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Internet of Things for Green Building Management

Disruptive innovations through low-cost sensor technology and artificial intelligence

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Buildings consume 60% of global electricity. However, current building management systems (BMSs) are highly expensive and difficult to justify for small- to medium-sized buildings. The Internet of Things (IoT), which can collect and monitor a large amount of data on different aspects of a building and feed the data to the BMS's processor, provides a new opportunity to integrate intelligence into the BMS for monitoring and managing a building's energy consumption to reduce costs. Although an extensive literature is available on, separately, IoT-based BMSs and applications of signal processing techniques for some building energy-management tasks, a detailed study of their integration to address the overall BMS is limited. As such, this article will address the current gap by providing an overview of an IoT-based BMS that leverages signal processing and machine-learning techniques. We demonstrate how to extract high-level building occupancy information through simple, low-cost IoT sensors and study how human activities impact a building's energy use—information that can be exploited to design energy conservation measures that reduce the building's energy consumption.

Overview

Collectively, buildings are one of the major electricity consumers, representing 60% of total global electricity consumption. In the United States, for example, 70% of annual electricity use is due to buildings [1]. Such intense electricity usage by buildings is also true for many other countries (although detailed statistics may not be fully available due to lack of information or measurement). Therefore, there has been a significant push toward studying and developing ways to effectively manage electricity in buildings through efficient BMSs.

Current BMS solutions are, however, highly expensive and thus difficult to justify for use in small- and medium-size buildings. Additionally, due to a recent push for reducing electricity consumption and increasing operational efficiency, building managers need to deal with dynamic and diverse building requirements including anomaly detection, predictive maintenance, occupancy tracking, and electricity use optimization

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with renewable integration. For example, in the United States, heating, ventilation, and air conditioning (HVAC) airflow is regulated by the U.S. Occupational Safety and Health Administration and is tied to maximum occupancy. Consequently, if no sensors are present, a room must be ventilated during normal working hours according to the maximum number of people who can be in the room (maximum seating capacity), thereby wasting considerable energy. From this perspective, sensing capabilities can lead to better situational awareness as well as more efficient, dynamic, and adaptive management of electricity and energy storage devices by incorporating intelligence into the BMS. The IoT has emerged as a promising solution to make this integration a reality.

Essentially, the IoT is a platform that connects devices over the Internet, allows them talk to one another and to humans, and, by doing so, enables the realization of desirable context-specific objectives such as energy savings (e.g., scheduling HVAC based on occupancy), condition monitoring (e.g., fault detection of HVAC), and predictive maintenance (e.g., the servicing of air filters in HVAC). Considering that the IoT is expected to change the future of smart BMSs, this article describes an IoT-based BMS that makes use of signal processing and machine-learning techniques. We note that signal processing has been employed extensively in wireless sensor networks for assisted living and information filtering. Therefore, it could be very helpful for extracting crucial information about building health using different sensors, as depicted in Figure 1. Based on this, we describe an energy-efficiency study conducted in a building test bed. The test bed is equipped with IoT devices and uses signal processing with machine learning to understand human activity and its impact on a building's energy use. To this end, the main contributions of this article are as follows:

- providing a literature review on the application of the IoT in building management as well as a discussion of the desired features of a smart BMS
- implementing machine-learning techniques in low-level devices, such as sensors and other IoT devices, via transfer learning and semisupervised learning techniques to enable IoT devices with low computation capability to perform machine-learning algorithms locally via edge computation
- illustrating how such techniques can benefit building management by providing useful information that can better characterize energy efficiency
- presenting some case studies from experiments in a real-world environment.

State of the Art

As buildings undergo years of use, their thermal characteristics deteriorate, indoor spaces get rearranged, and usage patterns change. In time, their inner and outer microclimates adjust to the changes in surrounding buildings, overshadowing patterns, city climates, and building retrofitting [2]. As a consequence, their performance frequently falls short of expectations. In this context, the IoT opens new opportunities to integrate intelligence into the BMS in a cost-effective manner through seamless integration of various sensors, smart meters, and actuators: the BMS can use these to monitor and identify different energy and environment-related parameters [3], analyze the health of a building, determine energy and thermal requirements, and, ultimately, determine the electricity usage behavior of different subsystems intelligently. The

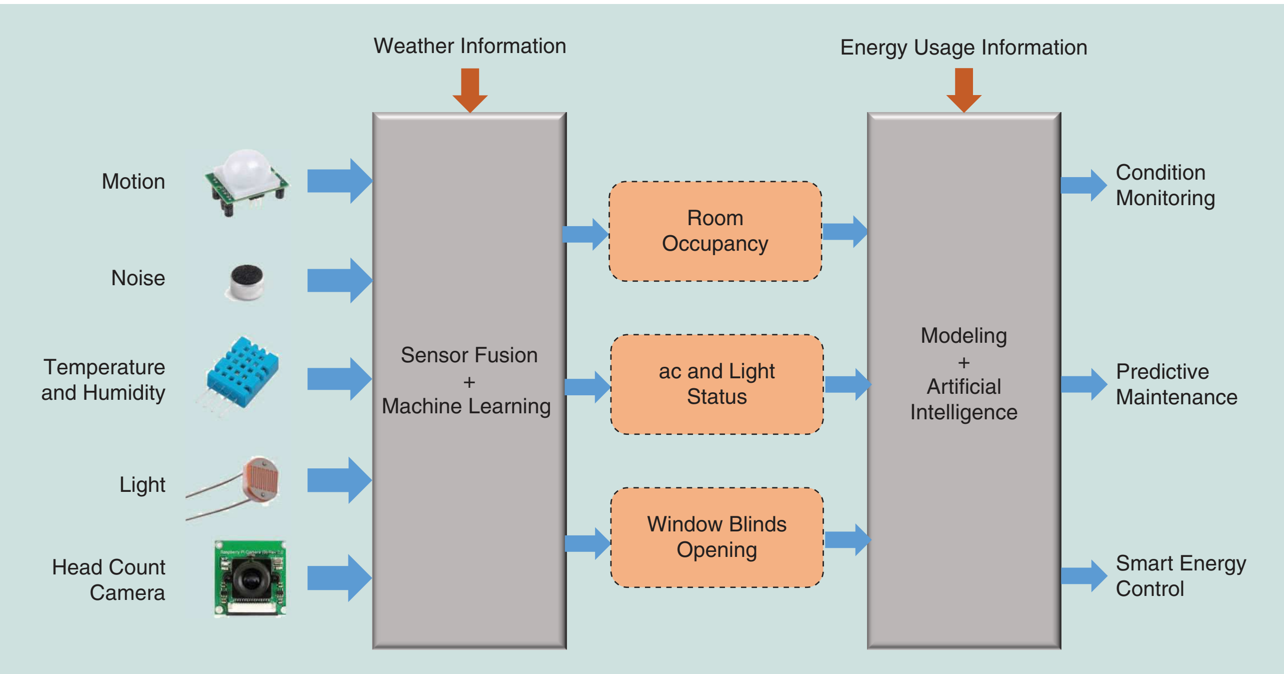

FIGURE 1. A demonstration of the use of sensor fusion and machine learning for IoT-based green building management.

performance of a BMS depends mainly on collecting large volumes of data from different building subsystems, which the BMS then analyzes and processes using various signal processing tools. Based on the application of IoT-based signal processing techniques in managing various subsystems within a building, existing studies can be divided into five general categories: 1) lighting, 2) HVAC, 3) flexible loads, 4) human detection, and 5) diagnostics and prognostics. We briefly describe these five categories in the following.

Lighting

Lighting accounts for a major fraction of global electricity consumption. In office buildings, for example, the electricity used for lighting can constitute up to 40% of total electricity consumption [4]. From this perspective, a number of studies have been conducted to develop solutions to help reduce electricity consumption based on a building's lighting. For instance, to achieve the desired illumination in a building having low electricity consumption, the authors in [4] propose a luminaire-based periodic sensor processing algorithm to implement a smart lighting control system. In [5], the authors present a Q-learning-based lighting control system that personalizes and employs users' perceptions of their surroundings as the feedback signal to better manage lighting intensity. In addition, [6] and [7] review lighting control techniques that use signal processing-based daylight-prediction and occupancy-detection methods, respectively.

HVAC

The HVAC system is another major consumer of electricity, accounting for 40% of total electricity consumption in U.S. buildings overall [1]. Consequently, developing some means to reduce the HVAC's electricity consumption has received considerable attention. In [8], the authors propose a Kalman filtering-based gray box model to predict and determine statistical process control limits for fault detection of HVAC systems. A similar signal processing technique is also used in [9] to control the power consumption of buildings without compromising the occupants' comfort level. An intelligent controller model is designed in [10] that integrates the IoT with cloud computing and web services; in addition, the authors develop wireless sensor nodes to monitor the indoor environment and HVAC inlet air as well as a wireless base station to control the HVAC actuators. Lastly, [11] proposes a smart home energy-management system using the IoT and big data analytics, predominantly focused on the HVAC system's electricity consumption; in particular, the proposed mechanism makes use of off-the-shelf business intelligence and big data analytics software packages to better manage energy consumption and meet consumer demand. Other examples of such studies in the context of HVAC can be found in [12] and [13].

Flexible loads

The third area of study focuses on monitoring and controlling electricity consumption by other flexible loads within buildings. Examples of such loads include washing machines, dishwashers, ovens, electric vehicles, and energy storage systems. IoT devices can effectively monitor the operational status of these loads and exploit signal processing techniques to predict their usage patterns and effectively control their operation for better energy management (or demand response). For example, a learning-based signal processing tool for demand management is designed in [14], and a deep-learning-based signal processing approach is implemented in [15] for nonintrusive monitoring of all loads in an entire building. In [16], the authors design a long- and short-term memory for load forecasting based on residential-behavior learning using recurrent neural networks, while, in [17], accurate indoor occupancy tracking within a building is implemented using multisensor fusion.

Human detection

In the area of human detection for BMSs, a number of machine-learning techniques have been used for head count and occupancy-detection purposes. For example, parametric and nonparametric algorithms (including background subtraction models and Gaussian processes [18]) have been used with a camera for head count; these algorithms are implemented using the OpenCV library. Further, for occupancy detection, thermal imaging [19], pyroelectric infrared sensors [20], and red-green-blue camera-based techniques have been used extensively. In addition, the authors of [21] present an example of sound-sensor-based applications for occupancy detection that use high sampling rates to classify activities.

Diagnostics and prognostics

The HVAC system is the most complex system and greatest energy consumer in most buildings. Faulty equipment within the HVAC system leads to inefficient system operation. Hence, keeping such systems in good operational condition is important. However, regular maintenance of HVAC systems is time consuming. Given this context, IoT devices allow us to develop advanced predictive-maintenance, fault-detection, and diagnostics applications for these systems. For instance, using data collected from IoT devices, a data-driven fault-detection method is developed in [8].

Based on the discussion here (summarized in Table 1), it is clear that the IoT makes possible numerous useful applications in designing smart and efficient buildings. Nevertheless, obtaining desirable BMS performance by applying different signal processing techniques depends significantly on the actual IoT devices that monitor and collect large amounts of data in respective contexts and then feed these data to the processor. Although, as noted previously, studies are available separately on IoT-based BMSs and applications of signal processing techniques for some aspects of building energy management, studies focused on their integration for overall building energy operation in practical settings are limited. We address this lack of integration by providing an overview of how IoT devices can be coupled with signal processing techniques to better understand a building's electricity usage performance.

Table 1. A summary of the surveyed literature on applying IoT-based signal processing for BMSs.

Category	Main Focus of the Study	Adopted Technical Approach	Surveyed Studies
Lighting	Use sensor-based data to shape the output of light-emitting-diode lighting systems to achieve desired illumination conditions and lower electricity consumption within a building	Proportional-integral-derivative control, custom-built android mobile applications, controller optimization	[4]–[7]
HVAC	Reduce electricity consumption by the HVAC system of a building without affecting the privacy and comfort level of the building's occupants	Kalman filtering, gray box models, cloud computing, big data analytics, business intelligence models	[1], [8]–[13]
Flexible loads	Monitor and schedule electricity consumption by flexible loads within a building to reduce electricity costs	Machine learning, deep learning, recurrent neural networks, behavioral modeling	[14]–[17]
Human detection	Monitor the number of people (or occupancy detection) in a room within a building to facilitate energy-consumption modeling	Background subtraction models, Gaussian processes, sound-sensor-based approaches	[18]–[21]
Diagnostics and prognostics	Advance predictive maintenance, fault detection, and diagnostics applications of systems using IoT-based data	Kalman filtering, gray box models	[8]

Trending technologies for BMS

Here, we provide an overview of trending technologies being used for the effective design and development of a BMS data acquisition, management, and control platform. These technologies treat the BMS as a cloud-based ecosystem that 1) uses social interaction among the people within communities to establish sophisticated global behavior patterns that can achieve different social, financial, and scientific goals; 2) uses green energy and storage resources for environmental sustainability; and 3) affirms the overall establishment of a smart system with autonomous decision-making capability.

IoT for seamless integration and processing

At present, it is difficult and expensive for a building manager to be fully aware of a building's health in real time, due to current buildings' limited sensing and control capabilities. Hence, the design of an integrated data-acquisition and control system based on an open architecture and a cloud-enabled IoT can help reduce the cost of setting up a BMS. An integrated IoT system allows the building manager to monitor and sense the building's different environmental parameters (e.g., through motion and noise detectors, temperature and humidity sensors, and electricity and water flow meters), collect the relevant human activity information (occupancy, heat map, etc.), and estimate the energy usage (e.g., by comparing the current information with previously collected historical data), which will be fed into a smart management system that will manipulate actuators (e.g., switches, controllers, and thermostats) to efficiently manage the building's environment according to expectations and designated rules.

Such an IoT platform (which is an open platform) can interface and connect with various subsystems of different vendors, e.g., sensing subsystems (people counting, temperature, humidity, light, noise, and motion), control subsystems (thermostats, switches, smart plugs, and actuators), and metering subsystems (energy consumption, water flow, etc.). Currently, various off-the-shelf products and systems are available for the IoT; for example, utility use worldwide is trending toward smart energy profiles, such as batteryless energy harvesting switches (e.g., Enocean), low-cost Wi-Fi controllers (e.g., Particle) and thermostats (e.g., Nest by Google), and many others. As these technologies advance, we expect that more and more IoT devices will be available on the market. Hence, there are great opportunities to tap the capability of these growing IoT systems. Nevertheless, to implement an IoT system, one needs to address the challenges of scalability, flexible provisioning, interoperability, and low latency [22].

Attribution of energy usage to human activities

One of the key technologies receiving considerable attention for deployment as a part of a BMS is the integration of human activity tracking within the control system as a way to understand how a building's electricity usage is affected by the number of occupants and their various activities. By "tracking human activity," we refer to the tracking of human movement within a designated area, which can be accomplished using a smartphone scanning sensor. Essentially, such a sensor can scan smart devices in the vicinity (smartphones, mobile tablets, and the like) and, at the same time, record the smart device's duration of stay and media access control address. This determines not only the heat map (i.e., human count) of the designated area but also presents information concerning the duration of stay and the movement path—and, potentially, social relationships as well. Such tracking can provide building managers with information on occupants' efficient use of different areas in a building and help them in recommending further modification (architectural or electrical system) of a space if necessary for greater overall energy efficiency.

Big data analytics for insightful analysis

Big data management is, in essence, the core software layer that ultimately drives the BMS through big data analytics, including prediction (e.g., predictive maintenance), model building, complexity mapping, and visualization. Big data analytics aids the dynamic management of energy consumption via monitoring and analyzing energy-related activities to minimize unintended energy and water consumption. This is basically a process of examining the large data set obtained through the IoT. Using this process, a building manager can identify information on human activity, weather conditions, the microclimate within the building, and related energy wastage. Doing so requires designing algorithms that can accurately extract the intercorrelations among load consumption, human occupancy and movement activity, energy wastage, renewable energy generation, and weather conditions, allowing the creation of effective models from real-time large-scale data sets to perform predictive maintenance.

Renewable energy and storage for increasing the flow of green energy

To facilitate the flow and use of green energy, BMSs also explore possible provisioning of renewable energy resources in buildings through dynamic scheduling and control. In particular, the BMS first collects data on weather conditions and subsequent renewable energy generation through the low-cost IoT system. Then, together with the information about human activity within the building, the BMS exploits big data analytics to determine how to optimally schedule the dispatch of renewable energy from its distributed sources as well as the charging and discharging of the respective storage devices.

For example, a solar thermal system integrated with hot water storage is becoming very popular in commercial buildings. Based on the previously discussed process (i.e., using the available solar generation for heating water to meet demand based on human activity), a building's BMS can use its big data analytics to predict how much hot water will be needed for the building. Thus, it can dynamically schedule the heat pump to turn on to heat hot water based on the availability of renewable energy.

IoT-based human activity detection and building efficiency

As mentioned earlier, understanding human activity is particularly important to energy efficiency. In this section, we provide a brief case study to illustrate how low-cost IoT devices can be used along with signal processing and machine-learning techniques to understand the number of people in a particular area of a building and provide building management with key insights for effectively managing the building's electricity consumption.

Head counting with an overhead camera

To realize a low-cost head count camera, we use a camera with a fish-eye lens that captures images at 30 frames/s. The camera is installed directly on top of the entrance door of the selected room. The images captured by the camera are processed locally. Only the head count number is uploaded to the cloud. For head counting, we explore a number of signal processing techniques including the following.

OpenCV image processing

We first use the OpenCV library with traditional image-processing techniques for head counting. To overcome the influence of moving objects such as a door, the background subtraction method is fused with the color detection method in head count detection. Unfortunately, the accuracy of this method becomes unacceptable when the light inside the room is switched off. This motivates us to use deep-learning techniques in the head count camera.

Motivation for transfer learning

Recently, deep learning—and, especially, convolutional neural networks (CNNs)—has made great progress in object recognition. However, building an object-recognition model with CNNs is tedious due to the significant amount of data and the resource requirements for training purposes. For instance, the model for the ImageNet Large Scale Visual Recognition Challenge was trained on 1.2 million images over a period of 23 weeks in multiple graphics processing units. As a consequence, it has become popular among researchers and practitioners to use transfer learning and fine-tuning (i.e., transferring the network weights, which have been trained on a rich data set, to the designated task, e.g., detecting people on images in this study). In particular, we use the pretrained single shot detection (SSD) multibox model [23] as the network due to its higher accuracies, high frame rate, and suitability for embedded application.

SSD multibox

SSD matches objects with default boxes having multiple feature maps with different aspect ratios. Each element of the feature map has either four or six default boxes associated with it. Any default box having a Jaccard overlap higher than a threshold of 0.5 with a ground truth box is considered a match. SSD has six feature maps in total, each responsible for a different scale of objects, thus allowing it to identify objects across a large range of scales. SSD runs 3×3 convolution filters on the feature map to classify and predict the offset to the default boxes.

Transfer learning and fine-tuning

There are two main procedures we adopt when using the pretrained SSD multibox model. The first is transfer learning. We use an SSD model that is pretrained for the Microsoft Common Objects in Context (COCO) data set [24]. Then, we change the number of classes in the box predicator according to our requirement. Second is fine-tuning. We keep the pretrained weights of the feature extractor and use them as initial values for retraining. Note that, because the feature extractor is trained for a large rich data set over millions of iterations, the weights are stable and converged. As such, we only fine-tune the feature extractor weights according to our data set.

In Figure 2, we depict results based on OpenCV libraries using only our pretrained SSD model and transfer learning. Figure 2 also demonstrates a frame captured under low lighting conditions. One can observe that OpenCV and the pretrained SSD model do not show good results under low lighting conditions. As illustrated in Figure 2(b), the OpenCV method captures the same person as two instances, and the pretrained SSD model does not capture anything at all [Figure 2(c)]. Nonetheless, the transfer learning method is well generalized for both good and low lighting conditions [Figure 2(d)] and can be used for the people-counting algorithm.

It is important to note that, to reduce the processing complexity and power consumption for occupancy detection, the

MobileNet architecture is used as the feature extractor for the SSD model. The input image size was restricted to 250 × 250 pixels without losing accuracy, which greatly reduces the computational power. Further, while the original pretrained SSD MobileNet can detect 99 object classes accurately, we reduce the number of classes to two. This helps lower the power consumption of the module without limiting the performance of the detection (because our intention is to detect only person versus nonperson cases).

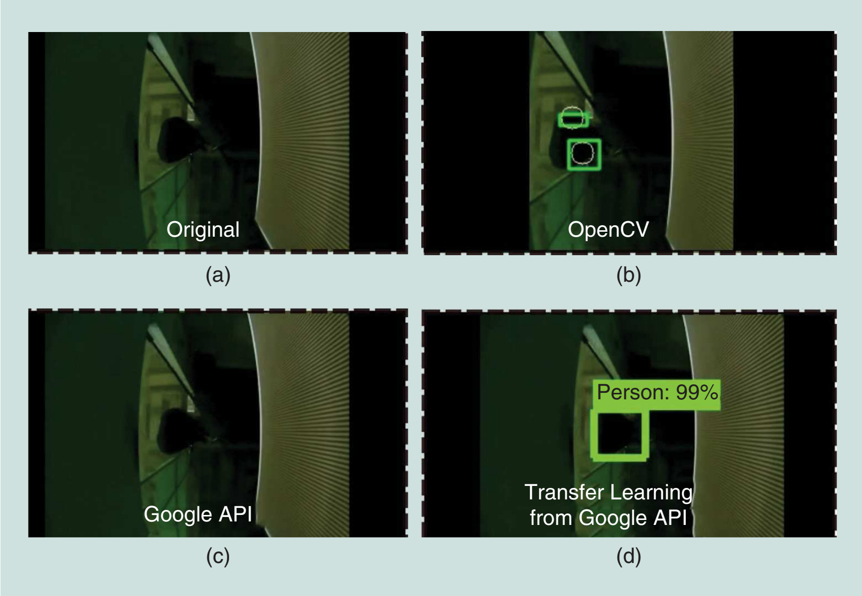

FIGURE 2. Detection results using four different methods in low lighting conditions: (a) the original frame, (b) using OpenCV libraries, (c) using the SSD model trained for the COCO data set, and (d) using transfer learning. API: application programming interface.

Occupancy detection with a sound sensor

Because a motion sensor has limited range, we also explore the suitability of using a sound sensor for occupancy detection. We are motivated to explore sound sensors because the visual approach using a camera can capture occupants' identity and record their activities within a selected space of the building—which not only violates user privacy but also requires a very large storage space and data rate for processing in real time. As such, existing studies of occupancy detection in building environments, such as [25] and [26], have used techniques that exploit environmental information (including carbon dioxide level, noise level, humidity level, and particulate matter concentration) instead of using a camera. From this perspective, an acoustic approach using a sound sensor is a potential alternative being explored here.

A sound sensor is typically used to detect the loudness in ambient conditions, with an input taken from a microphone and amplified. We use a low-cost analog sound sensor with a signal-to-noise ratio of 55 dB at 1-kHz maximum input frequency. Note that, due to different room structures (room size, wall material, furniture, etc.), sensors are placed at different locations in different rooms, which results in a collection of different noise levels. The sensor data are sampled every 100 ms. Based on our empirical research and previous study [27], a sampling rate of 10 Hz is enough to distinguish human activities within the environment. In addition, such low-rate sampling can help reduce the sensors' energy consumption and computation without losing necessary information.

To accurately detect human occupancy in selected areas, we explore four different techniques: 1) the threshold method, 2) the unsupervised learning through clustering method, 3) the supervised learning through deep-learning method, and 4) a semisupervised learning technique that employs the deep classifier to label the unsupervised results.

Thresholding method

We accumulate the sound-sensor data for every 5-min period and measure an empirical threshold value for each room to determine occupancy. We observe that threshold values are different for different rooms and sometimes even for different days. As Figure 3 shows, the appropriate threshold for human activity detected for room P04 is 8,000, while the threshold becomes 12,000 for room P02. Here, P02 and P04 are two selected rooms of the test bed (Figure 4). Therefore, simply using the threshold method is not robust. Further, it is tedious to calibrate and find the optimal threshold for each individual room.

Unsupervised learning using clustering

To achieve robust occupancy detection using a noise sensor with no calibration, we employ unsupervised learning. Instead of sending just the accumulated noise value, we send the noise histogram for each 5-min interval according to the following arrangement:

- bin 1 (sample values range: 0–6)
- bin 2 (sample values range: 6–10)
- bin 3 (sample values range: 10–15)
- bin 4 (sample values range: 15–30)
- bin 5 (sample values range: 30–50)
- bin 6 (sample values range: 50–75)
- bin 7 (sample values range: 75–100)
- bin 8 (sample values range:100 and above).

The noise histogram refers to a set of bins (ranges), in which each bin represents a specific range of data collected by the sound sensors. While these eight levels of the histogram are used in our case, we believe four or even fewer levels could also be sufficient.

We adopt a similar unsupervised learning process in our previous work [27] in an outdoor smart city environment. To generate meaningful features of the histogram data, we use the localized behavior of wavelet transformation; the Haar basis function is used as the mother wavelet, due to its own discontinuous nature (the Haar basis function is a mathematical function that generates the feature set for the histogram's representation of data). We represent each 5-min histogram in terms of the Haar basis function. Further, principal component analysis is used to remove the high correlation between histogram bins. In addition, we remove the redundant noise in the data by using only the *n* principal components that capture 95% of the variation in the data. Moreover, we use hierarchical clustering and calculate the optimal number of clusters using the Calinski-Harabasz index.

Supervised learning through deep learning

A major issue in terms of the unsupervised learning technique is that it is up to a human to interpret the outcome. For example, in our case, we may get three to five different clusters as the output of the unsupervised learning, as shown in Figure 3 (four clusters for room P02 and five clusters for room P04). In some cases, one cluster represents the unoccupied duration; in other cases, two clusters may represent the unoccupied duration. Because the unsupervised learning method does not provide any meaningful understanding of the clusters, we employ a deep neural network (DNN) classifier, using the thresholding method with a "reasonable threshold" as the "ground truth." The output of the classifier is the probability of occupancy. For instance, if the probability of occupancy is greater than 0.5, we determine that the space is occupied.

To this end, we first use a sparse autoencoder to extract meaningful features for histograms. When training for feature extraction, we use only histograms related to one class of data (i.e., only those histograms related to the occupied class) to train the autoencoder rather than using the data of both classes (i.e., occupied and unoccupied). By doing so, we expect to construct more distinguishable features for histograms.

When training the classifier, we fix the weights of the pretrained autoencoder and thus optimize only the weights of the DNN. To do so, we first use the sparse autoencoder to construct sparse features for the histogram and then use these features

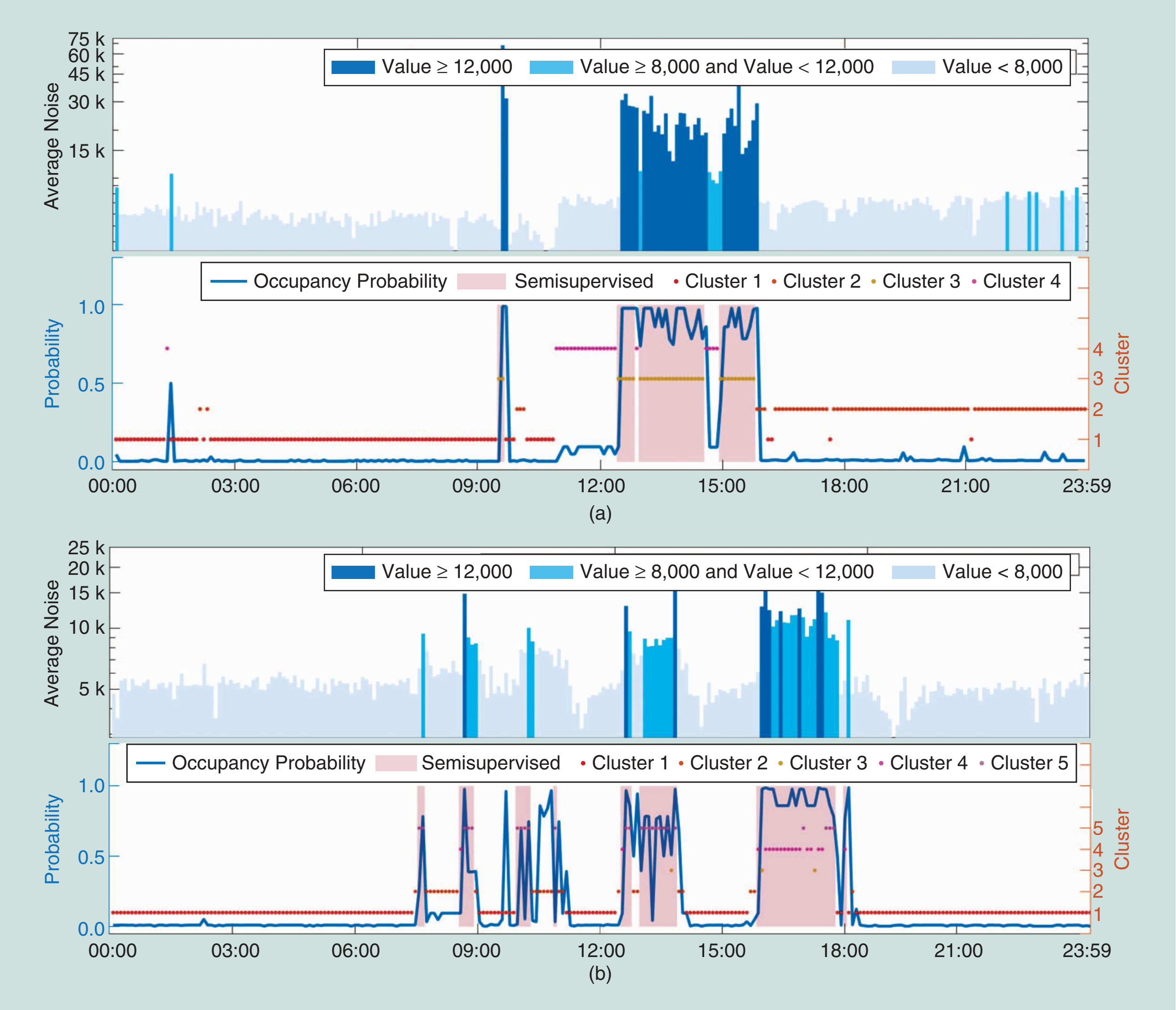

FIGURE 3. The results of occupancy detection in two different meeting rooms (labeled P02 and P04). We visited the site for one day and recorded the ground truth for evaluation. (a) Meeting room P02 and (b) meeting room P04.

as inputs for the deep classifier. In the training stage, we use a data set of 5,000, half of which are used to train the autoencoder. In both cases, training is performed in 30,000 training epochs. As mentioned earlier, we use only a single class to train the autoencoder. We can thereby improve the overall classification accuracy by approximately 3% compared to training using both classes.

Semisupervised learning method

To improve detection accuracy, we use the following semisupervised learning technique. For a particular cluster based on unsupervised learning, we consider the corresponding probability obtained by the deep classifier. If the majority say "occupied," then we label that whole cluster "occupied"; if the majority say "unoccupied," we label that whole cluster "unoccupied." Therefore, we obtain more consistent results compared to using the deep classifier only.

The results for these methods are depicted in Figure 3 for two different meeting rooms, P02 and P04. To summarize, we can observe that the optimal threshold values are different for different rooms (e.g., 12,000 for P02 and 800 for P04): finding those values in a large-scale deployment could be tedious. In the following, we demonstrate how semisupervised learning that combines both clustering and a deep classifier overcomes this problem. We train the deep classifier using data from another two meeting rooms (P01 and P06, with thresholds of 11,000 and 12,000, respectively), which we verify on P02 and P04, as shown in Figure 3. Finally, we see that the semisupervised learning method provides robust and consistent occupancy detection for P02 and P04, even though the training set comes from P01 and P06.

Building efficiency via IoT-based BMSs

In this section, we demonstrate how our designed IoT-based BMS can provide insights for buildings' HVAC efficiency in the future. The HVAC system, in particular, is chosen because this system is responsible for more than 50% of the energy consumption in commercial buildings. A commercial facility in Singapore is considered as the green building test bed. In the selected building, the HVAC system is set up with a modern chiller plant and central air-handling unit (AHU) that can be managed by a typical BMS. The AHU contains an available-speed supply fan, cooling coils, filters, a mixing box, a return air fan, dampers, and several variable air volume (VAV) terminal units that supply chilled air from the AHU to the terminal zones.

We select a specific area of the commercial facility for experiment, i.e., the meeting room P03 in Figure 4 (which shows the schematic of the selected floor plan). On this floor, there is one AHU as well as several rooms with VAV units. Each room is equipped with IoT sensors and, at the entrances, head count cameras. The multipurpose node is responsible for collecting the surrounding environmental information. The environmental information collected for this experiment includes temperature, humidity, light intensity, motion, and noise. Head count cameras are used to count people who enter and exit the rooms within the selected area.

Note that the occupancy within a selected space has a direct influence on the energy consumption of the HVAC system, which (in conjunction with information on the respective energy consumption pattern of the HVAC system) can be exploited to regulate the energy consumption of the HVAC. For example, in [28], the authors propose a data-driven approach

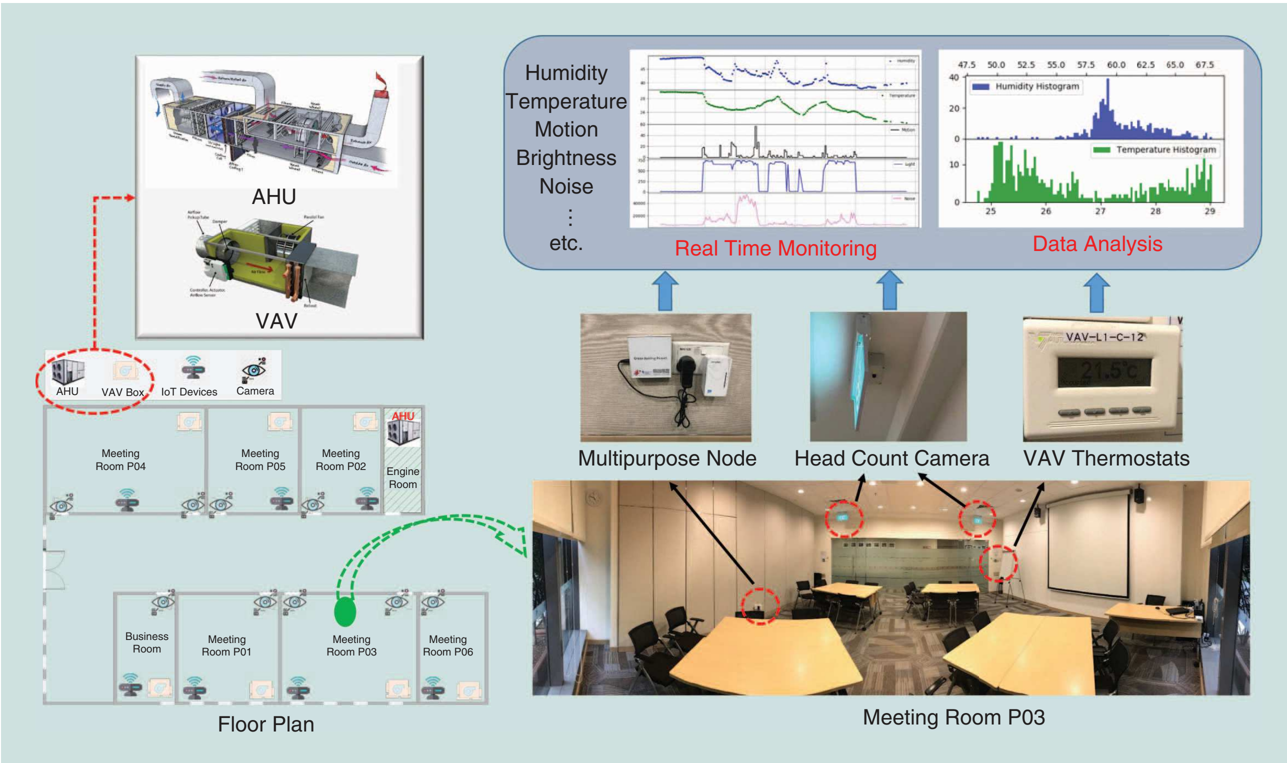

FIGURE 4. A demonstration of the green building test bed.

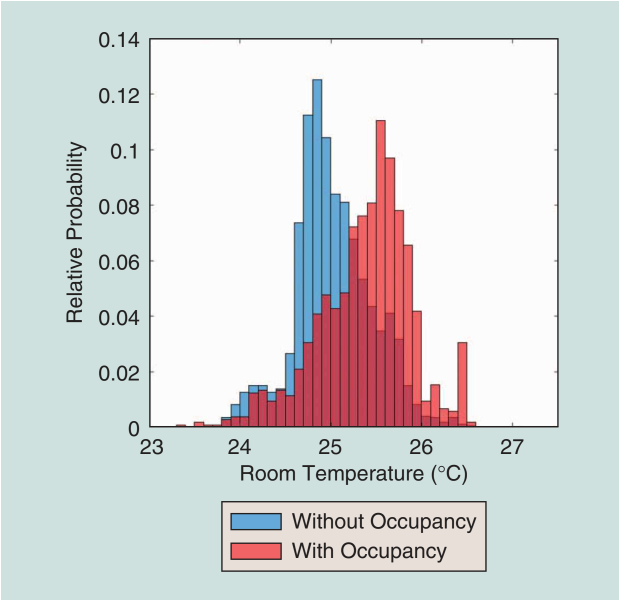

FIGURE 5. An illustration of the distribution of room temperature with and without human occupancy.

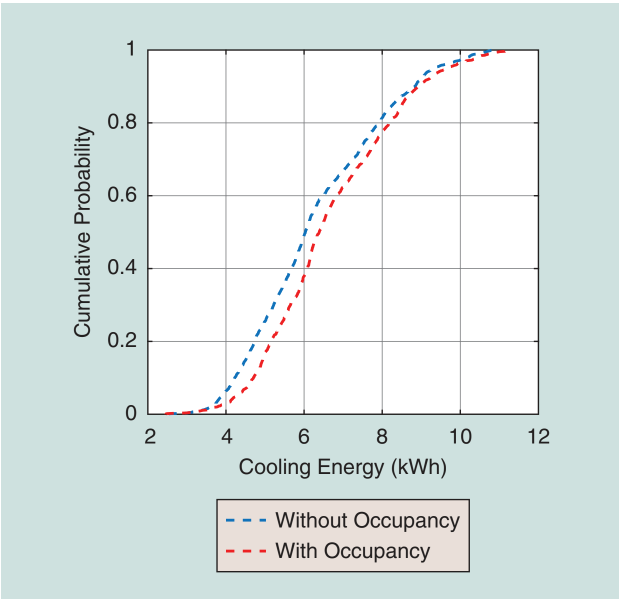

FIGURE 6. A comparison of cooling energy use with and without human occupancy.

for the energy consumption of an HVAC system in which the set-point temperature of the HVAC is regulated according to the people activity and occupancy to control energy consumption. Such control is shown to be very effective and can reduce an HVAC's energy consumption in a house by 33%. An example of another study that uses people occupancy patterns to control the energy consumption of the HVAC can be found in [12].

We select one meeting room of the test bed to demonstrate the energy use analysis. To do so, we extract historical data for the time span between 1 November and 7 December 2017. After filtering out the weekend days and days with missing data (due to maintenance and/or network faults), we have data for a total of 21 days to analyze. The AHU operates from 7:40 a.m. to 7:40 p.m. each weekday; this schedule is maintained by the building manager. However, we consider the office hours from 8:00 a.m. to 7:00 p.m. for our study, because the building is, for the most part, occupied by people only during this period of time.

Based on the collected data on room temperature, chilled air temperature, and air flow, we compute the cooling energy for the energy use analysis. In this context, the required cooling energy for a room is considered as $Q_{\text{cooling}} = \rho_{\text{air}} C_{\text{air}} m_a (T_{\text{room}} - T_{\text{supply}})$ [29], where ρ_{air}, C_{air}, m_a, T_{room}, and T_{supply} represent the air density at 20 °C, the specific heat of air, the volume of air supply, room temperature, and chilled air temperature, respectively. According to the Q_{cooling} formula, the energy consumption of a room for cooling relies on three variables: room temperature, chilled air temperature, and air flow. Among these, chilled air temperature and airflow are controlled by the AHU and are responsible for reducing room temperature to achieve the set point, which is established as 20 °C for the selected room. As such, the higher the room temperature, the more cooling energy is consumed.

The air density and specific heat coefficient are given as 1.204 kg/m^3 and 1.012 kJ/°C/kg, respectively. Then, the room temperature data are extracted for our IoT sensors. The supplied air volume and temperature are monitored by the BMS; hence, the date of volume and temperature can be fetched from the BMS database. We divide the total time period of each experiment into multiple time slots, with each time slot constituting a 5-min interval. Then, we classify the time period with occupancy and without occupancy, respectively, using the occupancy detection technique explained earlier in this section. We obtain two sets of room temperatures for time periods with and without human occupancy. Figure 5 shows the distribution of these two sets of room temperatures. Noticeably, the room temperature is higher when the room is occupied compared to the case without occupancy. Consequently, we infer that more cooling energy will be necessary for consumption during those time periods with occupancy than those with no occupancy.

In addition, we classify the cooling energy usage based on the occupancy status. In Figure 6, we show the cumulative distributions of energy use with and without human occupancy; a gap between the cooling energy use for the two considered occupancy states is clearly visible. Based on this figure, the average cooling energy consumption with occupancy and without occupancy in each time slot is 6.57 and 6.04 kWh, respectively. Hence, the average cooling energy consumption with occupancy is 8.7% higher than that without occupancy. Furthermore, the average room temperature with and without occupancy is 25.37 °C and 25.02 °C, respectively, which indicates an increase of 0.35 °C in average room temperature due to human occupancy.

Based on the previous analysis, it is clear that energy consumed by a building's HVAC system depends to a large extent on its occupancy status, in addition to other factors such as the building's thermal characteristics, use of various appliances, the status of window blinds, and the outdoor climate. Thus, this study provides useful insights concerning the energy efficiency of a building's HVAC systems by exploiting its human occupancy status, which can be determined easily by simply deploying IoT devices in the building. For instance, the occupancy information can be used to develop suitable control strategies or optimization tools via signal processing techniques to opportunistically reduce HVAC energy consumption and subsequently help the occupants reduce their energy costs. For more information about how occupancy information can be used to develop suitable control strategies or optimization tools, readers may refer to [7], [13], and [30].

Conclusions

In this article, we first reviewed the application of IoT-based signal processing techniques for managing various subsystems within a building. Then, we provided an overview of how machine learning can be applied with an IoT device to detect human occupancy within a building, which contributes significantly to the building's energy consumption. In particular, we considered

- a transfer learning-based technique that counts people based on images captured at the entrances of the selected areas of a building
- an unsupervised learning technique labeled by deep-learning-based occupancy detection that uses information obtained by sound sensors.

Further, we provided a short description of the test bed where these techniques are deployed for occupancy detection and showed how the information can help gain insights on the use of the HVAC system within the test bed. The correlation between occupancy and energy use, as demonstrated in this study, has the potential to be used in developing different energy-management schemes that will help reducing energy consumption and electricity costs for building managers.

There are many areas into which the work reported here can be extended.

- *Widespread deployment*: The discussed study was conducted on a relatively small scale in a commercial building in Singapore. While using a real facility provides actual user and system data for our study and analysis, it would be interesting to see how the findings from the study can be extended to a larger scale, e.g., the entire building, via widespread deployment of IoT devices.
- *Detailed modeling of energy usage*: Another interesting extension of the proposed work would be to use machine-learning techniques to perform more detailed modeling of energy use by various appliances in the building and then design suitable techniques to optimize this use to reduce electricity costs.
- *Applying the IoT beyond building energy*: IoT sensors also provide valuable data for predictive maintenance and anomaly detection. Hence, it would be interesting to explore how the collected data from IoT sensors can be used to help a building perform asset management, which, in addition to energy reduction, may reduce other building costs.
- *Exploring quantitative performance*: This article presents qualitative results for the head counting and occupation detection study and their importance for building management. However, there is a need to extend this work to present more quantitative analysis in terms of performance compared with existing studies in the literature and analyze how head counting impacts the energy consumption of the building.

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