Enhancing Non-intrusive Occupant Load Monitoring through Occupancy Matrix

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ABSTRACT
It has been universally accepted that energy consumption in commercial buildings is highly related to occupant behaviors. Improving occupants’ energy-use behaviors is regarded as the most cost-effective approach to enhance overall energy saving in commercial built environments. However, effective behavior intervention pursuits rely on the availability of occupant-specific energy-use information, which is extremely expensive to capture with existing technologies. In this context, the author’s previous studies proposed the non-intrusive occupant load monitoring (NIOLM) approach that captures individual occupants’ energy-consuming information at their entry and departure events in an economically feasible manner. The NIOLM assigns energy-load variations \( ev \) of a building to individual occupants and relies on two variables: Time delay intervals and magnitudes of \( ev \). This paper extends the existing NIOLM concept with the inclusion of a new variable, the occupancy matrix which manifests the information of present occupants at the moment of \( ev \). An experiment has been conducted in an office space to validate the feasibility and accuracy of the proposed approach. Outcomes of this research could be a great help for studies on occupant energy-use behaviors intervention and simulation.

KEYWORDS: Occupant energy-use behavior; non-intrusive load monitoring; load disaggregation; Wi-Fi networks; commercial buildings

1. Introduction

Commercial buildings currently account for a substantial amount of energy usage in the United States,\(^{1,2}\) and the energy-demand rate of this sector is higher than other sectors.\(^{2}\) Among recent advancements and efforts such as appliances update and building envelope retrofitting, adopting energy-saving behaviors among occupants is always regarded as the most cost effective approach to reduce the energy consumption of commercial buildings.\(^{3-9}\) In this context, current intervention techniques typically collect data from individual workstations in a commercial building to understand individual occupants’ energy-use behaviors. These approaches could lead to motivating occupants to efficiently control over their personal workstation appliances. However, such studies have little emphasized on the impact of occupants regarding shared energy resources and this area is relatively unexplored.\(^{10}\) Shared energy resources such as ceiling lights typically consume a significant portion of energy consumption in a commercial building; about 20% of commercial sector’s total energy consumption is used by lighting systems.\(^{1}\) On the other hand, miscellaneous electric loads at the level of occupants’ workstations typically account for \(<10\%\) of total energy consumption.\(^{9,11}\) Therefore, understanding and improving occupants’ behaviors regarding shared energy resources has a great potential to significantly reduce energy consumption of the commercial buildings.

In response, the author’s previous research work\(^{12-16}\) introduced and developed the non-intrusive occupant load monitoring (NIOLM) approach which economically captures individual occupants’ energy-load variations \( ev \) created at their entry and departure events in a commercial building. NIOLM was developed based on two occupancy-related energy-use behavioral variables: Time delay \( te \) interval and magnitude of \( ev \).\(^{14}\) These two variables were demonstrated being sufficient and able to derive \( ev \) created by individual occupants.\(^{12-16}\)
In particular, the results from the NIOLM approach have indicated that this approach has a potential to detect individual occupants’ control over shared energy resources. Motivated by this, the paper enhances the NIOLM approach by adding a new variable, occupancy matrix (om), which demonstrates individual occupants’ behaviors regarding these energy resources. The om is developed in such a way to assess the presence and absence of occupants in a building at the time of arrival and departure events of each occupant. The following sections provide the detailed description of the methodology, data analysis, and results.

2. Literature Review

To acquire the electric energy-use information of an occupant of interest, behavior-modification techniques typically utilize intrusive monitoring approaches which require plug-level metering device installed for the occupant’s personal appliances. These sensors then provide the energy-consuming information of the appliances and accordingly estimate the occupant’s energy consumption. While this leads to obtaining data with a high level of resolution and accuracy, the intrusive methods are not economically feasible due to high cost of implementation, especially for a large-scale deployment. In a feedback study, the personalized energy-use data of the residents of a six-story commercial building was collected through individual plug-level meters. This highlights the high cost and installation complexity associated with intrusive-based methods, and thereby, offering alternative cost-effective data sensing techniques is necessary.

To address this, non-intrusive monitoring concept has been developed, and the related techniques have been employed to economically perform energy monitoring of major appliances in built environments. Such techniques rely on the data provided in building operations to identify which appliance uses how much electricity and when. Thereby, non-intrusive techniques are perceived as less expensive approach to monitor individual appliances in commercial buildings. However, there is still a need for tools to economically monitor individual occupants’ energy consumption in commercial buildings. As a solution, extending non-intrusive concept to individual occupants has been suggested. In other words, a tool can be developed in a way to extract occupant-specific usage from data provided in building operation. Given that the building operation data includes the usage of all appliances/systems, it provides an opportunity to track occupant usage of shared appliances. Motivated by this idea, the literature has introduced and developed a non-intrusive method, NIOLM, to track individual occupants’ ev at their entry and departure events in a commercial building. In Rafsanjani et al., it has particularly been discussed that NIOLM is able to track occupant usage of shared appliances. To check this functionality, the paper introduces, om, as a new feature for NIOLM. This feature allows to assess the presence of all occupants in a building at the time of arrival and departure events of a single occupant.

3. Methodology

3.1. Om definition

The om assesses the entry and departure event of an occupant based on the presence of other occupants in a commercial building as follow:

- For entry events:
  1. The occupant is the first person entering to the building.
  2. The occupant is not the first person entering to the building.

- For departure events:
  1. The occupant is the last person leaving the building.
  2. The occupant is NOT the last person leaving the building.

For scenario (1) of the events, the occupant is typically responsible for shared energy resources used throughout a working day. For example, within an office space, when the occupant enters as the first person, she turns the ceiling light and fan on. Similarly, when she leaves as the last person, she is responsible for turning these appliances off. If the ceiling light or fan left on during night, the occupant who left the office space as the last person is responsible in this case. Therefore, assessing individual occupants’ behavior regarding shared energy resources when they enter to/departure from a building as the first/last person could help understanding their energy-use behaviors.

In scenario (2), knowing who entered to the office before the occupant is valuable. For example, an appliance is typically used by two occupants in an office space. One of the occupants enters to the office as the first person and see the appliance is in-use. If there is no information available for the entry event of the other occupant, two distinct conclusions...
can be made: (i) The appliance has been left on during night or (ii) another occupant also controls over this shared energy resource.

Therefore, studying individual occupants’ behaviors in each situation could provide information regarding their overall behaviors about shared energy resources.

### 3.2. Om development

The $om$ is developed in such a way to be considered as a new variable for NIOLM. In NIOLM, each energy data point (i.e., $ev$) correlated with an occupancy event (i.e., entry or departure event) is characterized by two variables: $te$ and $ev$.[13,15] $Om$ as a new variable provides information about the presence and absence of individual occupants for each data point. Therefore, each data point will be characterized by three variables. Therefore, each data point will be characterized by three variables: $te$ and $ev$ identify who created the data point and when, and $om$ tells about the presence of occupants.

$Om$ is considered as an occupant-specific matrix where the number of columns is equal to the total number of occupants; each column represents one of the occupants. In addition, the number of row represents different occupancy situations. Each occupancy situation is demonstrated with a specific identification number (IN). Figure 1 as an example presents $om$ for two occupants in a case study with total numbers of five occupants.

The first matrix shows occupancy situations for the data points correlated with Occupant #1’s events, while the second matrix shows occupancy situations related to data points caused at Occupant #2’s events. Since there are five occupants, the number of columns is 5 in each matrix. Each element of a matrix is a binary element; 1 represents the presence of an occupant while 0 indicates her absence. There are sixteen different INs (i.e., occupancy situations) for each matrix. The INs for the first and second rows of Occupant #1’s matrix are IN-1-1 and IN-1-2, respectively; the first number determines who the occupant is and the second number shows an occupancy situation. Accordingly, the third and fourth rows of Occupant #2’s matrix are presented with IN-2-3 and IN-2-4, respectively. In addition, for entry events, an IN demonstrates who entered to the building before an occupant of interest while for departure events, it shows who left the building after her. For example, IN-1-6 (i.e., the 6th row of Occupant #1 matrix) for an entry event demonstrates Occupant #2 and #3 entered to the building before entering of Occupant #1 while this IN for a departure event shows Occupant #2 and #3 left the building after Occupant #1.

### 3.3. Experiment design and data collection

To check and validate the $om$, the data collected although the author’s previous research experiment for developing NIOLM framework[14] was used for this study. The experiment was designed and conducted in an office space located in the College of Engineering of University of Nebraska-Lincoln. Figure 2 shows the plan of the office space including

![Figure 1. Occupancy matrix of two occupants with total number of five occupants: (A) Occupant #1. (B) Occupant #2](image-url)
three rooms: (i) Graduate student suite, (ii) computer laboratory, and (iii) meeting room. Within the office space, there were several shared energy resources including ceiling lights, printers, coffee makers, and water boilers. Five graduate students who used the graduate student suite were selected as the occupants for the experiment and their data collected for a 3-month period of time. During the experiment, aggregate energy data correlated with occupancy events were collected by a smart meter which covered the entire of the office space. Individual plug-load meters collected the ground-truth data at occupants’ workstations. This ground-truth data did not include the energy-use data of shared energy resources. Please refer to author’s previous research[14] for further information regarding the experiment set up and data collection procedure.

3.4. Data analysis

Ground-truth data points caused by occupants were identified and removed form aggregate energy data points since ground-truth data did not include energy-information about shared energy resources. Then, for each occupant, the remaining data points (i.e., non-ground-truth data points) put into two datasets. One dataset includes the data points for entry events and the other one includes data point for departure events. Accordingly, there were finally ten datasets including the non-ground-truth data points of five occupants. Each dataset then was divided into two groups. Group 1 included data points created when an occupant entered/left the office as the first/last occupant (scenario 1). Group 2 contained data points for scenario 2. Finally, data points in Group 2 were divided based on different INs to different groups. Visual analyzing and assessing of the data points in different groups leded to understanding occupant behaviors regarding shared-energy resources.

4. Results and discussion

Figure 3 shows the non-ground-truth data points for when occupants left the office as the last person. The horizontal axes of each plot show $te$ intervals for data points created before departure events of the occupants, while the vertical axes show the value of $ev$. Since occupants created energy load decreases at departure events, Figure 3 only presents the negative load variations. In addition, data points were cut at level of $-500$ watts for a better visual demonstration.

Figures 4 and 5 show data points based on different INs for Occupant #1 and #2, respectively, when they did not leave as the last person. Observed through Figures 3-5, a specific data point with $ev$ of 280 watts is typically repeated throughout data of all occupants. It was finally found that these data points were created by the ceiling light of the meeting room (Figure 2). In fact, although the occupants were used the graduate student suite (Figure 2), they also had actions regarding the ceiling light of the meeting room and turned the light off before leaving the office. Figure 5 shows that Occupant #2 typically turned off this light when he/she left, which could indicate that he/she checked the light whenever left even when other occupants were in the office space. On the other hand, Figure 4 shows that Occupant #1 did not typically turn the light off when he/she did not leave as the last person, except the time that Occupant #3 left the office after Occupant #1 (IN-1-3). While it might show that other occupants turned the light off, it could also indicate that Occupant #1 did not care well regarding this light when he/she left. The result of the author’s previous research[16] has also shown that Occupant #1 typically left the appliances at his/her workstation on. To this end, it can be concluded that this occupant overall has non-energy saving behavior and he/she should be targeted for behavior intervention approaches to improve his/her energy-use behavior.

Figure 2. Floor plan of the office space: (A) graduate student suite. (B) Meeting room. (C) Computer laboratory
Research on commercial occupant usage\cite{26-34} mainly studied intervening energy-use behaviors to influence energy consumption. The correct understanding of occupancy-related usage is a key aspect to ascertain utilizing appropriate intervention technique. Gulbinas et al.\cite{35} Coleman et al.\cite{33} and Yun et al.\cite{36} tracked individual occupants’ energy usage in commercial building through individual sensors. Such studies mainly allow to understand personalized energy-use behaviors of personal appliances, and no information of shared appliances is provided. On the other hand, Staats et al.\cite{37} and Carrico and Reimer\cite{28} utilized data provided in building operation to display the average reduction in the building energy consumption. Such studies’ results did not represent the behavior of each occupant at the non-workstation level.
In response, this paper utilized a new occupancy-related feature to identify occupant-specific usage of shared appliances. The granular data at individual occupants’ level by enhanced NIOLM allows to understand commercial occupant usage with a reasonable accuracy to produce better feedback.

5. Conclusion

This research enhanced the NIOLM framework by adding a new variable, om, which is able to demonstrate how occupants exercise control over shared energy resources in a commercial building. The results from exploring the variable in an office space show the potential of this variable in understanding individual occupants’ energy-use behaviors regarding these energy resources. Since shared energy resources typically consume more energy than appliances controlled by individual occupants at workstations, the author believes the enhanced NIOLM framework could significantly contribute to the reduction of the energy consumption in commercial settings by economically providing occupants’ energy-use information regarding these resources.

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