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Energy Saving Recommendations and User Location Modeling in Commercial Buildings

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ABSTRACT

Commercial buildings consume a large portion of the total electricity in the United States. One method for energy saving in commercial buildings targets inefficiencies of unoccupied spaces by relaxing the setpoint temperature. However, energy savings are severely limited when occupants are assumed to be "immovable objects"; instead, by encouraging occupant participation in the optimization, a much greater amount of energy savings can be achieved. In this work, we build on this idea and introduce energy saving recommendations based on occupant location. We introduce two types of energy saving recommendations based on location: move recommendations, which recommends the occupant to move from one space to another, and shift schedule recommendations, which recommends the occupant to arrive or depart a set amount of time earlier or later. To investigate the effects of the energy saving recommendations, we introduced a tightly coupled system composing of a simulator and a recommender system. Simulations in our building testbed revealed that energy saving recommendations coupled with occupancy-based HVAC energy management saves 25% more energy than occupancy-based HVAC energy management alone.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; • **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computer systems organization** → *Real-time systems*; • **Spatial-temporal systems** → Location based services;

KEYWORDS

Recommender systems; building optimization; reinforcement learning; user modeling

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1 INTRODUCTION

Buildings consume a large portion of the total electricity in the United States. In residential homes, products such as Nest smart thermostats have emerged in recent years to help people reduce their daily energy consumption; however, people spend a significant portion of their active moments during the day inside commercial buildings such as office spaces. There exists a great opportunity for us to consciously modify our behaviors to reduce energy usage when at work and inside offices spaces.

While buildings are becoming smarter with increasing numbers of energy monitoring endpoints, the effect of an occupant's *personal actions* on the *overall energy consumption of the building* is still unknown. As a result, any energy inefficiencies in commercial buildings are often unnoticed since public resources and appliances are shared across multiple occupants. In comparison to homes where families pay their own energy bills, occupants in offices are not liable for energy usage on their behalf, and therefore have little incentive to save energy.

One popular research topic towards energy savings in commercial buildings is occupancy-based heating and air conditioning energy management [1, 3, 6–8, 10]. These works take advantage of unoccupied spaces by reducing the service requirements; for example, lowering the setpoint temperature of a room by 1.5 degrees can reduce the energy consumption of the space significantly. The percentage of energy saved ranges between 10 − 40% of the total energy, according to these studies.

However, there are substantial limitations to the occupancy-based HVAC management methods. By assuming that occupants are immovable, occupancy-based HVAC management is only able to optimize energy **given human occupancy constraints**. Spaces with high potential energy savings cannot be optimized if the space is occupied, even if only by one person. By encouraging occupant participation through recommendations, the potential energy savings of these spaces can be realized.

In this work, we introduce human concepts such as user models and recommender systems to the traditionally non-human field of building energy optimization. Building on the ideas of occupancy-based energy management and recommender systems, we propose a system for generating *personalized energy saving recommendations* for encouraging occupants to reduce energy consumption. Our system is composed of two integrated subsystems: an energy consumption simulator and a recommender system. The simulator incorporates models of the building based on EnergyPlus simulations, as well as user models based on collected historical location data over a four month period, to simulate energy consumption. The recommender system utilizes the simulated energy consumption to learn personalized recommendations.

We present the following contributions:

- We extend traditional space-level energy models to incorporate effects of varying levels of occupancy to improve building level energy simulations.
- We generate novel, personalized, energy saving recommendations through building simulation, reinforcement learning, and occupant location models.
- We demonstrate a 25% improvement in energy savings using energy saving recommendations over traditional occupancy-based energy management.

2 BACKGROUND

This work draws primarily from two drastically different sets of research areas: building energy optimization and location-based recommender systems. We focus on the intersection of these research areas towards a recommender system capable of significantly reducing a **building's energy consumption** with the aid of **user location models**.

2.1 Building Energy Optimization

Recently, building energy optimization has become a popular topic in commercial buildings. Energy monitoring is a critical research topic towards optimization, allowing building managers to identify inefficient energy consuming resources. Occupancy-based energy optimization utilizes energy monitoring, as well as occupancy sensing, to optimize inefficient energy consuming resources.

Energy monitoring in commercial buildings often includes monitoring of miscellaneous electric loads (MELs), lighting, and HVAC (heating, ventilation and air conditioning). In MELs monitoring, plug-load meters, both wired [11] and wireless [12, 14], have been used to monitor plug-loads directly. Lighting and HVAC in commercial buildings can be monitored directly by connecting to the building management system (BMS) through protocols such as BACNet, LonTalk, and Modbus [2].

Occupancy-based energy management largely focuses on optimizing HVAC systems in empty spaces. Different research studies [1, 3, 6–8, 10] have found potential energy savings between 10 – 40% by relaxing the setpoint temperatures of the HVAC systems by 1.5 degrees. These studies optimize HVAC usage based on the schedules of the people within the building. The general idea behind these approaches is that we can relax setpoint temperatures of the HVAC systems when periods of vacancies are detected. This approach has limitations, however. In many situations, a large space is occupied by a single occupant; even though a significant amount of energy is used to service the space, no optimization is possible with this method due to the constraint of occupancy. By encouraging mobility of these occupants through recommendations, occupancy-based energy management of these spaces becomes possible.

In this work, we use the building energy monitoring and occupancy sensing subsystems developed in [22] to collect occupant location data. This data is used to explore how providing the **right type** of recommendation to the **right occupant** at the **right time** can substantially reduce the overall energy consumption, while having minimal impact on the occupant's comfort. The building energy monitoring subsystem consists of a software interface through BACNet to monitor HVAC and wind sensing nodes for HVAC resources not connected to BACNet, light sensing nodes to sense lighting, and electric plugmeters to sense electrical consumption. For occupancy sensing, we deployed 41 Bluetooth beacons throughout the deployment testbed, and implemented Bluetooth localization on Android and iOS mobile applications.

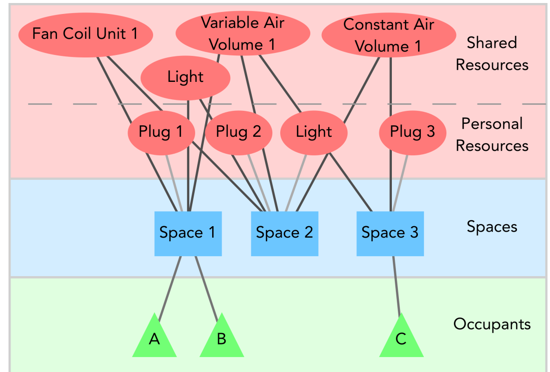


Figure 1: Tripartite graph representation of the building-occupant model, taken from [22].

2.2 Location-Based Recommender Systems

Recommender systems have become an important part of daily life, with companies such as Netflix and Amazon learning about user preferences and recommending items that are relevant to the user. Recently, a variant of recommender systems has emerged, called **location-based recommender systems**. Location-based recommender systems recommend suggestions (e.g. places to eat and visit) based on the current and past locations as well as the personal preferences of the user [4]. Generally, these methods match user preferences with features that characterize a location [17], or analyze the similarity between multiple locations to recommend suggestions [23] [16]. Additionally, location-based recommender systems often make use of collaborative filtering, using the data collected from existing users to recommend suggestions to similar or new users [24] [18].

In context of building energy optimization, this work aims to model how suggesting changes in human behavior through recommendations (e.g. move from one room to another, or come in 15 minutes earlier) can be used to achieve a reduction of total energy consumption in commercial buildings.

3 CHALLENGES

To create a recommender system that generates **personalized**, **actionable**, and **energy saving** recommendations, three challenges must be addressed: what types of recommendations are effective in saving energy, how much energy can a recommendation save, and how to personalize these recommendations.

3.1 Recommendations

The ultimate goal of the recommender system is to influence user behavior to reduce energy consumption within the building. To determine potential recommendations, we borrow the building-occupant representation developed in a previous work [22] which utilizes a tripartite graph data structure as shown in Figure 1. The graph is separated into three partitioned layers consisting of the energy consuming resources (HVAC, lighting, electric loads), spaces, and occupants. This representation emphasizes the relationship between spaces and occupants, which is critical in our recommendation definitions.

In this representation, there are two events that cause changes in the total energy consumption: energy resource consumption changes and occupant location changes. This work focuses on the latter; occupant location changes are common in commercial buildings. Occupant location changes have two characteristics that affect energy consumption: spatial and temporal. Spatially, a location change can occur between any two spaces, including outside of the commercial building. Temporally, a location change can occur at any time during the day. We leverage these characteristics in our recommendation definitions.

We define two types of energy saving recommendations:

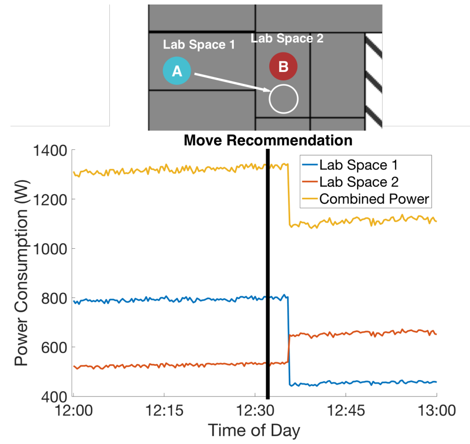
- Recommend an occupant to **move** to a different space.
- Recommend an occupant to **change schedule** for entering and exiting the commercial building.

Illustrations of example scenarios when each recommendation saves energy are shown in Figures 2a and 2b. In Figure 2a, occupant A is given a recommendation to move from Lab Space 1 to Lab Space 2. The energy service decreases significantly in Lab Space 1 and increases in Lab Space 2; however, there is an overall reduction in energy consumption. In Figure 2b, occupant A arrives in Lab Space 1 at 8:15, thus increasing the energy consumption of Lab 1 at 8:15. The next week, occupant A receives a recommendation to arrive **30 minutes later**, when occupant B arrives in Lab Space 1. The increase in energy requirement of Lab A occurs 30 minutes later, thus saving energy. There may be other types of recommendations that can help reduce energy consumption, but we defer those recommendations to future work.

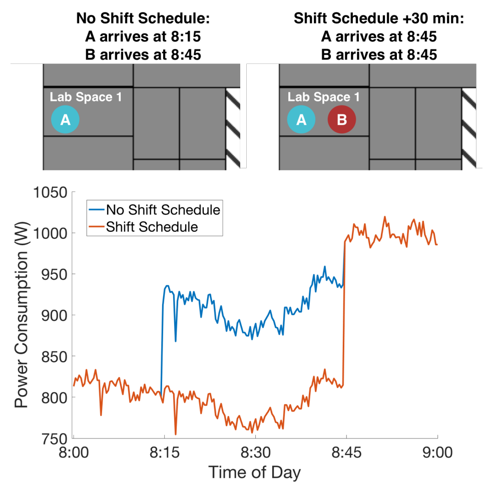
3.2 Building Response

The second challenge is to determine how much energy a recommendation saves. There are many factors that influence the energy consumption of a space, including: outside temperature, internal thermal load (such as appliances, or people), adjacent room air temperature, and the thermal setpoint. To model all of these factors requires complex models and computational resources. In this work, we focus on two important factors: outside temperature and occupancy. We run simulations using a standard building simulation program to generate approximate models for each space; these simulations are discussed in Section 4.1.

The Northwest Corner Building at Columbia University does not provide an interface for programmatically changing the setpoint of a room as in [1]; this prevents us from directly studying the effects of the recommendations on the building energy consumption. However, we are able to monitor the energy consuming resources through BACNet. We utilize the monitored energy data, along with the building models developed in Section 4.1 to produce more accurate simulations.



(a) Example of energy consumption savings from a move recommendation. Occupant A receives and accepts a move recommendation at 12:30.



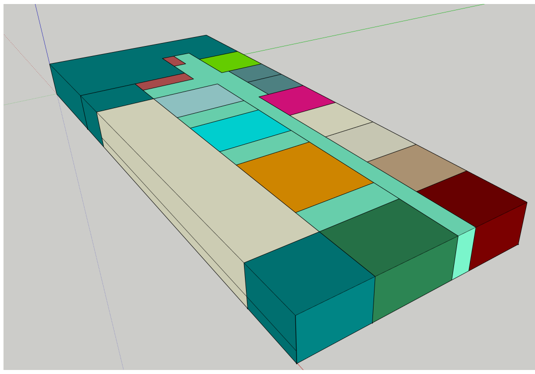
(b) Example of energy consumption savings from a shift schedule recommendation.

Figure 2: Example scenarios of energy savings for a move recommendation and a shift schedule recommendation.

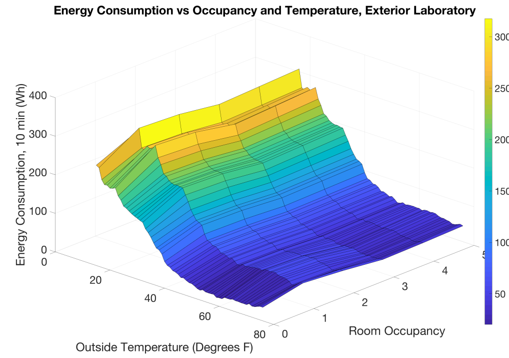
3.3 Personalization

The final challenge that arises is the personalization of the recommendations. A recommender system that gives recommendations unlikely to be accepted by a certain occupant may quickly lose the attention of the occupant. To illustrate the challenge in personalizing recommendations, we present two realistic scenarios.

In our first example, occupant A spends the majority of time alone in Laboratory A. Office Space B consumes less energy than Laboratory A; thus, if occupant A moves to Office Space B, energy service can be reduced in Laboratory A. However, occupant A does not spend time in Office Space B, and would not accept a recommendation to move. A recommender system without knowledge of **occupant behavior** may require a significant amount of feedback



(a) Model of the 10th floor laboratories in the Northwest Corner Building at Columbia University. Different colors indicate different thermal zones.



(b) Energy Consumption vs Occupancy and Temperature of an exterior laboratory.

Figure 3: Space level modeling using EnergyPlus.

Occupant	Office 1	Laboratory 1	Laboratory 2	Work Space 1	Public Space 1	Avg Change Location Time
Professor 1	87%	5%	0%	0%	5%	1.5 hr
Student 1	2%	25%	12%	51%	6%	1.0 hr
Student 2	1%	74%	6%	8%	6%	1.25 hr
Student 3	1%	3%	21%	70%	5%	1.0 hr

Table 1: Occupant location preferences and average location change times extracted from historical location data.

to learn these behaviors, which is an undesirable characteristic in a real deployment.

The second example concerns occupant A who is the first to arrive at work at 8 am on Monday. After 30 minutes, other occupants arrive and join occupant A. A naive recommender system may recommend occupant A to shift schedule 30 minutes later on Tuesday; however, occupant A may have a meeting every Tuesday at 7:30 am that cannot be skipped. Again, without knowledge of occupant behavior, the recommender system will require significant amounts of feedback from the occupants.

These examples demonstrate the importance of a user model. In both examples, the recommendations can be altered based on past location behavior to be more relevant to the occupant. Human behavior is incredibly complex, but certain features can be extracted from historical location data to better inform recommendations.

4 SYSTEM DESIGN

4.1 EnergyPlus

Although we do not have access to HVAC or lighting actuation in the Northwest Corner Building (NWC), modeling the behavior of NWC as if it were a smart building through simulation is possible. For simulating HVAC, we use EnergyPlus [5], an open source software program for simulating energy consumption of user defined space models. A model of the testbed was constructed in SketchUp as shown in Figure 3a, and EnergyPlus was used to simulate HVAC requirements in each room.

In order to account for different types of weather conditions, we simulated the service requirements of each space over a year of weather data in New York City. Further, we simulated the effects of occupancy in each space for the various weather conditions. Similar to [1], we relax the setpoint requirement by 1.5 degrees when the space is unoccupied. A multivariate energy curve was generated for each space. An example for an exterior space is shown in Figure 3b.

In Figure 3b, there is a noticeable change in energy consumption between an unoccupied space and an occupied space over the entire range of outdoor temperatures. This is due to the relaxation of the setpoint by 1.5 degrees. Note that the thermal load from the occupants contributes to the heating requirements of the space, which accounts for the decrease in HVAC energy consumption for higher occupancies.

4.2 User Location Model

Both types of recommendation relate to different features of an occupant's historical location history. The move recommendation is closely tied to the location preferences of an occupant, and the shift schedule recommendation is closely tied to the arrival and departure times of an occupant. These features are extracted from collected historical location data, and used to construct the user's location model.

4.2.1 Data Collection. To construct the user model for each occupant, we sought to discover patterns through historical location data. As both types of recommendation rely on the occupancy of each space, location data of each occupant reveals information about the recommendations an occupant is more likely to accept. Four months of location data were collected from 20 occupants using the ePrints system [22]. Location data was collected every

Occupant	Day of Week	Arrival Time μ	Arrival Time σ	Departure Time μ	Departure Time σ
Professor 1	Monday	12:00	15 m	17:00	15 m
	Tuesday	13:45	15 m	17:30	15 m
	Wednesday	12:45	15 m	20:00	60 m
	Thursday	14:00	30 m	16:15	60 m
	Friday	8:30	15 m	17:00	15 m
Student 1	Monday	10:30	45 m	21:15	30 m
	Tuesday	11:45	30 m	21:00	90 m
	Wednesday	11:30	60 m	20:30	90 m
	Thursday	11:30	90 m	21:00	90 m
	Friday	11:30	90 m	20:15	60 m
Student 2	Monday	11:45	30 m	21:30	90 m
	Tuesday	11:30	60 m	20:30	30 m
	Wednesday	11:45	90 m	21:30	90 m
	Thursday	12:15	90 m	20:00	60 m
	Friday	11:45	60 m	19:30	90 m

Table 2: Arrival Time and Departure Time Gaussian model parameters for three example occupants.

minute, and includes arrival and departure times to the testbed building. This location data is used to build the user model as well as inform the occupant survey discussed in the next section.

4.2.2 Location Preferences. The likelihood for an occupant to accept a move recommendation depends highly on the source and destination spaces. A commercial building is divided into many different spaces; if an occupant historically does not spend any time in a certain space, a move recommendation to that space is unlikely to be accepted.

Using the historical data, occupant "location preferences" were extracted. The location preferences consist of the distribution of time over the spaces for an occupants. A few examples are shown in Table 1. From the data, we observed that occupants tend to spend a constant proportionate amount of time in certain spaces, even across different days and different times of day. For the few occupants whose time spent in certain spaces varies throughout the day, a separate model of location preferences is generated for each part of the day (morning, early afternoon, late afternoon).

Another important feature is the average time an occupant spends in a certain location. After a move recommendation is given and completed, the occupant can change location at any time, thus ending the energy savings of the recommendation. This feature gives an estimate for how long the benefit of a recommendation persists. In simulation, this feature aids in the estimation of the recommendation's energy savings.

4.2.3 Arrival and Departure Time. The arrival and departure time of an occupant varies depending on multiple factors. In order to create an approximate model, we utilized the historical location data collected in Section 4.2.1 and extracted the arrival and departure times of each occupant over the four month study.

Though different occupants have differing arrival and departure patterns, there exist underlying similarities. Firstly, arrival and departure times vary depending on the day of the week; this observation was sensible, as people often had different schedules for each day of the week. Secondly, arrival and departure times for a specific day of the week (e.g. Monday) can often be approximated by a Gaussian distribution, as shown in Figure 4.

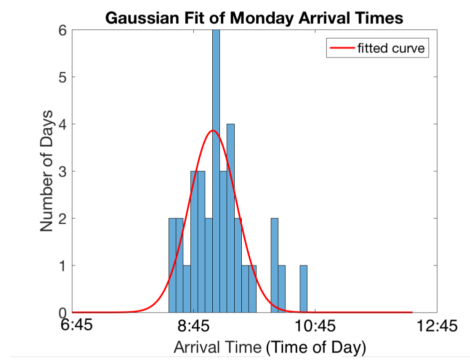


Figure 4: Gaussian fit of the arrival times of one occupant on Mondays.

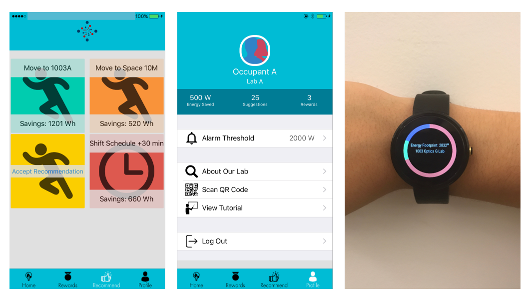


Figure 5: From left to right: iOS recommendations tab, iOS settings tab, Android Wear application.

With these observations, we modeled each occupant's arrival times and departure times separately for each day of the week according to a Gaussian distribution. In the simulations discussed in Section 5.1, these Gaussian distributions are sampled to simulate the arrival and departure times of an occupant. The Gaussian model parameters of three example occupants are shown in Table 2.

4.2.4 Occupant Survey. Using the occupant location preferences and arrival and departure times, move recommendations and shift schedule recommendations can be formulated. However, a difficult question arises: how likely is an occupant to accept one of these recommendations? Many factors influence an occupant's decision, such as: time of day, how "busy" the occupant is, the recommendation's destination space, or the recommended shift in schedule. Empirically deriving this data by sending recommendations to the occupants would require a long deployment, as well as significant investment from the occupants. Thus, to obtain an informed estimate, we directly ask the occupants about the likelihood of accepting certain move recommendations between these spaces.

We conducted a focus group survey to gauge how likely an occupant is to accept different recommendations. Six occupants participated in the survey. In the survey, we present recommendations as we would in a real deployment, and asked the occupants how likely they are to accept different types of recommendations. We present the recommendations through an iOS mobile application, built off of the ePrints application [22]. A screenshot of the recommendations tab is shown in the left screenshot of Figure 5.

As the number of possible move recommendations can be large, we reduced the number of questions by considering occupant location preference. Using occupant location preferences such as in Table 1, we can partition spaces into spaces frequently visited and infrequently visited. We use these categories in forming the recommendation survey questions. A summary of the questions and the recommendations they pertain to are shown in Table 3.

The reason for collecting this data via survey is to overcome the "cold start" problem of many recommender systems. While sending these recommendations in a real deployment may eventually converge to a better estimate of the true acceptance likelihood, this method would require a **significant** amount of time and occupant effort. A survey, on the other hand, provides an informed estimate that can be gathered with little effort from the occupant.

5 IMPLEMENTATION AND EVALUATION

Based on the building simulator described in Section 4.1, recommendation types described in Section 3.1, and user model described in Section 4.2, we implemented a tightly coupled system as shown in Figure 6. The system has two subsystems: the energy simulator, and the recommender system. Monitored energy data is discretized into 15 minute time steps, and each phase of the system runs at each time step.

5.1 Energy Simulation

The energy simulation uses the space energy models, occupant locations, and the energy monitoring inputs to determine the current energy consumption of the building testbed. The simulator also takes as input the occupant location models, and the space level energy models. The simulator can change the location of occupants in the building and observe the change in energy consumption, which enables testing of the effects of different recommendations. A diagram of the simulator is shown in Figure 7.

At each timestep, the simulator sends to the recommender system a reward, and the current power state of the building. For a set of spaces, S, the HVAC energy consumption of a single space, $s_i \in S$ with occupancy p_i, is defined as:

$$H(s_i, p_i, t, T) = H(s_i, t)\beta(s_i, p_i, T)$$

where $H(s_i, t)$ is the monitored energy consumption of a room at time t. $\beta(s_i, p_i, T)$ is the HVAC discount factor of a space s_i with occupancy p_i and outside temperature T, derived from the model generated in Section 4.1. The lighting energy consumption of space s_i is defined as a function

$$L(s_i, p_i) = \begin{cases} 0 & \text{if } p_i == 0 \\ L(s_i) & \text{if } p_i > 0 \end{cases}$$

The algorithm for computing the total power of all spaces is shown in Algorithm 1.

Algorithm 1: Testbed Power Computation

procedure TESTBEDPOWER(S, P, β, H, L, T)
  $testbedPower \leftarrow 0$
  for $s_i \in S$ **do**
    $H(s_i, p_i, t, T) \leftarrow H(s_i, t)\beta(s_i, p_i, T)$
    $L(s_i, p_i) \leftarrow L(s_i)\mathbb{1}_{(p_i==0)}$
    $testbedPower \leftarrow testbedPower + H(s_i, p_i, t, T) + L(s_i, p_i)$
  end for
end procedure

5.2 Learning Energy Saving Recommendations

The output of the energy simulator is fed into the recommender system as a reward and a building state, as shown in Figure 6. In order to learn the potential energy savings of the recommendations, the recommender system utilizes Q-learning. A Q-Table is maintained for each move and shift schedule recommendation, as these recommendations are independent (they are not given at the same time). The value iteration update for learning the Q-Table is shown in Equation 1. This update is used for learning both move recommendations, and shift schedule recommendations.

5.2.1 Move Recommendation Learning. There are two parts to learning the move recommendations: contextual prefiltering and the value iteration update. During the training phase, a random occupant is selected. Initially, all recommendations **except** the move recommendations related to the occupant and the occupant's current space are prefiltered. Based on the occupant's location preferences, a different space is selected, using an ϵ-greedy method. With an occupant, source and destination spaces selected, the recommendation is fully defined.

Once the recommendation has been given and either completed or not, the energy simulator provides the recommender system with a reward, r. This reward represents the power reduction due to the move recommendation. As the benefit of the recommendation is not limited strictly to the current power reduction, the discount factor γ is set to a low, but non-zero, value in order to reward high energy saving future states.

$$Q(s_t, a_t) \leftarrow (1 - \alpha_t)Q(s_t, a_t) + \alpha_t(r_t + \gamma \max_a Q(s_{t+1}, a)) \quad (1)$$

5.2.2 Shift Schedule Learning. The value iteration update is also implemented for shift schedule learning. To learn the shift schedule

Recommendation Type	Recommendation	Accept %
Move Recommendation	Move from Frequent to Frequent	62%
Move Recommendation	Move from Frequent to Infrequent	3%
Move Recommendation	Move from Infrequent to Frequent	83%
Shift Schedule	Shift Schedule Later	15%
Shift Schedule	Shift Schedule Earlier	75%

Table 3: Example survey questions and responses for each type of recommendation.

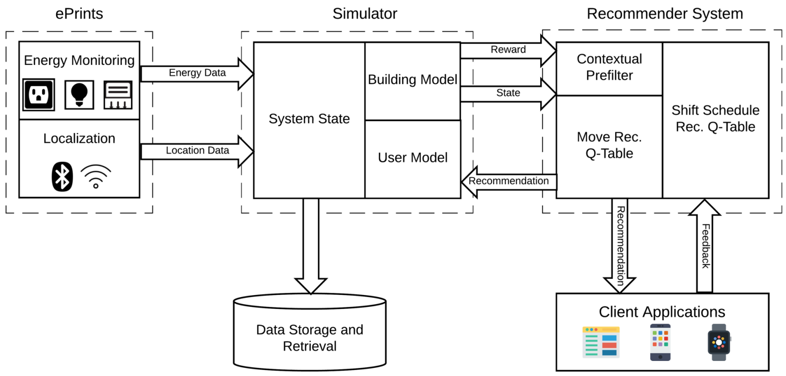


Figure 6: Architecture diagram of the complete system.

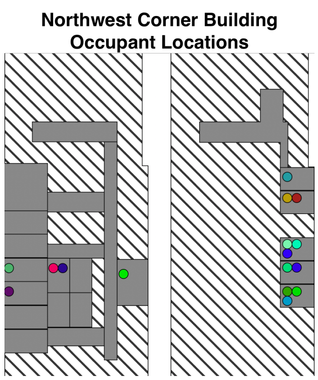


Figure 7: Screenshot of the simulator. Colored dots indicate simulated locations of the occupants.

recommendations, a random occupant is selected each day to shift their schedule. The schedule can be shifted 15, 30, or 60 minutes either earlier or later. The longer the shift in schedule, the larger the effect on energy saving; for example, a shift of 60 minutes later potentially postpones the normal HVAC operation of a space more than a shift of 30 minutes can.

Thus, the reward for the shift schedule is generated by the energy simulator at the end of the day. Two simulations are generated: one that assumes a shift in schedule, and the other which does not. The simulations are run in parallel, and the difference in energy consumption throughout the day is passed to the recommender system as a reward. The future states $Q(s_{t+1}, a)$ are not required for learning the potential energy savings of shift schedule recommendations, so γ is set to 0.

5.3 Energy Savings

In this section, we evaluate the energy saving potential of the learned recommendations. In the following studies, the evaluation was performed using four weeks of monitored energy data and location data from two floors in the Northwest Corner Building. Move recommendations were given every 15 minutes to an occupant, and shift schedule recommendations were given to occupants before the beginning of the day.

5.3.1 Move Recommendation. To evaluate the learning of the move recommendations, we simulated giving move recommendations, and measured the energy saved. The move recommendations are sorted by energy saved and shown in Figure 8. A small percentage of the move recommendations lead to increases in building energy consumption; this is due to variations in the energy and location data in the test days. However, most of the recommendations lead to a reduction in the total energy consumption.

5.3.2 Shift Schedule. To evaluate the shift schedule recommendations, we simulated shift schedule recommendations for −15, −30, −60, +15, +30, and +60 minutes. The simulated recommendations were compared to the ground truth monitored data. Because occupants' schedules often change between days of the week, each day of the week was simulated individually and averaged. Figure 9 shows the average simulated energy consumption savings of an occupant. This example occupant often arrives earlier than other occupants; thus, the higher energy savings for shifting schedule later is reasonable. Additionally, the energy savings for each shift schedule recommendation change depending on the day of the week. The variations in energy savings throughout the week demonstrate the importance of generating different arrival/departure models for each day for an occupant.

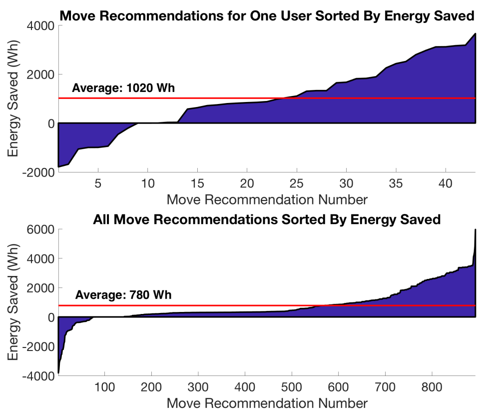


Figure 8: Sorted move recommendations by saved energy consumption for one occupant and all occupants.

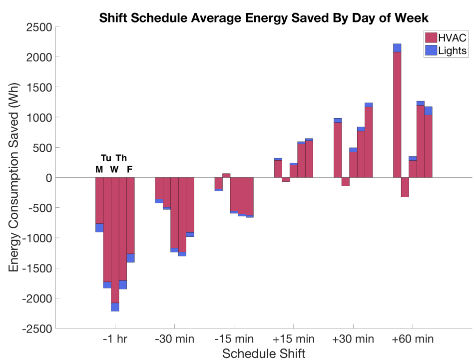


Figure 9: Simulated energy savings for different shift schedule recommendations for an occupant. Each group consists of the five days of the week, with Monday as the leftmost bar, and Friday as the rightmost bar.

5.3.3 *Total Energy Saved.* Figure 10 shows the simulated energy savings for five days and the average over the four weeks of test data. The "no recommendations" bars show the simulated energy savings by only relaxing the setpoint temperature, with no recommendations given. The "realistic recommendations" bars utilize the responses from the occupant survey in Section 4.2.4 to determine how often recommendations are accepted. The "all recommendations" curve demonstrates the maximum energy savings if all occupants took every energy saving recommendation.

Using the occupant responses, the recommendations led to 25% more energy saved than relaxing setpoint temperature alone **in commonly occupied spaces**. Though the optimal energy savings (shown by the "all recommendations" bars) can save up to 50% more energy than without recommendations, only a fraction of the recommendations need to be accepted in order to see substantial energy savings.

6 FUTURE WORK

The largest point of uncertainty in this recommender system is: how likely is an occupant to accept a recommendation? In this

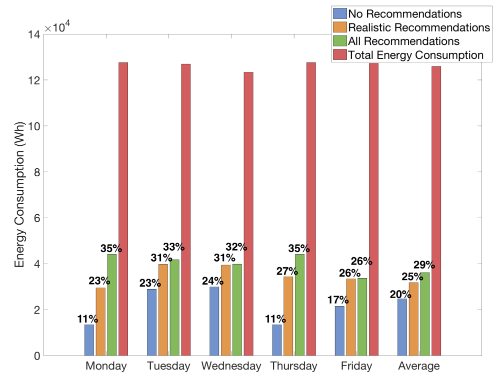


Figure 10: Move recommendation energy savings for five test days and average over two weeks.

work, a survey was used to gauge an occupant's *attitude* towards a type of recommendation. However, a variety of literature exists showing the "intention gap" between attitudes and intention; works such as [9, 13, 15], cover various models and case studies used to demonstrate the gap between environmental awareness and behavior. The "intention gap" also appears in recommender systems of other applications such as sustainable food consumption and physical exercise [20, 21]. In recommender systems for energy saving, this intention gap can be seen between an occupant's attitude towards a recommendation and an occupant's intention (likelihood) to accept a recommendation. Towards this end, a study on a physical deployment with real occupants, along with considerations of existing literature on the intention gap, is a crucial next step.

Further, we sought to personalize recommendations by tailoring to each individual occupant. In [19], the authors show that tailoring recommendations by reducing perceived and actual effort led to positive user experiences. Additional parameters can be included to increase personalization of location recommendations, such as available work facilities, whether the occupant can be productive in the new work space, and convenience.

7 CONCLUSION

In this work, we introduce a novel idea: applying human modeling and recommendations to the traditionally non-human building energy consumption optimization problem. We introduced two new energy saving recommendations based on location: move recommendations, which recommends the occupant to move from one space to another, and shift schedule recommendations, which recommends the occupant to arrive or depart a set amount of time earlier or later. To investigate the effects of the energy saving recommendations, we introduced a tightly coupled system composing of a simulator and a recommender system. The simulator utilized building models, based on simulations from EnergyPlus, and user location models, extracted from collected historical location data, to generate simulations of the building energy consumption. The simulations were given to the recommender system to learn recommendations. The simulations revealed that in our testbed, energy saving recommendations along with occupancy-based HVAC energy management saves 25% more energy consumption than occupancy-based HVAC energy management alone.

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