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Towards Utilizing Internet of Things (IOT) Devices for Understanding Individual Occupants' Energy Usage of Personal and Shared Appliances in Office Buildings

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ABSTRACT

Energy consumption in office buildings highly depends on occupant energy-use behaviors and intervening these behaviors could function as a cost-effective approach to enhance energy savings. Current behavior-intervention techniques extensively rely on occupant-specific energy-use information at the workstation level and often ignore shared appliances. It is because an occupant typically has full responsibility for her workstation appliances energy consumption and shares the responsibility of the shared appliances energy consumption. However, understanding energy-use behavior of both workstation and shared appliances is necessary for applying appropriate behavior-intervention techniques. Despite this importance, there is still no practical and scalable method to capture personalized energy-use information of workstation and shared appliances since the conventional methods use plug-in power meters that are extremely expensive and difficult to maintain over long period of time. To address this gap, we propose a comprehensive occupant-level energy-usage approach which utilizes the data from the internet of things devices in office buildings to provide information related to energy-use behavior of workstation and shared appliances of each occupant in an economical and feasible manner. In particular, we introduce an energy behavior index which quantitatively compares individual occupants' energy-consuming data to identify high energy consumers and inefficient behaviors. Results from an experiment conducted in an office building equipped with internet of things devices demonstrate the feasibility of the proposed approach to classify occupants to different energy-usage categories. Our proposed approach along with appropriate behavior-intervention techniques could be used to impact occupant energy-use behaviors.

Keywords

Office buildings; Energy-use behavior; Energy Efficiency; Energy Intensity; Internet of things.

1. Introduction

Office buildings are the largest subsector of commercial buildings and they currently account for more than 15% of energy usage in the United States [1,2]. While the energy efficiency of building physical systems (e.g., HVAC&R, lighting, and water heating) has substantially been improved through technological advancements, energy savings through more energy-conscious behaviors are often ignored [3,4]. Adopting energy-saving behaviors among occupants is widely accepted as one of the most economical and feasible approaches to reduce the energy consumption of office buildings [5–12]. If occupants are educated to adopt appropriate energy-saving behaviors and practice such behaviors, it provides an opportunity for energy savings within all built environments [13].

Current behavior intervention techniques typically collect data from individual workstations in an office building to understand personalized energy-use behaviors at the workstation level. However, compared to workstation appliances (e.g., personal computers) which typically account for up to 10% of total energy consumption in an office building [13,14], shared appliances such as HVAC systems and ceiling lights consume a significantly bigger portion of the energy [15]; more than 38% and 25% of office buildings' total energy consumption is typically consumed by HVAC and lighting systems, respectively [1,16–19]. Thus, in order to impact occupant behaviors of shared appliances, energy-use behaviors of such appliances should be identified. In fact, without understanding comprehensive energy-use behaviors of occupants (i.e., energy usage of personal and shared appliances), there is a high possibility that behaviors are inappropriately interpreted and thereby modified incorrectly. However, the impact of occupants on shared appliances is relatively unexplored [20].

Utilizing additional sensors (e.g., plug-in meters) to collect energy-use information of personal and shared appliances is foreseeably a costly and difficult data collection procedure [13,21]. On the other hand, building/zone level energy data provided by existing metering devices includes information about the energy consumption of all appliances and systems [22–29] but since such devices typically provide low-temporal-resolution trend data, it is often difficult to directly associate their energy usage with individual occupants. In addition, such trend data could incorporate round-off errors during data analysis [5]. On the other hand,

building-level commercial off-the-shelf (COTS) internet-enabled electric meters (as a hardware system of the internet of things -IoT [30,31]) provide high-temporal-resolution energy data in real-time which could be utilized for understanding comprehensive energy-use actions of individual occupants. However, despite the advancement of such metering devices, there is still a gap in terms of the approach for associating individual occupants with such high-resolution energy-use data.

In response, we propose a novel cost-effective and feasible approach, comprehensive occupant-level energy-usage (COLE), which utilizes the data of IoT devices to identify energy-related behaviors of workstation and shared appliances in office environments. The approach uses occupancy data provided by existing Wi-Fi networks (as the major subset of IoT hardware systems [30,32–34]) to detect the first and last occupants in a daily working schedule. Then, the approach correlates the building-wide load data (provided by COTS internet-enabled meters) with the occupants' entry and departure events to provide occupant-specific energy-consuming data. In particular, an energy-use behavior index (EBI) is introduced to quantitatively compare individual occupants' energy consumption to identify high-energy consumers and inefficient behaviors. As the major contribution, this study benefits the conventional behavior-intervention efforts (which rely on workstation-level energy usage) through providing comprehensive energy-use behaviors of individual occupants.

2. Related Work

2.1. Behavior intervention in office buildings

The vast majority of research on occupant energy-use behaviors has focused on intervening energy-use behaviors to influence energy consumption in office buildings [13,35–43]. Understanding energy-use behaviors requires occupant energy-use data which is a key element in such studies to ascertain using an appropriate intervention technique. Depending on data sensing approaches for collecting energy-use data, conventional intervention techniques could be divided into two groups.

The first group includes studies that use additional newly-installed sensors (e.g., plug-in meters) to collect personalized energy-use information at the workstation level. Gulbinas et al. [44] collected energy-use data of individual occupants in a six-story commercial building through plug-in sensors. Coleman et al. [42] utilized individual data loggers to collect consuming information of individual occupants in offices. Likewise, Yun et al. [45] and Rafsanjani et al. [46] tracked individual occupants' energy usage in a university office. The individualized energy-use data of such studies only allows to understand personalized energy-use behaviors at the workstation level and no information regarding shared appliances is usually provided. In addition, the cost and installation difficulty of deploying plug-in sensors negatively impact large-scale implementation of such intervention methods.

The second group of studies uses building/zone level energy consumption to calculate the overall improvement achieved through an intervention technique. Staats et al. [47] provided feedback to the occupants of a university building and achieved 6% reduction in total energy consumption. The behavior-modification study conducted by Carrico and Reimer [48] on twenty four office buildings showed an average reduction of 7% in the building energy consumption. Since the building-wide load data provides information of all appliances/systems of a building, such studies' results could not directly represent the changes in the behavior of each occupant at workstation (personal) and non-workstation (shared) levels. Therefore, there is still a gap in a cost-effective method to provide the comprehensive energy-use information of each occupant in an office building.

2.2. Non-intrusive occupant energy-use monitoring

To address the data-sensing limitations associated with the conventional behavior-intervention techniques (Section 2.1.), researchers has recently started to develop non-intrusive load monitoring (NILM) techniques to deliver granular occupants' usage information. NILM has been utilized for more than two decades to utilize building-wide energy consumption for monitoring energy-usage of individual appliances [28,49–53] and recently, through adding occupancy information to conventional NILM approaches, the NILM concept has been extended from individual appliances to individual occupants. In residential buildings, Shahriar et al. [54]

used motion sensors for identifying residents' presence and determined HVAC usage associated with occupancy presence. Likewise, Yoo et al. [55] and Paradiso et al. [56] linked occupancy information of residential settings with building energy usage to identify in-use appliances and correlate their usage with occupancy presence. In commercial buildings, Rafsanjani et al. [57] developed NILM-based methods to identify individual occupants' energy-usage of workstation appliances usually utilized in office buildings. Despite the contribution made by these efforts to utilize NILM in tracking occupants' usage, they are (1) mainly limited to residential buildings, (2) do not directly provide the information (such as energy-use efficiency) required for intervention techniques, and (3) do not provide occupant-specific usage of shared appliances.

2.3. IoT-based occupant energy-use monitoring

Recent technological advances in internet-enabled sensors/devices, electric circuits, and wireless communication provide the possibility of IoT implementation in every web-based environment including residential, commercial, and industrial settings [58–61]. IoT utilizes low-cost COTS sensors to enable physical things to record/generate high-resolution real-time data on the internet [32,33]. With regards to the occupants' actions/usage, a growing number of recent studies have developed IoT-based approaches for sensing occupancy in the built environments. Jeon et al. [62] utilized particulate matter concentration and a point extraction algorithm to propose an IoT-based occupancy detection method in residential environments. Zou et al [63] developed a device free occupancy detection and crowd counting approach using Wi-Fi enabled IoT devices in commercial building. In addition, they [64] utilized such IoT devices to develop an occupant activity recognition approach for the commercial buildings. In the terms of occupant energy-usage, Fotopoulou et al. [31] proposed an energy-aware ecosystem which can support the development of IoT-based personalized energy management systems in commercial buildings. Rafsanjani and Ghahramani [65] demonstrated that how IoT infrastructure information displays occupants' energy-use patterns in commercial buildings. Despite the efforts of such studies, there is still much research to be done to understand the full potential of occupancy-related IoT applications. Specifically, the current research lags to provide personalized energy-use information.

2.4. Occupant energy-use behavior at entry and departure events

Previous studies [46,66–70] revealed that within office buildings, major energy-use actions typically occur at entry and departure events (i.e., start and end of working schedules). A building occupant usually stop by her workstation after entering to the building, and start consuming energy by changing the power status of her personal appliances (e.g., turn personal computer on). These appliances are then in-use during working hours and she turns those off before leaving the building (i.e., departure events). In addition, when she enters to the building as the first person or departure from the building as the last person, there is a possibility that she controls over shared appliances (specifically HVAC systems, fans, or/and ceiling lights) besides her personal appliances [46]. It is thereby expected that the energy-load changes observed in building-level energy data upon her entry/departure events as the first/last person, resulted from her energy-consuming behaviors.

Accordingly, assessing the building-wide load data at such entry/departure events could present an opportunity to understand an occupant's energy behavior of personal and shared appliances. Chen and Ahn [5] correlated the occupancy data of entry/departure events with building energy consumption and suggested that it is possible to identify the energy data of a single occupant from building-wide data. Rafsanjani et al. [57] demonstrated how personalized data at a workstation level could be extracted from building-wide data at entry/departure events. Despite such interesting studies, we still lack research in a method which could identify comprehensive energy usage at entry/departure events. This lack has mainly been resulted from low-temporal-resolution trend data (provided by conventional metering devices) which does not allow to properly associate the building energy usage with individual occupants. On the other hand, building-level COTS internet-enabled metering devices provide high-temporal-resolution energy data in real-time which can address the gap, but it has not been well addressed in the literature.

In response, we propose the COLE approach which economically provide personalized energy-use behavior data through existing/COTS IoT devices of office buildings. In this approach, a building's Wi-Fi networks (as an existing IoT device) identify the entry/departure

events and COTS internet-enabled building-level energy meters provide the building energy consumption. In addition, the approach uses the energy behavior index (EBI), for interpreting and comparing individual occupants' data in a quantitative manner to classify occupants to (1) high, medium, and low energy consumer categories based on their energy-use intensity and (2) efficient and inefficient behaviors based on their energy-use efficiency. An experiment conducted in an office building equipped with the IoT devices demonstrates the COLE feasibility for associating the data of the devices to classify building occupants. The following sections provide the detailed information of the approach, EBI, experiment, and results.

3. Comprehensive Occupant-Level Energy-Usage (COLE) Approach

The COLE approach consists of three major steps: (1) detecting first entry and last departure events in daily working schedule, (2) correlating building load data with the events, (3) normalizing the correlated load data to identify personalized energy usage. Figure 1 demonstrates the framework of the approach.

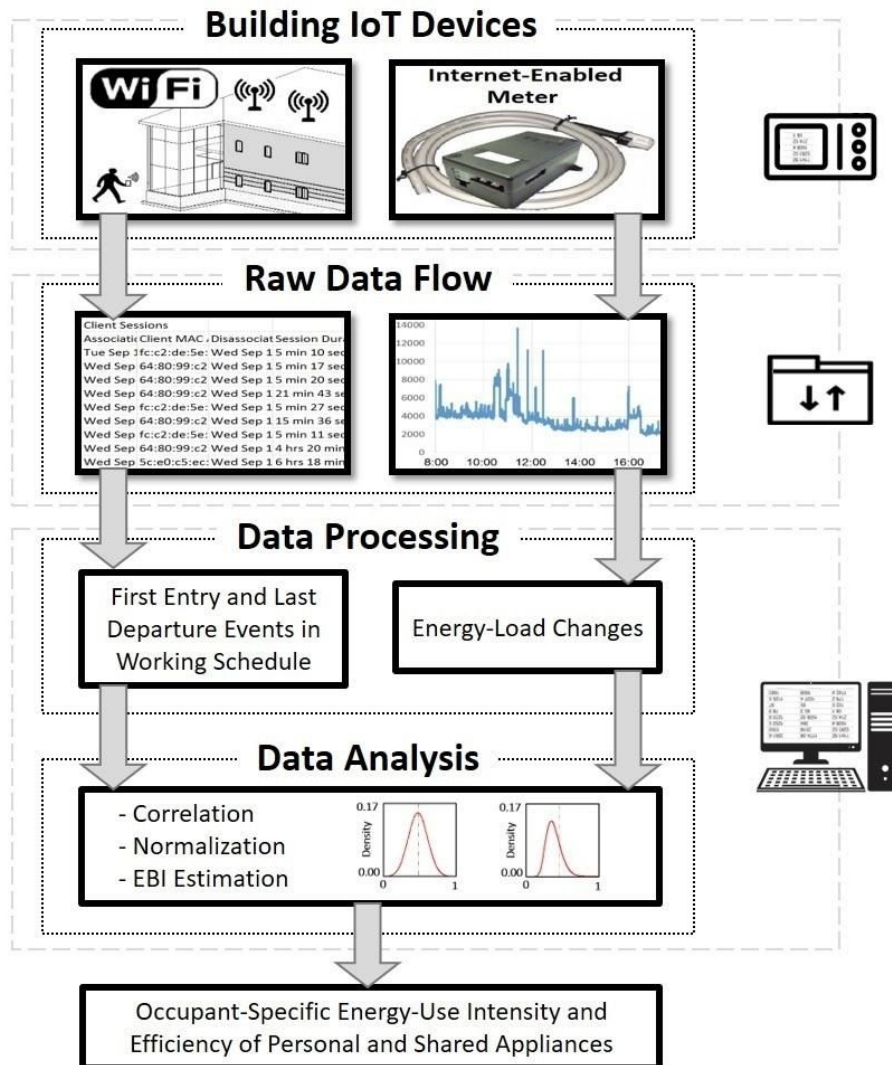


Figure 1. Comprehensive occupant-level energy-usage (COLE) framework

3.1. Detecting first entry and last departure events in daily working schedule

In the first step, COLE uses occupancy data collected from existing Wi-Fi networks of a building to identify who entered to the building as the first occupant as well as who left the building as the last occupant. The major difficulty in detecting the entry/departure events of individual occupants in office buildings arises from overlapping of multiple events at the beginning/end of working days. Given that, the resolution of occupancy detection is very important to properly

identify the events of an occupant of interest. In recent years, due to widely utilizing of Wi-Fi-enabled devices by occupants, Wi-Fi systems have predominately been utilized as a relatively new and cheap tool for occupancy detections in office buildings [71–79]. Wi-Fi-based occupancy sensing utilizes MAC addresses of mobile devices to differentiate between building occupants which determines occupancy presence with a high level of accuracy even in a large-sized building [80,81]. Thus, COLE utilizes a Wi-Fi based occupancy sensing methodology, where the entry/departure events of building occupants are detected based on passively tracking the Wi-Fi packets of the occupants' smartphones. Then, this information identifies the first entry and last departure events and accordingly the first and last occupants in a daily working schedule.

3.2. Correlating building energy load data with the events

In the second step, COLE collects the building load data through internet-enabled COTS metering devices of the building. Then, a time window captures the load data correlated with the events of the first and last occupants in each day. For this reason, the load data before and after each event is captured and energy-load changes are identified. Comparing the energy-load changes before and after an event could determines an occupant's actions at the event. The size of time window (T_{SIZE}) which captures load data before and after of each event, is empirically determined for a building.

3.3. Normalizing the correlated load data

To compare the behaviors of different building occupants and identify efficient and inefficient behaviors, normalized energy-load data is generally utilized [20,66]. In this context, the minimum and maximum values among all the correlated energy-load changes at the events of the occupants of the building (where they are the first/last persons) are utilized for the normalization process.

Figure 2(a) shows an example of normalized energy-load data correlated with an occupant's events when he/she is the first/last person in a building; the data for the figure was collected during a preliminary experiment conducted by the research team over two weeks in a

small office space with three occupants. In Figure 2(a), the box plots represent the range of energy-load changes at the events. In addition, the horizontal axis shows four segments at his/her entry/departure events; T_{SIZE} determines the size of each segment. The vertical axis also displays the normalized energy-load changes; 0 and 1 on the vertical axis represent the minimum and maximum values of energy-load changes correlated with the events of the three occupants, respectively. In addition, the mean line on this axis shows the arithmetic mean of the normalized data of the three occupants for when the office was occupied (i.e., Segment 2 and 3).

It is noteworthy that as Figure 2(a) shows, only the absolute magnitudes of the energy-load changes at the events are considered, regardless of they were positive (load increases) or negative (load decreases). In other words, considering the fact that occupancy-related load increases and decreases predominantly occurs at the beginning and end of working days, respectively [46,82], we only focused on the magnitude of energy-load changes. Figure 2(b) shows the distribution of data for the segments presented in Figure 2(a).

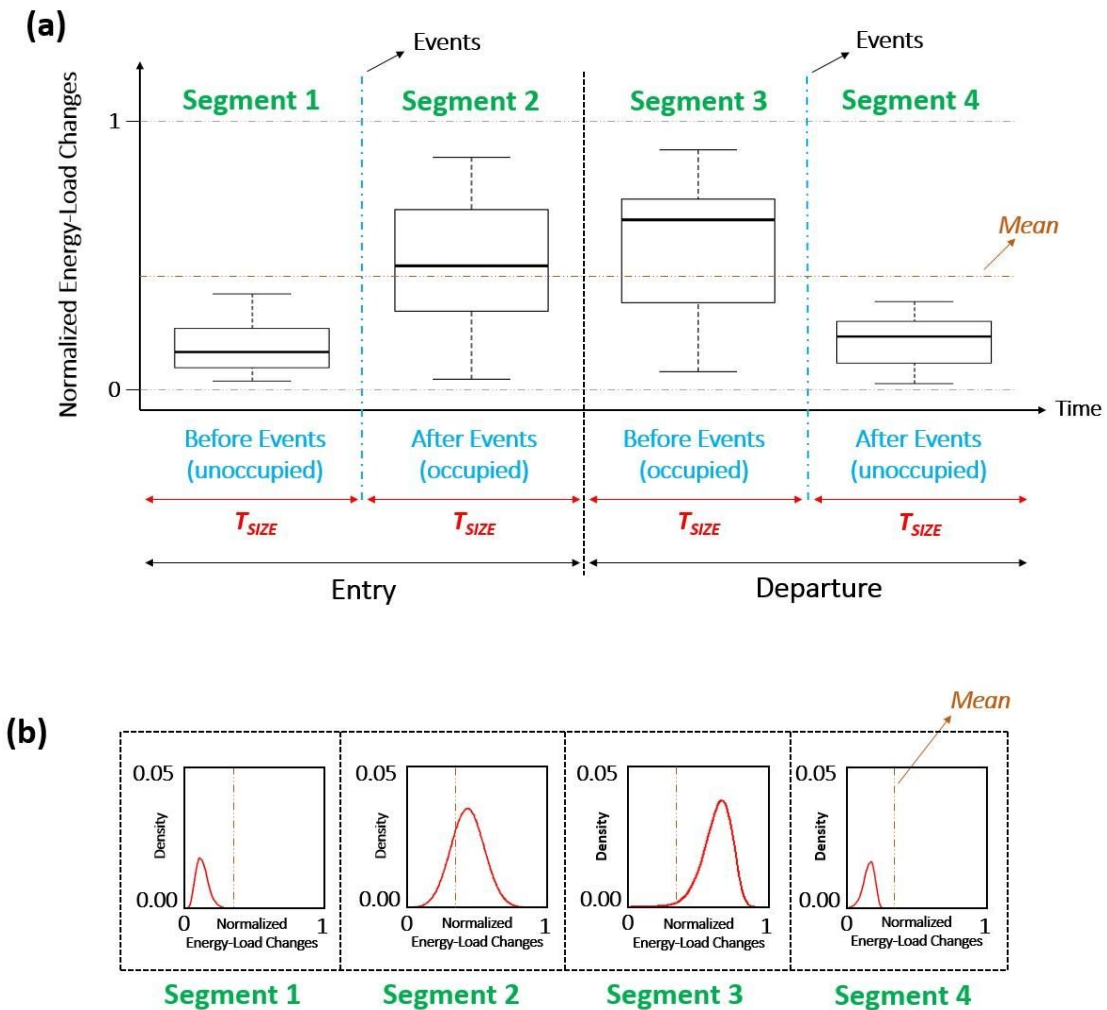


Figure 2. Example of normalized energy-load changes correlated with an occupant’s entry and departure events in two weeks: (a) box-plots of the data, (b) distribution of the data

3.3.1. Energy Behavior Index (EBI)

The EBI is defined as the perpendicular distance between the center of a distribution [83] and the mean line. Figure 3, as an example, shows the EBI for Segment 3 and 4 of the data presented in Figure 2(b); the plus and minus signs of the EBIs represent the position of the center of the distribution with reference to the mean line. Since the mean line shows the average value of normalized energy-load changes of all the occupants at the events for when office is occupied

(i.e., Segment 2 and 3), the EBI particularly allows to compare the data of an occupant with her peers' data in a quantitative manner.

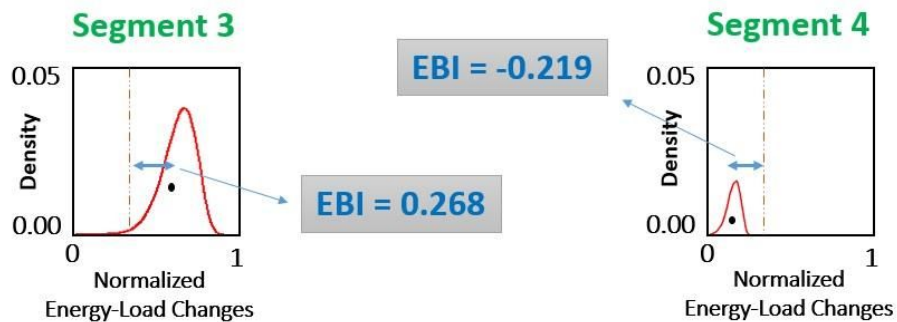


Figure 3. Energy behavior index (EBI) for Segment 3 and 4 of data presented in Figure 2(b)

Several energy-use behavior metrics (e.g., energy-use intensity, energy-use entropy, and energy-use efficiency) [66,67,84–91] have been introduced to classify building occupants to different categories such as low and high energy consumers; however, the literature lacks to provide a metric for interpreting the behaviors occurring at the entry/departure events. In response, COLE uses EBI to segment and classify building occupants based on their energy-use intensity and energy-use efficiency at these events. Since energy-consuming data represents energy-use intensity [66,67,84] and since EBI is constructed based on energy-consuming data (see Figure 2), EBI directly displays energy-use intensity. In addition, considering the fact that comparing individual occupant's energy-load data correlated with the entry events (or departure events) determines occupants' energy use efficiency [3,46,92], EBI quantitatively compares the load data before/after an event to assess the energy-use efficiency of occupants compared to her peers. For this reason, we define a compiled EBI as the absolute value of horizontal distance between the centers of the distributions of the entry events (or the departure event) when the distributions overlay each other. Figure 4 displays the compiled EBI for the data presented in Figure 3. It is noteworthy that due to the plus and minus signs of EBIs, the compiled EBI of the

departure events is estimated by subtracting the EBI of Segment 4 from that of Segment 3. Accordingly, for the entry events, the subtracting the EBI of Segment 1 from that of Segment 2. Figure 5 presents the pseudocode of the normalization process and estimation of EBI and compiled EBI.

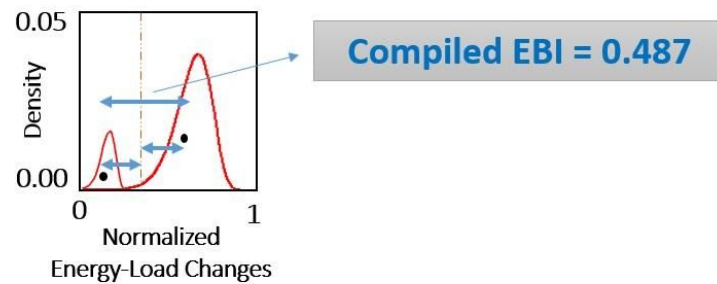


Figure 4. Compiled EBI for data presented in Figure 3

input : EC

```

normalized.EC ← ∅, Center ← ∅, EBI ← ∅,
entry.compiledEBI ← ∅, departure.compiledEBI ← ∅
function
  min.value ← minimum (ECji); j ∈ {1,2, 3,4}; i ∈ {1,2, ..., n}
  max.value ← maximum (ECji); j ∈ {1,2, 3,4}; i ∈ {1,2, ..., n}
  for Oi, i ∈ {1,2, ..., n} and Sj, j ∈ {1,2, 3,4} do
    normalized.ECji ← (ECji - min.value)/(max.value - min.value)
  end for
  mean.value ← arithmetic mean (normalized.ECji); j ∈ {2, 3}; i ∈ {1,2, ..., n}
  for Oi, i ∈ {1,2, ..., n} and Sj, j ∈ {1,2, 3,4} do
    f(j) ← construct distribution for normalized.ECji
    Centerji ← center f(j)
    EBIji ← (center f(j) - mean.value)
  end for
  for Oi, i ∈ {1,2, ..., n} do
    entry.compiledEBIi ← (EBI2i - EBI1i)
    departure.compiledEBIi ← (EBI3i - EBI4i)
  end for
end function
ouput : EBI, entry.compiledEBI, departure.compiledEBI
ECji : a set of energy.load changes for segment j of occupant i      Oi : occupant i      Sj : segment j
normalized.ECji : a set of normalized energy.load changes for segment j of occupant i

```

Figure 5. Pseudocode of normalization process

To demonstrate the feasibility of the proposed approach, we selected an office building equipped with IoT devices to present the approach process and to explain how the approach results could lead to classifying occupants to various categories based on their energy-use intensity and efficiency. The following sections describe the experiment and results and discuss how the results identify the energy usage of individual occupants.

4. Experiment

4.1. Test bed

To illustrate the COLE functionality, an experiment was designed and conducted in an office building during a six-week period in Summer 2018. Figure 6 presents the floor plan of the building. Within the building, there were ten single-occupant workstations, one director room, one meeting room, one copy/storage room, one kitchen, and one mechanical room. Each

workstation included one desktop computer which was similar to the computers of other workstations. In addition, there were several shared appliances including a variable air volume (VAV) system, ceiling lights, fans, scanners, printers, coffee makers, a refrigerator, and a microwave. All appliances within the building (except the VAV system) were manual switching which allowed building occupants to control over a variety of end-users. In particular, the ceiling lights of the main space (where the workstations were located) were on four separate circuits with four separate switches. Also, two levels of brightness were set for all the ceiling lights of the building.

In addition, the total number of occupants was ten in the building over the experiment and they agreed to participate in this study. Due to the similarity of the workstation and shared appliances controlled over by occupants at the building, approximately similar energy-use data might have expected at entry events as well as departure events.

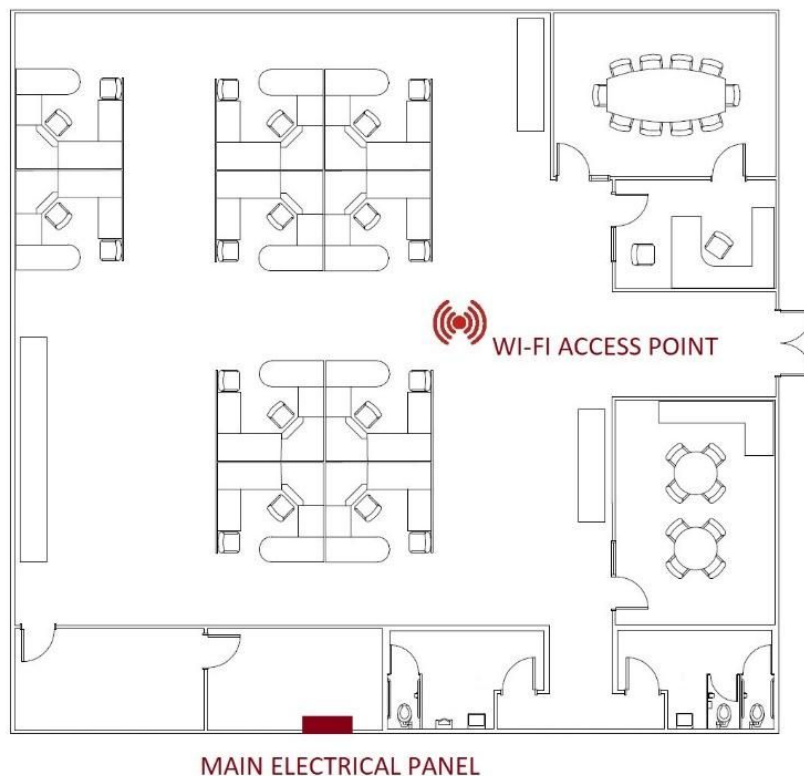


Figure 6. Floor plan of the office building

4.2. IoT devices and data collection

Building-wide energy-load data with one-second interval resolution was collected by the building meter. The building was renovated in 2018 and during the renovation, an advanced internet-enabled meter was installed inside the main electrical panel of the building (see Figure 6) which covered all circuits, outlets, systems, and appliances of the building. The meter, “TEDPro”, was designed for three-phase electrical service and commercially certified to provide data within $\pm 1\%$ of displayed value; the meter sampling rate was 1024 KHz. In addition, the meter included two separate internet-enabled parts: one measuring transmitting unit and one energy control center. Figure 7 shows the measuring transmitting unit which was installed inside the electrical panel. This unit acted as a data logger and collected energy-load data in real-time and sent the data through the building network to the energy control center installed at the director room. The collected energy-load data included active power (kW), voltage (V), and cost at one-second interval resolution.

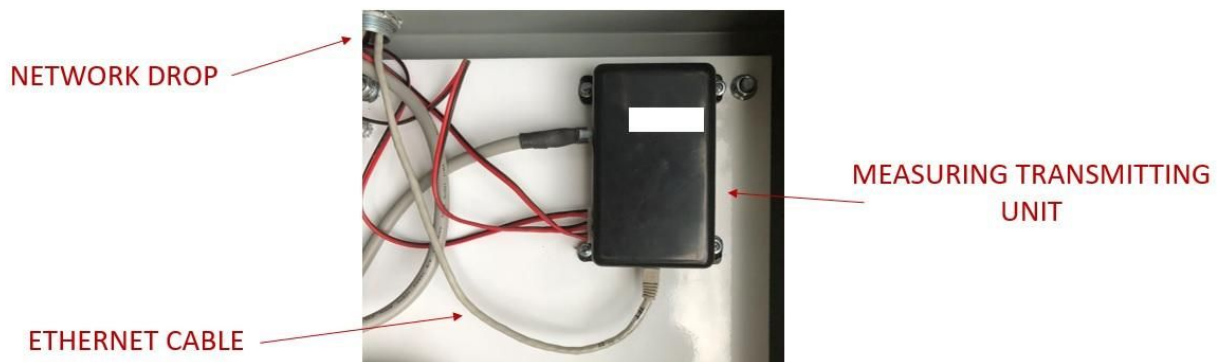


Figure 7. Measuring transmitting unit

The energy control center received the data through the building network and a footprint software [93] embedded in the energy control center was set to deliver the real-time load data to the desktop computer of the director of the building. This allowed the director to monitor the

usage as well as to save the data on his/her desktop computer as CSV files. The director shared the CSV files with us.

To collect Wi-Fi data, we used the data provided by the ceiling-mounted Wi-Fi access point of the office building (see Figure 6). The access point supported IEEE 802.11 standard and recorded transmitted packets of Wi-Fi enabled devices at one-second interval resolution. Similar to the smart meter, the director was able to save daily data of the access point on his/her computer as CSV files (one file per day) and thereby, shared the data with us.

4.3. Data analysis

The data analysis process began by checking the accuracy of the energy-load data where we used the voltage (V) information and a Kalman method [94] to identify and filter the noise. Then, we analyzed the active power (kW) information of the events, while focusing on the entry/departure events. In this context, based on the collected energy-load and occupancy data as well as the building director's suggestion, we selected 30-min time intervals at the beginning and end of each daily working schedule for data analysis step. In other words, the working hours of the building were 9:00 a.m.-6:00 p.m. and we used the data in 8:45-9:15 a.m. and 5:45-6:15 p.m. intervals for the data analysis.

Accordingly, the Wi-Fi data of the 30-min intervals was checked and ten MAC addresses which usually displayed in daily data was selected as the MAC addresses of the ten human subjects of this study. It is worth mentioning that due to the privacy concern, we did not ask the occupants to share the MAC addresses of their smartphones with us, and did not collect ground-truth occupancy data. However, before the experiment, we conducted a survey which revealed that the occupants usually carried their smartphones every day and used the building wireless network while working. The occupants also mentioned that they used other Wi-Fi enabled devices (e.g. laptops) less often than their smartphones. Accordingly, we considered the ten MAC addresses usually displayed in the Wi-Fi data with highest number of occurrences as the addresses of the occupants' smartphones and randomly assigned one of the MAC addresses to one of the occupants; this allowed us to protect the occupants' privacy.

Finally, the first connection of a day (in the 8:45-9:15 a.m. interval) among the MAC addresses was identified and energy-load data was correlated to this event. Similarly, the last connection of a day in the 5:45-6:15 p.m. interval was identified and load data was correlated to the event. Accordingly, this process was checked for all the working days during the experiment. In addition, based on the data, building, and information/recommendations received from the director of the building, T_{SIZE} was empirically set on 210 seconds for the entry and departure events of all the occupants in this study.

5. Results and Discussion

5.1. EBI results

Table 1 lists the EBIs of the occupants. As the table shows, there was no data for the entry events of Occupant 7 which means this occupant never entered to the building as the first person during the experiment. Likewise, Occupant 3 and 10 never left the buildings as the last person during the experiment.

Table 1. Energy Behavior Index (EBI) for the occupants of the building

Occupant	EBI			
	Entry Events		Departure Events	
	Segment 1	Segment 2	Segment 3	Segment 4
1	-0.153	0.011	-0.009	-0.093
2	-0.153	0.046	0.126	-0.149
3	-0.153	0.027	NA**	NA**
4	-0.153	0.033	0.082	-0.123
5	-0.153	0.093	0.108	-0.111
6	-0.153	0.043	0.058	-0.077
7	NA*	NA*	0.041	-0.056
8	-0.153	0.035	0.037	-0.064
9	-0.153	0.068	0.049	-0.095
10	-0.153	0.031	NA**	NA**

*The occupant never entered to the building as the first person during the experiment.

**The occupant never left the building as the last person during the experiment.

Table 1 demonstrates similar EBIs for Segment 1 of the occupants. These segments present the energy-load changes for the unoccupied time right before the entry event of the first person which means the segments present the background changes happened during night (due to some in-use appliances such as the refrigerator). Since the workstation appliances (i.e., desktop computers) left on by occupants typically go to sleep modes after a short time and the state of shared appliances (e.g., ceiling lights) left on at night is not typically changed during unoccupied time, occupant energy actions have typically no effect on background energy-load changes right before the first entry event. Therefore, the similar EBIs for Segment 1 could be expected for all occupants at a building which was also seen in our data.

Segment 2's EBIs represent the energy-load changes caused by the occupant who entered the building as the first person. A larger EBI for an occupant, compared to his/her peers, might suggest that he/she controlled over shared appliances more than the others. Consequently, Occupant 5 might have controlled over shared appliances more compared to the peers.

Segment 3's EBIs represent the energy-load changes caused by the occupant who left the building as the last person. A larger EBI for an occupant, compared to his/her peers, might suggest that he/she was more concerned about in-use appliances and turns in-use appliances/systems off before leaving the buildings (energy-saving behaviors). Accordingly, Table 1's data could suggest that Occupant 2 followed the most efficient energy-saving behavior.

Conversely, a smaller value of EBI of Segment 3 for an occupant might indicate that he/she follows non-energy saving behavior. Table 1 shows that Occupant 1 has a very low EBI compared to the peers. The minus sign of his/her EBI particularly demonstrates that the average of his/her energy-load changes at departure events is lower than the average of energy-load changes caused by the other occupants at entry/departure events. Consequently, it could be interpreted that Occupant 1 typically followed non-energy saving behaviors over the experiment; such results are significantly useful to find target occupants for behavior modification. Therefore, a small value of Segment 3's EBIs might be able to identify occupants who follow non-energy-saving behaviors.

Segment 4's EBIs represent the energy-load changes for the unoccupied time after departure events of the last persons. The smaller values of EBI for this segment might suggest that an occupant turned off all in-use appliances/system before his/her departure events (since there are small energy-load changes after his/her departure events). Based on the Table 1 results, it may suggest that Occupant 2 turned off all in-use appliances/systems before his/her departure events.

In addition, if the last person turns off all in-use appliances/systems, his/her energy-load changes in Segment 4 could be expected to be close to those in Segment 1. Therefore, approximately a similar EBI could be expected for Segment 1 and 4. Those segments' EBIs for Occupant 2 might therefore reveal how much he/she were careful to turn off in-use appliances before his/her departure events. Therefore, (1) smaller values of Segment 4's EBI and (2) the similarity of EBIs of Segment 4 and 1, could demonstrate the energy efficient behaviors.

Although the comparison between EBIs of Segment 1 and 4 could be helpful to identify energy efficient/inefficient behaviors, such comparisons between the value of EBIs of Segment 2 and 3 could not provide valuable information. Rafsanjani et al. [46] statistically revealed that office building occupants do not typically represent similar energy-load changes during occupied times at entry and departure events, regardless of whether they follow energy-saving behaviors or not. Therefore, comparing the EBIs of Segment 2 and 3 of an occupant could not lead to a correct interpretation regarding his/her energy-use behavior.

5.2. Energy-use intensity

Energy-use intensity generally measures the amount of energy an occupant using during working hours and enables classifying building occupants to distinct categories of energy-consuming levels, which are generally considered: high energy consumer (HEC) category, medium energy consumer (MEC) category, and low energy consumer (LEC) category [20,67,84,89]. Understanding the differences between the three categories in a building depends to several factors including the building type, envelope, systems, occupants' duties, and working hours. Accordingly, studies [95–99] highlighted that such categories are building-specific and thereby, are needed to be determined on a case by case basis.

In this paper, based on our approach, case study, the current literature methodologies/suggestions [20,67,84,89], and the discussion with industry professionals and the building director, we finally considered a 20 percent range for HEC, 60 percent range for MEC, and a 20 percent range for LEC. Figure 8 shows these categories for the occupants. Since the data of Segment 2 and 3 represent the amount of energy used/controlled by the occupants when office was occupied, these segments demonstrate the energy-use intensity. In addition, since there were no data for the entry events of Occupant 7 and the departure events of Occupant 3 and 10 (see Table 1), no data points are provided for these events in Figure 8.

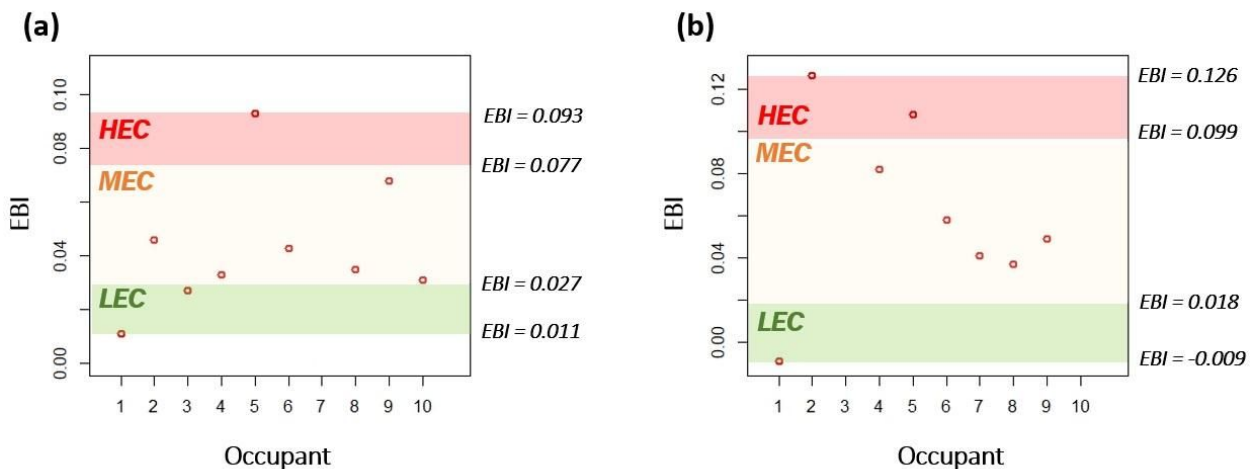


Figure 8. EBI for the occupants: (a) Segment 2, (b) Segment 3

(HEC: high energy consumers, MEC: medium energy consumers, LEC: low energy consumers)

Figure 8(a) displays the energy-use intensity at entry events. Since occupants had similar desktop computers at workstations, the results show that Occupant 1 controlled over the shared appliances less compared to his/her peers which might suggest that this occupant did not follow energy-saving behaviors regarding the shared appliances. Conversely, Occupant 5 had more control over shared appliances at the entry events. Accordingly, since our approach particularly investigates comprehensive energy-use behavior only at entry/departure events, Figure 8(a) suggests that LEC and HEC at entry events indicates low and high control over shared

appliances, respectively. Similarly, Figure 8(b) results in similar interpretation between Occupant 1's and 5's behaviors (Occupant 5 controlled over shared appliances more than Occupant 1).

Several studies on energy-use behaviors at the workstation level (personal appliances) [13,66,67] have indicated that energy-use intensity and accordingly, HEC, MEC, and LEC categories do not necessarily reflect energy-saving and non-energy-saving behaviors but might lead to other conclusions about occupants' behaviors (such as appliance replacement/upgrade for the HEC category). With this in mind, our work identifies HEC as the people who are concerned about building energy consumption. Accordingly, the identified LEC in our work could be targeted for feedback prompting energy saving in office buildings.

5.3. Energy-use efficiency

By utilizing daily workstation-level data (collected through individual sensors), researchers [66,67] have defined energy-use efficiency as a function to assess how often a person unnecessarily consumes energy at her workstation. However, in this study, we used the compiled EBI (see Figure 4) which we believe allowed to assess the occupant efficiency not only of workstation appliances but also of shared appliances. As mentioned in Section 3.3.1., the compiled EBI allowed to compare behaviors occurring before and after of an event; this comparison has been demonstrated [13,46,92] to benefit in classify occupants to efficient and inefficient behaviors. Table 2 lists the compiled EBIs of the occupants for the departure events. Since the collected data presented similar EBIs for Segment 1 of the occupants (see Table 1) and since departure events are considered as the critical events to understand energy-use efficiency [3,46,92], we focused on the departure events of our case study to investigate the functionality of the compiled EBI.

Table 2. Compiled EBI for departure events

Occupant	Compiled EBI
1	0.084

2	0.275
4	0.205
5	0.219
6	0.135
7	0.097
8	0.101
9	0.144

Similar to the energy-use intensity, the differences between efficient and inefficient behaviors are building-specific and should practically be determined. Given that, based on the literature suggestion [66,67], the characteristics of the case study, and the industry recommendations, we finally considered two equal quantiles for efficient and inefficient behaviors in this study. In fact, the industry professionals pointed out that since the focus of this research is identifying behaviors and displaying the functionality of compiled EBI and since no behavior-intervention technique has been implemented in this research, two equal quantiles could properly fit the goals of this study. Accordingly, considering the smallest and largest compiled EBIs are 0.084 and 0.275 (see Table 2), compiled EBI of 0.180 was considered as the boundary of efficient and inefficient behaviors. Figure 9 shows how these quantiles classify the occupants.

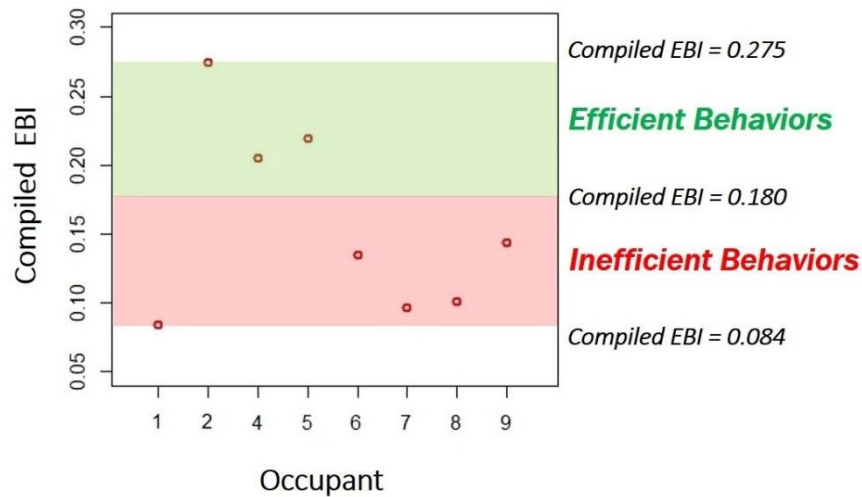


Figure 9. Compiled EBI for the departure events

Larger compiled EBI indicates more efficient behavior compared to peers and accordingly, the figure suggests that Occupant 2 follows the most efficient behavior. In addition, five occupants were tagged with inefficient behaviors that could be targeted for behavior modification. Furthermore, while the results of energy-use intensity (see Figure 8-b) provide distinct behaviors for Occupant 1 compared to Occupant 7, and 8, these occupants showed approximately similar compiled EBIs. This reveals how efficiency of energy-use behaviors could be distinct from the intensity of the behaviors. As literature suggests [13,66,67], we discussed in Section 5.2., and per recommendations received from the industry professionals (during this study), we believe that compared to energy-use intensity, studying energy-use efficiency results in more proper interpretations regarding energy-use behaviors.

In this study, considering that occupants have similar desktop computers (i.e., personal appliances), similar energy-use behaviors at workstation-level could be expected. Given that, as Figure 9 shows, the compiled EBI particularly reveals that the occupants' energy-use behaviors of shared appliances were considerably different (while the occupants had similar access/control over shared appliances such as ceiling lights). This thereby highlights the importance of studying comprehensive energy-use behaviors (i.e., energy use behavior of personal and shared

appliances) of individual occupants in a built environment to modify inefficient behaviors; however, this point has not been studied well in the literature [13,20,66,67,84,89]. When such individualized behaviors are determined incorrectly, feedback outcomes result in negative influences on energy-use behaviors [37,41,100].

5.4. Discussion of impact

This study introduced the COLE approach which utilizes the data from existing Wi-Fi networks and COTS internet-enabled electric meters of an office building to provide individual occupants' energy-use intensity and efficiency information regarding personal and shared appliances. To show the functionality of the approach, the energy-use behaviors of ten occupants in an office building were tracked. Such small-sized office buildings (with up to twelve residents [101]) are the most common type of offices in the United States and worldwide [102,103] and offer the most ideal test beds for studying energy-use behaviors [13,104]. Accordingly, the results properly revealed the capability of the approach to provide individualized energy-use information at the occupant-level.

While the literature [20,67,84,89] utilizing the data of entire working days to estimate intensity and efficiency metrics for the individual occupants, we (through developing and utilizing EBI and compiled EBI) revealed that the building-wide energy-use data at entry and departure events could explain these metrics. In addition, even if this study only checked three and two categories for energy-use intensity and efficiency, respectively, the proposed approach could be extended to various categories for each metric. This particularly allows to understand occupant usage in office environments with a reasonable accuracy and benefits to produce better informed, contextually aware feedback.

Conventional approaches predominantly utilize individual plug-in meters at workstations to track personalized energy-use information in office buildings. While this provides high-resolution data of workstation appliances, no information of shared appliances is provided. On the other hand, COLE is able to provide occupant-specific information of shared appliances. Accordingly, our proposed approach could be integrated with the conventional approaches in order to address their limitation. This allows to collect information regarding shared and personal

appliances in office buildings equipped with individual plug-in meters and offers a better solution for a comprehensive energy behavior monitoring.

Recently, researchers [62–64] have developed IoT-based occupancy-sensing approaches with the ultimate goal of enhancing energy saving of built environments. In particular, such approaches are typically developed in a way to use Wi-Fi networks/systems for communication layers and predominately attempt to collect data from existing or COTS internet-enabled sensors in built environments. With these in mind, our study benefits into such approaches through displaying (1) how Wi-Fi network information leads to tracking energy-use behaviors, (2) how the information of the existing or COTS occupancy/energy sensors (with different degrees of granularity) of a building could be utilized to understand individualized energy-use behaviors, and (3) how energy-use intensity and efficiency metrics for individual occupants could be developed based on total building energy consumption.

As mentioned, the occupant privacy is considered as a major concern in implementing such occupancy-related approaches. Accordingly, we did not collect the personalized information of occupants to identify the users of MAC addresses. This could prevent providing individualized feedback to individual occupants. To address this issue in a feedback mechanism, we recommend the future studies to develop a web application (as part of a feedback mechanism) and collect the smartphones MAC addresses of building occupants through the application. In this content, an occupant enters her smartphone MAC address to the application (without entering other personal information such as name and room number) and the application generates a random unidentifiable code and assigns it to the occupant; this process is done in the back-end system of the feedback mechanism. Then, this code is used to track the occupant, estimate her EBI and compiled EBI, and identify her behavior categories. Finally, tailored feedback is provided to her through her unidentifiable code and the web application. Accordingly, while this process allows to modify energy-use behaviors, it does not identify who the owners of MAC addresses are which allows to protect the occupants' privacy. In addition, by identifying the MAC addresses of the permanent occupants of a building through the application, the proposed approach could be implemented even in large-sized office buildings; a great portion

of occupants in such buildings are temporary and their Wi-Fi connections/disconnections could distort data analysis.

6. Conclusion

This paper proposed a novel approach that utilizes the information of existing or/and commercial off-the-shelf internet of things devices of office buildings to deliver comprehensive energy-use behaviors of individual occupants. The experimental results revealed the effectiveness of the approach in utilizing the data of internet of things devices to assess individual occupants' energy-use intensity and efficiency. Current behavior modification efforts extensively rely on individual plug-in sensors which typically lead to understanding of occupant's behaviors at a workstation level. However, our approach utilizes building energy consumption for comprehensive understanding of individual occupants' energy-use behaviors of both workstation and shared appliances.

We believe that our proposed approach is scalable to a wide range of office buildings for understanding personalized energy usage. In addition, this approach contributes to occupancy-related internet-of-things-based research via displaying how energy-use intensity and efficiency of individual occupants could be extracted from the internet of things devices of a building. Through utilizing the findings of this study, our future work focuses on developing an internet-of-things-based energy assistant tool which would be able to track individual occupants' energy-use actions, to identify inefficient behaviors, and to drive energy-saving behaviors.

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References

- [1] U.S. Energy Information Administration, Annual Energy Review, (2014).
- [2] J. Lausesen, Energy Efficiency Requirements in Building Codes - Policies for New Buildings, (2008).
- [3] O.T. Masoso, L.J. Grobler, The dark side of occupants' behaviour on building energy use, *Energy Build.* 42 (2010) 173–177. doi:10.1016/j.enbuild.2009.08.009.
- [4] A. Ghahramani, G. Castro, B. Becerik-Gerber, X. Yu, Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort, *Build. Environ.* 109 (2016) 1–11. doi:10.1016/j.buildenv.2016.09.005.
- [5] J. Chen, C. Ahn, Assessing occupants' energy load variation through existing wireless network infrastructure in commercial and educational buildings, *Energy Build.* 82 (2014) 540–549. doi:10.1016/j.enbuild.2014.07.053.
- [6] H.N. Rafsanjani, Factors Influencing the Energy Consumption of Residential Buildings: A Review, in: *Constr. Res. Congr. 2016*, American Society of Civil Engineers, 2016: pp. 1133–1142. <http://ascelibrary.org/doi/abs/10.1061/9780784479827.114> (accessed May 25, 2016).
- [7] H.N. Rafsanjani, Non-intrusive Occupant Load Monitoring in Commercial Buildings, Ph.D., The University of Nebraska - Lincoln, 2018. <https://search.proquest.com/docview/2088057228/abstract/638E697FC575442CPQ/1> (accessed February 28, 2019).
- [8] Karji Ali, Woldesenbet Asregedew, Rokooei Saeed, Integration of Augmented Reality, Building Information Modeling, and Image Processing in Construction Management: A Content Analysis, *AEI* 2017. (n.d.) 983–992. doi:10.1061/9780784480502.082.
- [9] A. Ghahramani, M. Zhu, R.J. Przybyla, M.P. Andersen, P.J. Galicia, T.E. Peffer, H. Zhang, E. Arens, Measuring air speed with a low-power MEMS ultrasonic anemometer via adaptive phase tracking, *IEEE Sens. J.* (2019) 1–1. doi:10.1109/JSEN.2019.2920648.
- [10] A. Ghahramani, K. Dutta, B. Becerik-Gerber, Energy trade off analysis of optimized daily temperature setpoints, *J. Build. Eng.* 19 (2018) 584–591. doi:10.1016/j.jobe.2018.06.012.
- [11] A. Ghahramani, J. Pantelic, C. Lindberg, M. Mehl, K. Srinivasan, B. Gilligan, E. Arens, Learning occupants' workplace interactions from wearable and stationary ambient sensing systems, *Appl. Energy.* 230 (2018) 42–51. doi:10.1016/j.apenergy.2018.08.096.
- [12] Rafsanjani Hamed Nabizadeh, Ahn Changbum, Chen Jiayu, Analysis of Delay Interval and Energy-Load Variation for Non-Intrusively Extracting Occupant Energy-Use Information in Commercial Buildings, *Comput. Civ. Eng.* 2017. (n.d.) 191–197. doi:10.1061/9780784480847.024.
- [13] H.N. Rafsanjani, C.R. Ahn, M. Alahmad, A Review of Approaches for Sensing, Understanding, and Improving Occupancy-Related Energy-Use Behaviors in Commercial Buildings, *Energies.* 8 (2015) 10996–11029. doi:10.3390/en81010996.
- [14] K. McKenney, M. Guernsey, R. Ponoum, J. Rosenfeld, Commercial Miscellaneous Electric Loads: Energy Consumption Characterization and Savings Potential in 2008 by Building Type, (2010).

- [15] A. Ghahramani, S.A. Karvigh, B. Becerik-Gerber, HVAC system energy optimization using an adaptive hybrid metaheuristic, *Energy Build.* 152 (2017) 149–161. doi:10.1016/j.enbuild.2017.07.053.
- [16] A. Ghahramani, K. Zhang, K. Dutta, Z. Yang, B. Becerik-Gerber, Energy savings from temperature setpoints and deadband: Quantifying the influence of building and system properties on savings, *Appl. Energy.* 165 (2016) 930–942. doi:10.1016/j.apenergy.2015.12.115.
- [17] energy.gov.au, HVAC factsheet - Guide to best practice maintenance and operation of HVAC systems for energy efficiency, (2018). <https://www.energy.gov.au/publications/hvac-factsheet-guide-best-practice-maintenance-and-operation-hvac-systems-energy> (accessed May 29, 2019).
- [18] C. Residovic, The New NABERS Indoor Environment tool – the Next Frontier for Australian Buildings, *Procedia Eng.* 180 (2017) 303–310. doi:10.1016/j.proeng.2017.04.189.
- [19] A. Ghahramani, F. Jazizadeh, B. Becerik-Gerber, A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points, *Energy Build.* 85 (2014) 536–548. doi:10.1016/j.enbuild.2014.09.055.
- [20] A. Khosrowpour, J.E. Taylor, One Size Does Not Fit All: Eco-Feedback Programs Require Tailored Feedback, in: *Sustain. Human–Building Ecosyst.*, American Society of Civil Engineers, 2015: pp. 36–43. <http://ascelibrary.org/doi/abs/10.1061/9780784479681.004> (accessed November 21, 2016).
- [21] H.N. Rafsanjani, Feature Identification for Non-Intrusively Extracting Occupant Energy-Use Information in Office Buildings, *J. Archit. Environ. Struct. Eng. Res.* 1 (2018). doi:<https://doi.org/10.30564/jaeser.v1i1.189>.
- [22] M. Milenkovic, O. Amft, An Opportunistic Activity-sensing Approach to Save Energy in Office Buildings, in: *Proc. Fourth Int. Conf. Future Energy Syst.*, ACM, New York, NY, USA, 2013: pp. 247–258. doi:10.1145/2487166.2487194.
- [23] W. Kleiminger, C. Beckel, T. Staake, S. Santini, Occupancy Detection from Electricity Consumption Data, in: *Proc. 5th ACM Workshop Embed. Syst. Energy-Effic. Build.*, ACM, New York, NY, USA, 2013: pp. 10:1–10:8. doi:10.1145/2528282.2528295.
- [24] D. Chen, S. Barker, A. Subbaswamy, D. Irwin, P. Shenoy, Non-Intrusive Occupancy Monitoring Using Smart Meters, in: *Proc. 5th ACM Workshop Embed. Syst. Energy-Effic. Build.*, ACM, New York, NY, USA, 2013: pp. 9:1–9:8. doi:10.1145/2528282.2528294.
- [25] W. Kleiminger, C. Beckel, S. Santini, Household Occupancy Monitoring Using Electricity Meters, in: *Proc. 2015 ACM Int. Jt. Conf. Pervasive Ubiquitous Comput.*, ACM, New York, NY, USA, 2015: pp. 975–986. doi:10.1145/2750858.2807538.
- [26] O. Ardakanian, A. Bhattacharya, D. Culler, Non-Intrusive Techniques for Establishing Occupancy Related Energy Savings in Commercial Buildings, in: *Proc. 3rd ACM Int. Conf. Syst. Energy-Effic. Built Environ.*, ACM, New York, NY, USA, 2016: pp. 21–30. doi:10.1145/2993422.2993574.
- [27] A. Zoha, A. Gluhak, M.A. Imran, S. Rajasegarar, Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey, *Sensors.* 12 (2012) 16838–16866. doi:10.3390/s121216838.

- [28] G.W. Hart, Nonintrusive appliance load monitoring, in: Proc. 1999 IEEE, 1992: pp. 1870–1891.
- [29] M. Zeifman, K. Roth, Nonintrusive appliance load monitoring: Review and outlook, *IEEE Trans. Consum. Electron.* 57 (2011) 76–84. doi:10.1109/TCE.2011.5735484.
- [30] NSF Award Search: Award#1833276 - NSF Workshop on Internet-of-Things (IoT) Hardware Systems, (n.d.).
https://www.nsf.gov/awardsearch/showAward?AWD_ID=1833276 (accessed January 18, 2019).
- [31] E. Fotopoulou, A. Zafeiropoulos, F. Terroso-Sáenz, U. Şimşek, A. González-Vidal, G. Tsiolis, P. Gouvas, P. Liapis, A. Fensel, A. Skarmeta, Providing Personalized Energy Management and Awareness Services for Energy Efficiency in Smart Buildings, *Sensors*. 17 (2017) 2054. doi:10.3390/s17092054.
- [32] C. Perera, A. Zaslavsky, P. Christen, D. Georgakopoulos, Context Aware Computing for The Internet of Things: A Survey, *IEEE Commun. Surv. Tutor.* 16 (2014) 414–454. doi:10.1109/SURV.2013.042313.00197.
- [33] That “Internet of Things” Thing - 2009-06-22 - Page 1 - RFID Journal, (n.d.).
<https://www.rfidjournal.com/articles/view?4986> (accessed February 7, 2019).
- [34] F. Xia, L.T. Yang, L. Wang, A. Vinel, Internet of Things, *Int. J. Commun. Syst.* 25 (2012) 1101–1102. doi:10.1002/dac.2417.
- [35] H. Allcott, Social norms and energy conservation, *J. Public Econ.* 95 (2011) 1082–1095. doi:10.1016/j.jpubeco.2011.03.003.
- [36] The Effectiveness of Energy Feedback for Conservation and Peak Demand: A Literature Review, (n.d.). <http://www.scirp.org/journal/PaperInformation.aspx?PaperID=28957> (accessed October 19, 2016).
- [37] A.R. Carrico, M. Riemer, Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education, *J. Environ. Psychol.* 31 (2011) 1–13. doi:10.1016/j.jenvp.2010.11.004.
- [38] H. Allcott, T. Rogers, How Long Do Treatment Effects Last? Persistence and Durability of a Descriptive Norms Intervention’s Effect on Energy Conservation., (2012).
- [39] G. Peschiera, J.E. Taylor, J.A. Siegel, Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data, *Energy Build.* 42 (2010) 1329–1336. doi:10.1016/j.enbuild.2010.03.001.
- [40] R.K. Jain, J.E. Taylor, G. Peschiera, Assessing eco-feedback interface usage and design to drive energy efficiency in buildings, *Energy Build.* 48 (2012) 8–17. doi:10.1016/j.enbuild.2011.12.033.
- [41] M.J. Bekker, T.D. Cumming, N.K.P. Osborne, A.M. Bruining, J.I. McClean, L.S. Leland, ENCOURAGING ELECTRICITY SAVINGS IN A UNIVERSITY RESIDENTIAL HALL THROUGH A COMBINATION OF FEEDBACK, VISUAL PROMPTS, AND INCENTIVES, *J. Appl. Behav. Anal.* 43 (2010) 327–331. doi:10.1901/jaba.2010.43-327.
- [42] M.J. Coleman, K.N. Irvine, M. Lemon, L. Shao, Promoting behaviour change through personalized energy feedback in offices, *Build. Res. Inf.* 41 (2013) 637–651. doi:10.1080/09613218.2013.808958.

- [43] N. Murtagh, M. Nati, W.R. Headley, B. Gatersleben, A. Gluhak, M.A. Imran, D. Uzzell, Individual energy use and feedback in an office setting: A field trial, *Energy Policy*. 62 (2013) 717–728. doi:10.1016/j.enpol.2013.07.090.
- [44] R. Gulbinas, R.K. Jain, J.E. Taylor, BizWatts: A modular socio-technical energy management system for empowering commercial building occupants to conserve energy, *Appl. Energy*. 136 (2014) 1076–1084. doi:10.1016/j.apenergy.2014.07.034.
- [45] R. Yun, B. Lasternas, A. Aziz, V. Loftness, P. Scupelli, A. Rowe, R. Kothari, F. Marion, J. Zhao, Toward the Design of a Dashboard to Promote Environmentally Sustainable Behavior among Office Workers, in: S. Berkovsky, J. Freyne (Eds.), *Persuas. Technol.*, Springer Berlin Heidelberg, 2013: pp. 246–252.
- [46] H.N. Rafsanjani, C. Ahn, K. Eskridge, Understanding the Recurring Patterns of Occupants' Energy-Use Behaviors at Entry and Departure Events in Office Buildings, *Build. Environ.* 136 (2018) 77–87.
- [47] H. Staats, E. van Leeuwen, A. Wit, A longitudinal study of informational interventions to save energy in an office building., *J. Appl. Behav. Anal.* 33 (2000) 101–104. doi:10.1901/jaba.2000.33-101.
- [48] A.R. Carrico, M. Riemer, Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education, *J. Environ. Psychol.* 31 (2011) 1–13. doi:10.1016/j.jenvp.2010.11.004.
- [49] N. Batra, O. Parson, M. Berges, A. Singh, A. Rogers, A comparison of non-intrusive load monitoring methods for commercial and residential buildings, in: 2014.
- [50] L.K. Norford, S.B. Leeb, Non-intrusive electrical load monitoring in commercial buildings based on steady-state and transient load-detection algorithms, *Energy Build.* 24 (1996) 51–64. doi:10.1016/0378-7788(95)00958-2.
- [51] M. Zeifman, K. Roth, Nonintrusive appliance load monitoring: Review and outlook, *IEEE Trans. Consum. Electron.* 57 (2011) 76–84. doi:10.1109/TCE.2011.5735484.
- [52] A. Zoha, A. Gluhak, M.A. Imran, S. Rajasegarar, Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey, *Sensors*. 12 (2012) 16838–16866. doi:10.3390/s121216838.
- [53] S. Moayed, S. Shom, A. Harms, M. Alahmad, Real Time Power Monitoring Detection Based on Sequence Time Domain Reflectometry Approach, *J. Comput. Commun.* 06 (2017) 92. doi:10.4236/jcc.2018.61010.
- [54] M.S. Shahriar, A. Rahman, D. Smith, Applying context in appliance load identification, in: 2013 Ninth Int. Conf. Nat. Comput. ICNC, 2013: pp. 900–905. doi:10.1109/ICNC.2013.6818104.
- [55] J. Yoo, B. Park, K. Hur, Context Awareness-Based Disaggregation of Residential Load Consumption, *IFAC Proc. Vol.* 44 (2011) 13691–13695. doi:10.3182/20110828-6-IT-1002.01783.
- [56] F. Paradiso, F. Paganelli, D. Giuli, S. Capobianco, Context-Based Energy Disaggregation in Smart Homes, *Future Internet*. 8 (2016) 4. doi:10.3390/fi8010004.
- [57] H.N. Rafsanjani, C.R. Ahn, J. Chen, Linking Building Energy Consumption with Occupants' Energy-Consuming Behaviors in Commercial Buildings: Non-Intrusive Occupant Load Monitoring (NIOLM), *Energy Build.* 172 (2018) 317–327. doi:10.1016/j.enbuild.2018.05.007.

- [58] J. Louis, P.S. Dunston, Integrating IoT into operational workflows for real-time and automated decision-making in repetitive construction operations, *Autom. Constr.* 94 (2018) 317–327. doi:10.1016/j.autcon.2018.07.005.
- [59] M. Wei, S.H. Hong, M. Alam, An IoT-based energy-management platform for industrial facilities, *Appl. Energy*. 164 (2016) 607–619. doi:10.1016/j.apenergy.2015.11.107.
- [60] D. Miorandi, S. Sicari, F. De Pellegrini, I. Chlamtac, Internet of things: Vision, applications and research challenges, *Ad Hoc Netw.* 10 (2012) 1497–1516. doi:10.1016/j.adhoc.2012.02.016.
- [61] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, Internet of Things (IoT): A vision, architectural elements, and future directions, *Future Gener. Comput. Syst.* 29 (2013) 1645–1660. doi:10.1016/j.future.2013.01.010.
- [62] Y. Jeon, C. Cho, J. Seo, K. Kwon, H. Park, S. Oh, I.-J. Chung, IoT-based occupancy detection system in indoor residential environments, *Build. Environ.* 132 (2018) 181–204. doi:10.1016/j.buildenv.2018.01.043.
- [63] H. Zou, Y. Zhou, J. Yang, C.J. Spanos, Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT, *Energy Build.* 174 (2018) 309–322. doi:10.1016/j.enbuild.2018.06.040.
- [64] H. Zou, Y. Zhou, J. Yang, C.J. Spanos, Towards occupant activity driven smart buildings via WiFi-enabled IoT devices and deep learning, *Energy Build.* 177 (2018) 12–22. doi:10.1016/j.enbuild.2018.08.010.
- [65] H.N. Rafsanjani, A. Ghahramani, Extracting occupants' energy-use patterns from Wi-Fi networks in office buildings, *J. Build. Eng.* 26 (2019) 100864. doi:10.1016/j.jobe.2019.100864.
- [66] A. Khosrowpour, R. Gulbinas, J.E. Taylor, Occupant workstation level energy-use prediction in commercial buildings: Developing and assessing a new method to enable targeted energy efficiency programs, *Energy Build.* 127 (2016) 1133–1145. doi:10.1016/j.enbuild.2016.05.071.
- [67] R. Gulbinas, A. Khosrowpour, J. Taylor, Segmentation and Classification of Commercial Building Occupants by Energy-Use Efficiency and Predictability, *IEEE Trans. Smart Grid.* 6 (2015) 1414–1424. doi:10.1109/TSG.2014.2384997.
- [68] H.N. Rafsanjani, C.R. Ahn, M. Alahmad, Development of Non-Intrusive Occupant Load Monitoring (NIOLM) in Commercial Buildings: Assessing Occupants' Energy-Use Behavior at Entry and Departure Events, in: *Sustain. Human–Building Ecosyst.*, 2015. <http://ascelibrary.org/doi/abs/10.1061/9780784479681.005> (accessed January 17, 2017).
- [69] G. Kavulya, B. Becerik-Gerber, Understanding the Influence of Occupant Behavior on Energy Consumption Patterns in Commercial Buildings, in: *Comput. Civ. Eng. 2012*, 2012: pp. 569–576.
- [70] A.C. Menezes, A. Cripps, R.A. Buswell, J. Wright, D. Bouchlaghem, Estimating the energy consumption and power demand of small power equipment in office buildings, *Energy Build.* 75 (2014) 199–209. doi:10.1016/j.enbuild.2014.02.011.
- [71] J. Chen, H. Chen, X. Luo, Collecting building occupancy data of high resolution based on WiFi and BLE network, *Autom. Constr.* 102 (2019) 183–194. doi:10.1016/j.autcon.2019.02.016.

- [72] W. Wang, J. Chen, T. Hong, Occupancy prediction through machine learning and data fusion of environmental sensing and Wi-Fi sensing in buildings, *Autom. Constr.* 94 (2018) 233–243. doi:10.1016/j.autcon.2018.07.007.
- [73] W. Wang, J. Chen, T. Hong, N. Zhu, Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology, *Build. Environ.* 138 (2018) 160–170. doi:10.1016/j.buildenv.2018.04.034.
- [74] W. Wang, J. Wang, J. Chen, G. Huang, X. Guo, Multi-zone outdoor air coordination through Wi-Fi probe-based occupancy sensing, *Energy Build.* 159 (2018) 495–507. doi:10.1016/j.enbuild.2017.11.041.
- [75] H.N. Rafsanjani, C. Ahn, Linking Building Energy-Load Variations with Occupants' Energy-Use Behaviors in Commercial Buildings: Non-Intrusive Occupant Load Monitoring (NIOLM), *Procedia Eng.* 145 (2016) 532–539. doi:10.1016/j.proeng.2016.04.041.
- [76] C. Martani, D. Lee, P. Robinson, R. Britter, C. Ratti, ENERNET: Studying the dynamic relationship between building occupancy and energy consumption, *Energy Build.* 47 (2012) 584–591. doi:10.1016/j.enbuild.2011.12.037.
- [77] A.J. Ruiz-Ruiz, H. Blunck, T.S. Prentow, A. Stisen, M.B. Kjærsgaard, Analysis methods for extracting knowledge from large-scale WiFi monitoring to inform building facility planning, in: 2014 IEEE Int. Conf. Pervasive Comput. Commun. PerCom, 2014: pp. 130–138. doi:10.1109/PerCom.2014.6813953.
- [78] R.S. Campos, L. Lovisolo, M.L.R. de Campos, Wi-Fi multi-floor indoor positioning considering architectural aspects and controlled computational complexity, *Expert Syst. Appl.* 41 (2014) 6211–6223. doi:10.1016/j.eswa.2014.04.011.
- [79] M.M. Ouf, M.H. Issa, A. Azzouz, A.-M. Sadick, Effectiveness of using WiFi technologies to detect and predict building occupancy, *Sustain. Build.* 2 (2017) 7. doi:10.1051/sbuild/2017005.
- [80] B. Balaji, J. Xu, A. Nwokafor, R. Gupta, Y. Agarwal, Sentinel: Occupancy Based HVAC Actuation Using Existing WiFi Infrastructure Within Commercial Buildings, in: Proc. 11th ACM Conf. Embed. Networked Sens. Syst., ACM, New York, NY, USA, 2013: pp. 17:1–17:14. doi:10.1145/2517351.2517370.
- [81] W. Wang, J. Chen, X. Song, Modeling and predicting occupancy profile in office space with a Wi-Fi probe-based Dynamic Markov Time-Window Inference approach, *Build. Environ.* 124 (2017) 130–142. doi:10.1016/j.buildenv.2017.08.003.
- [82] J. Chen, C. Ahn, Assessing occupants' energy load variation through existing wireless network infrastructure in commercial and educational buildings, *Energy Build.* 82 (2014) 540–549. doi:10.1016/j.enbuild.2014.07.053.
- [83] M.K. Simon, *Probability Distributions Involving Gaussian Random Variables: A Handbook for Engineers and Scientists*, Springer Science & Business Media, 2007.
- [84] E. Azar, C.C. Menassa, Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings, *J. Comput. Civ. Eng.* 26 (2012). doi:10.1061/(ASCE)CP.1943-5487.0000158.
- [85] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, *Energy Build.* 41 (2009) 295–302. doi:10.1016/j.enbuild.2008.09.008.

- [86] CM. Clevenger, J. Haymaker, The impact of the building occupant on energy modeling simulations, (2006).
- [87] Understanding Consumer Preferences in Energy Efficiency – Accenture, (2010).
- [88] E.E. Elattar, J. Goulermas, Q.H. Wu, Electric Load Forecasting Based on Locally Weighted Support Vector Regression, *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 40 (2010) 438–447. doi:10.1109/TSMCC.2010.2040176.
- [89] A. Albert, R. Rajagopal, Smart Meter Driven Segmentation: What Your Consumption Says About You, *IEEE Trans. Power Syst.* 28 (2013) 4019–4030. doi:10.1109/TPWRS.2013.2266122.
- [90] B.A. Smith, J. Wong, R. Rajagopal, A Simple Way to Use Interval Data to Segment Residential Customers for Energy Efficiency and Demand Response Program Targeting, in: n.d.
- [91] G. Chicco, R. Napoli, F. Piglione, Comparisons among clustering techniques for electricity customer classification, *IEEE Trans. Power Syst.* 21 (2006) 933–940. doi:10.1109/TPWRS.2006.873122.
- [92] Smart Applications for the Integrated Sensing, Simulation, and Feedback of Occupant Behaviors to Enable Personalized Interventions for Energy Saving in Buildings, in: *Constr. Res. Congr.* 2016, n.d. doi:10.1061/9780784479827.097.
- [93] TED Pro Documents & Downloads, (n.d.). <http://www.theenergydetective.com/prodocs> (accessed June 12, 2019).
- [94] F. Tusell, Kalman Filtering in R, *J. Stat. Softw.* 39 (2011).
- [95] D. Bourgeois, C. Reinhart, I. Macdonald, Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control, *Energy Build.* 38 (2006) 814–823. doi:10.1016/j.enbuild.2006.03.002.
- [96] C.A. Webber, J.A. Roberson, M.C. McWhinney, R.E. Brown, M.J. Pinckard, J.F. Busch, After-hours power status of office equipment in the USA, *Energy.* 31 (2006) 2823–2838. doi:10.1016/j.energy.2005.11.007.
- [97] M. Sanchez, C. Webber, R. Brown, J. Busch, M. Pinckard, J. Roberson, Space Heaters, Computers, Cell Phone Chargers: How Plugged In Are Commercial Buildings?, (2006).
- [98] J.A. Davis, D.W. Nutter, Occupancy diversity factors for common university building types, *Energy Build.* 42 (2010) 1543–1551. doi:10.1016/j.enbuild.2010.03.025.
- [99] T. Jackson, Motivating sustainable consumption: A review of evidence on consumer behaviour and behavioural change, (2005).
- [100] R.K. Jain, J.E. Taylor, P.J. Culligan, Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings, *Energy Build.* 64 (2013) 408–414. doi:10.1016/j.enbuild.2013.05.011.
- [101] E. Azar, C.C. Menassa, Framework to Evaluate Energy-Saving Potential from Occupancy Interventions in Typical Commercial Buildings in the United States, *J. Comput. Civ. Eng.* 28 (1061) 63–78. doi:10.1061/(ASCE)CP.1943-5487.0000318.
- [102] U.S. Energy Information Administration, Commercial buildings energy consumption survey, (2003).
- [103] E. Azar, C. Menassa, Sensitivity of Energy Simulation Models to Occupancy Related Parameters in Commercial Buildings, in: *Constr. Res. Congr.* 2012, American Society of

Civil Engineers, n.d.: pp. 1381–1390.

<http://ascelibrary.org/doi/abs/10.1061/9780784412329.139> (accessed October 21, 2014).

- [104] O.T. Masoso, L.J. Grobler, The dark side of occupants' behaviour on building energy use, *Energy Build.* 42 (2010) 173–177. doi:10.1016/j.enbuild.2009.08.009.