

# **iSEA: IoT-based Smartphone Energy Assistant for Prompting Energy-Aware Behaviors in Commercial Buildings**

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## **Abstract**

Providing personalized energy-use information to individual occupants enables the adoption of energy-aware behaviors in commercial buildings. However, the implementation of individualized feedback still remains challenging due to the difficulties in collecting personalized data, tracking personal behaviors, and delivering personalized tailored information to individual occupants. Nowadays, the Internet of Things (IoT) technologies are used in a variety of applications including real-time monitoring, control, and decision-making due to the flexibility of these technologies for fusing different data streams. In this paper, we propose a novel IoT-based smartphone energy assistant (iSEA) framework which prompts energy-aware behaviors in commercial buildings. iSEA tracks individual occupants through tracking their smartphones, uses a deep learning approach to identify their energy usage, and delivers personalized tailored feedback to impact their usage. iSEA particularly uses an energy-use efficiency index (EEI) to understand behaviors and categorize them into efficient and inefficient behaviors. The iSEA architecture includes four layers: physical, cloud, service, and communication. The results of implementing iSEA in a commercial building with ten occupants over a twelve-week duration demonstrate the validity of this approach in enhancing individualized energy-use behaviors. An average of 34% energy savings was measured by tracking occupants' EEI by the end of the experimental period. In addition, the results demonstrate that commercial building occupants often ignore controlling over lighting systems at their departure events that leads to wasting energy during non-working hours. By utilizing the existing IoT devices in commercial buildings, iSEA significantly contributes to support research efforts into sensing and enhancing energy-aware behaviors at minimal costs.

## **Keywords**

Internet of Things; Smartphone; Wi-Fi network; Energy-use behavior; Deep learning; Commercial buildings.

## 1. Introduction

Even when compared to other major characteristics of energy consumption in commercial buildings (such as building physical characteristics and appliance/system characteristics), occupant energy behavior characteristics have predominantly been considered as a more cost-effective approach toward reducing building energy consumption [1–7]. Commercial buildings are responsible for more than 30% of United States energy-use [8] and up to 30% of this amount could be saved through adopting energy-aware behaviors among building occupants [9]. In fact, a large body of research [10–18] demonstrates a strong promise in utilizing various feedback-based techniques/systems to enhance energy-use behaviors. In particular, it has been shown that compared to group-level feedback, individualized feedback (i.e., providing individual occupants with personalized energy-use information) offers better opportunities to adopt energy-saving behaviors [19–21].

However, the implementation of individualized feedback remains limited in commercial settings. This is largely because of difficulties associated with (1) collecting personalized data, (2) identifying anomalous behaviors, (3) delivering personal tailored information to individual occupants, and (4) tracking individual's energy-use behaviors over time [9,22–25]. In particular, a feedback mechanism not only should properly perform each of the mentioned steps but also needs to appropriately link these steps to enhance energy-use behaviors. This linkage cannot be provided by conventional feedback mechanisms available in commercial buildings. Currently, functional structured feedback mechanisms are often tailored to residential settings and are not suitable for implantation in commercial settings [26,27]. Therefore, there is still a dearth of applicable approaches for commercial buildings.

Recently, the Internet of Things (IoT) as a prominent technology is transferring conventional building energy management systems (BEMS) into smart, scalable, efficient, secure, flexible, and real-time systems for easier and greater energy-savings in both residential [28–32] and commercial buildings [33–38]. In particular, IoT-based approaches more accurately estimate thermal and scheduling models to minimize energy used by HVAC systems [39–44]; these systems currently consume about 50% of building energy consumption in developed countries [45–47]. IoT also enables manipulating the energy-use of a fleet of buildings [48] and facilitates the development of demand-response energy management platforms [49]. In addition, IoT benefits in controlling and automating building lighting systems [50,51]. With regards to building occupants,

IoT benefits into occupancy detection and activity recognition [52–54] and has been used for monitoring energy usage of commercial building occupants [55] and increasing their energy-saving awareness [56–59].

In particular, IoT uses internet to connect internet-enabled objects of a system (such as sensors and processors of BEMS) to each other for real-time communications and interactions which leads to achieving a high-level of intelligence and efficiency for the system. With the rapid development of sensor technology which provides commercial off-the-shelf (COTS) low-cost internet-enabled sensors (that allow to sense, store, transfer, and display high-temporal resolution data of a system in real-time), IoT-based approaches could be implemented in any web-based environment including residential and commercial buildings (while these approaches might have privacy issues of unwanted public data/profiles and eavesdropping). Accordingly, IoT along with COTS internet-enabled sensors could be utilized to develop a feedback mechanism which is able to monitor individual occupants' energy usage in real-time, to analyze the data for identifying efficient and inefficient behaviors, and to deliver tailored feedback to each occupant.

Leveraging the described opportunities, we propose an IoT-based smartphone energy assistant (iSEA) framework which acts as a personal feedback mechanism to prompt energy-aware behaviors in commercial buildings. iSEA tracks individual occupants based on their smartphones' Wi-Fi disconnection events and uses a supervised deep learning approach to identify their energy-use actions. In particular, iSEA utilizes an energy-use efficiency index (EEI) to understand individual's behaviors and categorizes the occupants to efficient and inefficient groups. Then, iSEA delivers personalized tailored feedback to enhance individualized energy-use behaviors. To assess the iSEA validity, we conducted a pilot experiment in a commercial building (with ten occupants) over a twelve-week duration. The findings demonstrate the iSEA ability to address the current limitations of literature in collecting personalized data, tracking personalized behavior, and delivering personal tailored information to individual occupants in a holistic fashion.

## **2. Related Work**

### **2.1. Energy feedback in commercial buildings**

Researchers [10–19] have utilized various feedback-based techniques to influence energy consumption in commercial buildings. For example, Staats et al. [60] provided feedback to occupants in a commercial building and their results showed that 80% of occupants considered

energy-saving behaviors. In particular, it has been indicated that there are certain characteristics that allow feedback to be more effective. A key characteristic is the resolution of occupant-specific energy-consumption data [17,61,62], considering that low-temporal-resolution data may lead to misunderstanding about energy-use behaviors [55]. Another characteristic is to ascertain the appropriate frequency of feedback [10,11]. Feedback provided too frequently may positively influence energy-use behaviors in a short period but may also lead to information overload which discourages occupants from positively reacting to the feedback [26,63]. The next characteristic is improving engagement between building occupants and relevant feedback [13,14]. Jain et al. [15] found a significant correlation between feedback/occupant engagement and energy savings over time, and thereby insufficient engagement to feedback systems leads to decay of energy-saving behaviors.

Researchers have also examined other non-critical feedback characteristics such as the role of goal setting [64] and normative aspects of feedback [65]; however, the fundamental challenge that prevent large-scale implementation of feedback-based methods is the lack of methodologies for understanding the proper (1) resolution of personalized consuming data, (2) flow of feedback information (without creating an overload situation), and (3) occupant/feedback engagements. While functional methodologies have been developed in residential buildings [66–73], there is still a need for a methodology to provide a relevant and context-aware individualized feedback that effectively engages with the diverse array of commercial building occupants.

## **2.2. Occupant energy-use monitoring in commercial buildings**

In order to monitor personal energy-use data which are required for individualized feedback, there are generally two categories of methods in commercial buildings. The first category which have been widely employed and observed in feedback studies, is intrusive load monitoring [74]. In this method, a power meter is installed at the cubicle/workstation assigned to a single occupant and tracks energy-consuming data of the occupant. Yun et al. [62], Coleman et al. [17], Rafsanjani et al. [75], and Gulbinas et al. [61] are examples used intrusive-load approaches to collect individual occupants' usage data in commercial buildings. The second category is non-intrusive load monitoring. In this category, without installing additional meters, data provided in building operation (e.g., data provided by building-level meters) are utilized to monitor individual occupants' usage. Rafsanjani and Ghahramani [55], Kavulya and Becerik-Gerber [76], Moayed

et al. [77,78], Jazizadeh and Becerik-Gerber [79], and Rafsanjani et al. [80,81] developed non-intrusive approaches to track occupant-specific usage in commercial buildings.

While intrusive methods provide data with high precision and resolution and non-intrusive methods benefit in economically providing occupant data, these two categories of methods have rarely been adopted to be utilized in practice. Expensive implementation is the largest obstacle for intrusive methods while complexity of implementation and uncertainty in results are considered as the major obstacles for non-intrusive methods. Accordingly, it is often impossible to economically estimate the accurate energy usage for each occupant and provide each with meaningful feedback in practice. Thus, a simple and inexpensive system which can provide occupant-specific usage is needed for enhancement of the current practice of individualized feedback techniques.

### **2.3. Occupancy sensing in commercial buildings**

Occupancy information could be used to significantly increase the accuracy of tracking occupant energy usage [27,82–84]. Currently, conventional sensing solutions (such as CO<sub>2</sub> sensors [85], infrared sensors [86], motion sensors [87], sound sensors [88], and temperature sensors [89]) are available for occupancy detection in commercial buildings. However, low degree of occupancy resolution, intrusiveness, and cost of execution are considered as the disadvantages of such methods [26]. To address these limitations, researchers [90–100] have leveraged Wi-Fi information for occupancy sensing (such as detection [101] and localization [102]) in commercial buildings. Wi-Fi networks are able to create databases based on the MAC addresses of Wi-Fi enabled devices (such as laptops and smartphones) to easily differentiate between users (i.e., occupants) in a building [103,104]. In addition, since most of commercial buildings are currently equipped with Wi-Fi networks and since most of the building occupants routinely use Wi-Fi-enabled devices (such as smartphones), no additional sensors are required to implement Wi-Fi based occupancy sensing approaches.

It has particularly been indicated that Wi-Fi networks are able to provide occupancy information required to tracking energy-use behaviors. Martani et al. [105], Rafsanjani and Ghahramani [84], and Chen and Ahn [27] utilized the number of Wi-Fi connections as a building occupancy indicator and revealed how closely the energy flows correlate with occupancy flows in commercial buildings. In addition, Wi-Fi networks are a substantial part of IoT hardware systems

[106–109] and thereby, Wi-Fi based occupancy sensing could benefit in developing IoT-based occupancy-related approaches at minimal costs.

#### **2.4. IoT-based occupancy sensing and energy-use monitoring in commercial buildings**

IoT is considered as a network of physical things (such as sensors and devices) which are connected through internet and able to generate, extract, and record data as well as to communicate for processing and utilizing the data in real-time [49,110–112]. The advent of advanced electric hardware systems (such as power circuits) and internet-enabled sensors/devices provides a unique opportunity for implementing IoT in every web-equipped commercial building. For example, Ruano et al. [39] and Png et al. [40] proposed IoT platforms for intelligent HVAC control in commercial buildings. Ronen and Shamir [50] revealed how IoT provides smart lighting systems by modifying color and intensity of the lights of each room in a commercial building.

With respect to occupancy sensing in commercial buildings, Zou et al. [53,54] proposed IoT-based approaches for occupancy detection, crowd counting, and activity recognition in commercial buildings. With regards to occupants' energy-use monitoring, Rafsanjani and Ghahramani [84] revealed a dynamic relationship between IoT infrastructure information and occupants' energy-use patterns in commercial buildings. Later, they [55] developed an approach which utilizes the information provided by IoT devices to monitor individual occupants' energy-use behaviors in commercial buildings. Mylonas et al. [56], Paganelli et al. [57], and Tziortzioti et al. [113] demonstrated how IoT along with gamification (i.e., interactive services, games, and web applications for occupants to increase their overall awareness) can be utilized to promote energy-aware behaviors and getting occupants engaged into energy-efficient activities. In addition, research projects such as Green-Awareness-In-Action (gaia-project.eu), Personal-Energy-Administration-Kiosk-App (peakapp.eu), Entropy (entropy-project.eu), and Tribe (tribe-h2020.eu) have designed IoT-based systems including web applications and deployed those to increase energy awareness and modify behaviors. While there is a limited number of empirical IoT-based occupancy-related research into commercial settings, their findings along with IoT advantages (such as real-time monitoring) hold promise that IoT could be utilized in developing a feedback mechanism which is able (1) to sense high-resolution personalized data, (2) to provide a proper and adjustable flow of feedback information, and (3) to engage occupants to follow the feedback.

Motivated by this, we propose iSEA which is an IoT-based personalized feedback mechanism. iSEA leverages the occupancy data (received from Wi-Fi networks) with aggregate load data (received from internet-enabled meters) of a building to track occupants' energy-use behaviors at their departure events and to learn each occupant's behavior (through utilizing a supervised deep learning approach). Then, iSEA provides each occupant with a personalized comparative-historical feedback to enhance energy-use behaviors which ultimately decrease energy-consumption in commercial buildings. An experiment conducted in a commercial building demonstrates the feasibility of the approach to prompt energy-aware behaviors. The following sections provide the detailed descriptions of iSEA methodology and its IoT architecture as well as the experiment and results.

### **3. IoT-based Smartphone Energy Assistant (iSEA) Framework**

This section first introduces the EEI index and explains the algorithm to calculate it. Then, iSEA methodology is described and finally, the iSEA IoT architecture is presented.

#### **3.1. Energy-use efficiency index (EEI)**

Commercial building occupants routinely work during a daily working schedule (e.g., 8:00 a.m. to 5:00 p.m.) and their energy-use behaviors are very closely related to this schedule [75,114]. In fact, each day, a commercial building occupant typically starts using her appliances when she arrives at her workstations (which is named her entry event) and ends using the appliances upon her departure from the building (which is named her departure event). Accordingly, research [22,23,75,76,115–117] has revealed that major energy-use actions of commercial building occupants typically occur at these entry and departure events, and accordingly, studying energy-use behaviors at these events functionally provide information required to properly understand occupants' energy-use behaviors in commercial buildings.

While entry/departure events have been utilized for sensing energy-use information required to simulate and predict energy-use behaviors, several studies [55,75,118,119] have particularly indicated that departure events (compared to entry events) are considered more critical in order to identify and understand efficient and inefficient behaviors (i.e., energy-saving and non-energy-saving behaviors). Less than half of most buildings' appliances/systems are turned off by occupants after operational hours which leads to more energy wasted during non-working hours



than energy used during working hours [120]. These facts shift the focus of behavior-modification studies of commercial settings to the departure events to understand energy-use efficiency of individual occupants. Accordingly, iSEA uses the energy-use information of individual occupants at their departure events.

In particular, in a commercial building, the occupant who leaves the building as the last person (last departure event) not only should turn her personal appliances off but also is responsible to turn off most of the in-use shared appliances (such as ceiling lights and fans). The building electric meters record these energy-use actions and accordingly, aggregate energy-load data (building-level energy-load data provided by the meters) upon her departure event mainly reflects her energy-use actions (since there is no other occupant in the building) [55]. Therefore, when an occupant leaves the building as the last person, there is a possibility to understand her comprehensive energy-use behaviors of personal and shared appliances through aggregate load data (without installing additional energy sensors).

With this in mind, we introduce an energy-use efficiency index (EEI) which allows to utilize aggregate load data to quantitatively estimate energy-efficiency of an occupant and compare her efficiency with her peers. This index is defined as a comparison between an occupant's energy-use actions at a departure event and her most efficient energy action at the event, as summarized by:

$$EEI = \frac{AL_{t_1} - AL_{t_2}}{AL_{t_1} - BL} \quad (1)$$

Where  $0 \leq EEI \leq 1$  and  $EEI=1$  represents the most efficient behavior.

In Equation 1,  $AL_{t_1}$  represents the average of aggregate-energy load data within time frame  $t_1$  right before the departure event of the last occupant in a working schedule.  $AL_{t_2}$  represents the average of aggregate-energy load data within time frame  $t_2$  right after the departure event of the occupant.  $BL$  is the base line of aggregate energy load data and is generally estimated based on the building background load during non-working hours (e.g., 10:00 p.m. to 5:00 a.m.). In addition,  $t_1$  and  $t_2$  are empirically determined for a building.

Accordingly, for a dataset including  $D$  days of aggregate load data of a building with  $n$  occupants,  $Mat_{EEI}$  is defined as a matrix including  $n$  rows and  $D$  columns where each element of

$Mat_{EEI}$  represents the EEI of occupant  $i$  on day  $d$ ;  $i \in \{1, 2, \dots, n\}$  and  $d \in \{1, 2, \dots, D\}$ . If occupant  $i$  does not leave the building as the last occupant on day  $d$ ,  $Mat_{EEI}(i, d) = 0$ .

Finally, the average (arithmetic mean) of non-zero elements of row  $i$  of  $Mat_{EEI}$  is calculated and assigned to occupant  $i$  as her  $EEI_{avg}$ , as follows:

$$EEI_{avg.i} = \frac{\sum Mat_{EEI}(i, 1:D)}{m_i} \quad (2)$$

Where  $0 \leq EEI_{avg} \leq 1$  and  $m_i (\leq D)$  represents the number of days that occupant  $i$  left the building as the last occupant.

Using this method, the  $EEI_{avg}$  of all the occupants of a building are estimated; Figure 1 shows the algorithm of this process. This allows to rank occupants based on their energy-use efficiency, where a larger  $EEI_{avg}$  for an occupant compared to her peers indicates more efficient behaviors. Ideally, the  $EEI_{avg}$  for an occupant with the most efficient behavior could reach 1 while this index for the worst situation could be 0 which indicates inefficient behaviors; the difference between efficient and inefficient behaviors should empirically be determined in a building [22,24,121–126]. Accordingly, seeking to assess personalized energy-use behaviors at departure events, iSEA uses  $EEI_{avg}$  to quantitatively categorize occupants and identify those who should be targeted for behavior modifications.

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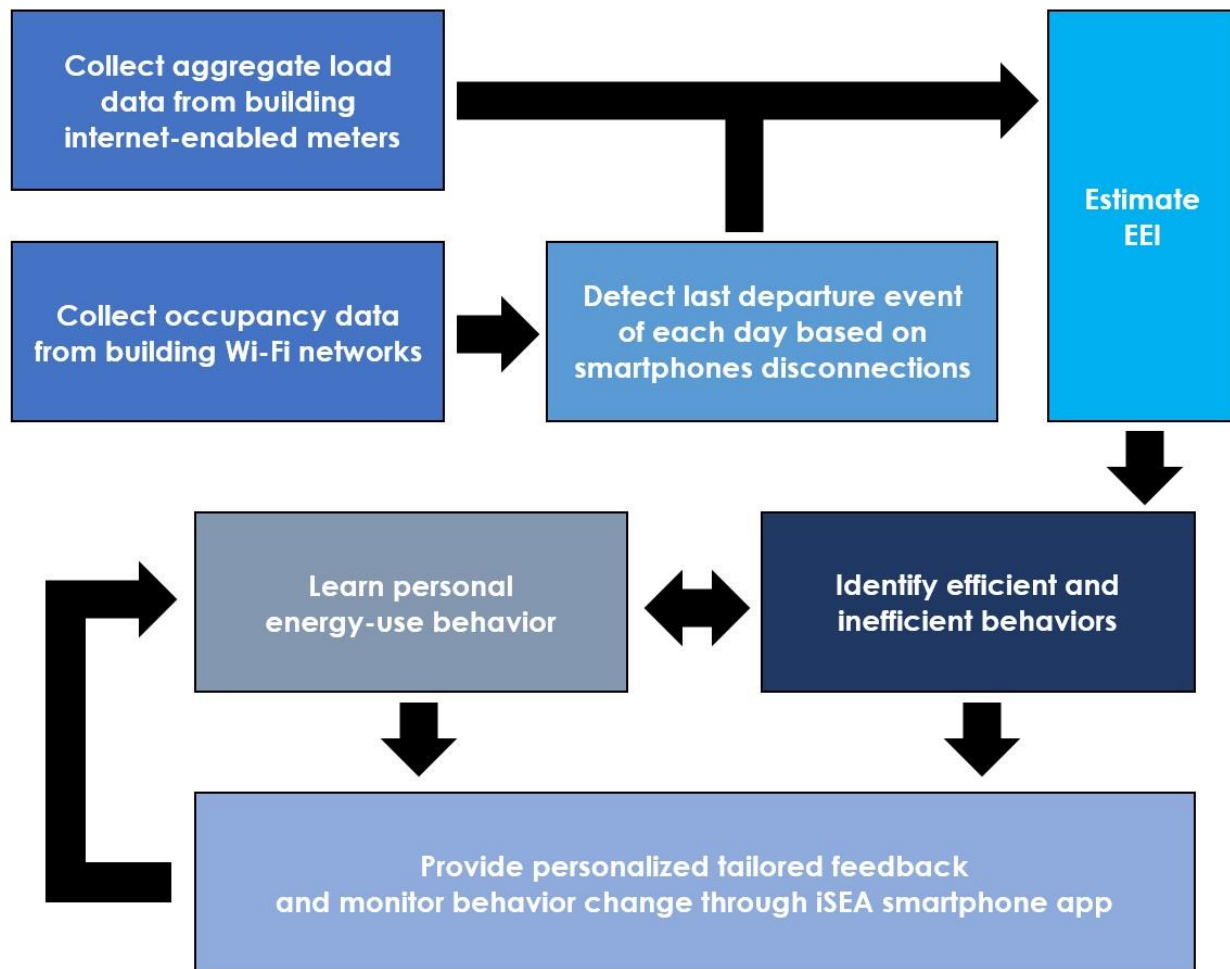
1: input:  $AL \leftarrow$  Aggregate energy load data of a building with  $n$  occupants
2:  $Mat_{EEI} \leftarrow \emptyset$ ,  $BL \leftarrow$  Baseline of  $AL$ ,  $m \leftarrow 0$ 
3: if occupant  $i, i \in \{1, 2, \dots, n\}$ , left the building as the last occupant on day  $d, d \in \{1, 2, \dots, D\}$  do
4:    $AL_{t1} \leftarrow$  Average  $AL$  during  $t_1$ 
5:    $AL_{t2} \leftarrow$  Average  $AL$  during  $t_2$ 
6:    $Mat_{EEI}(i, d) \leftarrow [(AL_{t1} - AL_{t2}) \div (AL_{t1} - BL)]$ 
7:    $m_i \leftarrow m_i + 1$ 
8: end if
9:  $EEI_{avg.i} \leftarrow [\text{sum}(Mat_{EEI}(i, 1:D)) \div m_i]$ 
10: output:  $EEI_{ave.i}$ 

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**Figure 1.**  $EEI_{avg}$  algorithm

### 3.2. iSEA Methodology

iSEA uses a seven-step methodology to estimate  $EEl_{avg}$  of individual occupants of a building, identify inefficient behaviors, and deliver feedback to modify these behaviors. Figure 2 presents the iSEA framework.



**Figure 2.** iSEA framework

#### **Step 1: collect aggregate load data from building internet-enabled meters**

In the first step, iSEA collects the aggregate load data of the building through its internet-enabled meters. Industry currently offers a variety of low-cost COTS electric meters which can be installed in different type of electric panels of small-to-large-sized commercial buildings. These meters could appropriately communicate with BEMS for information exchange. It is noteworthy that

industry has shifted to use such meters for commercial buildings, specifically for the modern buildings, which enables IoT implementation in commercial settings. Accordingly, iSEA utilizes high-temporal-resolution data provided by such meters in building operations.

In this step, iSEA also uses a pre-processing filtering stage for checking the accuracy of data in order to identify and filter the data corrupted or/and missed due to network disconnection, power loss, or/and electrical noise [127,128]. Since IoT utilizes real-time data instead of trend data (typically utilized by conventional data sensing approaches), this filtering stage should be trained in a way to identify corrupted/missed data in real time. In this context, historical data collected by a meter in a building could be useful to properly train the filtering process for taking real-time actions.

### **Step 2: collect occupancy data from building Wi-Fi networks**

In the second step, iSEA collects the information provided by the building Wi-Fi networks to track occupancy. The advent of advanced Wi-Fi hardware technologies (such as access points) allows to actively/passively track in real-time any Wi-Fi enabled devices presented within the range of Wi-Fi networks. In addition, Wi-Fi network interferences are not bounded by building physical components which specifically let track devices with a high-level of accuracy [82,129].

In particular, due to the people continued carrying of smartphones [130,131], iSEA uses MAC addresses of occupants' smartphones to collect the required individualized occupancy data. In this step, to protect privacy (which is usually a major concern while using occupancy sensing system [132]), iSEA particularly uses a MAC randomization process [133] to produce randomly generated IDs (which are fake unidentifiable codes) and mask true MAC addresses (presented in network data) with these IDs. The IDs are utilized for data processing and analysis throughout the framework.

### **Step 3: detect last departure events in daily working schedule based on smartphones' information**

In the third step, iSEA detects the last disconnection of smartphones on each day to identify who left the building as the last occupant. The information provided by Wi-Fi networks includes the connection/disconnections of all Wi-Fi enabled devices (such as laptops and tablets), and accordingly, identifying the IDs of smartphones is a challenging task. To address this, based on the

experience of the research team working with Wi-Fi-based sensing approaches [55,80,84,99,100,115], smartphones connection/disconnections to building Wi-Fi networks predominantly occur at occupants' entry/departure events which is the start/end of building working schedule for permanent occupants (i.e., long-term residents such as employees), while connections/disconnections of other devices (such as laptops) predominantly occur within working schedule. In addition, the smartphones' IDs of occupants are not present during non-working hours (such as night hours) while the IDs of other devices (such as a laptop used in a laboratory) could be presented in such hours. Accordingly, such facts are useful in categorizing the information delivered by Wi-Fi networks to properly identify smartphones' IDs.

Another challenge in this step is to distinguish the events of permanent occupants from those of temporary occupants (i.e., short-term residents such as customers/clients). Temporary occupants create Wi-Fi connections/disconnections but they may not create energy-load changes [27,84] and thereby, wrongly identifying the events of temporary occupants and correlating the event with energy-use data could result in biases in data analysis. To ignore the Wi-Fi connections of temporary occupants, a minimum number of connections (e.g. ten connections) is empirically determined for a building and considered as Wi-Fi threshold,  $th_{wi-fi}$ , for iSEA. Then, if an ID is presented in data less than  $th_{wi-fi}$ , the ID is tagged as a temporary occupant and accordingly, removed from data analysis.

#### **Step 4: estimate EEI**

After collecting the required energy data and occupancy information, iSEA correlates the pre-processed aggregate load data of the building with the departure event of the last smartphone ID on a day to estimate the EEI of the ID for that day (see equation 1). Accordingly, the EEI for each day is found and  $Mat_{EEI}$  is constructed. Finally,  $EEI_{avg}$  of the IDs are estimated (see equation 2).

#### **Step 5: identify efficient and inefficient behaviors**

In the fifth step, iSEA utilizes the  $EEI_{avg}$  values to rank IDs and assign them into categories of efficient behaviors ( $CATEB$ ) and inefficient behaviors ( $CATIB$ ). In this process, the larger  $EEI_{avg}$  indicates the more efficient behaviors.

Literature [22,24,120–122,124–126] demonstrates that the difference between  $CATEB$  and  $CATIB$  should empirically be determined for a building since several factors (such as building type,

architectural design, insulation, systems, occupants' duties, and working hours) functionally affect energy-use behaviors. Accordingly, iSEA determines the range of each category on a case by case basis.

### **Step 6: learn personal energy-use behavior**

By leveraging the EEI information collected in step 4, iSEA learns each occupant's energy-use actions to identify the set of appliances that she typically leaves on at her departure events; this information will be utilized later for feedback. Studies [134–144] have indicated that individual occupants have their own energy-use patterns/behaviors and typically follow those over time. This provides opportunities to learn their behaviors to monitor/simulate/predict occupants/buildings energy consumption. Accordingly, this fact indicates that an occupant with inefficient behaviors typically leaves on a same set of appliances (during non-working hours) over time which allows to identify the appliances and to ask the occupant to turn those off before leaving the building.

In this context, iSEA uses a supervised deep learning method to learn each occupant behaviors. Compared to the conventional learning methods such as neural network, deep learning as a novel subset of machine learning methods allows for more accurate and faster learning of complicated and detailed structures even in large datasets [145,146]. Due to existing of multiple appliances/systems and occupants (with different/distinct energy-use behaviors) in a building which create a challenging task to identify each occupant's behavior through aggregate energy-load data, iSEA uses deep learning approach.

In particular, in a building with  $n$  occupants and  $K$  appliances, each appliance has a specific power usage in watts,  $W_k, k \in \{1,2, \dots, K\}$ , which is considered as a feature for the appliance. Accordingly, these features are used to train the deep learning method. Then, based on the differences between  $AL_{t_2}$  and  $BL$  for different days of an occupant, deep learning discovers the set of appliances that she predominantly leaves on at her departure events. This process for occupant  $i, i \in \{1,2, \dots, n\}$ , on day  $d, d \in \{1,2, \dots, D\}$ , is:

$$P(i, d) = [ \sum (W_k)_{i,d} = (AL_{t_2} - BL)_{i,d} ] \quad k \in \{1,2, \dots, K\} \quad (3)$$

Where  $P(i, d)$  represents the probability function which determines the appliances that their total energy consumption (in watt) should be equal to the residual load in aggregate data right after occupant  $i$ 's departure event on day  $d$ .

Accordingly, collecting information form several days of occupant  $i$  when she leaves the building as the last person, allows deep learning to identify the possible appliances (i.e., the appliance with high probability of occurrence) that she typically leaves on at her departure events. Thus, the probability function of occupant  $i$  of the building is summarized by:

$$P(i) = [d . P(i, d)] \quad i \in \{1, 2, \dots, n\}, d \in \{1, 2, \dots, D\} \quad (4)$$

### **Step 7: provide personalized tailored feedback through iSEA smartphone app**

After assigning occupants to  $CATEB$  and  $CATIB$  (in Step 5) and identifying the appliances each occupant typically leaves on at departure events (in Step 6), iSEA allow BEMS users to deliver feedback to occupants to enhance their energy-use behaviors. The feedback includes personalized tailored graphical messages which not only modifies  $CATIB$  members' behaviors but also encourages  $CATEB$  members to continue practicing their energy-saving behaviors.

In particular, iSEA uses a comparative-historical feedback approach. The comparative feature compares an occupant behavior with her peers that provides competitive feelings between occupants and the motivation for better performance [147]. The historical feature allows an occupant to make a comparison regarding her own energy-use behavior over time [15].

To deliver the feedback to occupants, iSEA is planned to use an app developed by research team for iOS/Android based smartphones. A web-application is also planned to be utilized by BEMS users to track occupants. It is worth mentioning that IDs (generated and assigned to smartphones in Step 2) are used for information exchange through the app and web-application to protect the occupants' privacy.

### **3.3. IoT architecture**

Figure 3 shows the IoT architecture of iSEA framework. As demonstrated, iSEA includes four major layers: (1) physical, (2) cloud, (3) service, and (4) communication layers. These layers cover hardware, software, network, and integration aspects considered for IoT approaches.



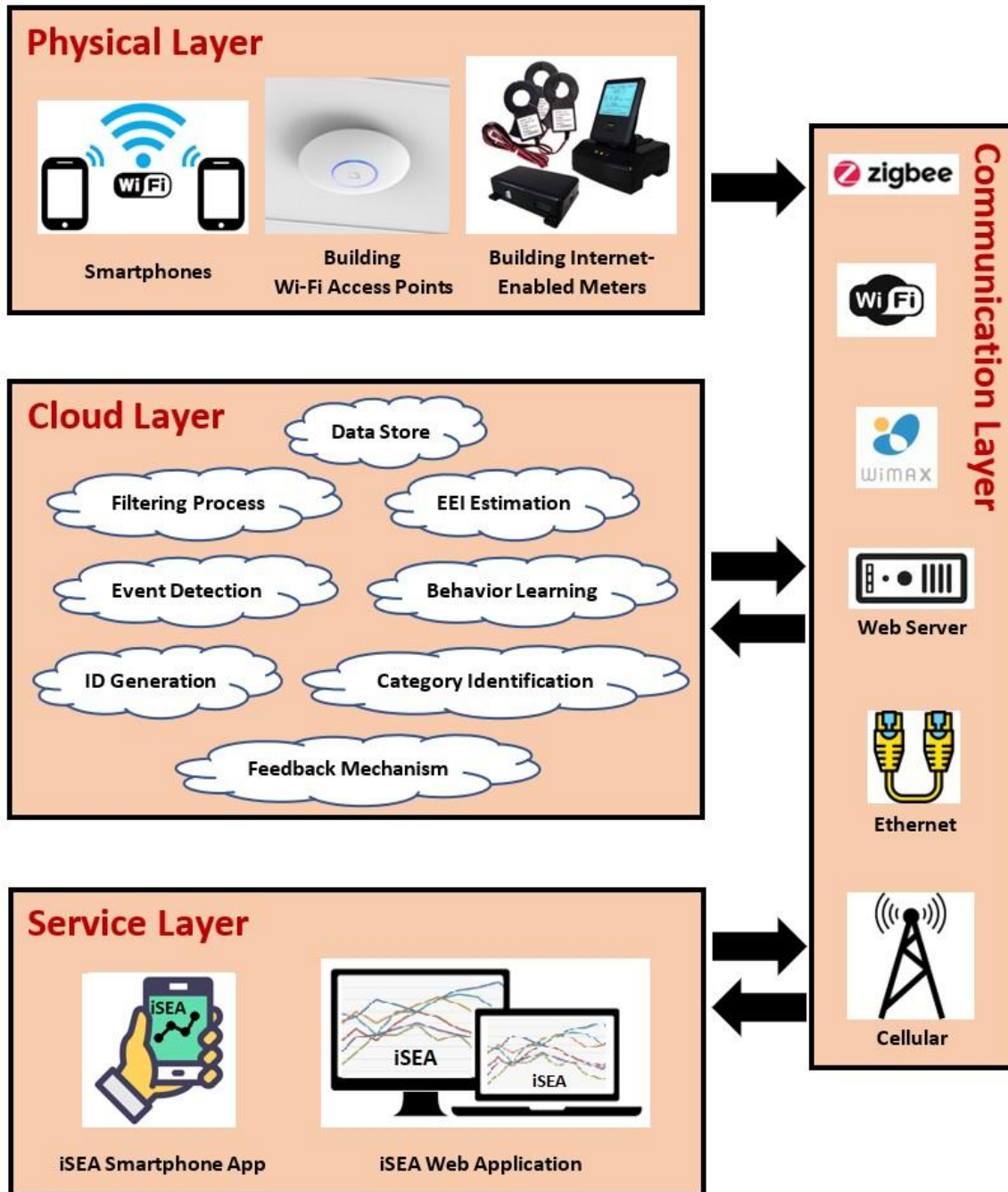


Figure 3. iSEA IoT architecture

### 3.3.1. Physical layer

The physical layer includes energy and occupancy sensors which collect the required data from a building. The energy sensors are low-cost COTS internet-enabled electric meters that are widely



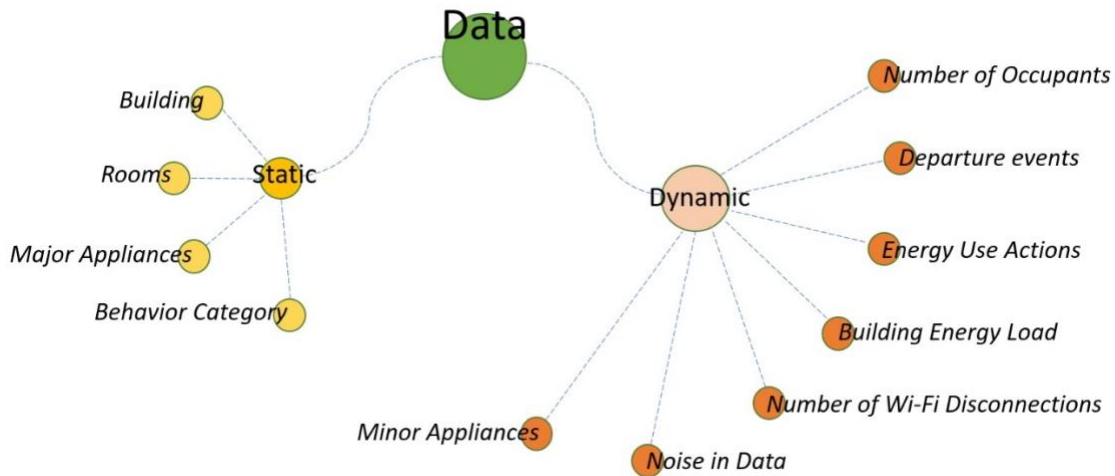
based on the Ethernet technologies (such as Ethernet Powerlink [148] and EtherCAT [149]) and typically use IEEE 802.3 standards. Functionally, internet-enabled meters are IP based objects interoperating with a variety of external data processors. Low-cost wireless routers which typically uses IEEE 802.11 and 802.15 standards, could be used to connect the meters to building wireless networks; IEEE802.15.4 standard has recently been utilized for IoT developments [150].

In addition, the meters should collect power and voltage data. Power data displays the building energy usage and should include real power (measured in watts), apparent power (measured in volt-amperes), or reactive power (measured in volt-amperes-reactive). The voltage data (measured in volt) allows to identify the noise in data. In addition, such meters generally have their own software systems which are typically web applications to allow users to monitor data in real-time.

The occupancy sensors are building Wi-Fi access points (APs) and occupants smartphones. APs are hardware devices of Wi-Fi networks and are mainly based on IEEE 802.11 and 802.15 standards. APs usually capture the packets of Wi-Fi enabled devices with a high-resolution (e.g., milliseconds) and provide information regarding association/disassociation time of client MAC addresses, their status, session durations, IP addresses, and service set identifiers.

### **3.3.2. Cloud layer**

The second layer is cloud which includes data storage, queries, and processing as well as data analysis steps of iSEA. Each of these could be done in real-time to meet the requirement of BEMS goals to take immediate actions toward prompting energy-saving behaviors. Figure 4 displays the iSEA data ontology and demonstrates the statics and dynamics data.



**Figure 4.** Data ontology

In addition, the cloud layer includes the feedback mechanism of iSEA approach. The feedback mechanism (in the cloud layer) could act as a semi-automatic or fully-automatic mechanism based on the BEMS preferences. The semi-automatic process allows BEMS to check and adjust the message notifying occupants regarding the appliances left on, while the fully-automatic option performs this step automatically. Functionally, the cloud layer acts as the decision-making layer for the iSEA.

While several programming languages could be utilized for data processing and analysis, we propose XML or Python for iSEA since they have widely been used for faster and more accurate data analysis in IoT approaches and web environments [40,49,151].

### 3.3.3. Service layer

The third layer is service which include two different sublayers. The first sublayer is a prototype web application developed by HTML. This application is installed on the BEMS computers and enables BEMS team to access to the cloud layer. This application visualizes the EEI,  $EEI_{avg}$ , and category ( $CATEB$  and  $CATIB$ ) of individual occupants for the BEMS team which allows BEMS to track each occupant information/index and to compare building occupants' behaviors. This application also provides the information regarding the possible appliances occupants typically leave on during non-working hours. It is noteworthy that, as mentioned, the web application

tracks/recalls occupants' information based on their assigned IDs which protect the privacy of occupants.

In addition, the web application allows BEMS to take actions on intervening occupants through the feedback mechanism (semi-automatic or fully-automatic) in the cloud layer. In the semi-automatic process, a BEMS user selects one of the proposed options of the web applications and then this preference is sent to the cloud layer for further actions.

The second sublayer of service layer is a prototype smartphone app. The app is developed based on an application programming interface and is installed on iOS/Android smartphones. The app allows each occupant to see her personal energy-use information and category ( $CAT_{EB}$  or  $CAT_{IB}$ ) and to compare her behaviors with her peers. In fact, the BEMS team uses the app to communicate with the building occupants. The app is able to receive data through cellular and Wi-Fi networks.

#### **3.3.4. Communication layer**

The fourth layer is communication which is the most important IoT layer to generate/keep the proper flow of data, information, and communication among the other layers. Due to the privacy of Wi-Fi information, the proper data transferring which keeps the information secure is also required. Accordingly, while there are different protocols (such as CoAP and MQTT), iSEA uses the protocols of IP over Ethernet and wireless networks. Functionally, IPv6 currently offers more efficient routing protocol and self-determining forming/configuration for networks [152].

In addition, due to the existence of Wi-Fi and Ethernet networks in a building, these networks are preferred to be used as the major component of communication layers in iSEA. Wi-Fi networks are predominantly based on IEEE 802.11 and 802.15 standards and Ethernet networks generally uses IEEE 802.3 standards. In addition, other wireless communication technologies such as Zigbee and WiMAX could also be utilized for data transferring/exchange (depends to the type of building and the BEMS preferences); compared to Wi-Fi, Zigbee uses a lower bandwidth while WiMAX uses a higher bandwidth.

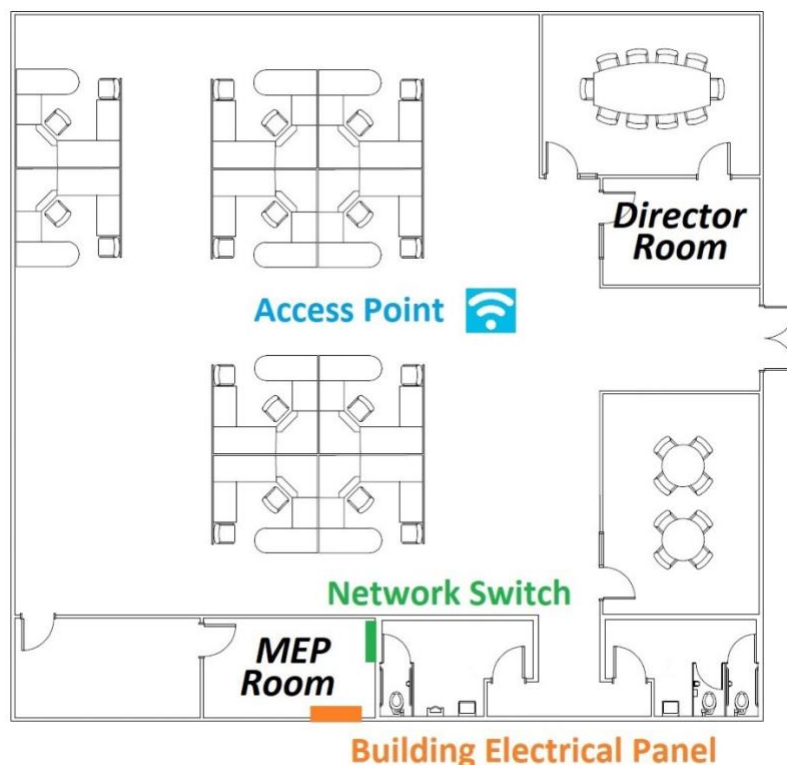
To deliver the feedback to the smartphone app, the communication layer uses the building Wi-Fi networks. In this process, iSEA uses the ID assigned to an occupant to recall her and sends the feedback to her smartphone. It is noteworthy that for this process, depends to the BEMS

preferences, cellular networks could also be utilized. This process requires collecting data about cellular specification/address of smartphones to identify and deliver feedback.

In the communication layer, the building web server allows the web application installed on different computers to communicate with each other. The server also provides the communication among different components of the communication layer.

#### 4. Pilot Experiment

To demonstrate the iSEA functionality, a pilot experiment was designed and conducted in a commercial office building over a twelve-week duration. Figure 5 displays the floor plan of the building. The building included one director room, one main room, one MEP room, one meeting room, one storage room, and one lunchroom. The main room included ten cubicles for the building employees. In addition, the total number of building occupants was ten during the experiment and their working hours were 9:00 a.m.-6:00 p.m.



**Figure 5.** Floor plan of the office building

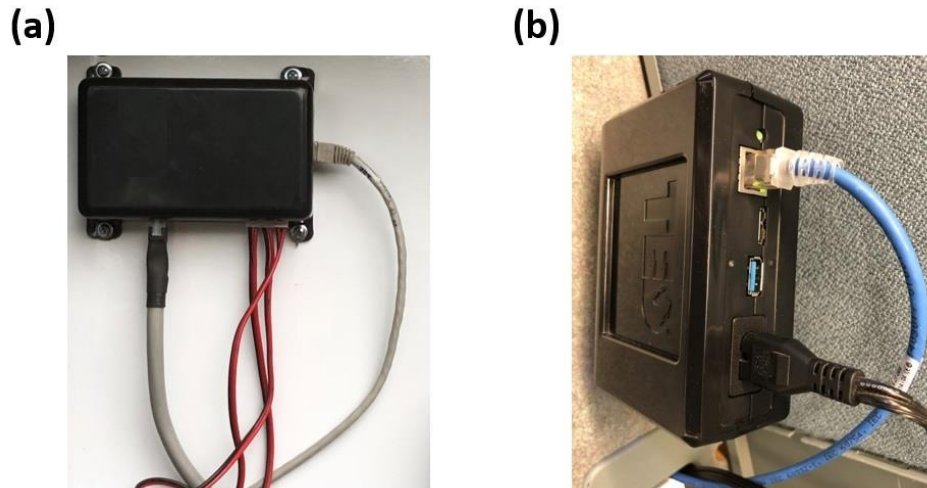
With regards to the major appliances and systems, the building included an HVAC system, a water heater, ceiling lights, ceiling fans, multifunction copiers, coffee makers, water boilers, a microwave oven, and a refrigerator. In addition, the ten cubicles included ten identical desktop computers, desk lamps, and desk fans. Except the HVAC system and water heater, all the mentioned appliances/systems utilized manual switches. The ceiling lights of the main room were particularly set on four separate electric circuits with four individual switches. In addition, two levels of brightness were set for the building ceiling lights in all rooms.

## **4.1. Data collection**

### **4.1.1. Energy-load data**

The energy-load data of the building was collected through an internet-enabled meter, “TEDProCommercial”. The meter included two parts: a measuring transmitting unit (MTU) and an energy control center (ECC). MTU acted as the data logger and was installed inside the main electrical panel of the building (Figure 5 displays the location of the panel). In addition, MTU was designed for three-phase electrical service (at the sampling rate of 1024 KHz) and was certified to deliver data within  $\pm 0.01$  of displayed value.

MTU collected building energy-load data including real power (measured in kW) and voltage (measured in V) at one-second interval resolution and sent the data to ECC in real time through the building ethernet network; ECC was installed at the director room. Both MTU and ECC were connected to the building network switch installed at the MEP room. Figure 6 shows MTU and ECC.



**Figure 6.** (a) measuring transmitting unit (MTU), (b) energy control center (ECC)

ECC embedded with footprints software [153] which sent the data to building sever in real-time. In order to collect the data provided by ECC, we installed a laptop computer at the MEP room during the experiment. Through a network cable, the laptop was connected to the network switch and was able to receive the data send by ECC through using a Python code developed by the research team. Accordingly, we collected the energy-load data as CSV files (one file per 45 minutes). In addition, a free cloud service was utilized as the cloud layer in this research and we saved the load CSV data on this cloud layer.

#### **4.1.2. Wi-Fi information**

We utilized the data collected by the ceiling-mounted Wi-Fi access point of the office building. The access point was installed in the main room (see Figure 5) and recorded the information of Wi-Fi enabled devices (presented within its range) at one-second interval resolution; the range of the access point provided full coverage for the building. The information included MAC addresses, the association and disassociation time of each address, their session durations, IP addresses, status, and service set identifiers. The building director was able to save daily data of the access point on his/her computer as CSV files (one file per day). Figure 7 shows a sample of the Wi-Fi information. Accordingly, we asked the director to share the CSV files with us and the data was saved on the cloud layer.

	A	B	C	D	E	F	G
1	Client MAC Address	Association Time	Disassociation Time	Session Duration	Client IP Address	Status	SSID
2	6c:8c:cd:47:16:b4	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:52:16 2018	7 hrs 21 min 16 sec	19.201.8.79	Disassociated	Building-Floor1-AP
3	04:4b:ed:4f:16:b4	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:56:10 2018	1 hrs 14 min 10 sec	19.201.8.79	Disassociated	Building-Floor1-AP
4	18:f6:83:0a:0f:1d	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:48:35 2018	1 hrs 3 min 35 sec	19.201.8.79	Disassociated	Building-Floor1-AP
5	e4:2e:zd00e:bf1	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:54:50 2018	1 hrs 29 min 50 sec	19.201.8.79	Disassociated	Building-Floor1-AP
6	f0:db:2a:7c:1d	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:52:14 2018	7 hrs 37 min 44 sec	19.201.8.79	Disassociated	Building-Floor1-AP
7	f4:f1:5c:79:6f:2b	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:57:26 2018	2 hrs 53 min 36 sec	19.201.8.79	Disassociated	Building-Floor1-AP
8	bc:3b:f1:b3:c1:94	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:53:30 2018	8 hrs 14 min 30 sec	19.201.8.79	Disassociated	Building-Floor1-AP
9	f4:f1:5c:79:6f:2b	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:57:26 2018	2 hrs 22 min 27 sec	19.201.8.79	Disassociated	Building-Floor1-AP
10	78:4b:4f:b3:c1:94	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:53:40 2018	15 hrs 9 min 40 sec	19.201.8.79	Disassociated	Building-Floor1-AP
11	90:b8:6d:61:b5:92	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:56:09 2018	1 hrs 23 min 9 sec	19.201.8.79	Disassociated	Building-Floor1-AP
12	f4:f1:5c:79:6f:2b	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:57:26 2018	1 hrs 34 min 23 sec	19.201.8.79	Disassociated	Building-Floor1-AP
13	78:4b:4f:b3:c1:94	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:53:07 2018	4 hrs 17 min 7 sec	19.201.8.79	Disassociated	Building-Floor1-AP
14	00:1f:5b:be:ce:db	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:50:20 2018	4 hrs 54 min 20 sec	19.201.8.79	Disassociated	Building-Floor1-AP
15	fc:db:b3:c6:6f	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:51:53 2018	36 min 53 sec	19.201.8.79	Disassociated	Building-Floor1-AP
16	60:f8:1d:4f:7d	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:51:27 2018	6 hrs 44 min 27 sec	19.201.8.79	Disassociated	Building-Floor1-AP
17	88:6d:1c:8f:94	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:57:50 2018	1 hrs 2 min 50 sec	19.201.8.79	Disassociated	Building-Floor1-AP
18	40:8f:0f:18:5d	Thu Jun 14 10:45:00 2018	Thu Jun 14 10:58:40 2018	31 min 40 sec	19.201.8.79	Disassociated	Building-Floor1-AP

Figure 7. Sample of Wi-Fi information (SSID: service set identifier)

#### 4.1.3. Smartphone information

To collect the information about occupants' smartphone during the pilot experiment, we developed a web application and asked the director to email the link of the application to the building occupants. Figure 8 shows the application and demonstrates that we asked each occupant to enter his/her cell number and the last six digits of the MAC address of his/her smartphone. No more information (such as name or cubicle number) was asked. This information was stored on the cloud layer as one CSV file. The CSV file only included two columns, one represented the cell numbers and one represented MAC addresses.

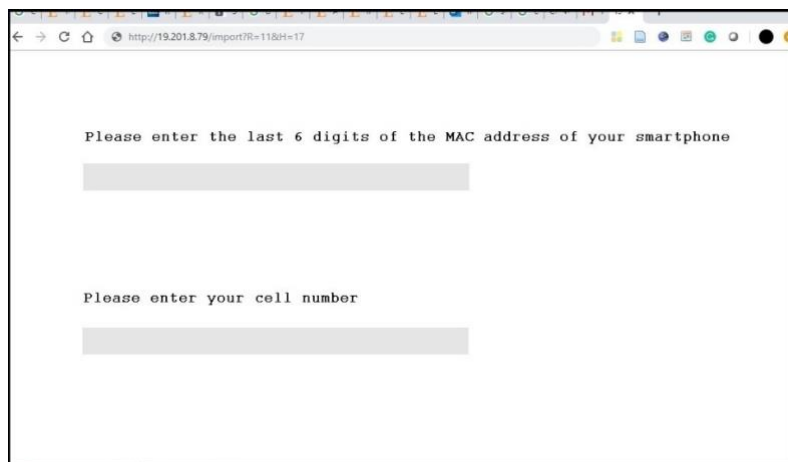
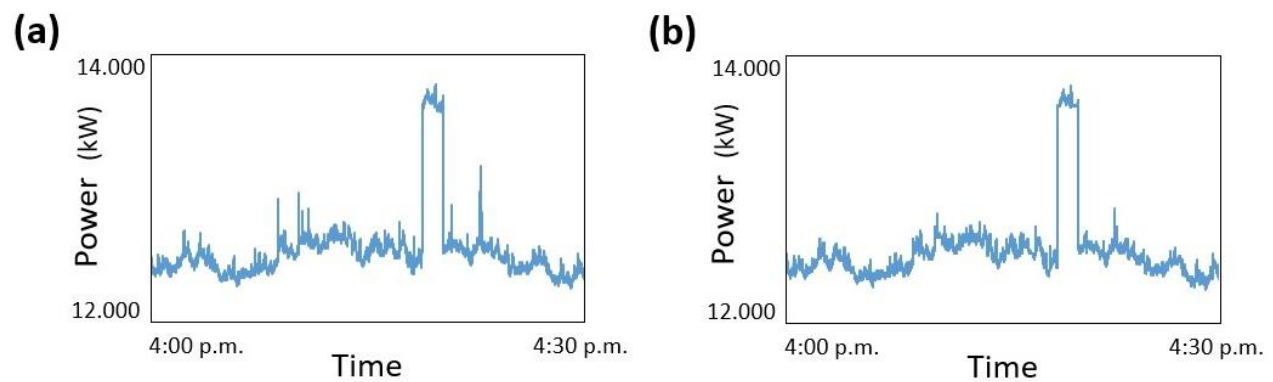


Figure 8. Web application to collect smartphone information



## 4.2. Data analysis

We utilized the cloud service for the data analysis. In the first step, we used Python and the historical data of the meter to develop a filter which was able to check the accuracy of energy-load data in real-time and filtered noise and corrupted/missed data. Figure 9 shows a sample of the filtering process. It is noteworthy that we also checked the power loss [128] in the building circuits and the estimated power loss was 0.00381 watts. Since the power loss was very low, we neglected the impact of the loss on energy-load data.



**Figure 9.** Sample of filtering process (a) MTU raw data, (b) processed data

In the second step, a Python code was developed to analyze the Wi-Fi information. For this reason, the code created one big dataset which included the information provided by building access point (see Figure 7) as well as the information of smartphones (including the last 6 digits of MAC addresses and cell numbers). Then, through correlating the six digits of the occupants' MAC addresses with the MAC addresses predominantly presented in our data at the departure events, the Python code identified each occupant's MAC address and generated a random ID to mask the MAC address with the ID. The ID format included two letters and three digits (e.g., BK738). Next, for each day of the experiment, the last disassociation time of each MAC address (presented in smartphone information) was identified (from the data provided by access point) and considered as the departure event of the address. It is worth mentioning that the Wi-Fi information



analysis was completed in the back-end system and we, as the research team, were able to see/track only the IDs and the time of their departure events; this let protect the privacy of the occupant.

In the third step, the last departure event of each day and its responsible ID was found. Accordingly, by using the preprocessed energy-load data, the EEI of each day was estimated (see Equation 1). In this step, based on the collected data and information received from the director of the building,  $t_1$  and  $t_2$  were empirically estimated and set on 210 and 600 seconds, respectively, for all the occupants of the building. To estimate the base line ( $BL$ ), the energy-load data at morning from 8:30 a.m. to 9:00 a.m. was utilized. As mentioned, the working days of the office started at 9:00 a.m. during the experiment and the director mentioned that HVAC systems was set to turn on at 8:30 a.m. Accordingly, the time-window of 8:30-9:00 presented the background energy load (including HVAC system usage) for the unoccupied time of the office which was used as  $BL$ . After estimating EEI,  $Mat_{EEI}$  was constructed and used to calculate the  $EEI_{avg}$  of each ID (see Equation 2).

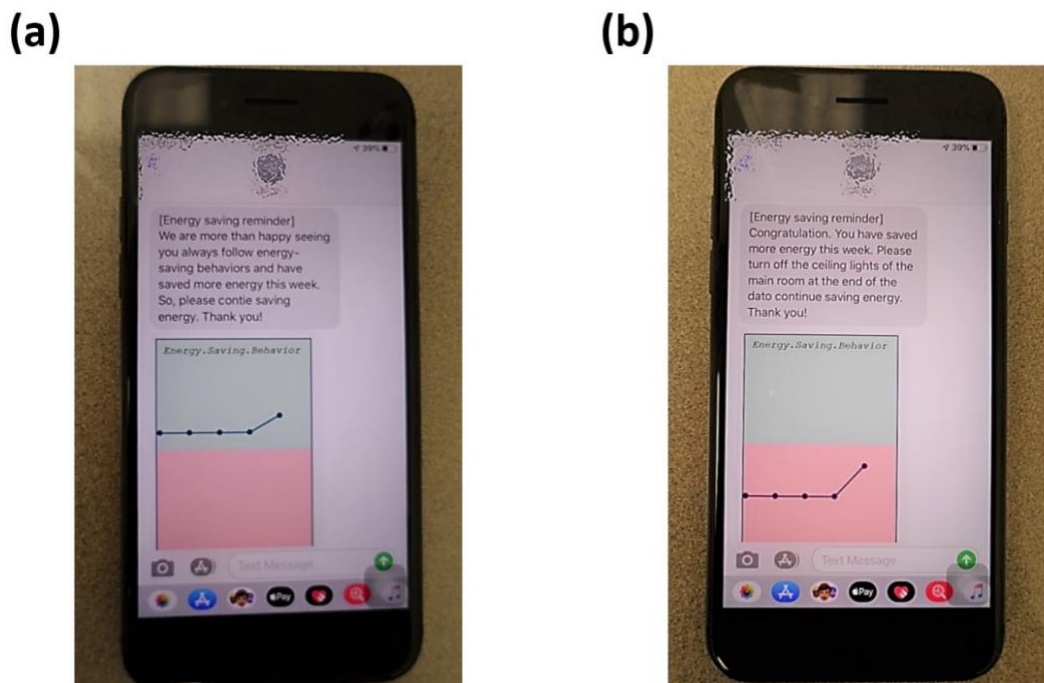
In the fourth step,  $CATEB$  and  $CATIB$  were empirically defined and occupants were assigned to one of the categories; higher  $EEI_{avg}$  indicated more efficient behaviors. In fact, based on the building type, appliances/systems, building occupants' duties, the discussion with the director, and the literature methodologies [22,24,55,121–126], we finally considered two equal quantiles for  $CATEB$  and  $CATIB$ . To determine the boundary of each quantile, based on the data of the first four weeks, we estimated the  $EEI_{avg}$  of each ID and based on the smallest and largest  $EEI_{avg}$  values, the boundary of each category was identified. It is noteworthy that we divided the experiment duration (twelve weeks) to two sub-durations: (1) First four-week sub-duration, and (2) last eight-week sub-duration. The data of the four-week sub-duration was utilized to understand the behavior of each occupant while the feedback was implemented during the last eight weeks.

In the fifth step, the power usage (in watts) of office appliances/systems were found through their nameplates/labels and used as input information to train the deep learning approach for identifying the set of appliances that an occupant typically left on at his/her departure events (see Equation 3 and 4).

In the last step, a tailored personalized feedback message was developed and sent through a text application to each ID's smartphone. It is worth mentioning while a series of prototype smartphone apps were developed and tested for iSEA, we decided to use a text application to deliver feedback to the occupants in this study (based on the request/preference of the director and

occupants of the building). The text application was an open-source and free-to-use software without licensing constraints.

The structure of the message was comparative-historical and included texts and figures. Figure 10 shows the samples of message delivered to occupants of each category. In order to find the frequency at which feedback messages should have been provided to the occupants, we conducted a pre-survey before the experiment. The results revealed that occupants preferred to receive up to two messages per week. The occupants also determined on which day of week they prefer to receive the feedback message. Accordingly, we decided to provide two messages (on Monday's and Thursday's mornings) to occupants. The messages content was developed in a way to encourage the occupants of *CAT<sub>EB</sub>* to continue with their energy efficient behaviors and to motivate the occupants of *CAT<sub>IB</sub>* to follow the energy efficient behaviors. In addition, based on the literature recommendation [26,63], we provided the occupants with positive comments rather than negative ones (e.g., using “saved” instead of “wasted”).

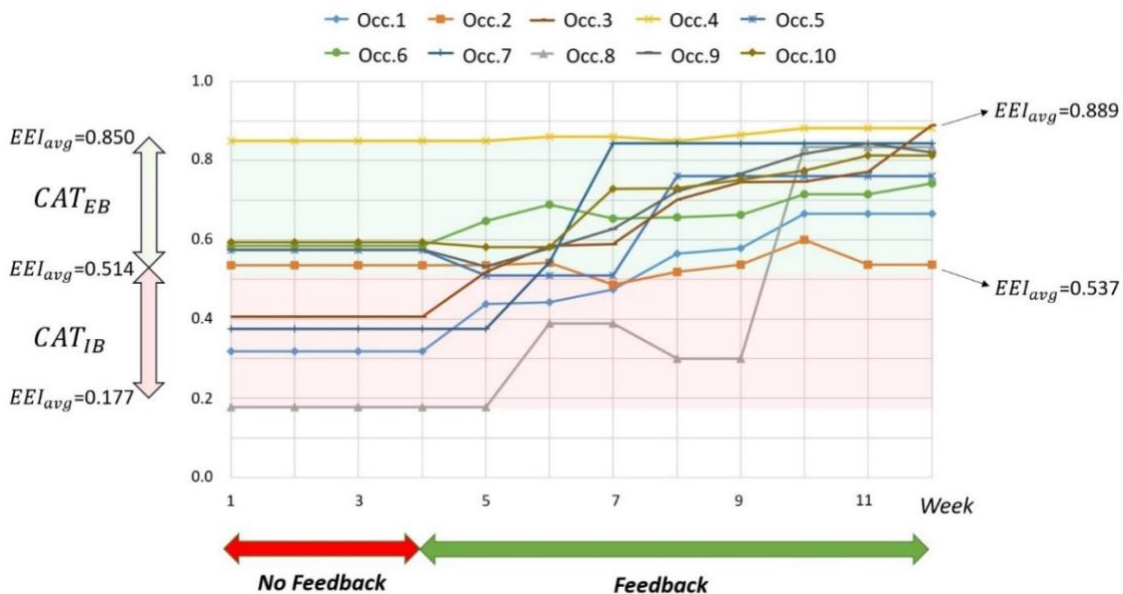


**Figure 10.** Samples of feedback message (a) for occupants with efficient energy-use behaviors, (b) for occupants with inefficient energy-use behaviors

Before the feedback period, we provided the occupants with the description of the feedback figure. The green area demonstrated  $CAT_{EB}$  and the red area demonstrated  $CAT_{IB}$ ; this was considered as the comparative feature of the feedback. In addition, by using  $EEl_{avg}$ , the progress of each occupant was demonstrated with a dot plot which was considered as the historical feature. It is worth mentioning that the message contents sent to each occupant included few typographical errors (e.g., “dato” instead of “day to” in Figure 10-b) which was resulted from the text application.

## 5. Results

Figure 11 summarizes the results of the energy-use behavior variations over time; the vertical axis presents  $EEl_{avg}$ . As mentioned, the data of Week 1-to-4 was utilized to estimate the initial  $EEl_{avg}$  of the occupants and these values are presented for these weeks on Figure 11. In addition, based on these four weeks, Occupant 4 with  $EEl_{avg}$  of 0.850 was identified as the occupant with the most energy efficient behavior while occupant 8 with  $EEl_{avg}$  of 0.177 was tagged with the worst behavior. Accordingly, based on these two values, the ranges of  $CAT_{EB}$  and  $CAT_{IB}$  were estimated in a way that both have equal quantiles. Overall, Figure 11 displays that we influenced occupant energy usage.



**Figure 11.**  $EEl_{avg}$  of the occupants during the experiment (Occ.: occupant,  $CAT_{EB}$ : category of efficient energy-use behaviors,  $CAT_{IB}$ : category of inefficient energy-use behaviors,)

Figure 11 shows that four occupants followed non-energy-saving behaviors before the feedback and five occupants from *CATEB* had potentials for presenting better energy-saving behaviors (since their  $EEI_{avg}$  were close to the minimum  $EEI_{avg}$  of *CATEB*). In addition, as the figure indicates, by the end of the experiment, the minimum and maximum of  $EEI_{avg}$  were 0.537 and 0.889, respectively, which means that the feedback was able to modify the behaviors of the *CATIB* to energy efficient behaviors.

To assess the feedback progress, we compared the arithmetic mean of  $EEI_{avg}$  of the occupants before and after the feedback (the first and the last week) which were 0.521 and 0.789, respectively. Accordingly, based on the  $EEI_{avg}$ , there was 34% improvement in energy-use behaviors at departure events when the occupants left the office as the last occupants (which does not necessarily mean 34% reduction in energy consumption).

Furthermore, through the deep learning approach, iSEA revealed that occupants typically left on ceiling lights of the main room, storage room, and lunch room as well as the desk fans over the experiment. Due to (1) having two levels of brightness for the building ceiling lights, (2) existing four separate electric circuits (with four individual switches) for the main room lights, and (3) different locations of the cubicles, occupants displayed different behaviors in controlling over the lights. Such differences in behaviors resulted in distinct  $EEI_{avg}$  demonstrated in Figure 11.

In particular, the deep learning approach revealed that Occupant 8 (as the occupant with worst energy-use behavior) predominantly controlled over the ceiling light which covered his/her cubicle and did not change the state of the other lights at his/her departure events (when he/she left as the last occupant). In addition, the approach did not detect any in-use lighting systems after the departure events of Occupant 4 over the experiment which indicates this occupant followed efficient behaviors over time; Occupant 4's  $EEI_{avg}$  on Figure 11 highlights this type of behavior. Furthermore, the deep learning identified that Occupant 5, 6, 9 and 10 did not regularly turned off the ceiling lights of the lunch room (while controlled over the other lighting systems) at the departure events before the feedback implementation. This resulted to roughly similar  $EEI_{avg}$  for these occupants for the first-four weeks (see Figure 11).

In addition, Figure 11 shows the maximum  $EEI_{avg}$  achieved during the experiment was 0.889 while based on the definition of this index, the maximum value could be 1. This difference could have been resulted from the *BL* estimation in this study (see Equation 1). In addition, there

was a possibility that some occupants left their desktop computers on after working hours and such appliances went to sleep mode during non-working hours. Accordingly, even if the last occupant of a working day followed energy-saving actions, there were still residual loads (at his/her departure events) which did not allow  $EEI_{avg}$  to achieve to the maximum value of 1.

## 6. Discussion

While current literature [52–55] of occupant-related IoT studies mainly focuses on occupancy sensing approaches and does not necessarily improve energy-use behaviors, this study introduced an IoT-based approach, iSEA, with the ultimate goal of enhancing individual occupants energy usage in commercial buildings. iSEA uses the occupants' smartphones to track them and correlates this information with building energy consumption to understand each occupant's comprehensive energy-use behavior on personal and shared appliances in a non-intrusive manner; this point has not been well studied in the current literature of non-intrusive monitoring [55,76–81] since the available approaches predominately provide the usage of personal appliances. In addition, iSEA utilizes an IoT-based technique to provide each occupant with tailored personalized feedback to promote energy-saving behaviors in real-time. The results of the pilot experiment revealed the iSEA capability in addressing the current gaps of literature [9,22–25] in collecting personalized data, identifying anomalous behaviors, delivering personal tailored information, and tracking behavior change in real-time.

Occupants directly and indirectly control appliances and systems of commercial buildings and modifying their behaviors contributes to save one-third of energy consumption in such buildings [9]. We believe that iSEA improves such behaviors at minimal costs, without installing new hardware in commercial built environments. Conventional personalized feedback techniques predominantly install individual power meters per cubicle/workstation (i.e., intrusive methods) to collect personalized energy-use data in commercial buildings [26]. Accordingly, these techniques demand large capital investments to purchase, install, and maintain the power meters (roughly \$100.00 per meter according to our information/experience working with these devices). This demonstrates that it is often impossible for BEMS to economically estimate the accurate personalized usage in commercial building. Comparatively, iSEA provides more pleasant information for BEMS since this method only utilizes the data provided by existing sensing infrastructure of commercial building.

The cost of purchasing the internet-enabled meter used in this study (including the MTU and ECC parts) was around \$600.00 which was approximately three times as much as that of a conventional building-level power meter for office buildings. In addition, the building director mentioned that during the major renovation of the building, the meter was installed inside the main electrical panel and the installation cost was approximately similar to the installation of a conventional meter. The director also indicated that the maintenance cost of the meter (including its network services) is very low and can be neglected. Therefore, compared to the conventional building-level meters, this meter has costed around \$400.00 more (resulted from purchasing) for the entire process of purchasing, installation, and maintenance. However, considering that prices are subject to fluctuations and the prices of internet-enabled devices are dropping (due to popularization of such devices), the aforementioned difference in purchasing prices has reduced with time. In addition, as mentioned, internet-enabled meters provide data with higher resolution and enable the execution of IoT-based approaches which benefits to move toward smart buildings (with the ultimate goal of energy saving in the built environments). Such facts justify the additional costs that internet-enabled meters provide compared to the conventional building-level meters.

During our study, the cost of electricity was roughly 10.50¢/kWh and daily non-working hours were around 15 hours (due to working hours of 9:00 a.m.-6:00 p.m.). In addition, the deep learning approach identified that building ceiling lights with approximately 515 watts typically left on during non-working hours for four nights per week (before the feedback implementation). Accordingly, this wasted at least \$13.00 per month for the studied office building (which was a small-sized building) and we were able to save it through the feedback experimental period; the building director mentioned that it was a considerable cost in monthly building electric bill. Nowadays, lighting systems account for more than one-fourth of building energy usage [47,154,155] and our results, similar to feedback literature (e.g., [26,55,119,120,156–160]), demonstrated that commercial building occupants typically leave lighting systems on at departure events (which could be considered as the main source of wasting energy during non-working hours). Due to using of manual switches for lighting systems in most commercial buildings, occupants' energy-use behaviors thereby critically control these system operations (compared to other major appliances/systems -e.g., HVAC system- which are typically automatic-programmable systems). Considering this aspect in future feedback studies provide better opportunities to build more efficient tools to modify behaviors.



Through the pilot experiment, we have taken an initial step in applying iSEA. While the smartphone app was developed and initially tested before the experiment, due to the occupants' preferences, we used the text software to deliver feedback messages to occupants (see Figure 10). In addition, during the experiment, we controlled over the iSEA web application. Thus, there was no opportunity to ask the occupants to use the iSEA app and web application and to evaluate their user-friendliness to make sure they are simple and straightforward to use. With this in mind, the experimental period allowed us to assess the back-end of iSEA and we were able to properly test the physical, cloud, and communication layers (see Figure 3). Further assessing of the iSEA service layer will therefore be conducted in our future study.

In addition, due to the privacy concern and occupants' preferences in this research, we did not collect occupancy ground-truth data and therefore, we were not able to report the accuracy of occupancy. However, literature [90–98] has demonstrated that Wi-Fi networks determine occupancy presence with a high level of accuracy (at least 83%). Thanks to the literature and based on our experience in working with Wi-Fi-based occupancy sensing methods [55,80,84,99,100,115], we believe that the data analysis in this study might have been slightly impacted, but was not distorted by occupancy information provided by Wi-Fi networks.

While the need to use MAC addresses might be considered a privacy issue, iSEA requires no personal information about the owners of MAC addresses. During the pilot experiment, as Figure 8 shows, we only collected the last six digits of MAC addresses of the occupants through the web application and no personal information was collected. In addition, iSEA generated random IDs and masked the MAC addresses with the IDs. This process was done in the back-end system on the cloud layer and thereby the occupants' privacy was protected. It is worth mentioning that as Figure 7 shows, existing Wi-Fi networks of commercial buildings typically track data from different Wi-Fi enabled devices, which let find and track a specific MAC address to see how many days and when (in each day) that MAC address appeared in a building. Thus, such information (regardless of the privacy) always exists and iSEA was not specifically monitoring any extra information.

Due to the similarity of the workstation and shared appliances controlled over by the occupants, similar energy-use behaviors had been expected before the experiment. However, Figure 11 revealed that occupants displayed distinct energy-use behaviors before the feedback implementation (over the first four weeks) and showed individual difference in working patterns.

In addition, Figure 11 demonstrated the entropy in each occupant behavior over the feedback duration. Occupant 2, 5, 6, and 8 had a drop in their  $EEI_{avg}$  during the feedback period. Also, the  $EEI_{avg}$  of Occupant 2 at the first and last weeks were approximately similar which might indicate we did not properly identify his/her behavior and accordingly, the feedback messages delivered to him/her might negatively have impacted his/her behavior. Such results might also be due to the human flexible/changeable behaviors [75,161]. More investigation into the explanation of such behavior changes will be done in our future research.

With such findings in mind, while Figure 11 visually demonstrates the proper performance of the feedback to modify behaviors, we further investigated whether the behavior changes were statistically significant or not. For this reason, we developed a hypothesis to statistically assess the differences in energy-use behaviors before and after feedback implementation. The null hypothesis was defined as no statistically significant difference among the  $EEI_{avg}$  of the occupants before and after the feedback implementation while the alternative hypothesis was defined as statistically greater  $EEI_{avg}$  for the occupants after the feedback implementation. Due to having two groups of data for the hypothesis, we utilized a two-sample  $t$ -test and a Mann-Whitney  $U$  test to test the hypothesis. The test statistic was 5.247 and 4.362 for the  $t$ -test and  $U$  test, respectively. In addition, the level of significance resulted from each test was significant ( $P$ -value  $< 0.00001$ ) which statistically confirmed that occupants displayed larger  $EEI_{avg}$  after receiving feedback.

While we conducted a comparative-historical feedback technique to modify behaviors, peer pressure might also have influenced the behaviors; the peer pressure displays the fact that occupants influenced by feedback could interact with other occupants of their built environment to modify their energy-use behaviors [26]. In the studied building, occupant shared a working space and accordingly, word-of-mouth (which represents informal, occupant-to-occupant, face-to-face communication [162]) might have been effective in encouraging peers following energy-aware behaviors. Future studies are thereby recommended to study the peer pressure influence and to determine the changes generated by this factor (considering that social influence might be less effective when occupants use single-occupant rooms in a building). Utilizing emerging modeling methods introduced in the social and computer sciences could be helpful in peer pressure analysis.

In order to ascertain that we were providing feedback with an appropriate frequency (to avoid information overload discouraging occupants from properly reacting to the feedback), based on the occupants' preferences, we provided two messages per week to each occupant and our



results demonstrate that all the occupants were active to positively response to the feedback during the experimental period. This could demonstrate that future studies might use this frequency for their feedback in small-sized commercial buildings. In addition, higher frequencies might be helpful when occupants predominantly follow inefficient behaviors, and/or where there is a large population (such as large-sized buildings). In a large-size commercial building, it is often impossible for the last occupant to control over all the in-use appliances/systems (such as ceiling lights) at her departure events. Therefore, other occupants (leaving nearly close to the last departure event) should also be remind to take energy-saving actions at the end of their working hours. Accordingly, in such cases, researchers are recommended to study the behavior of a group of occupants (instead of one occupant) at departure events.

## **7. Limitations and Future Research**

While our results demonstrate that we properly modified energy-use behaviors during the experiment, literature [14,60,156,163–166] points out that the promoted energy-saving behaviors during feedback experimental periods could rarely be remained over time by occupants and they typically get back to their original behaviors after the experimental periods. In our research, due to the request/permission of the building director, we were able to collect data only for the twelve-week duration and we decided to use this duration for studying and modifying energy-use behaviors (since literature [26] indicates that eight-to-sixteen-week duration should be considered for properly understanding/modifying energy-use behaviors). Given that, we failed to check a long-term energy-saving contribution of iSEA. Thereby, future studies are recommended to assess and evaluate the long-term effectiveness of feedback. A long-term technique could be flyers displayed in public settings of a building to remind the occupants about the main energy-saving tips identified during the feedback experimental period. Accordingly, in our future study, we will divide the duration to three major steps; (1) collecting preliminary data for understanding energy-use behaviors, (2) implementing feedback for improving behaviors, and (3) tracking behaviors (after feedback experimental period) for assessing the long-term effectiveness of the feedback. In particular, during Step 3, we will utilize flyers/posters including energy-saving tips identified during Step 2.

In addition, we acknowledge that the findings of this study regarding iSEA performance and energy-use behaviors could be benefited from a larger sample size of commercial buildings.

Accordingly, in our future study, we will utilize medium- and large-sized buildings for further iSEA evaluation, especially for testing its service layer (the web application and smartphone app). In particular, in a medium-/large-sized building, there is a high possibility of overlapping of departure events that could adversely impact iSEA performance due to the difficulty raised from properly identifying the last departure events and correlating the aggregate energy-load data with the events. To address this, in our future study, we will focus to enhance the resolution of occupancy sensing to a zone level in medium-/large-sized buildings (compared to the building level utilized in this study). Since such buildings are equipped with multiple Wi-Fi APs, we will divide a building to several zones (each zone is covered by one AP) and leaving each zone will be considered as departure events. This granularity in events is therefore expected to address the difficulty of identifying the last departure events.

## **8. Conclusion**

This paper proposed iSEA which is an IoT-based energy assistant tool providing personalized tailored feedback to the smartphones of commercial building occupants to enhance their energy-use behaviors. In addition, this tool enables the BEMS to monitor individual occupants and their energy-usage changes. Compared to the conventional feedback techniques installing additional sensors for data collection steps, iSEA collects the required data from existing IoT sensors in a web-based commercial setting which allows to implement feedback at minimal costs. The results from the pilot experiment conducted in a building with ten occupants over a twelve-week duration demonstrated the proper performance of iSEA for engaging occupants to feedback and enhancing their behaviors. In particular, through the experiment, we properly tested the back-end system of iSEA that includes physical, cloud, and communication layers.

iSEA could be implemented into small-to-large sized commercial buildings with the ultimate goal of enhancing building energy consumption. In addition, iSEA contributes into IoT-based building energy management efforts by demonstrating how IoT can save energy in built environments through modifying individualized energy-use behaviors. Our future work will mainly seek to assess the front-end system of iSEA (the service layer) through iSEA execution in test beds of commercial buildings.

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