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Using smart technologies to identify occupancy and plug-in appliance interaction patterns in an office environment

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Abstract. There has been a widely documented phenomenon identifying an energy performance gap between the building's design and operational phases. This result has been attributed to the stochastic behaviours exhibited by the occupants, who are assumed to follow deterministic and routine schedules. With the recent advancements in smart monitoring technologies, the increasing affordability of wireless sensors has allowed researchers to collect detailed information on the occupants' dynamic behaviours. However, past applications of such technologies have been highly intrusive and limit the validity of the data collected due to the Hawthorne effect. Therefore, this paper proposes a non-intrusive data collection methodology using a comprehensive range of wireless smart meters, Bluetooth beacons, and questionnaires to capture the occupants' movement and appliance interaction patterns. The feasibility of the approach is demonstrated during a two-week data collection effort in a university office. By combining the occupants' presence with appliance energy consumption data, the authors were able to identify the occupants' appliance interaction patterns. An extension of this work includes the use of the data collected to identify different occupancy and appliance interaction profiles, which contributes to the development of an appliance interaction model that addresses the energy performance gap caused by occupants' appliance interaction.

1. Introduction

Plug-in appliances generally refer to different types of equipment which are powered by an ordinary AC plug and exclude heavy end uses such as HVAC, lighting, and water heating systems [1]. Over recent years, the total energy consumption of plug-in appliances has become increasingly significant, contributing between 12% to 50% of the total energy consumption in commercial buildings [2]. Taking into account the significant energy contributions and the heavy reliance on the occupant's presence and dynamic interactions to perform their core functions, these building systems introduce a substantial source of uncertainty when simulating the building's overall energy consumption. Therefore, there is an urgent need for empirical studies to be conducted to study occupant interaction with plug-in appliances and develop occupant behaviour (OB) models to accurately quantify the impact of those interactions.

With the recent advancements in wireless sensing technologies, the use of Bluetooth Low Energy (BLE) technology in occupancy detection systems has enabled researchers to collect detailed information on occupant presence and movement patterns within an indoor environment [3]. Filippoupolitis et al. proposed the use of BLE beacons to infer the location of the occupant by communicating with the occupant's smartphone device through a mobile application during emergencies [4]. A similar approach has also been proposed by Choi et al. who used a combination of BLE beacons, smartphone devices, and a mobile application to develop a smart office energy management system that activates the power saving mode of plug-in appliances when the occupant is detected to have left the office [5]. In these studies, the occupants are either instructed to carry around a wearable sensor or install a mobile application on their smartphone devices. These approaches intrude upon the occupants' daily routine and have an unknown impact on the occupants' natural behaviours [6]. This phenomenon is known as the Hawthorne effect as it describes the change in the occupants' behaviour towards social acceptability due to their awareness of being studied [7]. Furthermore, the increased power consumption

on the occupant's smartphone device due to the mobile application might also deter other interested participants. Given the limitations highlighted above, past occupant monitoring studies are limited in its participation rates, thus impacting the reliability and validity of the data collected. Other studies have also proposed the use of smart meters to track the energy consumption levels of plug-in appliances in order to collect information about the occupants' appliance interaction patterns. For instance, Zhao et al. conducted a two-week study to monitor the energy consumption data of various plug-in appliances in an office building through the use of wireless smart meters. By using a data mining approach, the authors were able to infer the occupant's appliance interaction and presence information [8]. Masoudifar et al. further proposed a novel approach of combining occupant location data with the appliance energy consumption data to infer occupant interaction patterns with office appliances [9].

In this study, we propose a non-intrusive OB data collection methodology, which follows a three-pronged approach. This comprehensive approach includes the installation of wireless smart meters, BLE beacons, and a paper questionnaire to collect detailed information about the occupant's socio-demographic information, daily presence and movement patterns, as well as appliance ownership and interaction patterns. The feasibility of the proposed methodology is demonstrated by conducting a two-week data collection effort in a multi-room office environment at a university building in Singapore. Based on the insights gained from this study, an extension of this work will involve the identification of different OB profiles which will be used to develop an appliance interaction model that addresses the energy performance gap caused by occupants' appliance interaction.

2. Data Collection Methodology

2.1. Bluetooth Low Energy (BLE) Beacons

To monitor the presence and movement patterns of the occupants within the office environment, we have proposed a non-intrusive terminal-based occupant monitoring method which utilises the existing BLE technology found in smartphone devices to perform indoor localisation using BLE beacons. The BLE beacons are built using the Raspberry Pi 3 Model B, which are inexpensive and readily available in the commercial market. Once the occupants provide their smartphone device's Bluetooth MAC address, the BLE beacons are programmed using the Bluetooth Proximity Detection library [10] to scan the vicinity for the occupant's Bluetooth-enabled device. When a particular device is detected by the BLE beacon, the MAC address and the Received Signal Strength Indicator (RSSI) value of the device are recorded and timestamped. The RSSI value is affected by the distance between the device and the BLE bacon. Next, the RSSI values recorded by all of the BLE beacons are collected and merged based on their timestamps to obtain a tuple of RSSI values. This tuple is subsequently passed through a machine learning algorithm to infer the occupant's location within the office. This approach is commonly known as the Bluetooth Fingerprinting method. Since the occupants are not required to carry around a wearable sensor or install a mobile application on their devices, this approach is less intrusive on the occupants' daily routine and reduces the power consumption burden on the occupant's device.

2.2. Smart Energy Meters

Wireless smart meters were installed on various plug-in appliances to enable real-time energy monitoring through a smart home system. Through the use of popular clustering algorithms, such as the K-Means algorithm, the energy consumption data, collected through the smart meters, were clustered and categorised into the different states of the plug-in appliance such as ON and SLEEP/OFF. In the case of personal appliances, the occupant's interaction patterns will be inferred by combining the appliances' energy consumption data with the occupant's presence information. This information includes the occupant's appliance usage frequency, appliance switch-off behaviour, as well as appliance interaction duration.

2.3. Paper Questionnaire

A paper questionnaire has also been used to complement the data collected by the BLE beacons and smart energy meters. In this study, two versions of the questionnaire have been designed to cater for both the permanent and temporary occupants. Permanent occupants are defined as users who are

assigned a workspace in the office, while temporary occupants are users who frequently visit the office environment for work-related purposes but do not have an assigned workspace. The questionnaire for permanent occupants is divided into four main sections: socio-demographic information, occupancy patterns within the office, number and types of personal appliances used in the office, as well as plug-in appliance usage frequency and switch-off habits. The occupants were also asked to justify their reported plug-in appliance interaction patterns to understand their motivations. The questionnaire for the temporary occupant is identical to the permanent occupant but does not contain the questions related to appliance ownership.

3. Case Study

3.1. Study Area Description

We demonstrated the feasibility of the proposed methodology by conducting a two-week data collection effort in an office environment in a university. The study area is approximately 650 square meters and houses a facilities management office, open spaces for group meetings, a pantry, an open-concept office area for in-house researchers, as well as several prototyping and manufacturing facilities to support research projects. Figure 1 depicts the layout of the study area, where the Researcher Area and Lab Manager Office is combined into a single zone (named Office Area) to form a total of eight zones.

3.2. Smart Energy Meter Deployment

In this case study, we are interested in monitoring occupant interaction with plug-in appliances commonly found in office buildings such as personal monitors, laptops, and desktops. By installing Z-Wave TKB TZ69E wall plug meters on the plug-in appliances of interest, we were able to track the power consumption patterns of these appliances during the data collection period. The deployment locations of the smart meters are labelled in Figure 1. The energy consumption data from the plug-in appliances was transmitted wirelessly and stored on a centralised smart home system by Fibaro, where it will be extracted for further processing.

3.3. BLE Beacon Deployment and Bluetooth Fingerprinting Model

A total of twenty-one BLE beacons were deployed at various locations within the study area, as depicted in Figure 1. The Bluetooth Fingerprinting model was developed based on a one-vs-all model architecture whereby a binary classifier is developed for each of the eight zones identified in the study area. By comparing the probabilistic outputs of each classifier, the zone corresponding to the classifier with the highest probability is selected as the final predicted location. As a result, the model achieved an accuracy of approximately 80% on the cross-validation set. The details of the model selection process fall outside the scope of this study and will be elaborated in future publications.

3.4. Data Collection Results

3.4.1. Descriptive Statistics of Appliance Ownership Patterns. The paper questionnaire was distributed among twenty-one permanent occupants and seven temporary occupants who regularly visit the study area for work-related purposes one week before the data collection period. Among all of the permanent occupants who participated in the survey, we observed that most occupants will either own a laptop or a combination of a laptop and an external monitor for their daily work. For a small group of occupants, we also observe the ownership of an additional desktop in addition to the usual configuration described earlier. In total, we collected data on eleven personal monitors, three desktops, and seventeen laptops.

Figure 1. Study area showing the deployment locations of the BLE beacons and smart energy meters.

3.4.2. Occupant Presence and Movement Patterns. In this section, we will present the occupancy information that was collected using the Bluetooth Fingerprinting approach. To first validate the performance of the approach, we plotted the occupancy levels of the study area based on the Bluetooth Fingerprinting approach, the paper questionnaire, as well as a manual observation of the occupants' movement patterns over five working days (see Figure 2).
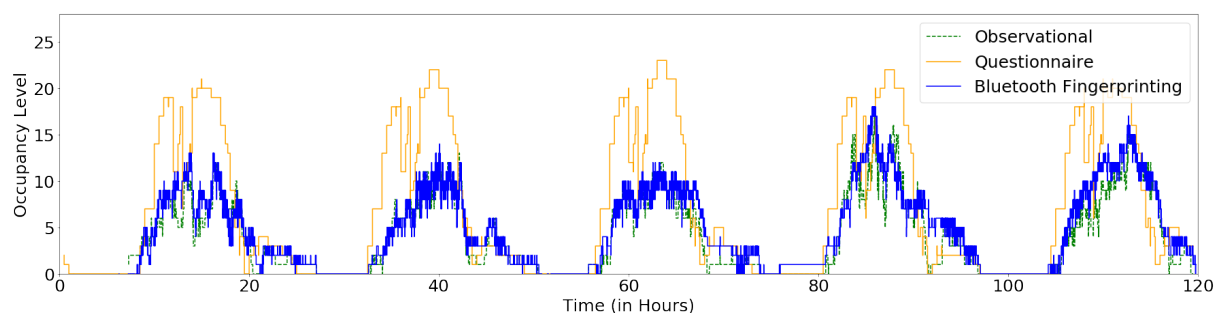

Figure 2. Occupancy level of study area over five weekdays based on various approaches (n = 28).

Figure 2 shows that the predicted occupancy levels based on the Bluetooth Fingerprinting approach carefully match the observed occupancy levels of the study area. However, a closer examination also shows several instances where the levels deviate. The reasons for these deviations could be due to the result of the low scanning frequency of the BLE beacons (1-2 minutes intervals) as well as cases where a small group of occupants leaving their smartphone devices at their desks when making short trips out of the office. Furthermore, an examination of the self-reported occupancy information obtained through the questionnaires consistently overestimates the occupancy levels of the study area. This occurrence could be attributed to the occupants' tendency to over-report their visiting frequencies or their total duration spent in the office by either reporting an earlier first arrival time or a later last departure time.

Based on the observations obtained via the Bluetooth Fingerprinting approach (Figure 3), we observe two distinct peaks representing the permanent occupants' first arrival and last departure times of the day. The temporary occupants' first arrival time and last departure times also show a strong preference towards visiting the study area after lunch and departing evenly throughout midday, according to the time they have achieved their purpose of visit. Through an examination of the weekly visiting frequencies for both the temporary and permanent occupants, it can be inferred from the low visiting frequencies of several permanent occupants that they tend to work remotely from their assigned desks. Similarly, in the case of a small group of temporary occupants, the high visiting frequencies can be explained by their dependency on certain facilities that can be found in the study area which led to them work remotely from their own assigned desks.
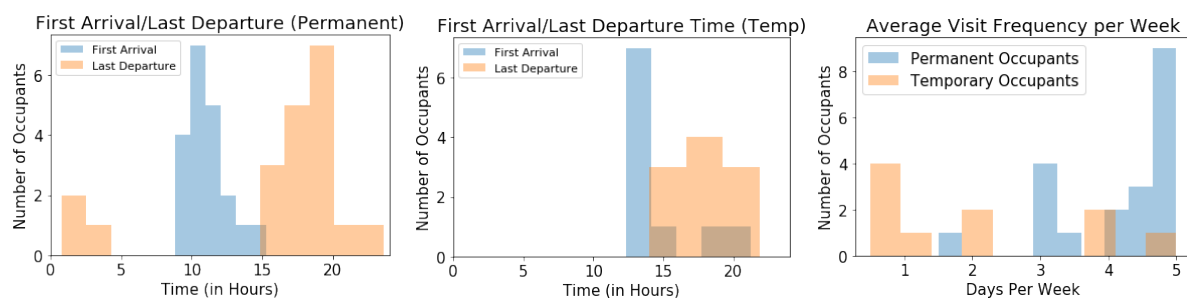

Figure 3. Occupancy information for both temporary and permanent occupants (n = 28).

3.4.3 Permanent Occupant Appliance Interaction Patterns. In this section, we analysed the occupant appliance interaction patterns by combining the appliance energy consumption data with the occupant's presence information. Appliance interaction refers to the occupant's use of different appliances based on his/her presence, followed by an appliance switch-off behaviour after use. To quantify the occupant's appliance interaction patterns, we calculated the occupant's probability of appliance use by counting the number of times the occupant uses an appliance when arriving at a particular zone divided by the total number of times the occupant enters that zone. The appliance switch-off probability is calculated by counting the number of times an appliance is switched off when the occupant leaves his desk divided by the total number of times the occupant leaves his desk. In this scenario, we do not consider the cases where the occupant puts the appliance to sleep or leaves the appliance to enter sleep mode as "switching-off" the appliance. In the case where the occupant leaves the study area, we are also interested in their appliance switch-off probabilities during a short-term and long-term absence event. A short-term absence event refers to the situation where the occupant leaves the study area and returns back after some time during that day. On the other hand, a long-term absence event involves the occupant leaving the study area at the end of the day (last departure), before returning on the next working day. In this study, the temporary occupants' appliance interaction patterns were not collected as they do not own any appliances (i.e., monitors and desktops) within the study area and are not bounded to a particular area while visiting the study area. This issue creates several challenges when using static smart meters to capture appliance interaction data. When comparing the probability of use between the different appliances in Figure 4, we observe that the high usage probabilities of both the desktop and laptop indicate that the occupant frequently alternates between both appliances or uses them at the same time. A comparison of the occupants' appliance switch-off behaviour during short-term and long-term absence events in Figure 4 indicates that the occupants are more likely to switch off their appliances when they are leaving the office for the day as compared to during short-term absence events. This behaviour could be explained by the occupants' concern that switching off their appliances would reduce their overall work efficiency as was reported in the survey.
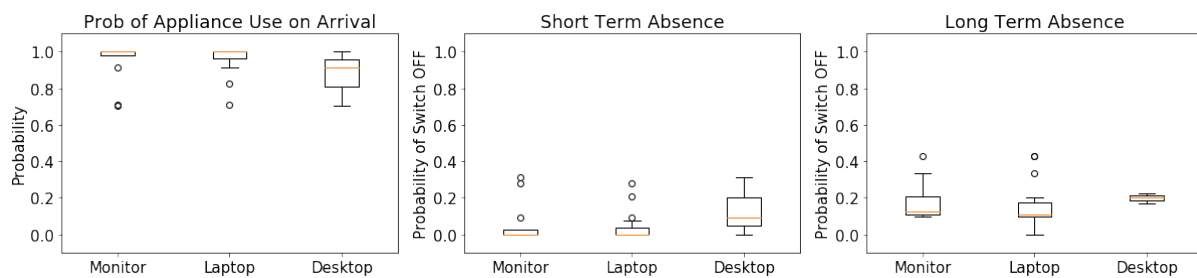
Figure 4. Appliance interaction patterns based on smart meter and Bluetooth Fingerprinting approach (n = 28).

In general, the occupants' self-reported appliance switch-off behaviours were observed to be more environment-friendly as compared to their actual behaviours, thus demonstrating the Hawthorne effect.

4. Conclusion

In this study, we proposed a non-intrusive OB data collection methodology that involves the use of wireless smart meters, BLE beacons, and questionnaires to collect detailed information about occupant movement and interaction patterns with plug-in appliances. The feasibility of the approach is demonstrated during a two-week data collection effort in an office environment. Based on the insights gained from this study, future extension of this work includes implementing the approach in a different office environment to ensure the generality of the results as well as the identification of different OB profiles to address the energy performance gap.

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