Brick Schema Standardized Plug Load Control Strategies for Load Reduction

Preprint

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Brick Schema Standardized Plug Load Control

Strategies for Load Reduction

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ABSTRACT

Plug loads comprise a significant percentage of commercial building energy consumption. Applying intelligent controls to turn off plug loads when unused can provide dynamic load reduction and flexibility, which are key traits of grid-interactive efficient buildings. This capability is important for equitable decarbonization as it can enable disadvantaged communities to electrify buildings without costly upgrades to electrical infrastructure. In this work, we present the effectiveness of various control strategies along with the operational lessons that informed their design. During a three-year period, we operated over 600 smart outlets in 12 university office buildings. The attached plug loads consisted primarily of printers, TVs, water dispensers, and copiers. After recording baseline power measurements for one year, we designed plug load control (PLC) strategies for each plug load type, use, and for different risk tolerance levels because PLC can potentially be disruptive to daily work. We used the Brick Schema to facilitate the management of plug load locations and other metadata. For advanced controls, we integrated the smart plugs with heating, ventilation, and air conditioning (HVAC) systems through the campus building automation system. We found static schedules to be the least disruptive and most predictable for occupants, resulting in 38% and 66% energy savings in two studies. For printers, print server-triggered PLC produced 86% savings, the highest of all strategies with minimal occupant impact. Scheduling of water dispensers and digital signage TVs produced 49% and 70% savings respectively with opportunities to improve performance with the use of HVAC occupancy data.

Introduction

Plug load control (PLC) is becoming increasingly important as buildings further electrify, and the power grid decarbonizes. Plug loads are plug-in electric loads in a building and account for over 50% of whole-building energy consumption in high-efficiency buildings (Lobato et al. 2011). Plug loads offer an opportunity for electricity and carbon reductions. PLC enables building operators to reduce operating costs by eliminating wasted plug load electricity consumption and reducing peak electricity demand. Baseloads, the lowest constant power often occurring during unoccupied times, can also be reduced to allow for the electrification of other building systems. Implementing PLC is challenging due to the large number of devices and types that typically exist in commercial buildings. Additionally, plug loads are highly occupant-dependent, and proper engagement with occupants is vital to the success of a PLC system. While standalone plug load management programs exist, coupling PLC with other building systems, such as via the building energy management system (BEMS), creates opportunities for more advanced and effective PLC strategies. Lack of interoperability between heterogeneous systems is a well-documented issue in commercial BEMS (Hardin et al. 2015) and presents many challenges, such as varying data formats and protocols, inconsistent data quality, and the need for complex integration processes, which prevents such integration. Semantic interoperability is the ability to exchange data in a manner that ensures shared comprehension and a clear understanding of the data's meaning, thereby maintaining data semantics consistently across different systems. The Brick Schema (Balaji et al. 2016), a standardized ontology and taxonomy for building systems, was developed to provide structure to the basic metadata commonly found in building management systems, including for PLC, to achieve semantic interoperability (Bergmann 2020). Not only does this streamline PLC integration and development of controls, but it also makes the PLC software transferable to other buildings that use the Brick Schema.

This work seeks to answer the following research questions: how can PLC strategies be designed to maximize energy savings while not disrupting occupants? And how can PLC be made scalable, using the Brick Schema? In this paper, we describe the best practices, infrastructure, and data used in several case studies involving PLCs deployed on the University of California, San Diego (UCSD) campus.

Deployment

The deployment of PLCs in departments across the UCSD campus provided valuable insights into the diversity of occupant preferences and the operational constraints that PLCs must work within. This section describes the deployment of PLCs as well as the Brick Server infrastructure needed to store and utilize all of the information required for successful PLC implementation.

Plug Load Controllers

We used two types of plug load controllers (PLC). The first is produced by Best Energy Reduction Technologies (BERT). These are commercial PLCs with the capability to integrate with a building energy management system (BEMS) via a BACnet gateway. BACnet is the ANSI/ASHRAE standard for Building Automation and Control networks (ASHRAE 2016). The second type of PLC is produced by Shelly and offers MQTT (Message Queuing Telemetry Transport) and scripting capabilities. MQTT is a lightweight publish/subscribe messaging protocol typically used in IoT (Internet of Things) devices. Both PLCs are installed directly into existing wall outlets and have power metering capability, relay control, Wi-Fi connectivity, and a button to manually override a control if the PLC is OFF. We installed over 600 PLCs on office equipment such as TVs, printers, copiers, scanners, hot/cold water dispensers, coffee makers, and portable air conditioning units. These types of plug loads usually consume power at all hours even when in standby or OFF modes. The PLCs are located in twelve different UCSD campus facilities that reflect standard office buildings. They are used primarily for administration and are composed of office-type spaces such as private offices, shared offices, shared workspaces, storage rooms, conference rooms, and kitchenettes.

Brick Server

The potential benefits of the Brick Schema are realized through our Brick Server. The software stack of this system consists of four main components, as shown in Figure 1: (1) graph database, (2) time series database, (3) data pipeline, and (4) Brick API (Application Programming Interface) for applications.

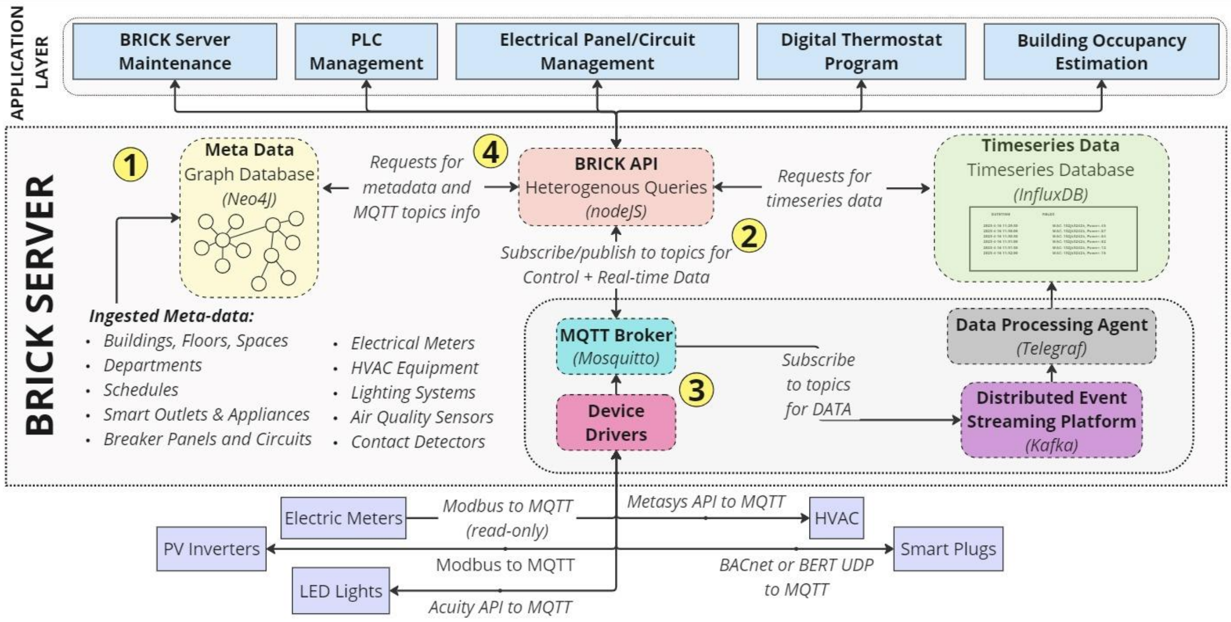

Figure 1. Block diagram of the Brick Server architecture

Graph database. This database stores all of the metadata related to the PLCs including device properties, what appliance they control, and their spatial relationship to the building as well as to other relevant equipment such as thermostats and lighting systems. All entities are created as nodes, each with a label that comes from the Brick Schema as well as standard Brick relationships to other nodes such as 'hasLocation' or 'feeds', as shown in Figure 2.

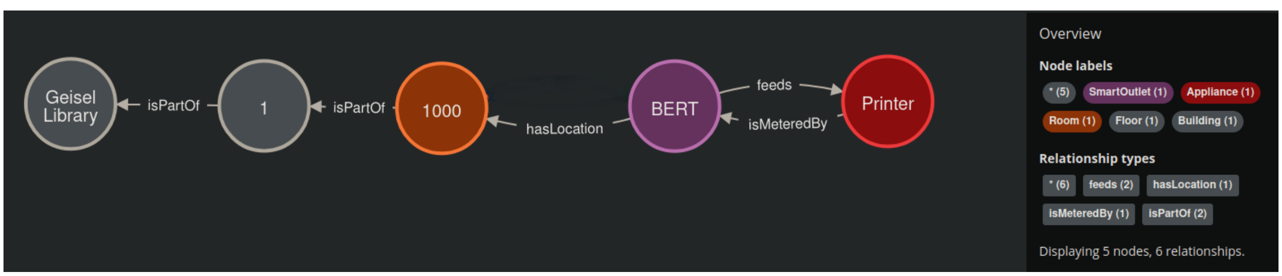

Figure 2. Screenshot from the neo4j graph database showing an example of the relationships between a building (Geisel Library), floor (1), room (1000), smart outlet (BERT), and printer.

Time series database. The data generated by the sensors is stored in a time series database at their native resolution. PLC data is recorded in one-minute intervals.

Data pipeline. To get data into the BRICK Server, we developed different software device drivers to communicate with the devices using their native communication protocol and converting it into MQTT. These messages are then queued using Kafka[1], an event streaming

[1] Apache Kafka is an open-source distributed data buffer for collecting data from a stream before storage to an end application or service.

platform, and formatted using Telegraf[2], a data processing agent, before being stored in InfluxDB[3], the time series database.

Brick API for applications. A primary challenge of equipment interoperability is interfacing with the different communication protocols that each system uses. Providing the framework to bring these heterogeneous systems together and providing a common point of interaction is one of the key values that Brick provides. This is done by creating an API that allows Brick users or applications to interact with the data. There are API calls that enable exploration of the metadata, retrieval of desired time-series data, and control. The Brick schema standardization streamlines development and increases the portability of applications.

PLC Management Application

This software runs at the application layer and interfaces with the Brick Server via the Brick API. The PLC Management Application is custom software by the UCSD research team that is designed for PLC at scale and with the advantage of leveraging data from all other systems integrated into the Brick Server. Key features of the application include:

- Management of PLCs by grouping them into accounts and assigning points of contact. PLC highly depends on the preferences and risk tolerances of the users so taking a people-first approach to organizing PLCs is beneficial.
- Ability to filter, sort, and configure PLCs in batches.
- A library of control strategies.
- Ability to draw from metadata stored in the Brick Server such as relationships to departments and operating schedules.
- Capability to develop custom alerts and automation specific to PLC management.

Plug Load Control Design

Control Levels

A challenging aspect of PLC is striking a balance between energy savings and the risk of interrupting occupants if plug loads are OFF when needed. To manage this balance, we classified controls into different levels that represent the risk of disrupting occupants. These levels are defined in Table 1 and can be used by the PLC operator by noting how many ON/OFF events a control strategy can have and if the schedule of those events repeats weekly or is dynamic. Higher levels offer great energy savings but at higher risk. Defining these levels helps align the controls with the risk tolerance of the building occupants. Additionally, if the plug load management system is tracking manual overrides, then a fail-safe program can be made to default plug loads to lower risk level controls if too many overrides are detected. A manual override is required when the PLC is OFF, but an occupant needs to use the appliance. Note that proper application of PLC is dependent on knowing what appliance is being controlled. Future work involves algorithms to detect appliance changes that are not reported to the PLC operator.

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[2] Telegraf is an open-source server agent for collecting, processing, aggregating, and writing metrics with an ever-expanding collection of plug-ins allowing for extensive integrations with existing widely used software applications and databases.
[3] InfluxDb is an open-source time series database that is optimized for the storage and retrieval of time series data.

Table 1. Description of Plug Load Control Levels.

Control Level	Description
Level 0 – No Control	PLC remains ON to provide uninterrupted power to its attached load.
Level 1 – Static Schedule	Only one ON and OFF event per day. A static, weekly schedule is used that starts before and ends after occupants are typically in a building. E.g. Facility manager programs PLCs to turn ON at 7:30 am and OFF at 5:30 pm every day.
Level 2 – Tightened Schedule	Only one ON and OFF event per day. The schedule may change weekly and have a reduced time buffer before occupants arrive. E.g. Front door contact sensor turns PLCs ON when the first person arrives. PLCs turn OFF at 5:30 pm.
Level 3 – Usage Optimized	May have multiple ON and OFF events per day to align power consumption more closely with actual plug load usage. E.g. Print server turns PLC ON when a print job is received and turns it OFF after 30 minutes of inactivity.
Level 4 – Special Events	Similar to Level 3, but more aggressive for cases such as demand response events, building peak load reduction, or islanded operation when the economic benefits of load shedding are orders of magnitude greater than in regular operation.

Input Data Types

When designing PLC strategies, it is helpful to first identify what information and data is available to you. Four categories are defined in Table 2 and control strategies may use a combination of them.

Table 2. Types of information and data that can be used when designing PLC strategies.

Information Type	Description
Static Schedules	Schedules that repeat weekly and are typically defined by the building or department managers. Schedules for HVAC zones are typically programmed into the BEMS and can be reused for PLC as long as there is a mapping between PLC locations and HVAC zones.
User Input	User input can be used as a trigger for PLC. Examples include users sending print jobs, pushing a specially programmed button, or using another related plug load.
Plug Load Use	Power measurements can be used to detect when certain plug loads are used to generate schedules that align with the usage.
Environmental Data	This includes data such as occupancy from thermostats or lighting systems or CO_2.

Example Controls

Table 3 presents an example of how different levels of controls can be designed based on the types of information available as well as what strategy is most appropriate given the appliance type, its use, and the risk tolerance of its users. Several of these strategies are demonstrated as case studies in this paper.

Table 3. Example progression of control strategies for different Plug Loads.

	Control Level		
Load Type	**Level 1**	**Level 2 - Schedule Tightening**	**Level 3 - Usage Optimized**
Shared Printers	Static Schedule	User Input: connect the printer to a central print server that triggers the PLC to turn ON when the first print job of the day is received. The PLC can be scheduled to turn OFF at the end of the business day. Alternatively, usage data can be used to determine a better OFF time.	User Input: Connect the printer to a central print server which can trigger PLCs to turn ON when a print job is received. Turn the printer OFF after 30 minutes of inactivity.
Individual, Shared Scanners and TVs (digital signage)	Static Schedule	Occupancy-Driven Schedule: Use historical occupancy data from BEMS to generate a tightened schedule for the devices to be ON based on when people are nearby.	Occupancy-Triggered: Turn ON when any occupancy in designated areas is detected. Turn OFF after 60 minutes of inactivity in all areas.
Individual and Shared Water Dispensers	Static Schedule	Occupancy-Driven Schedule: Use historical occupancy data from BEMS to generate a tightened schedule for the dispenser to be ON based on when people are nearby.	Occupancy-Triggered: Turn ON 60 minutes before the area is forecasted to be occupied. Turn OFF after 60 minutes of inactivity in all areas.

Note that as the levels increase, so do the savings and corresponding risks.

Methodology

Case Study 1: Level 1 Control with Building Schedules

We ran two building-wide interventions that used static schedules. We sent a list of plug loads to the facility managers who then returned a subset of approved plug loads to control as well as the desired schedule for them. We then programmed these schedules into the PLCs.

At Building 1, a total of 33 plug loads were approved for PLC. All of them were to follow the same schedule of being ON from 07:00 h to 18:00 h on weekdays and staying OFF on weekends. At Building 2, 14 plug loads were approved for controls. Six TVs were to be ON Mondays to Sundays from 06:00 h to 23:00 h. Eight water dispensers were to be ON Mondays to Fridays, from 07:00 h to 22:00 h.

Case Study 2: Print Server

Printers are of high interest for PLC as they comprise nearly 50% of our deployment (363 printers on campus have a PLC installed on them). We developed Level 2 and 3 control strategies that leverage user input to turn a printer ON when a print job is received.

System architecture. The system operates by monitoring the print log of a print server (Figure 3). When a user submits a print job to the server, our software installed on the print server detects the new job and identifies the relevant printer. It will then request the PLC Management Application to turn ON the appropriate printer. The print server queues the print job until the printer is in Ready Mode and then sends the job to be printed. The PLC Management Application and the Brick Server also play key roles in storing the mapping between the printer's name and the PLC connected to it.

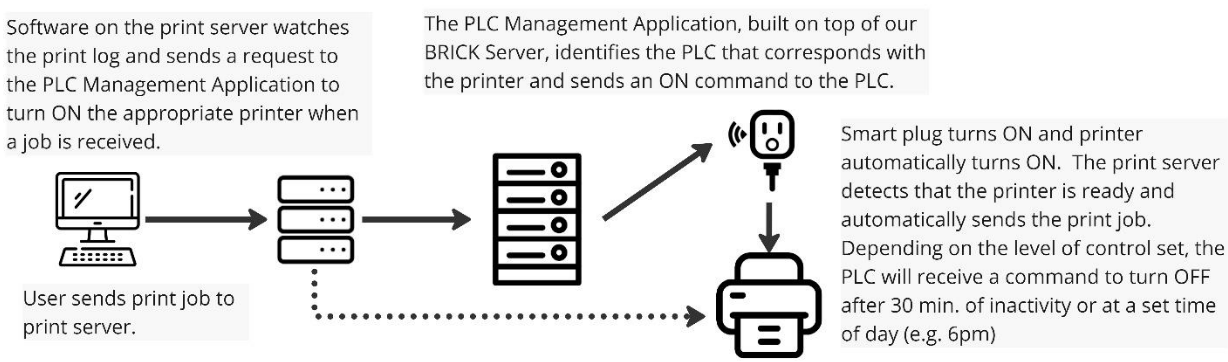


Figure 3. Architecture of the print server + PLC system.

From prototype to pilot. After successfully demonstrating a working prototype in our laboratory, a business department on campus agreed to participate in a two-week pilot study. One printer, an HP Color Laserjet, in the lobby, was chosen for the study. This lobby printer is used primarily by staff in the business office as well as some other staff in the building. Prior to starting controls, we posted an instructional flier detailing the use of our print server at the printer and sent emails to schedule time for research members to configure staff computers, a three minute process.

Controls. Two control strategies were tested.

- Week 1 (1/22 to 1/28/2024) - Level 2: The printer starts OFF and turns ON when the first print job is received. It then turns OFF at a preset time of 18:00 h.
- Week 2 (1/29 to 2/4/2024) - Level 3: The printer starts OFF and turns ON anytime a print job is received. It turns OFF after 30 minutes of inactivity.

Case Study 3: Water Dispenser

Water dispensers on campus have the second highest average daily energy consumption as the dispensers maintain hot and cold water 24/7. Water dispensers are thermostatically controlled devices that maintain water within a certain temperature range. Water is cooled/heated until reaching the target temperature. Then the cooling/heating is turned OFF until the water reaches the higher/lower end of the temperature deadband and the cycle repeats. As seen in

Figure 4, power measurements from water dispensers without PLC generally have two cyclical patterns with heating events as three to five-minute long 550 W loads every 20 minutes and 30-45 minute long 110 W cooling events every three hours.

Figure 4. Example of baseline power measurements [mW] from the water dispenser in an administrative department. The x-axis shows time in HH:MM.

We selected a water dispenser in an administrative department for the study and collected baseline power measurements from January 2 to 19, 2024. From January 19 to February 2, we applied controls and collected ground truth data by placing a clipboard on the dispenser and instructing occupants to write down the day and time they used the dispenser and whether it was hot or cold water.

For the first week of controls (Level 1), the department contact provided a static schedule of 08:00 h to 16:00 h Monday to Friday. Water dispensers need up to an hour to cool/heat the water, so a buffer was added resulting in a schedule of 07:00 h to 17:30 h Monday to Friday. This schedule was programmed directly into the PLC, allowing it to operate regardless of connectivity to the rest of the system.

For the second week of controls (Level 2), we aggregated baseline normalized energy consumption of all 52 monitored water dispensers. A Level 2 schedule was then generated by setting a threshold for energy consumption and identifying when usage starts and ends each day, resulting in 55 hours OFF during the week.

Case Study 4: TV Digital Signage

TVs are the fourth-highest average daily energy consumer on campus. TVs used as digital signage typically play a looping slideshow that showcases student projects, promotes upcoming events and announcements, or provides information to visitors. Since it is not possible to know when someone is actually looking at the digital signage, occupancy must be used to infer usage. We selected two digital signage TVs in a hallway outside of an engineering lab for study. We recorded baseline measurements for several weeks before applying Level 1 controls to them. The lab manager provided the Level 1 static schedule to us, which we then programmed into the PLCs.

For Level 2 & 3 controls, we used occupancy data from the hallway to generate more optimal schedules. Due to limitations with access to occupancy data from the HVAC system, we pursued an alternative solution by placing a Shelly Motion portable battery-operated PIR motion detector on a door frame opposite the TVs. We then aggregated this motion data into a heat map. Motion detections are summed each hour, and the Level 2 control then identifies a start and end time for each day. The Level 3 control has a max of three ON & OFF events per day, as prescribed by the research team, and turns the TVs OFF during periods of historically at least one hour of no motion. Since permission to implement the Level 2 & 3 schedules was not granted due to concerns about the TVs being off during unexpected visits, we simulated results by applying the schedules to recorded power measurements and setting the power to 0 W whenever the TV was scheduled to be OFF.

Case Study 5: Thermostat Occupancy-Triggered PLC

Based on learnings from the water dispenser and TV case studies, an alternative approach is explored that uses PIR occupancy data collected from HVAC thermostats to trigger PLCs ON and to determine when it is appropriate to turn them OFF. This strategy takes full advantage of the Brick infrastructure as it must programmatically identify which thermostats are relevant (those in the same department and floor of the PLC) and retrieve the appropriate historical and real-time occupancy data. Three versions of this control strategy are defined with increasing complexity.

Level 2a. Turn PLC ON when any occupancy is detected from thermostats in the department or at 08:00 h, whichever occurs first. Turn PLC OFF at a preset time of 18:00 h. This strategy ensures that the plug load will be ON during the times provided by the department contact, but also accounts for edge cases where people may arrive early which was observed in our prior water dispenser case study.

Level 2b. Turn PLC ON when any occupancy is detected from any thermostat in the department/floor. Turn PLC OFF at a preset time of 18:00 h. This strategy is similar to the Level 2 print server controls and automatically accounts for changes in staff arrival times.

Level 3. Figure 5: This version addresses the issue of certain plug loads needing additional time before they are ready for use. A startup time is defined for each plug load type. For example, water dispensers require one hour of startup time to pre-condition water and TVs require five minutes to turn ON and display content. This startup time variable can be tuned as needed. The control algorithm then uses historical occupancy data from a defined area (e.g. a group of spaces that are interconnected and associated with the same department) to forecast daily occupancy for that area. As long as any part of that area is occupied, then plug loads should be ON and ready for use. For each hour of the day, the probability of occupancy is calculated. To determine the time to turn ON a PLC, the algorithm finds the first 15-minute increment that has a probability for occupancy above a set threshold. The plug load's startup time is then subtracted. To forecast the turn OFF time of the plug load, the algorithm identifies sequential hours where occupancy is consistently below the probability threshold. This forecasted schedule is stored in the PLC. Additional control logic is added to account for unexpected occupant behaviors including logic to automatically turn ON PLCs if a thermostat detects any motion, as in the case of people arriving unexpectedly early. Also, if no motion in the department is detected for 120 minutes, then PLCs can be turned OFF early. To further enhance the system's operational efficiency and comply with departmental requirements, a blackout period has been established from 22:30 h to 4:30 h. This predefined interval ensures that the device remains inactive during these hours. Two primary challenges are identified and explored. The first is that the quality of the occupancy data affects the reliability of this control strategy. Thermostats are not always positioned in the ideal spots to consistently track occupancy. Also, thermostats in private offices are likely not as useful as those placed in shared workplaces. Secondly, some plug loads such as water dispensers require time to pre-condition water before use. Thus, there needs to be sufficient time between the occupancy trigger and the first use.

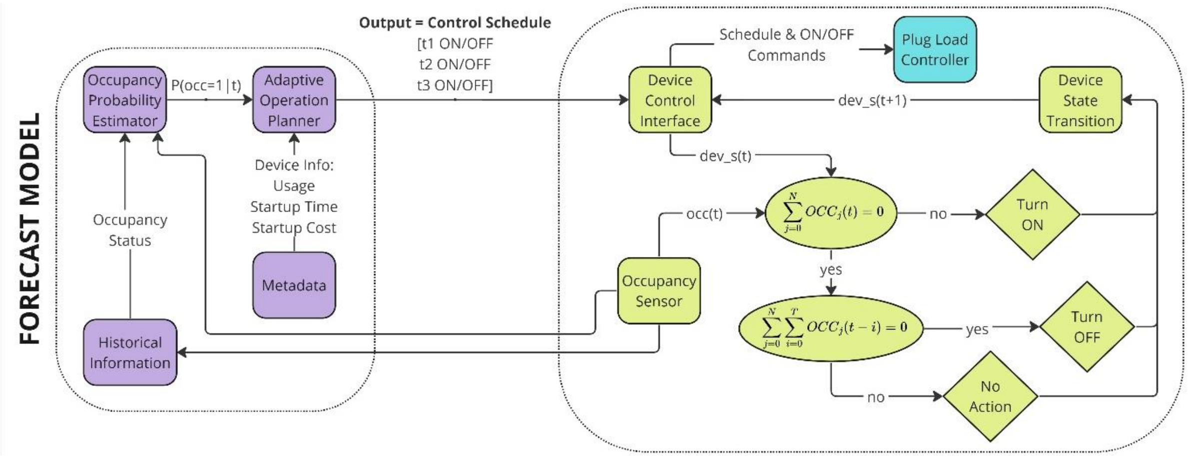


Figure 5. Control block diagram for Level 3 thermostat occupancy-triggered PLC, incorporating occupancy forecasting. Here, dev_s represents the state of the PLC's attached device, occ(t) is the binary occupancy measurement at time t, and j = 1, . . . , N indexes occupancy sensors in N rooms. Note: dev_s = 1 indicates the device is on (e.g., printers, TVs, water dispensers), dev_s = 0 off; occ(t) = 1 detects occupancy, 0 no occupancy.

We chose to study a water dispenser located in the kitchenette of an administrative department. Occupancy data from thermostats in the department is collected from the campus BEMS and through our BRICK Server. We installed additional portable motion detectors near the entrances and the water dispenser to check the reliability of data from thermostats. To get ground truth data for water dispenser usage, we placed a clipboard at the dispenser with instructions for occupants to note the date and time of their use as well as if it was hot or cold water.

The control versions rely on robust occupancy detection; in particular false negatives should be avoided. False negatives refer to no occupancy detection even though there was occupancy as indicated by the water usage log. The robustness of occupancy detection was tested using data for the water dispenser located in the kitchenette, room 361 (Figure 6), by analyzing the relationship between thermostat occupancy (o) and water usage (u). For this analysis, we employed a 15-minute time window to evaluate the temporal association between events, calculating the probability of occupancy in a space given water usage within this interval [P (o|u = 1)]. There is a high probability of 0.968 that occupancy in room 361 was detected within the past 15 minutes whenever the water dispenser was used. This is logical as one must be physically at the water dispenser to use it, but it at least confirms that the occupancy sensor operates as intended. In fact, in a different department, we observed that the thermostat in the kitchenette is located behind a refrigerator and does not detect occupancy reliably. To explore the relationship between other thermostats and water use in room 361, a time window of 15 minutes is used. This is because there will be a time lag (the walking travel time) between when occupants trigger a thermostat further away from the dispenser and when they use the water dispenser. Here we can see higher probabilities with the two thermostats in the central, shared workspace. From this probability analysis, we conclude that there are enough well-placed thermostats in this department to execute PLC strategies based on occupancy.

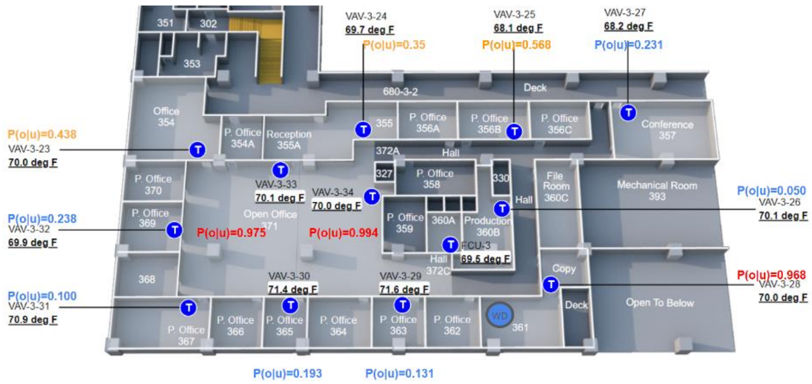


Figure 6. Floor plan showing thermostat locations in the administrative department and their probabilistic relationship to water dispenser (wd) usage.

Results

Case Study 1: Level 1 Control with Building Schedules

After collecting baseline power measurements, we found eight plug loads that had been removed at Building 1 which reduced the number of PLCs to 25. The 25 plug loads consisted of 15 printers, four water dispensers, three copiers, a coffee maker, a projector, and a TV. Compared to a baseline week, a week of Level 1 controls used 67.4 kWh (66%) less energy. Assuming an average cost for electricity of 34¢ per kWh in San Diego (USURDB 2024), this equates to an annual savings of $1,192. Further details of this study can be found in (Chia et al. 2023). For Building 2, compared to a baseline week, one week of Level 1 controls used 7.1 kWh (38%) less energy, equating to an estimated cost savings of $126 per year. In this case, students and faculty were more likely to use the facilities during the evenings so most of the savings were achieved from turning the plug loads OFF on the weekends.

Case Study 2: Print Server

We recorded nine weeks of baseline data and chose four of those weeks, November 6th to December 3rd, 2023, for our baseline data sets, as other weeks had missing data due to server outages and networking issues. The daily energy consumption of these four weeks was then averaged. The baseline data resulted in an average energy consumption of 3,870 Wh per week (Table 4). Level 2 controls resulted in an energy consumption of 1,215 Wh for one week, which is 69% less than the baseline and equates to an estimated annual savings of $47 per printer. Applying Level 3 controls resulted in a consumption of 496 Wh for one week, which is 86% less than the baseline and equates to an estimated annual savings of $60 per printer. The printing process takes longer though, two minutes compared to 15-20 seconds without PLC, which resulted in a reported issue where an occupant mistook the delay for an equipment fault. Four other reported issues were likely caused by occupants not following the posted instructions for sending print jobs to the print server instead of directly to the printer.

Table 4. Summary of energy savings from the application of Level 2 and 3 PLC on a printer

Week	Energy Consumed	% Saved vs Baseline	Annual $ Saved Per Printer	Energy Per Print Job
Baseline	3,870 Wh	----	----	184 Wh

Level 2 Control	1,215 Wh	69%	$47	110 Wh
Level 3 Control	496 Wh	86%	$60	33 Wh

During the week 1 pilot (Figure 7), the printer was not used at all on Tuesday and Friday and therefore no energy consumption was recorded on those days. On the other hand, on Monday and Wednesday, the printer was used early in the day and more frequently and it remained ON until 18:00 h, resulting in a similar energy consumption to the baseline. During the week 2 pilot, the printer was used every day, but since it turned OFF after 30 minutes of inactivity the energy use was minimal. During both pilots, the printer was never used on the weekend and remained OFF then.

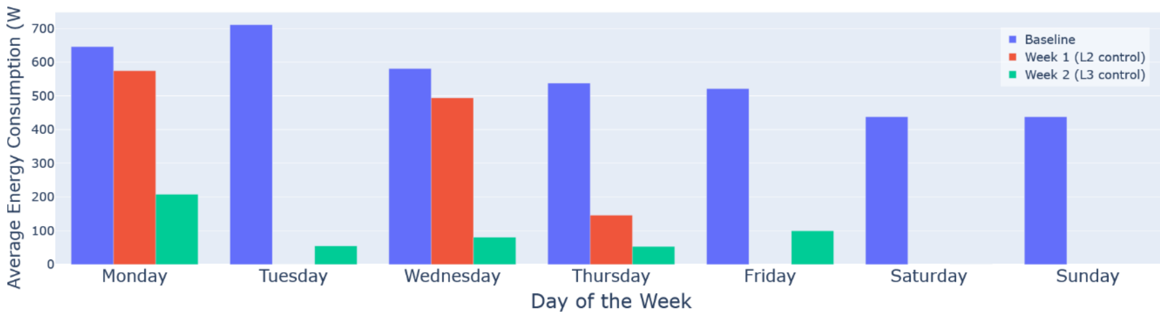


Figure 7. Comparison of daily energy consumption of one printer in a business department for baseline weeks and control weeks.

Case Study 3: Water Dispenser

Without any controls, the water dispenser used an average of 9.48 kWh per week. Applying the Level 1 control resulted in an energy consumption of 5.10 kWh for the week, a 46% savings compared to the baseline. The Level 2 schedule used 4.88 kWh for the week, a 49% reduction in energy compared to the baseline and equating to an estimated $53 saved annually per water dispenser. The Level 1 and Level 2 schedules were similar with an ON-time of 52.5 hours (31.2%) and 55.2 hours (32.9%) hours during the week, respectively. Therefore, similar savings are expected. From the ground truth data, we identified two cases during the Level 2 schedule where an occupant used the water dispenser before it turned ON that morning, however, no complaints were received.

Case Study 4: TV Digital Signage

Level 1 control. The TVs were programmed to be ON every day from 08:00 h to 20:00 h. The additional weekend hours are to account for tours that may visit the studio. The controls resulted in an average savings of 7,535 Wh per TV, a 50% reduction in energy consumption. This was expected as the TV was OFF for 50% of the hours of the week.

Level 2 & 3 simulation. Savings with Level 2 and 3 controls depend on the occupant's preference for energy savings versus ensuring the TV is ON for any possible visitors. Turning ON the TV for any historical occupancy detection, we simulated the following energy savings (Figure 8):

- Level 2 consumes 4.88 kWh per week (68% less than baseline)

- Level 3 consumes 4.58 kWh per week (70% less than baseline)

The Level 2 and 3 schedules result in annual savings per TV of $180 and $187 respectively.

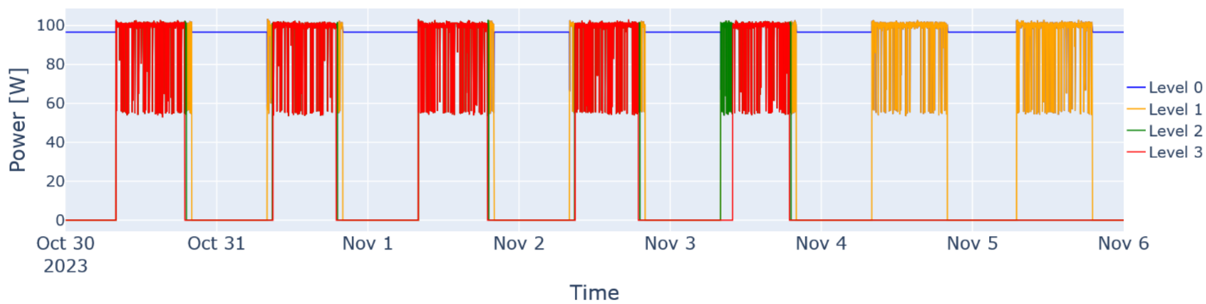


Figure 8. One week of power measurements from a TV outside of an engineering lab with different levels of control applied. All levels are simulated except for Level 1.

Case Study 5: Thermostat Occupancy-Triggered PLC

We simulated control levels 2a and 2b to check their operational viability using recorded occupancy data and the ground truth water dispenser usage (Figure 9). No usage occurred outside of the ON periods in both cases indicating that there is sufficient occupancy coverage to keep the PLC ON while people are nearby. However, there were six times when the PLC was triggered ON by a thermostat and then the water dispenser was used before the one-hour preconditioning period was completed. For these cases, the time difference between the first detection of occupancy and the first water usage was 36, 41, 39, 1, 24, and 9 minutes. Adding an additional sensor by the entrance doors may provide more advance warning for this administrative department, but for other departments, the water dispenser is right by the entrance and there would not be enough time to prepare if someone entered and immediately used it. Therefore, Level 3 control is pursued.

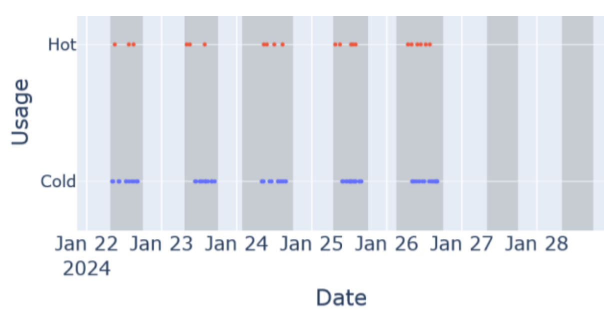
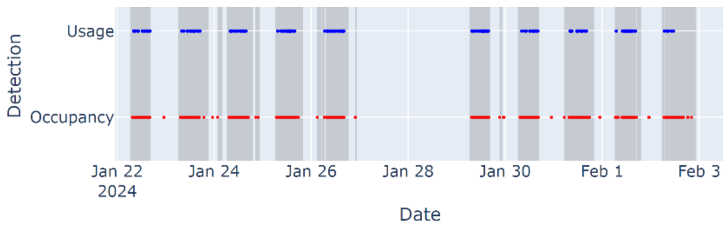
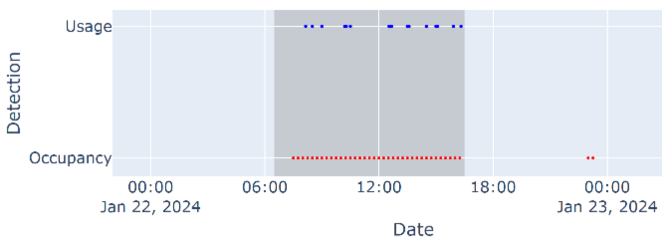


Figure 9. Simulation of Level 2b control showing usage (blue for cold, red for hot) and periods when the PLC was ON (gray) based on occupancy triggers. January 27 and 28, 2024 were weekend days.

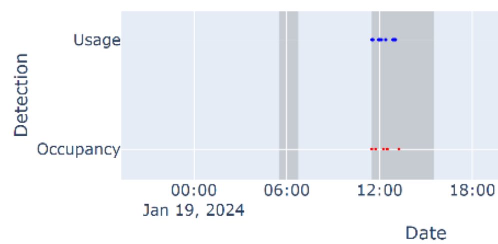
Level 3 control (Figure 10) rectified the prior limitation of insufficient pre-conditioning time, ensuring the water dispenser turned ON and OFF according to our control logic and remained inactive during department-mandated hours. A notable instance (Figure 10b) occurred on January 22, where the first occupant's arrival, at approximately 07:30 h, was preceded by the activation of the water dispenser at 06:15 h, as dictated by the forecasted schedule. This lead time ensured the water was appropriately pre-conditioned to meet immediate demand. However, an inherent challenge remains in scenarios where occupancy deviates from the forecast due to unforeseen circumstances, such as holidays or inclement weather. Such was the case on January 19 (Figure 10c), wherein the first arrival was recorded at 11:30 h, followed by departure at 13:15 h. According to our control logic, the water dispenser turned ON at the initially forecasted time (06:15 h). Subsequently, it turned OFF upon detecting an absence of occupancy for a 120-minute duration, only to reactivate with the detection of the first occupant's arrival and turning OFF once more post a 120-minute non-occupancy period.



(a) Simulation of Level 3 control.



(b) Example showing proper startup of the Plug Load approximately one hour before occupancy is first detected.



(c) Example of occupants arriving late and the dispenser turning back ON when they are detected.

Figure 10. Simulation of Level 3 control with occupancy data (red), and water usage (blue for both hot and cold). Two scenarios are highlighted in (b) and (c) to verify the ability of the control logic to handle edge cases.

The simulation results encapsulated in Figure 16a showcase the robustness and reliability of our control strategy. During the observation period from January 19 to February 2, 2024, the simulated average energy consumption under Level 3 control was measured at 4.27 kWh per week, indicating a reduction of 53% when compared to the baseline. The implemented control logic not only conserves energy by avoiding unnecessary operation in the absence of demand but also ensures the availability of pre-conditioned water in alignment with actual usage patterns, thereby substantiating its efficacy and adaptability.

Conclusions & Future Work

Level 1 Control with Building Schedules

Conclusions. Level 1 control is the simplest control strategy to implement, and it generally goes unnoticed by occupants, as long as the schedule has sufficient buffer time before and after typical occupancy periods. Occupants also prefer predictable controls so that PLC can fit naturally into their daily routines. Regular training and awareness are required though to maintain the PLC deployment as on several occasions we found PLCs removed by occupants and that the manual override buttons were ignored or assumed to be malfunctioning when the PLC was OFF at a needed time. From a PLC operator perspective, Level 1 control is similar to other "set it and forget" systems. The only issue is scalability as reprogramming efforts to tune the schedules of each PLC is not reasonable. Proper PLC management software is required to address this. Consumer PLCs are readily available and can realize a payback period of less than three years. Commercial PLCs are more costly but can still achieve a three to five-year payback period if used on plug loads that consume 75 watts or more during unused periods.

Future Work. The project's custom PLC Management Application will be ready for use in June 2024 with the goal of operating and monitoring as many PLCs as possible with Level 1 control to verify the features needed to properly manage a large fleet of PLCs.

Print Server + PLC

Conclusions. The system is very effective for energy savings and provides an automated process for users. It is robust enough to handle changes in occupant behavior such as printing at odd hours. Level 2 control appears to be very conducive to user adoption, having only resulted in one minor user issue. Level 2 controls are ideal for printers that are used frequently and for copiers that have a longer bootup time. Level 3 control requires more education and communication with occupants. It is ideal for printers that are used less frequently. There continue to be concerns about PLC degrading printer health due to the hard stop of power. The research team reached out to printer manufacturers and the general feedback is PLC is okay as long as power is not cut while the printer is actively printing, which our control successfully avoids.

Future Work. Additional work is required to get the system to a production and commercialized level that can be used in daily operations. A key improvement that must be developed is to transition to a different print server that can support both Windows, Apple, and mobile devices. Additional fail-safes continue to be developed such as the ability to default PLCs to ON if connectivity is lost to the control system whether due to the Wi-Fi network or server error.

Water Dispensers, TVs, & Thermostat Occupancy

Conclusions. Level 1 control of water dispensers and digital signage TVs provides reliable savings if the user does not already have a routine for turning OFF the devices at the end of the day. Schedules provided by department contacts are a good start, however, due to holidays and variable work schedules they may not reflect true occupancy patterns or appliance usage. To achieve greater savings with Level 2 and 3 control, additional data is required. Identifying water usage from power measurements alone proved challenging and digital signage TVs do not have a way of reporting when people are viewing them. Therefore, occupancy data from thermostats is required. Simulated results proved the concept of using occupancy data with PLC. For water dispensers occupancy forecasting is necessary to account for the long startup time needed to precondition water before use. Generally, PLCs do not inherently have occupancy data so the interoperability that the Brick Schema provides is crucial for the scalability and portability of these types of control strategies.

Future Work. For the Thermostat Occupancy-Triggered PLC, we will run a trial to test the control strategy in the field and across different plug load types. A similar trial will also be performed at a building with a connected lighting system that has near-complete coverage of all rooms with occupancy detectors. PLCs that integrate with lighting motion sensors for simple occupancy-driven control exist in the market, however, further work is required to commercialize the advanced PLC strategy shared in this work.

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