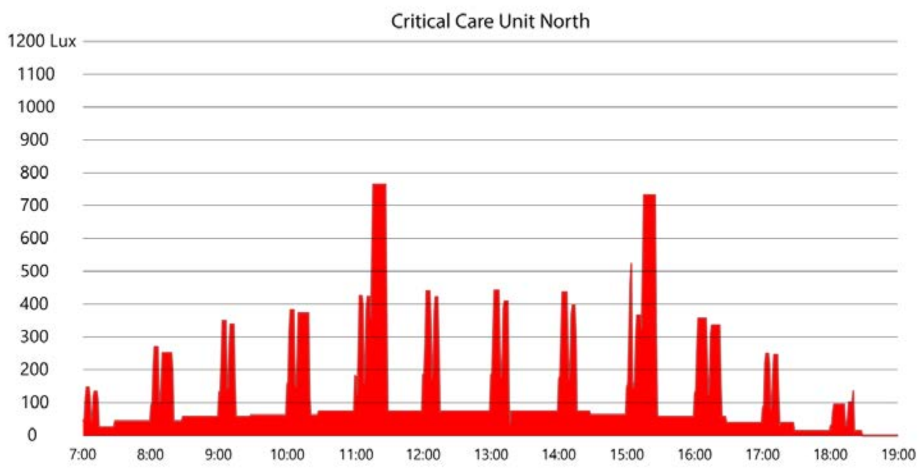

Figure 7. Exposure of Nurse N° 04 during the 7am to 7pm shift on March 21th.

Consistently, across the three evaluated thresholds, the four groups show radically different levels of exposure while executing similar tasks on the same floor. The discrepancies across nurse groups highlight the importance of the design of the occupancy schedule from an equity perspective. Even though Fig.7 is a sample of one shift of one nurse on a specific day, it is a clear example of nurses exposed to higher illuminance levels while are in the inpatient room. This exposure in the inpatient rooms is consistent with Fig.6, which shows the corridors and other spaces at 300lux and below, except for the break room.

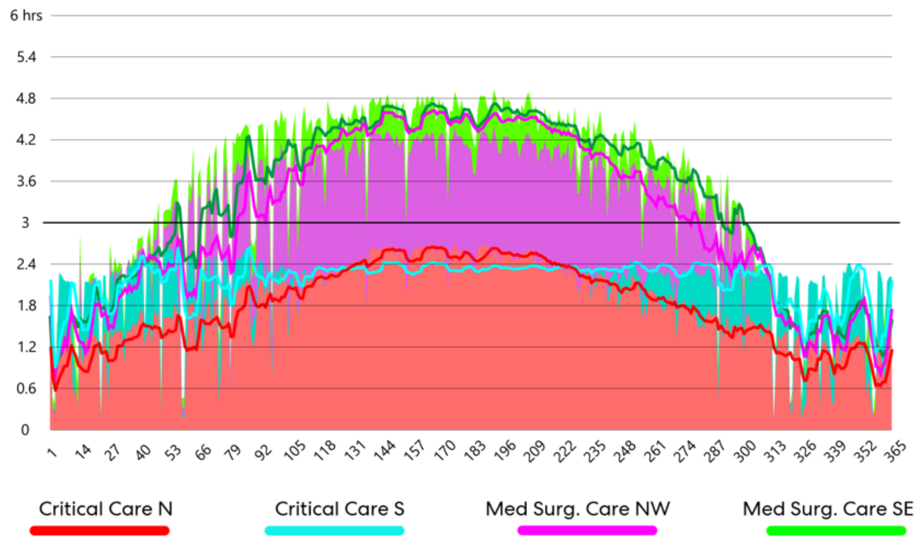

Figure 8. Seven days average time over 300lux per zone across 365 days.

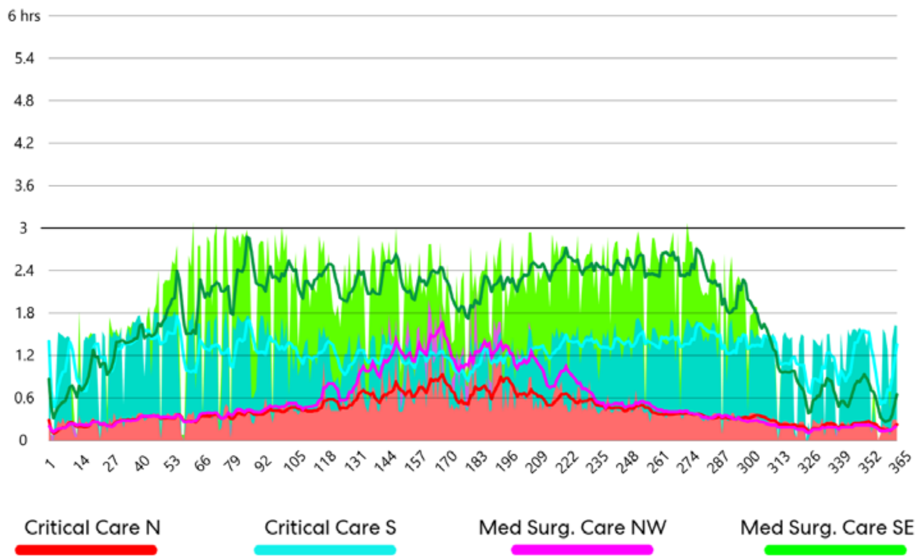

Figure 9. Seven days average time over 600lux per zone across 365 days

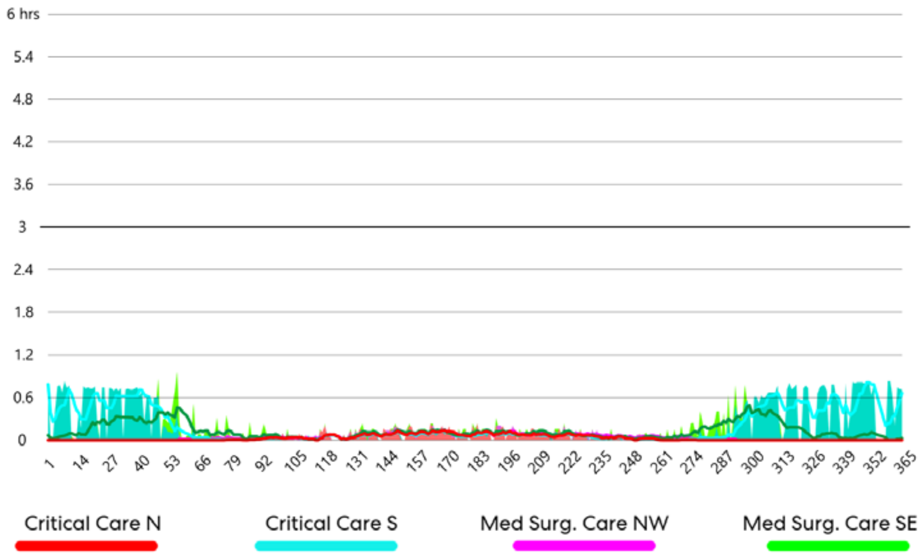

Figure 10. Seven days average time over 1500lux per zone across 365 days

4 Discussion

This approach proposes the migration from a building-centric to a human-centric type of analysis by quantifying and demonstrating the potential differences to exposure to environmental conditions among different occupants of the same facility. Even though the general characterization of the building performance provides a reliable context to make assumptions regarding the quality of the space, discrepancies in terms of schedules can situate similar occupants sharing similar tasks in different conditions. Despite the dependency on the schedules' accuracy or the limitations to represent the unplanned behaviors, the proposed method provides valuable feedback to anticipate the actual occupancy of the space. The occupancy, or the schedule driving the occupancy, is a design itself. While the annual daylight performance of the building remains constant, the design of the occupancy schedules in such a strong program can be adapted to distribute the access to daylight and other environmental factors equitably.

Considering the amount of data per agent by location, intensity, hour, shifts across the entire year, and the variety of questions regarding the combination of illuminance levels, time of the day, accumulated exposure, and impact of specific tasks, a data visualization interface seems to be the logical next step in this research to support the interpretation of the results.

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