Building and Environment 223 (2022) 109472

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Plug-Mate: An IoT-based occupancy-driven plug load management system in smart buildings

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ARTICLE INFO

Keywords:
Plug loads
Internet-of-Things
Occupancy-based control
Building automation
Smart energy management systems

ABSTRACT

Plug load management systems are touted as promising solutions to reduce the rising energy consumption of plug loads in commercial buildings through different load monitoring and control strategies. However, their real-world applications remain relatively unexplored due to several issues related to deployment viability, energy-saving potentials, and system acceptance. Given these limitations, this paper proposes Plug-Mate, a novel IoT-based occupancy-driven plug load management system that reduces plug load energy consumption and user burden through intelligent plug load automation. The proposed system uses an interconnected network of modules and subsystems to perform plug load automation based on the users' (1) high-resolution occupancy information obtained through a non-intrusive indoor localisation system, (2) plug load type information inferred through an advanced plug load identification feature, and (3) diverse control preferences through a personalised user interface. To demonstrate the system's feasibility, six control strategies were evaluated during a 5-month field study in a university office space. Each control strategy involved different levels of plug load automation (i.e., manual, predefined schedules, and occupancy-driven) and was assessed based on their energy savings and user satisfaction levels to identify the optimal balance between automation and user control. Based on this evaluation, the best control strategy reported an average energy savings of 51.7% among different plug load types evaluated, achieving a 7.5% reduction in the building's energy use and the highest user satisfaction score of 4.7 out of 5. Finally, we concluded this work by highlighting the system's deployment feasibility for a building-wide implementation to guide future real-world applications.

1. Introduction

Plug load usage in the workplace has been steadily rising over the last two decades and contributes up to 30% of the total energy consumption in a standard office building [1]. In this context, plug loads refer to electrical devices that draw power from the building's electrical sockets and exclude conventional heating, cooling, and lighting loads in the building. Based on the latest projections released by the U.S. Energy Information Agency, the energy consumption of office plug loads such as laptops, desktops, and monitors is expected to experience the highest rate of growth of up to 2.5% each year till the year 2050 [2]. Especially in the case of high-efficiency buildings, the energy contributions of plug loads can reach up to 50% due to the increased efficiencies of other building systems such as HVAC and lighting systems [3].

In view of these energy trends, plug load management systems have been touted as a promising solution to reduce the rising energy consumption of plug loads. This is achieved by utilising a network of smart plugs to monitor the real-time and historical power consumption information of different plug loads operating within the building. Other useful capabilities of such systems include using different control features such as remote control and schedule-based control to empower users to actively manage their plug loads based on predefined operating schedules to reduce energy wastage.

While plug load management systems have been commonly applied within the residential context under the broad definition of smart home systems, their application within commercial workplaces have not been well investigated. Despite the rising energy contribution of plug loads towards the building's overall energy use, more attention has been placed on developing smart energy management systems for other building systems such as lighting and HVAC systems due to their high energy contributions. The few studies that investigated the adoption of plug load management systems within commercial spaces also reported user concerns related to the inconvenience of actively managing their plug loads while performing their jobs and the worrying prospect of losing control of their critical devices [4]. These findings highlight the need to develop more intelligent plug load management systems

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https://doi.org/10.1016/j.buildenv.2022.109472
Received 28 May 2022; Received in revised form 31 July 2022; Accepted 2 August 2022
Available online 17 August 2022

capable of reducing the users' burden by automating their plug load's operation to reduce energy wastage while ensuring that users can still maintain control over their plug loads.

Given these findings, several promising advancements have been made in the field of occupancy-driven control systems, which can automate the operation of different building systems based on the occupancy information in the building [5]. Successful applications of such technologies have been found in HVAC and lighting systems where the temperature setpoint and luminaries' brightness levels can be adjusted based on the building's real-time occupancy levels to reduce energy wastage [6,7]. However, the application of this technology in plug load management systems is still in the infant stages and requires more investigation regarding its feasibility in real-world applications.

1.1. Study objective and contributions

The objective of this study is to address the rising energy contributions of plug loads in the workplace by proposing a novel IoT-based occupancy-driven plug load management system named Plug-Mate. The contributions of this study are listed as follows:

- The proposed system is equipped with a non-intrusive indoor localisation system, advanced plug load identification capabilities, and a personalised user interface to automate the users' plug loads based on their high-resolution occupancy information, plug load type and diverse usage preferences.
- Six different plug load control strategies (i.e., manual controls, predefined schedules, occupancy-driven controls, and hybrid controls) were evaluated based on their energy savings and user satisfaction levels during a 5-month field study within a university office space.
- An analysis for a building-wide implementation of the proposed system and deployment considerations were discussed to highlight the system's feasibility and financial viability for real-world implementations.
- A comprehensive review of existing plug load management approaches was provided, categorised based on different load monitoring and control strategies while highlighting the limitations of existing systems.

2. Literature review

This section provides a comprehensive review of existing plug load management systems based on different energy monitoring approaches and control strategies proposed by past studies.

2.1. Energy monitoring in plug load management systems

Energy monitoring is one of the core features found in existing plug load management systems that enable users to monitor their plug load energy consumption patterns over time.

2.1.1. Load monitoring approaches

There are two different approaches to perform plug load energy monitoring: non-intrusive load monitoring (NILM) and intrusive load monitoring (ILM) approaches [8].

NILM approaches usually require installing a smart power meter at the building's main electrical panels to capture the building or floor's aggregated power consumption information. The recorded data is subsequently passed through a load disaggregation algorithm to identify the individual plug loads currently operating within the building [9]. While this approach has a low setup cost and does not intrude upon the occupants during data collection, the performance of the load disaggregation algorithm is affected by the number of operational plug loads in the building, where a large number of plug loads can lead to significant signal distortion and a complex energy signature [10]. Furthermore, NILM approaches also perform poorly when identifying plug loads that do not consume a significant amount of power [11]. Therefore the use of NILM approaches in office buildings are severely limited due to the large number of plug loads (i.e., laptops and monitors) that are typically found operating during office working hours.

On the other hand, ILM approaches involve installing smart power plugs at each electrical socket in the building to obtain a high-resolution view of each plug load's power consumption information by eliminating the load disaggregation step. On top of the increased resolution, the declining sensor cost and improved software integration support with existing smart home systems have led to the rising popularity of ILM approaches and various applications related to the users' plug load usage patterns [12,13].

2.1.2. Plug load management through energy monitoring

By tracking the users' plug load usage patterns through the various load monitoring approaches highlighted in Section 2.1.1, the information can be processed and presented to the users to encourage them to adopt positive energy management habits. Some examples of these behavioural intervention strategies include using an interactive visual display to provide eco-feedback about the users' historical energy consumption and inform them of their environmental impacts [14]. Other information-driven strategies, albeit more intrusive, include sending out scheduled email reminders to prompt users to switch off their plug loads at the end of the day as well as providing educational tips on how to reduce their current energy consumption [15]. Some studies have also assessed the effectiveness of different incentives, such as monetary and social rewards, in encouraging workers to adopt sustainable energy management practices in the workplace [16]. Apart from these strategies, other innovative solutions include using gamification approaches to increase the users' knowledge and awareness of different energy conservation strategies within the workplace [17]. Some studies have also attempted to engage users in friendly competition as they form teams within the organisation and compete to complete the highest number of resource-saving actions [18].

However, these strategies' long-term effectiveness is highly uncertain as they are heavily dependent on successfully influencing the users to voluntarily change their existing behaviours and begin actively managing their plug loads. This limitation is especially relevant in commercial workplaces where users are often not responsible for paying for their electricity usage and are hence less motivated to reduce their current energy consumption, unlike in residential spaces [19].

2.2. Energy control in PLMS

On top of energy monitoring, the recent advancements in sensing and control technologies made it possible for users to control their plug loads remotely, by setting operating schedules or automating their plug loads based on their presence information. The following section provides more details of these control strategies.

2.2.1. Remote and schedule-based controls

Some of the standard control features found in most plug load management systems include remote control and schedule-based controls. Remote control allows users to control their plug loads remotely through a digital interface while they are not physically present at their desks, while schedule-based controls allow users to set operating schedules for their devices to reduce standby power consumption during non-active periods.

An example of such a system was proposed by Yun et al. which comes equipped with remote and schedule-based controls and users also are provided with eco-feedback about their energy usage. Based on a 27-week field study with 80 office workers, the study concluded that the inclusion of schedule-based control on top of eco-feedback can lead to energy savings up to 38%, which is greater than the inclusion of remote control (i.e., 25%) and a purely eco-feedback-based approach (i.e., 13%) [20]. Tsai et al. also proposed an intelligent control system that uses wireless smart sockets and IoT technology to automatically detect and switch off unused plug loads to reduce their standby power consumption [21]. Lastly, Metzger et al. evaluated the effectiveness of schedule-based controls by allowing users to set operating schedules for two buildings to achieve energy savings between 13%–54% and 14%–27% for laptops and monitors, respectively [22].

2.2.2. Occupancy-driven controls

Apart from remote and schedule-based controls, a small number of studies have also proposed occupancy-driven plug load management systems that use various sensing and IoT technologies to infer the building's occupancy levels and automate the users' plug loads based on their presence information. With the plethora of technologies capable of collecting user location data with varying degrees of accuracy and resolution [23], existing plug load management systems generally adopt less advanced technologies such as motion sensors based on passive infrared, ultrasonic or microwave technologies to detect the users' presence at their desks. For instance, Park et al. proposed a smart plug load management system that uses motion-based occupancy sensors and predefined schedules to control the power supply to different appliances connected to a power strip. The proposed system was reportedly able to significantly reduce the power consumption of the appliances evaluated based on a five-day field study [24]. Another study conducted by NREL evaluated three different approaches for reducing plug load energy consumption in a commercial building. The approaches evaluated includes an automated energy management system that switches off plug loads in an area when it is unoccupied for a certain period, inciting behavioural change using information feedback and selective messaging, and encouraging competition between different office workers. In the end, the occupancy-driven energy management system was able to achieve a 21% energy reduction when compared to the baseline strategy [25]. A study conducted by Zhang et al. also concluded that a system combining schedule-based and occupancy-driven controls could result in annual savings between 0.42–0.74 kWh/sqft after evaluating different integrated designs in small and large office buildings [26]. The study further concluded that by maximising the occupancy sensors' utility, it is possible to increase energy savings by an additional 30%.

2.2.3. Limitations

Despite the different energy monitoring and control strategies proposed in the earlier sections, the main limitations of existing plug load management systems can be attributed to issues related to deployment viability, low energy savings reported, and user resistance towards the acceptance of such systems. This is especially true in the context of commercial spaces as occupants are often not responsible for their energy usage. A recent field study involving the deployment of a plug load management system, equipped with remote and schedule-based controls, reported low energy savings between 11%–18% due to poor system adoption [27], thereby severely limiting the cost-effectiveness and financial viability of the overall system [28]. Another study evaluating different plug load management strategies also reported frequent occurrences of sensor detection errors when using passive infrared sensors to detect the users' occupancy within the room, leading to user frustration when the plug loads are erroneously switched off [29].

These limitations highlight the need for more intelligent systems that can reduce both the energy consumption of plug loads and user burden while maintaining an optimal balance between plug load automation and user control. In this study, we aimed to bridge this gap by proposing Plug-Mate, a novel IoT-based occupancy-driven plug load management system. Our proposed system is capable of automating the users' plug loads based on (1) their high-resolution occupancy information captured through an non-intrusive indoor localisation system, (2) plug load type information inferred through an advanced plug load identification feature, and (3) their diverse control preferences for each plug load type through a personalised user interface, capable of visualising the users' historical energy consumption.

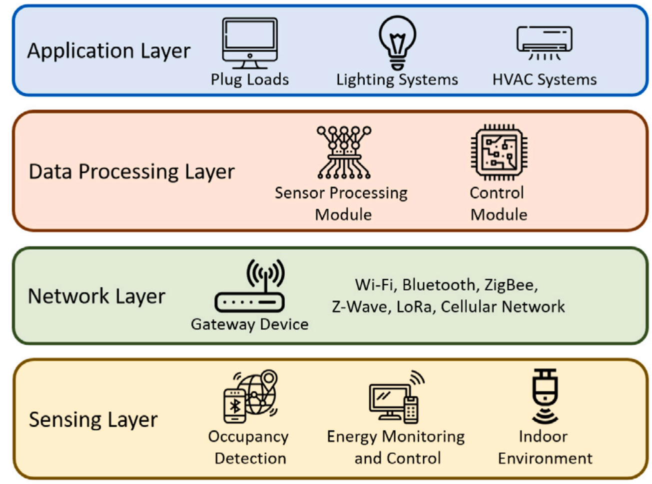

Fig. 1. The IoT framework for occupancy-driven smart energy management systems, on which Plug-Mate was based. The framework consists of four interacting layers (i.e., Sensing layer, Network layer, Data Processing layer, and Application layer) that perform different functions to enable the automation of different plug loads based on the users' occupancy information and other sensing data.

3. Plug-Mate system architecture

This section covers a detailed description of our proposed system architecture, starting with a general overview of the IoT framework that the system is designed based on, followed by a detailed description of each component and subsystem within Plug-Mate.

3.1. IoT framework

Plug-Mate is based on a custom 4-layered IoT framework for occupancy-driven smart energy management systems, which consists of a Sensing layer, a Network layer, a Data Processing layer, and an Application layer, as depicted in Fig. 1.

Sensing Layer: The Sensing Layer comprises different sensors to collect information about the occupants and the building's current state to inform Plug-Mate's automation logic. These sensors include occupancy sensors to capture the wireless signals emitted by the occupants' smartphone devices and smart plugs to support real-time energy monitoring of the occupants' plug loads. In the case that the system is extended to other building systems (i.e., lighting and HVAC systems), additional sensors such as indoor environmental sensors and illuminance sensors can be deployed within this layer to support the system's control logic.

Network Layer: The Network Layer serves as a data bridge between the sensors in the Sensing Layer and the sensor processing and control modules in the Data Processing Layer. More specifically, the Network Layer facilitates the transmission of sensing data via various wireless communication protocols to the system servers running the sensor processing and control logic, before transmitting the control instructions to the actuators controlling the plug loads' operation.

Data Processing Layer: The Data Processing Layer is responsible for processing the sensing data captured by the sensors deployed in the Sensing Layer and generating the appropriate control instructions via the Control Module to optimise the operation of each plug load and reduce its energy wastage. In the case of Plug-Mate, multiple sensor processing modules were also developed to infer the occupants' high-resolution location and plug load type information based on the sensor data captured in the Sensing Layer to allow the system to make advanced control decisions based on these inputs.

Application Layer: Finally, the Application Layer is a hardware layer that encompasses the various building systems, including plug

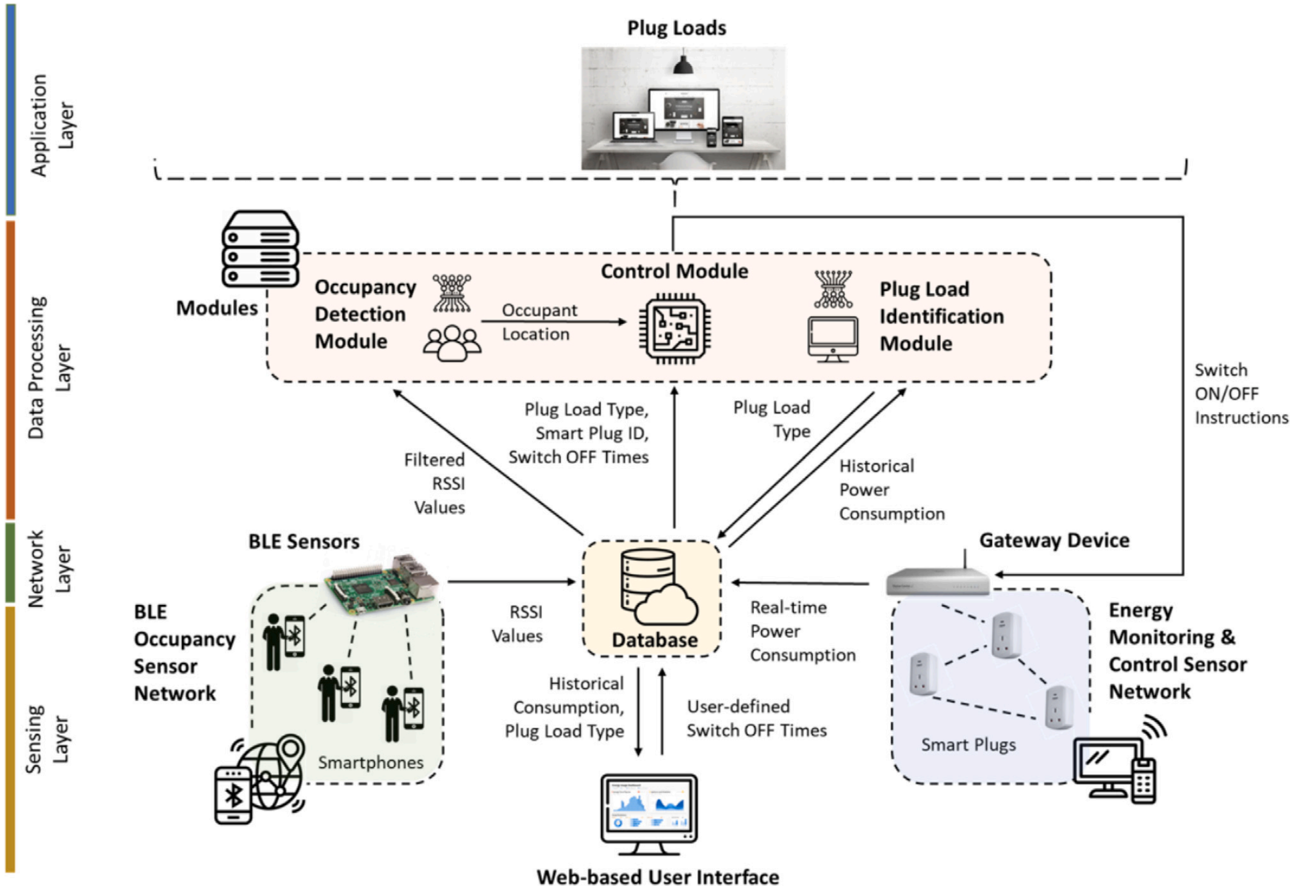

Fig. 2. System architecture of Plug-Mate and the system interactions between different modules and sensor networks.

loads, HVAC systems, and lighting systems, by integrating their existing controls with the system's actuators. In the case of Plug-Mate, this layer consists of the personal devices used exclusively by a single individual or shared devices that are used by multiple individuals throughout the day.

The following section provides a detailed description of the major components and subsystems within Plug-Mate based on the IoT framework described in this section.

3.2. System description and components

Plug-Mate comprises a system of interconnected modules and sensor networks to infer real-time information about the users' high-resolution occupancy information, plug load type, and usage preferences to automate their plug loads and reduce energy consumption. The remainder of this section provides a detailed description of each component within our system, as depicted in Fig. 2.

3.2.1. Energy monitoring & control sensor network

The Energy Monitoring & Control Sensor Network comprises of an interconnected network of smart plugs that records the users' real-time plug load power consumption information, which is transmitted to a gateway device using the Z-wave communication protocol. Through the gateway device, the power consumption information is subsequently transmitted to the system's database for storage via the Wi-Fi communication protocol. Each smart plug is configured to record the plug load's power consumption once every minute (i.e., 1/60 Hz) to reduce network latency and data storage cost. Moreover, each smart plug is equipped with an inbuilt actuator that enables it to be programmatically switched ON and OFF through an API call, which is triggered based on Plug-Mate's automation logic.

The benefit of adopting the Z-wave communication protocol is that it utilises a mesh network of smart plugs to relay the information collected by each sensor, thereby allowing the data to be transmitted over longer distances beyond the original range of the gateway device. This feature is especially useful in a built environment where the network range is often limited by the obstacles and wall partitions found within the building. Moreover, the Z-wave communication protocol is an energy-efficient and practical alternative to other wireless protocols such as Wi-Fi and ZigBee, making it a popular choice in many existing smart home and office automation systems [30].

3.2.2. BLE Occupancy Sensor Network

The BLE Occupancy Sensor Network consists of a system of BLE sensors built using Raspberry Pi model Bs, which are programmed to detect the users' proximity to each sensor by periodically scanning for the users' Bluetooth-enabled smartphone devices based on their devices' MAC addresses. When a user is within the scanning range of one of our sensors, the BLE wireless signals emitted by the user's smartphone device will be captured by a nearby sensor and processed to generate a received signal strength indicator (RSSI) value.

The magnitude of the RSSI value provides a indication of the relative quality of the received signal from the users' device. By combining multiple RSSI values captured by different sensors deployed within the area and passing them through advanced machine learning algorithms, it is possible to infer the user's location within the area in real-time. The details of this inference process is covered in greater detail in the following section when describing the Occupancy Detection module. This indoor localisation approach is considered to be more scalable and less intrusive than existing approaches in the literature as users are not required to install a mobile application or carry around wearable sensors to accurately identify their location within the building [31].

By combining the generated RSSI value with the device's MAC address and timestamp information, this record is transmitted to the Database for storage in real-time using the BLE sensors' inbuilt wireless Wi-Fi adapter.

3.2.3. Database

Our proposed system comes equipped with a commercial-grade PostgreSQL cloud database hosted by Heroku to store information about the users, their assigned plug loads, and the sensor data captured by the various sensor networks for subsequent retrieval. Some examples of the information stored include the users' smartphone MAC addresses, the unique IDs of the smart plugs assigned to each user, the RSSI values captured by the BLE beacons in the BLE Occupancy Sensor Network, and the power consumption information captured by the smart plugs in the Energy Monitoring & Control Sensor Network. Each user is also assigned a unique user ID, which serves as a primary key connecting the different SQL tables together.

3.2.4. Web-based user interface

A personalised web-based user interface is also integrated within Plug-Mate to allow users to customise the system's automated controls via an intuitive control interface and inform users of their historical energy consumption through an interactive energy dashboard. The user interface is developed using the Python-based Django web framework, with the users' energy consumption information visualised using the Dash Plotly library and the control interface implemented using the React.JS library.

Control Interface The control interface allowed users to manage the automation settings for each plug load type through three different control features supported by the Plug-Mate system. These control features include remote control, presence-based control, and schedule-based control (refer to Fig. 3).

- **Remote Control**: The remote control feature enables users to switch ON/OFF their plug loads remotely by toggling the corresponding switches on the control interface. This control feature is especially useful for users who constantly forget to switch off their plug loads when leaving their desks for long periods, such as at the end of the workday.
- **Presence-based Control**: Under presence-based controls, users can set specific time intervals for each plug load to be switched off after the users have left their desks. The users' presence information is inferred through the Occupancy Detection module by processing the sensor data captured by the BLE occupancy sensors.
- **Schedule-based Control**: The schedule-based control allow users to set operating schedules for each plug load type based on different days of the week. After an operating schedule has been assigned to a particular plug load, it is automatically switched ON at the start of the schedule and switched OFF at the end of the schedule. Therefore, users can still switch ON/OFF their plug loads using other control features during or beyond the scheduled operating periods.

It should be highlighted that the presence-based control and schedule-based control only require a one-time setup process, following which Plug-Mate can proceed to automate the users' plug loads based on their preferred control settings. Furthermore, when multiple control features are enabled simultaneously for the same plug load type, the control hierarchy obeys the following order: remote control > presence-based control > schedule-based control. This order ensures that the users' plug loads are not scheduled to be switched off when they are still present at their desks, and users can overwrite the system's controls anytime by using the remote control feature.

Energy Dashboard The energy dashboard allows users to learn more information about their consumption patterns by providing interactive visualisations of the users' historical energy consumption for

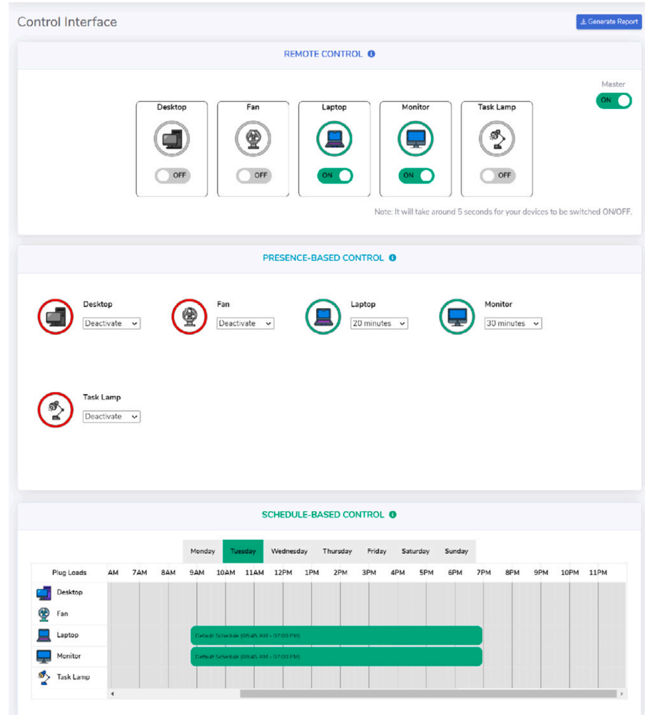

Fig. 3. Plug-Mate Control Interface.

different plug load types, cumulative energy and cost savings based on past consumption, and includes an achievement system where users are awarded points for adopting positive plug load management habits.

3.2.5. Modules

Within the Modules component, the power consumption data recorded by the smart plugs in the Energy Monitoring & Control Network and the RSSI values recorded by the BLE occupancy sensors are processed to identify the occupants' plug load types and their real-time location within the building, respectively. By combining this information with the users' preferred control settings in the Control Interface, the most appropriate control instructions are determined based on a series of advanced control rules, where the users' plug loads will be switched ON/OFF accordingly. This process is executed by three interconnected modules: the Plug Load Identification module, the Occupant Detection module, and the Control module.

Plug Load Identification Module The plug load identification module's function is to infer the users' plug load type information based on the real-time power consumption information captured by the smart plugs assigned to each user.

The plug load identification process is achieved using a multi-staged approach (refer to Fig. 4) by first identifying the periods where the plug load is in the active state for a prolonged period (i.e., active period). An active period is identified by first differentiating when the plug load is in the active state and inactive state by setting a power threshold of 2.5 W. This threshold is set based on our observation that the standby power consumption of most plug loads does not exceed 2.3 W. Given that certain plug loads may fluctuate between the active state and inactive state while in use, a threshold duration of 10 min is set such that the plug load must be in the inactive state for this minimum duration before the active period is considered to have ended. Otherwise, they will be considered random power fluctuations within an active period.

After identifying the plug load's active periods, a feature extraction step is performed within each active period to extract a set of

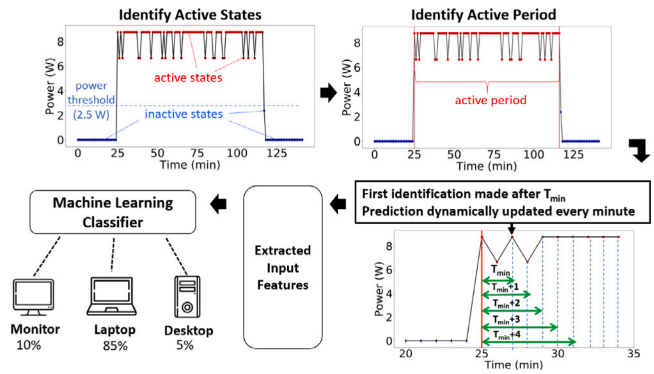

Fig. 4. The data processing pipeline used within the Plug Load Identification module to process the users' power consumption information and identify their corresponding plug load types.

time-series features based on a predefined time window T. These features include the plug load's instantaneous power p_t, maximum power recorded during time window T, p_{max}, minimum power recorded during time window T, p_{min}, average power during time window T, p_{ave}, power variance during time window T, p_{var}, average power consumption when the plug load is in the active state during time window T, $p_{aveactive}$, average peak power during time window T, $p_{avepeak}$, absolute power difference from the previous power value at time t, d_t, the fraction of time where the plug load is in the active state during time window T (i.e., duty cycle), and the corresponding bin sizes and the average time interval between the energy delta values of each bin in an 8-bin histogram (i.e., histogram features). The equations for some of these time-series features are provided below.

$$p_{max} = max\{p_i\},\ where\ i \in T \tag{1}$$

$$p_{min} = min\{p_i\},\ where\ i \in T \tag{2}$$

$$p_{ave} = \frac{\sum_{i\in T} p_i}{|T|} \tag{3}$$

$$p_{var} = \frac{\sum_{i\in T}(p_i - p_{ave})^2}{|T|} \tag{4}$$

$$p_{aveactive} = \frac{\sum_{i\in T,\ p_i>2.5W} p_i}{\sum_{i\in T,\ p_i>2.5W} 1} \tag{5}$$

$$p_{avepeak} = \frac{\sum_{j\in S} max\{p_k\},\ where\ k \in s_j}{\sum_{j\in S} 1} \tag{6}$$

$$d_t = |\ p_t - p_{t-1}\ | \tag{7}$$

The length of the time window used during feature extraction is also defined using a dynamic time window strategy by first setting it at a minimum length of 5 min, T_{min}. As the active period continues to extend, the length of time window T will also increase accordingly to utilise the maximum amount of historical data available for feature extraction and ensure high classification accuracy.

After extracting the relevant time-series features following the processing steps described above, they are subsequently passed into an ensemble machine learning model based on the Bagging algorithm to infer the plug load type information. A comprehensive evaluation of the plug load identification model has been conducted in a previous study using different classification algorithms, plug load types, and parameter settings to identify the best performing model to be used within the Plug-Mate [8]. Finally, the inferred plug load type information is stored in the Database for subsequent retrieval.

Occupancy Detection Module The Occupancy Detection module is responsible for processing the RSSI values captured by the BLE occupancy sensors and using the processed RSSI values to infer the users' location within the building in real-time through a machine learning model.

The process begins by extracting the RSSI values from the Database based on the user's device MAC address and sorting them based on the timestamp information tagged to each RSSI value. Following this, each entry is transformed into an RSSI tuple $\langle x_1, x_2, x_3, \ldots, x_n, t\rangle$, where each item in the tuple, $x_i, i = 1, \ldots, n$, corresponds to the RSSI values recorded by a particular BLE occupancy sensor in the area, followed by the timestamp information, t. However, due to the unsynchronised nature of the sensors' scanning patterns, this can result in the presence of missing values in the RSSI tuple for certain sensors. This issue of missing values in the RSSI tuple is addressed by performing a forward fill of the corresponding sensors' last recorded RSSI values if it is within the BLE sensors' scanning window of 1 min. Otherwise, an arbitrarily large RSSI value is assigned for that particular BLE sensor to signify that the user is outside the sensor's scanning region. This imputation strategy is found to be less computationally intensive and performs relatively well compared to more advanced imputation algorithms proposed in the literature [32] as users do not tend to change their locations frequently throughout the day. This observed behaviour allows each sensor's last recorded RSSI value to remain valid for a short time window.

Based on the processing and imputation steps described above, the resulting RSSI tuple is passed into a machine learning model (i.e., occupancy detection model) to infer the users' zone-level location within the building in real-time. The model follows an ensemble 1-vs-all architecture where a Gradient Boosting binary classifier is trained for each zone, z, to output a probability, $P_{z,u}$, of the user u's presence within the zone based on an RSSI tuple of the nearby sensors. By comparing each classifier's probabilistic output, $P_{z,u}$, the zone with the highest probability will be selected as the user u's inferred location, l_u (refer to Eqs. (8) and (9)).

$$P_{z,u} = f_z(\langle x_{1,u}, x_{2,u}, x_{3,u}, \ldots, x_{n,u}\rangle) \tag{8}$$

$$l_u = argmax(P_{z,u}, z \in 1, 2, \ldots, Z) \tag{9}$$

A comprehensive evaluation of the occupancy detection model was conducted in a previous study between different model architectures using supervised and semi-supervised learning approaches to identify the best model architecture to be used within Plug-Mate [33]. Based on the evaluation conducted, the occupancy detection model was able to report an average localisation accuracy of 91% when evaluated in two different office spaces.

Control Module Based on the users' plug load type and presence information, the control module is responsible for automating the users' plug loads following a set of control rules depending on the users' arrival or departure from their desks.

During an arrival event, the Occupant Detection module first detects the user's arrival and triggers an arrival event sequence within the Control module by passing the user's unique ID. The Control module then retrieves the ID information of the smart plugs assigned to the user from the Database using the user's ID information. Following this, a series of API calls are constructed based on the list of smart plug IDs retrieved before sending the control instructions to the corresponding smart plugs via the gateway device to instruct them to switch ON the users' plug loads in real-time (refer to Fig. 5).

During a departure event, the Occupant Detection module first detects the user's departure and triggers a departure event sequence within the Control module by passing the user's unique ID and departure time. The Control module then retrieves the ID information of the user's smart plugs that are currently active, together with their plug load type information using the user's ID information. Following this, the Control module then retrieves the switch-off times for each plug load type from the Database, which was predefined by the user via the

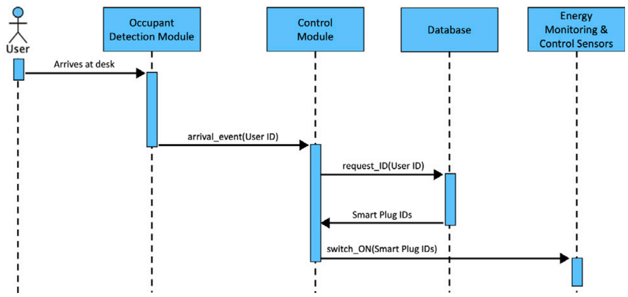

Fig. 5. Sequence diagram of an arrival event.

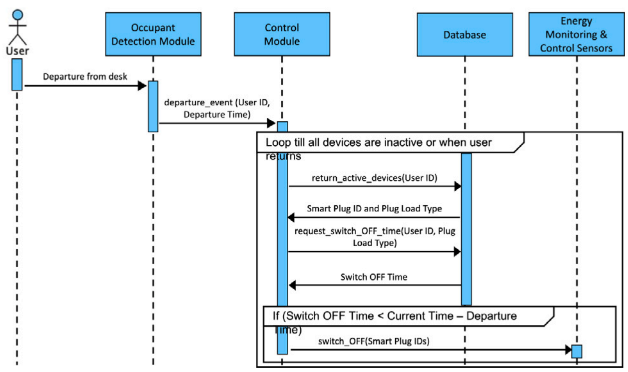

Fig. 6. Sequence diagram of a departure event.

Control Interface. By keeping track of the user's departure time and the assigned switch-off times for each plug load type, the plug loads that are active for periods longer than their assigned switch-off times will be switched OFF by performing an API call to their respective smart plugs (refer to Fig. 6).

In the case of operation-critical plug loads, such as desktops, that follow a specific switch-off procedure, a command-line shutdown application was also set up on the users' devices to allow the Plug-Mate system to remotely execute a shutdown command on their devices based on the same control logic described above to avoid damaging the plug loads.

4. Field study

4.1. Setup

Based on the system architecture described in Fig. 2, Plug-Mate was implemented and evaluated during a field study, which lasted over a period of 5 months and involved 10 participants in a medium-size office. The study area selected for this field study is a university office space that spans over 338 m^2 and houses over 43 researchers, administrative staff, and faculty members. The layout of the study area contains a mixture of single private offices, open and closed office spaces, as well as a meeting room, printer area, and pantry as shown in Fig. 7. Before the commencement of the study, the BLE occupancy sensors and smart plugs were installed at the participants' desks, where the setup of the various sensors is shown in Fig. 8. The participants' login credentials into the web-based user interface were also prepared in advance and distributed to the participants, where they were provided a short hands-on tutorial on how to use the user interface and its various features.

The list of plug loads considered in this field study includes 10 monitors, 10 laptops, 3 desktops, and 7 miscellaneous plug loads comprising 2 task lamps, a coffee machine, and 4 chargers. These plug loads were considered in this field study as they are the most common plug load types typically found in a standard office space and can contribute up to 70% of the total plug load profile in an office building. [34].

4.2. Control strategies

Throughout the field study, a total of six control strategies were evaluated involving the use of different control features, including complete manual control (CS1), pre-defined schedule-based controls (CS2 and CS3), occupancy-driven controls (CS4 and CS5), and hybrid controls (CS6). Each control strategy was evaluated over 3 weeks, and a detailed description of each control strategy is provided as follows:

CS1 Baseline: In the baseline strategy, all participants have complete manual control over their plug loads with no automation features in place.

CS2 Pre-defined operating schedules: The second control strategy involves introducing pre-defined operating schedules for the participants' plug loads. More specifically, the Control module is configured to retrieve the smart plug IDs assigned to all system users at 7 PM every day and perform the necessary API calls using the smart plug IDs to switch OFF all devices simultaneously (refer to Fig. 9).

CS3 Pre-defined operating schedules with occupancy profiles: The third control strategy extends upon the second control strategy by introducing pre-defined operating schedules to manage the users' plug loads and accounts for the differences in the users' occupancy patterns by assigning different shutoff timings based on their occupancy profiles. By referencing a previous study examining the occupancy patterns of 46 participants in a similar study area, the authors identified three distinct occupancy profiles, namely Regulars, Mobile Workers, and Flexi-timers [33]. Regulars follow a regular office worker's daily schedule by coming to work around 9–10 AM, taking their lunch between 12–1.30 PM, and leaving work for the day after 6 PM. Mobile Workers tend to follow a similar first arrival and last departure time as Regulars but are less likely to be found present at their desks during office hours due to their mobile nature. Finally, Flexi-timers tend to follow non-regular office hours by having a much later first arrival and last departure time than the other two profiles. Of the 10 participants involved in the study, 4 were identified as Regulars, while the remaining 6 were categorised as Flexi-timers based on their occupancy patterns collected during the first three weeks of the study (i.e., during CS1). Based on this categorisation, this control strategy involves configuring the Control module to retrieve the smart plug IDs assigned to the Regulars at 7 PM and performing the necessary API calls using the smart plug IDs retrieved to switch OFF their devices simultaneously (refer to Fig. 10). Similarly, the Control module is configured to switch off the devices belonging to Flexi-timers at 1 AM every day using the same control sequence described above.

CS4 Occupancy-driven controls: The fourth control strategy introduces occupancy-driven controls where the participants' plug loads are configured to be switched off 5 min after they are detected to have left their desks by the Occupant Detection module. The control sequence is based on a simplified version of Fig. 6 where the shutoff time for all plug loads is set at 5 min, regardless of their type and user preferences (refer to Fig. 11).

CS5 Occupancy-driven controls with plug load identification: The fifth control strategy extends upon the fourth control strategy by combining occupancy-driven controls with plug load identification capabilities. More specifically, the Plug Load Identification module is activated to infer the users' plug load type information based on their energy signatures in real-time. By combining the users' departure time with their plug load type information, each device is assigned a different shutoff time based on its plug load type and criticality level. The shutoff times for operation-critical devices such as laptops and desktops are assigned a longer shutoff time of 15 min and 30 min, respectively, to avoid any accidental loss of work when participants leave their desks for short periods. On the other hand, non-critical plug loads such as monitors and other miscellaneous devices are assigned a shorter shutoff time of 10 min and 5 min, respectively. The control sequence is based on a slightly simpler version of Fig. 6 where the shutoff time does not account for user preferences (refer to Fig. 12).

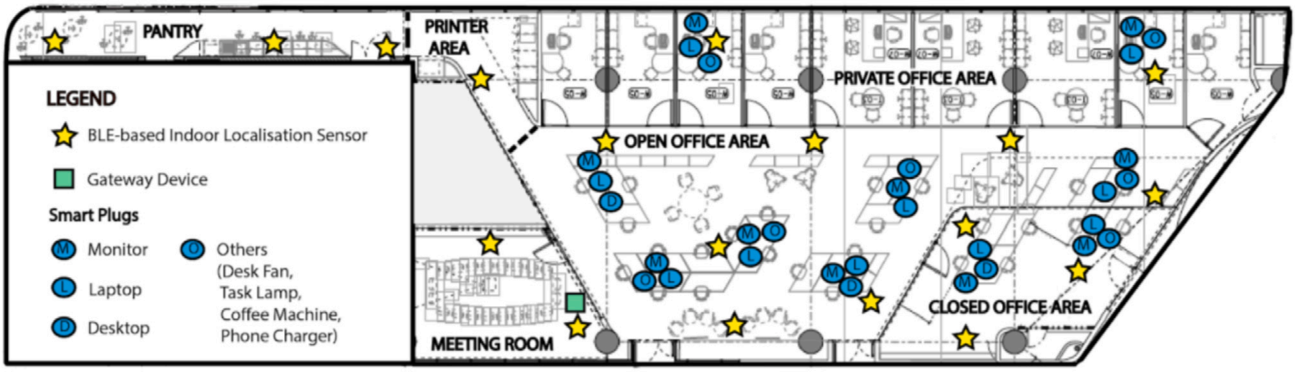

Fig. 7. Layout of the study area showing the locations of the various BLE occupancy sensors (18), gateway device (1), and smart plugs (30).

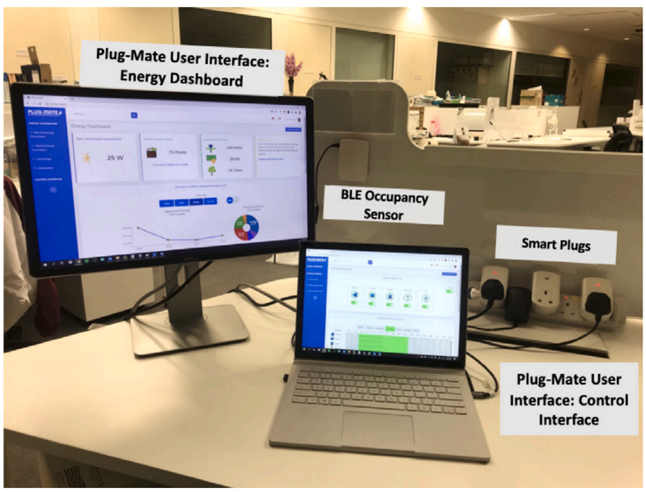

Fig. 8. Sensor setup at a participant's desk.

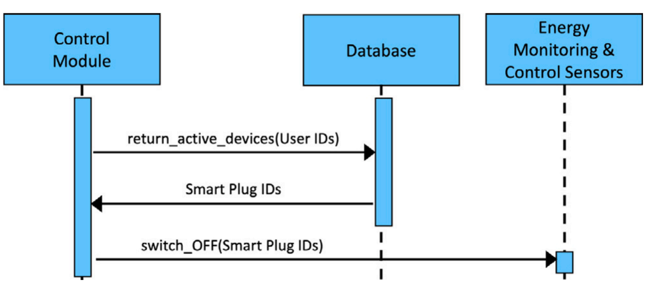

Fig. 9. Sequence diagram of Control Strategy 2.

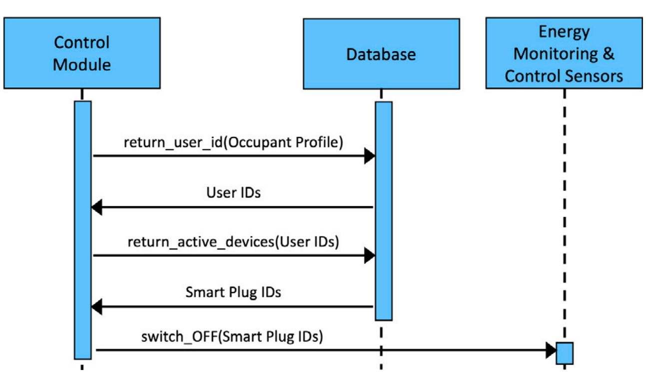

Fig. 10. Sequence diagram of Control Strategy 3.

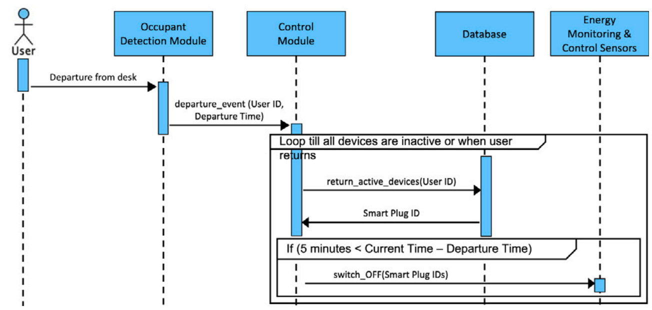

Fig. 11. Sequence diagram of Control Strategy 4.

CS6 Occupancy-driven controls with plug load identification and user preferences: The last control strategy involved the full activation of Plug-Mate's capabilities, where the users' plug loads are automated based on their presence information detected via the Occupant Detection module, plug load type information inferred via the Plug Load Identification module, and user-assigned shutoff timings provided via the User Interface. The complete control sequence has already been described above and depicted in Fig. 6. Users can also combine occupancy-driven controls with other control features such as remote control and schedule-based control to develop hybrid control strategies for specific plug load types to suit their current plug load usage preferences.

5. Results

5.1. Impact of control strategies based on energy savings and user satisfaction

Each control strategy is evaluated based on the energy savings that is achieved relative to the baseline strategy (i.e., CS1) and the participants' overall satisfaction levels.

The participants' user satisfaction levels are evaluated based on three evaluation metrics adapted from various technology adoption studies [35–37]: convenience, usefulness, and user acceptance. Convenience refers to how easily the participants can incorporate the prototype system in their daily routines to help manage their plug load energy consumption. Usefulness is defined as how well the prototype system can help the participants in managing their plug load energy consumption. Lastly, user acceptance refers to how likely the participants would accept using the prototype system to manage their plug load energy consumption in the long run. After the study participants have experienced each control scenario for three weeks, a short interview was conducted at the end of each control scenario to learn more

Table 1
Energy performance of each plug load type based on the six control strategies evaluated over 18 weeks. The energy savings achieved in each control strategy is expressed as a percentage of the baseline strategy. "Others" refer to all miscellaneous loads including coffee machines, task lamps, and chargers.

Plug load types	Baseline	Pre-defined schedules		Occupancy-driven controls		
	S1 (kWh)	S2 (kWh)	S3 (kWh)	S4 (kWh)	S5 (kWh)	S6 (kWh)
Monitor (10)	67.1	44.36 (33.9%)	36.81 (45.2%)	28.29 (57.8%)	28.94 (56.9%)	28.39 (57.7%)
Laptop (10)	111.56	66.09 (40.8%)	55.45 (50.3%)	45.94 (58.8%)	47.50 (57.4%)	46.12 (58.6%)
Desktop (3)	154.02	81.11 (47.3%)	69.62 (54.8%)	56.83 (63.1%)	60.67 (60.6%)	84.72 (58.6%)
Others (7)	12.23	7.76 (36.6%)	7.18 (41.3%)	6.43 (47.4%)	6.42 (47.5%)	7.39 (39.6%)
Total (30)	**344.97**	**199.32 (42.2%)**	**169.06 (51.0%)**	**137.49 (60.1%)**	**143.53 (58.4%)**	**166.62 (51.7%)**

Table 2
Mean and standard deviation (SD) of user satisfaction levels for the six control strategies rated based on a maximum score of 5.

User satisfaction metrics	Pre-defined schedules		Occupancy-driven controls		
	S2	S3	S4	S5	S6
Convenience	Mean: 3.2 SD: 1.1	Mean: 3.6 SD: 1.1	Mean: 4.6 SD: 0.7	Mean: 4.7 SD: 0.7	Mean: 4.7 SD: 0.6
Usefulness	Mean: 3.3 SD: 0.9	Mean: 3.9 SD: 1.3	Mean: 4.3 SD: 0.7	Mean: 4.8 SD: 0.7	Mean: 4.8 SD: 0.6
User acceptance	Mean: 2.8 SD: 0.9	Mean: 3.5 SD: 1.1	Mean: 3.8 SD: 1.0	Mean: 4.5 SD: 0.5	Mean: 4.8 SD: 0.7
Total	**Mean: 3.1 SD: 1.0**	**Mean: 3.7 SD: 1.2**	**Mean: 4.2 SD: 0.8**	**Mean: 4.6 SD: 0.8**	**Mean: 4.7 SD: 0.7**

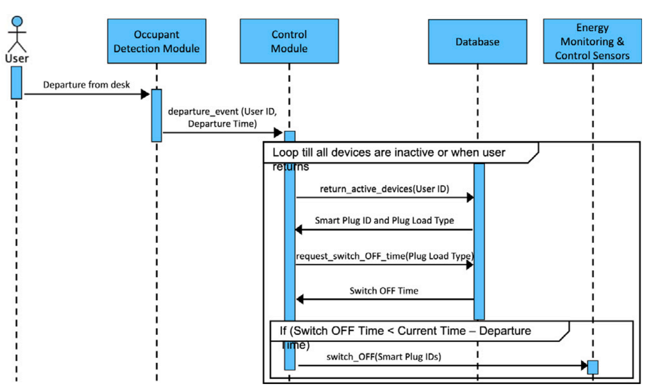

Fig. 12. Sequence diagram of Control Strategy 5.

about their experiences. Participants were also asked to rate each control scenario based on the three evaluation metrics highlighted above following a 5-point Likert scale to quantify their experiences. In this case, the lowest score of 1 indicates that the system is not convenient, useful or acceptable under a particular control scenario, while the highest score of 5 indicates that the system is very convenient, useful or acceptable. Based on the responses provided by the participants for each control scenario, the average rating and standard deviation for each metric are calculated and provided in Table 2.

Based on the results reflected in Table 1, the introduction of pre-defined operating schedules (i.e., CS2) achieved an average energy saving of 42.2%. Furthermore, by customising the switch off schedules for each participant based on their occupancy profiles (i.e., CS3), we were able to further increase the resulting energy savings to 51.0% by reducing the likelihood of accidentally switching off the participants' plug loads while they are still present at their desks. This occurrence not only has a negative impact on the users' satisfaction levels, as observed when comparing between CS2 and CS3 in Table 2, but this also limits the energy-saving potential of the system as participants are observed to switch their plug loads back on immediately and may forget to switch them off at the end of the day. Overall, CS3 demonstrated a better system performance when compared with CS2, as it achieved higher energy savings and user satisfaction levels for all three metrics.

Despite CS3's better performance over CS2, the overall energy savings and user satisfaction levels achieved through setting pre-defined operating schedules are still significantly lower when compared to occupancy-based controls (i.e., CS4 and CS5). While CS3 attempted to account for the users' occupancy patterns by setting different switch off schedules for different users, this is still unable to fully account for the stochastic nature of the participants' occupancy patterns, which may differ each day, leading to user frustration when their plug loads are switched off while they are still at their desks. Furthermore, participants found the pre-defined operating schedules to be very inconvenient as they have to be constantly aware of the switch off schedules and save their work beforehand to prevent losing their progress.

On the other hand, participants found the occupancy-based controls (i.e., CS4 and CS5) to be significantly more convenient and useful than CS2 and CS3 as the system can react in real-time to the participants' stochastic movement patterns and automate their plug loads accordingly. The additional benefit of occupancy-based control is that it can also reduce energy wastage both during office hours and after office hours when participants leave their desk for extended periods, thereby further boosting the amount of energy savings achieved (i.e., 58.4%–60.1%). When comparing CS4 and CS5, we start to observe a trade-off between energy savings and user satisfaction levels as CS4 achieved a higher overall energy saving of 60.1% but obtained a lower user satisfaction score of 4.2 out of 5.0. On the other hand, CS5 reported a slightly lower energy saving of 58.4% but achieved a significantly higher user satisfaction score of 4.8 out of 5.0 when different switch off intervals are assigned to each plug load type. The longer switch off intervals assigned to critical plug loads such as laptops and desktops were viewed to be especially useful by the participants as they do not have to worry about losing their work when they leave their desks for short periods without saving their work beforehand. This additional feature, made possible through the plug load identification module, resulted in a significant boost in the system's user acceptance score from 3.8 to 4.5 out of 5.0.

Lastly, CS6 can be considered an extension of all of the different control scenarios involving the full system capacity of Plug-Mate. Participants are given more control over the system's automation by allowing them to define different operating schedules for each plug load type and set their corresponding switch off intervals after the participants have left their desks. The inclusion of the user control feature was well-received as it significantly boosted the system's user acceptance score from 4.5 to 4.8 out of 5.0 and resulted in an overall user satisfaction score of 4.7 out of 5.0. This increase is observed despite the slight drop in convenience score, from 4.8 to 4.7 out of 5.0, due to the initial setup process where participants are asked to provide their preferred control settings through the user interface. However, this is a one-time setup process, and its impact is unlikely to be significant over the system's entire lifespan. By referring to Table 1, we also observe a drop in the system's overall energy savings from 60.1% to 51.7% when users are provided with more control over the system's operation. A close examination of each plug load type's energy savings reveals that the drop in overall energy savings can be primarily attributed to the increased energy consumption of desktops, followed by other miscellaneous plug loads. In contrast, the energy savings for monitors and laptops remained relatively consistent. This finding is intuitive as some participants were observed to set very long switch off intervals for their desktops as they are occasionally used to run programs overnight, thereby limiting the amount of energy savings achieved. Similarly, the same observation is found to be true for other miscellaneous plug loads such as chargers. While there seems to be a trade-off between energy savings and user satisfaction levels, CS6 is still deemed to be the best control scenario as having a high user satisfaction score is a strong indication that system users will continue engaging with the system and achieve energy-savings over the lifespan of the system.

6. Discussion

This section provides a detailed analysis of our proposed system for a building-wide implementation and deployment feasibility for large-scale setups.

6.1. Analysis for a building-wide implementation

We have performed a detailed analysis of our proposed system by applying our field study results to the study building to assess a building-wide implementation. All calculations listed below are represented in terms of US dollars.

Based on the energy consumption data collected during the field study, we observed that the baseline energy consumption for 30 plug loads was approximately 345 kWh over three weeks, which is equivalent to 5980 kWh per year (52 weeks). In the case that our proposed system is extended to other office spaces within the building, we can calculate the overall building-wide energy savings by first estimating the total number of plug loads that can be found in the building. This is achieved by calculating the density of each plug load type in the study area (i.e., 12.43 monitors/100 m^2, 11.24 laptops/100 m^2, 3.55 desktops/100 m^2 and 4.14 others/100 m^2.) and multiplying it by the amount of office space in the building (i.e., 7634 m^2). This calculation adds up to a total of 949 monitors, 858 laptops, 271 desktops, and 316 other miscellaneous loads. Next, by multiplying the number of plug loads against their average energy consumption recorded during the baseline period (i.e., S1), the building's total plug load energy consumption for 3 weeks sums up to 30,406.9 kWh. This is equivalent to 14.6% of the building's total energy consumption (207,965.89 kWh) during the same period based on the utility data available. By applying the energy savings achieved during the best control scenario (i.e., 51.7% in CS6), this results in a 7.5% reduction in the building's overall energy consumption and an annual cost saving of USD$49,024 based on a unit energy cost of USD$0.16/kWh [38,39], thereby demonstrating the financial viability of our proposed system.

Considering the significant energy savings that are achievable through our proposed Plug-Mate system, it is worth highlighting that this result is calculated based on several assumptions in mind, which may have an impact on its true value. The first assumption assumes that the study participants' plug load usage patterns are representative of all occupants in the building and will remain consistent throughout the other periods of the year. The second assumption also considers that the study participants' plug load ownership patterns are representative of all occupants within the building.

Lastly, it should be noted that other plug loads such as printers, projectors, and personal heaters are also significant energy contributors, which were not considered in this study. Therefore, a broader application of Plug-Mate to other plug load types can potentially increase the overall energy savings achieved further.

6.2. Feasibility of deployment

Apart from the system's cost-effectiveness, it is also crucial to carefully consider and evaluate the feasibility of deploying the system in a real-world setting based on the amount of time taken during deployment and other deployment considerations.

During the field study, a total of 18 BLE occupancy sensors, 30 smart plugs, and one gateway device was configured and deployed within the study area (refer to Fig. 7), which was completed within half a working day by two members of the research team. The sensors used in Plug-Mate can be easily retrofitted within existing or new buildings without the need for any electrical rewiring and do not result in any operational downtime during deployment. This feature is crucial, especially when targeting office spaces, as any operational downtime can result in a high financial cost to the company. The system is also easily maintainable as the users can physically remove any faculty sensors from the electrical sockets to return their plug loads to full manual controls and avoid any disruption to their work while they wait for the sensor to be replaced. When the web-based user interface was first introduced to the participants, they were provided with a 1 h hands-on tutorial on using the system and its various features. In the case where the system is deployed within the same study area with all existing occupants (i.e., 43 occupants), it is estimated to take one working day as we will be required to configure a total of 106 smart plugs, which corresponds to the number of plug loads found within the study area. In contrast, the number of BLE-based indoor localisation sensors and gateway devices required is identical to the current setup as they are not dependent on the number of occupants but rather the intended coverage of the study area.

Several considerations should also be highlighted during the deployment process when deciding the deployment location of the BLE occupancy sensors and gateway device within the study area. In the case of the BLE occupancy sensors, their deployment locations are highly dependent on the available power sockets in the study area as the sensors require a constant power source to operate. Furthermore, given that the communication range of a Bluetooth signal is around 10–15 m, the sensors should be placed at most 10–15 m apart from each other and evenly distributed around the deployment area to ensure complete signal coverage. The gateway device should also be deployed in a location where it can connect directly to at least two or more smart plugs while connecting to the rest of the smart plugs indirectly through the Z-wave mesh network. Therefore, to ensure that all smart plugs can form a reliable connection with the gateway device, there should also be an even distribution of smart plugs deployed throughout the deployment area.

7. Conclusion

In this study, we proposed an IoT-based occupancy-driven smart plug load management system, named Plug-Mate, to reduce energy wastage in office spaces by automating the users' plug loads based on their high-resolution occupancy information, plug load type, and plug load usage preferences. The users' occupancy information is captured using an non-intrusive indoor localisation system that detects the wireless signals emitted by the users' Bluetooth-enabled smartphone devices before using advanced machine learning models to identify the users' zone level location. A network of smart plugs is also deployed to monitor the users' real-time power consumption and infer their plug load types based on their energy signatures. Lastly, a web-based user interface is integrated within Plug-Mate to allow users to adjust the system's automated controls based on their preferred control settings and view their historical consumption patterns. The system's feasibility is demonstrated during a 5-months field study in a university office space with 10 participants and evaluated under six different control scenarios. Each control scenario is designed to allow participants to experience different degrees of automation and user control, where it is assessed based on the amount of energy savings achieved relative to the baseline scenario (i.e., CS1) and user satisfaction levels. By comparing the evaluation results among all control scenarios, we were able to identify the control scenario (i.e., CS6) that provided an optimal balance between automation and user control, which reported an overall energy savings of 51.7% and the highest user satisfaction score of 4.7 out of 5.0. Using the energy saving results obtained during the field study, we have also provided a comprehensive analysis for a building wide implementation. Based on our calculations, it is found that the implementation of Plug-Mate is likely reduce the building's overall energy consumption by up to 7.5%. Finally, we highlighted several considerations that should be accounted for during system deployment, including the deployment location of the BLE occupancy sensors, gateway device, and smart plugs to ensure that the system performs reliably in the long run.

Given that the current version of the Plug-Mate system has been evaluated on a specific set of personal devices (e.g., monitor, laptop, desktop, and other miscellaneous devices), future field studies can consider a broader range of plug loads that are commonly found in commercial office spaces and are likely to benefit significantly from such a system. Future system improvements can also extend the system's control beyond personal devices to shared or communal devices such as printers, coffee machines, paper shredders, and projectors by automating the operation of these devices based on the building's occupancy levels. Another possible future direction is extending this system beyond the automation of plug loads to other building systems, such as lighting and HVAC systems, to form a highly advanced and unified occupancy-driven building control system.

CRediT authorship contribution statement

Zeynep Duygu Tekler: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft. **Raymond Low:** Software, Visualisation, Writing – review & editing. **Chau Yuen:** Supervision, Writing – review & editing. **Lucienne Blessing:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

[1] T. Schwartz, M. Betz, L. Ramirez, G. Stevens, Sustainable energy practices at work: understanding the role of workers in energy conservation, in: Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries, 2010, pp. 452–462.

[2] B.P. Center, Annual Energy Outlook 2020, Vol. 12, Energy Information Administration, Washington, DC, 2020, pp. 1672–1679.

[3] A. Cortese, C. Higgins, M. Lyles, et al., Getting to zero: The 2014 net zero energy status report findings for commercial buildings, 2014.

[4] Z.D. Tekler, R. Low, K.T.W. Choo, L. Blessing, User perceptions and adoption of plug load Management systems in the workplace, in: Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 2021, pp. 1–6.

[5] S. Naylor, M. Gillott, T. Lau, A review of occupant-centric building control strategies to reduce building energy use, Renew. Sustain. Energy Rev. 96 (2018) 1–10.

[6] N. Cao, J. Ting, S. Sen, A. Raychowdhury, Smart sensing for HVAC control: Collaborative intelligence in optical and IR cameras, IEEE Trans. Ind. Electron. 65 (12) (2018) 9785–9794.

[7] H. Zou, Y. Zhou, H. Jiang, S.-C. Chien, L. Xie, C.J. Spanos, WinLight: A Wifi-based occupancy-driven lighting control system for smart building, Energy Build. 158 (2018) 924–938.

[8] Z.D. Tekler, R. Low, Y. Zhou, C. Yuen, L. Blessing, C. Spanos, Near-real-time plug load identification using low-frequency power data in office spaces: Experiments and applications, Appl. Energy 275 (2020) 115391.

[9] I. Abubakar, S. Khalid, M. Mustafa, H. Shareef, M. Mustapha, Application of load monitoring in appliances' energy management–A review, Renew. Sustain. Energy Rev. 67 (2017) 235–245.

[10] A. Cominola, M. Giuliani, D. Piga, A. Castelletti, A.E. Rizzoli, A hybrid signature-based iterative disaggregation algorithm for non-intrusive load monitoring, Appl. Energy 185 (2017) 331–344.

[11] A. Ridi, C. Gisler, J. Hennebert, A survey on intrusive load monitoring for appliance recognition, in: 2014 22nd International Conference on Pattern Recognition, IEEE, 2014, pp. 3702–3707.

[12] W. Kleiminger, C. Beckel, T. Staake, S. Santini, Occupancy detection from electricity consumption data, in: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings, 2013, pp. 1–8.

[13] Z. Tekler, R. Low, L. Blessing, Using smart technologies to identify occupancy and plug-in appliance interaction patterns in an office environment, in: IOP Conference Series: Materials Science and Engineering, Vol. 609, IOP Publishing, 2019, 062010.

[14] J. Froehlich, L. Findlater, J. Landay, The design of eco-feedback technology, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2010, pp. 1999–2008.

[15] R.K. Jain, J.E. Taylor, P.J. Culligan, Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings, Energy Build. 64 (2013) 408–414.

[16] M.J. Handgraaf, M.A.V.L. de Jeude, K.C. Appelt, Public praise vs. private pay: Effects of rewards on energy conservation in the workplace, Ecol. Econom. 86 (2013) 86–92.

[17] B. Orland, N. Ram, D. Lang, K. Houser, N. Kling, M. Coccia, Saving energy in an office environment: A serious game intervention, Energy Build. 74 (2014) 43–52.

[18] P. Gandhi, G.S. Brager, Commercial office plug load energy consumption trends and the role of occupant behavior, Energy Build. 125 (2016) 1–8.

[19] Z.D. Tekler, R. Low, L. Blessing, User perceptions on the adoption of smart energy management systems in the workplace: Design and policy implications, Energy Res. Soc. Sci. 88 (2022) 102505.

[20] R. Yun, A. Aziz, P. Scupelli, B. Lasternas, C. Zhang, V. Loftness, Beyond eco-feedback: adding online manual and automated controls to promote workplace sustainability, in: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, 2015, pp. 1989–1992.

[21] K.-L. Tsai, F.-Y. Leu, I. You, Residence energy control system based on wireless smart socket and IoT, IEEE Access 4 (2016) 2885–2894.

[22] I. Metzger, D. Cutler, M. Sheppy, Plug-Load Control and Behavioral Change Research in GSA Office Buildings, Tech. Rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2012.

[23] R. Low, Z.D. Tekler, L. Cheah, An end-to-end point of interest (POI) conflation framework, ISPRS Int. J. Geo-Inf. 10 (11) (2021) 779.

[24] S. Park, M.-i. Choi, B. Kang, S. Park, Design and implementation of smart energy management system for reducing power consumption using ZigBee wireless communication module, Procedia Comput. Sci. 19 (2013) 662–668.

[25] I. Metzger, A. Kandt, O. VanGeet, Plug Load Behavioral Change Demonstration Project, Tech. Rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2011.

[26] Y. Zhang, C. Bonneville, N. Arora, R. Higa, Integrated lighting and plug load controls, 2021.
[27] A.J. Kandt, M.R. Langner, Plug Load Management System Field Study, Tech. Rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2019.
[28] S. Wang, A. Kim, E. Johnson, Understanding the deterministic and probabilistic business cases for occupant based plug load management strategies in commercial office buildings, Appl. Energy 191 (2017) 398–413.
[29] C. Lobato, M. Sheppy, L. Brackney, S. Pless, P. Torcellini, Selecting a control strategy for plug and process loads, Tech. Rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2012.
[30] S.S.I. Samuel, A review of connectivity challenges in IoT-smart home, in: 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), IEEE, 2016, pp. 1–4.
[31] Z.D. Tekler, R. Low, L. Blessing, An alternative approach to monitor occupancy using bluetooth low energy technology in an office environment, in: Journal of Physics: Conference Series, Vol. 1343, IOP Publishing, 2019, 012116.
[32] R. Low, Z.D. Tekler, L. Cheah, Predicting commercial vehicle parking duration using generative adversarial multiple imputation networks, Transp. Res. Rec. 2674 (9) (2020) 820–831.
[33] Z.D. Tekler, R. Low, B. Gunay, R.K. Andersen, L. Blessing, A scalable bluetooth low energy approach to identify occupancy patterns and profiles in office spaces, Build. Environ. 171 (2020) 106681.
[34] S. Clemente, S. Beauchêne, E. Nefzaoui, Generation of aggregated plug load profiles in office buildings, Energy Build. 252 (2021) 111398.
[35] C. Yoon, S. Kim, Convenience and TAM in a ubiquitous computing environment: The case of wireless LAN, Electron. Commer. Res. Appl. 6 (1) (2007) 102–112.
[36] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. (1989) 319–340.
[37] C. Ataman, B. Tuncer, Urban interventions and participation tools in urban design processes: A systematic review and thematic analysis (1995–2021), Sustainable Cities Soc. (2021) 103462.
[38] Building and Construction Authority, Building energy benchmarking report 2020, 2020, https://www.bca.gov.sg/bess/benchmarkingreport/benchmarkingreport.aspx [Online; accessed 19-July-2008].
[39] Energy Market Authority, Electricity tariff from 1 march to 30 april, 2020, 2020, https://www.ema.gov.sg/Electricity_Commercial_or_Industrial_Consumers_Consumers.aspx [Online; accessed 19-July-2008].