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# Linking Building Energy-Load Variations with Occupants' Energy-Use Behaviors in Commercial Buildings: Non-Intrusive Occupant Load Monitoring (NIOLM)

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**Abstract**

Studies indicate that occupancy-related energy-use behaviors have a significant influence on overall energy consumption in commercial buildings. In this context, understanding and improving occupants' energy-consuming behaviors shows promise as a cost-effective approach to decreasing commercial buildings' energy demands. Current behavior-modification pursuits rely on the data availability of occupant-specific energy consumption, but it is still quite challenging to track occupant-specific energy-consuming behaviors in commercial buildings. On the other hand, individual occupants have unique energy-consumption patterns at their entry and departure events and will typically follow such patterns consistently over time. Thus, analyzing occupants' energy-use patterns at the time of their entry and departure events plays a critical role in understanding individual occupants' energy-use behaviors. To this end, this paper aims to develop a non-intrusive occupant load monitoring (NIOLM) approach that profiles individual occupants' energy-use behaviors at their entry and departure events. The NIOLM approach correlates occupancy-sensing data captured from existing Wi-Fi networks with aggregated building energy-monitoring data in order to disaggregate building energy loads to the level of individual occupants. Results from a 3-month long period of tracking individual occupants validate the feasibility of the NIOLM approach by comparing the framework's outcomes with the individual metering data captured from plug-load sensors. By utilizing existing devices and Wi-Fi network infrastructure, NIOLM provides a new opportunity for current industry and research efforts to track individual occupants' energy-use behaviors at a minimal cost.

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*Keywords:* Commercial buildings; Energy consumption; Non-intrusive approach; Occupant energy-use behavior; Profiling energy-use behavior

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## 1. Introduction

In the U.S., buildings account for 40% of the country's total annual energy consumption; approximately half of this energy goes to the commercial sector, whose demand also continues to grow faster than other energy-use sectors [1, 2]. Such energy-use intensity and increasing consumption rates raise critical concerns about improving the energy performance of the commercial sector during the operational phase.

A general overview of current literature shows that conventional approaches to enhancing buildings' energy savings focus on retrofitting the building envelope and updating appliances. However, such approaches require large capital investments and sometimes are infeasible for existing buildings [3]. A growing number of recent studies emphasize the importance of understanding and improving occupant energy-use behaviors as a cost-effective approach for saving energy in commercial buildings [4–7]. However, the success of such studies critically relies on the availability of information regarding occupant-specific energy consumption. For example, if occupant-specific energy use is not determined correctly, the feedback outcome can have negative effects on occupants' energy-use behaviors [8,9]. However, an overview of the current literature shows that due to the difficulties in tracking the energy consumption of various occupants in commercial buildings, few researchers have addressed this issue [5,10]. Estimating individual occupants' energy loads in commercial building is still an extremely challenging task [5].

Conventional approaches to monitoring individual occupants' energy consumption typically have estimated an occupant's energy consumption in commercial built environments by using individual plug-load monitoring devices; unfortunately, such approaches are not applicable in practice as they need a large capital investment. Being able to economically and accurately estimate energy-use of individual occupants in a commercial building requires linking energy-consuming data with occupancy-sensing data [5]. Such links can lead to disaggregating building energy loads to the level of individual occupants. In our previous studies [10,11], we demonstrated that Wi-Fi connection and disconnection events within a commercial building are viable indicators for the starting and ending of individual occupants' energy-consuming behaviors, respectively; this finding can be targeted as a link between occupancy sensing and energy-consuming data. In addition, we found that individual occupants have unique energy-consumption patterns at their entry and departure events and will typically follow such patterns on a daily basis.

Based on these findings, our previous study [10] presented a non-intrusive occupant load monitoring (NIOLM) concept that estimates individual occupants' energy-load variation at their entry and departure events in commercial buildings. NIOLM extends the concept of non-intrusive load monitoring (NILM) to observe occupant-specific energy consumption—NILM techniques apply to the total energy data collected from a single meter to identify large appliances [5]. The current prevalence of NILM indicates its success and feasibility, especially in residential buildings; however, NILM's effectiveness in commercial buildings is quite limited due to the large number of similar appliances in use simultaneously [10].

The foundational pursuit behind NIOLM is to link energy-use data with occupancy-sensing data. The current status of occupancy-sensing technologies provides a good opportunity for economically monitoring individual occupants and their specific energy consumption [12]. NIOLM leverages existing Wi-Fi networks to track each occupant and links these data with aggregated energy-use data provided by buildings' energy management systems (BEMS). Since there is no need to install new infrastructure for NIOLM's execution, this tool would be especially economical for commercial buildings. This research extends the NIOLM concept into a real tool.

## 2. NIOLM algorithmic framework

In order to profile individual occupants' energy-load variations at their entry and departure events, the NIOLM algorithm consists of four major stages, as follow:

### *2.1. Detecting occupancy events*

In the first stage, the entry and departure events of individual occupants in possession a Wi-Fi enabled device (i.e., smartphone) are detected based on the signal of their smartphones' transmitted packets received by building's Wi-Fi network's access points (APs). It is worth mentioning that there are usually multiple overlapping APs in a commercial building, and therefore Wi-Fi-based occupancy sensing can work at a minimal cost. The event detection is then associated with the individual occupant's smartphone MAC address, which is stored in a database to determine who enters or departs from the building and when.

*2.2. Measuring aggregate energy consumption*

At the next step, the energy-load data of the building provided by BEMS will be collected, pre-processed, and stored in the database. It should be noted that the electrical energy-load data must be pre-processed before it is used to find the true load variations of occupants. Corrupted or missing data could lead to biased or incorrect results. Electrical noise can degrade the quality of data. Similarly, power loss in a circuit may affect the data. Therefore, at the second stage, the accuracy of data will be checked through a pre-processing stage.

*2.3. Correlating occupancy events with energy-load variations*

Wi-Fi based entry and departure event detections function as variable indicators for the starting and ending of energy-consuming behaviors [11], and each individual occupant has a unique energy-consuming behavior at his/her events that follows a consistent pattern over time [10]. As the third stage, these findings allow us to correlate occupancy events with energy-load variations to identify the true energy-load variations caused by each occupant upon his/her entry and departure events.

*2.4. Profiling occupants' energy-use behavior patterns at entry and departure events*

Collecting and analyzing long-term data (e.g., one-to-three months) of energy-load variations for individual occupants finally leads to profiling the energy-use behavior patterns of occupants at their entry and departure events. These profiles are believed to be critical prerequisites for understanding and implementing proven approaches to adjusting energy-saving behaviors among occupants. In fact, these profiles provide an opportunity for identifying metrics that characterize individual occupants' energy-consuming behavior patterns according to the occupants' energy-load variations. The current literature has identified various behavioral metrics: "intensity," "entropy," "efficiency," and "duration" [13–16]. Redeveloping these metrics in such a way as to be computable with profiles resulting from NIOLM could lead to understanding occupants' behaviors.

## 3. Research objective

To achieve our ultimate goal of developing a NIOLM framework, this research develops an algorithm to correlate occupancy events with building energy-load variations and tests this algorithm within a commercial building's typical small office space (i.e., offices with the gross floor area of up to 5000 ft$^2$ [17,18]).

There is a critical challenge in correlating occupancy events with energy-load variations. A commercial building typically has a lot of occupants, and therefore, multiple occupancy events or multiple energy-load variations may occur within a short period of time or may overlap with each other. In such cases, assigning the true load variation to an occupancy event is a challenging task. Figure 1(a), as an example, shows a case of multiple entry events and load variations. In this case, two occupants' entry events happen approximately at the same time, and there are three load variations after their entry events.

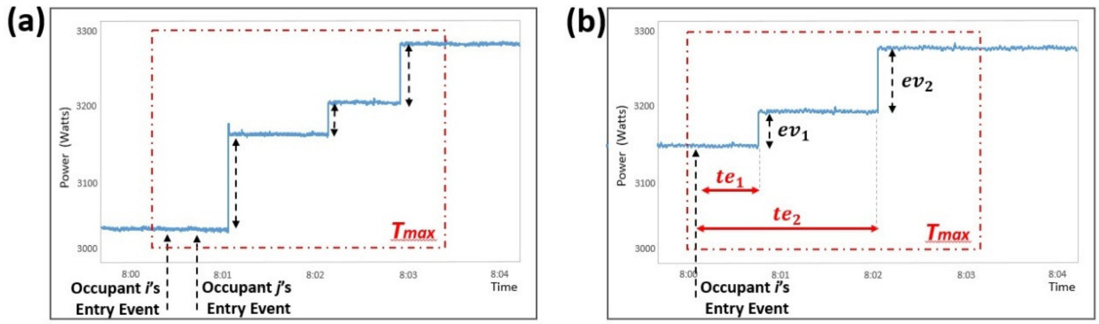


Fig. 1. (a) multiple entry events and energy load variations; (b) multiple candidate load variations upon an occupant's entry event. (*ev*: energy-load variation, *te*: time interval between entry event and energy-load variation, $T_{max}$: time-window for *te*)

To this end, determining who creates how much load increase is challenging. Therefore, the emphasis of this study is to show how the NIOLM algorithm performs when finding the true load variation of each occupant. This is the first step toward understanding the effectiveness of NIOLM.

In order to address this challenge, a Discriminant Analysis (DA) is used to construct a mathematical rule for assigning a load variation to its occupant. DA can predict the true group (i.e., true occupant) of a new observation (i.e., energy-load variation) among various groups when the probability density of each group is known [19,20]. In this context, the discriminant rule predicts the group of a new observation, $x$, among $n$ groups. If $f_i(x;\theta_i)$ denotes the probability density function for group $i$ with a vector of parameters, $\theta$, a new observation will be assigned to group $j$ when:

$$f_j(x;\theta_j) > f_i(x;\theta_i) \text{ for } i=0, 1, .., n; \text{ except } j \tag{1}$$

In DA method, the Bayes rule is used to minimize the average cost (i.e., risk) of misclassification as much as possible, which leads to assigning a new observation to its true group with the fewest number of errors [21]. In this research, it is assumed that the cost of misclassification is the same for all observations and groups. In addition, we assume that there is no prior knowledge to guide a new observation's assignment to a specific group (i.e., occupant). Accordingly, the likelihood rule (1) will be used for classification.

The probability density function for each occupant (i.e., group) is constructed from the time interval and energy load variation data at his/her entry and departure events. Figure 1(b) shows that there is a time interval (*te*) between the occupant's entry event and the energy-load variation (*ev*).

In our previous study [10], we proved that each occupant has a specific time-interval pattern that is consistent over time. In addition, we observed that each occupant typically creates a specific amount of energy-load variation at his/her events. Building upon these observations, we use the probability density functions of time intervals and load variations of individual occupants to solve equation (1).

It is worth mentioning that when there is only an entrance event and a load increase related to it, or, inversely, when there is only a departure event and a load decrease related to it, the load variation is assigned to the event without using the DA analysis. This data is named ***clear data***. Such clear data is critically important to construct the probability density functions.

In particular, there is a need to consider a time ($T_{max}$) as the maximum threshold for *te*. $T_{max}$ is determined empirically for a commercial building. As shown on figure 1, $T_{max}$ defines a time-window to determine the number of finite energy-load variations for an occupancy event.

In general, the procedure to estimate true energy-load variations for individual occupants is as follow:

(1) An episode of interest, $a$, is defined where an energy-load variation, *ev*, can be correlated with an occupancy event, *oe*. *oe* determines the type of event: entry, or departure. In addition, a time interval, *te*, correlates *ev* with *oe* ($te \leq T_{max}$). Therefore, an episode is defined as $a = (oe, te, ev)$. Then, for occupant i, the probability density functions, $f_i(x;\theta_i)$, will be constructed based on a set of $m$ episodes ($a_{1i}, a_{2i}, \ldots, a_{mi}$) from clear data. It is worth mentioning that for occupant i's entry events, there are two probability density functions: *te* probability density function, and *ev* probability density function. Likewise, there are two probability density functions for departure events.

(2) In the next step, for $l$ numbers of *oe* correlating with $w$ numbers of *ev* within a time-window, a set of $l \times w$ episodes will be constructed. Then, the occupant i's event will be linked to an *ev* by checking the *te* probability density function; the *te* with the highest probability and its *ev* will be assigned to occupant i. If an *ev* is assigned to more than one occupancy events, then this *ev* will be checked further by *ev* probability density function; the *ev* with the highest probability and its *tv* will be assigned to occupant i. In fact, since we proved that each occupant has a specific time-interval pattern, the second step is first checked by *te* probability density. Finally, the episode defined by the selected *te* and *ev* will be assigned to occupant i, and based on this new episode, the probability density functions for occupant i will be updated.

## 4. Experiment design

### *4.1. Test bed*

An experiment was designed and carried out in a small office space with five occupants for a 3-month period of time. The office space is located on the main campus of the University of Nebraska-Lincoln (UNL) and features a gross footprint of 2200 sq ft. This entire office space includes three rooms: one graduate student workspace (1100 sq ft), one computer lab (500 sq ft), and one meeting room (600 sq ft). Within this office space, there are appliances and systems, including personal computers, desk lamps, a microwave, a refrigerator, water boilers, coffee makers, scanners, and printers. The occupants are graduate students who visit the office for a couple of hours per day, seven days a week, and they have full control over the appliances. The five occupants chosen for this experiment use similar appliances (e.g., personal computers, desk lamps) at their own workstations.

### *4.2. Data collection*

#### *4.2.1. Energy data*

A commercial metering device was installed in the three rooms of the office space to collect aggregate energy-consumption data at a 1-second interval resolution. In order to verify the data collected by this main metering device, five plug-load meters—"watts-up?.net"—were installed on the five occupants' workstations. All appliances controlled by each occupant at his/her workstations were connected to a plug-load meter. The plug-load meters also collected data at a 1-second interval resolution.

All of the energy data collected by the main and plug-load meters were sent through the network to the database we created to store the experiment's data.

#### *4.2.2. Occupancy-sensing data*

A local Wi-Fi stationary sniffer was set up to collect occupants' sensing data; occupancy entry and departure events were detected based on the continuity of smartphones' transmitted packets recorded by the sniffer. Before the experiment, the occupants were requested to answer a survey to determine the conditions of their smartphones' Wi-Fi. The results revealed that occupants always leave their smartphone's Wi-Fi on, which means that their smartphones' transmitted packets were always recorded by the sniffer. Similar to energy data, all occupants' sensing data was stored in the database.

## 5. Experimental data analysis

The data-analysis stage began with a pre-processing of the energy-load data. First, any missed energy-load data lost due to a network disconnection was found and corrected. Then, the noise in the data was identified and appropriately filtered by using a Kalman filter. Finally, the power loss in the office-space circuit was calculated. Since the power loss was too low (i.e., less than 0.01 watts), the influence of the power loss on data was neglected.

After pre-processing the step, all occupancy sensing and energy-load data were analyzed and correlated in order to find individual occupants' load variations at their events. It is noteworthy that probability densities for each occupant were constructed and employed for this step. Figure 2, as an example, shows probability densities of time intervals for occupant #1.

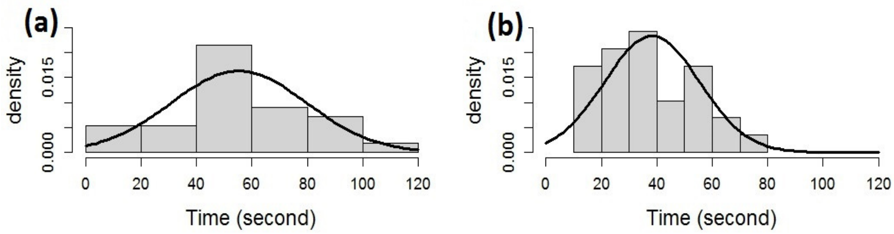


Fig. 2. Occupant #1's time interval probability densities for (a) entry events; (b) departure events

## 6. Results and discussion

Figure 3 presents the box plots of energy-load variation data collected by NIOLM (i.e., the main smart meter) for entry and departure events of all five occupants. DA was employed for the cases with multiple occupancy events/load variations. It is worth mentioning that $T_{max}$ for this study was determined based on the results of previous study [10] conducted on the same case study with same occupants. The maximum time interval for all five occupant was 697 seconds, and we considered 15 minutes as $T_{max}$ for this study.

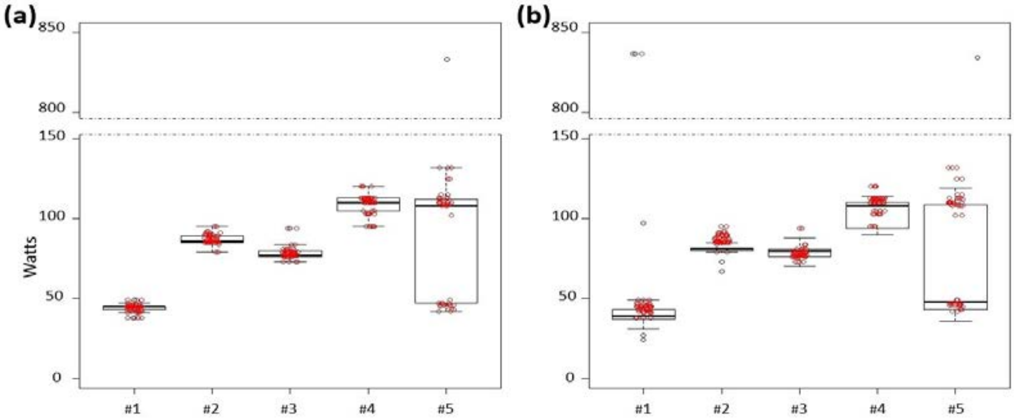


Fig. 3. Box plots for energy-load variation data by NIOLM for individual occupants at (a) entry events; (b) departure events

Table 1 provides the data resulted from implementing DA by NIOLM framework for departure event of occupant #1. The data collected by individual plug-load meters (i.e., the ground-truth data) allows us to compare the DA results. Meter internal timer accuracy and lost network connections cloud lead to time differences. In addition, meters accuracy and electrical noises in circuit are main reasons leading to differences between an end-user energy-load data provided by different meters [22].

Table 1. Data by NIOLM vs. ground-truth data and their differences for departure events of occupant #1.

| Time Interval (seconds) | | | | | | | | Energy-load Decrease (watts) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # | NIOLM | G.T.[1] | Diff.[2] | # | NIOLM | G.T. | Diff. | # | NIOLM | G.T. | Diff. | # | NIOLM | G.T. | Diff. |
| 1 | 64 | 62 | 2 | 25* | 34 | 34 | 0 | 1 | 49 | 47 | 0 | 25* | 97 | 95 | 2 |
| 2 | 50 | 49 | 1 | 26 | 55 | 55 | 0 | 2 | 46 | 44 | 2 | 26 | 43 | 44 | 1 |
| 3 | 93 | 93 | 0 | 27 | 39 | 39 | 0 | 3 | 45 | 48 | 3 | 27 | 40 | 43 | 3 |
| 4 | 43 | 43 | 0 | 28 | 72 | 65 | 7 | 4 | 43 | 40 | 3 | 28 | 41 | 45 | 4 |
| 5* | 86 | 84 | 2 | 29 | 59 | 58 | 1 | 5* | 44 | 44 | 0 | 29 | 47 | 46 | 1 |
| 6 | 52 | 52 | 0 | 30 | 50 | 49 | 1 | 6 | 51 | 46 | 5 | 30 | 38 | 44 | 6 |
| 7 | 59 | 60 | 1 | 31* | 40 | 38 | 2 | 7 | 45 | 44 | 1 | 31* | 48 | 49 | 1 |
| 8 | 54 | 50 | 4 | 32* | 54 | 53 | 1 | 8 | 45 | 47 | 2 | 32* | 42 | 45 | 3 |
| 9 | 40 | 40 | 0 | 33* | 64 | 66 | 2 | 9 | 41 | 40 | 1 | 33* | 46 | 45 | 1 |
| 10 | 101 | 100 | 1 | 34* | 77 | 76 | 1 | 10 | 42 | 44 | 2 | 34* | 48 | 46 | 2 |
| 11 | 61 | 60 | 1 | 35* | 35 | 34 | 1 | 11 | 45 | 45 | 0 | 35* | 39 | 41 | 2 |
| 12* | 65 | 64 | 1 | 36 | 37 | 37 | 0 | 12* | 30 | 42 | 12 | 36 | 40 | 44 | 4 |
| 13 | 71 | 70 | 1 | 37 | 42 | 43 | 1 | 13 | 43 | 43 | 0 | 37 | 40 | 41 | 1 |
| 14* | 77 | 77 | 0 | 38 | 31 | 30 | 1 | 14* | 28 | 47 | 19 | 38 | 43 | 45 | 2 |
| 15 | 65 | 66 | 1 | 39 | 61 | 60 | 1 | 15 | 46 | 44 | 2 | 39 | 40 | 42 | 2 |
| 16 | 43 | 35 | 8 | 40 | 36 | 35 | 1 | 16 | 45 | 45 | 0 | 40 | 47 | 45 | 2 |
| 17 | 73 | 72 | 1 | 41 | 53 | 54 | 1 | 17 | 47 | 48 | 1 | 41 | 40 | 40 | 0 |
| 18* | 101 | 101 | 0 | 42* | 33 | 33 | 0 | 18* | 46 | 46 | 0 | 42* | 37 | 48 | 11 |
| 19 | 38 | 35 | 3 | 43 | 91 | 86 | 5 | 19 | 42 | 45 | 3 | 43 | 41 | 41 | 0 |
| 20 | 48 | 47 | 1 | 44 | 43 | 42 | 1 | 20 | 47 | 45 | 2 | 44 | 43 | 42 | 1 |
| 21 | 46 | 45 | 1 | 45 | 57 | 57 | 0 | 21 | 46 | 44 | 2 | 45 | 42 | 46 | 4 |
| 22 | 91 | 90 | 1 | 46* | 62 | 62 | 1 | 22 | 43 | 46 | 3 | 46* | 41 | 45 | 4 |
| 23* | 43 | 42 | 1 | 47 | 35 | 36 | 1 | 23* | 44 | 48 | 4 | 47 | 49 | 44 | 5 |
| 24 | 52 | 51 | 1 | 48 | 51 | 50 | 1 | 24 | 41 | 45 | 4 | 48 | 46 | 45 | 1 |

[1]ground-truth data; [2]difference; *clear data

Through the results provided in figures 3 and table 1, we can observe the ability of the NIOLM approach to detect the energy-load variation of each individual occupant at his/her entry and departure events. Such data leads to profiling occupants' energy-use behavior patterns at their entry and departure events, which is the main goal of the NIOLM approach. Figure 4 shows the profiles of energy-use behaviors (i.e., the distribution of the energy-load variations) for occupants #4 and #5. The horizontal axis of each profile shows the value of energy-load variation in watts, while the vertical axis shows the density of distribution. The density curve (i.e., the red line) is the energy-use behavior profile of the individual occupants at their entry/departure events.

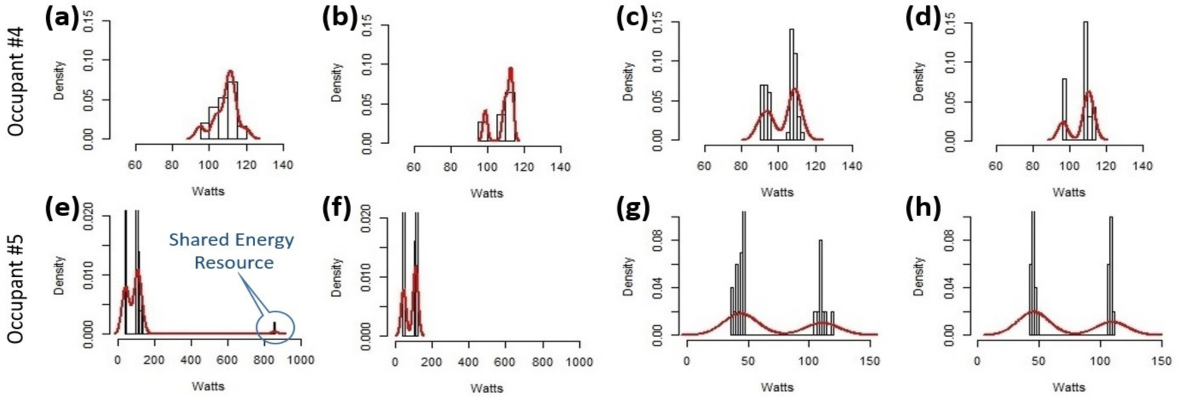


Fig. 4. Profile of energy-use behavior for occupants #4 and #5: (a, e) entry event by NIOLM, (b, f) entry event by ground-truth, (c, g) departure event by NIOLM, (d, h) departure event by ground-truth.

The entry-event profile of occupant #5 in figure 4 and the box plot of this event in figure 3 show that the NIOLM approach can also detect how occupants exercise control over shared energy resources—which is an added benefit since even individual plug-load meters would not be able to determine these activities. Figure 3 also shows that occupant #1 controlled the same shared-energy resource at his departure events. While the individual plug-load meters cannot detect the occupants' control over shared-energy resources, NIOLM provides this opportunity for capturing such controls.

In our case, the shared-energy resource detected by NIOLM was the ceiling light, which means that occupants #1 and #5 turned the light on after entering or turned it off before leaving the office. Detecting and correlating the energy-load decrease of the ceiling light with an occupant departure event could help find the energy-use behavior of occupants. Within an office space, if turning the ceiling light off is not detected for any occupants, it may show that no occupant has an energy-saving behavior related to this shared-energy resource. Such behaviors are common within commercial buildings since occupants have no financial responsibility for energy bills [5, 20]. Therefore, NIOLM results could provide a critical opportunity for understanding the overall energy behavior of individual occupants.

Traditional NILM approaches lead to estimates of the amount of energy consumed by appliances, which can help managers update or replace energy-hungry appliances. However, as discussed earlier, such NILM-based enhancements need large capital investments. Comparatively, NIOLM has an ability to profile energy-use behavior of different occupants with similar appliances. Since the built environment's energy use is highly connected to the energy-use behavior of its occupants [5], failure to improve occupant behaviors undermines the investment in retrofitting building envelopes and appliances [11]. For this reason, NIOLM is a critical tool to help profile individual occupant's energy-use behaviors in order to understand occupant behavior.

## 7. Conclusion and future work

This paper presented and explored the potential of the NIOLM framework. The results showed NIOLM's effectiveness in detecting the true energy-load variations of individual occupants at their entry and departure events in order to profile occupants' energy-use behavior. To the best of the authors' knowledge, there is no other such cost-effective technique for monitoring individual occupants' energy-load variations; alternative approaches do not use existing infrastructure in a commercial building. Individual plug-load meters installed at each point of interest may perform better than NIOLM; however, they require a large capital investment. In addition, current research into improving occupant energy-use behaviors has mainly used the overall results from a smart meter of a whole building to understand how much improvement was achieved. While whole building data could provide values, the granular data at the individual occupants' level provided by NIOLM offers a better opportunity to assess the effectiveness of any behavior improvement approaches.

We believe that NIOLM can greatly contribute to the growing body of literature that addresses simulating or improving occupants' energy-use behaviors in commercial buildings. The NIOLM framework can be extended to small- or medium-size office buildings. In addition, while current research and industry efforts mainly concern NILM approaches, NIOLM provides a hint for how to extend the NILM concept to other areas. Our future research will focus on the next step of NIOLM research: how energy-use profiles resulting from NIOLM can be interpreted to understand energy-use behaviors of individual occupants. We believe these profiles will provide insight into understanding commercial building occupants' energy-use behaviors.

## Acknowledgements

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## References

[1] U.S. Department of Energy, Building Energy Data Book, (2011).
[2] U.S. Energy Information Administration, Annual Energy Review, (2014).
[3] J. Chen, C. Ahn., Assessing Occupants' Energy-load Variation in Commercial and Educational Buildings: Occupancy Detecting Approach Based on Existing Wireless Network Infrastructure, in: Constr. Res. Congr. 2014, American Society of Civil Engineers, n.d.: pp. 594–603. http://ascelibrary.org/doi/abs/10.1061/9780784413517.061 (accessed March 8, 2015).
[4] E. Rieur, M. Alahmad, On the Discourse of Energy as Material: Future Feedback Technologies and Directions for Experiencing Energy, IEEE Trans. Ind. Inform. 10 (2014) 742–751. doi:10.1109/TII.2013.2245909.
[5] H.N. Rafsanjani, C.R. Ahn, M. Alahmad, A Review of Approaches for Sensing, Understanding, and Improving Occupancy-Related Energy-Use Behaviors in Commercial Buildings, Energies. 8 (2015) 10996–11029. doi:10.3390/en81010996.
[6] A. Ghahramani, F. Jazizadeh, B. Becerik-Gerber, A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points, Energy Build. 85 (2014) 536–548. doi:10.1016/j.enbuild.2014.09.055.
[7] A. Ghahramani, C. Tang, B. Becerik-Gerber, An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling, Build. Environ. 92 (2015) 86–96. doi:10.1016/j.buildenv.2015.04.017.
[8] M. Berges, E. Goldman, S. Matthews, L. Soibelman, Training Load Monitoring Algorithms on Highly Sub-Metered Home Electricity Consumption Data, Tsinghua Sci. Technol. 13 (2008) 406–411.
[9] R.K. Jain, J.E. Taylor, P.J. Culligan, Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings, Energy Build. 64 (2013) 408–414. doi:10.1016/j.enbuild.2013.05.011.
[10] H.N. Rafsanjani, C. Ahn, M. Alahmad, Development of Non-Intrusive Occupant Load Monitoring (NIOLM) in Commercial Buildings: Assessing Occupants' Energy-Use Behavior at Entry and Departure Events, in: First Int. Symp. Sustain. Hum.-Build. Ecosyst. ISSHBE, American Society of Civil Engineers, Pittsburgh, PA, 2015: pp. 44–53.
[11] J. Chen, C. Ahn, Assessing occupants' energy load variation through existing wireless network infrastructure in commercial and educational buildings, Energy Build. 82 (2014) 540–549. doi:10.1016/j.enbuild.2014.07.053.
[12] R. Gulbinas, J.E. Taylor, Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings, Energy Build. 84 (2014) 493–500. doi:10.1016/j.enbuild.2014.08.017.
[13] R. Gulbinas, A. Khosrowpour, J. Taylor, Segmentation and Classification of Commercial Building Occupants by Energy-Use Efficiency and Predictability, IEEE Trans. Smart Grid. PP (2015) 1–1. doi:10.1109/TSG.2014.2384997.
[14] A. Albert, R. Rajagopal, Smart Meter Driven Segmentation: What Your Consumption Says About You, IEEE Trans. Power Syst. 28 (2013) 4019–4030. doi:10.1109/TPWRS.2013.2266122.
[15] One Size Does Not Fit All: Eco-Feedback Programs Require Tailored Feedback, in: Sustain. Human–Building Ecosyst., American Society of Civil Engineers, n.d.: pp. 36–43. http://ascelibrary.org/doi/abs/10.1061/9780784479681.004 (accessed October 10, 2015).
[16] E. Azar, C. Menassa, Framework to Evaluate Energy-Saving Potential from Occupancy Interventions in Typical Commercial Buildings in the United States, J. Comput. Civ. Eng. 28 (2014) 63–78. doi:10.1061/(ASCE)CP.1943-5487.0000318.
[17] U.S. Energy Information Administration, Commercial buildings energy consumption survey, (2003).
[18] E. Azar, C. Menassa, Sensitivity of Energy Simulation Models to Occupancy Related Parameters in Commercial Buildings, in: Constr. Res. Congr. 2012, American Society of Civil Engineers, n.d.: pp. 1381–1390. http://ascelibrary.org/doi/abs/10.1061/9780784412329.139 (accessed October 21, 2014).
[19] D. Zelterman, Applied Multivariate Statistics with R, Springer, n.d.
[20] R.A. Johnson, D.W. Wichern, Applied Multivariate Statistical Analysis, 6 edition, n.d.
[21] D.E. Johnson, Applied Multivariate Methods for Data Analysts, Duxbury Press, 1998.
[22] G. Gooday, The morals of measurement: accuracy, irony,and trust in late Victorian electrical practice, Cambridge University Press, 2004.