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# Extracting Occupants' Energy-Use Patterns from Wi-Fi Networks in Office Buildings

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## Abstract

Wi-Fi networks are currently considered as an efficient and economical tool for occupancy sensing in office buildings. Studies particularly indicated that these networks could be utilized to understand/predict occupants' energy-use patterns. Despite the value that investigating this possibility could provide for the current research, it has not been well explored how energy-use pattern information could be extracted from Wi-Fi system information. In response, this study utilizes statistical analyses to investigate the correlation of Wi-Fi flows with miscellaneous electric loads (MELs) in office buildings. MELs account for more than one-third of office-building energy consumption and are the best representative of occupants' energy-use patterns. In the pursuit of the objective, data from two offices were collected over a 3-month period of time. Results from the analyses show that an average 92 percent of MELs energy consumption could be predicted through the Wi-Fi flows in a building. This finding thereby demonstrates that occupants' energy-use patterns are highly positively correlated to Wi-Fi flows in a building and accordingly, the information of Wi-Fi networks could be utilized to understand/interpret these patterns. This significantly contributes to the current body of research and can be used to support efforts into understanding/enhancing occupants' energy-use behaviors. In addition, since Wi-Fi networks are a major subset of internet of things (IoT) hardware systems and IoT implementation for intelligent energy management in buildings significantly depends on occupant energy-use patterns, this research helps IoT-based efforts by displaying how these patterns could be extracted from IoT infrastructure.

## Keywords

Wi-Fi networks; Occupants' energy-use patterns; Miscellaneous electric loads; Office buildings; Internet of things.

## 1. Introduction

Office buildings are the main subsector of commercial buildings and are responsible for more than 15 percent of commercial building energy consumption in the United States [1]. Accordingly, they have received increasing attentions in recent years for enhancing energy efficiency. Recent research [2–9] shows that energy conservation in office buildings require a detailed understanding of occupants' energy-use patterns/behaviors and intervening in these patterns/behaviors contributes to the energy savings up to 30 percent in such buildings [10]. In this context, it has been indicated that due to the direct control of occupants on miscellaneous electric loads (MELs) [11,12], adopting energy conservation behaviors among occupants could greatly reduce these loads energy consumption [10,13]; MELs represent more than 35 percent of energy consumption in office buildings [14]. Therefore, a correct monitoring of energy-use patterns is critical to achieve the ultimate goal of optimizing building energy consumption.

Monitoring energy-use patterns has received considerable attention over the last decade and various approaches have been developed to estimate occupants' energy-use profiles [8,9,15–19]. In general, these approaches are divided to two categories: (1) Intrusive approaches where a plug-load meter installed at an occupant's workstation in an office, monitors her personal appliances [20,21], and (2) non-intrusive approaches where the data provided by circuit-level meters is utilized to estimate occupant-specific energy-use profile [13,15]. While the information resulted from the current intrusive/non-intrusive methods is useful in understanding energy-use patterns, due to economic issues in implementing intrusive methods as well as the high degree of uncertainties for non-intrusive data, the industry hesitates to implement these methods in a real world.

On the other hand, several studies [6,13,22–24] have suggested that the advent of advanced Wi-Fi networks/facilities could help capturing occupants' energy-use information based on circuit-level energy-load data (i.e. aggregate load data) in office buildings. In fact, since the information of Wi-Fi systems can serve as a building occupancy indicator [22], there is a possibility of using

such information to monitor energy-use patterns in a non-intrusive manner. However, linking Wi-Fi data with aggregate load data to extract such information of occupants has not been well addressed. In particular, a gap still remains in the terms of linking MELs data (as the best representative of energy-use patterns) with Wi-Fi data to understand how closely MELs consumption is correlated with Wi-Fi flows (the number of Wi-Fi connections) in office buildings.

To address this gap, we used data collected in two buildings to examine the correlation between Wi-Fi information and MELs usage through a time window approach. To validate the results and investigate the effect of bias factors, we developed and tested three hypotheses: (1) the consistency of the correlation of Wi-Fi and MELs flows over time, (2) the consistency of this correlation across weekdays, and (3) the consistency of the correlation across AM and PM hours. The findings of this study demonstrate how Wi-Fi system information could be utilized for understanding MELs consumption and accordingly explaining occupancy-related energy-consuming actions. This provides helpful information for building energy management teams and policy makers in energy saving programs. Considering Wi-Fi networks are a subset of IoT hardware systems [25–28], this study also contributes to research in developing IoT-based energy management programs in buildings.

## **2. Related Work**

### ***2.1. Monitoring occupant energy-use pattern***

Energy-use patterns are generally defined as the presence of occupants in a building and their energy-related actions such as temperature setpoint changing [7,29–33] and light switching [34,35] which influence the building's energy consumption. In office buildings, the most detailed level of energy-use data for individual occupants is currently provided through individual plug-level meters installed at occupants' workstations. However, this data sensing approach requires high capital investments [15,20,36] and fails to provide information about occupants' usage of shared resources such as shared office appliances.

To address these limitations, researchers has recently developed non-intrusive monitoring approaches [13,37–39] to track individual occupants' energy consumption. These approaches particularly add occupancy information into conventional load disaggregation methods (e.g., [40]) to deliver individual occupants' energy-use information. However, such research is mainly limited to residential buildings and typically delivers uncertain data (compared to plug-level meters).

Therefore, a gap still remains in terms of economically monitoring occupant energy-use pattern in office buildings.

## ***2.2. MELs energy consumption***

In a building, there are typically four types of electric loads: HVAC systems, lighting, water heating, and MELs [11,12,41]. In fact, MELs includes the plug/hardwired electric loads consumed by appliances/systems outside of building's core functions [42]. MELs are currently responsible for approximately 30 and 36 percent of total building energy consumption in the residential and commercial buildings, respectively [43]. In addition, the energy demand of MELs currently has an increasing rate of 13 percent in the residential sector and 27 percent in the commercial sector [44]. Therefore, researchers are currently looking for strategies/policies to reduce the MELs energy consumption.

In particular, among the four types of electric loads in office buildings, occupants have more direct control over MELs [11,12] through using office appliances such as personal computers laptops, desk lamps, scanners, and printers. Therefore, understanding occupant energy-use actions over MELs could provide opportunities in reducing these loads energy consumption at a minimal cost in office buildings [13].

## ***2.3. Wi-Fi-based occupancy sensing in office buildings***

Currently, Wi-Fi networks with full coverage are widely installed in office buildings and play an important role in communication between a building's facility management team and its residents [22,45]. Accordingly, Wi-Fi based tracking is currently considered as the predominant and widely implemented occupancy sensing method within office buildings [46–54]. In particular, since office building occupants have Wi-Fi enabled devices (e.g. smartphones) [55,56] and typically carry these devices [57], Wi-Fi-based sensing is more accurate and reliable compared to the other occupancy sensing approach (e.g., motion or temperature sensors) [58,59]. This method is able to practically determine occupancy presence with an 83 percent accuracy [23]. In addition, this approach uses Media Access Control addresses (MAC addresses) and/or Universally Unique Identifier of Wi-Fi-enabled devices to differentiate between occupants in a building. The high

degree of occupancy resolution as well as non-intrusiveness are also considered as the advantages of Wi-Fi based occupancy sensing [60].

In terms of studying occupant energy-use pattern through Wi-Fi systems, there is a limited number of studies. Martani et al. [22] showed the number of Wi-Fi connections (as a building occupancy indicator) could be correlated with energy flows in commercial buildings. Chen and Ahn [6] presented that Wi-Fi connection events are viable indicators for occupancy-related load increases in office buildings. Rafsanjani et al. [13] utilized Wi-Fi connections/disconnections to extract energy-use information from aggregate load data in office buildings. Despite these interesting efforts, there is still much research to be done to achieve the full potential of Wi-Fi networks in understanding energy-use patterns.

#### ***2.4. Problem statement***

Martani et al. [22] could not successfully build a strong correlation between occupancy flows and building energy-use because they studied overall energy load of large multi-story educational buildings. In such buildings, the overall energy load mainly depends to the energy consumption of HVAC systems which does not necessarily reflect occupant energy-use actions. Chen and Ahn [6] also could not successfully correlate Wi-Fi disconnections to occupants' energy-load reductions. In addition, they used low-resolution trend data which could distort to build a strong correlation between energy and occupancy flows. Rafsanjani et al. [13] focused on smartphones' Wi-Fi signals and ignored the effect of other Wi-Fi enable devices (e.g., laptops) in their study. Add to these limitations, the current body of research has not well studied the correlation of Wi-Fi flows and MELs energy consumption.

To address this gap, we collected MELs load data as well as Wi-Fi network information of two offices (from their existing metering devices and wireless networks) over a 3-month period; two-to-four month durations are typically considered as the logical long-term length in studies related to energy-use patterns/behaviors in office buildings [2]. Then, the data of each office were statistically analyzed to assess the aforementioned correlation. Finally, we tested through three hypotheses whether the correlation could be affected over time or/and by a specific duration. The hypotheses are as follows: there is a consistency of the correlation of Wi-Fi and MELs flows (1) over time, (2) across weekdays, and (3) across AM and PM hours. The following sections provide detailed descriptions of the methodology and findings.

### **3. Methodology**

#### **3.1. Data collection**

##### **3.1.1. Case Study 1**

The first case study was an office space located on the second floor of a multi-story commercial building. The office had a gross floor area of 4172 square feet and includes one main space with fifteen workstations and one director room. Fifteen identical desktop computers were used at the workstations. In addition, one desktop computer, two printers, one coffee maker, one microwave, and one refrigerator were utilized during the data collection step. The lighting system of the office was automatic using occupancy sensor which was set to turn the lights off after five minutes of infrared inactivity. The total number of electrical outlets of the office was 102.

The office had one main electric panel with several circuits fed all outlets and appliances. One electric meter installed in the panel monitored power consumption of the office with 15-second interval resolution. It is noteworthy that the office water heating system was a gas heater and the commercial building utilized a central HVAC system controlled over by building facility management (i.e., the meter data did not include the HVAC data). In addition, in the office, there was one ceiling-mounted wireless access point which passively recorded (at one-second interval resolution) Wi-Fi packets transmitted from Wi-Fi enabled devices including smartphones, tablets, and laptops; the access point provided full coverage for the office.

The data collection was conducted from June 6, 2018 to September 1, 2018 and during this time, fifteen employees and one director worked in the office on weekdays; the office working hours were 7:00 a.m.-6:30 p.m. Due to the company duties, the employees typically left the office a couple of times each day. In fact, this office was purposefully selected since (due to the irregular occupancy flows) it provided a unique opportunity to understand the correlation of Wi-Fi flows (resulted from occupancy flows) and energy consumption.

To collect data, the internal memory of the office electric meter was able to store the data for two weeks and then this data was manually transferred to a database created to store Case Study 1's data. In addition, the building facility management always recorded the access points' information of the entire buildings and shared the data of the office with us. This data was also stored in the database.

Before the data collection, the employees and director were asked to answer a survey about their appliance usage and the condition of their wireless devices. The survey results suggested that employees had control over the shared appliances and routinely used those every day. The results also showed that employees usually connected their wireless devices to the office's access point which allowed the access point to record their information. In addition, the survey results showed that the desktop computers were set to go to sleep mode after five minutes of inactivity.

### **3.1.2. Case Study 2**

The second case study was an office space located in a one-story commercial building; this office was a second location of the company which occupied Case Study 1. The entire office was 3090 square feet and contained twelve cubicles. Each cubicle included one desktop computer which was not identical to the other desktop computers. In addition, there were one printer, one coffee maker, one microwave, and one refrigerator within the office, and the lighting system was manual switching. The total number of electrical outlets of the office was 74.

There was one electric meter inside the main panel of the office that tracked office power consumption with one-min interval resolution. In this office, the building facility management controlled over water heating and HVAC systems and accordingly the meter data did not include these appliances data. In addition, there was one ceiling-mounted access point with a full coverage within the office and recorded the information of Wi-Fi enabled devices at one-second interval resolution.

Over June 18, 2018 to September 29, 2018, we collected data from the office. Similar to Case Study 1, the energy-load data stored inside the internal memory of the meter was manually transferred a database created for Case Study 2 and the building facility management shared Wi-Fi data. In addition, in office, eleven employees used the office on working days and (due to their duties) typically left the office a few of times per day; the working hours were similar to Case Study 1.

We also conducted a survey (similar to the Case Study 1's survey) and the employees mentioned they usually left their devices' Wi-Fi on (which let the devices connected to the access point) and they had control over all office appliances and routinely used those during working days. They also mentioned that their desktop computers were set to go to sleep modes after three-to-five-min inactivity (varies depending to the computers). In addition, there was one manual



switch for the lighting systems and the employees indicated that the first person who entered to the office each day typically turn the ceiling lights on and the last person who left the office was responsible to turn the lights off.

Table 1 summarizes the information of the case studies.

**Table 1.** Summary of the case studies information

<b>Information</b>	<b>Case Study 1</b>	<b>Case Study 2</b>
Floor area (square feet)	4172	3090
Number of Occupants	16	11
Number of Outlets	102	74
Resolution of Power Meter Data (seconds)	15	60
Resolution of Wi-Fi data (seconds)	1	1
Duration of Data Collection (weeks)	13	15

### **3.2. Data analysis**

#### **3.2.1. Pre-processing and assumptions**

After collecting the data, all corrupted data which might lead to bias in analysis were identified and filtered. Then, based on the office working hours (7:00 a.m.-6:30 p.m.), data between 6:30 a.m.-7:00 p.m. of working days were selected for data analysis step; the 30-min extended durations at the start/end of working hours were empirically estimated.

As mentioned, the meters of the offices recorded all loads except HVAC and water heating systems. Given that, the collected aggregate load data included MELs and lighting systems. Since there is a very low possibility that on/off state of lighting systems is changed during working hours in offices (lights are usually in-use during office hours), we assumed that all changes in load data were resulted from MELs.

In addition, as mentioned, the workstation desktop computers were identical in Case Study 1 and the occupants had a same control over shared appliances. Accordingly, we considered an equal weight for occupants' energy consumption in Case Study 1. In Case Study 2, even if the

workstation desktop computers were not similar, the differences among their energy consumption were up to 11 percent; a plug-load meter was used to find the consumption of each device before the experiment. We neglected these differences and assumed that the occupants similarly contributed to the energy consumption in Case Study 2.

In order to handle temporary occupants who visited the case studies very few times during data collection, we empirically considered a same unique MAC address that appeared less than 10 times in the Wi-Fi data as a temporary occupant and its connections were ignored during data analysis process. In addition, since temporary occupant typically create Wi-Fi connections but they may not create energy-load changes [6], no adjustment in energy-load data was made during data analysis.

### **3.2.2. Correlation analysis**

To correlate Wi-Fi flows (the number of Wi-Fi connections) with MELs consumption, the data of each day of each case study were divided into six-min time windows. The six-min duration was empirically estimated based on the resolution of energy data as well as the conditions/states of appliances (e.g., the power sleep mode of desktop computers); this duration reasonably covered a delay between a Wi-Fi connection/disconnection and its respective load changes in our case studies. Then, the average number of Wi-Fi connections in each time window was found and considered as the number of Wi-Fi connections of the time window. Accordingly, the average energy consumption of a time window was considered as its representative energy consumption. It is noteworthy that there were 7492 and 8731 time windows for Case Study 1 and 2, respectively. In addition, due to the resolution of energy-load data (15 and 60 seconds for Case Study 1 and 2, respectively), there were typically 24 and 6 energy-use data points in a time window of Case Study 1 and 2, respectively.

Then, the correlation of Wi-Fi flows and MELs usage for each case study was investigated. In the correlation analysis, the number of Wi-Fi connections was considered as an independent variable while the MELs energy consumption was a dependent variable. R-programming language was utilized for the correlation analysis.

### 3.2.3. Hypothesis tests

In the correlation analysis, there were three potential factors which might cause biases in the data analysis. (1) Long-term data as a one dataset: a bias might appear in data analysis when all data of a case study were checked at once. (2) Weekdays: a weekday might have its own correlation pattern which could significantly be different from other weekdays. (3) AM vs PM: there is a possibility that occupancy flows and energy-use patterns in the morning might be different with those in the afternoon/evening.

To explore these possibilities, we divided the data of each case study to several groups in three distinct ways. (1) Four observation groups: In our databases, there were 61 and 73 days for Case Study 1 and 2, respectively. Given that, we divided the data of each case study into four observation groups to have enough numbers of groups as well as enough numbers of observations (i.e., days) in each group (to check the possible bias in data analysis) [61]. Accordingly, Case Study 1's database was divided into three groups of 15 days and one group of 16 days, and Case Study 2's database was divided into three groups of 18 days and one group of 19 days. (2) Five days groups; each of which included data for a weekday. (3) Two groups; one group included AM data and the other one included PM data.

Then, for each group the correlation of Wi-Fi and MELs flows was estimated and compared to its peer groups. Given that, three hypotheses were developed to statistically investigate whether the bias factors misled the correlation analysis. The hypotheses follow:

**Hypothesis 1.** There is a consistency of the correlation of Wi-Fi and MELs flows across the four observation groups.

- $H_0$  = There is no statistically significant difference among the correlation of Wi-Fi and MELs flows across the four observation groups.
- $H_A$  = There is a statistically significant difference among the correlation of Wi-Fi and MELs flows across the four observation groups.

**Hypothesis 2.** There is a consistency of the correlation of Wi-Fi and MELs flows across weekdays.

- $H_0$  = There is no statistically significant difference among the correlation of Wi-Fi and MELs flows across the weekdays.

-  $H_A$  = There is a statistically significant difference among the correlation of Wi-Fi and MELs flows across the weekdays.

**Hypothesis 3.** There is a consistency of the correlation of Wi-Fi and MELs flows across AM and PM groups.

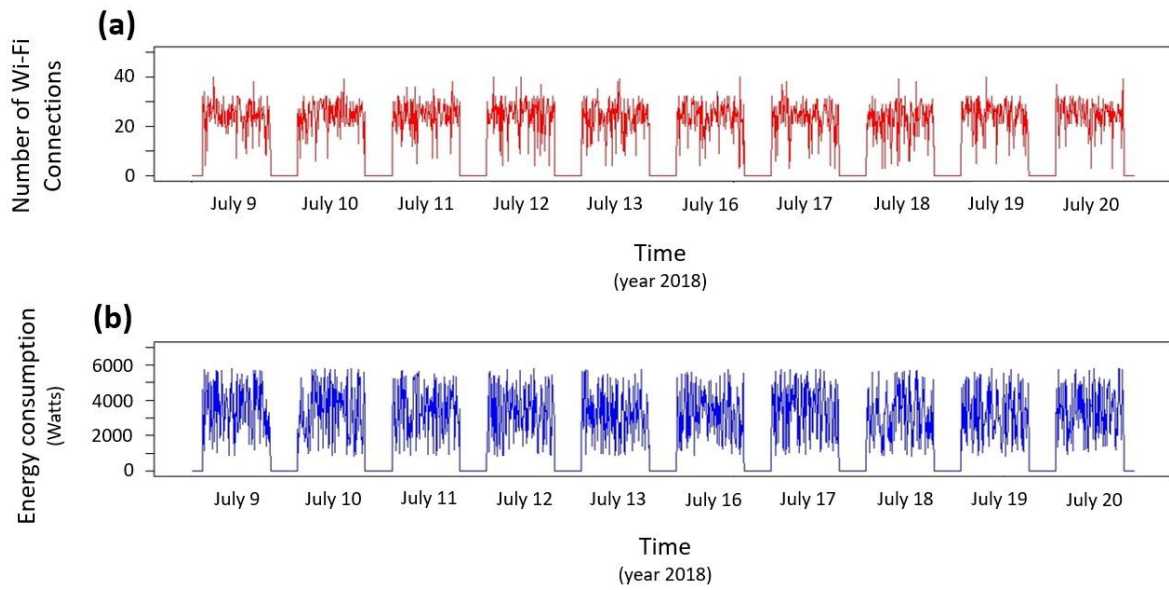
-  $H_0$  = There is no statistically significant difference between the correlation of Wi-Fi and MELs flows in the morning with that in the afternoon/evening.

-  $H_A$  = There is a statistically significant difference between the correlation of Wi-Fi and MELs flows in the morning with that in the afternoon/evening.

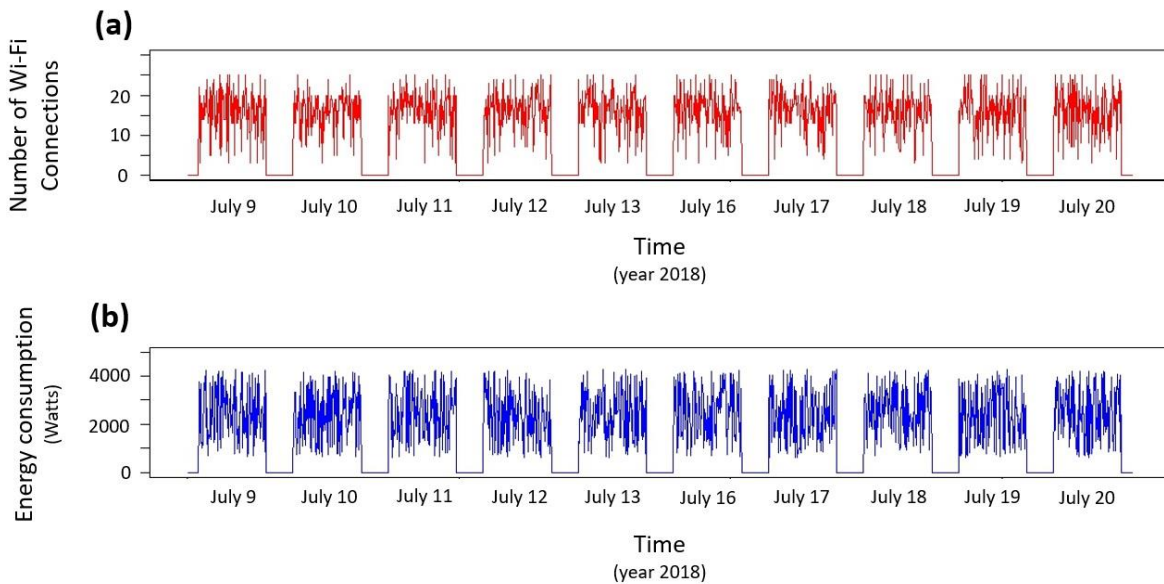
Due to having more than two groups of data for Hypothesis 1 and 2, we utilized a one-way ANOVA and a Kruskal-Wallis test to test these hypotheses. To test Hypothesis 3 (which included two groups), a two sample  $t$ -test as well as a Mann-Whitney  $U$  test were constructed. For all the tests, a rejection threshold of 0.05 ( $\alpha=0.05$ ) was selected. Similar to the correlation analysis, R-programming language was utilized for the tests.

## 4. Results

Figure 1 and 2 present data collected from July 9, 2018 to July 20, 2018 for Case Study 1 and 2, respectively; since the data during working hours were only utilized for the data analysis, a base line with the value of zero was considered for non-working hours. Figure 1 and 2, as a sample of data, visually presents the trends in Wi-Fi and energy profiles of the case studies. The variances in Wi-Fi connections resulted from the occupancy flows; Case Study 2 displays more variance compared to Case Study 1. In addition, these figures show no significant difference for the range (minimum and maximum values) of data across different days for each case study.

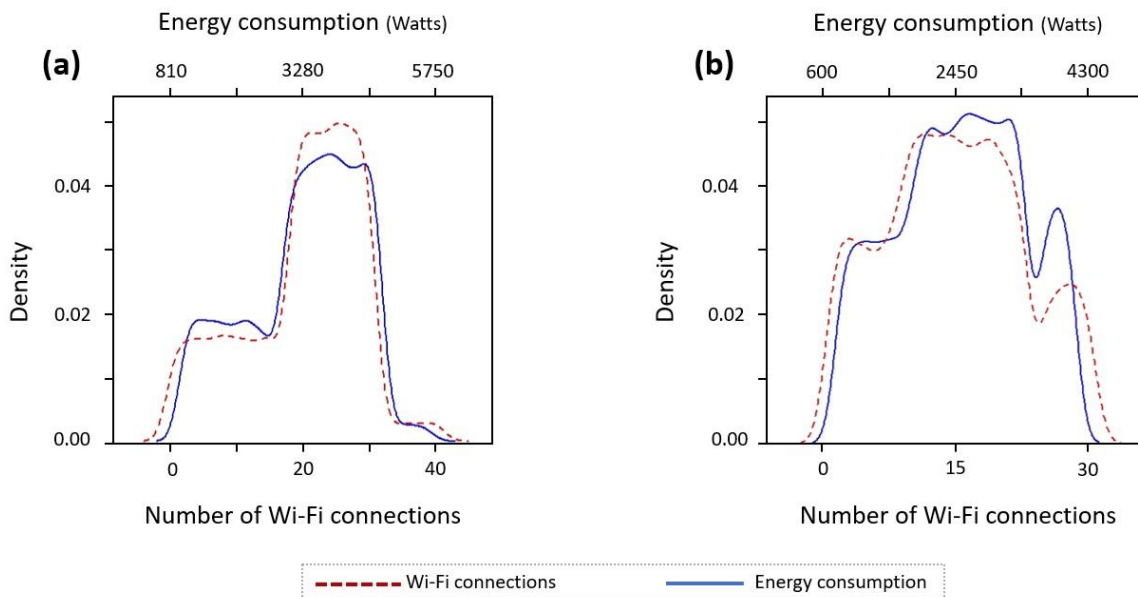


**Figure 1.** Time series of Wi-Fi flow and energy consumption of Case Study 1 from July 9, 2018 to July 20, 2018: (a) Wi-Fi flow, (b) energy consumption



**Figure 2.** Time series of Wi-Fi flow and energy consumption of Case Study 2 from July 9, 2018 to July 20, 2018: (a) Wi-Fi flow, (b) energy consumption

Figure 3 shows the distribution of Wi-Fi connections and energy consumption of the data collected for each case study. The minimum energy value of the case studies (810 and 600 watts for Case Study 1 and 2, respectively) presents the level of energy consumed by the ceiling lights. As mentioned, due to assuming no changes in the state of ceiling lights during working hours, these values were considered as the base value to present MELs energy distribution. Figure 3 particularly displays that energy distribution in an office building approximately follows the distribution of Wi-Fi flow which could indicate Wi-Fi connections are able to clearly predict MELs energy consumption.



**Figure 3.** Distribution of Wi-Fi flow vs. energy consumption: (a) Case Study 1, (b) Case Study 2

Table 2 presents the results of the correlation analysis. The results show that 90.5 and 93.2 percent of variations in MELs consumption were predicted through Wi-Fi flow in Case Study 1 and 2, respectively; the high level of significance ( $p\text{-value} < 2.2e-16$ ) for the case studies indicates that the correlations are statistically significant.

**Table 2.** Results of the correlation analysis

Case Study	Degrees of Freedom	Residual Standard Error	R <sup>2</sup>	F	P-Value
1	7490	3.849	0.905	7.136e+04	< 2.2e-16
2	8729	2.515	0.932	1.204e+05	< 2.2e-16

Note: Wi-Fi flow: independent variable, MELs consumption: dependent variable

Table 3, 4 and 5 list the results of the statistical tests for Hypothesis 1, 2, and 3, respectively. Based on the level of significance ( $p\text{-value} > 0.05$ ) resulted from each test, we failed to reject the null hypotheses of 1, 2, and 3 for both case studies which means that the impact of each factor on the correlation on different time scales are not statistically significant. This demonstrates the consistency of the correlation between Wi-Fi flows and MELs usage over time and also indicates that this correlation is not generally affected by weekdays or AM/PM. In addition, it particularly implies that temporal changes in occupants' usage patterns on a daily, weekly, or monthly scale do not impact the correlation of the Wi-Fi flows with energy consumption.

**Table 3** Results of Hypothesis 1

Case Study	one-way ANOVA Test		Kruskal-Wallis Test	
	F	P-Value	H	P-Value
1	0.368	0.776	1.016	0.797
2	0.502	0.680	0.921	0.820

Note: rejection threshold = 0.05

**Table 4.** Results of Hypothesis 2

Case Study	one-way ANOVA Test		Kruskal-Wallis Test	
	F	P-Value	H	P-Value
1	0.920	0.451	0.051	1
2	0.811	0.518	0.102	0.998

Note: rejection threshold = 0.05

**Table 5.** Results of Hypothesis 3

Case Study	Two Sample <i>t</i> -Test		Mann-Whitney <i>U</i> Test	
	T	P-Value	W	P-Value
1	0.292	0.771	7216233	0.983
2	0.360	0.718	9920500	1

Note: rejection threshold = 0.05

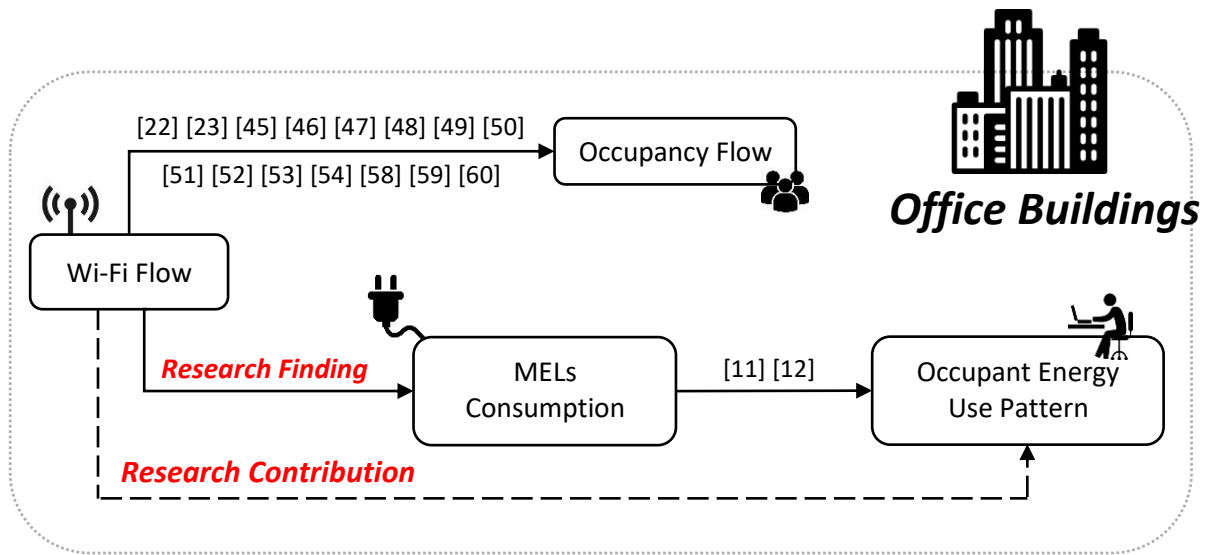
## 5. Discussion

This research investigated the correlation of Wi-Fi flows (number of Wi-Fi connections) and MELs flows (MELs consumption) in office buildings through the data collected from two offices. Office buildings with the gross floor area of up to 5000 square feet are the most common type of offices [62,63] and most ideal cases for studying occupants' energy-use behaviors since these spaces offer occupants more control over their built environments [64]. Accordingly, the selected case studies were logical representatives of office buildings. In addition, the timeframe of this study covered thirteen and fifteen weeks for Case Study 1 and 2, respectively which is in accordance with the eight-to-sixteen weeks duration typically considered for studying energy-use patterns/behaviors [2]. Moreover, while the average number of employees per company in office buildings in the United States is eleven-twelve [65], the number of occupants during our study was sixteen and eleven for Case Study 1 and 2, respectively. In addition, occupants of the case studies left the offices a few times each day (occupancy flows were very changeable) which particularly helped us to investigate the research objectives in more accurate and logical way.

The correlation values which were resulted from analyzing 16,223 independent time windows, indicated the number of Wi-Fi connections could be utilized to understand/predict MELs usage; the results of hypotheses indicated that the correlation of Wi-Fi and MELs flows is not generally affected over time, by a specific day, and/or a specific duration of a day. Since occupants directly control over MELs [11,12] and the changes of these loads are predominantly resulted from occupants' energy-use behaviors, Wi-Fi flows could particularly be utilized to explain and predict occupants' energy-consuming actions in buildings. This could significantly contribute to the research working on occupancy-related energy-use patterns/behaviors. Figure 4 displays the contribution of this research. In addition, this figure particularly indicates that prior research has



predominantly focused on the dynamic relationship between Wi-Fi systems and occupancy sensing.



**Figure 4.** Research contribution to the current literature

In addition, Martani et al. [22] considered all the loads of buildings to estimate the correlation and showed that Wi-Fi connections could be able to account for up to 69 percent of building-wide energy load variations. However, since the building-wide variations were resulted from all loads of the buildings (which do not necessarily result from occupancy-related actions), this correlation might not be able to explain occupants' energy-use patterns. Compared to Martani et al. research [22], our study considered MELs usage variations to directly investigate occupant energy-use actions. In addition, Chen and Ahn [6] and Rafsanjani et al [13] research indicated the possibility of a high correlation; however, their studies were limited to beginning/end of daily energy-consuming behaviors. On the other hand, we investigated this objective for the entire working hours when occupants are present in a building.

While existing Wi-Fi network in an office building usually records the information of Wi-Fi enabled devices presented within the buildings; building facility management teams rarely use

this information to enhance building energy consumption. However, the findings of our study motivate such teams to utilize this ready-to-use information to understand/forecast MELs consumption as well as occupancy-related energy-use patterns at a minimal cost. Low numbers of Wi-Fi connections in a building during high-level of MELs usage could indicate that building occupants follow non-energy-saving behaviors. Accordingly, facility management teams could distribute feedback to prompt energy-saving behaviors.

In addition, this research particularly indicates that existing Wi-Fi infrastructure of buildings can be utilized to contribute to the current efforts in smart buildings. The information of this infrastructure could identify the number of occupants in real-time and accordingly building appliances and systems would be adjusted to a level to provide occupant comfort. Additionally, since this information directly predicts MELs demands, it could contribute to current effort in smart grids by predicting MELs energy-use trend. Due to the need for no new sensor, the industry would like to execute such ideas at full scale.

Currently, as we move towards IoT, this term has a remarkable growth in research and industry. Since IoT is implemented through a network of interconnected things [66], Wi-Fi networks are predominantly considered as the main part of IoT infrastructure [25–28] and widely used for developing IoT-based intelligent systems especially in residential and commercial buildings. In particular, existing advanced Wi-Fi networks in office buildings make these buildings as a prime candidate for IoT implementation with different applications. As an application, an IoT-based system could be developed to assist building facility management teams to prompt energy saving behaviors, a practice to yield long-term energy savings in built environments [2]. We believe that our research provides insight into developing such intelligent systems to monitor/enhance occupants' energy-use patterns/behaviors.

## **6. Limitations**

This research yields five limitations. (1) We acknowledge that the findings of this study could have been benefited from a larger sample size of office buildings. In particular, each of the studied offices included one Wi-Fi access point, but larger offices feature several access points within their physical spaces. Accordingly, while a device is present in an office, it could have multiple connections/disconnections to the office access points which does not allow to properly correlate

an access point's information flow with energy-usage flow. Thereby, such connection multiplicities should be identified and differentiated in data analysis.

(2) The reported correlations and statistical results highly relied on the regular usage of Wi-Fi-enabled devices. Even if the survey results suggested that the case studies' occupants always left their devices' Wi-Fi on, they may have temporarily turned Wi-Fi off or changed their devices' settings during few days of the data collection process, which might distort the data. We believe this issue could lead to decreasing correlation coefficients and detection accuracies in such studies. Identifying such anomalies and understanding their effects on the correlations could be an interesting avenue for future research.

(3) Due to the interference of the Wi-Fi networks in the studied buildings (overlapping of Wi-Fi access points), while the studied occupants presented in the office spaces, their devices might have connected to the access points of the other offices. Accordingly, the device connections might have been wrongly recorded or missed. Wi-Fi network interferences (which are not bounded by physical spaces) generally help to locate Wi-Fi-enabled devices more accurately [6,54]; however, in our study, we were focusing on the physical spaces and access points of the offices and therefore such interferences might have led to inaccurate recording of the Wi-Fi packets sent by the devices. It is worth mentioning that due to having no ground-truth for Wi-Fi networks and occupancy data, we made no attempt to report the Wi-Fi accuracy.

(4) The need of using MAC addresses could be considered a privacy challenge for this study. Currently, different masking techniques such as MAC randomization [67] are utilized to protect users from being identified in Wi-Fi networks. Accordingly, in the envisioned application of the method, the MAC addresses of Wi-Fi enabled devices will be masked with unidentifiable codes in a back-end system which prevents facility managers to track the owners of MAC addresses. We believe that this privacy-protecting technique can minimize the privacy issues associated with the implementation of this research.

(5) While the recorded data, state of appliances, and case studies' conditions suggested a six-min duration for the time windows, the findings of this study could have benefited from studying various size of time windows. When the size of time windows is changed, it affects the number of energy-load changes and Wi-Fi connections of the time windows and thereby, the average of the energy-usage and connections of time windows could be different. In addition, this size change also affects the total numbers of time windows which could alter the results of

correlation analysis and hypothesis tests (due to changing the degree of freedom). Future research is recommended to seek this effect for more robust conclusions.

## **7. Conclusion**

This research examined the correlation between the Wi-Fi and MELs flows during working hours in two office buildings. The results demonstrated 90.5 and 93.2 percent of MELs' consumption were predicted through Wi-Fi flows at Office 1 and 2, respectively. We particularly found that this correlation is independent of time; no temporal bias to time of day, day of week, and even longer periods. Since occupants are mainly responsible for MELs usage, Wi-Fi flows could thereby be utilized to understand occupants' energy-use patterns. This adds benefits to the current application of existing Wi-Fi networks of office buildings and they can be used to predict energy-use patterns/behaviors as well as MELs consumption. Accordingly, Wi-Fi network information could contribute to advance smart buildings/grids.

Two main research lines are identified for our future studies. While in this research we hypothesized three factors which could affect the correlation, further investigation of such factors will be investigated. In addition, as the main line, we will develop an IoT-based tool which could act as a smart personal energy assistant. This tool will be installed as an app on occupants' smartphones to monitor individual occupants' energy-use actions and prompt energy-saving behaviors. In addition, this app will understand their preferred environmental conditions and personalize the environment around an occupant which particularly allows to drive better behavior performance.

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