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Non-Intrusive Data Monitoring and Analysis of Occupant Energy-Use Behaviors in Shared Office Spaces

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ABSTRACT A non-intrusive data collection framework is developed to analyze the desk-level occupancy and energy use patterns of occupants in shared office spaces. The framework addresses the limitations of previous studies in the literature, which either lacked the granularity to study individual occupants' behaviors or relied on data from complex Building Management Systems (BMS). The framework is applied to a shared office space of an academic institution in the United Arab Emirates (UAE), where occupancy, lighting, and plug-load data were collected from individual desks for 6 months. The results highlight weak relationships between the occupancy status and the total electric loads, with 35% of the total electric loads consumed when the area is completely vacant, and 64% of the plug-load energy consumed when the desks were reported as unoccupied. While specific to the studied building, the results highlight the role that a high-resolution data monitoring framework plays in capturing inefficient consumption patterns. The findings also confirm the contribution of occupant behavior (OB) to the energy performance gap commonly observed between predicted and actual energy levels.

INDEX TERMS Buildings, energy conservation, monitoring, occupant behavior, performance analysis, shared office.

I. INTRODUCTION

A. BACKGROUND

Building energy management is an increasingly used process to control energy consumption and costs in buildings while maintaining comfortable indoor environmental conditions for occupants and fully meeting functional needs [1]. In commercial buildings, facility managers are often tasked with managing building energy demands and indoor conditions by continually monitoring, evaluating, and optimizing the operation efficiency of different building systems [2]. A common way to gather the needed data for analysis is through Building Management Systems (BMS). A BMS is a system of sensors, communication networks, and controls, which can be used to monitor the performance of various building systems and control their operation patterns. Benchmarking can then be performed (with the help of additional utility data), which consists of comparing the energy performance of a building to a baseline or "benchmark" [3]. The baseline can be obtained from a group of similar buildings (i.e., cross-sectional benchmarking), or from past performances of the building under study (i.e., longitudinal benchmarking). This method allows facility managers to identify higher than expected energy consumption levels. Along the same lines, Fault Detection and Diagnostics (FDD) is another method that helps identify abnormal operation patterns that can cause excessive energy use levels [4]. Based on the faults detected in different building systems, facility managers can perform corresponding maintenance actions to reduce energy consumption levels [5], [6]. Despite significant advancement in the design of efficient building systems and energy management strategies, important discrepancies are commonly found between the energy levels estimated for buildings during the design phase, and those observed during operation [3], [7]. This is often referred to as the energy performance (or efficiency) gap.

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B. OCCUPANT BEHAVIOR

Among various contributing factors to the energy performance gap (e.g., faults in systems or weather variations), recent studies indicate that occupant behavior (OB) is one of its major drivers since actions taken – or not taken – by occupants can significantly impact building performance [3], [7]–[10]. In [7], the authors demonstrated that different OB patterns could vary the total energy used by 150% for commercial buildings. In [8], different occupant profiles were created and used as inputs to building energy models. The authors found that occupant behavior can save up to 50% of current energy use levels or increase them by 89%.

The growing body of knowledge on the impact of OB on buildings' energy performance has motivated further research on OB data acquisition [11], analytics [12]–[15], and predictive modeling [12]. Previous studies analyzed occupancy and energy consumption data using different data granularity. For instance, zone-wise energy use data, in combination with estimated occupancy levels, were used in [13]. The authors in [16] fused measured binary zone-wise occupancy with zone-wise energy consumption. In other studies, the energy use per device type was investigated while no data regarding the measured occupancy count was available [17]–[19], or, in conjunction with binary occupancy states (e.g., [20]). In parallel, a higher granularity of the energy consumption data for single occupants has been explored. Here, the energy consumption has commonly been analyzed as a sum of all used devices [12], [21], [22]. Resultantly, the device-wise data, in combination with the occupancy data for each in-situ monitored occupant, has been rarely analyzed in the scope of existing studies. It is also important to note that the majority of studies typically gather their data through a centralized BMS, which makes their analysis replicable only to buildings with similar monitoring capabilities. Such systems are often incompatible with other existing systems (especially for old buildings) or might be too expensive to install.

C. NON-INTRUSIVE LOAD MONITORING

Non-intrusive load monitoring (NILM) is a mature technology [23] that has been widely researched and can offer an alternative to centralized data collection approaches, such as through BMS. The concept of NILM is based on having a monitoring system in the form of energy meters, smart sensors, or other sensing technologies, that separates the aggregated data regarding the electrical consumption in the area of study into individual appliance consumption profiles. The novelty of this method stems from the involvement from the user-end since it requires little to no intervention on behalf of the occupants [23], [24], and its negation of the necessity to connect the monitoring devices or sensors to existing infrastructure. It was acknowledged as a suitable data collection procedure, especially in cases where the connection to a BMS is restricted. NILM was applied to recognize the appliance types in commercial and residential buildings [24]–[28]. For instance, the authors of [26] disaggregated device types collected by NILM using Hidden Markov Model (HMM). Others proposed unsupervised learning for recognizing the device type and load segregation in household energy consumption, based on load classification and source separation [24].

However, the non-intrusive monitoring commonly applied in the context of energy analysis often lacked explicit and granular occupancy information [29]–[32]. As a consequence, the potential of NILM in combination with high-resolution occupancy data remains an open question. As an example of non-intrusive monitoring efforts, the authors of [30] investigated the relationship between the energy consumption and occupancy that was implicitly detected based on WiFi count. They concluded that the number of connected WiFi devices correlated with the resulting energy consumption. However, their scope was limited to zone-level energy load values that were estimated from trends reported by a BMS. In a more recent study, researchers proposed a non-intrusive occupancy count in an effort to optimize Heating, Ventilation, and Air Conditioning (HVAC) energy consumption [31]. They argue that reheat energy use can be reduced by 38% if the HVAC settings are adjusted to reflect actual occupancy levels. While the authors did not explore end-uses such as plug-loads or lighting levels, their findings support the potential of non-intrusive monitoring of OB in identifying energy-saving opportunities.

D. OBJECTIVES

The goal of this study is to develop a non-intrusive data collection framework that can be used to capture the energy use patterns of individual occupants in a shared office space and quantify energy-saving opportunities. The framework is unique in its ability to monitor – at the desk level – the occupancy status and energy consumption levels by type of device (e.g., monitor, laptop, task light), in addition to general lighting loads. Such a level of granularity is rarely achieved in the literature, especially for shared office spaces. Furthermore, the non-intrusive nature of the proposed data collection approach makes the framework completely independent from a BMS, and hence applicable to any building. In this context, the framework is deemed as non-intrusive in terms of the non-invasive nature of data collection to existing building systems and its independence from any BMS infrastructure. The independence from a BMS was a crucial factor in this work, which is why HVAC data was excluded since any kind of HVAC data is reliant on an existing BMS. The framework instead focused on the energy consumption patterns generated directly by the occupant at their desks, with emphasis on granularity and device utilization.

The framework is demonstrated through a case study of a shared office space in an educational facility where data is collected for a duration of 6 months. The data is then used to:

1) Quantify the relationship between the presence of individual occupants at their desks and the amount of energy they consume for two end-uses: plug-loads and lighting.

TABLE 1. Related work.

Author and year	Building type	Region (associated KGCC climate)	Occupant-related data collected	Sensing modality	Granularity
Anand et al. (2019) [33]	Academic	Singapore (Af)	Occupancy, plug-loads	Vision-based sensors, plug-load meters	Office-level
Bennet and O'Brian (2017)[13]	Commercial	Ontario, Canada (Dfb)	Lighting, plug-loads	Electricity meters	Floor-level
Gunay et al. (2016) [12]	Office (private)	Ottawa, Canada (Dfb)	Occupancy, plug-loads	PIR sensors, plug-load meters	Office-level
Gandhi and Brager (2016) [34]	Office (private, shared)	Oakland, USA (Csb)	Plug-loads	Plug-load meters	Desk-level
Rafsanjani and Ahn (2016) [35]	Academic	Lincoln, USA (Dfa)	Occupancy, plug-loads	Wi-fi, plug-load meters	Desk-level
Murtagh et al. (2013) [27]	Academic	Surrey, England, UK (Csb)	Plug-loads	Plug-load meters	Desk-level
Webber et al. (2006) [19]	Commercial (offices, schools, medical)	San Francisco, Pittsburgh, and Atlanta, USA (Csb, Dfb, Cfa)	Equipment status	Energy Audits (field investigations)	Building-level
Kawamoto et al. (2004) [17]	Office	Japan (Cfa)	Plug-loads	Field investigations	Office-Level

2) Estimate the potential energy savings from reducing consumption during unoccupied periods, both at the office level and by device type (e.g., monitors or task lights).
3) Compare the monitored energy consumption profiles of the occupants to the standard profiles (obtained from ASHRAE) that are commonly used by energy modelers when designing and simulating the performance of a similar building environment. Such an assessment can help explain – or contribute to the discussion of – the role of OB in the energy performance gap commonly observed in commercial buildings.

In summary, the main contributions of this work stem from the granularity and resolution of the data collection, coupled with the multiple sensing modalities and data streams effectively capturing the occupant presence status, the environmental parameters, and the associated plug loads of each device. This data was captured at the individual desk level, in a shared office space in Abu Dhabi, UAE, thereby also contributing a new regional perspective to a body of case studies (highlighted in the next section) that commonly originate from western countries.

II. RELATED WORK

This section explores previous research works relevant to this study, particularly OB and NILM applications. The summary is presented in Table 1, organizing the studies according to the type of buildings they covered, the region that they were conducted in, the specific type of occupant data collected, the sensing modalities used for data acquisition, and the granularity of this data. The regional information column is accompanied by the respective Köppen–Geiger climate classification (KGCC), which is one of the most commonly used classifications systems. The first letter of the classification represents one of five broad climate types (A: tropical, B: dry, C: temperate, D: continental, and E: polar). The second and third letters represent subcategories corresponding to seasonal precipitation and heat levels. For instance, 'fb', represents a warm summer humid sub climate.

The following two main observations from Table 1 reconfirm the gap in the literature and the need for the current work: (i) while plug loads have been the primary focus of the listed studies, very few of them consider occupancy parameters, especially at desk level, to better explain the impact of OB on the monitored energy data; (ii) along with the granularity and resolution of the data collection, the lack of studies from the Middle East region (e.g., KGCC of Bwh) is clear, which is another viable gap to address given the complex and case-specific nature of OB.

III. METHODOLOGY

The area of study is an open-office space in an educational building in Abu Dhabi, UAE, as shown in the bottom part of Fig. 1 (View A). It is occupied by graduate students and research employees where an individual desk is assigned to each student. The working hours vary due to the absence of official working hours, and the building operating 24/7. The shared office space consists of 6 individual desks, 2 main computer workstations (designated as shared), and a common table, as shown in Fig. 1. A total of 8 students occupied the space over the evaluation period of six months. A maximum of 6 students were present at the same time since 2 students graduated during the study period and were replaced by 2 new ones. The area is illuminated by motion-controlled area lights, while each desk is equipped with its own manually operated desk light. The area is accessible throughout the week by the employees of the educational facility. It may be noted that this is not a completely controlled environment, since the working hours are flexible, and though there are 6 primary occupants, there are no restrictions for visitors, who often do occupy the common table. This suited the

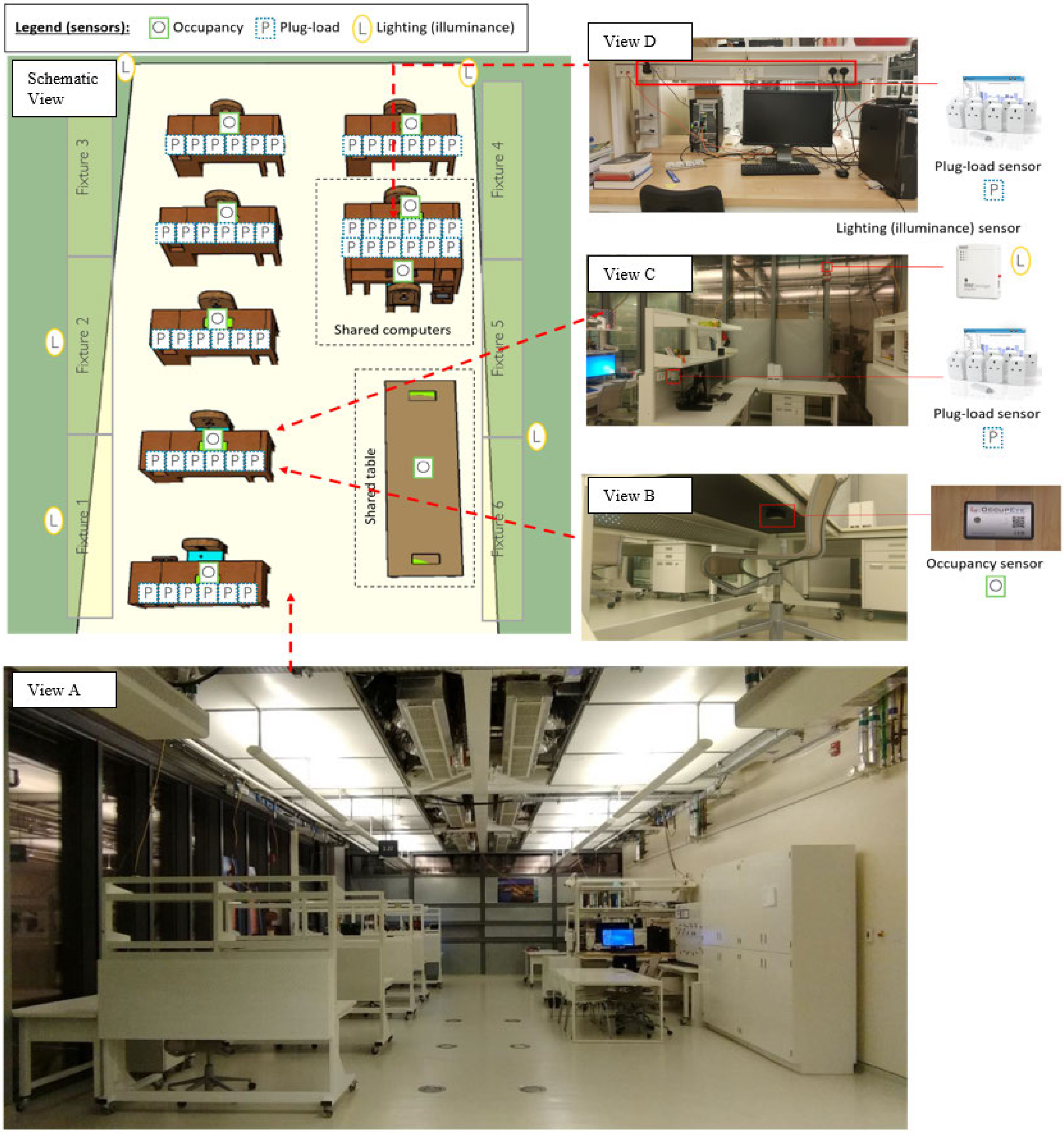

FIGURE 1. Area of study and sensor placement.

objectives of the work since the non-intrusive nature of the proposed monitoring and analysis approach signified that the occupants should not be imposed upon by the nature of the study, such as adding rigid working hours or restricting access.

Fig.1 presents a schematic view of the area showing the number and placement of different sensors around each workstation along with four closer looks at representative setups (views A-D). Fig.1 also shows the back-end wall of the office, which is the only façade exposed to the outdoor environment. The window-to-wall ratio (WWR) of the studied area is 26%. Overall, access to daylight was limited in the building due to the low WWR stated above in addition to external shading devices installed on the windows. These shading devices were part of passive cooling strategies meant to reduce the heat gains in the building considering the extremly hot climate of the region. This resulted in low daylight availability, which is further examined in [36], leading to a high reliance on the artificial lighting system. Moreover, the artificial lighting system was motion-based, eliminating the potential for the occupant to control its status, regardless of the amount of daylight available.

A. SENSOR INSTALLATION AND CALIBRATION

In the scope of this study, occupancy, plug-load, and lighting (illuminance) sensors were installed. The latter is used to determine the on-off status of lighting fixtures and calculate their electric energy use accordingly. The sensors were commercially available and required no connection to BMS, which allows the replicability of the study to other built environments.

1) OCCUPANCY SENSORS

A total of 9 PIR-based (passive infrared) occupancy sensors are placed in the study area, including 6 at the individual desks, 2 at the shared computer workstation, and 1 at the shared table (Refer to Fig. 1, Schematic view). Each sensor is installed under the desk it monitors, has a unique ID, and reports the occupancy status of the desk (i.e., occupied or unoccupied) in real-time to a host receiver over WiFi. More specifically, the sensor only communicates with the server (without noticeable delays) whenever there is a change in the occupancy status, such as from 'occupied' to 'unoccupied', and vice-versa. The detection range of the sensor was up to 80 meters, provided there was no obstruction. In order to calibrate the sensors, three factors were taken into account: detection of the occupant at all positions at their desk, avoidance of false triggers from passersby, and no occlusions.

The exact placement of the sensors is an essential factor in the installation/calibration process. At each desk, the sensor needs to register the presence of the occupant in all extents of their position in front of the desk. At the same time, it should avoid false triggers from people passing in the area or sitting at nearby desks. To understand the sensors' radius of influence, sensitivity, and trigger points, a sensor was first placed in a fixed position on the desk while an occupant was seated. The authors then asked the occupant to move between the ends of the desk as well as away from it while recording the occupancy status reported by the sensor. An optimal position was found and shown in Fig. 1 (View B), reporting an 'occupied' status only when the occupant was within the boundaries of the desk and up to half a meter away from it. The process was repeated for all 9 occupancy sensors, which were then connected to the host WiFi receiver. The sensors were evaluated for a period of one week by comparing their measurements to manually recorded occupancy at different times of the day. This process confirmed that the occupancy sensors were calibrated and properly placed. Additional information on the specifications of the occupancy sensors can be found on the manufacturer's website [37].

2) PLUG-LOAD SENSORS

The office space has a total of 48 different power outlets, 6 per desk, which are used by the occupants to connect their plug-loads devices (refer to Fig. 1, Schematic view). A plug-load monitoring device is installed for each power outlet (48 in total), allowing the authors to monitor the energy consumed at each outlet at a 15-min interval. Each sensor has a unique ID and connects to a host receiver over WiFi. Fig. 1 (Views C and D) show sample pictures of the sensors and their placements in the electric sockets.

The authors configured and installed each sensor, connected it to the receiver's network, and labeled it to clarify what type of plug-load it is measuring. This was done in collaboration with the occupants who agreed to connect their devices (e.g., laptops, monitors) in the specific plugs that are labeled for that use. Each occupant had 6 power outlets at their desks, which were used for different devices as follows: 1 desk lamp, 1 docking station, 2 computer monitors, 1 laptop, and 1 miscellaneous. Apart from the necessity of connecting each device to its associated power source, the occupants were free to leave any device switched on during their absence, or take it with them. The overall list of plug-loads that are measured in the shared office are listed next along with their instances: 6 docking stations, 6 laptops/notebooks, 2 desktop computers (shared), 14 computer monitors, 6 desk lamps (task lights), and 14 miscellaneous loads. Following the installation, the authors confirmed the accuracy of the sensors during a one-week evaluation period by comparing their reported energy use to the power specifications of the devices they are monitoring. This concluded the verification process for the plug-load sensors. Additional information on the specifications of the plug-load sensors can be found on the manufacturer's website [38].

3) LIGHTING SENSORS

The area of study is illuminated by 6 ceiling fixtures, which were positioned as shown in Fig. 1 (Schematic view and View A). Each of the fixtures is equipped with and is activated by motion sensors, without any option for manual control and/or dimming. In addition, natural daylight was also available, which led to a low need for using desk lamps. Given the non- intrusive nature of the proposed research approach, it was important to monitor the energy consumption of the lighting system without having to connect to the existing building's infrastructure (e.g., BMS or electric supply lines). This is achieved by installing light illuminance sensors that measure the intensity of the light (in lux) near each lighting fixture at 15-min intervals. Then, based on the monitored levels of illuminance, the on/off status of each lighting fixture can be inferred and used to determine the energy consumed by simply multiplying the duration of use by the power wattage of the fixtures.

The placement of the lighting sensors was carefully done to first, have each lighting fixture monitored by one lighting sensor, and second, minimize the noise in the measurement from neighboring lighting fixtures, or daylight. The final placement of the sensors is shown in Fig. 1 (Schematic view). It should be noted that Fixtures 5 and 6 are triggered by the same motion sensor; hence, one lighting sensor was placed between these fixtures. Following the installation of the sensors, the illuminance output of the sensors was monitored for one week, and thresholds were set to distinguish between the on/off statuses of the fixtures. Put differently, it was important to identify a reference illuminance value (for each light illuminance sensor) above which the neighboring lighting fixture is ''on'', and below which it is ''off''. After analyzing the data that was collected, it was noticed that the average value between the lowest and highest illuminance value monitored by each sensor is a good and reliable threshold. In addition, since the sensors were positioned very close to the light sources, the availability of daylighting did not create a significant difference in these illuminance thresholds. Observations at different times of the day confirmed the adequacy of this approach in implying the actual on/off status of each fixture.

Finally, unlike the previous occupancy and plug-load sensors, lighting sensors stored the data locally. Manual data transfers were performed bi-weekly through the USB ports of the sensors and stored on a local computer. Additional information on the specifications of the lighting sensors can be found on the manufacturer's website [39].

B. DATA COLLECTION AND PROCESSING

Following the verification process for the three types of sensors described above, data was collected for a period of 6 months, covering the months of April-May, July-August, and October-November 2017. A routine check (weekly or bi-weekly) was carried out to ensure that the sensors are working properly, restarting, or reconfiguring malfunctioning sensors when needed. All the collected data (over WiFi or manually) were gathered in one CSV Excel spreadsheet file for data processing and analysis.

In this study, the plug-load and lighting sensors reported data in a 15-min interval, while the occupancy sensors only reported data when the occupancy status changes (i.e., a space became 'occupied' or 'unoccupied'). To ensure consistency between the different datasets, the occupancy sensor data was converted to a 15-min format by setting the last recorded trigger type (i.e., occupied/unoccupied) within each 15-min time as the new occupancy status for that period. If no triggers are observed within a period, the state of the preceding period is taken by default. Lighting energy consumption was calculated for each fixture in 15-min intervals. If the fixture was estimated to be ''on'', then its energy consumption is calculated by multiplying the power wattage of each fixture, which consists of two lamps consuming 28W each, by 15 minutes.

C. VALIDATION PROCESS

As mentioned in the previous section, routine checks were carried out every week to ensure the proper functioning of sensors. This would comprise of manual notation of occupancy triggers and checking them with the reported data, along with checking the functionality of plug-load sensors to ensure that they are representational of the occupant activities. The illuminance sensors were battery-operated and had to be accessed through their respective dashboards to ensure that they had enough power to function for the next few weeks. Written consent was obtained from all the occupants included in the study. The weeks that had a significant amount of missing data, or malfunctioning sensors, were removed before the final data analysis. However, it should be noted that those weeks were mostly at the beginning of the course of study, and after conducting the required adjustments, the study was able to operate smoothly.

D. DATA ANALYSIS

The data analysis consists of three main stages. The first stage is to quantify the relationships between the presence of occupants in the office space and the levels of energy that are consumed. A distinction is made between the energy consumption of plug-loads and that of general lighting loads. Plug-loads are directly controlled by the occupants, which makes it their responsibility to operate these loads efficiently (i.e., turning them off when leaving a space). Lighting loads are triggered by dedicated motion sensors that are installed and maintained by facility managers (FMs). Therefore, it is the responsibility of FMs to ensure the proper calibration and operation of these systems to avoid over-lighting (e.g., passing occupants triggering the lighting system) or under-lighting (e.g., motion sensors failing to capture occupancy presence). The link between occupancy presence and different end-use consumption is studied using box-whisker-plots of the monitored power levels for varying levels of occupancy; the minimum occupancy level being zero occupancy sensors indicating an ''occupied'' status while the maximum occupancy level being all 9 sensors indicating an ''occupied'' status. Such a representation helps visualize how dependent energy demand is given a certain level of occupancy in the space.

The second stage consists of quantifying the amount of energy that is consumed while the occupants are away from their desks. In theory, this portion of energy can be considered as unnecessary or as a potential for energy conservation. In practice, some plug-loads such as the shared desktop computers may be used to run experiments or simulations without the presence of occupants at the desk, which may explain a portion of any energy consumed during vacant periods. Therefore, it is essential to make such a distinction before labeling some of its energy consumed as unnecessary. Two particular analyses are presented. The first is an office level analysis comparing the energy consumption of the office during ''vacant'' periods (i.e., zero occupancy sensors triggered) and ''occupied'' periods (i.e., at least one occupancy sensor triggered). This approach is commonly used in the literature when occupancy is monitored at the office level rather than the desk and corresponding device (i.e., plug-load level). The second analysis covers the performance of specific device- types (e.g., laptops, monitors, and docking stations) while distinguishing between their energy consumption while occupants were present at or away from their desks. In this stage of the analysis, the ''vacant'' and ''occupied'' occupancy statuses refer to the presence and absence of occupants from their desks (respectively), while a specific plug-load was consuming energy.

The last stage of analysis consists of developing diversity profiles (i.e., schedules) of the occupancy, lighting, and

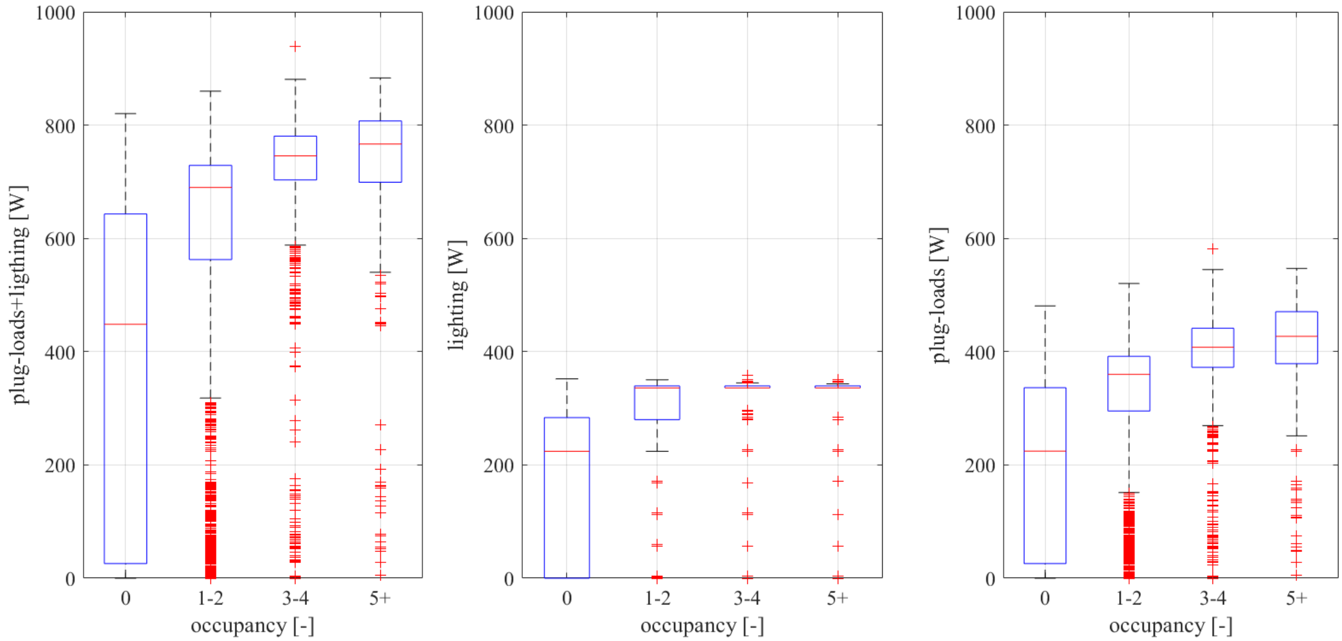

FIGURE 2. Box-and-whisker plots of electric load function of the number of occupants' sensors that are indicating occupied status.

plug- load patterns observed in the studied area. Diversity profiles show the intensity of a variable (i.e., occupancy, lighting, and plug-load) over the 24 hours of a typical day. The intensity is expressed in numerical values from 0 to 1, where 0 represents the minimum possible value (e.g., no occupancy or no energy consumption), and 1 represents the maximum possible value (e.g., maximum occupancy or maximum energy consumption). Diversity profiles are commonly used by energy modelers when simulating/predicting the performance of actual buildings.

The American Society of Heating and Refrigeration Engineers (ASHRAE) has developed profiles for common building types (e.g., office), which are extensively used in the literature (e.g., [40]). However, recent research (e.g., [41]) shows significant discrepancies between ASHRAE profiles and those observed in actual buildings. Moreover, since the developed profiles are for common building types, academic buildings are not explicitly covered; there is often a need to build new schedules for these buildings to achieve an efficient energy management system [42]. This has motivated the current stage of the analysis, where a comparison is conducted between the ASHRAE profiles and those of the studied area. In total, diversity profiles are developed for occupancy levels, lighting, and plug-loads energy consumption. A distinction is also made between weekdays and weekends, which typically witness different occupancy and energy use patterns.

The occupancy diversity value for a typical hour h of the day (e.g., 00:00-01:00 am) is computed using (1), which averages the ratio of sensors with "occupied" status over the total number of sensors over the study period from the first day "d" of the study to day N. Equation (2) is used to compute the diversity factors for plug-loads and lighting energy use. The diversity for the end-uses is defined as the ratio of the observed energy (i.e., monitored) to the maximum energy observed throughout the study. Here again, to obtain the diversity value for an hour h, the values observed for that hour over the N days of the study are averaged.

$$Occupancy\ Diversity = \frac{\sum_{d=1} N \frac{\#Sensors\ Occupied}{\#Sensors\ Total}}{N} \tag{1}$$

$$Energy\ Diversity = \frac{\sum_{d=1} N \frac{Energy\ Consumed}{Max\ Energy\ Observedl}}{N} \tag{2}$$

IV. RESULTS

A. RELATIONSHIPS BETWEEN OCCUPANCY LEVEL AND ELECTRIC LOAD

The relationship between the occupants' count and electricity consumption in the space is analyzed using box (and whisker) plots (Fig. 2). Here, the median consumption (central red-colored line), 25^{th} and 75^{th} quartiles (blue-colored box limits), and the outliers (red-colored crosses outside of the boxes) are used to present the distribution of the measured power loads. The resulting boxplots show that the total lighting and plug-loads power could be correlated to the number of present occupants. However, the baseline energy values corresponding to the null occupancy are higher than expected, as detailed next.

Starting with the lighting system (central box plot in Fig. 2), during vacant periods (i.e., 0 occupants present in the space), the mean power values for the lighting system exceeds 200 W, with 25% and 75% quantiles between approximately 0 W and 300 W, respectively. The lighting system, which is controlled by motion sensors, seems to be triggered

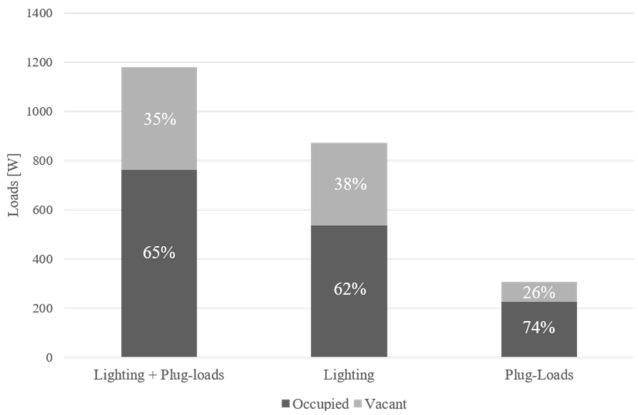

FIGURE 3. Office-level comparison of the energy consumed during vacant and occupied periods. "Vacant" refers to periods where there are no people in the office space. "Occupied" refers to periods with at least one occupant in the office.

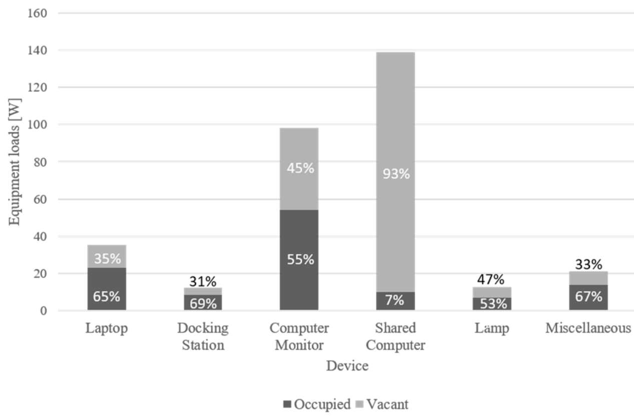

FIGURE 4. Device-level comparison of the energy consumed during vacant and occupied periods. "Vacant" refers to periods where a specific device was running without the presence of an occupant at the desk. "Occupied" refers to periods where an occupant was present at the desk during the operation of the device.

by occupants passing by the monitored workspace. Such a scenario was tested by the researchers who confirmed that walking in the hallway near the office space was triggering the lighting system. Additionally, for the three higher ranges of occupancy (i.e., 1-2, 3-4, and 5+ occupants), the average power level is almost the same (~350W). The results indicate that the presence of 1-2 occupants was sufficient to activate the lighting for the whole workspace, despite having 5 lighting zones that are controlled by independent occupancy motion sensors. These results pointed out the importance of the choice of suitable light control systems and the crucial role of the building operation management to ensure the proper calibration and maintenance of the systems.

The box-plots of the plug-loads, shown on the right side of Fig. 2, reveal similar inefficient patterns as with the lighting system. High power levels are observed during vacant periods, here again exceeding 200 W in average value. The results imply that occupants are constantly leaving plug-load equipment running when leaving their desks, which is further explored in the upcoming sections. However, unlike the lighting systems, there is a positive relationship between the average power levels and the occupancy count bins of 1- 2, 3-4, and 5+ occupants. Such a trend was expected as an office space with a higher number of occupants is expected to consume more, and vice-versa.

Finally, the patterns of total electric loads shown on the left side of Fig. 2 are simply an addition of the lighting and plug-load power values. The box plots are characterized by high consumption values during vacant periods (average power levels exceeding 400 W) and a moderate positive relationship between occupancy count and total electric loads.

B. ENERGY CONSUMPTION DURING "OCCUPIED" AND "VACANT" PERIODS

1) OFFICE-LEVEL ANALYSIS

The energy consumption of the lab was analyzed for the periods of occupancy (i.e., with 1 occupant or more) and vacancy (i.e., 0 occupants). The results are presented in Fig. 3. The bar chart on the left side shows that 35% of the lab's electric consumption occurs during the vacant hours. A similar trend could be observed when energy consumption was separately analyzed by end-use. Here, 38% and 26% of the consumption occurred during vacant hours for the lighting system and plug-loads, respectively. These results confirmed the findings of previous studies (e.g. [12], [43], [44]) that have observed a significant proportion of building energy systems running after hours.

It is important to note that the observed values for the plug-loads are conservative due to the definition of the office-level "occupied" period that was used; the space is considered occupied if there is at least one occupant present. Such an assumption might lead to an overestimation of the plug-load energy consumed during operation and an underestimation of the portion consumed during "vacant" periods. For instance, in a scenario where occupant A is the only occupant present in the shared office while the computers and monitors of all occupants are running during that period, the energy consumed by all occupants would be labeled as energy during an "occupied" period. Hence, the results presented in Fig. 3 (right side) can be considered conservative, and in reality, more plug-load energy is consumed when individuals are away from their desks, as shown in the next subsection.

2) DEVICE-LEVEL ANALYSIS

Eventually, the energy consumption for occupied and absent periods was analyzed at the device-level granularity. In this section, the occupancy status of each desk was evaluated separately and was used to classify the energy consumption of associated plug-loads between "vacant" and "occupied". As presented in Fig. 4, between 31% and 93% of the energy consumed by each type of the plugged-in device was consumed while no occupancy was detected at the respective desk. Hence, by recalculating the total plug-load energy consumed during "vacant" and "occupied" periods at the desk-level, it is seen that 64% of the plug-load energy is actually

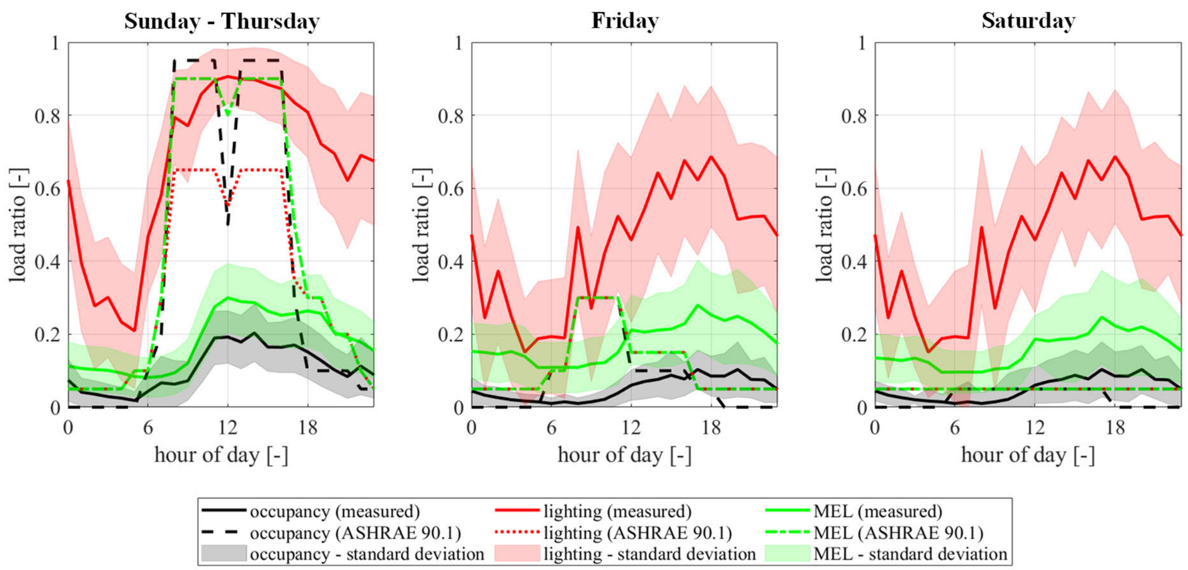

FIGURE 5. Comparison between the ASHRAE 90.1 profiles with the measured occupancy, plug loads, and lighting energy consumption.

consumed when the occupancy status of the desks is reported as 'vacant'. As such, even though all the 8 desks cannot be occupied at the same time, the occupants are responsible for switching off relevant equipment when leaving the workstation, which is why any consumption at a desk when it is unoccupied is classified as 'unnecessary consumption'.

A major contributor to this misbalance is the use of the shared personal computer, with 93% of its energy consumption occurring without the presence of an occupant. This can be caused by the use of computers to run experiments scheduled by occupants for unoccupied periods, and, resultantly, could not be identified as a clear saving potential. While such kind of shared computer is specific to this particular academic setting, shared equipment (e.g., printers and appliances) is an integral part of office spaces and commercial buildings. Therefore, the need to identify instances of unoccupied consumption can be beneficial in cases wherein they do represent a clear saving potential.

In parallel, end-uses, such as monitors and lamps, also show important energy consumption during vacant periods and can be easy targets of energy curtailment efforts. In summary, the adopted device-wise monitoring granularity revealed important energy-saving potentials that were not observed when considering occupancy in the office as a binary variable, as in the previous section.

C. DIVERSITY PROFILES AND COMPARISON TO ASHRAE

Eventually, the mean daily occupancy and energy consumption patterns were analyzed and compared to the schedules recommended by ASHRAE 90.1 [40] for office buildings (Fig. 5). The figure illustrates the difference between the measured loads and the ASHRAE-proposed profiles for each operating schedule, including workdays and the two profiles defined for weekends. The workdays, as defined by ASHRAE, were the typical working days (i.e., Sunday to Thursday in Abu Dhabi). Consequently, the ASHRAE 90.1 schedules proposed for Saturday and Sunday were compared to the data collected on Fridays and Saturdays, respectively.

The results showed that the schedules proposed by the guidelines could not realistically depict the magnitude nor the course of the occupancy and energy consumption in the building in question. Significant deviations are observed between the standard schedules and the measured occupancy and energy consumption. To shed more light on the discrepancies, Fig. 6 presents the absolute hourly error between the theoretical and observed occupancy, lighting, and plug-loads. The error values show that occupancy and plug-loads were (for the most part) overestimated over the typical working hours of workdays while being underestimated outside of working hours. In contrast, lighting loads were consistently underestimated throughout the week. The following are potential contributing factors to the observed discrepancies.

Firstly, the studied area is a shared office space in an educational facility, where the occupants are graduate students. Unlike a traditional office space with clear working hours, the studied environment provides the researchers with a flexible working schedule that allows them to attend classes, events, or work remotely. The students often choose to work over the weekends, which is less common in traditional office environments. Secondly, the number of occupants studied is relatively low, which makes the impact of individual behavior significant on the general patterns shown in Fig. 5. Such an effect will be less significant if the office has a higher number of occupants. Thirdly, schedules, such as ASHRAE's, assume a good correlation between occupancy patterns and the energy use levels of systems, such as lighting

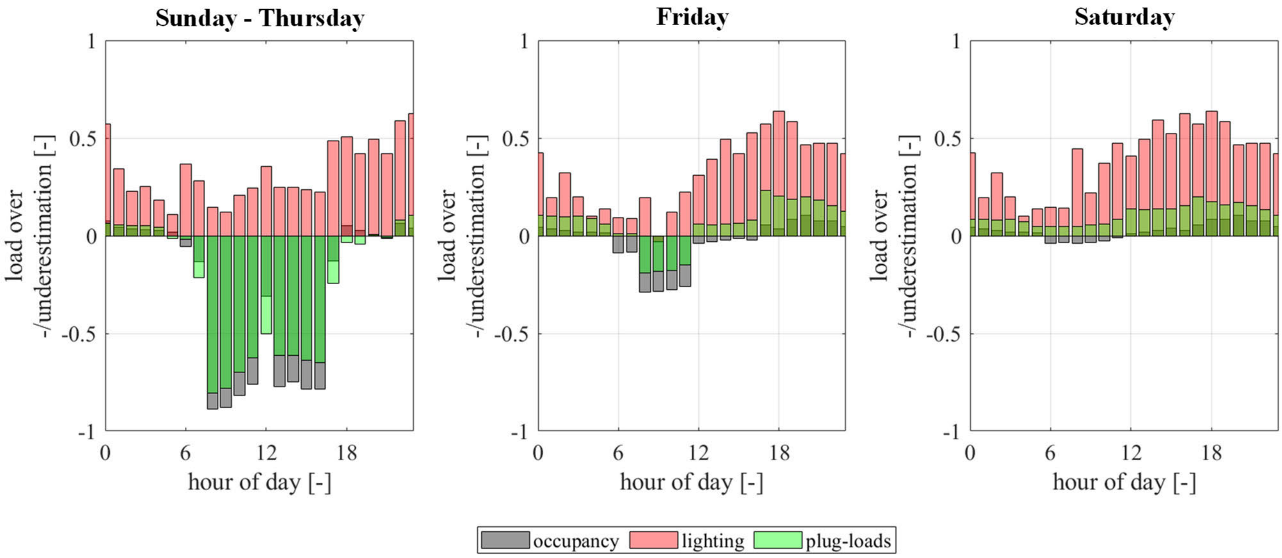

FIGURE 6. Error bars of the measured and standard diversity factors for occupancy, plug loads, and lighting energy consumption. The colors overlap in cases where the direction of over/underestimation of the variables is the same at a particular hour of the day.

and plug-loads. The results from Fig. 5 show that the lighting and plug-load patterns seem to follow the occupancy patterns to a good degree. However, there is an important difference in the scale or magnitude of the profiles. From an operation perspective, the observed gap reconfirms the inefficient use of the lighting and equipment, where a low occupancy level can lead to electric consumption levels near their maximum possible values. From a design perspective, the observed discrepancies are difficult to account for during the design stage and could contribute to misestimations of the actual energy use levels (i.e., energy performance gap).

V. DISCUSSION, LIMITATIONS, AND FUTURE WORK

The framework presented in this paper evaluated and quantified the weak relationships between occupancy patterns and electric loads in the studied space. More importantly, the granularity of analysis ensured the identification of the causes of those discrepancies. As discussed earlier, one primary source of unnecessary lighting consumption at the office level was attributed to the improper calibration and maintenance of the motion sensors activating the lights. This can be an indication of mismanagement by facility managers, as well as miscommunication from the occupants who failed to report inefficiencies in building systems. A non-intrusive framework with high levels of granularity has the potential to identify such discrepancies and bring it to the notice of the facilities management, so that appropriate action can be taken to avoid more unnecessary consumption. As such, this framework can be vital to the FDD process as well. It can also motivate the need for more effective communication channels between FM and occupants.

It is important to highlight some assumptions that were made in the study, along with its limitations. The first assumption was regarding lighting consumption. In order to maintain the framework's non-reliance on a functioning BMS, the lighting consumption was calculated based on the nominal wattage and the light status (i.e., on or off), which works on the assumption that the nominal wattage is a good approximation of the actual consumption. While such an approach has been used in the literature [45], [46], deviations from the actual levels can be observed due, for instance, to inefficiencies in electronic components.

Another limitation of the framework is that it does not currently measure or estimate HVAC loads. Such an addition is essential to make the proposed framework comprehensive and provide a holistic evaluation of building energy performance. Another potential expansion of the work can include indoor environmental factors and various metrics of occupants' comfort (e.g., thermal, visual, acoustic, etc.). This will allow understanding and capturing adaptive actions that occupants may take to maximize their comfort, which in turn affect building performance (e.g., window opening).

When it comes to the "non-intrusive" description of the framework, the term in this paper referred to the concept of minimal deployment of sensors on the property [23], [25], with a special emphasis put on the independence from existing BMS infrastructure. This was rarely achieved in similar studies in the literature. However, "non-intrusive" can also refer to data collection methods that protect and anonymize information collected from individuals. While important steps were taken in this study to protect the occupants' information, this process can be further developed and standardized as part of future research and before any deployment of the framework at larger scales.

Finally, an important limitation pertaining to the case study is the small sample size used. However, it is important to note that the aim of the case study was to illustrate and validate the capabilities of the proposed framework, which, in the opinion of the authors, was well achieved. Nonetheless, applications of the framework on a large number of occupants can further confirm the observed findings and draw general conclusions on the role of occupants in achieving low-energy building performance.

VI. CONCLUSION

This paper proposed a non-intrusive data collection and framework that was used to capture the energy use patterns of individual occupants in a shared office space and identify areas for energy savings. The framework is characterized by its ability to capture occupancy presence and plug-load usage at the desk level. This helped identify energy-saving opportunities that could not be captured with a more general office-level analysis of energy use. Moreover, the non-intrusive characteristics of the framework make it independent of a BMS infrastructure and easily applicable to other building environments.

The application of the framework to a shared office space of an educational facility confirmed the capabilities of the framework by observing: (1) large amounts of energy being observed when no occupants are in the office; (2) 64% of the energy consumed by plug-load devices occurring when the desks are unoccupied; and (3), large discrepancies between the observed occupancy and energy consumption profiles on the one hand, and those provided by ASHRAE, on the other.

It is important to note that the specific results that were obtained are not meant to be generalized nor extrapolated to typical academic buildings. Rather, they serve to showcase the capabilities of the proposed high-resolution data monitoring infrastructure in identifying unexpected (and potentially wasteful) energy consumption patterns in office spaces. More specifically, the findings highlight the important impact of people on building energy performance. These include facility managers, in their role of maintaining and calibrating centralizing systems (e.g., lighting), and occupants, in their role of operating end-uses that they control (e.g., plug-loads).

Moreover, the difference observed in the diversity profiles (Fig. 5 and Fig. 6) from ASHRAE contributes to the growing body of literature on the drivers of the energy performance gap commonly observed between predicted and actual energy use levels. While predicting occupancy patterns and behaviors during the design phase is a highly complex – if not impossible – task, designers can apply methods, such as uncertainty analysis and parametric variation, to quantify the performance risk and then apply robust design practices to mitigate it. In parallel, large-scale data collection efforts can help refine the diversity profiles used in building standards, adjusting for different building types, levels of automation, and geographical locations.

REFERENCES

[1] *Energy Efficiency in Existing Buildings: Applications, Updates and Plans*, Standard ANSI/ASHRAE/IES Standard 100-2015, 2015.

[2] M. Donnelly, *Building Energy Management: Using Data as a Tool*. Cork, Ireland: Johnson Control, 2012.

[3] J. Granderson, M. A. Piette, and G. Ghatikar, "Building energy information systems: User case studies," *Energy Efficiency*, vol. 4, no. 1, pp. 17–30, Feb. 2011.

[4] X. Li, C. P. Bowers, and T. Schnier, "Classification of energy consumption in buildings with outlier detection," *IEEE Trans. Ind. Electron.*, vol. 57, no. 11, pp. 3639–3644, Nov. 2010.

[5] G. P. Henze, G. S. Pavlak, A. R. Florita, R. H. Dodier, and A. I. Hirsch, "An energy signal tool for decision support in building energy systems," *Appl. Energy*, vol. 138, pp. 51–70, Jan. 2015.

[6] S. Katipamula and M. R. Brambley, "Review article: Methods for fault detection, diagnostics, and prognostics for building systems—A review—Part I," *HVAC R Res.*, vol. 11, no. 1, pp. 3–25, 2005.

[7] C. M. Clevenger, J. R. Haymaker, and M. Jalili, "Demonstrating the impact of the occupant on building performance," *J. Comput. Civil Eng.*, vol. 28, no. 1, pp. 99–102, Jan. 2014.

[8] T. Hong, Y. Chen, Z. Belafi, and S. D'Oca, "Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs," *Building Simul.*, vol. 11, no. 1, pp. 1–14, Feb. 2018.

[9] D. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, and A. Mahdavi, "Occupant behavior modeling for building performance simulation: Current state and future challenges," *Energy Buildings*, vol. 107, pp. 264–278, Nov. 2015.

[10] K. Schakib-Ekbatan, F. Z. Çakıcı, M. Schweiker, and A. Wagner, "Does the occupant behavior match the energy concept of the building?—Analysis of a german naturally ventilated office building," *Building Environ.*, vol. 84, pp. 142–150, Jan. 2015.

[11] B. Dong, M. B. Kjærgaard, M. De Simone, H. B. Gunay, W. O'Brien, D. Mora, J. Dziedzic, and J. Zhao, "Sensing and data acquisition," in *Exploring Occupant Behavior in Buildings*. Cham, Switzerland: Springer, 2017, pp. 77–105.

[12] H. B. Gunay, W. O'Brien, I. Beausoleil-Morrison, and S. Gilani, "Modeling plug-in equipment load patterns in private office spaces," *Energy Buildings*, vol. 121, pp. 234–249, Jun. 2016.

[13] I. E. Bennet and W. O'Brien, "Office building plug and light loads: Comparison of a multi-tenant office tower to conventional assumptions," *Energy Buildings*, vol. 153, pp. 461–475, Oct. 2017.

[14] E. Azar and C. C. Menassa, "A comprehensive framework to quantify energy savings potential from improved operations of commercial building stocks," *Energy Policy*, vol. 67, pp. 459–472, Apr. 2014.

[15] K. Sun and T. Hong, "A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures," *Energy Buildings*, vol. 146, pp. 383–396, Jul. 2017.

[16] Z. Wang, T. Hong, and M. A. Piette, "Data fusion in predicting internal heat gains for office buildings through a deep learning approach," *Appl. Energy*, vol. 240, pp. 386–398, Apr. 2019.

[17] K. Kawamoto, Y. Shimoda, and M. Mizuno, "Energy saving potential of office equipment power management," *Energy Buildings*, vol. 36, no. 9, pp. 915–923, Sep. 2004.

[18] L. Moorefield, B. Frazer, and P. Bendt, "Office plug load field monitoring report," ECOS, Durango, CO, USA, Tech. Rep., 2008.

[19] C. Webber, J. Roberson, M. Mcwhinney, R. Brown, M. Pinckard, and J. Busch, "After-hours power status of office equipment in the USA," *Energy*, vol. 31, no. 14, pp. 2823–2838, Nov. 2006.

[20] C. Lobato, S. Pless, M. Sheppy, and P. Torcellini, "Reducing plug and process loads for a large scale, low energy office building: NREL's research support facility," Natl. Renew. Energy Lab.(NREL), Golden, CO, USA, Tech. Rep., NREL/CP-5500-49002, 2011.

[21] A. Mahdavi, F. Tahmasebi, and M. Kayalar, "Prediction of plug loads in office buildings: Simplified and probabilistic methods," *Energy Buildings*, vol. 129, pp. 322–329, Oct. 2016.

[22] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in *Proc. 2nd ACM Workshop Embedded Sens. Syst. Energy-Efficiency Building BuildSys*, 2010, pp. 1–6.

[23] G. W. Hart, "Nonintrusive appliance load monitoring," *Proc. IEEE*, vol. 80, no. 12, pp. 1870–1891, Dec. 1992.

[24] R. Bonfigli, S. Squartini, M. Fagiani, and F. Piazza, "Unsupervised algorithms for non-intrusive load monitoring: An up-to-date overview," in *Proc. IEEE 15th Int. Conf. Environ. Electr. Eng. (EEEIC)*, Jun. 2015, pp. 1175–1180.

[25] A. Zoha, A. Gluhak, M. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," *Sensors*, vol. 12, no. 12, pp. 16838–16866, Dec. 2012.

[26] O. Parson, S. Ghosh, M. Weal, and A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types," in *Proc. 26th AAAI Conf. Artif. Intell.*, Jul. 2012, pp. 1–7.
[27] N. Murtagh, M. Nati, W. R. Headley, B. Gatersleben, A. Gluhak, M. A. Imran, and D. Uzzell, "Individual energy use and feedback in an office setting: A field trial," *Energy Policy*, vol. 62, pp. 717–728, Nov. 2013.
[28] S. Makonin, F. Popowich, I. V. Bajic, B. Gill, and L. Bartram, "Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2575–2585, Nov. 2016.
[29] H. Rafsanjani, C. Ahn, and M. Alahmad, "A review of approaches for sensing, understanding, and improving occupancy-related energy-use behaviors in commercial buildings," *Energies*, vol. 8, no. 10, pp. 10996–11029, Oct. 2015.
[30] J. Chen and C. Ahn, "Assessing occupants' energy load variation through existing wireless network infrastructure in commercial and educational buildings," *Energy Buildings*, vol. 82, pp. 540–549, Oct. 2014.
[31] O. Ardakanian, A. Bhattacharya, and D. Culler, "Non-intrusive occupancy monitoring for energy conservation in commercial buildings," *Energy Buildings*, vol. 179, pp. 311–323, Nov. 2018.
[32] T. Zhang and O. Ardakanian, "A domain adaptation technique for fine-grained occupancy estimation in commercial buildings," in *Proc. Int. Conf. Internet Things Design Implement.*, Apr. 2019, pp. 148–159.
[33] P. Anand, D. Cheong, C. Sekhar, M. Santamouris, and S. Kondepudi, "Energy saving estimation for plug and lighting load using occupancy analysis," *Renew. Energy*, vol. 143, pp. 1143–1161, Dec. 2019.
[34] P. Gandhi and G. S. Brager, "Commercial office plug load energy consumption trends and the role of occupant behavior," *Energy Buildings*, vol. 125, pp. 1–8, Aug. 2016.
[35] H. N. Rafsanjani and C. Ahn, "Linking building energy-load variations with Occupants' energy-use behaviors in commercial buildings: Non-intrusive occupant load monitoring (NIOLM)," *Procedia Eng.*, vol. 145, pp. 532–539, Jan. 2016.
[36] M. S. Andargie and E. Azar, "An applied framework to evaluate the impact of indoor office environmental factors on occupants' comfort and working conditions," *Sustain. Cities Soc.*, vol. 46, Apr. 2019, Art. no. 101447.
[37] *Home Page—OccupEye | IoT*, Occupeye, Blackburn, U.K., 2019.
[38] *Plugwise o Intelligent Heating Control*. Accessed: Jul. 7, 2020. [Online]. Available: https://www.plugwise.com/nl_NL/
[39] *HOBO Data Loggers for all Measurements or Applications*. Accessed: Jul. 7, 2020. [Online]. Available: https://www.onsetcomp.com/products/
[40] *Energy Standard for Building Except Low-Rise Residential Buildings*, Standard ANSI/ASHRAE/IES Standard 90.1-2019, 2019.
[41] C. Duarte, K. Van Den Wymelenberg, and C. Rieger, "Revealing occupancy patterns in an office building through the use of occupancy sensor data," *Energy Buildings*, vol. 67, pp. 587–595, Dec. 2013.
[42] J. A. Davis and D. W. Nutter, "Occupancy diversity factors for common university building types," *Energy Buildings*, vol. 42, no. 9, pp. 1543–1551, Sep. 2010.
[43] E. Azar and C. C. Menassa, "Optimizing the performance of energy-intensive commercial buildings: Occupancy-focused data collection and analysis approach," *J. Comput. Civil Eng.*, vol. 30, no. 5, Sep. 2016, Art. no. C4015002.
[44] O. T. Masoso and L. J. Grobler, "The dark side of occupants' behaviour on building energy use," *Energy Buildings*, vol. 42, no. 2, pp. 173–177, Feb. 2010.
[45] M. Sepehr, R. Eghtedaei, A. Toolabimoghadam, Y. Noorollahi, and M. Mohammadi, "Modeling the electrical energy consumption profile for residential buildings in iran," *Sustain. Cities Soc.*, vol. 41, pp. 481–489, Aug. 2018.
[46] D. Bonino, F. Corno, and L. De Russis, "Poweront: An ontology-based approach for power consumption estimation in smart homes," in *Internet of Things. User-Centric IoT* (Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering), vol. 150. Cham, Switzerland: Springer, 2015, pp. 3–8.

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