Modeling and Analyzing Occupant Behaviors in Building Energy Analysis Using an Information Space Approach

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Abstract— **Buildings account for a majority of energy consumption in the United States. One of the major factors affecting the energy performance of buildings is occupant behaviors. Decoding occupant behaviors is a key to identifying energy waste and to discovering strategies to curtail energy consumption in buildings. We propose an information space approach for automated detection and proactive monitoring of energy waste due to occupant behaviors. In this paper we present a set of filtering algorithms to capture the minimum amount of information necessary to detect wasteful states and trajectories that occupants may have, in order to pro-actively modify occupant behaviors. We also describe and implement a sensor network consisting of inexpensive distance, light, temperature sensors and electricity consumption monitors utilized in order capture data related to occupancy behaviors. By keeping count of the number occupants and energy expenditures in different regions of a building, we accurately estimate how occupancy behavior is affecting energy use, in a non-invasive way. Furthermore, we present a methodology to pro-actively eliminate energy expenditure by calculating a score associated with occupants in different regions. This score will be used to suggest policies to users or facility managers to help reduce energy costs related to occupancy behaviors.**

I. INTRODUCTION

Buildings consume 73% of electricity load in the United States [23]. In addition to the climate factors and building design parameters (e.g., orientation, envelope, materials, and HVAC system), a main factor affecting the energy performance of buildings is occupant behaviors. In fact, the energy performance of a building is an emergent property arising due the interaction of occupants with the building units and appliances. Hence, a better understanding of emergent occupant behaviors is critical in discovering opportunities for energy saving in buildings [24], [11]. However, decoding emergent occupant behaviors at the interface of human-building-appliance interactions is a challenging task. Data related to occupancy behaviors could be captured indirectly or directly. The indirect measurement of occupants behavior is done using occupant surveys. Such self-report surveys are susceptible to different errors such as the social desirability bias. Direct measurements of occupant behaviors could be problematic as well due to privacy issues. Various studies (e.g., [6] and [5]) have utilized sensors for detecting occupants behaviors and building energy parameters (such as lighting and temperature). Despite the growing literature in this area, a formalized methodology for understanding emergent behaviors affecting the energy performance and pro-actively detecting energy waste in the building is still missing.

Our study contributes to two major streams of research related to the analysis of occupant behaviors in building energy assessment: (1) automated detection of energy waste due to occupant behaviors, and (2) monitoring and tracking occupancy movements for smart building systems.

Our ideas are complementary to the areas of heating, ventilation, and air conditioning (HVAC) control [22] building automation systems (BAS) [13], and Smart Buildings [20]. We also aim at developing the formalized approach for automated detection of energy waste at the interface of human-building-appliance interactions. Our ideas differ from the existing approaches in several important aspects: 1) We are concerned about the general problem of modeling emergent energy performance at the interface of human-building-appliance interactions; these emergent behaviors could be captured by *state spaces* and *information spaces* in buildings. 2) We would like to obtain simple minimalist solutions that are inexpensive, easy to deploy, and avoid state estimation for automated detection of energy waste in buildings. 3) We include in our formulation and in our experimental setup smaller residential units that are usually out of the scope of HVAC, BAS, and Smart Building analysis.

Another stream of research related to our efforts are approaches that attempt to count and track occupants in buildings through occupancy sensors such as [1], [25], [19], [14], [18], [2] and [3]. Tracking and counting occupants in different regions of buildings is a key for development of smart building solutions. Our work borrows from ideas that try to monitor in a non-invasive manner the behavior of one [21] or multiple agents [4] using detection beams.

The contributions of the paper are the following: 1) We formalized the physical state space of buildings and concretely formulated three problems of energy waste in buildings that include occupant behavior, temperature, lighting, and plug load consumption. 2) We presented easy to implement filtering algorithms in the information space that can detect states, trajectories, and attempt to positively modify occupant behaviors in buildings. 3) We proposed an inexpensive, non invasive, hardware architecture to implement our ideas. 4) We tested the system in a residential setting.

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The rest of the paper is organized as follows. Section II presents the preliminaries and formulates three problems related to energy waste. Section III presents the mathematical methodology and hardware used to solve the problems proposed in section II. Section IV presents a complete case study in a household residence to illustrate the practical use of our methodology. Finally, section V presents conclusions and directions for future work.

II. Problem Formulation

A. Physical State Space

In this section, we will formalize the problems of detecting wasteful energy states, analyzing energy trajectories, and proposing policies to save energy. Our notation is heavily influenced by Motion Planning [15], physical state spaces and information space approaches [16], [17].

A buildings indoor environment (or *work space*) is modeled as a collection of floors in a building, each of them in 2-dimensions such that $\mathcal{W} = \mathbb{R}^2$, since we are only concerned with the location of people in a building, and not their exact orientations and positions. We will do a complete analysis and formulation of energy problems concerning a single floor which can be extended without loss of generality to a building with multiple floors. Each of the floors will have a set of obstacles, $\mathcal{O}$, that represent areas that are not accessible.

A set of n *occupants* will move in the *free space* of a floor defined as $E = \mathcal{W} \setminus \mathcal{O}$. Let C^i represent the configuration space or set of all possible positions and orientations of the i^{th} occupant in an environment. More precisely, $C^i = E \times [0, 2\pi)$, where E is the position of an occupant in the free space and $[0, 2\pi)$ is the set of all possible orientations of an occupant. Then, the configuration space for all n occupants is defined as $C = C^1 \times C^2 \times \ldots \times C^n$.

Another interesting physical variable is lighting. A particular lighting configuration is modeled as the function, $l : E \rightarrow \mathbb{R}^{\geq 0}$, which assigns any given point in the environment a positive light intensity. Then, $\mathcal{L}$ is the set of all the possible energy assignments such that $l \in \mathcal{L}$.

Temperature is another variable of interest in building energy performance. Like the lighting definition, temperature can be modeled as a mapping, $k : E \rightarrow \mathbb{R}^{\geq 0}$, which assigns a positive temperature to every point in the environment. Then, $\mathcal{K}$ can be defined as the set of all possible temperatures such that $k \in \mathcal{K}$.

Lastly, we will consider the *plug load* of the physical state space of a building. We will denote the configuration of each power socket of a building as $P^j = \mathbb{R}^{\geq 0} \times E$ where the value $\mathbb{R}^{\geq 0}$ represents the power sockets (or *plug loads*) energy consumption (as a positive, increasing value) and E represents the location of one of the m sockets. Then, $P = P^1 \times P^2 \times \ldots \times P^m$ can represent the joint configuration of all the plug loads in a building.

Collectively, the physical state-space of a building is given by $X = C \times \mathcal{L} \times \mathcal{K} \times P$. A particular state, $x \in X$, is represented by a tuple, $x = (q, l, k, p)$, which defines the complete state of the building. Here, $q \in C$ and $p \in P$.

The physical state space of a building can be represented as a collection of static snapshots as described above. However, the state of a building evolves over time. Let $T = [0, \infty)$ represent a time interval of execution for analysis. We define a *state trajectory* as $\tilde{x} : T \rightarrow X$. A particular value $\tilde{x}(t)$ represents the building state at time t, for example $\tilde{x}(0)$ represents the state of the building at time 0.

B. Wasteful Energy States and Trajectories

There exist certain *wasteful energy states* in the physical state space. Some examples of these wasteful energy states are: a) An empty room with high lighting levels. b) A high level of plug load consumption in a room with few occupants. c) When there is a discrepancy between the indoor temperature and the comfort level of the occupants. We will call $X_w \subset X$ the set of wasteful states. This motivates the first problem of our paper:

Problem 1: Determination of wasteful states

Characterize the set of wasteful states, X_w, and detect if a certain state in a building belongs to the set of wasteful states such that $x \in X_w$.

When evaluating a buildings energy performance, we will also want to know if an occupants trajectory is wasteful in terms of energy consumption. This evaluation of particular physical trajectories for energy waste is different from an evaluation of wasteful states as formulated in Problem 1. For example, suppose that a plug load associated with an appliance has stayed on and has been consuming energy for a long time. Each particular $\tilde{x}(t)$ is not particularly wasteful but this long interval of activity can be a cause for energy concern, and possibly form a negative, wasteful energy trajectory. This helps to motivate our next problem:

Problem 2: Trajectory Evaluation

Given a physical space trajectory, $\tilde{x}$, evaluate if it is energy wasteful.

C. Action Spaces, State Transition Functions, and Plans

The action space represents the actuation components of the system and is denoted by U. Several actuation elements can be found in a building. For instance, in the classical thermostat problem the goal is to control the temperature of the building. Lights can be turned on and off, so the action space is $U_l = \{on, off\}$. Technology, such as LED lighting, allows for more fine grained control of lighting intensity. In this case, the the action space is $U_{led} = \{0, l_{max}\}$, where 0 means that the light is off and l_{max} represents the maximum intensity of the light. A similar definition can be made for plug load consumption levels of appliances and other electronic devices.

Action spaces for temperature control have been widely studied. In the case of action spaces for building occupants, it is difficult to tightly control occupants and force them to change their configurations, since occupant behavior is usually autonomous. However, action spaces for humans can become useful in evacuation scenarios in building evacuation and emergencies [10], [8].

Using action spaces, we can define a state transition function, $f : X \times U \rightarrow X$, to model how a buildings state changes with the application of actions. In order to have a proactive approach to curtail energy waste in buildings, we need to define *plans* that will indicate what actions should be taken in particular states. A common example of plans and control policies in the context of building energy performance are given in examples of controlling HVAC systems. However, our system differs from HVAC control systems, since we try to characterize wasteful energy states and pro-actively prevent them.

A plan is formally defined as a mapping from physical states to actions, $\pi : X \rightarrow U$, that allow us to solve some problems of interest. A simple example of this will allow us to turn off the lights of a room when it is empty. This motivates our third problem:

Problem 3: Energy Saving Plans and Policies

Can we find suitable plans, π, that try to avoid energy wasting configurations or steer the system away from such configurations?

Occupants can visit different regions of the building, creating a trajectory of movement. Many trajectories exist, but not all the trajectories are the same. A trajectory is wasteful if an occupant frequently forgets to turn appliances off after changing regions. Also, some trajectories are partially wasteful if the occupant has left appliances on for a part of his trajectory. Some trajectories are more wasteful than others, which leads to our next problem:

Problem 4: Trajectory Ranking

Given a trajectory $\tilde{x}$ and its wasteful energy information, calculate its rank, or how wasteful it is as compared to an optimal trajectory.

In the following sections, we will propose solutions for the four problems described above.

III. METHODS

A. Decomposition of the Environment

In order to solve the problems above, we will decompose an environment or work space using the following Motion Planning formulations. The work space, $\mathcal{W}$, is decomposed into a countably finite set of regions R where $R = \{R_1, R_2, \ldots, R_m\}$. The set of regions R is a partition of the free space E with $E = \bigcup_i R_i$. Each region $R_i \in E$ has an *occupancy count* denoted by $o : R \rightarrow \mathbb{N} \cup \{0\}$, in addition to lighting, temperature and plug load information defined in the section above. We will create these decompositions using two Infrared distance sensors placed side by side and we will collect lighting, plug load, and temperature information utilizing additional sensors - creating a sensor network as described below.

B. Information Space

Since the state space defined in section II is impossible to completely detect using available sensors, we need to reduce our state space to a smaller, more manageable *information/observation space*.

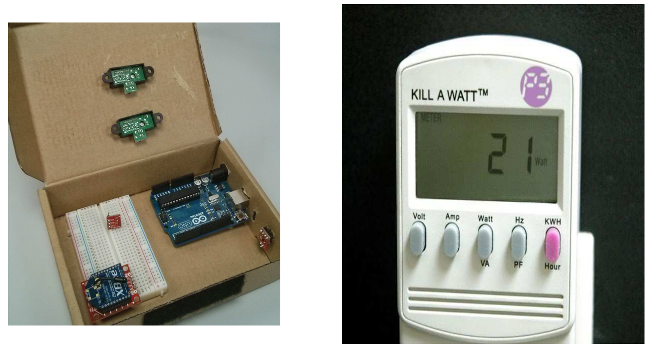

Fig. 1. **Left**: The sensors inside a node (with connections removed for clarity). The components are (from left hand side moving clockwise): a xBee communications module, a TEMT6000 light sensor, two Sharp 2Y0A02 distance sensors, an Arduino micro controller, and a TMP102 temperature sensor. **Right**: *Kill A Watt* energy consumption monitor.

To begin, we can define a generalized light sensor output as $Y_l = \{on, off\}$. We defined the output of the light sensor, l, as a positive real number, however, it is difficult to observe this output in practice so we define an approximation function, $h_l : \mathcal{L} \rightarrow Y_l$, for its output. This function maps the set of all possible light values, $\mathcal{L}$, to a value that is either 0(light is off) or 1(light is on).

Similarly, temperature is measured in the range from 0 to a max temperature, k_{max}, and the corresponding observation is $Y_k = \{0, \triangle k, 2\triangle k, \ldots, k_{max}\}$. The function $h_k : \mathcal{K} \rightarrow Y_k$ approximates all the continuous valued output of $\mathcal{K}$ to a discrete interval Y_k.

Next, the observation space for plug loads are defined as $Y_p = \{0, \triangle p, 2\triangle p, \ldots, p_{max}\}$ and their mapping is defined as $h_p : P \rightarrow Y_p$. Lastly, the observation for occupant count is defined as $h_o : E \rightarrow \mathbb{N} \cup \{0\}$.

Using the condensed definitions above for our sensor observations, we can define the observation space for the entire environment as $Y = Y_l \times Y_k \times Y_p \times Y_o$ and in a finite time interval, $T = [0, t]$, we can define a continuous observation sequence as $\tilde{y} : [0, t] \rightarrow Y$.

C. Hardware

Our hardware setup consists of low-cost Infrared (IR) sensor beams, a temperature sensor, a lighting sensor and a wireless communication system which are all packaged into an enclosure. We will refer to these packaged sensors as *"nodes"*. The internal components of a node are shown in Figure 1. Separate from our nodes, but also part of our sensor system, are *Kill A Watt* energy usage monitors (see Figure 1). These energy usage monitors collect plug-load information for any electronic devices or appliances plugged into the apparatus.

We chose to to create sets of parallel directed beams using paired IR emitter-sensors, because they will allow us to track which region an occupant is crossing into, depending on which beam is occluded first. Each node also contains an Arduino Uno micro-controller which processes the data collected from the distance, light, and temperature sensors.

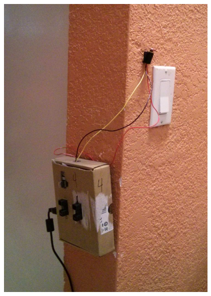

Fig. 2. Placement of a node at a crossing. The light sensor is placed outside, pointing towards the light source of a region.

Results are then transmitted through an xBee wireless Radio-Frequency (RF) module [9], [7]. The xBee modules are connected using the DigiMesh networking protocol, providing a peer-to-peer topology with minimal protocol overhead and optimized power consumption for longer deployment times. Moreover, its network is self-healing and automatically expandable, allowing for simple and quick deployment.

Each node's Xbee module transmits its data to a single receiver which is connected to a computer. A program running on this computer aggregates and stores the data with corresponding time stamps.

The light sensor used in the node units is a SparkFun TEMT6000 Ambient Light Sensor Breakout board, which sends the Arduino a voltage reading, depending on the intensity of light in a room. It sits outside of the node enclosure and is placed so that it is facing the primary light source of a given region (see Figure 2). It is calibrated depending on the intensity of light in the region, which accounts for such factors as window lighting, and how strong the artificial lighting in a room is.

The temperature sensor is a Texas Instruments TMP102 Digital Temperature Sensor Breakout board. It is attached on the enclosure on the outside wall of the box so that it can accurately detect ambient temperature.

The hardware and design of the node modules were based on the need for an easy deployment in a commercial, business, or residential setting. These nodes can be battery operated or plugged into a wall and they utilize wireless networking technology which requires almost no configuration.

The materials chosen are small, have a low-cost, and and are easy to use as compared to expensive camera systems [1]. The total cost for a single node is $115, including the cost of cables, batteries, and breadboard which can be bought in bulk, further lowering the cost for large scale deployments.

D. Identifying the Wasteful States of an Environment

In this section, we will use data collected from our experimental setup in order to identify the *wasteful* or non-energy-efficient states of a given environment over a period of time. These wasteful states are those periods of time when the lights are *on*, energy is being consumed by appliances, and/ or an HVAC system is *on* but there are no occupants in a region. Our sensor system can be used to identify these states by recording occupancy, light usage, temperature, and power consumption information.

We can imagine the space comprised of these four attributes as a 4-dimensional hyper-rectangle defined as $\mathcal{H}$. Certain regions of $\mathcal{H}$ are considered wasteful states, as defined by energy experts. An example of a wasteful state can be modeled if the parameters exceed some threshold, to be set by the expert.

Let $\lambda_l^{th}, \lambda_k^{th}, \lambda_p^{th}, \lambda_o^{th}$ be the thresholds for lighting, temperature, plug load and occupant count, respectively. The region $H_l = \{(l,k,p,o) \in \mathcal{H} | l > \lambda_l^{th}\}$ is defined as the wasteful space for $lighting$. Similarly $H_k = \{(l,k,p,o) \in \mathcal{H} | k > \lambda_k^{th}\}$, $H_p = \{(l,k,p,o) \in \mathcal{H} | p > \lambda_p^{th}\}$, $H_o = \{(l,k,p,o) \in \mathcal{H} | o < \lambda_o^{th}\}$ are the wasteful spaces for temperature, plug load and occupant count, respectively. A wasteful region in the hyper-rectangle is , $\mathcal{H}_w = H_l \times H_k \times H_p \times H_o$. Let a function $f_o : C \times R \rightarrow \mathbb{Z}^{\geq 0}$ give the occupant count in a region $R_i \in R$ based on configuration $q \in C$. Then, the wasteful state space for a region R_i can be defined as:

$$X_w^i = \{(q,l,k,p) \in X | (l,k,p,f_o(q,R_i)) \in \mathcal{H}_w\}. \quad (1)$$

Utilizing the nodes described in section III-C, we can record this information for every region inside an environment. In order to capture this information, a sensor node will be placed at an entrance to a region, and another node will be placed at the exit of a region. This node will detect people crossing into a region and keep a log of how many people are currently in a region, along with a time stamp indicating when people enter and leave a region. Our node units will also have a light sensor in order to record when a light is turned on or off, along with a time stamp of when this happens. The final component, an energy consumption recording device, will record how much energy is consumed in a particular region in kilowatts per hour (kWh).

This information will be recorded and analyzed to identify wasteful states. For example, if node 1 and node 2 are set up in the entrance and exit of region 1, respectively, they will help to determine the occupancy of the region at any given point of time during a data recording session. If from time, t_1, until time, t_2, there are no occupants in the region and there is a light on and/or energy is being used, as determined by the energy consumption meter, then this period of time can be identified as a wasteful state.

E. Identifying the Wasteful Trajectories in an Environment

As mentioned in section II-B, wasteful trajectories need to be identified. These trajectories are formed when users move among regions and produce wasteful states in the different regions they visit. For example, if there is some occupant in a given region, R_1, and he moves to another region, R_2, but he leaves the light on in R_1 and/or leaves some appliances on in R_1 and then moves to R_3, leaving the light on in R_2 as well, this user has produced a wasteful trajectory which can be identified as such by our sensor system.

Therefore, a trajectory is a sequence of visited regions. We define an index set, $\mathcal{I} = \{1, 2, \ldots, m\}$, and formally we define a trajectory as $\tilde{x} = \langle R_i : i \in \mathcal{I} \rangle$. A score, $s_{\tilde{x}}$, is associated with each trajectory, $\tilde{x}$, and is defined as:

$$s_{\tilde{x}} = \sum_{R_i \in \tilde{x}} [h_l \circ l(R_i) + h_k \circ k(R_i) + h_p \circ p(R_i)]. \quad (2)$$

A trajectory is *wasteful* if the calculated score is greater than a certain *threshold*. In order to solve this particular problem of identifying wasteful trajectories, information will be collected using the same method as described in the previous section. First, we will define a period of time that we want to analyze for wasteful trajectories (from t_1 to t_2). Then, we will find the occupancy data for the regions in the environment using our captured sensor data. We will identify any shifting of occupancy from R_1 to R_2 and determine if R_1 is no longer occupied. If it is empty, we will check if any lights and/or appliances where left on. If they were left on, we can identify this movement of occupancy from R_1 to R_2 and from t_1 to t_2 as a wasteful trajectory.

F. System Policies to Conserve Energy

Using data related to wasteful states and trajectories, the next step will be to eliminate these instances of energy wasting behavior, solving problem 3 as stated in II. Policies could be enforced through our system to automatically eliminate instances of waste. For example, a light can be turned off automatically when a region has no occupants for a certain duration of time. Another policy could be that a buildings HVAC load is determined based on trajectories of occupancy. Although not implemented in our current system, creating such policies will be a direction for future work.

G. Ranking the Trajectories

We need to rank trajectories to know how energy efficient they are, as stated in problem 4 in section II. We use the ranking method defined in [26]. Let us perceive an observation trajectory $\tilde{y} = y_{R_1}, y_{R_1}, \ldots, y_{R_E}$ generated by visiting the regions $\tilde{x} = R_1, R_2, \ldots, R_F$. We assume that we already know the ideal observation trajectory defined as $\tilde{y}' = y_{R_1}, y_{R_1}, \ldots, y_{R_F}$ which has the optimal energy usage.

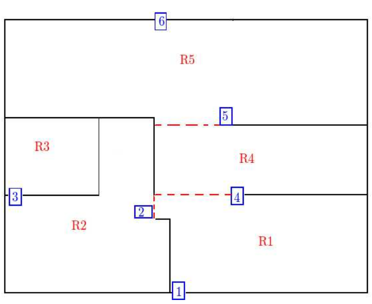

Fig. 3. Residence where experiment was conducted in. Node placement is indicated in blue, along with the corresponding partitioned regions in red. The red-dashed lines that there is no actual wall present but a partition is created by the IR sensor beams.

Therefore, the *Manhattan* distance between a trajectory, $\tilde{y}$, and an ideal trajectory, $\tilde{y}'$, is $d(\tilde{y}, \tilde{y}') = \sum_{R_i \in \tilde{x}} |y_{R_i} - y'_{R_i}|$.

To do the ranking we need a set of training trajectories for which we know the ranks. A weighted network is computed based on the pairwise distances, d. Consequently, these source trajectories spread a rank to the unknown trajectory $\tilde{y}$ and are included into the known set of trajectories [12]. This spreading process will converge once the ranking is computed for a large number of trajectories. Then, the new trajectories will receive an accurate ranking score.

We computed a set of rankings for some sample temperature data trajectories using a ranking script in the *R Programming language* and obtained the results shown in Figure 4. Note that these rankings are computed using temperature only, however, we can choose other features to rank on like lighting and energy consumption. The rankings shown compare trajectories of temperature information, created by occupants moving among different regions, against an optimal trajectory. The fourth trajectory is the highest ranked trajectory as it is most similar to the optimal trajectory.

IV. Results

This section will report the findings of our experimental deployment of nodes throughout a single-story residential home. We will also evaluate our results to solve the problems described in section II.

A. Experimental Setup

Hardware nodes, such as in Figure 1, were placed throughout a single-story residential home. Paired IR beams on the nodes allowed us to detect the crossing direction of an occupant moving from one region to another region. This is unlike previous studies which have used single beams which cannot detect the direction of a crossing such as [25].

Figure 3 shows the setup of the nodes throughout the home. Each blue box represents a node, which is placed at doorways and crossings between different rooms. The house is divided into 5 regions (R_1-R_5) with 6 nodes creating the partitions. The front entrance/exit of the house is monitored by node 1 and crossing past this node leads into R_1- the living room. Node 2 leads into R_2 which contains a bathroom, bedroom and hallway. The hallway from R_2 leads into R_3 which is a home office. At another side of R_1 is node 4 which leads into R_4, a kitchen/dining room. It is bordered by node 5 which leads into R_5, a multipurpose room in the

Trajectories of Occupants Using Temperature Data

	R_a	R_b	R_c	R_d	R_e
1	30°	30°	30°	30°	30°
2	27°	26°	24°	26°	27°
3	28°	28°	25°	22°	21°
4	30°	30°	30°	30°	31°
5	30°	30°	30°	30°	32°

Ranking of Temperature Trajectories

Trajectory	Distance	RANK
2	1.19587	3
3	1.393739	4
4	1.001249	1
5	1.042977	2

Fig. 4. Ranking of 4 temperature trajectories against an optimal trajectory. Occupancy movement is captured moving through 5 regions ($R_a - R_e$) and corresponding temperature is recorded (in C°). The optimal trajectory, 1, is shown in red and the highest ranked trajectory, 4, is shown in orange text.

back of the house. The last node is R_6, which leads to the back entrance/exit of the house.

Figure 5 shows a resident crossing in front one of the nodes. Using code uploaded to our Arduino micro controllers, our nodes can determine which region the occupant is crossing into, and a script uploaded on the receiving host computer determines how many occupants are in the region the occupant exited from and entered into. In this figure, an occupant is leaving R_2 and entering R_3 which is detected by node 3. Since the distance sensors on the nodes are placed side by side, distance sensor a will be triggered first(as it is closest to R_2, the region the occupant is leaving), followed by distance sensor b (the sensor closest to R_3, the region the occupant is going into). This will cause the direction of the crossing to be recorded as $a \rightarrow b$ on the node, which will increment the occupancy count of R_3 by 1 and decrement the occupancy of R_2 by 1.

Other components of our system included light sensors and kWh consumption monitors. Light sensors were attached to node units but placed outside the enclosures facing ceiling lights, as seen in Figure 2. There were a total of 5 light sensors used in this experiment: a light sensor was placed on node 2 to detect the hallway light in R_2, another sensor was placed on node 3 to detect the lighting in R_3, another on node 4 to detect lighting in R_1, another on node 5 to detect lighting in R_4 and finally one on node 6 to detect lighting in R_5.

We ran an experiment over a course of roughly 20 hours collecting occupancy data using the setup described above. We also present energy consumption data from the local electrical company, *Florida Power and Light (FPL)*, in order to compare our results with actual energy expenditure. The following data represents our solutions to problems 1 and 2 from section II. Note that kWh consumption information was only collected for region 3. Also, for analysis, we will only look at data collected from R_3, R_4 and R_5, as these had the most reliable sensor readings from the whole setup.

As shown in Figure 7, 12 PM was a time of high energy consumption(3.15 kWh) with an outdoor temperature of about 23° C. We can identify this time in our data using Figure 6. From 12 PM to 1 PM, R_3, had 2 people in the region and the temperature was 20° C, R_4 was empty with a temperature of $22°C$ and R_5 was also empty with a temperature of $23°C$. The dots on Figure 6 indicate if a light is turned on at a given time. We can see that the lights were on a majority of the time for R_4 and R_5, however, these regions were empty. This indicates that the regions were consuming electricity and these periods of time can be classified as a *wasteful state* as indicated by problem 1 above.

Another wasteful state can be seen at about 7 PM. During this time, the three regions are empty most of the time, but the lights are on a majority of the time. Again we can classify these times and regions as wasteful states since they were empty and had lights on. The corresponding data from FPL in Figure 7 indicates that there were some appliances being used causing high energy consumption during this time, indicating an overall wasteful state in the household.

In addition to wasteful energy states, we can identify *wasteful trajectories*, as introduced in section II-B, utilizing the data we collected from our nodes. For example, lets look

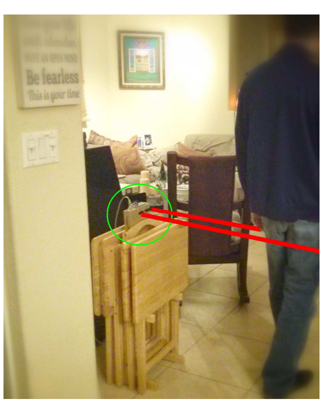

Fig. 5. Resident crossing in front of a node. The red lines represent the beams emitted by the IR distance sensors. The node is circled in green.

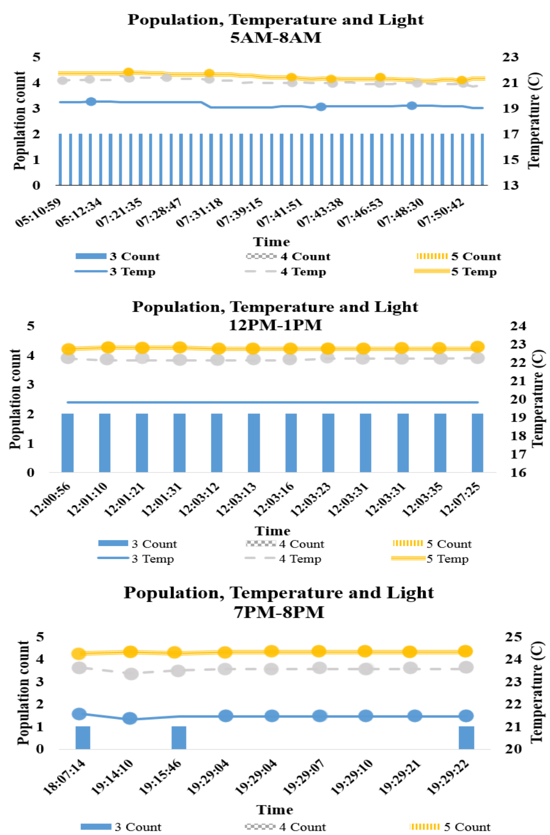

Fig. 6. Crossing data recorded from 3 regions, the dot on the temperature line indicates whether a light is on/off in a region. Also note, that any time *"skipped"* in the x-axis indicates that no changes occurred for that period of time.

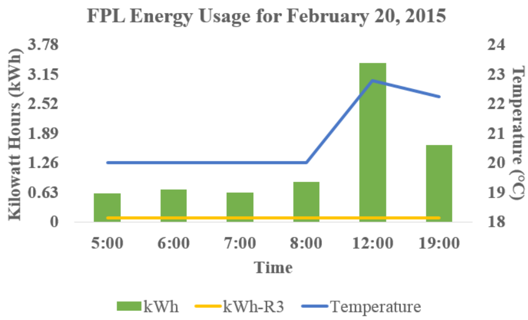

Fig. 7. Data recorded from electric company along with outdoor temperature. The yellow line is the average kWh consumed by the home office.

at the time period from 5 AM to 8 AM. Looking at Figure 6, we can see that R_4 is empty. Although not shown in the graph, a detailed view of the activity during this time period indicated that an occupant was moving throughout the house and turning on lights. This occupant entered R_4 from R_1 and turned on the light, then entered R_5 and turned on a light. This occupant therefore created a wasteful trajectory for this time period while traveling from $R_1 \to R_4 \to R_5$.

V. Conclusions and Future Work

The methods presented in this paper contribute to the efforts towards automated building operation and smart buildings. While the majority of the existing studies in these areas focus on automated operation of building systems (such as HVAC), our study is geared toward capturing, modeling, and analyzing occupant behaviors for proactive monitoring of energy waste in buildings. This could lead to more adaptive and proactive approaches toward automated building energy control. We presented our problem formulation and ideas for the solutions through our methodology, and a preliminary case study in this paper. Our ongoing work is geared toward improving the accuracy of sensed data, developing robust policies for automated elimination of wasteful states, and implementing these policies based on real time feedback to building systems (e.g., HVAC) and occupants.

Some future directions for our work include expanding our sensor system to larger areas, including business or commercial settings, which will allow us to explore other concerns such as communications systems for such large areas. We also can create more complicated geometric spaces in our regions and more finely analyze occupants behaviors in a region. Another possible direction for further study is making more policy suggestions and exploring that area as well as improving our current hardware configurations to obtain more accurate results.

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