# Assessing Occupants' Energy-load Variation in Commercial and Educational Buildings: Occupancy Detecting Approach Based upon Existing Wireless Network Infrastructure

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## ABSTRACT

Providing energy-consumption feedback has the potential to change people's behavior, a reality that has led to significant energy-usage reductions in residential buildings. However, it is challenging to provide feedback in commercial and educational buildings because it is difficult to track occupants' behaviors and their corresponding energy usage—especially for temporary occupants. In order to make providing such feedback possible in commercial and educational buildings, this paper presents a coupled system that monitors the energy load for occupants who have Wi-Fi-enabled devices. The system benchmarks energy loads using an energy monitoring system that simultaneously detects occupancy and roughly estimates the residents' location through Wi-Fi access points. A preliminary experiment was conducted in an educational building to illustrate the data processing procedure and to test the validity of the system. The experiment results suggest the event of wireless connection is a valid indication of energy load variation. The proposed system is the prototype of a coupled system that, in the future, will be able to estimate individual's energy load through an indoor positioning system and, in turn, provide corresponding energy-consumption feedback.

## INTRODUCTION

Buildings account for 40% of all energy consumed every year, making them the largest consumer of energy in the U.S. (U.S. Department of Energy 2011). Residents in commercial and educational buildings significantly contribute to and exercise a great control over a significant amount of the energy end-uses, such as lighting, space heating, space cooling, electronics and appliances (U.S. Department of Energy 2011). Conventional approaches toward enhancing building energy efficiency focus on building envelope retrofitting and system update. However, such approaches require large capital investments and sometimes are infeasible.

Recently, researchers propose that changing people's behavior by providing high resolution feedback has a great potential to contribute to the reduction of energy consumption. Feedback, in the context of energy-related research, means all levels of information related to energy consumption that may be provided to energy end-users. By providing real-time energy feedback to occupants, researchers observed up to a 46% reduction in consumption in residential buildings (Abrahamse et al. 2007;

Peschiera et al. 2012; Petersen et al. 2007; Ueno et al. 2006). More recent research suggests that by providing feedback through attractive interface designs (Jain et al. 2013), social networks (Azar and Menassa 2013; Chen et al. 2012) and multi-layer channels (Chen et al. 2013; Chen and Taylor 2012), occupants could achieve a significant reduction in residential buildings.

However, commercial and educational buildings, who are consuming more than 19% of all energy annually (U.S. Department of Energy 2011) and have a potential 24.7% energy reduction through occupant behavior changes (Azar and Menassa 2013), are seldom studied. This void is because of two challenges. First, due to the large number of residents in commercial buildings, tracking occupants' energy consumption is extremely difficult. Second, the mobility of occupants results in complex energy usage patterns. Each occupant could be responsible for energy loads at multiple locations at various time periods. Existing wireless network (Wi-Fi network) could be used to identify the rough location of the occupants, but it is still unclear if the information of wireless connection could be used to track the energy load variation in commercial and educational buildings (Martani et al. 2012). Therefore, this research aims at confirming whether the events of wireless connection could indicate the energy load variation through real-time energy monitoring systems and Wi-Fi networks.

## BACKGROUND

### Challenges of energy-load estimation in commercial buildings

Compared to residential buildings, estimating occupants' energy load is a challenging task in commercial and educational buildings. The difficulty arises from several major issues: (1) Scale of Occupants. Commercial buildings and educational buildings have more residents in a relatively dense but larger space. It is extremely difficult to estimate the energy load of a single occupant from a large group of people. (2) Term of Stay. Occupants in residential buildings normally have a longer term of residency. However, a great portion of occupants in commercial buildings are temporary. Therefore, the temporal resolution of data (how often the data is collected) is crucial to estimate the energy load during the time of temporary occupants' stays. (3) Responsibility of Bill Payments. Occupants in commercial and educational buildings are not responsible for the payment of energy bills. Considering the fact that bill-payment provides consistent feedback that has been shown to modify behavior, these commercial and educational building occupants may have different energy-usage patterns compared to those in residential buildings. (4) Components of Energy Consumption. The structure of energy usage is different in commercial and residential buildings (EIA 2013). For example, cooking is a major component for energy consumption in residential buildings but negligible in commercial buildings. The portion of occupants' controllable energy load is different in commercial buildings.

### Building occupancy detection

There are many solutions available for indoor occupancy tracking, such as extended GPS, sensor networks (Michel et al. 2006; Niculescu 2004), InfraRed (IR) (Aitenbichler and Muhlhauser 2003), Ultra-Wideband (UWB) (Correal et al. 2003) and RFID ( Ni et al. 2004). A relatively new option is the Wi-Fi solution, which offers a more efficient, affordable, and less complex option for indoor tracking (Lassabe et al. 2006). The system is especially suitable for urban areas because of the frequency of signal overlapping, which creates a natural reference system (Zandbergen 2009). The Wi-Fi access points (AP) are able to create a database where the MAC address of the access points may be stored together with the symbolic name of the location. The position of the user may then be calculated through the location of APs and the single strength.

A Wi-Fi network is extremely suitable for commercial and educational buildings, which have multiple overlapping access points as the reference system. The drawback of this approach is that if an access point is removed or changed, the estimated position of the user may be distorted (Lashkari et al. 2010). Additionally, a Wi-Fi network approach may not take into account the scale or activities of occupants. Martani et al. (2012) and Li et al. (2012) utilized the number of Wi-Fi connections as indicators of building occupancy to promote smart energy management for lighting and HVAC; however, their research failed to build the correlation between occupancy and energy use because of some limitations: first, the building scale was too large to capture the energy-load variation caused by single connections; second, a large number of occupants may not have had or used their wireless devices, thereby distorting the total number of Wi-Fi connections. While their research contained these limitations, their approach offers an interesting springboard for the current research.

## RESEARCH FRAMEWORK

In addition to a Wi-Fi network, tracking individual occupant energy load requires a high resolution, or real-time, energy monitoring system and a coupled framework to combine information from both the Wi-Fi network and the energy monitoring system. An energy management system is a computer-aided tool to monitor, control and optimize the performances of energy usage in buildings. One energy management system, Java Energy Management System (jEMS) could appropriately be adopted for our preliminary research. jEMS is a specifically designed energy monitoring system used by University of Nebraska – Lincoln (UNL) to track energy usage data over 130 campus buildings.

To achieve our ultimate goal of estimating and correlating the physical location of occupants' with their energy load, the integration of systems would be necessary. The Wi-Fi network would be able to capture the position of occupants based upon the coordination of access points (as defined by blueprints of the building) and signal strength. The calculated position information could then be associated with the occupant's device's mac address, given a timestamp, and be stored in a database. The system could also assign event tags to that mac address at certain time points. For example, if the unique mac address appeared in the building for the first time, the tag would be "entering the building" (or "entering a room"); if the mac address disappeared from the system for a time period, a tag of "leaving the building" (or "leaving a room") would be assigned to the mac address at the time of disappearing. The energy-load data for that room or that building would then be saved and correlated to the location database with a timestamp. The variation of the energy-load could then be calculated based upon the event tags. The process of the estimation framework is demonstrated in following figure:

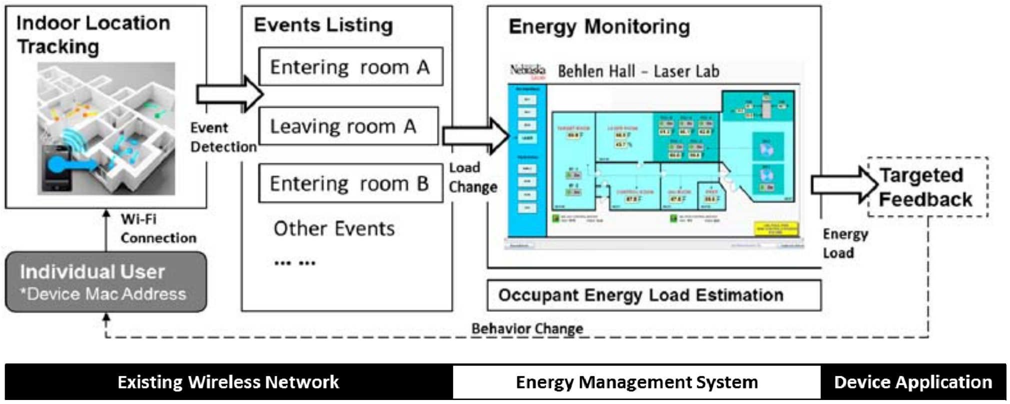



**Figure 1. Occupants' energy-load estimation framework**

## EXPERIMENT DESIGN AND METHODOLOGY

### Preliminary experiment design

To simplify the preliminary experiment and validate the proposed system, we studied a small building on the UNL campus that had few occupants during the test dates of July 18, 2013 to August 6, 2013 and the preliminary experiment only focus on the electricity consumption. The test bed was Mussehl Hall, an office space for the Institute of Agriculture and Natural Resources at UNL. The building has a gross area of 8,289 square feet and contains 2 floors, 11 office, 6 classrooms, and 2 conference rooms. The cooling system of the building relies on electric fans. The major energy load in the building is the steaming water heating (71%, gas), electrical fan cooling, ventilation and other appliances (29%, electricity). During the preliminary experiment there were a total of 16 long-term residents in the building. Before the experiment, the residents were requested to answer a survey to determine their energy usage and the conditions of their wireless devices. The survey results suggested that the residents of the Mussehl Hall have substantial control over a set of energy-consuming devices, including, personal computers, water heaters, desk lamps, microwaves, refrigerators, washers, dryers, scanners and printers. The survey also suggested that more than half of the residents can control the room temperature (electrical fans and heater) and lighting, and usually connect their wireless devices to the university Wi-Fi network. The coupled-system in this preliminary experiment estimated whether the occupants were located in the building based upon the presence of their wireless devices. A database was created to store the information of Wi-Fi connection, real-time energy load and time stamps. The timestamps served as linkages to synchronize both the Wi-Fi connection and the energy load.

### Time window approach

Instead of documenting time points, the experiment utilized time windows. Three reasons justified a time-window approach to capture the energy-load variation events. First, the energy-load data logged by the management system are trend values rather than true values; the trend data collected by UNL energy management systems are an average value of the energy load over the past hour—the energy monitoring system documents each new trend data point every five minutes. By comparing the trend data within the time window, the energy-load variation could be estimated. Second, there is a delay between when the occupants enter the building and when they create additional load. Third, the time window is helpful to mitigate the impact of temperature. Within a small time window, local temperature is relatively stable and electric fans will not cause a dramatic increase/decrease on the energy load.

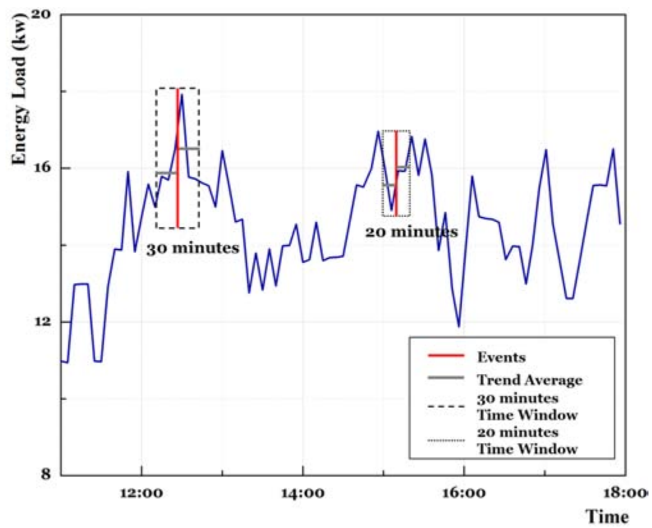



**Figure 2. Sample time-windows for a piece of energy-trend data (July 23 2013)**

To address the uncertainty in potential time discrepancy between occupants' Wi-Fi connection/disconnection events and energy usage events, we adopted two different sizes of time-windows: a 30-minute time-window and a 20-minute time-window (Figure 2). Given the energy-load data has a resolution of 5 minutes, the first time-window includes 6 data points, and the second time-window contains 4 data points. There are two reasons for choosing 20-minute as the size the time-windows: (1) Due to the resolution of the UNL energy management system, 20-minute time window is the smallest reasonable size. (2) The smaller time window could minimize the impact of the environmental temperature change. The 30-minute time window was selected as a comparison to 20-minute to evaluate the impact of the selection of time window. Within a time window, by comparing the data points logged before the connection/disconnection events with the data points logged after the events, the magnitude of load variation of that time window could be estimated. Moreover, the operation of electronic fans dramatically affects energy consumption. The sudden energy-load drop caused by electronic fans could mislead the experiment; therefore, only the data from 7:00 to 22:00 were used in the preliminary data analysis (the fans would be turned off after 22:00 and turned on after 7:00).

**Data analysis**

When APs detected a Wi-Fi device connection/disconnection event, the timestamp, energy-load data, and unique mac address associated with the event were recorded. Three comparing groups for all time-windows were then constructed as follows: The time-windows that have a Wi-Fi connection event were grouped into the "Connection" (C) group. Similarly, the "Disconnection" (DC) group contains all time-windows that have a Wi-Fi disconnection event. The control group — the "No

Connection" (NC) group — consisted of the rest of the time-windows that do not contain any connection or disconnection event. There are 2185 data points for the NC group, 145 data points for the C group, and 48 data points for the DC group.

According to the pre-experiment survey, some residents not only use smart phones but also other wireless devices—such as a laptop, which is not a strong indicator of occupancy. More specifically, some devices were observed during the experiment period as having an extremely long connection period (more than 18 hours). These devices would not disconnect from the network until the APs automatically reset at 24:00 every day. Therefore, as this study sought to determine occupancy, such passive disconnection data were marked as incomplete data and were excluded during data analysis. After the data collection stage of the preliminary experiment, all data were converted into the form of time-windows. Based upon the timestamp of events, the time-windows were separated into two parts. By comparing the average energy load before and after the event, the variations were summarized. The outputs would indicate if the energy loads increased or decreased. For the NC group, the separation of time-windows was divided evenly.

**Hypotheses**

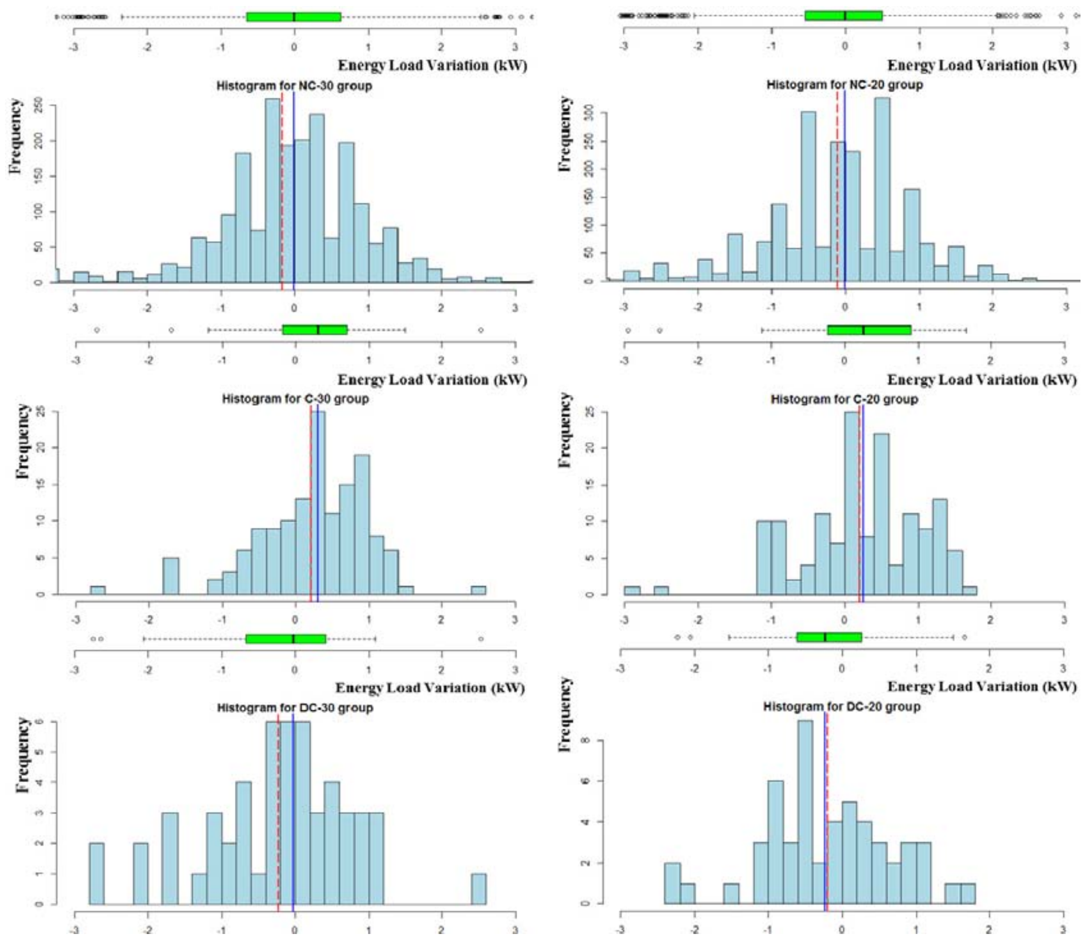
The preliminary experiment targets at utilizing the events of Wi-Fi connections and disconnections to detect the starting and ending of energy-consuming behaviors. As the objective of this preliminary research is to ascertain if the wireless connection could be an indicator of occupant energy-load variation, our choices allowed us to test the following hypotheses:

Hypothesis 1: The events of wireless connection have a statistically significant correlation with energy-load variation. $H_0$: There is no statistically significant difference of energy-load between C group and NC group. $H_A$: There is a statistically significant difference of energy-load between C group and NC group.

Hypothesis 2: The events of wireless disconnection have a statistically significant correlation with load variation. $H_0$: There is no statistically significant difference of energy-load between DC group and NC group. $H_A$: There is a statistically significant difference of energy-load between DC group and NC group.

## RESULTS

Figure 3 shows the distribution of the energy-load variations for each group. The vertical axis shows the frequency of the distribution (the number of time-windows in each bin), while the horizontal axis shows the value of energy-load variation in kW. The vertical red dash line is the mean of the variations, while the blue solid line is the median. Through the box plot, we can observe that the distributions of the NC groups are almost symmetric at 0. However, the mean and median of C groups drifted to right, which suggests that the C groups tend to have a trend toward energy-load increase (positive variations). The DC-30 group has long left tail, but still manifests a mean and median that are close to zero as NC group. By comparing the results from all groups in Table 1 (above), we were able to test which groups (C groups or DC groups) have a statistically significant difference from the control groups (DC groups). The p-values from the NC groups and the C groups' comparisons are lower than a 0.01 threshold, which statistically proves that the event of wireless connection significantly impacts the energy-load variation. More specifically, both the t-test and the Wilcoxon test gave a similar statistically significant p-value for both time-windows.




*Blue solid line: Median; red dash line: mean.

**Figure 3. Distributions of energy-load variations**

**Table 1. Group comparisons of energy-load variations**

| Groups | T | DOF | t test p-value | 95% Conf. Int. | | Wilcoxon test W | p-value |
|---|---|---|---|---|---|---|---|
| ***Same Group Comparing*** | | | | | | | |
| NC.30 vs. NC.20 | 0 | 4368 | 1 | -0.059 | 0.059 | 2387113 | 1 |
| C.30 vs. C.20 | 0 | 288 | 1 | -0.215 | 0.215 | 10512.5 | 1 |
| DC.30 vs. DC.20 | 0.194 | 103.99 | 0.846 | -0.346 | 0.422 | 1431 | 0.848 |
| ***Inter-group Comparing*** | | | | | | | |
| NC.30 vs. C.30 | -4.992 | 166.65 | 1.49e-6*** | -0.468 | -0.082 | 126597.5 | 2.82e-06*** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| NC.20 vs. C.20 | -4.992 | 166.65 | 1.49e-6*** | -0.483 | -0.098 | 126597.5 | 2.82e-06*** |
| NC.30 vs. DC.30 | 0.6895 | 54.54 | 0.493 | -0.182 | 0.374 | 60679.5 | 0.490 |
| NC.20 vs. DC.20 | 0.966 | 54.57 | 0.338 | -0.036 | -0.169 | 61772 | 0.336 |

*Note 1: “NC” means No Connection; “C” means Connection; “DC” means Disconnection; “30” means 30 minutes time window; “20” means 20 minutes time window; Note 2: * p-value ≤ 0.1; ** p-value ≤ 0.05; *** p-value ≤ 0.01

In addition, the results from Figure 3 suggest that when the Wi-Fi connections were detected by the APs, energy loads tend to increase. Therefore, we reject the null hypothesis of the Hypothesis 1. However, we have to reject alternative hypothesis of the Hypothesis 2 based on the observation from Table 1, because the p-values for the DC groups and the DC groups’ comparison are much higher than the 0.05 threshold. At the same time, there is no obvious drift of DC groups shown in Figure 3.

## DISCUSSION AND CONCLUSION

Findings from the preliminary experiment revealed that the wireless connection and behavior pattern of the building occupants could be an exceptional indicator of energy load changes. However, based upon the results, the wireless disconnection cannot be used for predicting energy-load decreases. The rejection of Hypothesis 2 could result from some limitations of this preliminary experiment. First, the daily resetting of the APs disconnect all devices until they connect back again. Because of this limitation, we have to omit a great amount of disconnection data, which could result in a bias. However, this may also be an indicator that many people leave their devices on after they have left the building. We could utilize this information to identify inefficient behavior. Second, the recorded data from the energy management system is trend data rather than real-time data. Although we adopted a time-window approach, more investigation into the effects of this choice is necessary. Third, the highest resolution we have is five minutes. To more accurately estimate the energy load, high resolution is still essential. Fourth, the building scale is relatively small compare to regular commercial buildings. For larger building, there are much temporary occupants and multiple occupants could show up at the similar location at the same time. It is extremely hard to differentiate which connection causes the energy load variation. To overcome some portion of the limitations and fully understand how Wi-Fi connections correlate to the energy-load variation, in future research we will propose another logistic regression test for multiple variables that closely relate to energy consumption, such as location, staying term and Wi-Fi association time. In addition, an experiment on a larger scale building is favorable.

The proposed system could be extended to all other building types, such as industrial buildings and residential buildings. The system will be able to serve as a supplementary for other occupancy-detecting ambient sensors (Dong and Andrews 2009; Yang et al. 2012) and enhance their accuracy. In addition, the system is also scalable to multiple buildings and will be able to the shape the energy conservation research intensively in future. Moreover, the final system could also make a great contribution to behavior-related energy research, such as interfering feedbacks. This research would facilitate consumption estimations through easily implemented Wi-Fi networks and extend current energy feedback research to commercial and educational settings. Estimating the energy load of long-term occupants and temporary occupants is essential to improving energy consumption predictions and to supporting the development of feedback systems. Although various occupancy-detecting systems have been developed to track residents' energy load in residential buildings, the dynamic feature of occupants in commercial and educational buildings creates a barrier to accurately assessing their energy consumption. This paper proposed an innovative approach that employs existing Wi-Fi system as a novel tool for occupancy detection and individual level load monitoring. The results of the prototype's experiment confirm our hypothesis that the Wi-Fi connection information could be an effective indicator of energy-load variation. However, this research is also subject to some limitations, such as interfering by other buildings and inaccurate recording. There are multiple APs and networks coexisting in the test bed, although the test bed is geospatially isolated from other buildings; therefore, the device connections or disconnections could be missed or wrongly recorded. The future research will focus on addressing those limitations.

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