Modeling and Analyzing Occupant Behaviors in Building Energy Analysis Using a State Space Approach and Non-Invasive Sensing

Triana Carmenate
and
Md Mahbubur Rahman
and
Diana Leante
and
Leonardo Bobadilla
and
Ali Mostafavi
Florida International University

Buildings represent one of the most significant sources of energy consumption in the United States and other countries in the world. One of the most significant factors affecting buildings' energy performance is the behavior and actions of their occupants. Monitoring, understanding, and decoding occupant's activities are fundamental to identify energy waste and for proposing strategies to reduce excessive energy consumption in buildings. In this paper, we present an approach for automatic detection and proactive monitoring of energy waste caused by occupants' behaviors. We first introduce a mathematical formalism to model states and trajectories arising in buildings in the context of energy consumption by occupants. Then, we present a set of easy to implement algorithms that used sensing information to detect wasteful states and trajectories. We also describe and implement a prototype of a non-invasive, sensor network consisting of inexpensive temperature, light, and distance sensors, as well as electricity consumption plug monitors that capture data related to occupancy behaviors in energy consumption. By combining occupancy counts, sensing information, and energy expenditures in different regions of a building, we can estimate how occupancy behavior is affecting energy use in a non-invasive way. Our ideas are tested experimentally in a study case in a residential building.

Keywords: Sensor Networks, Minimalism, Smart Buildings; Power and Energy Systems

1. INTRODUCTION

More than 70% of the electricity load in the United Statesis consumed by buildings ((USGBC), 2015). Though several factors such as weather and building design parameters affect its energy consumption, a primary factor is their occupants' behaviors. The energy performance of a building can be explained in great part by the interaction of occupants with the building sections and appliances. Therefore, a better understanding of occupant behaviors is essential to discover energy-saving opportunities for in buildings (Gunay, O'Brien, and Beausoleil-Morrison, 2013; Hong, 2014; Yu, Fung, Haghighat, Yoshino, and Morofsky, 2011). However, understanding occupant behaviors at the interface of human-building-appliance interactions is a hard task. Data related to occupancy behaviors as they moved in a building and interact with appliances can be captured in two ways: indirectly or directly. The indirect measurement of occupants' behavior is usually done through occupant surveys. However, such self-report surveys are prone to errors such as inaccurate activities recall and social desirability bias. On the other hand, direct measurements of occupants' behavior can be hard to obtain due to privacy issues. Several studies (Garg and Bansal, 2000; Erickson, Lin, Kamthe, Brahme, Surana, Cerpa, Sohn, and Narayanan, 2009; Nguyen and Aiello, 2013)) have used different sensor modalities for detecting occupants' behavior and estimating and building energy parameters (e.g lighting and temperature). Despite the growing literature and importance of this area, we believe that a formalized methodology for understanding emergent behaviors affecting the energy performance and pro-actively detecting energy waste in the building is still missing in the literature.

Our work contributes to three critical directions of research concerning the analysis of occupant behaviors in building energy assessment: (1) monitoring and tracking occupancy movements for smart building systems; (2) detecting automatically energy waste caused by occupant behaviors; and 3) design of plans (policies) for avoiding energy wasting behavior.

Our ideas are related to research on Heating, Ventilation, and Air conditioning (HVAC) control (Åström, Hägglund, and Wallenborg, 1993; Afram and Janabi-Sharifi, 2014; Underwood, 2002) building automation systems (BAS) (Kastner, Neugschwandtner, Soucek, and Newmann, 2005; Zhou, Li, Chan, Cao, Kuang, Liu, and Wang, 2016), and Smart Buildings (Snoonian, 2003; Rutishauser, Joller, and Douglas, 2005). We also aim for a formalized approach for automated detection of energy waste at the interface of human-building-appliance interactions. Our ideas are different from existing work in different crucial aspects. First, we want to tackle the general problem of modeling energy performance at the interface of human-building-appliance interactions; these emergent behaviors can be captured by *state spaces* based modelings. Second, We are interested in finding *minimalist* solutions that are easy to deploy, inexpensive, and respect privacy for automated detection of energy waste in buildings. Finally, we include in our problem formulations and experiments small residential units which are usually out of the scope of HVAC, BAS, and Smart Building analysis.

Also connected to our efforts are approaches that attempt to count and track occupants in buildings using occupancy sensors such as (Agarwal, Balaji, Gupta, Lyles, Wei, and Weng, 2010; Zappi, Farella, and Benini, 2010; Singh, Madhow, Kumar, Suri, and Cagley, 2007; Kim, Mechitov, Choi, and Ham, 2005; Shrivastava, Madhow, and Suri, 2006; Aslam, Butler, Constantin, Crespi, Cybenko, and Rus, 2003) and (Blonchek, Sinha, Simhal, and Dandeka, 2013). Tracking and counting occupants in different regions of buildings is an essential component key to the development of smart building solutions. Our work borrows from ideas that try to monitor in a non-invasive manner, the behavior of one (Tovar, Cohen, Bobadilla, Czarnowski, and Lavalle, 2014) or multiple agents (Bobadilla, Sanchez, Czarnowski, and LaValle, 2011; Erickson, Yu, Huang, and LaValle, 2013) using detection beams.

Our paper has several contributions. First, we create a mathematical framework to describe the physical state space of buildings and concretely formulated six problems of energy waste in buildings that include temperature, lighting, plug load consumption, and occupant behavior. Second, we present easy to implement algorithms to detect wasteful states and trajectories and attempt to modify occupant behaviors in buildings. Third, we show a non-invasive, economical, hardware architecture to implement our ideas. Finally, we test our approach in a small residential setting.

This paper is an improved and extended version of the conference paper presented in (Carmenate, Rahman, Leante, Bobadilla, and Mostafavi, 2015). Compared to the conference submission, this version of the paper: 1) improves and generalizes the formulation to include not only residential buildings but potentially commercial and industrial settings; 2) extends the problem formulation and solutions by adding three new problems; 3) expands the literature review; 4) broadens the discussion to cover the practical relevance of the approach and details the ideas for future work.

Our work on understanding the occupant's movement patters and energy consumption behavior can serve as an accurate way to obtain parameters for agent-based simulation models to understand the dynamic behavior of occupants in a building at the interface of human-building-appliance interactions (Carmenate, Inyim, Pachekar, Chauhan, Bobadilla, Batouli, and Mostafavi, 2016; Abdallah, Basurra, and Gaber, 2018, 2019). Additionally, the results of our methods can be fed into smartphone applications to suggest energy behavior to users (Inyim, Batouli, Reyes, Carmenate, Bobadilla, and Mostafavi, 2018).

The rest of the paper is organized as follows. In Section 2, we present a mathematical framework and formulate six problems related to energy waste. Section 3 presents the algorithm methodology as well as the hardware used to solve the questions proposed in section 2. Section 4 presents a complete case study in a small residential setting to illustrate the practical applications of our methods. Finally, in section 5, we present conclusions and potential directions for future work.

2. PROBLEM FORMULATION

2.1 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 terminology (LaValle, 2006; Latombe, 1991; Choset, Lynch, Hutchinson, Kantor, Burgard, Kavraki, and Thrun, 2005), physical state space modeling approaches (LaValle, 2006, 2012) in Robotics and autonomous systems.

We will model an indoor building environment (or *workspace*) as a collection of floors in a building and each of these floors is modeled as a planar 2-dimensional workspace denoted by $\mathcal{W} = \mathbb{R}^2$. In this paper, we will do a complete analysis and formulation of energy problems concerning a single floor; however, our approach can be extended easily to buildings with multiple levels with minimal modification. The floor $\mathcal{W}$ will have a set of obstacles, $\mathcal{O}$, that represent areas that are not accessible by humans. To extend our approach to multiple floors to account for commercial and business settings, instead of having one level, $\mathcal{W}$, a collection of 2D floors $\{\mathcal{W}_1, \mathcal{W}_1, \ldots, \mathcal{W}_p\}$ where p is the number of floors in the building. In this case, each floor $\mathcal{W}_i$ will have its own set of obstacles $\mathcal{O}_i$.

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

One crucial physical variable in building energy consumption analysis is *lighting*. A particular lighting configuration will be model as a *scalar field* $l : E \to \mathbb{R}^{\geqslant 0}$, which assigns to a given point in the environment a positive light intensity. Then, we define $\mathcal{L}$ as the set of all the possible lighting assignments such that $l \in \mathcal{L}$.

Another variable of interest in the building's energy performance is the indoor building *temperature*. Similar to lighting definition above, we model temperature as a mapping, $k : E \to \mathbb{R}$, which assigns a temperature to every point in the environment. $\mathcal{K}$ represents the set of all possible temperatures mapping such that $k \in \mathcal{K}$.

Also, we will include in the physical state space of a building the *plug load* (electrical consumption). We assume that there are m plug outlets placed in the environment. We will denote the configuration of each plug outlet in the building as $P^j = E \times \mathbb{R}^{\geqslant 0}$ where $1 \leq j \leq m$ and E represents the location for each of m sockets, and $\mathbb{R}^{\geqslant 0}$ represents the plug load (a nonnegative scalar) used by the outlet. Then, $P = P^1 \times P^2 \times \ldots \times P^m$ represents the joint configuration of all the plug loads in a building.

Assembling together lighting, temperature and plug load, we define the building's physical state-space as $X = C \times \mathcal{L} \times \mathcal{K} \times P$. A state $x \in X$ will be represented by the tuple $x = (q, l, k, p)$ where $q \in C$, $l \in \mathcal{L}$, $k \in \mathcal{K}$,and $p \in P$.

The building's physical state space will be modeled as a series of static snapshots denoted as x. The building's state will change over time as occupants move inside the building and interact with the building's appliances. The time interval for energy analysis is denoted as $T = [0, \infty)$ which will help model changes over time. A *state trajectory* is expressed as $\tilde{x} : T \to X$. The value $\tilde{x}(t)$ represents the building's state at time t and $\tilde{x}(0)$ is the state of the building at the start of the analysis ($t = 0$).

2.2 Wasteful Energy States and Trajectories

In this paper, we are interested in detecting *wasteful energy states* in the physical state space that arise due to the occupant's behavior. Some examples of such states are a) high level of plug load consumption in a room with no or few occupants, b) An room with high light levels but is empty, and c) a measured discrepancy between the indoor temperature and the comfort level of the occupants. We will denote the set of wasteful states as $X_w \subset X$. These examples and definitions lead to our first problem of interest.

Problem 1: Characterization and Classification of Wasteful States

Create a representation for the set of wasteful states, X_w, and detect if a particular state x

belongs this set of wasteful states.

Furthermore, in building's energy analysis, another aspect of interest is finding out whether a particular trajectory is wasteful in its energy consumption. The problem of trajectory evaluation differs from Problem 1 as defined above since it takes into account the sequence of events. To illustrate this subtle difference, consider the plug load of an appliance that has been active and consuming energy for a while. In this case, no individual state x in the trajectory $\tilde{x}(t)$ belongs to X_w, but the prolonged duration of this activity may be a cause for concern regarding energy consumption. This difference leads to our next problem of interest.

Problem 2: Wasteful Trajectory Classification

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

2.3 Action Spaces, State Transition Functions, and Policies

The action space, denoted as U, represents the actuation components of the system. Buildings have several actuated elements. For example, in the context of HVAC systems, action spaces for temperature control have been widely studied in the control literature (Afram and Janabi-Sharifi, 2014; Åström et al., 1993) where the goal is to control the building's temperature through thermostats. In our modeling, a concrete actuation example is lights that can be turned off and on automatically. In this case the actuation space is $U_l = \{on, off\}$. Another example is LED lighting (Pimputkar, Speck, DenBaars, and Nakamura, 2009) which enables a fine-grained control of lighting intensity. In this example, the action space can be modeled as $U_{led} = \{0, l_{max}\}$, where 0 means the state where the light off and l_{max} is the maximum light intensity possible. Similarly, we can also model the situation where appliances can be remotely controlled.

Action spaces involving occupants' behavior in buildings are harder to obtain since it is difficult to tightly control the occupants and force them to change their state since their behavior is autonomous. Nevertheless, there has been work in the Robotics literature that attempts to moving bodies by subtly altering their environment (Bobadilla, Sanchez, Czarnowski, Gossman, and LaValle, 2011; Bobadilla, Martinez, Gobst, Gossman, and LaValle, 2012). These action spaces for occupants are useful in evacuation and emergency scenarios (Helbing, Farkas, and Vicsek, 2000; Gonzalez, Hidalgo, and Barabasi, 2008).

We model changes in building's states when actions are applied using an appropriate action space U and a transition function $f : X \times U \rightarrow X$. One of the purposes of this paper is working toward a proactive approach to reducing energy waste in buildings. To move towards this goal, we will search for *policies* that indicate what actions to take in a particular state. An example in the literature of plans for building energy performance are policies for controlling HVAC systems. Our approach differs from HVAC control systems since we try to: 1) characterize and detect wasteful energy states, and 2) proactively prevent them.

As occupants move inside the building visiting different parts of it and interacting with appliances, a trajectory in the state space $\tilde{x}$ is generated. A trajectory is considered wasteful, if, for example, the occupant forgets to turn off appliances when moving to a different region. Some trajectories could be slightly less wasteful if appliances were active for only a part of the occupant's trajectory. Since some trajectories are more wasteful than others, we are interested in the following problem:

Problem 3: Trajectory Comparison

Given two trajectories $\tilde{x}$ and $\tilde{x'}$ and their energy waste information, determine which of the two is the most wasteful

For the next problem, suppose that a building energy expert has given a model trajectory $\tilde{y}$ that outlines an ideal occupant's behavior in terms of energy consumption. Therefore, we want to extend the problem 3 to rank a group of trajectories when compared against a model trajectory.

Problem 4: Trajectories Ranking

Given a set of trajectories $\tilde{x}_1, \ldots, \tilde{x}_p$ and their wasteful energy information, calculate how they rank compared to a model trajectory $\tilde{y}$.

Related to the problem above, suppose that we are interested in grouping or *clustering* different trajectories according to their energy behavior. Solving this problem can find applications in scenarios where we have a set of apartments in a building, and we want to identify similar activities and perhaps detect outliers, which indicates unusual patterns. This motivation leads us to the formulation of our next problem of interest:

Problem 5: Trajectory Clustering

Given a set of p trajectories $\tilde{x}_i$ with $i \in \{1 \dots p\}$ group them accordingly to their similarity.

We are also interested in obtaining energy saving policies (also known as plans in the Robotics literature) as a mapping from the physical space states to actions, $\pi : X \to U$, that will enable us to model problems of interest regarding energy consumption in buildings. A sample of a policy is to turn off the lights inside a room when it is empty. This example motivates our next problem of interest:

Problem 6: Finding Energy Saving Policies

Find suitable policies, π, that attempt to avoid or steer the system away from energy-wasting configurations.

In the following sections, we will propose initial solutions for the six problems formulated above.

3. METHODS

3.1 Decomposition of the Environment

To solve the problems formulated above, we will first decompose the environment or workspace into a set of regions that can be easily monitored. The workspace, $\mathcal{W}$, is divided into a finite set of m regions $\mathcal{R} = \{R_1, R_2, \dots, R_m\}$. The set of regions $\mathcal{R}$ is a partition of the environment $E = \bigcup_i R_i$. For each region $R_i \in \mathcal{R}$ we define an *occupancy count* that denoted by $o : \mathcal{R} \to \mathbb{N} \cup \{0\}$. We will also include in each region information about lighting, temperature, and plug load as defined in the problem formulation.

3.2 Sensing

We will monitor the quantities of interest (occupancy, lighting, temperature, and plug load) using the region decomposition $\mathcal{R}$. More concretely, we will gather this information through a sensor network described below. Since the state space formulated in section 2 may be hard to monitor, we will instead simplify our state space to a smaller, more manageable *information space.*

Although in our problem formulation, we have initially defined the output of the light sensor, l, as a positive real number, it may difficult to measure precisely this value through sensors. Therefore, as an alternative, we define the function, $h_l : \mathcal{L} \to Y_l$ with $Y_l = \{on, off\}$. This sensor mapping associates a value that is either 0 (light is off) or 1 (light is on) to the set of all possible light values ($\mathcal{L}$) This mapping can be estimated through inexpensive lighting sensors.

The sensor network will also include sensors used to measure temperature. The sensors have a range from 0 to a max temperature, k_{max} and their observation space is modeled as $Y_k = \{0, \triangle k, 2\triangle k, \dots, k_{max}\}$ where $\triangle$ is the resolution of the sensor. The sensor mapping $h_k : \mathcal{K} \to Y_k$ approximates the continuous-valued output of $\mathcal{K}$ to the discrete range Y_k that can be measured by inexpensive sensors.

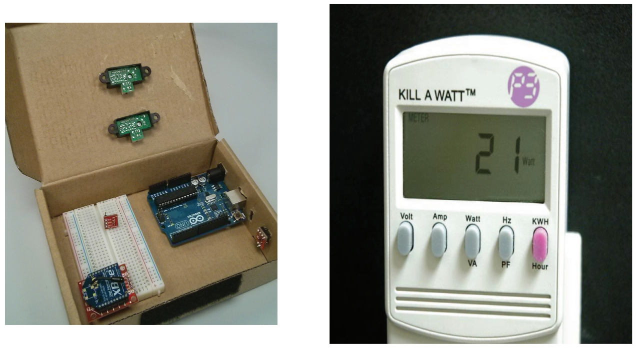
Similarly, for modeling plug load, the observation space is $Y_p = \{0, \triangle p, 2\triangle p, \dots, p_{max}\}$ where $\triangle$ represents and the sensor mapping is defined as $h_p : P \to Y_p$.

Finally, the occupant count is modeled as a function $h_o : E \to \mathbb{N} \cup \{0\}$ where $\mathbb{N} \cup \{0\}$ represents the number of occupants in a region. Counting information can be obtained through several modalities such as fixed cameras (Kettnaker and Zabih, 1999) and Wi-Fi signal strength (Depatla, Muralidharan, and Mostofi, 2015). However, sensor modalities, especially cameras, can invade the privacy of the occupants making this sensor unsuitable for use in residential setups. Instead, in our work, we will use non-invasive means to track occupancy in regions (Bobadilla et al., 2011; Tovar et al., 2014) by using two infrared distance sensors placed side by side at the boundary of two regions. If the initial count is known, the crossing events can keep an updated count in the regions (Bobadilla et al., 2011; Erickson et al., 2013).

Combining all the observation spaces defined above, the joint observation is $Y = Y_l \times Y_k \times Y_p \times Y_o$. Let $T = [0, t]$ represent a finite time interval with t the final time of the interval. We define an *observation sequence* as $\tilde{y} : [0, t] \to Y$.

3.3 Hardware

Our proposed sensing solution consists of a low-cost Infrared (IR) sensors, a light sensor, a temperature sensor, and a wireless communication component which are all placed inside an



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

enclosure. From this point onward, we will refer to these integrated sensors as *"nodes"*. The inside view of a node is presented in Figure 1. Physically separated from the nodes, but also incorporated in the system, we use *Kill A Watt* energy usage monitors (see Figure 1). These usage monitors will collect plug-load information of appliances and electronic devices connected into them.

To track the region an occupant is crossing into, we place parallel beams implemented using paired IR emitter-sensors. Depending on which beam is occluded first, we can detect the crossing direction. Each node contains an 8-bit Arduino Uno microcontroller which processes the data collected from the temperature, distance, light, and occupancy sensors. Results are sent through a Zigbee, XBee wireless Radio-Frequency (RF) module (Han and Lim, 2010; Gezer and Buratti, 2011). Each of these modules cost under 30 US dollars. We connected the XBee modules using the DigiMesh networking protocol, which supports peer-to-peer topology without a lot of protocol overhead and optimizes power consumption for longer deployment times. Other features of the protocol that are useful for our system is that the network is self-healing and automatically expandable, allowing for quick and straightforward deployment.

Each node sends its data through the XBee module to a single receiver connected to a central computer. This computer has a script that aggregates and stores the sensor data. Each sensor reading has an associated a time stamp.

For the light sensor, we used a SparkFun TEMT6000 Ambient Light Sensor Breakout board. This sensor transmits to the Arduino a voltage reading proportional to the intensity of light in the room. We placed the sensor outside of the node enclosure and oriented to face the region's primary light source as illustrated in 2. We calibrate the sensor based on the intensity of light in the area to account for factors such as artificial light strength and window light in the room.

For temperature measuring, we use the Texas Instruments TMP102 Digital Temperature Sensor Breakout board. This sensor is located outside of the box enclosure to detect the ambient temperature accurately.

Our hardware design is intended for easy deployment in residential, commercial, or business settings. The nodes can operate using a battery or connected into a plug. The wireless network protocols require little configuration. The components chosen have a small form, are low-cost and easy to use compared to expensive sensing and camera systems (Agarwal et al., 2010). We estimate that the cost for a single node is around $115 US, this includes the cost of batteries, cables, and the breadboard. This price will decrease if the components are bought in bulk for large-scale deployments.

3.4 Classification of Wasteful States

In this section, we will collect data from the hardware setup to identify the *wasteful* or energy inefficient states over some time. These wasteful states are those periods when, for instance, energy is consumed by certain appliances and lights are turned on, but there are no occupants in a region. Our hardware setup will help identify these states by capturing light usage, temperature,

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

power consumption, and occupancy information.

We will model the space composed of these four attributes (occupancy, light, temperature, power consumption) as a 4-dimensional hyperrectangle denoted as $\mathcal{H}$. Subsets of $\mathcal{H}$ are considered wasteful states as defined by energy consumption experts. As an illustration, consider a wasteful state that can be detected if the parameters of the hyperrectangle exceed some threshold set by an expert.

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

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

Using the nodes 3.3, we can obtain this information by placing the sensor node at the boundary between regions. The nodes will detect people going in and out of a region and how many people are currently inside. The nodes also have a light sensor that detects and record when turned on or off as well as the time of this event. Finally, the Kill A Watt Meter will record energy consumption in a particular region (in kilowatts per hour (kWh)).

We will store the information and analyze it to help identify wasteful states. For instance, if node 2 and node 3 are placed at the entrance and exit of the region 2, respectively, they can determine the region's number of occupants at any given point in time. If from a period starting in time, t_1 and ending until time t_2, there are no occupants in the region, the is light on, and energy is being used (determined by the energy consumption device) then this period will be classified as a wasteful state.

3.5 Wasteful Trajectory Classification

In our second problem of interest, as formulated in section 2.2, is the identification of wasteful trajectories. These trajectories occur, for instance, when occupants move between regions producing wasteful states. As an illustration, suppose that there is some occupant in the region R_3, and then continues to another region, R_4, but he leaves the light or some appliances on R_3 and then moves to R_3 and also lefts a light turned on. This occupant has produced a wasteful trajectory that should be identified by our methodology.

We define a *region trajectory* a sequence of visited regions. We we define a region trajectory as a sequence of regions $\tilde{r} = \langle R_i : i \in \mathcal{R} \rangle$. We also associate a score, $s(\tilde{r})$, to each trajectory, $\tilde{r}$ as follows:

$$s(\tilde{r}) = \sum_{R_i \in \tilde{x}} [h_l \cdot l(R_i) + h_k \cdot k(R_i) + h_p \cdot p(R_i)]. \tag{2}$$

We consider a trajectory *wasteful* if the score is greater than a defined *threshold*. To solve the problem of classifying wasteful trajectories, we collect information using the hardware system described before. First, we define a period of interest to analyze wasteful trajectories, which starts at time t_1 and ends at t_2. After this, we obtain the occupancy count for the regions from the sensor data. We identify any changes of occupancy from any two given regions R_i to R_j and determine if R_i empty. If R_i is empty; we check if any lights or appliances were left turned on. If they were, we would classify this trajectory that spans from t_1 to t_2 as a wasteful trajectory.

3.6 Trajectory Comparison

In the next problem of interest, we want to compare a given trajectory against an ideal trajectory in terms of energy consumption. We define an observation trajectory $\tilde{y} = y_{R_1}, y_{R_1}, \ldots, y_{R_f}$ that is generated by visiting regions $\tilde{x} = R_1, R_2, \ldots, R_f$. Here, we are assuming that that we we are given a trajectory as $\tilde{y}' = y_{R_1}, y_{R_1}, \ldots, y_{R_f}$ over the same regions which has close to ideal energy usage. In our notation y_{R_1} represents the sensor readings at region R_1. This ideal trajectory $\tilde{y}'$ can be proposed, for example, by consulting building energy consumption domain experts. We use the absolute differences in the sensor values distance between the trajectory, $\tilde{y}$, and the ideal trajectory, $\tilde{y}'$. This is written as $d(\tilde{y}, \tilde{y}') = \sum_{R_i \in \tilde{x}} |y_{R_i} - y'_{R_i}|$. This distance score allow us to quantitatively measure the difference between two trajectories by comparing a given trajectory's sensor readings against the desired behavior and report back how big is this difference.

3.7 Trajectories Ranking

In this subsection, we extend the previous problem from a comparison between two trajectories to comparing a set of trajectories. More concretely, we want to rank (order) trajectories based on their energy efficiency. We use a machine learning based ranking method proposed in (Zhou, Weston, Gretton, Bousquet, and Schölkopf, 2004) based on kernel methods. To do this ranking, we need a set of training trajectories with known the ranks. We compute weight-matrix based on pairwise distances using the distance d defined previously. These source trajectories induce a ranking on the unknown trajectory $\tilde{y}$ and are included in the known set of trajectories (Karatzoglou, Smola, Hornik, and Zeileis, 2004b). This process converges when the ranking is computed for a large number of trajectories. After this training stage, the new trajectories will receive an accurate ranking score.

3.8 Trajectory Clustering

In the next problem of interest, we have a set of p sensing trajectories $\tilde{x}_i$ with $i \in \{1 \ldots p\}$, and we want to group them according to their similarity. This problem can have applications, for example, when comparing similar units in an apartment complex to understand patterns of related behavior.

To obtain this grouping of trajectories, we will use *kernel based* clustering (Shawe-Taylor, Cristianini, et al., 2004). By using the kernel method in clustering, we could operate in an implicit feature space without the need of computing explicitly the coordinates of our data (in our case sensing trajectories). This process is done by calculating inner products for all the pairs of data in the feature space (Shawe-Taylor et al., 2004). This approach has been applied successfully to several domains by creating different kernel functions for images, strings, trees, and text.

In particular, we just need to define a suitable kernel function that computes the similarity between two trajectories $k(\tilde{x}, \tilde{x'})$. This kernel function $k(,)$ will be created as a linear combination of kernels that compare the components in lighting $k_l(,)$, temperature $k_t(,)$, energy consumption

$k_e(,)$, and occupancy $k_o(,)$. Therefore, the kernel function to compare the trajectories will be calculated as $k(,) = 0.25 * k_l(,) + 0.25 * k_t(,) + 0.25 * k_e(,) + 0.25 * k_o(,)$.

Each of the kernels will be calculated as follows. $k_l(,)$ is the Euclidean distance between two $\mathbb{R}^m$ vectors (one for each trajectory) where each of the components corresponds to the energy consumption throughout the trajectory for each of the m regions. The kernels for the other components of the trajectories are similarly computed as Euclidean distances from vectors containing information for each of the regions. Once we defined the customized kernel for comparing a pair of trajectories, we can apply the *kernel k-means* algorithm to group them (Dhillon, Guan, and Kulis, 2004).

3.9 Finding Energy Saving Policies

We want to propose approaches to eliminate energy-wasting behaviors, as defined in Section 2. Proposed policies could be enforced through our system to attempt to remove automatically waste. Ideally, we want to suggest policies to help prevent energy waste provided that we have actuation control on some of the elements of the building, such as plug load consumption, light, and temperature.

Policies are defined as a mapping between the state space and the action set $\pi : X \to U$. For instance, a light can be turned off automatically if a region has no occupants at the time. A similar principle has been used in systems that use passive infrared systems to conserve lighting. Another example of a policy would change HVAC values in buildings based on occupancy.

If not actuated components are available, another way to prevent energy waste is to apply the methodology presented and then show the results visually to the occupants. This procedure would be a subtle way to suggest building occupants save energy.

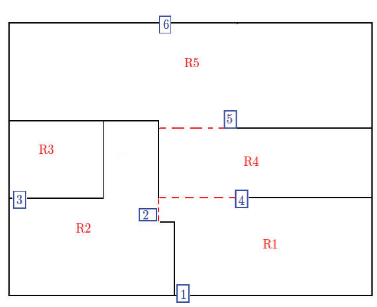
4. RESULTS

In this section, we present the results of our deployment of nodes in a single-story residential home. We will also show results of computations for the problems defined in section 2.

4.1 Experimental Setup

The designed hardware nodes (shown in Figure 1), were placed in a single-story residential home. A pair of IR beams in the nodes allowed us to detect the crossing direction of an occupant moving from one region to another. Our hardware setup differs from previous research that has used single beams which cannot detect the crossing direction such as (Zappi et al., 2010).

Figure 3 shows the placement of the nodes throughout the home. Each blue box represents a node placed at a crossing between different rooms. We divided the house into 5 regions (R_1-R_5) with 6 nodes used to partition the space in regions. The front part of the house was monitored by node 1, and crossing this node leads into R_1 (living room). Connecting R_1 to R_2 is node 2 connects. Region R_2 contains a bathroom, bedroom, and a small corridor. The small corridor of R_2 leads to R_3, which is a home office. Across R_1, node 4 is placed to connect with R_4 (kitchen/dining room). Region R_4 is limited by node 5 that connects to R_5, a multipurpose room in the back of the house. The last node, 6, monitors the connection that leads to the back entrance/exit of the house.



Residential location where the experiment was conducted. Node locations are shown in blue and the corresponding partitioned regions in red. The red dashed lines represent a partition that is created by the IR sensor beams.

A crossing event by a resident in front of one of the nodes is shown in Figure 4. The nodes are programmed to determine to which region the occupant is moving. A script at the central computer calculates how many occupants are in the region. In figure 4 an occupant is leaving R_2 and entering R_3, this crossing is detected by node 3. The distance sensor a will be activated first (as it is the closest to R_2, the region the occupant is leaving), followed by activation of distance sensor b (closest sensor to R_3, the region the occupant is entering). Therefore, this occupant crossing for the occupant direction is stored as $a \rightarrow b$ on the hardware node. The occupancy count of R_3 will increase by 1 the occupancy of R_2 will decrease by 1.

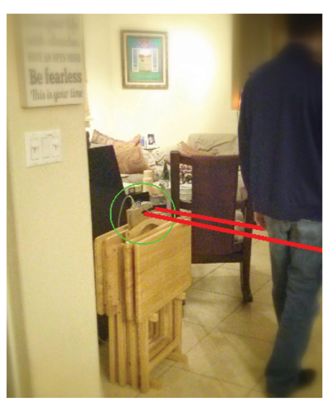
The other components of the node are the light sensors and the kWh plug load monitors. The light sensors were located outside the enclosures pointing towards the ceiling lights as shown in Figure 2. We use five light sensors used in this experiment. The first wan was located on node 2 to monitor hallway light in R_2, other was situated on node 3 to sense lighting in R_3, another was placed on node 4 to monitor lighting in R_1, another on node 5 for recording lighting in R_4 and finally one was located on node 6 to detect light in R_5.

The conducted experiment lasted around twenty hours, collecting occupant data using our hardware setup. In the experiment, we contrasted the found energy consumption data with consumption data from the local electrical company, *Florida Power and Light (FPL)*, to perform a comparison of our results with actual energy expenditure. The collected data addresses problems 1 and 2 from section 2. KWh consumption information was only collected for region 3 due to hardware availability. For analysis simplification, we will analyze data from regions R_3, R_4 and R_5 since they had the most reliable sensor readings during the deployment.

4.2 Classification of Wasteful States

As shown in Figure 6, noon (12 PM) was a peak for energy consumption(with 3.15 kWh), at that time the outdoor temperature was around 23° C. This time in highlighted in the data presented in Figure 5. From 12 PM to 1 PM region three (R_3), had 2 occupants and the temperature was 20° C. During the same period, both R_4 and R_5 were empty with a temperature of $22°C$ and $23°C$ respectively. The dots on Figure 5 show whether lights are turned on at that given time. In the figure, it is shown that see that lights were on in R_4 and R_5 for most of the period under consideration; however, these regions were empty. This results show that the regions are classified as a *wasteful state* as formulated in problem 1 above.

We have identified another wasteful state around 7 PM. During this time, the three regions monitored are empty for most of the time; however, the lights are on during this period. These states are classified as wasteful since they were empty and had lights on. The data from FPL in the same period (Figure 6) also shows that there were some appliances used causing excessive energy consumption at this time, confirming an overall wasteful state in the household.



An experiment where a resident is crossing in front of a node is shown. Drawn red lines represent the beams emitted by the IR distance sensors. The placement of the node is indicated with a green circle.

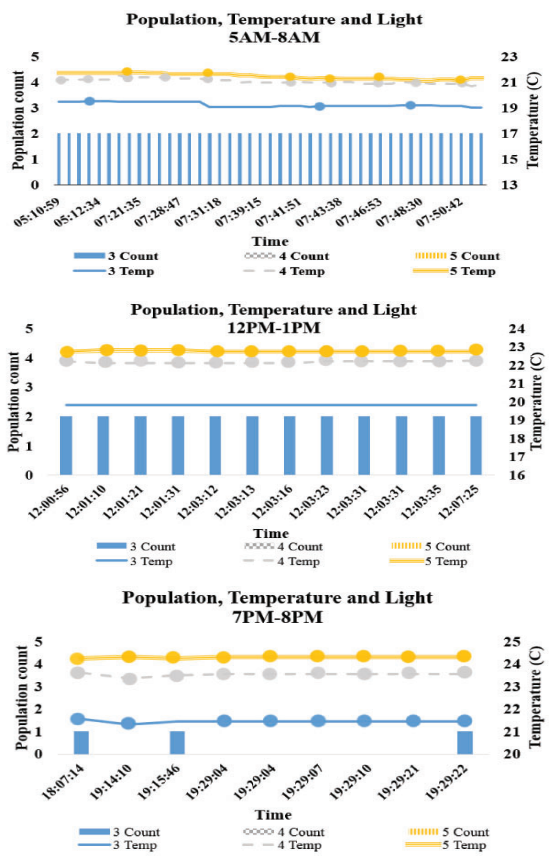
4.3 Wasteful Trajectory Classification

Beyond classifying wasteful energy states, we have also identified *wasteful trajectories*, as formulated in section 2.2 using the data collected from our experiments. For instance, during period from 5 AM to 8 AM, as shown in the Figure 5, R_4 is empty. A detailed view of the activity during this time indicates that an occupant was moving throughout the house and turning on lights. The occupant entered R_4 coming from R_1, turned the light on, then entered region R_5 and turned on a light. Therefore, this occupant created a wasteful trajectory for this period while traveling from regions $R_1 \rightarrow R_4 \rightarrow R_5$.

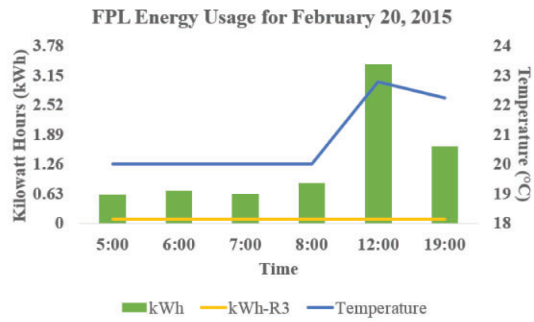
The results of these studies in this particular residence can also be used towards the solution of problem 5, where we can suggest policies that help save energy.

4.4 Trajectory Comparison and Ranking

To test our approach for trajectory ranking, we computed a set of rankings for some sample temperature data trajectories by using the *R Programming language* and obtained the results presented in Table I. Notice that the rankings presented are for temperature only. The same approach will work with other the other variables (e.e lighting and energy consumption). In our computed experiment, the rankings compare temperature trajectories against an ideal temperature trajectory. In our results, the fourth trajectory is the highest ranked trajectory since it is the most similar to the suggested trajectory.



Crossing data from 3 regions, dots on the temperature line shows whether a light is on/off in a region. Notice also that any time *"skipped"* in the x-axis indicates that no changes in that period of time.



Data obtained from the electric company along with outdoor temperature. Yellow line is represents the average kWh consumed by the home office.

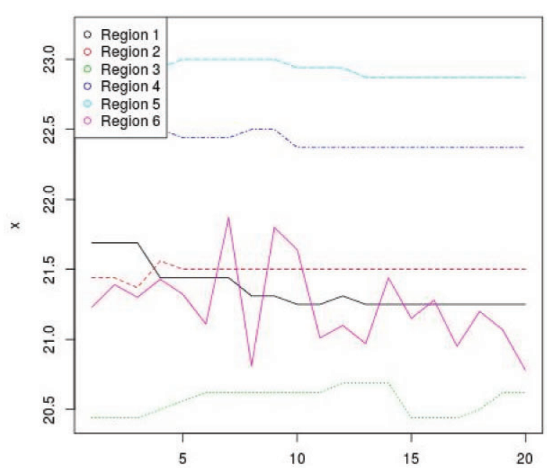
	Trajectories of Occupants using Temperature Data					Distance	Rank
	R_a	R_b	R_c	R_d	R_e		
1	30°	30°	30°	30°	30°		ideal
2	27°	26°	24°	26°	27°	1.19587	3
3	28°	28°	25°	22°	21°	1.393739	4
4	30°	30°	30°	30°	31°	1.001249	1
5	30°	30°	30°	30°	32°	1.042977	2

Table I: Ranking 4 temperature trajectories against a suggested trajectory. Occupancy movement is captured in the 5 regions ($R_a - R_e$) and the corresponding temperature values are recorded (in $C°$). The ideal trajectory, 1, is shown in blue and the highest ranked trajectory, 4, is shown in red font.

4.5 Trajectory Clustering

The clustering ideas were also tested with the data collected from our deployment. We tested our methodology only with temperature sensor data due to their availability, but the same procedure can be tested with all the data simultaneously.

We took a temperature time trajectory of size $t = 20$ for each of the 5 regions monitored, as illustrated in Figure 7. Since we had only 5 areas in our physical experiment and we wanted to test if our approach can be tested with more trajectories, we added 25 simulated trajectories for



Temperature data from regions 1 to 5, a set of to indexed observations are presented.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
9	6	6	7	2

Table II: Cluster sizes.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
15.796422	9.895883	13.828617	33.007514	5.966250

Table III: Within-cluster sum of squares.

a total of 30 trajectories to be clustered. We used the R package kernlab (Karatzoglou, Smola, Hornik, and Zeileis, 2004a) to test the clustering idea. In particular, we use their implementation of kernel k-means (Dhillon et al., 2004). The kernel k-mean algorithm is similar to the k-means algorithm but includes kernel weighting. This algorithm uses the kernel trick to help capture clustering relationships that are not linearly separable. We run the clustering procedure with the 30 trajectories and propose an initial number of 5 clusters. The results of the clustering procedure are shown in Tables II and III. Table II shows the number of elements assigned to each cluster and Tables II presents the sum of squares within each cluster.

4.6 Finding Energy Saving Policies

To find policies for energy saving, suppose that we can control the lighting components in each of the regions. In this, case, the action space would be $U = U_1 \times U_2 \times \ldots \times U_m$ where each of the components U_i of the *joint action space* represent a particular light.

We can, for example, propose a simple *reactive policy* (LaValle, 2006) that will react immediately to changes detected through sensors. These policies have the form $\pi : Y \to U$ where Y is an observation space. As an illustration of a reactive policy, we can model a situation where the lights turn off based on occupancy. In this case, the action space can be the lighting components of the region of interest $U_1 = \{off, on\}$, that can turn off lights in the region 1 for example. The observation space that this policy can use is the occupancy counting Y_o, which tells the number of occupants in a region. The policy will have the following form:

$$\pi = \begin{cases} off & \text{if } Y_o = 0 \\ on & \text{otherwise} \end{cases} \tag{3}$$

Another type of policies supported by our formulation is *time feedback policies* (LaValle, 2006) that will execute actions at specific times independent of sensing or building's state. As an illustration, consider a policy that will ensure that all lights on a room are turned off past midnight. This type of policies can model a scenario where occupants forget to turn the lights in a room, and the policy will ensure that the lights are off at a reasonable time. More concretely, let $T = [0, t_f]$ the time interval of the building execution monitoring, where t_f is the final monitoring time. This value can be preset or can be set to $t_f = \text{inf}$ if we are modeling a continuous monitoring time interval. Let, as in the example before, $U_1 = \{off, on\}$ the action that can turn off lights in the region 1. The policy will have the form $\pi : T \to U_1$ and can be defined as follows:

$$\pi = \begin{cases} off & \text{if } 0:0 \leqslant T \leqslant 5:00 \\ on & \text{otherwise} \end{cases} \tag{4}$$

where $0:0 \leqslant T \leqslant 5:00$ is the time interval from midnight to 5 AM, where lights should be off.

5. CONCLUSIONS AND FUTURE WORK

This paper formulated several problems related to detecting and preventing occupant behaviors leading to energy wastage. The problems were defined after formally defining a physical state space that represents a building and its features, which include lighting, temperature, plug load consumption, and occupant counting. Using these features, we were also able to define a series of physical state spaces of a building that evolve to produce a state trajectory. The first problem presented was to characterize wasteful energy states in the physical state space of the building, and the second problem was to describe associated wasteful trajectories. Action spaces were also presented to explain occupant behaviors, such as turning lights on and off. The next two problems were related to understanding this information and rank it. Our formulation led us to our final problem, the creation of energy savings plans to be able to suggest occupants for energy savings.

We defined a state space can realistically capture occupant and energy usage information from a building. This reduced space was presented to implement a case study utilizing our hardware nodes consisting of several inexpensive sensors. Using our sensor node system, we were able to identify several wasteful states and a wasteful trajectory that occurred during the execution of the experiment. We presented a simple implementation that is easy to duplicate in future investigations for various settings. Besides its low cost, it is also non-invasive as it does not rely on cameras or identification of building occupants.

We believe that the approach presented in this paper can contribute to efforts toward automated building operation and smart buildings. Although the majority of existing studies in these areas center on automating the operation of building systems (such as HVAC), our research has a different objective and is geared towards modeling, capturing, and analyzing occupant behaviors for the proactive monitoring of buildings' energy waste. Our results could lead toward more adaptive and dynamic approaches for automated building energy control.

Our near term work on this topic will focus on improving the accuracy of sensed data. We believe that there will be a trade-off between the quality of the obtained data and the price of our nodes. We will further study these trade-offs and try to test the accuracy of our measurements against more precise instrumentation. We will also study simple filtering algorithms that can detect outliers and false alarms and help to obtain better estimates from the sensor data. Another potential direction for future work is incorporating uncertainty in our models. In our hardware setup, although sensing output on lighting, temperature, and energy consumption may present temporary deviations, this may not alter the performance of our system dramatically. On the other hand, occupancy count errors may have a more significant impact. In our approach, we have calibrated and tested the directional detection sensors that are used for occupancy tracking; however, an improvement would be including error models to have reliable estimates.

Network protocols will take a more prominent role as we move our ideas from small residential buildings to commercial ones. Although our network setup was enough for the case study and we were able to relay information to a central location, if the area of energy monitoring is large, then different network topologies need to be proposed to accommodate this requirement. Additionally, the information that we are sending between the nodes is simple (temperature readings, lighting, crossings) and will likely not generate excessive traffic overhead.

Another compelling direction is finding the right locations for node placement. In our experiment, we placed our nodes based on their availability and the need to partition the environment into the regions of interest. However, in residential and commercial buildings, different placement of nodes will be necessary to cover the area of interest for energy monitoring. Related to this problem, we may need better spatial resolution, if certain behaviors need to be monitored with more details instead of at the region resolution.

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Triana Carmenate received the bachelors degree in information technologysoftware development and the masters degree in computer science from Florida International University, Miami, FL, USA, in 2014 and 2016, respectively. Her current research interests include mobile robotics, sensing, and energy analysis in buildings.

Md Mahbubur Rahman: obtained his PhD from Florida International University, School of Computing and Information Sciences. He also received a Masters Degree in Computer science from the same university and completed numerous projects on Robotics, Intelligent systems. His research interest includes robotics, motion planning, autonomous systems, smart building automation, vehicle navigation and multi robot formation. His solutions can be effective in military, long distance controlling, autonomous vehicle and sensor based robotics. He also has notable experience in medical robotics and has been granted with a US patent for works on hair transplantation robot. Dr. Mahub has published several journals and conference papers in top-ranked robotics, automation venus and most of his works are funded by the Army Research Office.

Diana Leante received the bachelors degree and the masters degree in Computer Science from Florida International University, Miami, FL, USA, in 2015 and 2017, respectively. Her research interests include cybersecurity, energy analysis in buildings, mobile robotics, and sensing.

Leonardo Bobadilla is currently an Assistant Professor in the School of Computing and Information Sciences at Florida International University. He is interested in understanding the information requirements for solving fundamental robotics tasks such as navigation, patrolling, tracking, and motion safety and has deployed test-beds that can track and control a large number of mobile units that require minimal sensing, actuation, and computation. He received his Ph.D. degree in Computer Science from University of Illinois at Urbana-Champaign. He has published several research papers journals and refereed conference proceedings in Robotics, Automation, and Sensor Networks. His research has been sponsored by the Army Research Office, Department of Homeland Security, and the Ware Foundation.

Ali Mostafavi received his Ph.D. degree in civil engineering from Purdue University, in 2013. He is an Assistant Professor with the Zachry Department of Civil Engineering, Texas AM University, College Station, TX, USA. He is the Director of the Urban Resilience, Networks, and Informatics Lab. His research focuses on a system-of-systems paradigm that bridges the boundaries between complex systems science, network theory, and civil infrastructure systems to address sustainability and resilience challenges.