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ARTICLE

Feature Identification for Non-Intrusively Extracting Occupant Energy-Use Information in Office Buildings

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ABSTRACT

Detailed energy-use information of office buildings' occupants is necessary to implement proper simulation/intervention techniques. However, acquiring accurate occupant-specific energy consumption in office buildings at low cost is currently a challenging task since existing intrusive load monitoring (ILM) technologies require a large capital investment to provide high-resolution electricity usage data for individual occupants. On the other hand, non-intrusive load monitoring (NILM) approaches have been proven as more cost effective and flexible approaches to provide energy-use information of individual appliances. Therefore, extending the concept of NILM to individual occupants would be beneficial. This paper proposes two occupancy-related energy-consuming features, delay interval and magnitude of power changes and evaluates their significances for extracting occupant-specific power changes in a non-intrusive manner. The proposed features were examined through implementing a logistic regression model as a predictor on aggregate energy load data collected from an office building. Hypotheses tests also confirmed that both features are statistically significant to non-intrusively derive individual occupants' energy-use information. As the main contribution of this study, these features could be utilized in developing sophisticated NILM-based approaches to monitor individual occupant energy-consuming behavior.

1. Introduction

Growing interest in reducing energy consumption in office buildings attract attentions from research and industry toward intervening occupants to keep energy-saving behaviors since this method has recently been considered as the most cost-effective approach for enhancing office buildings' energy conservation;[1-7] up to 24 percent energy savings can be achieved through intervening occupants' behaviors in an office building.[8,9] For achieving this goal, personalized feedback approaches have been mainly considered as the most effective intervention technique to adapt energy-efficient behaviors.[10,11] Effectively implementing of such approaches critically depends to the availability of occupant-specific energy-use

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information. Such information is also extremely important in advancement of occupancy-related simulation techniques.[12]

To acquire the energy-use information of an occupant of interest, conventional methods typically utilize intrusive load monitoring (ILM) approaches which require plug load sensors installed for the appliances controlled over by the occupant. These sensors then provide the energy-consuming information of the appliances and accordingly estimate the occupant's energy consumption. ILM methods generally provide data with high level of resolution and accuracy, however they are not economically feasible due to high capital investments and configuration efforts especially for a large scale deployment.[13] By installing a sensor per occupant's workstation, Gulbinas and Taylor[14] collected the data of individual occupants at a multi-story office building occupied by 115 employees; the data was used to examine the impact of organizational network energy-use feedbacks on intervening behaviors. Such studies highlight the high cost and installation complexity associated with implementing of ILM methods in an office setting. Therefore, utilizing alternative cost-effective methods for data acquisitions is necessary.

Increased interest in economically detailed energy sensing led to the emergence of non-intrusive load monitoring (NILM) which has been widely employed for more than two decades as an appropriate viable solution to perform energy monitoring of major appliances (e.g., HVAC systems) in residential and office settings.[13,15-17] NILM is a technique which relies on the aggregate electrical energy-use information provided by a building's meter to disaggregate energy information at the appliance level and identify which appliance and when uses how much electricity.[16] Accordingly, compared to the ILM, NILM is perceived as less expensive and more feasible approach to monitor appliance-specific energy consumption in office buildings.[15,17,18]

Although current research has made a great advancement in economically tracking the energy use of individual appliances through NILM techniques, there is still a need for tools to economically monitor individual occupants' energy consumption in office buildings.[2,9,19] As a springboard for developing a solution to address this need, extending the NILM concept from individual appliances to individual occupants could be investigated. Currently, the growing advancement in building' energy and occupancy sensors which deliver data with high granularities, provides the possibility of distinguishing the energy information of a single occupant from a group of people.[2,9,12,14] Given this, a NILM-based approach might help in extracting this information.[20-23] Recently, there has been an especial emphasis in extending NILM concept to the occupancy sensing area. Through utilizing aggregate data provided by electricity meters in residential buildings, Chen et al.[24] and Kleiminger et al.[25,26] demonstrated that a meter can be used as an occupancy sensor in houses; such occupancy information of houses has typically been exploited for promoting smart grids. Within the office settings, Ardakanian et al.[27] revealed how non-intrusive techniques could be utilized for real-time occupancy estimation; this information can make a great help in building system automation and demand-driven HVAC operation. Overall, such abilities in sensing occupancy information based on the NILM concept particularly indicate the possibility of extending this concept into occupancy energy consumption area.

In order to extend a NILM-based technique for monitoring occupant energy consumption, at the first step, the general structure of NILM approaches should be studied. In general, a NILM approach includes two main steps:[13,15,16] (1) selecting and characterizing appliance-specific features; (2) developing an algorithm to detect the features of different appliances in aggregate load data in order to identify how much electricity consumed by each appliance and when. In particular, each appliance has specific electrical/non-electrical features which should be precisely identified;[13,15,16,28-30] the success of a NILM approach critically depends on the features identification. The electrical features are generally defined as a set of parameters which can be measured from aggregate load data.[31] Real power[17,32-35] reactive power,[36-40] harmonic signals[41,42] power factor,[43] shape features of voltage-current trajectory,[44,45] voltage noise,[46,47] and transient power[48–52] are the electrical features mainly utilized by conventional NILM approaches. Non-electrical features of appliances such as usage duration and time of the day also contributes to more accurate load disaggregation performance.[53,54] For example, a printer in an office space is not used from 6:00PM to 7:00AM and this non-electrical feature could tell that any information derived by an NILM algorithm regarding printer usage during this time could be incorrect.

With the significance of features in mind and seeking to develop a NILM-based solution for monitoring occupant-specific energy consumption, identifying electrical/non-electrical features related to energy-consuming behaviors of occupants is necessary. Therefore, this paper identifies and examines occupancy-related energy-consuming features which could be utilized in developing NILM-based disaggregation approaches for estimating occupant-specific electrical energy consumption in office buildings, which is still an extremely challenging issue in these buildings [9]. The paper is structured as follows: Section 2 introduces the features. The research methodology, experiment and hypotheses are presented in Section 3. Section 4 provides the results and discussion. In section 5, the limitations of this study are presented. Finally, conclusions are provided in Section 6.

2. Occupancy-Related Energy-Use Features

In general, to understand energy-use behaviors of occupants, literature has typically studied their energy-use intensity, energy-use efficiency, and energy-use entropy patterns [8,12,20,55]. In particular, the energy-use intensity patterns account for the amount of energy that occupants consume during working hours. Due to this fact that a NILM approach estimates how much energy is consumed by an appliance, the energy-use intensity patterns could be utilized as the occupancy-related energy-use features in developing a NILM-based approach for monitoring occupant energy consumption. To this end, finding such the patterns of individual occupants is favorable.In[19,56], by collecting data through an ILM method, it was statistically confirmed that major energy-use actions (turn on/off appliances) of individual occupants are predominantly occurred right after entering to a building (entry event) and right before leaving a building (departure event). Therefore, it is of interest to extract energy-consuming information of individual occupants at these events. Through[19,56], it was also revealed that each occupant has a recurring pattern for the power changes at the entry and departure events since she typically use a same set of personal appliances repeatedly across different days. With these findings in mind and seeking to find occupants' energy-consuming features, the recurring patterns of occupants' power changes (as an energy-use intensity patterns) at entry and departure events could be utilized as a feature in load disaggregation processes.

Additionally, it was also found[19,56] that there is a delay interval between an occupants' entry/departure event to a building and the start/end of her energy-consuming behaviors (the creation of power changes at entry/departure events). Then, it was statistically proofed that each occupant has a recurring consistent pattern for the delay intervals at entry and departure events. This interval allows finding an occupant's time of starting/ending energy consuming behavior based on the time of her entry/departure event. Therefore, in a disaggregation procedure, the delay interval could act as a feature to detect the time when an occupant creates a power change at an event.

In summary, it can be concluded that there are two features related to occupant energy-consuming behavior at entry/departure events in office buildings: (1) delay interval (ΔT), and (2) magnitude of power change (ΔP). The information of these features can be collected through existing sensing infrastructures (occupancy attendance systems and electricity meters) of office buildings. Figure 1 shows an example of these features for an entry event. Since each occupant has a recurring pattern for each of ΔT and ΔP [19,56], incorporating the information of these features might allow extracting the power changes caused by occupants at the occupancy events (i.e., entry/departure events).

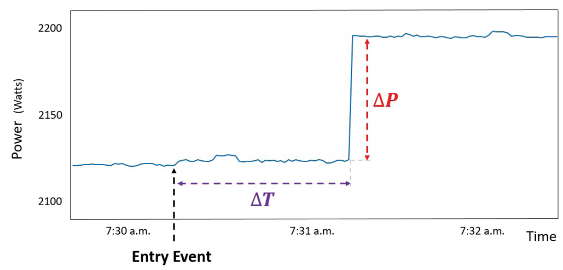

Figure 1. Occupancy-related energy-use features: delay interval (ΔT) and power change (ΔP)

In order to investigate this, an experiment was conducted to collect required data in office building and then to analyze the data through conventional supervised prediction methods used in NILM literature. In addition, hypotheses tests were also statistically checked the significant of features. The following sections provide the detailed description of the methodology and results.

3. Methodology

3.1 Experiment Design and Data Acquisition

An experiment was designed and conducted in an office building over two months. The entire building has 2200 square feet and it was fully occupied by eighteen staffs. Due to the different usage for each room of the building, various office building appliances such as personal computers, laptops, printers, scanners, video projectors, desk lamps, microwaves, refrigerators, and coffee makers, were used during the experiment. Five groups of staff were chosen as target occupants for this study.

In order to acquire the aggregate load data, a smart meter which collected data with 1-second interval resolution, was installed on a circuit which covered all outlets and end-users within the office space. Ground-truth load data with 1-second interval resolution was also collected through plug load meters installed at the occupants' workstations. To detect the entry and departure events, a Wi-Fi sniffer was installed at the building to passively track the transmitted Wi-Fi packets of the occupants' smartphones.

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3.2 Method Selection

Aggregate energy-use data correlated with occupancy events during the experiment was identified and collected for each occupant. Figure 2 shows data points correlated with entry events (i.e., data points captured after the entry events) of one occupants in 20-min time-windows. Each data point is plotted by two features: ΔT measured in seconds, and ΔP measured in watts. The vertical axes in figure 2 were limited to the range of -200 to 200 watts for better visual demonstration of power changes caused by occupants. Positive ΔP at the entry events suggest the occupant increased their loads when entered.

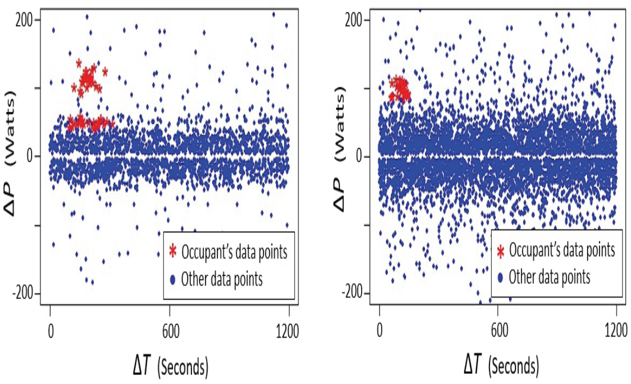

Figure 2. Power changes correlated with entry events of an occupant; other data points are the power changes are not caused by the occupant

Figure 2 particularly demonstrates that aggregate data points (i.e., power changes) correlated with an occupant's events could be divided into two groups: (1) power changes caused by the occupant (group 1), and (2) power changes not caused by the occupant (group 2). Figure 2 particularly shows that the data points caused by each occupant are within a specific range of ΔT and a few values of ΔP among aggregate data provided by meters. Therefore, the specific ranges/values might allow to utilize these features' information for extracting data points caused by occupants.

To check this, logistic regression model (logit model) was selected as a predictor to investigate the significance of ΔT and ΔP in predicting the correct group of the data points. Logit model is the most common and widely used statistical regression method utilized in the terms of prediction when there is a set of m independent predictor variables $X=\{X_1, X_2, \ldots, X_m\}$, and one binary response variable, Y [57,58]. Y determines two groups into one of which, a data point can be assigned. In general, a logit model is expressed by:

$$Logit\ (\pi)=\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_m X_m \quad (1)$$

Where $\beta=\{\beta_0, \beta_1, \ldots, \beta_m\}$ is a set of regression parameters, and π $(0<\pi<1)$ is the estimated of Y and determines the value of probability which is used to predict the group of a data point.

In addition, the logit model through estimated values for the set of regression parameters (β), particularly provides an opportunity to statistically test the importance of features (X) used in the prediction process. Therefore, in this research, the feasibility of ΔT and ΔP in the correct prediction of the groups of data points also tested through the following hypotheses:

- Hypothesis 1. Predicting the correct group of data points by using ΔT as a predictor is feasible.

- H0: ΔT is not statistically significant in the prediction process.

- HA: ΔT is statistically significant in the prediction process.

- Hypothesis 2. Predicting the correct group of data points by using ΔP as a predictor is feasible.

- H0: ΔP is not statistically significant in the prediction process.

- HA: ΔP is statistically significant in the prediction process.

3.3 Data Selection

Correct performance of the selected classifiers and predictor depends to the size of time windows which capture the data points correlated with occupancy events. The points within these time windows are the input data for the classifiers/predictor. Figure 2 as an example shows data points captured through a 20-min time window. Selecting a big size for time windows (e.g., 2-hour time windows) provides a lot of data points which are not caused by a specific occupant and could disturb the performance of a technique which derive the occupant's data points. On the other hand, small size time windows (e.g., 3-min time windows) cloud lead to losing some data points caused by occupants.

To address this issue, a size for time windows was selected in this study as follow. For entry events of an occupant, the maximum time of ΔT was estimated by the ground-truth data acquired for his/her entry events and considered as the size of the time window for his/her entry events. Then, this time window captured data points correlated with his/her entry events and put into a dataset which will be analyzed by the classifiers and predictor. Similarly, the size of time window for his/her departure events was also estimated and data points correlated with his/her departure events (data points caused before his/her departure events) were captured and put into another dataset. Figure 3 shows a time window which selected the data points for departure event of an occupant. The negative ΔP suggests that this occupant reduced energy load when left the building.

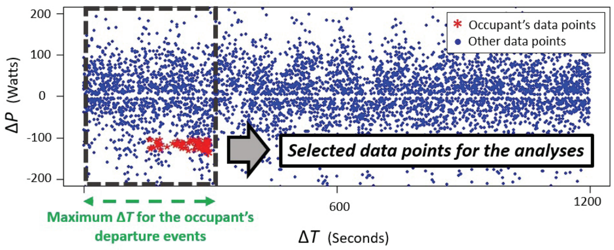

Figure 3. A time-window captures data points correlated with departure events of an occupant; other data points are not caused by the occupant

4. Results and Discussion

In order to run the predictor, and hypothesis testing on the datasets, R-programming, an open-source statistical language, was selected. The following results were achieved through the predictor implementations.

4.1 Predictor Performance

In this study, there were two possible groups for a data point: group 1 and group 2. ΔT and ΔP also act as independent predictors. Therefore, the logit model used in predicting the correct group of the data points was expressed by $Logit\ (\pi)=\beta_0+\beta_1\ \Delta T+\beta_2\ \Delta P$.

The performance of a logit model in predicting processes significantly depends on the cutoff point which is a threshold defined for . In this study, for each occupant, all possible values of the cutoff point (all values between 0 and 1) were examined to understand how the logit regression model performs for different cutoff values. Accordingly, receiver operating characteristic (ROC) curves were utilized to illustrate the performance of the logit model for all cut off values; a ROC curve visually demonstrates the performance of a binary classifier or predictor when the threshold is varied.[59,60] For each value of the cutoff point, a confusion matrix returned number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Then, the curve is allowed to show the tradeoff between true positive rates (TPR) against false positive rate (FPR) for all values of the point. TPR and FPR are defined as follows:

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

$$TPR = \frac{TP}{TP + FN} \tag{3}$$

These metrics are ranged between 0 and 1. While the higher value of TPR indicates the more accuracy, the lower values of FPR indicate the better results. Figure 4 demonstrate the ROC curve generated for the occupants' events. TP, FP, TN, and FN contributed with the same weight to TPR and FPR and the equal error cost was considered during the process.

The ROC curves in figure 4 typically demonstrate the higher TPR compared to FPR for all occupancy events. In particular, the curves for few events (e.g., entry events of occupant 2) touched the 45-degree line in a few points which indicates some values of cutoff points for these events leaded to worthless predictions (FPR is equal to TPR). The stochastic nature of ΔT and the possibility of coincidence in ΔP with similar magnitude could be the main source of errors in the prediction procedure. Fur-

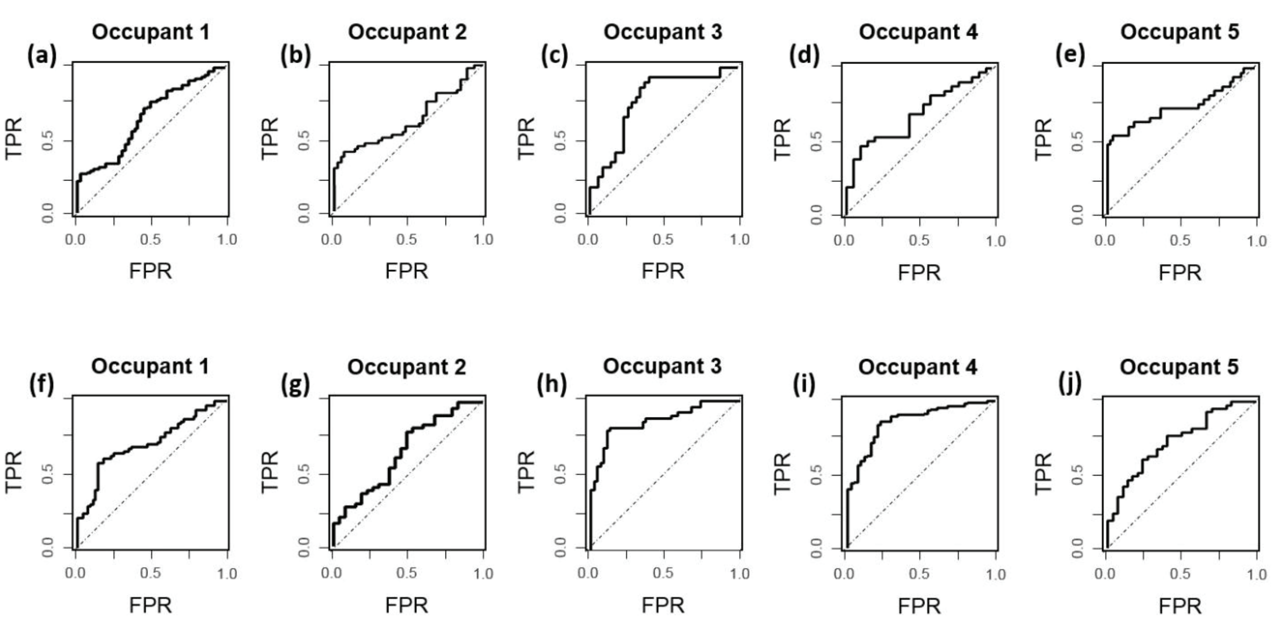

Figure 4. Roc curves: (a, b, c, d, e) entry events, (f, g, h, i, j) departure events

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thermore, more the area under curve (AUC) for departure events of occupant 3 compared to the events of all occupants, indicating more accurate prediction for data points of this occupant at departure events. Overall, the ROC curves in figure 4 demonstrated that using ΔT and ΔP for appropriately predicting power changes caused by occupants with higher TPR to FPR rates is feasible.

4.2 Hypotheses Test Results

For entry and departure events of each occupant, the maximum likelihood estimation was used to estimate the set of parameters for . Then, the estimated values were tested through Wald and Likelihood-Ratio (LR) tests for the constructed hypotheses; Wald and LR tests are the tests mainly utilized to statistically investigate the importance of parameters in a regression analysis [61]. Table 1 lists the results of the tests.

The results of LR and Wald test draw a same conclusion for events of individual occupants. The statistically significant p-values give evidences for rejecting null hypotheses for all events and indicate that ΔT and ΔP are statistically significant to derive power changes caused by occupants among aggregate data points.

4.3 Further Discussion on the Results

The ROC curves achieved through the logit model, and the statistically significant p-values obtained for the hypothesis tests revealed that using ΔT and ΔP for extracting power changes caused by occupants from data provided in building operations is feasible. The information of ΔT and ΔP is collected from existing occupancy and energy sensing infrastructures in office buildings, without installing new hardware. As discussed, the possibility of coincidence in data points with similar ΔT and ΔP could be interpreted as the main source of error which did not allowed the classifiers and predictor to achieve the maximum performance (highest accuracies).

Furthermore, Figure 2 and 3 demonstrate data points caused by occupants are limited to the few value of ΔP which means these data points caused by personal appliances typically used during the experiment. Through the help of the acquired ground truth data, it was finally found that these data points were caused by the personal computers used at the workstations. In fact, since the personal computers were typically used every day during the experiment, their caused data points (power changes) had most frequently in datasets which allowed making dense clusters; such clusters were utilized by classifiers/predictor.

Currently, NILM techniques typically provide the energy-use information of the major appliances (use the most energy) in a building [13,15,16]; this information is valuable in enhancing overall energy efficiency in built environments. Similarly, ΔT and ΔP helped extracting energy-use information of the personal computers which were the major appliances with maximum frequency of usage at the occupants' workstations during the experiment. Accordingly, the energy-use data of personal computers could provide valuable information for understanding occupants' energy-use behaviors.

5. Limitations

While current energy and occupancy sensing infrastructures in offices building have not been demonstrated to be suitable to provide real-time occupants' energy-use behavior information, the results of this study indicated that such infrastructures have capacity to provide occupant-specific energy-use information at entry and depar-

Table 1. Wald and LR tests results

Occupant	Hypothesis	Entry Events				Departure Events			
		Wald Test		LR test		Wald Test		LR test	
		Z-value	P-Value	-2log(Λ)	P-Value	Z-value	P-Value	-2log(Λ)	P-Value
1	1	2.637	0.00837	7.531	0.00606	2.722	0.00648	7.648	0.00568
	2	2.028	0.04258	9.527	0.00202	-3.419	0.00062	11.504	0.00069
2	1	2.504	0.01229	11.350	0.00075	-2.279	0.02266	12.151	0.00049
	2	-3.867	0.00011	16.942	3.85e-05	4.724	2.31e-06	24.688	6.74e-07
3	1	2.391	0.01679	14.831	0.00011	-3.416	0.00063	12.213	0.00047
	2	-5.029	4.94e-07	37.395	9.64e-10	4.753	2.01e-06	36.208	1.77e-09
4	1	1.960	0.04999	13.342	0.00025	-5.119	3.07e-07	37.654	8.447e-10
	2	4.707	2.51e-06	53.612	2.44e-13	6.279	3.40e-10	60.741	6.51e-15
5	1	2.471	0.01347	9.978	0.00158	2.911	0.00360	8.124	0.00436
	2	-3.750	0.00017	46.557	8.90e-12	3.559	0.00037	26.585	2.52e-07

ture events. The main objective of this paper was to assess whether the two proposed features are able to derive occupant-specific power changes based on the NILM concept. This objective was confirmed through the results from the logit model. However, this research is subject to some limitations.

As discussed, the results significantly depend on the size of time-windows which select data points. In this research, the size was selected based on the maximum ΔT in each dataset. In fact, due to the lack of enough data, no analysis such as a sensitivity analysis could result in strong conclusions. Accordingly, further research into different sizes of time windows through various datasets would be beneficial to recommend the optimal size for a time window which lead to higher accuracies.

Furthermore, in this study, all data points correlated with an occupancy event were studies together in a time window. However, considering one time-window for each day based on its ΔT and studying data points in individual daily time windows might suggest an optimal size for the time window. Such individual daily time windows might also help looking more in depth into occupants' energy-use information.

6. Conclusion

This research was the first step in developing a non-intrusive occupant load monitoring approach in office buildings. The results from implementing the predictor and hypothesis tests on aggregate load data from a building confirmed the feasibility of ΔT and ΔP in non-intrusively extracting power changes caused by occupants at entry/departure events. Compared to the previous research extended the NILM concept for occupancy sensing, this research extended this concept for monitoring occupant-specific energy consumption. Furthermore, within the office settings, building management systems have utilized increasingly extensive sensor networks, but these networks fail to leverage aggregate load data as a measurement of occupant-specific energy consumption. However, this study particularly shows that without installation any additional hardware in an office building, the information provided by current infrastructures (i.e., Wi-Fi networks and metering devices) could be utilized for monitoring individual occupants' energy-use information. Overall, this study presents promising options for future research into occupant energy sensing in office buildings at minimal costs.

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