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DATA-DRIVEN BUILDING LAYOUT OPTIMIZATION FOR ENERGY EFFICIENCY

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ABSTRACT

Optimization of building design has the promise to substantially reduce building energy consumption. Though typically considered in early design, we demonstrate in this paper that optimal re-design of building layouts has the potential to reduce energy use throughout the lifetime of a building and as occupant dynamics evolve over time. We introduce novel methods for (1) inferring occupant activities and schedules based on plug load sensor data, and (2) clustering occupants by activity patterns to create optimal layouts that take advantage of controllable HVAC and lighting systems. Combining data from a real small office building with the Department of Energy's small office reference building, we demonstrate that this near zero-cost occupant re-alignment strategy can save 3.3% in annual energy consumption.

Keywords: advanced energy technologies, energy conservation in buildings

1. INTRODUCTION

Building design decisions are the foundation for a building's energy performance. These choices are typically researched and made in the context of new construction. Research has shown that optimization algorithms can be used to aid building design by addressing physical parameters (e.g., materiality, building orientation, or window sizing) [1,2]. While these physical parameters can be crucial decision points for energy performance—especially when considered in early design stages [1]—recent work has shown that it is the building occupant that is the largest driver of building energy consumption [3]. Retrofitting and recommissioning existing buildings represents one of the largest pathways to decrease energy usage and associated environmental impacts [4]. Simultaneously, the explosion of real-time sensor data within buildings has created an opportunity to deepen our understanding of how occupants interact with their building and inform re-design interventions that can enhance a building's operation and energy performance.

Occupant behavior has been described broadly in recent work, ranging in detail from simple presence/absence data to occupant adaptive behaviors such as interaction with windows or thermostats [5]. One of the key aspects of occupant behavior when it comes to zone-level building control is *space utilization*—granular information about which spaces are being used at what time [6]. If we can more closely match the operation of zone-level building controls—heating, ventilation, and air conditioning (HVAC) and lighting—with occupants' utilization of space, we can reduce the amount of time spaces are conditioned or lighted unnecessarily. Modern HVAC and lighting systems are moving toward more real-time control, and new research is focusing on human-in-the-loop control of building systems [3]. However, two open questions remain: (1) How can we leverage new data-streams in buildings to infer true occupancy patterns?; (2) Can we recommend new layouts in those buildings that take advantage of such highly controllable building systems, thereby improving energy efficiency? Our hypothesis is that data-driven clustering of occupants with similar space-use patterns can reduce the operation time of HVAC and lighting systems and reduce energy usage.

In this paper, we introduce a novel method for creating new occupant layouts based on analysis of granular sensor data. We infer zone-level occupant schedules from plug-load energy data describing occupant activity patterns. We then use an unsupervised hierarchical clustering algorithm to spatially group occupants with similar patterns. By combining real data from a test-bed office building in Berkeley, CA with the Department of Energy (DOE) small office reference building, we simulate the energy impacts of our occupant re-alignment strategy.

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Our work introduces the opportunity to continually consider energy-related design decisions past initial occupancy and throughout the lifetime of the building.

2. METHODOLOGY

In this section, we outline our methodology for simulating building energy consumption with an occupant-driven approach and optimizing the layout of an office building using real data on occupant activities. We first map plug-load sensor data to occupant activities; we then develop zone-level schedules based on those activities. Finally, we use a hierarchical clustering algorithm to assign similar occupants to the same zones and simulate the change in energy consumption given the new layout.

2.1 Creating zone-level schedules

Energy consumption data at the individual desk level collected through plug-load sensors at 15-minute intervals form the basis for our method. Using the methodology introduced in [6], we map plug load energy consumption data ($\mathbf{X}_{i,d}$ indexed by occupant i and day d) to *activity states* of occupants: $\mathbf{X}_{i,d} \mapsto \mathbf{S}_{i,d}$. Through this process, we gain a highly-granular sense of space utilization across the floorplan and throughout the thermal zones of a building. Consistent with previous work, we define three possible states: low, medium, and high energy.

Given these *activity states* of occupants, we are able to define zone-level occupancy schedules on a percentage basis (i.e., full occupancy = 100%). In our previous work, we have shown that the low energy state can be associated with occupant absence from their desk with high confidence. When occupants are above the low state, we can take one of two perspectives: we can conservatively assume that all occupants in the medium or high states are present in the space, or we can optimistically assume that only occupants in the high state are present in the space. The reality is likely somewhere in the middle, so these perspectives represent virtual upper and lower bounds on the true occupancy profiles. Figure 1 shows a toy example illustrating these two perspectives, where 1 indicates the low energy state and 3 the high energy state.

	t=1	t=2	t=3	t=4
Occupant 1	1	3	2	1
Occupant 2	1	3	3	2
Occupant 3	1	3	3	3
Conservative	0.0	1.0	1.0	0.67
Optimistic	0.0	1.0	0.67	0.33

Figure 1: Demonstration of conservative and optimistic schedule creation based on activity. states.

It is important to note that our state classification algorithm was designed to more likely make false positive errors (type I error) (i.e., where the occupant is considered present when in reality they are not) compared with false negative errors (type II).

2.2 Optimizing layout by clustering occupants

Given activity data for all occupants across the floorplan, we cluster occupants who have similar patterns into the same zones. The number of clusters can be naturally defined as the number of available zones in the building. Assuming the building is fully occupied, the size of the clusters can also be defined as the number of occupants per zone. Traditional clustering techniques allow for the specification of the number of clusters, but specification of the cluster sizes is rare. We therefore take a hierarchical clustering approach that allows for user determination of the exact clusters based on a dendrogram. We employ an agglomerative approach, in which each occupant starts in their own cluster, and clusters are joined based on the distances between occupants' activity vectors. We define the distance between two activity vectors as the Euclidean distance, and we utilize the complete linkage criterion to agglomerate clusters. The complete linkage criterion minimizes the maximum distance between the clusters being merged. Yang et al. used a similar agglomerative approach to reduce occupant diversity in zones [7].

Using this agglomerative approach, occupants can be manually assigned into clusters based on the reading of a dendrogram (see section 3 for an illustrative example). Then, following the steps outlined in section 2.1, we create occupancy schedules for this new optimized layout.

2.3 Simulating building energy performance with an occupant-driven approach

Given the non-optimized and optimized layouts, we simulate the energy consumption of our commercial building using *EnergyPlus* [8] and *OpenStudio* [9]. The occupant-driven variables we consider in *EnergyPlus* are schedules associated with occupancy, lighting, equipment, and HVAC availability. We assume that real data on occupant activities—our conservative and optimistic schedules—can accurately serve as the occupant level schedule and the equipment schedules in *EnergyPlus*.

We consider a mixed-mode control schedule for HVAC and lighting, whereby a combination of automated controls and occupant behavior defines their operation. We assume that once occupants are present in the zone, HVAC and lighting are available and shared among all occupants. Once all occupants vacate the zone, HVAC and

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lighting are no longer available. While these are somewhat strong assumptions on HVAC and lighting performance, they are held consistent in both the non-optimized and optimized simulations, thus allowing for the comparison between scenarios. Because any inference from sensor data can be subject to the occasional false positive, we assume that any occupancy inferred at midnight in a commercial building is an error. Once occupancy increases from the midnight occupancy level—typically zero, but occasionally small—we make HVAC and lighting fully available. Once it decreases below the midnight level, we make HVAC and lighting unavailable.

Having calculated occupancy profiles for the two layouts and assigned them to the occupancy, equipment, lighting, and HVAC schedules, we run *EnergyPlus* through *OpenStudio*—holding all other variables constant.

3. CASE STUDY: SMALL OFFICE BUILDING

We demonstrate our methodology using the DOE's small commercial reference building geometry/systems combined with real sensor data from a small office building.

We deployed 18 Zooz Z-Wave [10] plug-load energy sensors at an office building in Berkeley, CA. The sensors recorded energy consumption values at 1-minute intervals, which we aggregated to 15 minutes (consistent with previous work [6]). We made no restriction on the types of equipment that could be connected to the sensors, making use of the deliberately adaptable methodology from our previous work. We collected data from August 9, 2018 to May 5, 2019 and developed schedules as described in section 2.1. To account for seasonal effects on behavior, we mapped these schedules to the default year in *OpenStudio*, where the data from January—though not collected first—was assigned to the first month of the year. We filled the gap in the data (May 5–August 9) with the default schedules from the reference building. We divided the building into four zones based on the building floorplan, with 8, 5, 5, and 0 occupants located in each zone (the last zone is a storage space). Figure 3 shows an example schedule from a single day using the conservative perspective after clustering).

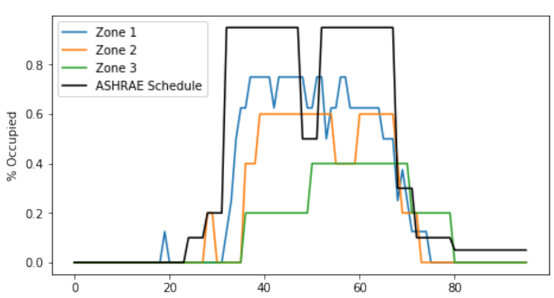

Figure 3: Sample generated schedule (after clustering).

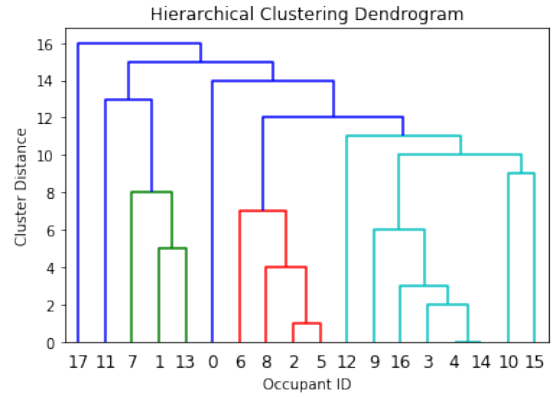

Figure 2: Agglomerative clustering dendrogram showing 3 relatively strong clusters and 3 outliers.

The DOE small commercial reference building is comprised of 5 zones, including 4 perimeter zones and 1 core zone. The reference building is designed for 28 occupants, with an even distribution across the building by floor area. We assign 8 occupants from the existing building zone of size 8 to the south-facing zone, and 5 each to the east and west zones based on the zones in the existing building. These values are held constant in both the non-optimized and optimized layouts, but the assignment of occupants to these zones changes after optimization. We assign 0 occupants to the north zone and the core zone in order to match the total occupancy of the Berkeley office building. We locate the reference building in the AHSRAE climate zone of 3C, which is based on data from San Francisco, CA and includes Berkeley, CA.

We cluster the occupants on their activity state data according to the process described in section 2.2. The dendrogram from the hierarchical clustering algorithm is shown in Figure 2, in which we see three relatively strong clusters of size 3, 4, and 8 as well as three relative outliers. We assign the group of 8 to the zone of size 8, and we assign the clusters of size 3 and 4 to the east and west zones of size 5. We assign occupants 17 and 11 to the cluster of size 3 and occupant 0 to the cluster of size 4.

Table 1 shows the total energy simulation results for the different scenarios considered, as well as the total amount of time throughout the year that HVAC and lighting systems are available (expressed as a percentage). As we can see, adapting the schedules to reflect the true states of occupancy in this building causes a dramatic reduction in total energy consumption. Moreover, optimizing the layout through occupant clustering results in a further reduction in energy consumption—both in the conservative and the optimistic cases. The reduction associated with the conservative schedules is significantly more than in the optimistic scenario (3.3% vs. 0.3%). In

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Table 1: Energy consumption and HVAC/lighting availability.

	Baseline	Non-optimized layout with adjusted schedules	Optimized layout with adjusted schedules
Energy			
Conservative	162.22 GJ	152.29 GJ	147.31 GJ
Optimistic		143.63 GJ	143.20 GJ
HVAC/lighting availability			
Conservative	54.76%*	37.46%	36.96%
Optimistic		35.99%	35.42%

* Only applies to HVAC in the baseline case

other words, the clustering is more effective in the conservative scenario. We interpret this to mean that our clustering method is better able to capture transitions between the low and medium energy states (as the conservative schedule only requires an occupant to be in a medium energy state to be considered present). This result demonstrates the opportunity to develop more advanced clustering methods that leverage the assumptions embedded in the meaning of the energy states as well as the conservative and optimistic viewpoints.

Figure 4 shows the comparison among the four simulations. It is clear from this figure that the largest change from optimization came in plug-load energy consumption in the conservative scenario. The clustering optimization reduced overall HVAC and lighting as well, but to a lesser extent.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we introduce a method for creating zone-level occupant schedules based on plug-load energy data collected at the desk level. We demonstrate that the temporal and spatial granularity in the data can create more realistic—while also conservative—schedules of occupancy that can be used to simulate the energy performance of occupant-adaptive building controls. We also introduce a method for clustering occupants based on similarity in activity patterns, and we find that doing so can save energy by leveraging localized control of building systems. We note that future work should consider developing clustering strategies that incorporate domain knowledge about the operation of HVAC and lighting systems (e.g., clustering occupants based on arrival time in the morning or departing time in the evening). In future work, we aim to combine energy-driven optimization of layouts with optimization of other occupant goals—such as collaboration and productivity in an organization. In the end, data-driven analysis and optimization of occupant-building dynamics will enable us to rethink how buildings and organizations can be co-optimally managed.

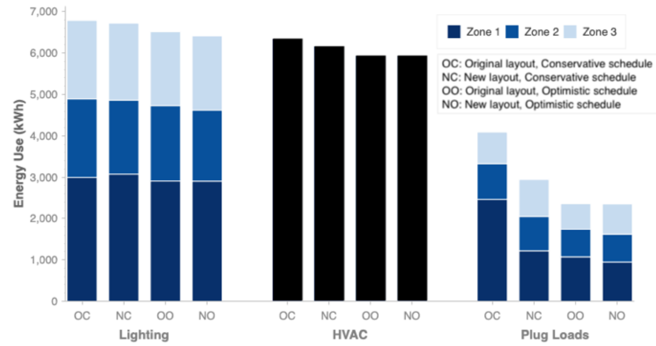

Figure 4: Comparison of energy consumption for each scenario by end use and zone (HVAC reported at building level).

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