Investigating the Impact of Space Allocation Strategy on Energy-Comfort Trade-off in Office Buildings

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ABSTRACT

With the global push to decarbonize the building sector and growing interest in occupant-centric building controls, numerous simulation and field studies have been conducted to explore the trade-off between energy efficiency and occupant comfort. These studies largely disregard individual differences in thermal comfort and assume each zone has a fixed occupancy schedule. In office buildings, there is often some leeway in how occupants are grouped and assigned to different building spaces (e.g., offices and meeting rooms). In this paper we investigate the extent of the impact of the space allocation strategy on the energy-comfort trade-off in office buildings, and whether it depends on specific building characteristics. Our simulation shows that varying the space allocation strategy in a medium office building can lead to over 3.5%/15.1% change in annual/monthly energy consumption, and over 15% change in average thermal comfort when using the personal comfort model. This finding calls for the joint optimization of HVAC operation and space allocation, possibly at different timescales.

CCS CONCEPTS

• **General and reference → Empirical studies**; • **Mathematics of computing → Discrete optimization**.

KEYWORDS

Space Planning, HVAC Energy Optimization, Thermal Comfort

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1 INTRODUCTION

Improving the energy performance of buildings is at the forefront of the global effort to decarbonize the buildings sector. The heating, ventilation, and air conditioning (HVAC) system is responsible for significant energy consumption across the world, e.g., the energy used for space heating, cooling, and ventilation in commercial buildings in the US amounted to 3.18 quadrillion British thermal units in 2022 [1]. Thus, most research in this area has focused on optimizing the HVAC operation while satisfying diverse needs of the occupants, from air quality to thermal comfort [7]. This includes the research on occupant-centric building controls, in particular developing models for estimating building occupancy and individual thermal comfort [12], and designing control algorithms that incorporate the observed or inferred occupancy schedule along with occupant comfort needs to ensure they are satisfied when reducing the building energy use and operational costs [11].

Most related work on occupant-centric building controls treats the occupancy state of each zone or the entire building as an exogenous variable, and evaluates a control policy using a generic thermal comfort model that does not truly reflect the thermal satisfaction of occupants in the building under study. While there is some prior work that utilizes personal comfort models [6] to evaluate the performance of an HVAC control strategy [8], the location of every occupant in the building is assumed to be fixed and given. Yang et al. [9] propose reducing the HVAC energy consumption by assigning occupants that have similar work schedules to the same space so as to minimize the number of occupied zones, thereby turning off the zone-level reheat system in unoccupied zones. Nevertheless, they do not investigate how this space assignment strategy would affect thermal comfort of the occupants.

Space planning is an important problem in commercial real estate, in particular office buildings, which typically have higher vacancy rates[1], and contain many shared offices, meeting rooms, and open-plan work spaces. Building owners and business managers decide which spaces should be occupied during business hours or can be reserved for meetings. They may reassign spaces occasionally (e.g., in a quarterly fashion) based on various factors, such as the group size, outdoor temperature, and solar heat gain. Similarly, rooms are often reassigned to different organizations and individuals in coworking spaces. While frequent space reassignment would cause discomfort for the occupants or could affect their performance negatively, there are always opportunities to reassign building spaces with negligible impact on productivity and comfort, e.g., when a lease ends or personnel changes occur in a tenant organization. Regardless of when space (re)assignment should be performed, it is important to understand how the way occupants are grouped and assigned to the zones in a building could impact the HVAC energy consumption and thermal comfort. This problem has remained largely unexplored to date.

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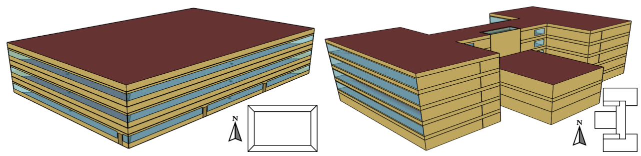
[1]The average vacancy rate of office buildings is 17.7% in Canada as per this article: https://www.cbre.ca/insights/articles/canadian-office-vacancy-hits-all-time-high-as-workplace-evolution-continues



(a) Building 1 (b) Building 2

Figure 1: The 3D view and floor plan of the buildings considered in this paper where north is marked on each floor plan.

The aim of this paper is to provide insight into how the space assignment strategy could change the trade-off between energy consumption and occupant comfort in an office building. We are inspired by the observation that (a) typical office buildings contain several thermal zones each having a separate setpoint, (b) there is some flexibility in setting the total number of people that can occupy each zone as long as it does not exceed the capacity of the respective rooms, and (c) grouping occupants with similar thermal comfort needs makes possible greater savings while maintaining the same level of thermal comfort. We use EnergyPlus to simulate two medium office buildings over one year, and consider different occupant distributions to identify the energy-comfort trade-off for each building. Finally, we redo the experiments using the personal comfort models developed in [12] by utilizing real data from the environment and occupants' feedback.

2 TEST BED

We explore the impact of changing the number of occupants and their distribution across the zones on the building energy use and occupant thermal comfort in two commercial buildings depicted in Figure 1. The buildings are simulated in EnergyPlus 9.3 [4] and COBS [10] is used to interface with EnergyPlus to change the number of occupants in each zone. The EnergyPlus model uses a 15-minute simulation time step, and our study is conducted over one year to smooth out seasonal fluctuations.

- **Building 1** is a 3-story 15-zone medium office prototype building that is defined by ASHRAE 90.1 [2] and located in Denver, Colorado. The floors are identical with respect to the floor plan, each containing a core zone and four perimeter zones. According to the default occupant density defined in ASHRAE 62.1 [3], the capacity of the core zone is 53 occupants, the capacity of north and south perimeter zones is 11 occupants, and the capacity of east and west perimeter zones is 7 occupants. The total floor area of this building is 4,982.19 m^2 and its total capacity is 267 occupants.
- **Building 2** is a medium educational building containing 9 labs, a library, and an amphitheater. This building is assumed to be located in San Francisco, California, and we use weather data for this city in our simulation. The capacity of each of the 8 smaller lab spaces is 20 occupants, and the capacity of the larger lab is 97 occupants. The library has the capacity of 27 occupants and the amphitheater has the capacity of 95 occupants. The total floor area of this building is 5,051 m^2 and its total capacity is 379 occupants.

3 EXPERIMENTAL DESIGN

We adopt a two-step strategy to obtain the total number of people assigned to each thermal zone in a building that contains m zones. In the first step, we create m groups of occupants by sampling the group that each occupant belongs to from a discrete power law probability distribution, namely the Zipf distribution. In the second step, we randomly assign these groups to the m thermal zones in that buiding. We use personal comfort models developed in [12] and Fanger's predicted percentage of dissatisfaction to evaluate thermal comfort of the occupants. We describe each step below.

3.1 Assigning occupants to zones

We group occupants into m groups, where m is the number of zones in the building. Specifically, each occupant is assigned to a group according to the Zipf distribution:

$$Pr(i) = \frac{i^{-\alpha}}{\sum_{k=0}^{\infty}(k+1)^{-\alpha}},$$

where $Pr(i)$ represents the probability of assigning an occupant to group i ($i \in \mathbb{N}$), and α is a distribution parameter. Notice that the Zipf distribution is unbounded, meaning that an occupant might be assigned to group i where $i > m$. To prevent this from happening, we clip the Zipf distribution to the first m groups and normalize the probabilities so they sum to 1.

Once the m groups are obtained, we randomly assign each group of occupants to a zone in the building. We resample the zone if the size of the respective group exceeds the zone capacity. To simplify the analysis, we assume occupants remain in the zone they are assigned to during the working hours (9:00am to 5:00pm), and keep the space assignment unchanged throughout the simulation. Note we use the Zipf distribution so we can get higher disparity between the group sizes by increasing the value of α (i.e., having some empty zones and some zones that are at their capacity). Additionally, we consider the uniform distribution for assigning occupants to thermal zones, to establish a baseline.

3.2 Controlling the HVAC system

To understand how varying the number of occupants and their work space affects the total energy consumption of the HVAC system, we adjust setpoints and control knobs in the HVAC system such that it continues to maintain the thermal comfort (as expressed by Fanger's comfort model described below) within acceptable limits. To this end, we use `EnergyManagementSystem`[2] in EnergyPlus to ensure the room temperature closely follows the setpoint defined according to ASHRAE 90.1.

3.3 Incorporating personal comfort models

Thermal comfort reflects an individual's satisfaction with their local thermal environment. Two widely used models to quantify the thermal comfort of an occupant are developed by Fanger, namely the predicted mean vote (PMV) and the predicted percentage of dissatisfaction (PPD). Since Fanger's models ignore the variability of individual satisfaction with the thermal environment, it is impossible to distinguish between two space allocation strategies that

[2]Refer to https://bigladdersoftware.com/epx/docs/9-3/input-output-reference/group-energy-management-system-ems.html

are identical in terms of the total number of occupants assigned to each zone but differ in terms of which occupants are grouped together [5] (e.g., one of them puts occupants that have similar thermal preferences in one group while the other one does not take that into account). Thus, we also use the personal comfort models proposed in [12] and assume that each individual may have a different thermal preference. In particular, we use the 15 group comfort models developed in [12] as our personal comfort models to estimate individual thermal comfort. Each model takes the ambient environment and outdoor weather data to estimate thermal sensations, and the output is the probability distribution of occupants feeling 'comfortable', 'hot', or 'cool'. To simplify the problem, we do not ensemble these group models as described in [12]. Instead, we assume thermal preferences of each occupant in this experiment can be fully described by one of the group models (rather than their mixture). We randomly assign group models to each occupant with the same probability, and compare the results obtained using personal comfort models with those under Fanger's model.

4 RESULTS

In this section we report the result of experiments conducted in EnergyPlus and answer the following questions: (a) How does the occupant distribution affect the trade-off between energy consumption and thermal comfort? (b) Is this effect unique to the building under study or can be generalized to other buildings? (c) How important is it to use personal comfort models in building controls when characterizing the energy-comfort trade-off?

4.1 Effects of occupant distribution on energy-comfort trade-off under the conventional comfort model

We first investigate how the occupant grouping and space allocation strategy could impact the trade-off between energy consumption and occupant comfort in a given building. Figure 2 shows the total HVAC energy consumption in one year and the thermal discomfort ratio averaged over the same period of time, assuming 100 occupants are assigned to the 15 (11) zones in Building 1 (Building 2) using different strategies. Note, instead of reporting the absolute value of energy consumption and discomfort ratio, we show the percentage increase/decrease in these quantities over the baseline scenario in which occupants are uniformly distributed across the zones in the buildings. To quantify thermal discomfort, we use two thermal comfort estimation models: the conventional Fanger's model, i.e. PPD (in Figure 2(a) and (c)) and the personal comfort model described in the previous section (in Figure 2(b) and (d)). Each dot in Figure 2 shows the result of a single run. The dots are color-coded based on the Zipf distribution parameter that was used to produce the occupant distribution, with light-yellow indicating $\alpha = 2$ (higher disparity between the group sizes) and dark-green indicating $\alpha = 1.1$. For each α value, the random assignment of occupant groups to zones is done 100 times (following the reject-and-resample method to ensure the zone capacity will not be exceeded), resulting in 100 dots of the same color.

Notice that the x-axis range is the same in the two plots that are put in the same row in Figure 2. By examining the x-axis alone,

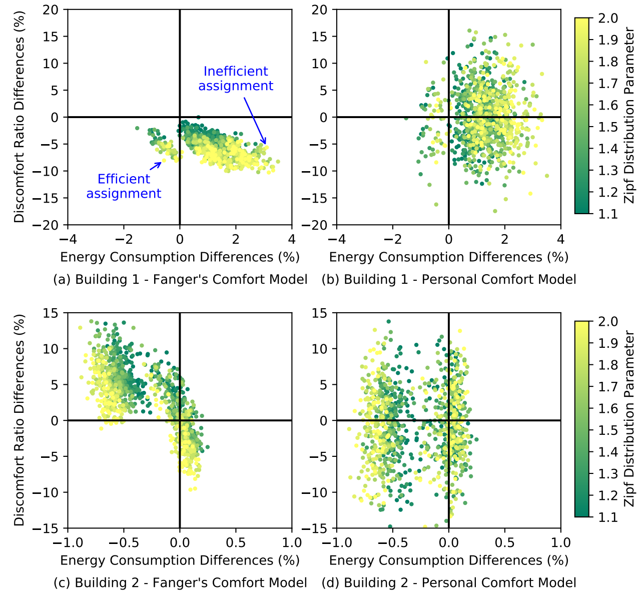


Figure 2: Simulation results in both buildings using two models to quantify thermal comfort and different occupant distributions, assuming a total of 100 occupants. Each dot represents the outcome of one run with occupants being assigned to groups following the specified Zipf distribution. The dot color shows the distribution parameter and we consider 100 independent runs for each parameter. The annual energy consumption of the baseline is 108.35 MWh and 57.93 MWh in Building 1 and Building 2, respectively.

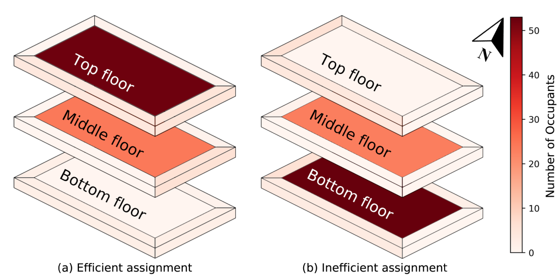


Figure 3: A visualization result to compare the actual occupant distribution obtained from the experiment between the energy-comfort efficient and energy-comfort inefficient results in Building 1, both with a Zipf distribution parameter equal to 2. The darker shade of red represents a higher number of occupants assigned to the corresponding zone.

it is evident that energy consumption rises in general when occupants are concentrated in a few zones in Building 1 (higher α values). This can be attributed to the fact that there is one air loop for each floor of Building 1, which is used to condition all zones on that floor. When a specific zone on a given floor has a high cooling/heating demand, all other zones will be conditioned to fulfill that demand, increasing the energy use substantially. However, by modifying the space allocation strategy, it is still possible to reduce energy consumption when $\alpha = 2$ compared to the baseline, i.e., uniformly distributing occupants. Figure 3 illustrates two allocation strategies that rely on the same occupant distribution, obtained with $\alpha = 2$, but exhibit vastly different performance in Building 1 (the corresponding dots are labelled in Figure 2(a)). One strategy, labelled efficient assignment, falls on the Pareto front, achieving a reasonable trade-off between energy consumption and thermal comfort. The other strategy, labelled inefficient assignment, results in about 3% more energy consumption than the baseline and a small improvement in thermal comfort. As depicted in Figure 3, the main difference between the two strategies is whether the core zone assigned to the larger group of occupants is on the top or bottom floor. We believe this is because the zone that contains many occupants has a higher cooling demand, as humans dissipate heat. In a colder climate (like in Denver), the heat transfer across the building envelope is higher in the top floor than the bottom floor, reducing the load on the HVAC system and its energy consumption consequently.

One interesting observation based on Figure 2(a) is that the dots form two distinct clusters. To better understand the cause of this phenomenon, we conducted an additional 200 experiments for each Zipf distribution parameter, this time without rejecting the space assignments that exceed zone capacities. We found that the gap between the two clusters disappears. Thus, we conclude that the gap in Figure 2(a) is a result of the reject-and-resample strategy that we employed to ensure the validity of the space assignment.

4.2 Comparision between the two buildings

Figure 2(c) shows the same trade-off in Building 2. In this case, the percentage change in the energy consumption is rather small (the x-axis range is four times smaller than the x-axis range in Figure 2(a)) regardless of how occupants are groups and space assignment is done. Moreover, in contrast to Building 1, a heavily imbalanced occupant distribution reduces energy consumption in most cases in Building 2. This is due to the fact that each zone in Building 2 has a separate air loop. Thus, an allocation strategy that puts most occupants in a few zones would lead to fewer occupied zones that must be conditioned, hence lower energy consumption.

Turning to thermal comfort, the results for the two buildings are different if Fanger's model is used to quantify occupant comfort (i.e., the plots in the first column). Specifically, in Building 1, a larger α value consistently leads to better thermal comfort than the uniform distribution. In contrast, it is challenging to surpass the baseline in Building 2 since all zones are adjacent to the outdoor environment (they are perimeter zones), which makes it difficult for the HVAC system to meet the comfort requirements at all times. Nevertheless, a clustered space allocation strategy can improve thermal comfort under Fanger's model in both buildings.

The dots in the lower left quadrant of each plot correspond to the experiments that result in lower energy consumption and better thermal comfort than the uniform occupant distribution (baseline). In Building 1, most results obtained using Fanger's model lie in the lower right quadrant, yet there are some dots in the lower left quadrant. This highlights the potential to enhance thermal comfort by changing the space assignment strategy while reducing energy consumption. On the other hand, most dots lie in the upper left and lower right quadrants in Building 2, with very few being in the lower left quadrant, suggesting that optimizing both objectives simultaneously is challenging in that building. Based on these observations, we can conclude that the impact of occupant grouping and space allocation strategy on the energy-comfort trade-off depends on certain building characteristics, such as its floor plan and the design of the HVAC system.

4.3 Importance of using personal comfort models

Figure 2(a) and (c) suggest that improving thermal comfort is possible when individual differences in thermal comfort and satisfaction are ignored, i.e., using the same comfort model for everyone. A higher value of α generally results in better thermal comfort, which can be attributed to the reduced number of zones that need conditioning. However, this does not hold true in real life because of the diversity in human thermal perception. Figure 2(b) and (d) illustrate the energy-comfort trade-off when using the personal comfort model to quantify thermal comfort. We get a completely different trade-off than the one obtained under Fanger's model. When thermal comfort is estimated using the personal comfort model, the dots are more spread out. Moreover, the distribution of results on the y-axis is not significantly different for different α values, indicating that occupant selection within each group is more critical than the group size. Figure 2(b) shows dots with positive y-values, while there is no dots in that area in Figure 2(a), suggesting that considering individual thermal comfort makes the HVAC optimization more challenging but there is greater potential for improving comfort. Turning to Building 2, there are more dots in the lower left quadrant in Figure 2(d) than Figure 2(c). Moreover, the lowest achievable discomfort ratio (the lowest y-value) is consistently lower when using the personal comfort model compared to using Fanger's model in both buildings. This suggests that considering individual thermal comfort can help achieve better energy efficiency and thermal comfort over the conventional Fanger's model.

Overall, the result of this experiment suggests that it is crucial to put occupants with similar thermal preferences in the same zone to improve thermal comfort; otherwise, changing just the group size and space allocation strategy does not necessarily result in better thermal comfort and satisfaction. When a zone contains people with dissimilar thermal preferences, it might be impossible to bring the average discomfort ratio below a threshold regardless of how the setpoints are adjusted by the controller.

5 DISCUSSION AND CONCLUSION

This paper explores two effective approaches for decarbonizing the building sector, namely optimizing space utilization and HVAC operation. Specifically, we characterized the energy-comfort trade-off in office buildings and elucidated the effect of occupant grouping and space allocation strategies on this trade-off. We established empirically that (a) better space planning practices make possible higher energy savings without sacrificing thermal comfort, (b) the effect of occupant grouping and space allocation on the whole-building energy use depends on building characteristics, and (c) using the conventional Fanger's model to identify the trade-off or quantify the energy-saving opportunity can be quite misleading.

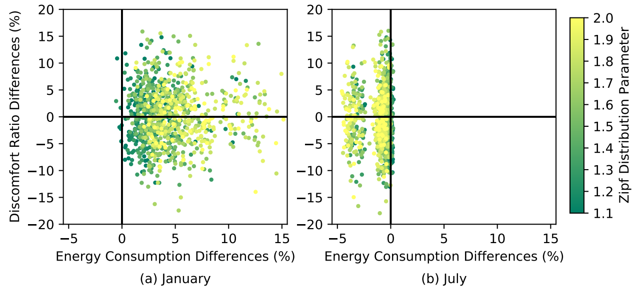


Figure 4: The energy-comfort trade-off obtained in January and July, using the personal comfort model in Building 1. The energy use and discomfort ratio are reported relative to the baseline in which the 100 occupants are uniformly distributed across the zones.

It is worth mentioning that the impact of the space allocation strategy on the energy-comfort trade-off varies across different months and seasons. Figure 4 shows the HVAC energy consumption and discomfort ratio of various occupant grouping and space allocation strategies in two months in Building 1, using the personal comfort model. For a fixed Zipf distribution parameter (α), the distributions are completely different in January and July. In January, larger α values generally result in higher energy consumption than the baseline, however they can lead to energy savings (and improved comfort) in July and over the one year period (as depicted in Figure 2(b)). This underscores the need for a seasonal redistribution of occupants, possibly using a different α value.

Our result suggests that it is possible to improve the energy performance of the building and occupant thermal comfort by jointly solving space planning and HVAC control problems. The joint optimization problem can be performed in simulation at two different timescales, which makes it possible to use reinforcement learning algorithms to find the best energy-comfort trade-off. This is an interesting research problem that we defer to future work. Additionally, we plan to model the discomfort caused as a result of changing the workspace of occupants, and investigate the ideal frequency for space reassignment in an office building.

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