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By

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Abstract

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Plug loads are an increasingly important end-use in commercial office buildings. They currently account for 12-50% of total commercial building energy consumption, and as the efficiencies of regulated major end-uses, such as space conditioning and lighting systems, continue to increase, plug load energy use is expected to rise. This study evaluates patterns in collected plug load data and the effect of a behavior-based intervention to reduce plug load energy consumption.

This project leverages a data collection effort originally funded for a study by the California Air Resources Board, where 100 plug load monitoring power strips were installed at individual workstations in the Franklin Building, an office building in Oakland owned by the UC Office of the President (UCOP). Each occupant received one power strip and connected up to four devices to be individually monitored. For this project, only the labeled devices (desktop, laptop, monitor, task light) are included.

An analysis of the collected data reveals a clear distinction between work days and non-work days (weekends and holidays). Overall, the monitored occupants have regular work schedules, turn off their equipment at the end of the work day, and do not often stay late or come in on the weekends. Desktops consume the most power per person, followed by monitors and then task lights. Laptop power trends were more difficult to discern because users often disconnect them to work in other locations (that were not monitored). Desktops demonstrate the widest range of power consumption among the devices monitored. During unoccupied periods (overnight and on non-work days), desktops draw the most power, followed by laptops. All devices draw more power overnight on work days than over weekends and holidays, indicating that users are more likely to turn equipment off before a longer break from the office.

Much of the literature on reducing plug load energy consumption in commercial buildings is focused on technology-based solutions, such as purchasing new equipment or installing sophisticated controls to turn off equipment when not in use. The literature on changing occupant behavior to reduce energy use is focused on residential occupants, however multiple studies show that even when occupants do not pay their own bills and have no financial incentive to save energy, other factors can encourage behavior change. One such motivating

method is by using gamification, or turning an everyday activity into a game to encourage behavior change by making it more fun and interesting.

With the help of leadership at UCOP, an online sustainability game, Cool Choices, was initiated in the Fall of 2014 and 30 employees signed up to play. Cool Choices encourages occupant behavior changes to save water, energy, and reduce waste; players earn points for each action they complete at work or at home and compete with each other on teams. Survey responses from game participants showed that players were motivated to play because the game looked fun, and because the actions suggested were easy to perform. An analysis of the energy impact revealed that because occupants were already engaging in relevant energy saving behaviors (e.g. turning equipment off at the end of the day), there was limited opportunity for further behavior-based reductions.

Using trends identified in the baseline analysis, a simplified plug load model was developed to predict power consumption based on device type, day type (work day or non-work day), and time step, using a Monte Carlo simulation. The model used day type and time step as proxies for occupancy, so when occupancy was not well predicted by the work day/non-work day dichotomy, the model became increasingly unreliable. Even after adding an additional variable (month), the model was still not able to predict power consumption to an acceptable degree of accuracy per industry standards. The model demonstrated a need for a new, more accurate proxy for occupancy, perhaps based on individual occupants, rather than devices.

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1. Introduction

1.1. Problem Statement

Plug load energy use is emerging as an increasingly important end-use in commercial buildings. While the efficiencies of heating, cooling and lighting systems have been steadily increasing due to code mandates and standards, plug loads are becoming a larger percent of overall consumption. Various sources report that plug loads currently account for 12%-50% of commercial building energy consumption, and they are expected to increase in proportion of energy use and actual energy use, as office equipment energy consumption is expected to rise at a rate of 0.8% per year (Cortese, Higgins, Lyles, & others, 2014; U.S. Energy Information Administration., 2003). The literature suggests that energy efficiency- and behavior-based strategies have the potential to reduce energy consumption, however existing studies are largely concentrated in the residential sector, and for those that do consider commercial buildings, there are a limited number that take into account long-term effects of intervention strategies.

The role of plug loads in energy modeling is also important to investigate, as the ability to model plug load profiles accurately is a limitation in modeling whole buildings accurately. Currently, plug load profiles used in building energy models are usually uniform across an entire building or space-type, with a peak value for occupied hours and a minimum value for unoccupied hours. When looking at long-term performance, the variability of plug load use is not critical, as long as average values are approximately correct. However, looking at cases where a single zone can drive changes in the HVAC system (e.g., rogue zones in VAV systems with static pressure reset), zone load variation plays an important role in determining overall energy consumption of the HVAC system. Understanding the variation in plug load use can help determine a way to generate zone load profiles to improve energy modeling inputs.

For this study, I had a unique opportunity to analyze plug load data from the UC Office of the President (UCOP), where the Center for the Built Environment (CBE) has been collecting data continuously since November 2012. Approximately 100 Enmetric plug load monitoring devices (power strips) have been installed on site, one per workstation. Each piece of equipment plugged into the power strip has been categorized by type (e.g. computer, monitor, task lights, etc.) and is being tracked online (power, at one second increments). This is the only known plug load monitoring study collecting detailed data in a conventional office setting for this long, representing a unique opportunity to build on baseline data that already exists.

The leadership at UCOP was also receptive to implementing a behavior-based intervention to study whether occupants could be persuaded to reduce their plug load energy consumption. Understanding what types of strategies will most influence occupants to change their energy consumption will be critical in determining how to reduce this unregulated building load in other commercial buildings. By studying a typical office building, I can gain insights into which intervention methods are most successful in commercial settings.

1.2. Background

This study used plug load monitors that were originally installed as part of a California Air Resources Board-funded study investigating cost-effective options for mitigating California's greenhouse gas emissions through energy reductions in commercial buildings (Lehrer, Levi, Fountain, & Uhl, 2014). A preliminary data analysis was conducted for the original study, however the data were never analyzed in depth.

The original study selected Enmetric powerports as the plug load monitors to provide device-level power data. Enmetric powerports are four-channel plug strip load meters which provide real time plug load data through an online interface. They plug into regular electrical outlets and can monitor standard electrical appliances up to 15 A. Each powerport transmits power consumption data to a wireless router ("bridge"), which then relays that information to Enmetric's servers. The bridges connected to the internet using UCOP's local area network (LAN).

100 workspaces were outfitted with one powerport each on the 6th and 7th floors of the Franklin building. The original research team labeled each device as either desktop computer, monitor, laptop computer, task light, hard drive, or miscellaneous. This information was uploaded to the online interface, which labeled each device using the occupant's workstation identifier (e.g. office or cubicle number) and the name of the device plugged into each port.

In the spring of 2014 I was made aware of this data collection effort by David Lehrer and Gail Brager. With my interest in energy use and occupant behavior, we felt that it would be beneficial to use the existing setup from the CARB-funded study to further analyze the collected energy data and conduct a behavioral intervention at the site.

1.2.1. Limitations

There are several important limitations of this study which provide bounds to my project's scope. Each occupant involved was provided with only one four-channel power strip, and any plug load equipment not plugged into the powerport was not monitored. Therefore, the results of this study will not represent the range of plug load devices available in an office setting, or an inventory of the devices found at each desk. The devices targeted by the original study were desktop computers, monitors, laptop computers, and task lights. Any other device was labeled as miscellaneous. Because I was interested in building on the existing baseline data collected since 2012, I did not change the scope of devices monitored.

In addition, although there were 100 devices installed for the original study, at the start of this study in the summer of 2014, there were 67 operating Enmetric devices (verified during a July 2014 inventory). We identified two main reasons why powerports were disconnected: through changes in personnel or office moves, and when users experience hardware malfunctions. With personnel changes, it is possible that occupants did not know what the powerports were for and assumed they were regular power strips. During an inventory conducted in July 2014, the plugged in devices were updated with any changes. Surprisingly, the majority of devices plugged into the operating devices were unchanged.

2. Research objective

The objectives of this research are to:

- Identify and characterize trends in the baseline plug load data to understand the patterns and variability of power use due to plug load device type, time of day, and occupancy.
- Develop a data-driven Monte Carlo plug load modeling tool to predict aggregated plug load power consumption based on the characteristics identified in the baseline plug load analysis.
- Evaluate whether a game-based behavior intervention can change occupant behavior to reduce plug load energy consumption without direct monetary incentives.

3. Literature Review

This literature review is focused on the current state of research regarding commercial building plug load energy consumption and how occupant behavior affects this important energy end use. This section begins with an overview of the current data on plug load energy use in commercial buildings and discusses why plug loads are important to study. It then provides an overview of methods to manage and reduce plug load energy use, with a focus on behavior-based strategies. Historically, behavior interventions targeting energy reductions in residential buildings have been more common and more widely studied, so residential studies that are relevant and can apply to commercial settings have been selectively included.

3.1. Plug load end-use in commercial office buildings

The term "plug load" is not used consistently within the literature and does not have a standardized definition. Fuertes (2014) evaluated the terminology used in codes, standards, peer-reviewed articles, surveys (e.g. Commercial Buildings Energy Consumption Survey), and whitepapers, finding that plug loads were also called "miscellaneous equipment," "miscellaneous electronic loads" (MELs), "process loads," "receptacle loads," or "office equipment." She found that different sources used different definitions for these terms, from very specific (e.g. only equipment plugged into an AC outlet), to more broad (e.g. all miscellaneous loads outside of the traditional categories of HVAC, lighting, water heating, and major appliances). For this paper, plug loads are considered to be devices plugged into an electrical outlet in commercial office building primarily including, but not limited to, IT equipment.

The 2003 Commercial Buildings Energy Consumption Survey (CBECS) estimates that plug loads account for 12% of energy end-use in commercial office buildings (U.S. Energy Information Administration., 2003). The 2006 California Commercial End Use Survey (CEUS) estimates that, among small and large offices, plug load energy use (categorized as office equipment) accounts for 14% of total building energy use (Itron, 2006). In a report conducted for DOE's Building Technologies Program, plug and process loads (PPLs) were estimated to account for 33% of total US commercial building electricity use (McKenney, Guernsey, Ponoum, & Rosenfeld, 2010). While these categories are not all defined equally, it is clear that these unregulated loads do account for a nontrivial percent of total building energy use.

For highly energy efficient buildings, plug loads are proportionately even more significant. At the net zero energy IDeAs Z2 Design Facility in San Jose, California, plug loads account for approximately 40% of total building energy use due to the extremely efficient space conditioning and lighting systems installed (Kaneda, Jacobson, Rumsey, & Engineers, 2010). Similarly, for NREL's Research Support Facility in Golden, Colorado, plug loads are responsible for 55% of total building energy use (including an on-site data center) (Lobato, Pless, Sheppy, & Torcellini, 2011). The New Buildings Institute's study of verified net zero energy buildings in the United States reports that for these highly efficient buildings with low energy lighting and space conditioning systems, plug loads can account for 50% of total energy use (Cortese et al., 2014).

While the exact numbers vary from study to study (and of course, building to building), it is clear that plug load energy use is a critical issue to address. They are increasing proportionately as well as absolutely as more and more electronic devices are used in office buildings. In fact, while electricity use due to personal computers (e.g. laptops, desktops, monitors) is decreasing due to improvements in energy efficiency, expanding use of unregulated miscellaneous electronic equipment is expected to result in a 21.4% increase in energy intensity (energy use per unit area) between 2012 and 2040. (U.S. Energy Information Administration, 2014). The buildings industry is also moving towards stricter energy targets on the way to achieving net zero energy status through regulatory and voluntary standards. In California, the Public Utilities Commission is using the state's energy code, Title 24, to push towards net zero energy status for all new residential construction by 2020 and all new commercial construction by 2030 (California Public Utilities Commission & others, 2008). Architecture 2030, a non-profit organization, issued the 2030 challenge in 2008, encouraging industry firms to sign up to commit to designing all net zero energy buildings by 2030 ("Architecture 2030," n.d.). As more buildings achieve high levels of efficiency, plug loads will become a larger percentage of overall energy use, as demonstrated by the aforementioned measured energy data from current net zero energy buildings. Understanding the daily, weekly, and monthly patterns will become increasingly important in achieving reductions in energy consumption.

3.2. Plug load profiles

The literature on plug load profiles (also known as plug load equipment schedules) is extremely varied. Figure 3.1 and Figure 3.2 illustrate the disparity in plug load profile recommendations from three respected sources: the Department of Energy's reference building models for small, medium, and large office buildings (Deru et al., 2011); results of a building survey of small, medium, and large office buildings conducted for ASHRAE's RP-1093 (Claridge, Abushakra, Haberl, & Sreshthaputra, 2004); and California's Title 24 schedules for medium and large office buildings (California Energy Commission, 2010).

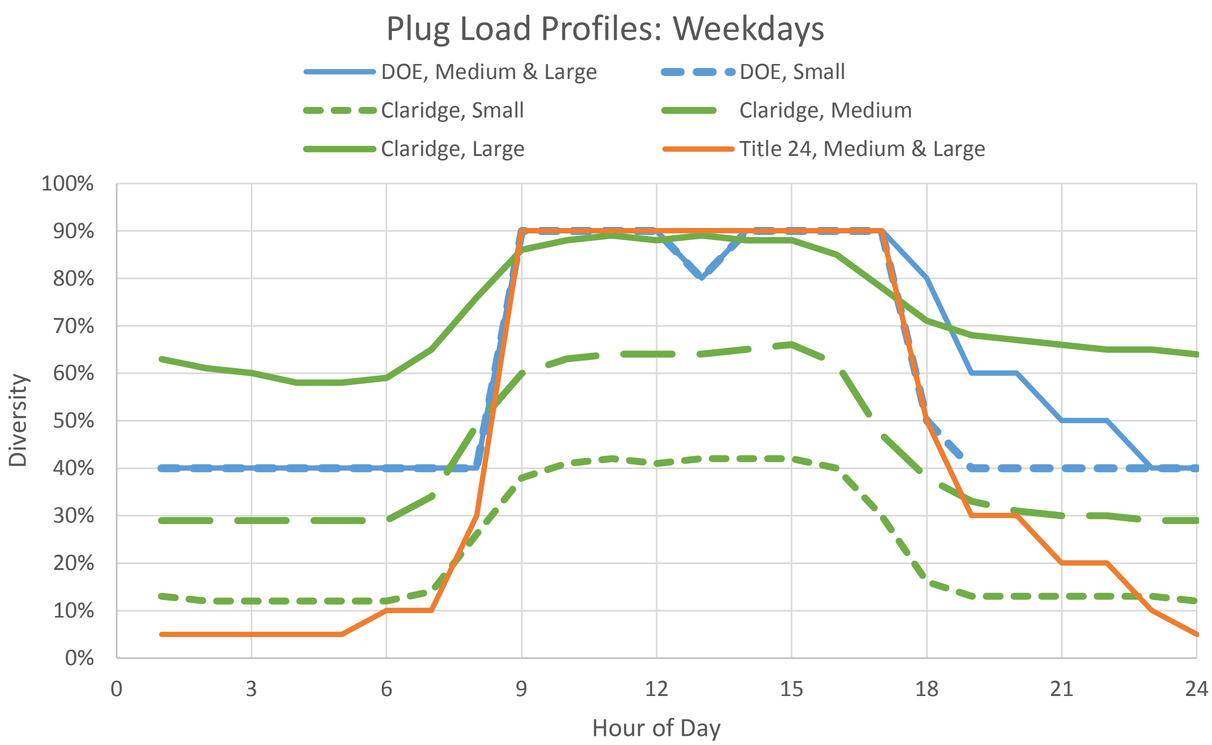


Figure 3.1 Published hourly plug load profiles for work days

All three sources separate out weekdays (Figure 3.1), but each categorize non-weekdays differently (Figure 3.2). Deru et al. (2011) classified non-weekdays as Saturdays and "Other." No explanation was provided for the latter category, so it is assumed that it includes Sundays and holidays. Based on measured data of 32 office buildings, Claridge (2004) classified both days of the weekend together, under one schedule (Weekend), while Title 24 has separate schedules for Saturdays and Sundays (California Energy Commission, 2010).

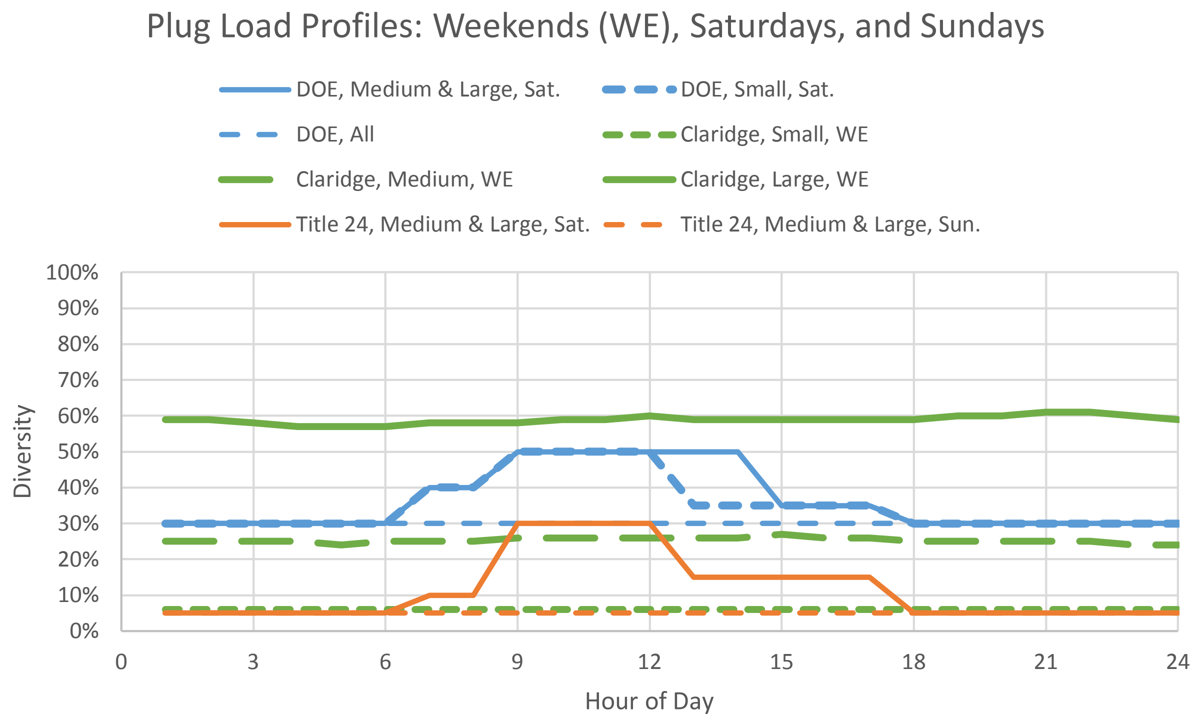


Figure 3.2 Published hourly plug load profiles for non-work days

The obvious disparity in recommended plug load schedules indicates that modeling plug load equipment in whole building energy models is not necessarily straightforward. Selecting the appropriate plug load profile when energy modeling will make a large difference in overall predicted energy use, as well as predicted peak power, which is used to size space conditioning equipment.

Among the literature reviewed, there is strong consensus that due to the nature of occupant-controlled plug loads, even a well-trained analyst may not be able to predict plug load energy usage accurately (De Wilde, 2014; Menezes, Cripps, Bouchlaghem, & Buswell, 2012; Zhang, Siebers, & Aickelin, 2011). This issue will become increasingly prominent as buildings become more energy efficient and plug loads account for a larger percentage of overall energy use (Cortese et al., 2014; Lobato et al., 2011).

3.3. Commercial building equipment surveys

This section outlines additional energy and power consumption findings on plug load energy usage in commercial office buildings, including a comparison of actual power consumption to nameplate power ratings and surveys of plug load equipment in office buildings.

3.3.1. Estimating plug load equipment use

It is not always easy to evaluate energy consumption of plug loads. Two studies were identified that provided guidance on setting up monitoring studies for MELs (Dirks & Rauch, 2012;

Lanzisera et al., 2013). Dirks and Rauch (2012) found that MELs are often not studied in detail because they are not well-defined as a commercial building end-use and they vary by building type. There is no established method for collecting energy consumption data, and metering at a device-level can be more expensive than the potential realized energy savings will pay back (Dirks & Rauch, 2012). To that end, Lanzisera et al. (2013) provide a method for assessing plug load energy use by monitoring only a subset of equipment after an inventory of the quantity and diversity of equipment is conducted.

Directly measuring plug load energy consumption is important because of the difficulties associated with estimated power draw based on nameplate rated power information. A device's nameplate power is the rated power found on a tag ("nameplate") attached to the device, which also includes information such as the brand name and serial number. Desktop computers, monitors, and other plug load equipment are accompanied with a nameplate rated power value. Various studies found that the actual power consumption of office equipment is only 14-36% of nameplate power ratings (Hosni, Jones, & Xu, 1999; Wilkins, Kosonen, & Laine, 1991; Wilkins & McGaffin, 1994).

3.3.2. Office building equipment surveys

A number of studies have conducted equipment surveys in office buildings to ascertain plug load equipment densities and power status during non-working hours.

In an audit of 16 buildings in San Francisco, Pittsburgh, and Atlanta, researchers found the quantity of office equipment ranged from 9 to 14 for small, medium, and large offices during the day (Sanchez et al., 2007), noting that equipment densities were lower at night in areas where occupants used laptops, as many were not present during non-working hours (Roberson et al., 2004). During an after-hours audit, researchers found that just 36% of desktop computers and 29% of monitors were turned off at night, while 50% of monitors and just 4% of desktop computers were in a low-power state (Sanchez et al., 2007). In another after-hours walkthrough of 11 office sites in San Francisco and Washington, DC, researchers found that only 44% of computers, 32% of monitors, and 25% of printers were shut off at night (Webber et al., 2001).

In a third comprehensive audit of five commercial buildings in Botswana and South Africa, Masoso and Grobler (2010) found that plug loads accounted for 19-38% of total electricity use and that a staggering 56% of the building's total energy use (including plug loads) was consumed during non-working hours.

These studies indicate that plug load equipment is often wasting significant amounts of energy at night and on the weekends, when equipment is not being used. By turning equipment off during non-working periods, it is clear that significant savings can be achieved. There are two main approaches to curb equipment power draw during non-working hours, one is centered around technology changes, while the other relies on changing occupant behavior.

3.4. Approaches to reducing plug load energy use: technology & behavior

There are multiple papers in the literature outlining recommendations for assessing and reducing plug load energy consumption based on case studies of existing buildings. Table 3.1 provides a summary of the key strategies found in 12 sources. These were selected because they based their recommendations on buildings that have been built and monitored, or were meta-studies, which sourced recommendations from multiple case study buildings.

The technology-based strategies listed in Table 3.1 fall into two categories: equipment and control. The first three strategies rely on the equipment to use less energy, either by using more energy efficient models, or by reducing the quantity of equipment installed. The remaining technology-based strategies are all about controlling energy use. Adjusting power management settings, setting equipment timers, and utilizing smart power strips that control energy use are ways to cut down on energy consumption when equipment is not in use. These strategies specifically address the issue of wasting energy during non-working hours, or when equipment is simply not being used.

Table 3.1 indicates that technology-based strategies are much more common and more widely studied than behavioral solutions. This is probably because technology solutions remove responsibility from the user, thereby removing the element of uncertainty associated with occupant behavior. However, behavioral strategies are important to consider as they can be more cost effective, especially in existing buildings where options available to replace old systems may be limited for a variety of reasons (cost, space constraints, historic regulations, etc.), which can also limit available options for devices to control equipment energy consumption. The remainder of this literature review is focused on strategies which aim to reduce energy consumption through occupant behavior changes.

Six of the recommended strategies fall under the umbrella of behavioral solutions. The first two are incentive and penalty strategies; which reward occupants for reducing energy consumption, or for staying within a set energy budget. In the case of Seattle’s Bullitt Center, tenants were rewarded with a full refund of their submetered electricity bill for staying within their agreed-on energy budget, while the penalty for exceeding their budget was payment of the full bill themselves. The remaining solutions in Table 3.1 are educational and feedback strategies in the form of informational tips and reminders to occupants to empower and encourage them to make behavioral changes. These, and other behavioral strategies, have been studied in residential and commercial settings. The next section provides deeper insight into the psychology behind behavior change, the variety of behavioral interventions, and their associated energy savings.

Table 3.1 Published strategies for reducing plug load energy consumption in office buildings.

			Buildings						Metastudies					
		Strategies	Bullitt Center[1]	DPR Phoenix[2]	IDeAs Z2 Design Facility[3]	Packard Foundation[3,4]	NREL RSF[5]	Stevens Library[3]	Reducing Plug Loads[6]	Ghatikar[7]	Mercier et al.[8]	Metzger et al.[9]	NBI Getting to Zero[10]	NBI Best Practices[11]
Technology-based	**Equipment**	Replace equipment with energy efficient versions	X		X	X	X	X	X		X		X	X
		Remove unused equipment and consolidate personal equipment to shared devices					X		X					X
		Utilize virtual server software to reduce physical server size	X		X	X								
	Control	Adjust power management savings to reduce energy use during non-working hours			X		X		X	X	X		X	X
		Set timers on equipment with regular schedules				X			X		X	X	X	X
		Install load-sensing outlets and power strips that turn equipment off when not used				X	X			X	x	X		X
		Use occupancy-sensing power strips to turn equipment off in unoccupied workspaces	X		X	X		X	X				X	X
		Control plug loads remotely	X							X				
		Wire plug loads on same circuit and turn off at night to reduce vampire loads		X	X									
Behavior-based		Offer rewards for reduced energy consumption												X
		Write energy budget into lease agreement, with overage penalty	X										X	
		Educate and train staff to use new devices and to reduce energy use							X					X
		Email occupants reminders to turn off equipment							X	X	X		X	
		Provide feedback displays showing real time energy use	X								X		X	
		Encourage changes in habits									X			

[1](Urban Land Institute, 2015)
[2](Ladhad & Parrish, 2013)
[3](Dean, 2014)
[4](Knapp, 2013)
[5](Lobato et al., 2011)
[6] (National Renewable Energy Laboratory, 2013)
[7](Ghatikar, 2014)
[8](Mercier & Moorefield, 2011)
[9](Metzger, Cutler, & Sheppy, 2012)
[10](Cortese et al., 2014)
[11](New Buildings Institute, 2012)

The importance of understanding occupant behavior is echoed in the international community through the establishment of the International Energy Agency's (IEA) Annex 66 under the Energy in Buildings and Communities Programme (EBC). Annex 66's tasks are to set up a standard occupant behavior definition platform, to establish a quantitative simulation methodology to model occupant behavior in buildings, and to understand the influence that occupant behavior has on building energy use and indoor environmental quality. Subtasks C and D are specifically relevant to this investigation, as their goals are to establish a systematic approach to measuring and modeling occupant behavior, and to integrate occupant behavior with current building energy modeling programs (Yan & Hong, 2014).

3.5. Psychology of occupant behavior

One hurdle associated with encouraging occupant behavior change in the workplace is a lack of the financial incentives that come with saving energy. However, research has shown that economics do not fully explain energy use behavior, and that the presence of financial incentives alone do not predict energy savings (Costanzo, Archer, Aronson, & Pettigrew, 1986; Dennis, Soderstrom, Koncinski, & Cavanaugh, 1990; Harrigan, 1991; Stern & Aronson, 1984). In fact, Stern (1992) and Hayes & Cone (1977) found that some consumers will ignore significant financial incentives associated with energy saving behavior, while others will continue to conserve energy even when the incentive is greatly reduced.

Another potential predictor of energy saving behavior is personal values or attitudes about energy conservation. However, studies in psychology have shown that there is not always a strong connection between personal values and attitudes about energy consumption that individuals espouse, and their measured energy use. McDougall et al. (1981) found that strong views on environmental conservation and claims of related actions did not definitely predict energy use reductions. Finger (1994) surveyed respondents in Switzerland and found poor associations between attitudes and knowledge of environmental issues and associated energy saving behavior.

McKenzie-Mohr (2000) summarizes the literature on investigating and establishing a link between behaviors and knowledge. In a residential study targeting those interested in increasing the energy efficiency of their homes, significant changes in attitudes and knowledge did not change their energy use behavior (Geller, 1995). McKenzie-Mohr goes on to state that behavior requiring repetitive actions (e.g. turning lights off daily) is more difficult to maintain than one-time changes in behavior (e.g. purchasing more energy efficient light bulbs) (Kempton, Darley, & Stern, 1992; Kempton, Harris, Keith, & Weihl, 1985; McKenzie-Mohr, 2000).

These findings suggest that there is not one primary predictor of energy saving behavior that can be generalized among different populations. For some individuals, financial incentives may be the best encouragement, while others may be motivated by their personal views on conservation and saving energy.

Behavior changes are more likely to be long lasting if new behaviors are framed as being beneficial to the individual (Becker, Seligman, Fazio, & Darley, 1981; Samuelson & Biek, 1991), and if new behaviors are convenient and neighbors or family are making the same changes (Costanzo et al., 1986; Harrigan, 1991; Siero, Bakker, Dekker, & Van Den Burg, 1996; Stern, 1992). This suggests that occupants in a commercial setting could be persuaded to change their behavior by participating in a program with their colleagues, and if those changes are presented as incremental and easy to make.

Individuals are also more likely to make permanent behavior changes if energy savings are visible to provide motivation (Kempton et al., 1992; Stern & Aronson, 1984), and if energy use feedback is personalized (Costanzo et al., 1986; Dennis et al., 1990; Stern, 1992; Stern & Aronson, 1984). This suggests that successful strategies will include feedback of energy use on an individualized level. However, individualized feedback is not always feasible due to the expense of monitoring plug load equipment.

3.6. Types of behavior interventions

This section provides an overview of the various types of behavioral interventions possible, from educational programs to energy reduction competitions, in both residential and commercial settings. Residential studies have been included to represent the breadth of strategies in use, as well as to provide precedents in situations specifically applicable to a commercial building (e.g. where occupants do not pay utility bills). Where provided, measured energy saving results are reported. The section closes with a discussion of the persistence of energy savings.

Abrahamse et al. (2005) summarizes 38 studies of interventions encouraging energy reduction in households, examining both behavioral and technological strategies. The study describes antecedent strategies (commitment, goal setting, information, modeling) and consequence strategies (feedback, rewards). The summarized studies also included those using efficiency techniques (e.g. one-time purchase of insulation or efficient equipment), and curtailment behavior (e.g. reducing energy use by lowering the set point of the space conditioning system). The latter strategies are not explored here.

3.6.1. Goal setting

Goal setting, where individuals are provided with a goal or set it themselves, has shown to be effective in combination with a commitment (promise) to save energy or with feedback in both residential (Abrahamse, Steg, Vlek, & Rothengatter, 2007) and commercial settings (Talbot & Love, 2014). In Talbot (2014), tenants were encouraged to reduce plug load energy consumption by setting measurable goals and receiving performance feedback via an online interface. For the 27 participants, estimated savings ranged from 22-34% after the three-month intervention period, compared to a baseline estimated by number of plug loads and energy use profiles sourced from Sanchez et al. (2007) (Talbot & Love, 2014). While their method of calculating the baseline may not accurately represent true baseline energy use, results are encouraging.

3.6.2. Information and education

Another antecedent strategy is providing information to individuals or educating them about the targeted behavior. Tailoring information to individuals can results in significant savings and increased knowledge (Abrahamse et al., 2007). In a commercial office building study that combined informational tips with individualized feedback, overall savings of 23% were achieved (Lasternas et al., 2014). In a residential study, researchers found that out of providing payments, feedback, and information, information alone was the least effective at inducing energy saving behavior (Hayes & Cone, 1977). Another method of providing information to occupants in a workplace setting is through peer educators, i.e., training a subset of occupants to disseminate energy saving behaviors throughout the office. In a commercial office building study focused on reducing whole building energy use, peer education was associated with a 4% energy reduction (Carrico & Riemer, 2011).

One study used a variety of methods to educate occupants about energy saving behaviors. McMakin et al. (2002) conducted an intervention on a military base in the U.S., where residents do not pay their own bills and houses are not individually metered. The study held focus groups to learn what behaviors could be targeted, and then organized campaigns to raise awareness of the energy saving initiative. Videos and printed materials were distributed among residents, and tickets were given out for behavioral violations. They used games to educate children and set up a competition among neighborhoods on base. The one-year intervention resulted in a 10% reduction in energy use. There were two types of survey responses that were particularly relevant to the commercial building setting: respondents who said their house was the problem, not their behavior, and those that said their job was stressful enough and they were not concerned about their home energy use (McMakin et al., 2002). In commercial settings, it is possible that these attitudes may be prevalent, given that occupants do not pay their own bills, do not choose their building (and usually have no voice in how efficiently it runs), and likely have more pressing responsibilities to attend to.

As demonstrated by these examples, information is often provided as part of a combined strategy. In fact, Abrahamse et al. (2005) found that the most effective interventions combined antecedent and consequence strategies, and that the least effective were interventions characterized by a single antecedent strategy. The authors recommend that future intervention programs begin by identifying behaviors that contribute to wasting energy and then examine what barriers prevent occupants from engaging in sustainable behavior patterns. A multidisciplinary approach is suggested to examine the problem from a sociological and environmental standpoint (Abrahamse et al., 2005).

3.6.3. Feedback and incentives

Darby (2006) conducted a focused review of residential feedback-based strategies and reported energy savings, stating that clear feedback of energy use is a necessary step for users to understand how to control their energy use. Savings from direct feedback of energy consumption (available for users to view immediately, e.g. a display connected to a meter) ranged 5-15%, while indirect feedback (processed before the user can view, e.g. billing statement) savings ranged 0-10%. Darby found that historic feedback, rather than comparative (e.g. with other households) was more effective. Lastly, pay-as-you-go systems with a display were found to result in 10-20% energy savings (Darby, 2006).

Other studies have also examined how feedback motivates occupants to save energy. Carrico and Riemer (2011) found that providing monthly feedback to occupants of a commercial office building resulted in 7% energy savings for the entire building. In another commercial office intervention, Lasternas et al. (2014) provided occupants with an online interface to view their own energy consumption by individual plug load (as well as informational energy saving tips), create schedules to control devices, and turn off equipment remotely. The intervention resulted in 23% overall energy savings, with 74% of these savings occurring during non-working hours. The study did not mention if savings were persistent (Lasternas et al., 2014).

Petersen et al. (2007) initiated a two-week energy competition among 22 dormitory buildings on a university campus where residents do not pay their own bills and thus had no financial incentive to participate. Two of the buildings were supplied with real-time energy feedback via a web-based interface, while the remaining dormitories were provided with weekly meter readings. The dormitories with real-time feedback reduced energy by 55%, while the other dormitories reduced energy by 31%. Less than 10% of students in the winning dorm attending the awarded ice cream social party, suggesting that this reward was not the only motivator. The study did not monitor energy use after the end of the competition (Petersen et al., 2007). Without a persistence study, no conclusions can be made about the longer term effectiveness of the intervention (and whether changes residents made were even sustainable beyond the two week period).

In a residential-based study of 91 apartments in four buildings, researchers found that the electricity savings achieved were not significantly different for residences provided with individual feedback (18.8%), comparative feedback with similar residences (18.4%), and comparative feedback with payment incentives (19.4%). However, the authors suggested that because the payments were delayed until the close of the study, it was not clear whether they were a true incentive to save energy (Midden, Meter, Weenig, & Zieverink, 1983). Hayes & Cone (1977) conducted a residential study using multiple methods, including payments that were scaled by percent reduction below an established baseline. Out of the methods they used (payments, feedbacks, information), payments resulted in the most immediate and stable energy reductions, even when the amount of payment decreased (Hayes & Cone, 1977). However, the authors stated that some of the changes made by occupants were unsustainable, such as using battery-operated equipment (Hayes & Cone). This suggests that even reduced payments were sufficient motivation to reduce energy consumption, and that the unsustainable energy saving behavior may stop once payments ceased altogether.

While these papers have underlined the importance of feedback for reducing energy consumption, commercial buildings are not always submetered to the granularity needed to provide disaggregated or individualized feedback, and the necessary equipment can often be expensive to install. Thus it is also important to look at programs conducted where feedback was not available.

3.6.4. Gamification

An approach that does not always rely on feedback is the idea of modifying occupant behavior through gamification. Gamification is the concept of changing an everyday activity in the physical world into a game in order to make real-world changes (Grossberg, Wolfson, Mazur-Stommen, Farley, & Nadel, 2015). Although gamified solutions for encouraging behavior change are not limited to energy saving behaviors, this will be the focus of this section. Approaching energy savings as a game can come in many forms, from competitions between different buildings (Petersen et al., 2007), to competing individually with other occupants (Orland et al., 2014).

Grossberg et al. (2015) conducted a review of 53 game-based solutions and evaluated case studies for 22 of them, examining them through a common framework to describe the game developers, the game's objectives, the target audience, how players are motivated, and what energy savings are achieved. Of the selected 22 case studies, five programs were workplace-oriented, five were centered on schools, and the remaining were focused on the residential sector. Nine programs had a social media component (i.e., interaction between users in an online space) and 14 were team-based. Fifteen games provided tangible rewards to a subset of players, while seven provided only virtual rewards. Only nine case studies documented energy savings, and while the results are not definitive, preliminary conclusions suggests savings of 3-6% were achieved (Grossberg et al., 2015).

Two of the case study programs Grossberg et al. (2015) evaluated in depth were Energy Chickens and Cool Choices. Both are workplace energy savings programs that encourage sustained behavior changes in occupants through daily game play, but they accomplish this goal differently.

Energy Chickens uses an individual occupant's own plug load data to feed into a virtual chicken farm, with one chicken for each device plugged in (Orland et al., 2014). Changes in daily energy use affect each chicken, with energy savings improving the health of individual chickens and earning the user points. Players can see each other's farms and progress over time. During the 16 week game, players saved an average of 23% during non-work days and 7% on work days, and although 69% of participants reported that the game made them more conscious about their daily energy use, the savings were not persistent and energy use patterns resumed to their pre-game baseline once the game concluded (Orland et al., 2014). This suggests that the game period was too short for occupants to form sustained habits, or that the daily feedback via the virtual chicken farm game interface was a primary motivator for players.

While Energy Chickens targets plug loads, Cool Choices takes a more general approach, targeting a variety of sustainable behaviors at the office and at home. Kuntz et al. (2012) discusses the founding principles of the game, which center around making change “fun, social, and easy” and acknowledging that change is more likely to occur when individuals want to make the change and when they have the support and knowledge to do so. To that end, Cool Choices is an online game where players earn points for making environmentally sustainable actions, and compete on teams to encourage participation. During a six month game, participation was awarded via weekly prizes, and 52% of actions taken during the game were reported as new behaviors by survey respondents (Kuntz et al., 2012). Although energy use was not measured, the high rate of participation and positive player responses suggest that the game may induce energy savings.

3.7. Persistence of savings

An important facet of behavioral interventions is the question of persistence, i.e., what happens to energy savings attained during the intervention, after the study has concluded? Darby (2006) looked at persistence of savings in the literature, finding that a behavior formed over at least three months appeared most likely to persist longer, but that continued feedback was required to maintain the change. This suggests that limited information is available to make a definitive statement about persistence of savings, a conclusion echoed in the present literature review.

One residential study that did examine persistence in depth was conducted by a utility company using Opower reports sent to households in a randomized controlled study of 234,000 households (Allcott & Rogers, 2012). Opower is a software company that works with utilities to provide home energy reports to customers that include energy efficiency tips and energy use comparisons with “similar” neighbors. The authors wanted to determine how persistent effects were after the intervention ended, and what incremental effects might exist with continued treatment, i.e., were customers habituated to the reports after a certain time span or not. They found that there was an initial pattern of “action and backsliding” where consumers immediately reduced their energy use after receiving the report, but then usage slowly crept back up until the next one. However, after the first four months of reports, the immediate decreases following a new report were five times smaller than initial decreases. After two years, when reports were discontinued for some households, effects decayed at 10-20%, which is four to eight times slower than decay rates between initial reports. The authors suggested this could be due to consumers making one-time purchases of more efficient equipment (new “capital stock”), reducing their baseline energy usage permanently. Finally, the study found that even after two years of monthly reports, consumers were not completely habituated and still made substantial incremental changes after continued reports. The authors concluded that understanding persistence, habituation and when consumers establish “capital stock” could help to design programs that reduce report frequency at the optimal time (Allcott & Rogers, 2012). The results of this study suggest that a prolonged intervention may continue to have incremental effects, even after major changes or savings have been achieved. It also suggests that energy savings will always decay over time, and if a continuous intervention is not possible, another strategy may be to reintroduce the intervention periodically to motivate occupants long-term.

3.8. Data-driven predictive models

An important reason for identifying trends and patterns in building energy use is to predict future use based on a set of variables. This type of predictive model can be used to evaluate energy savings incurred through building retrofits (Coakley, Raftery, & Keane, 2014). Although this study is focused on building plug loads, there are limited studies on predicting plug load consumption, so this section summarizes relevant literature surrounding predictive modeling techniques for overall energy use in buildings.

There are three types of models which can be used to predict energy performance: white box models, black box models, and a hybrid of the two (also called gray box models). White box models rely on first principles (e.g. First Law of Thermodynamics) and are appropriate when the system is governed by a physical principle. However, they are not appropriate when a main driver of the system is stochastic, such as occupant behavior (as is the case with plug load energy consumption). Black box models, also called data-driven models, are better suited for these non-deterministic systems. They are based only on the data provided (called "training" data), and do not describe any physical parameters within the system, however they can be powerful methods to predict energy consumption based on the data they are trained with (Coakley et al., 2014). The third type of model is a hybrid of white box and black box modeling techniques. These types of models may rely on some physical principles, but also have sources of uncertainty (e.g. occupant behavior) that require black box model techniques.

The literature contains various methods for commercial building load prediction. Jones et al. (2012) summarizes multiple methods for building load prediction, including seasonal regression, simple average, Fourier series, and artificial neural network models. They also present an alternative method using Modified Learning from Experience (MLFE) and Recursive Least Squares (RLS), incorporating uncertainty in the form of fuzzy logic (Jones et al., 2012). This incorporation of a stochastic element is important, as all real systems contain uncertainty (Ross, 2009).

Thus far, only one study has been identified that describes a method for predicting plug load energy usage specifically (Rysanek & Choudhary, 2014). Rysanek and Choudhary describe an open-source modeling tool they developed to predict demand of lighting and plug load equipment, based on user inputs of expected occupancy, equipment quantities and operational power consumption levels (e.g. on/active, low/standby, and off/inactive). They feed this user input into a stochastic modeling algorithm, with the intention of generating lighting and plug load profiles for use in building energy simulations (Rysanek & Choudhary, 2014).

While the number of plug load prediction studies may be limited, a number of studies have examined similar systems where occupant behavior is coupled with energy consumption, such as predicting occupant-controlled lighting energy use (Hunt, 1980; Newsham, Mahdavi, & Beausoleil-Morrison, 1995) and windows and blind use (Ackerly, Baker, & Brager, 2011; Fabi, Andersen, Corgnati, & Olesen, 2012; Gunay, O'Brien, & Beausoleil-Morrison, 2013), concluding that a stochastic model is most appropriate when predicting occupant behavior.

4. Methods

4.1. Data collection: field study

As described in the introduction, the plug load data were collected using four-channel Enmetric powerports. Each port was labeled with a workstation identifier and the type of plugged in device. Using routers (called "bridges") placed in the office, the powerports transmitted power data to the Enmetric servers in real time. This data were saved in 15 minute time steps. Data were collected from December 2012 to March 2015. There are some missing values at times when the plug strips or routers encountered technical difficulties.

The data collected by each of the four channel powerports included timestamp (date and time), average power, minimum power, maximum power, energy used, average frequency, average voltage, average current, and average power factor. For this project I was interested in the timestamp, maximum power, and average power. I focused on average and maximum power because of the implications for energy use and cost as commercial building energy costs are dependent on total energy consumption as well as peak power consumption. See Appendix A for a file header describing all the information collected by the plug load monitors.

The original data is comprised of 206 individual plug load office devices. After cleaning the initial data, there were 137 devices identified specifically as desktop computers, monitors, laptop computers, and task lights. Because the categories of the remaining devices were unknown, this study focuses on just the identified devices.

4.2. Plug load data analysis

4.2.1. Data analysis: overview

Using Rstudio, I organized and analyzed the plug load data to identify trends over time. I performed the following major tasks:

Table 4.1 Data analysis tasks performed in R

Task	Description	R packages used
Cleaning data for analysis	Extract relevant data from original dataset (device category, workstation identifier, timestamp, average power, maximum power)	dplyr lubridate plyr
Preparing data for analysis	Add columns with data identifiers (year, month, day, weekday, hour, and minute) and combine all files into one data frame	reshape2 timeDate plyr
Separating data by involvement in behavioral study	Create a dataset including only workstations of users involved in the behavior study, starting with the first day of the study (using workstation identifiers and dates) Remove these rows from the baseline dataset to create a dataset of users not involved in the behavior study (this includes data from all users prior to the study, and just non-participants after the start of the study)	-
Separating data by work and non-work days	Add column identifying each row as a working day or a non-working day (weekends, holidays) using calendar information from UCOP	plyr dplyr reshape2 timeDate chron
Graphing data for trends	Using boxplots, histograms, density, point, line, and tile (for heat map) plots to graph average and maximum power data by: time step, day of the week, month, workday, and weekend/holiday; participants and non-participants of the behavioral intervention Where appropriate, median (rather than mean) was used because data is non-normal	plyr dplyr ggplot2 data.table stats

4.2.2. Data analysis: comparison

When approaching the plug load data, I separated it in multiple ways to analyze it for trends. I looked at what the trends were for different days of the week and for each month of the year.

As will be illustrated in the results section, I decided to focus on the difference between work and non-work (weekends and holidays) days. This is because although there may appear to be monthly or weekly trends, these trends are not specifically dependent on that month or day of the week, but rather on whether or not occupants are in the office. The main driver of occupant plug load energy use is the presence of the occupants.

4.2.3. Data analysis: representing the results

For the daily profiles, power is represented as power per occupant (W/person) and power per square foot (W/ft^2). Not all occupants of the 6th and 7th floors participated in the field study, so the area per person was approximated using total areas and all occupants:

$$Area\ per\ person = \frac{A_{6th} + A_{7th}}{N_{6th} + N_{7th}} = \frac{(27{,}155 + 27{,}155)ft^2}{118 + 131} = 218ft^2/person$$

Where *A* represents gross floor area, and *N* the number of occupants.

UCOP supplied us with floor plans that included occupancy information (location of offices and quantity of occupants). The floor plans were also used to calculate gross floor area. Note that power values in this study do not represent all the plug loads present in the office, just the subset of desktop, laptops, monitors and task lights that were monitored.

4.3. Cool Choices game

As described in the literature review, Cool Choices is an online sustainability game which encourages players to make sustainable actions related to saving water and energy, conserving gasoline, and minimizing waste generation. The UCOP Cool Choices game was administered for occupants on the 6th and 7th floors of the Franklin Building. It started on November 4, 2014 and ended December 12, 2014. There was a one week recruitment period prior to the start of the game. This section provides an overview of the game and subsequent data analysis including how the game was customized for this study and how it was administered on-site.

4.3.1. Selecting Cool Choices

One of the main objectives of this project was to investigate the role of occupant behavior on plug load energy use. I implemented a behavior intervention at UCOP to determine if occupants could be persuaded to reduce their energy use even when they would not financially benefit from the potential energy savings. With an interest in using my time to focus on the energy data collection rather than the psychology of occupant behavior, it was important to find an existing intervention that could be implemented instead of designing one myself.

The online sustainability game, Cool Choices, was selected because it met the following criteria:

- Packaged program: Cool Choices is a developed sustainability game with a full staff to support game preparation and implementation. To limit the scope of the project (and stay within my field of knowledge) I wanted to use an existing program that leveraged behavioral psychology in its creation. The format and content of Cool Choices was informed by social science and behavioral research (Kuntz et al., 2012).
- Online interface: Cool Choices is played entirely online with no software installation required. This reduced the potential for players to experience IT problems, and if problems did arise, the Cool Choices staff would be available to fix them, rather than relying on UCOP's IT team.
- Social media-oriented: The Cool Choices website allows players to see each other's progress; there is a stream for user content and a leaderboard updated in real time that is visible to all participants. I was interested in selecting a program with a social media aspect to increase player engagement (Lehrer, Vasudev, & Kaam, 2014).
- Competition format: The literature suggested that a competitive intervention could provide motivation to players in settings where financial incentives are missing (Petersen et al., 2007). Rewarding players with points for actions can also provide a sense of accomplishment, and can prevent players from feeling like they can't make a difference on their own (Kuntz et al., 2012).
- Team structure: Players must be part of a team to compete in Cool Choices. This can give them a sense of responsibility to their teammates, and teammates can remind and encourage each other to keep playing (Kuntz et al., 2012).

Cool Choices had the added benefit of encouraging behavior changes at home and at work in order to reinforce repetitive habits. The game's contents include actions at home, work, and transportation. And although it was a packaged game, it was also easily customizable to meet the study's needs and focus on plug loads.

4.3.2. Preparing the game

4.3.2.1. Meeting with UCOP leaders

In October 2014, the researchers met with UCOP's director of sustainability and the group leaders for the 6th and 7th floor to discuss how Cool Choices would be implemented at the site. The gameplay and time commitment required were explained, and it was conveyed that IT support would not be necessary given the online nature of the game. At the time, UCOP was planning to roll out a Green Department Certification Program (GDCP) in Spring 2015 (Napolitano, 2014). To encourage the group leaders to agree to use the Cool Choices game in Fall 2014, it was suggested that this could be a pilot for a potential wider rollout that could coincide with the GDCP in Spring 2015. The group leaders were interested in going through with the implementation, so it was decided to start as quickly as possible.

4.3.2.2. Coordinating with Cool Choices

For the duration of the game, my primary contact at Cool Choices was their Program Coordinator. She worked with me to setup the game and prepared me for my role of game manager. She provided me with a game manager manual (including sample daily emails), information about managing the Cool Choices website before and during the game, a suggested list of actions to include in the game, a sample schedule for weekly challenges, and a copy of the pre-game and post-game surveys (see Appendix B). The surveys were developed by Cool Choices to be used on all games and include demographic questions, questions about resource consumption, and questions designed to reveal players' attitudes towards sustainable behaviors.

To prepare the game content I customized the list of actions we were provided to focus on actions related to energy, especially energy at work. I added cards to reward players for energy saving behaviors for the plug loads being monitored (desktops, monitors, laptops, and task lights) and included actions that were important to UCOP and would be included as a "green pledge" as a component of the upcoming GDCP. In total there were 42 actions available during the course of the game. Day 1 of the game there were four cards released, and players could claim up to two choices. Each weekday a new card was released. Most cards were available for the remainder of the game, however cards associated with the weekly challenges were only available that week. For each consecutive week players were allowed one extra action each day (e.g. Week 2 they could claim three actions), up to six during the last two weeks of the game. See Appendix B for the list of actions, the source of the action (e.g. UCOP pledge), and the release schedule.

4.3.3. Occupant recruitment

After the October meeting, I was notified that several group leaders had asked that their staff not participate in the study due to time constraints, which meant that there were approximately 60 employees eligible to participate in the game. It was unfortunate that all groups could not be involved, but that would not have been possible until Spring 2015.

The on-site contact for the game was the Director of Building and Administrative Services. He helped to publicize the game by posting flyers in the office (see Appendix B) and sending out three emails to eligible participants in the week before the game (10/27-11/3). The emails included information about Cool Choices, a link to the pre-game survey and to sign up for the game. Out of the approximately 60 eligible employees, 30 signed up to play and 24 claimed at least one action during the game. Of these 24 active participants, 12 had Enmetric powerports at their desks.

4.3.4. Game administration

4.3.2.3. Administrative tasks

My role of game manager included:

- Responding to questions from players and alerting Cool Choices to any website issues.
- Updating the Cool Choices stream with content, including photos players uploaded for specific actions and announcement about recent prize winners.
- Selecting prize winners each week and at the end of the game.
- Preparing the email announcing the weekly challenge and the previous week's winners. The regular daily reminder emails were sent automatically to players. During the last week, a link to the post-game survey was sent in the daily emails. See Appendix B for an example reminder email.

4.3.2.4. Prizes

Prizes were awarded primarily for participation. Two random winners received $15 gift cards to Peet's Coffee & Tea for completing the pre-game survey. Each week, three participation prizes were handed out (Cool Choices-brand t-shirts, reusable water bottles, and tote bags). Players were eligible for the drawing if they had taken at least one action that week. Given the limited pool of participants, drawings were not always entirely random in order to distribute the prizes among the most number of participants. At the end of the game, there was one individual winner for the most number of accumulated points, and one team winner for the most accumulated actions among all team members. All game end winners received $15 Target gift cards.

4.3.5. Post-game monitoring

The Enmetric powerports were left in place through March 2015 to continue collecting data to assess the persistence of any energy saving behavior changes in the short term.

4.3.6. Cool Choices survey

The pre- and post-game surveys were administered by Cool Choices through Survey Monkey. All responses were provided in text and numerical form. I used R to visualize the responses and allow for comparison between different survey questions and pre- and post-game responses.

4.3.7. Cool Choices data analysis

The data collected by Cool Choices included the daily actions each player made throughout the course of the game. The data were imported into R to analyze which cards were most popular based on category, specific action, and point value, to visualize which cards were played each day of the game and observe weekly trends, and the range of actions each individual player claimed.

4.4. Monte Carlo simulation

The goal of this plug load model is to generate power profiles with comparable median power and similar variability to the measured data. I identified the key variables influencing power consumption: device type, day type (work or non-work day), and time of day (at 15 minute time steps) using the baseline analysis. These were determined by analyzing the power consumption profiles for each device and for each weekday to detect patterns, similarities, and differences. Based on this analysis, day type and time of day were most indicative of occupancy, which is the real predictor of plug load power consumption (i.e., I am using these variables as proxies for occupancy).

During the modeling process, three versions of a Monte Carlo simulation were created. Monte Carlo simulations were deemed the most appropriate given the available input parameters and goal of creating a simple predictive model. The first two models, MCModelv1 and MCModelv2 were based on device type, day type, and time of day. MCModelv2 included an improved method for incorporating device quantities that more accurately reflected the validation dataset. The third model, MCModelv3, attempted to improve on MCModelv2 by including month as an additional variable. The second, MCModelv2, was the most successful and is detailed here.

Using R, the Monte Carlo simulation was created to generate power profiles for user-provided start and end dates. The program detected work days and non-work days based off of these dates, and calculated the quantity of devices in the validation set for this timespan. Using these variables, the program ran the Monte Carlo simulation:

$$MCModelv2 = f\left(D_{start}, D_{end}, qty_d, CDF_{d,t,h}\right)$$

Where

$$\begin{gathered} D = date\ [MM/DD/YY] \\ qty_d = quantity\ for\ each\ device\ type, d \\ CDF_{d,t,h} = CDF\ for\ all\ device\ types\ d, time\ steps\ t, and\ day\ types\ h \\ d \in \{desktop, laptop, monitor, task\ light\} \\ t \in \{0{:}00, 0{:}15, \ldots, 23{:}30, 23{:}45\} \\ h \in \{work, non-work\} \end{gathered}$$

The model was trained with data that encompassed the first full year of power data within the data set (December 2012-December 2013). The training data were used to generate cumulative distribution functions (CDF) for each device category (desktop, laptop, monitor, task light), time step (15 minute intervals for one day), and day type (work or non-work day) for a total of 768 distributions. The Monte Carlo simulation referenced these distributions by using the inverse of the CDF function to calculate power values based on probabilities generated by a random number generator.

I validated the model by running the simulation for different time periods (e.g. monthly or annually). I calculated the number of devices present in the validation data set to use as input for the Monte Carlo simulation. I ran a check for missing data to ensure that the comparison between measured and modeled data would be a reasonable one. For example, if a device was only recording data for a few days during the time period, I discarded that device from the validation set so that the model would not be over-predicting power use of that device. I incorporated this device count check into MCModelv2 so that the validation data used for comparison would only include those devices which have complete data, defined as 90% of the total possible data points:

$$T_i > 0.9 * t_{day} * n_{period}$$

Where

$$T_i = total\ time\ steps\ for\ device\ i$$
$$t_{day} = 96\ (possible\ time\ steps\ in\ one\ day$$

By defining complete data with some flexibility (i.e., not requiring 100% of data to be present), it ensures that the model does not throw out too much data.

4.4.1. Model validation

The model was validated by comparing the validation data, which consists of the remaining power data (January 2014-March 2015), to the output generated by the model. This included the comparison of the median, variance, and evaluating the normalized mean bias error (NMBE).

ASHRAE Guideline 14-2002 Measurement of Energy and Demand Savings provides guidance on comparing measured energy data with that generated by data-driven models for the same space (ASHRAE, 2002). Its scope includes residential, commercial, and industrial buildings, and it is intended to assist in calculating predicted savings due to energy retrofits. This guideline requires that hourly data must have an NMBE of no greater than 10%.

$$NMBE = \frac{\frac{1}{N}\sum_i^N (y_i - \hat{y}_i)}{\bar{y}} * 100 \leq 10\%$$

This same error calculation method is used in this study as a way to assess model accuracy, and subsequent improvements in accuracy. This same 10% metric was also used to compare the median and variance.

A description of the functions used (built-in or written) in R is provided in Table 4.2.

Table 4.2 Description of R functions written or used for the Monte Carlo simulation

Function	**Description**	**Inputs**	**Outputs**
distributions	Creates vectors of average power data for each device category, day type, and time step	Training data	Vector of average power data
runif() (R's stats package)	Calculates a random number [0,1] from a uniform distribution	Quantity of random numbers to be generated $\{\mathbb{Z} \geq 0\}$	Vector of random numbers [0,1]
quantile() (R's stats package)	Calculates the value of a cumulative distribution function (CDF) of a random variable using discontinuous sample quantile method 1 (inverse of empirical distribution function)	Vector of sample quantities for CDF (from *distributions*), Numeric vector of probabilities [0,1] from *runif()*	Vector of quantiles
plbaby	Calculates one day of power data, summed for all devices (of one type) at each time step using *quantile()* and *runif()*	Device type {DC, LC, MO, TL}, Quantity $\{\mathbb{Z} \geq 0\}$, day type indicator {TRUE, FALSE}	Vector of power data
holTest	Determines whether a date is a holiday, using UCOP's calendar data for 2012-2015	Date	Boolean {TRUE, FALSE}
plmodel	References *plbaby, holTest*, and R's chron package's *is.weekend()* function to calculate power data profiles	Quantities of all devices $\{\mathbb{Z} \geq 0\}$, Start date, End date	Data frame of power data for all devices, by date and time step
valTest	Compares validation data and model output using *plmodel*	Start date, End date	Median and Variance of validation data and model output, Normalized mean bias error (NMBE)

5. Results

5.1. Baseline data analysis

5.1.1. Testing for normality

Before analyzing the data, I performed a quick test to ascertain if the power data were normally distributed. I used the QQ Plot method rather than the Shapiro Test, because the Shapiro Test is not suited for sample sizes larger than 5,000. I looked at the average power data for each individual device type separately. The results in Figure 5.1 clearly show that the data were not normally distributed. I ran the same test with maximum power data and found that they were also not normally distributed. Therefore, when aggregating the data for this analysis I use the median rather than the mean.

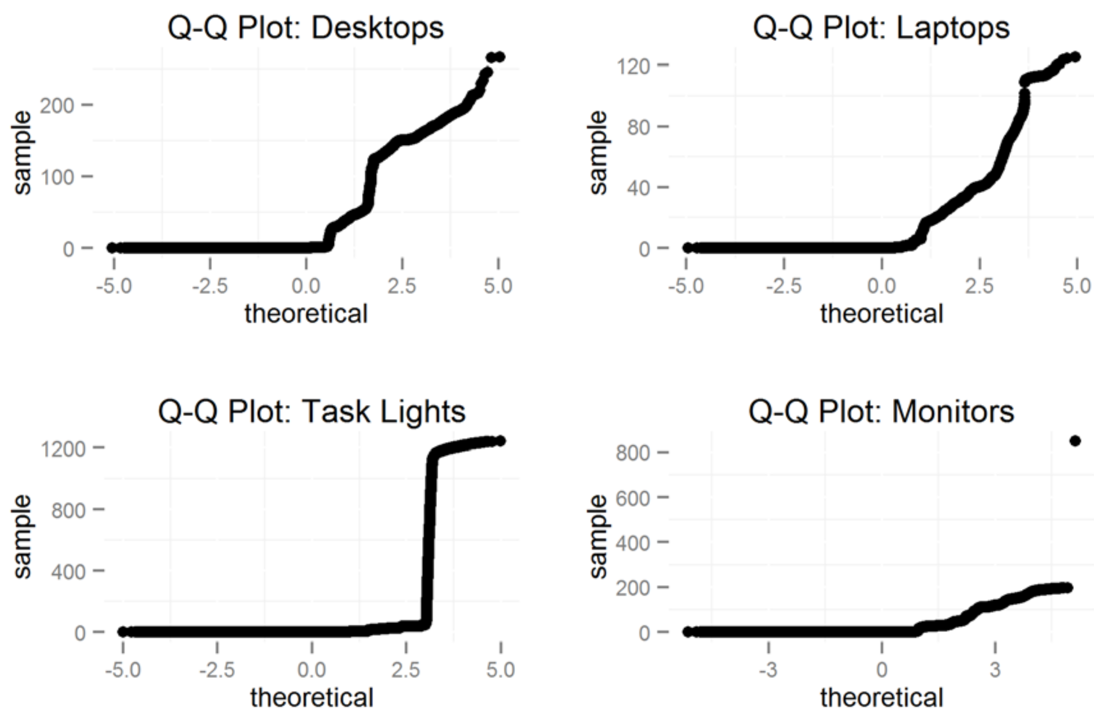
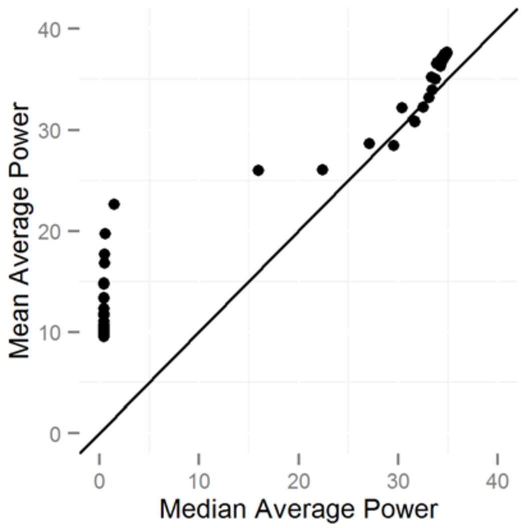
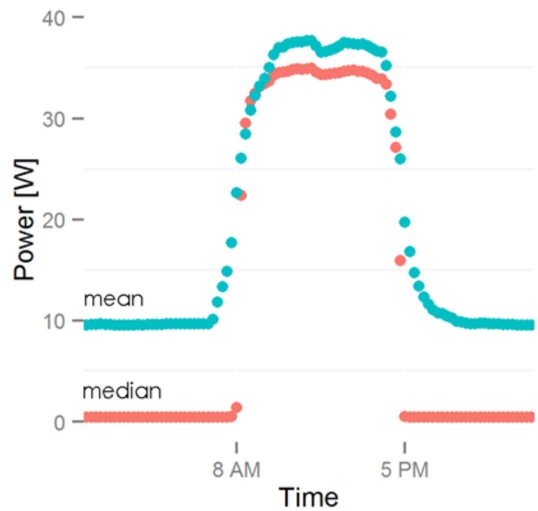


Figure 5.1 QQ plot for average power data for each device category

To illustrate just how different the mean and median are, Figure 5.2 plots mean workday average power use against median workday average power use for desktop computers (a) and a typical work day using both mean and median (b). Overlaid on Figure 5.2(a) is the line $y = x$. The closer the points are to this line, the closer the mean and median are (which is what one would expect for a normal distribution). As Figure 5.2(b) shows, during occupied times (8 AM – 5 PM), the mean and median are much closer together than during unoccupied times (5 PM – 8 AM). When the data include many small values (which is the case during unoccupied times), the median more accurately captures typical behavior.



(a)



(b)

Figure 5.2 Comparison of mean vs. median average power data for desktops

Note that in the following analysis any mention of “average power” data refers to the data collected by the Enmetric powerports, which was averaged over every 15 minute time interval. The median of the average power is used when this data is aggregated over longer time periods for analysis. For example, when I refer to the "median average power,” it is the median value of the 15 minute average measured data.

5.1.2. Data overview

This section provides a general overview in order to establish the scope of the collected data. Figure 5.3 is a heat map of hourly average power use over the data collection time span and Figure 5.4 provides a heat map of the hourly maximum power use. Although data were collected every 15 minutes, these have been collapsed to hourly time steps to make it easier to read the large amount of information presented in the graphs. In examining the heat maps it is important to note that the number of devices being monitored fluctuated over time due to disconnection or connection of devices, or technical problems with data transmission. However, these heat maps are useful in providing an overall macro-scale picture of the collected data and some information about general work patterns and this building, and the impacts on energy use trends on different time scales.

One of the first things evident from these heat maps is the regularity of the five day work week and two day weekend. On a daily basis, power consumption clearly ramps up between 7:00 am and 8:00 am and ramps down 5:00 pm to 6:00 pm, indicating a very regular 8:00 am to 5:00 pm daily work schedule. There is also clear evidence of three-day weekends for holidays. For example, Martin Luther King Jr. Day falls on the third Monday of February, and for all three Februaries in the dataset the third week is clearly occupied for only four days. This indicates that occupants have regular schedules and are generally not in the office during weekends and holidays.

When power usage is higher during the day (i.e., 8:00 am to 5:00 pm), unoccupied power usage is also higher (5:00 pm to 8:00 am). This is evident when comparing the first half of 2013 with the second half, when power use drops. This suggests that power consumption is strongly dependent on occupancy, rather than on different usage of the measured plug load equipment (e.g. more computationally-intensive computer work that may require higher power consumption).

In the latter half of 2013 and through 2014, there are daily striped patterns occurring midweek during unoccupied times. The pattern is very clear in September 2013. Compared to other unoccupied periods, on these days it appears that power use is elevated overnight. Microsoft frequently releases software bimonthly patches on Tuesdays (known as “Patch Tuesday”) so it is possible that this is the cause of elevated power consumption. However, because this happens nearly weekly starting in the middle of 2013 (and Patch Tuesday does not occur weekly), another explanation is that the UCOP IT staff conducts system updates to users’ computers during the middle of the week.

An interesting lack of a pattern is the consistency of power use during the day. While power use is not constant each day, there is no obvious dip in power at any consistent time – including in the middle of the day for the lunch. Unlike multiple published plug load equipment schedules cited in the literature review (California Energy Commission, 2010; Claridge et al., 2004; Deru et al., 2011), the plug load usage here does not appear to regularly decrease in a significant way during lunch time. Daily trends and trends for individually devices (some of which do show lunch time power dips) will be discussed in further detail below.

The last main observation from these heat maps is that power consumption does not appear to be strongly linked to month (or season). While power consumption fluctuates in different months, it is not consistent from year to year within the dataset. Some months may experience lower occupancy rates due to non-seasonal reasons, such as conferences or other events that affect a large number of people in the office. This suggests that for the plug load devices included in this analysis, power consumption is not related to season but rather to occupancy.

Figure 5.3 Average power consumption for all devices over entire data set

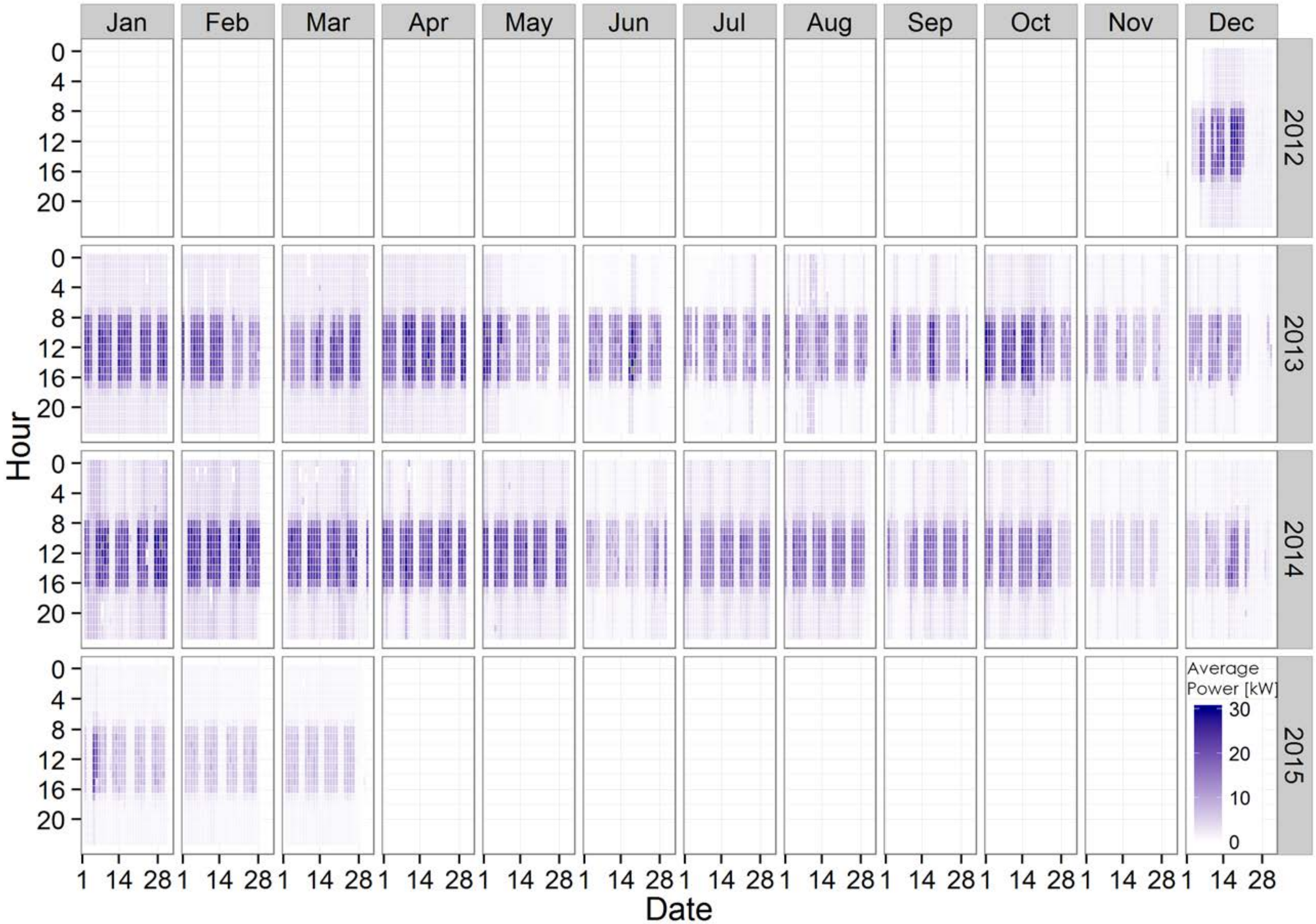


Figure 5.4 Maximum power consumption for all devices over entire data set

5.1.3. Daily profiles

In this section, I explore the daily patterns of energy use. The heat maps in the previous section indicated that power consumption of the measured plug load devices is most reliant on occupancy and did not appear to be related to time of year (i.e., seasons). Therefore, I decided to split the data into two categories: working days (Monday through Friday, excluding holidays) and non-working days (holidays and weekends). The graphs in this section illustrate the four plug load devices separately and combined, looking at average and maximum power consumption data.

Figure 5.5 illustrates the fractional power profiles over the course of a work day and non-work day for this dataset at 15 minute intervals (data were not smoothed). This is to provide a more direct comparison to the published plug load equipment schedules described in the literature review. These schedules provide a fractional profile of power consumption, where 100% is equivalent to maximum possible power. This was calculated as the maximum of the sum of maximum measured power for all devices *i*, for time step *t*. This is not the same as the rated power (also called the nameplate power), which was not available for this study.

$$Maximum\ possible\ power = max\left[\left(\sum_i MaxPower\right)_t\right]$$

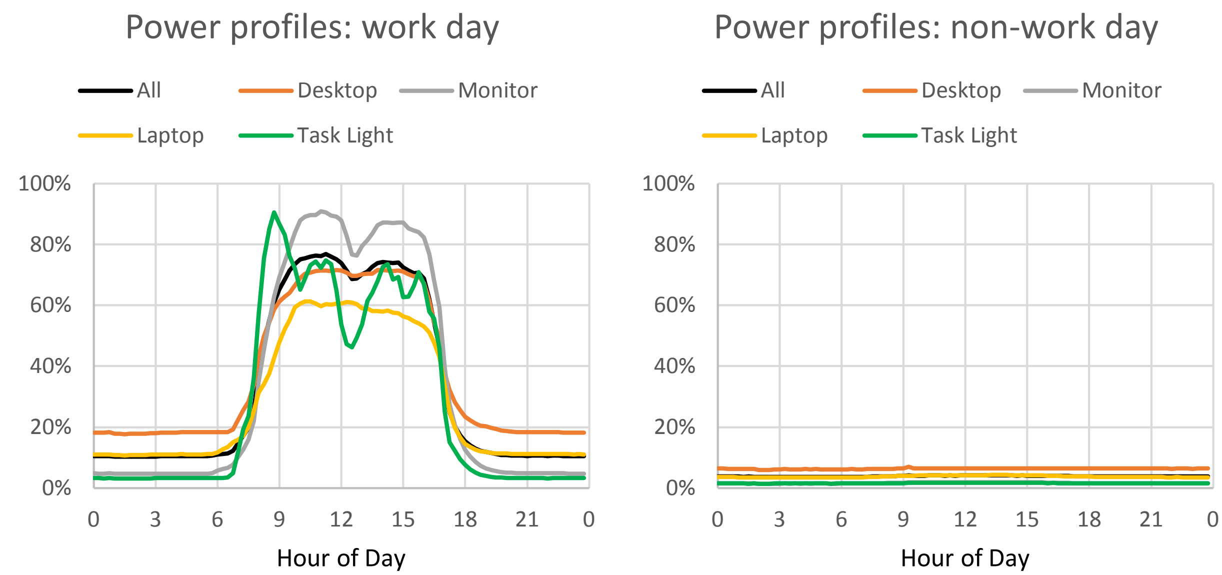
To generate these graphs, I divided the total power consumption at each time step by the maximum power consumption (over the entire data set), first for each device category individually, and then again with all devices combined.

$$Fractional\ power = \frac{(\sum_i AvgPower)_t}{Maximum\ Possible\ Power}$$

Comparing Figure 5.5(a) and (b), these graphs illustrate a stark difference in work and non-work day power consumption. Looking only at Figure 5.5(a), the work day profile shows that different devices have different daily profiles. Although the heat maps in Figure 5.3 and Figure 5.4 did not show a dip in midday power use (e.g., for lunch), these more detailed graphs allow us to see that there does appear to be a slight reduction in overall power use, as well as more pronounced reductions for task lights and monitors. However, laptop and desktop computers do not experience a power reduction. This suggests that some occupants may leave their workspace during lunch time, causing their monitors to go into sleep mode while their computers remain on.

In examining power use during unoccupied periods, the data shows that desktops tend to be left on overnight on work days to a larger degree than laptops (20% compared to 10%). This difference could be due to some occupants taking their laptops home and thus removing a portion of overnight phantom loads. Phantom loads refer to the power electronic devices draw even when turned off. Another interesting pattern depicted by Figure 5.5 is the difference in power levels between non-work days and unoccupied hours of work days (i.e., 5 pm to 8 am). Laptops and desktops appear to draw more power overnight during work days when compared to non-work days. One reason might be that occupants are more likely to turn their computers off before a weekend, rather than overnight before another workday.

Each graph also includes a profile for combined power usage (black line), which will be used in Figure 6.1 to compare the UCOP data to the published schedules described in the literature review.

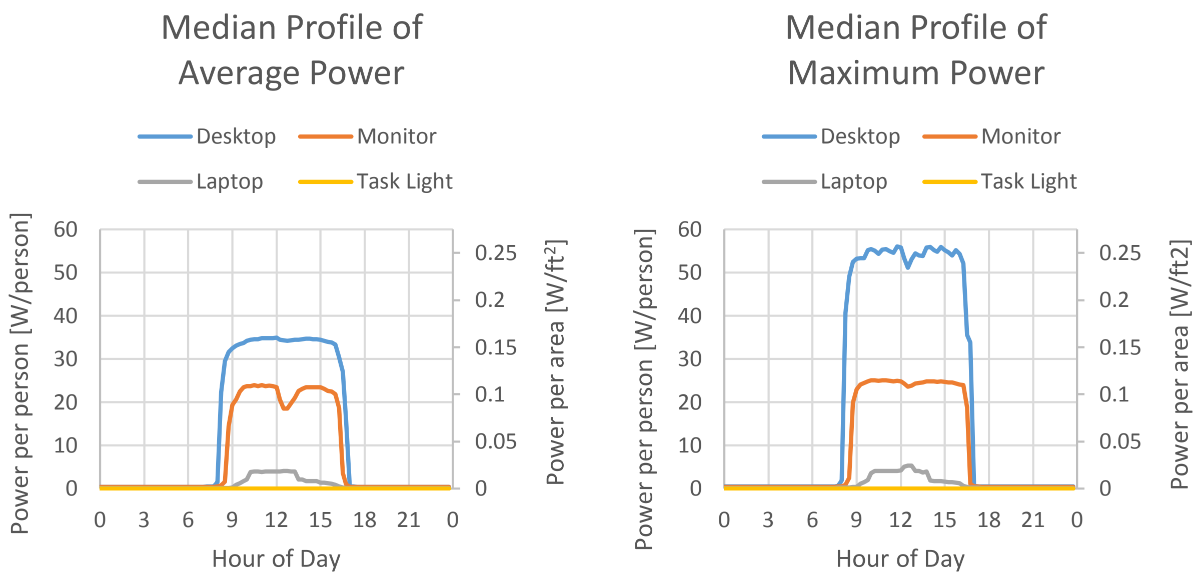


(a) (b)

Figure 5.5 Fractional power profiles for work and non-work days.

In addition to looking at these fractional profiles, it is important to understand the average power used by these devices, and by all devices in aggregate, in order to estimate overall energy costs. In Figure 5.6 power data are presented in daily profiles (with 15 minute time steps) for workdays, representing a median profile of the average power use within that time step, and the median profile of the maximum power use for each device category. These are presented side-by-side to more easily compare the difference in maximum and average power consumption by device. The primary (left) y-axis is power per occupant (W/person) while the secondary (right) y-axis is per area (W/ft^2), calculated as described previously.

Viewing these graphs together highlights important power consumption features of each device. Task lights are used so infrequently that even the median profile of maximum power is zero. This means that over half of the task light maximum power data at each time step is zero (since the median is the middle value of the data set). For monitors, the profiles for average and maximum power are not significantly different, suggesting that there is not a wide range in typical power consumption for monitors. The same is true for laptops, which show very little difference between the two graphs as well. Desktops are the one device category that do show a significant difference between the two graphs, indicating that there is a wider range in desktop power consumption in comparison to the other devices. This is likely due to the range of tasks that may be conducted on a computer, and the varying sizes of computers occupants have (e.g. low-power thin clients vs. CPU-intensive machines). It is interesting to note that this characteristic is not shared by laptops. The extremely low power profile (0-5 W) coupled with the mobility of laptops suggests that occupants with laptops frequently worked from other locations (within or outside of the Franklin Building), which is of course not an option for occupants with desktops. Although laptops do typically draw less power than desktops, this behavior can explain why there is such a significant difference in average and maximum laptop and desktop power consumption shown in these graphs.



(a) (b)

Figure 5.6 Work day profiles for median average and median maximum power

The last profile graph presented in Figure 5.7 illustrates the behavior profile for all devices individually and combined as a percent of maximum power by *individual* device (rather than overall maximum power) for all time steps:

$$behavior\ profile = median\left[\left(\frac{AvgPower_{t,j}}{MaxPower_j}\right)_i\right]$$

Where *MaxPower* represents the maximum power for an individual device *j* across the entire data set, and *i* represents the set of all devices.

By normalizing each individual device by its own maximum power, this metric better isolates the use patterns of the occupants. And by evaluating devices individually, I can account for the fact that different equipment within the same device category might have different maximum power consumption levels. For example, if there are two desktops with maximum power usages of 100 W and 200 W, but measurements show both use 50 W on average, the fractional power use will be 50% and 25%, respectively. This means that the first desktop is used at half of its maximum power, while the latter is used at just a quarter, revealing interesting information about occupant behavior, rather than absolute power information. This approach eliminates the effect of equipment efficiency and provides a way to look at how occupants use their devices. In other words, if these same occupants were given new, more efficient devices, but did not change their work habits, these profiles would remain approximately the same.

With Figure 5.7, I can examine how devices within each category are used. For example, the behavior profile for monitors shows that they are typically used at about 50% of their maximum power, while desktops are typically using about 38% of their maximum power. This suggests that many occupants are not using their desktop computers for CPU-intensive tasks (or potentially that the desktop computers are oversized). For laptops, the behavior is not quite as straightforward to interpret. The extremely low profile is most likely due to occupants relocating their laptops by disconnecting them and charging them elsewhere (inside or outside of the Franklin Building), and not necessarily due to using laptops at a lower rate.

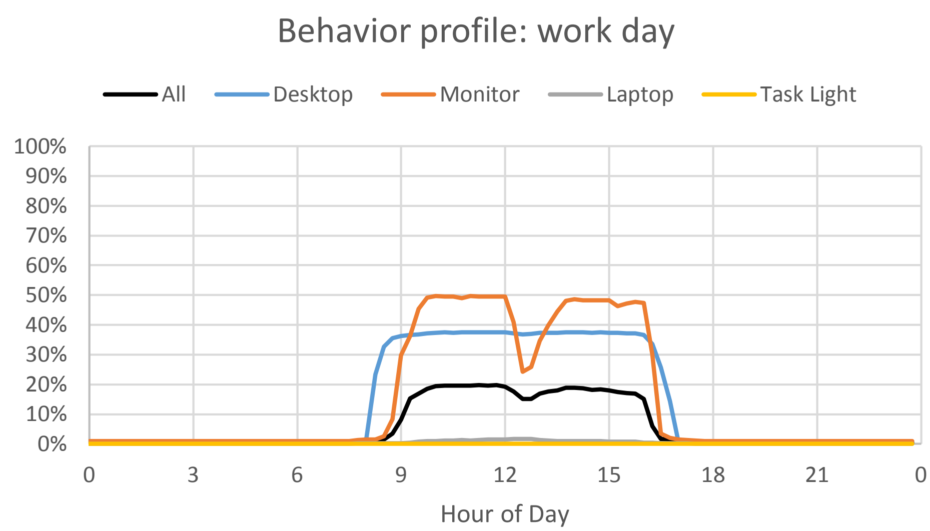


Figure 5.7 Fractional profile of daily behavior for all devices

5.1.4. Weekly trends

Figure 5.8 shows a median week of average and maximum power consumption to allow for comparison between different days of the week, and between working days and weekend/holidays. These graphs illustrate that there is no difference between Saturday and Sunday profiles for average or maximum power consumption. During the work week, there is some variation depending on the device, however the profile peaks daily between 8:00 am and 5:00 pm, indicating regularity of occupant schedule. This is reflected in the device profiles, which may vary slightly in magnitude, but in shape are very similar from one work day to the next. Desktop use fluctuates the most, with highest power consumption on Tuesday and Wednesday, and lowest on Friday. Laptop power consumption is similar, but drops significantly on Fridays. Monitor power consumption is generally consistent from day to day and between maximum and average power (reflecting the results found in the overall work profile).

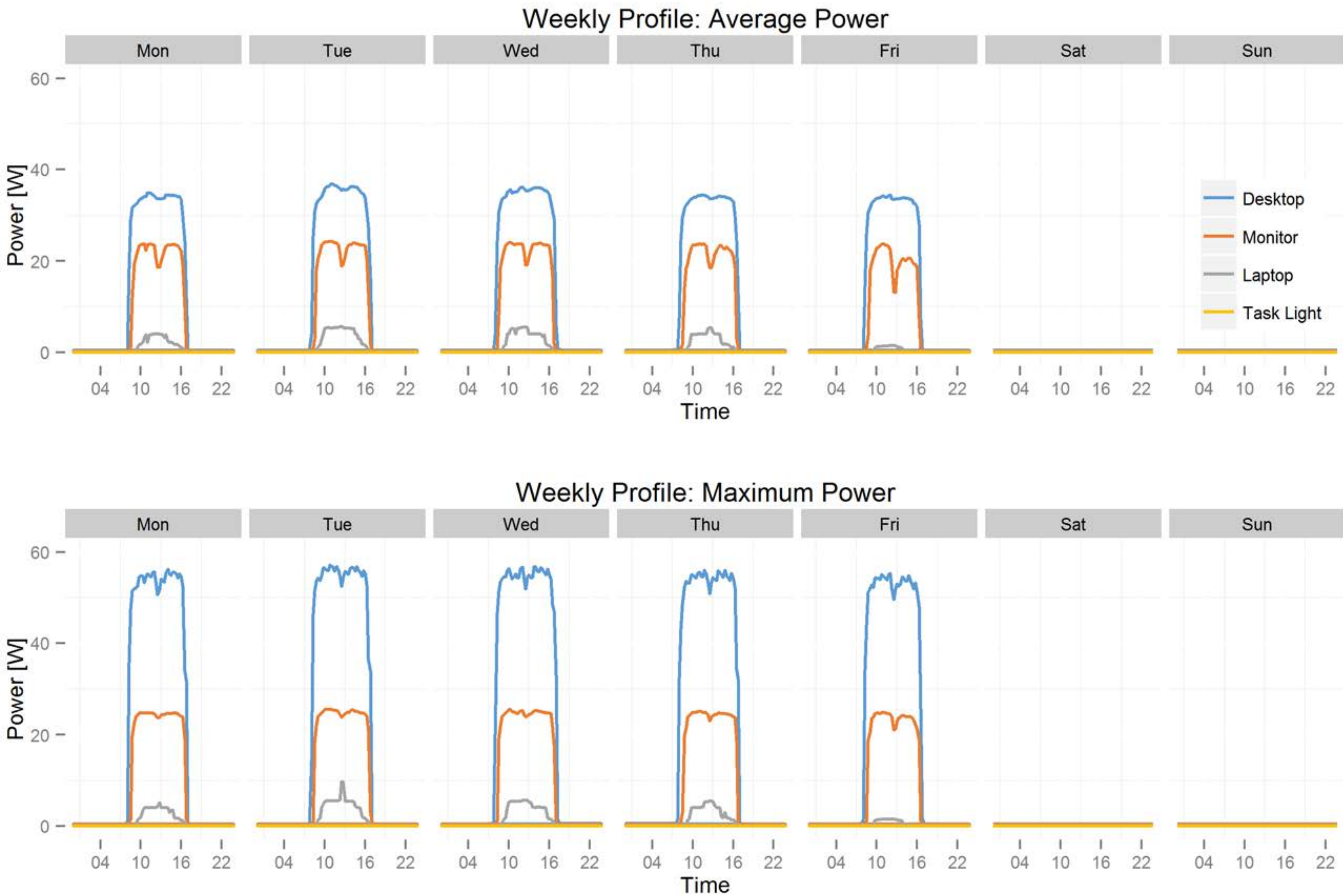


Figure 5.8 Weekly profiles of maximum and after power, by device category

5.2. Cool Choices survey

Of the 24 active participants, 15 completed the pre-game survey and 12 completed the end-of-game survey. This section summarizes the responses to questions about players' attitudes and outlooks. Not all survey questions were deemed relevant to this study because they centered on home energy use. Please see Appendix B for both surveys.

5.2.1. Pre-game survey

Cool Choices administers the same survey before each game. Many of the pre-game survey questions are intended to reveal players' attitudes towards sustainability related to energy use, water consumption, gasoline consumption, and waste generation. The primary purpose of this survey is to establish a baseline to evaluate if there are changes in players' attitudes after the game.

Figure 5.9 summarizes the responses when players were asked to compare their resource use with similar households. The majority of respondents stated that they were similar or used less (energy, gasoline, water and generated less waste) than similar households. Although there is no way to verify these responses, it does suggest that players generally felt they were not using more energy than average.

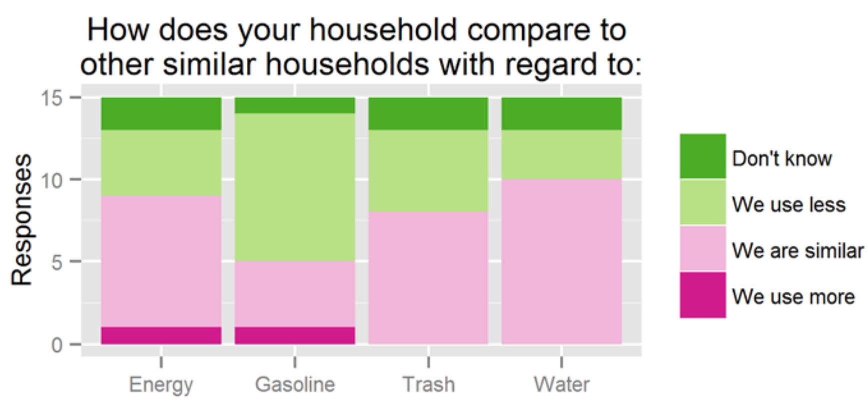


Figure 5.9 Pre-game survey question: household comparison

In Figure 5.10, players were asked to state how often they took certain actions related to saving energy, conserving gasoline, conserving water, and generating trash. The graph is organized so that the more resource-conserving behaviors are on the top. Players reported turning off unused work equipment most or all of the time, a response that is reflected in the baseline data analysis, where results showed that power consumption overnight and on unoccupied days (e.g. non-work days) drops considerably. A similar question was asked about electronics in general, and players responded that they rarely or never leave electronics on when not in use. Overall, players reported that they actively engaged in conservation behaviors, indicating a general high level of sustainable behavior.

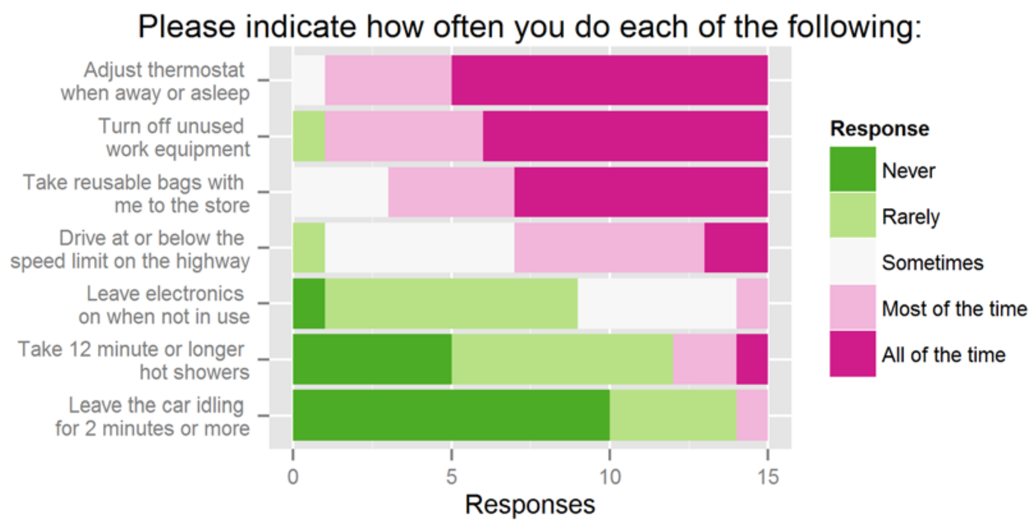


Figure 5.10 Pre-game survey question: conservation actions

In Figure 5.11, respondents were asked to rate their level of agreement with a series of statements to gauge attitude and levels of knowledge about specific energy saving behaviors and opinions. Like the previous figure, the graph is organized so that the more resource-conserving attitudes are on the top. In general, respondents agreed that it was worth saving energy to save money and preserve the environment, that they were interested in making energy-related home improvements, and that people are not entitled to using as much energy as they can pay for. Respondents were split on the statement “my household has already done its part to reduce resource usage,” with about one third agreeing, one third disagreeing, and one third neutral.

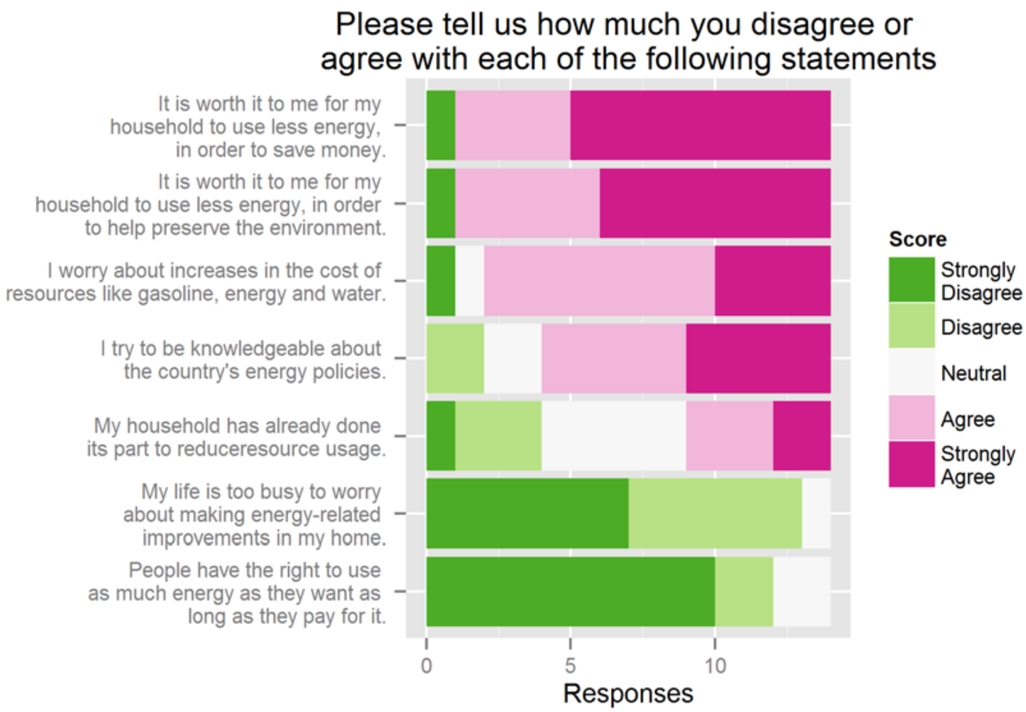


Figure 5.11 Pre-game survey question: attitudes and beliefs

5.2.2. Post-game survey

The post-game survey was administered during the last week of the game. It included questions intended to reveal any changes in players' attitudes and opinions, and to find out what motivated players to sign up for and play Cool Choices.

Figure 5.12 summarizes the responses to a question asking players about what motivated them to *play* the game. Respondents reported a variety of influential factors, which included (in order of highest influence) that they thought it was fun, they liked the lifestyle changes that could occur, that they wanted to win, Cool Choices made the game seem appealing, and they could save money. Cited as least influential were the chance to win a gift card and a sense of work obligation to play. These responses show that players felt there were both external motivators (e.g., potential to save money at home) and internal motivators (e.g., the game was fun) that interested them in signing up for the game.

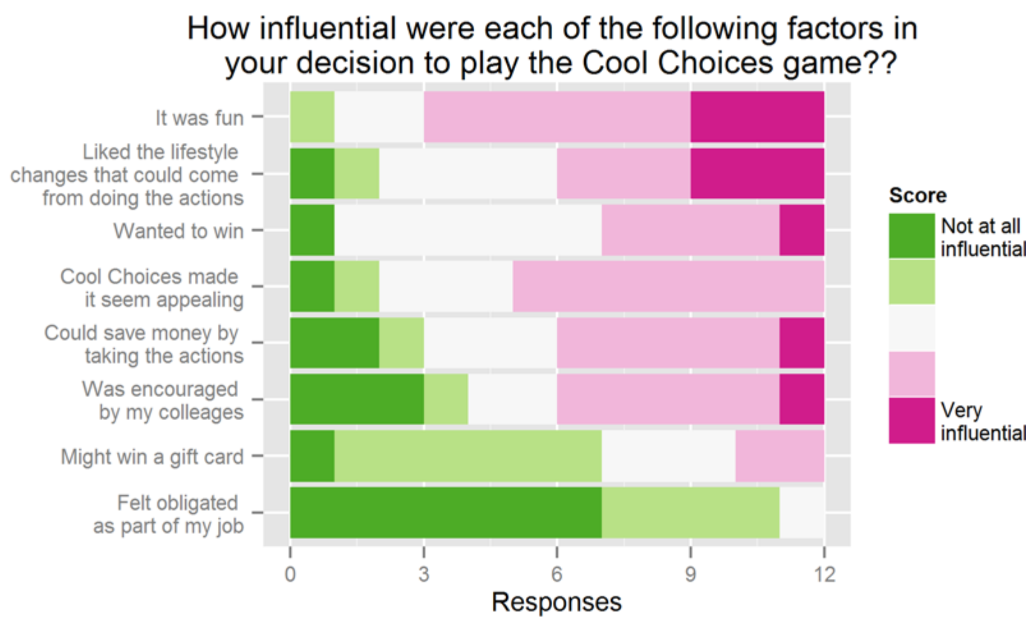


Figure 5.12 Post-game survey: reasons to sign up for the game

Figure 5.13 summarizes answers to a follow up question, which asked respondents to explain what influenced them to choose specific *actions* during the game. In order of highest influence, respondents said they selected actions that were easy to complete, ones they were already doing, and those they perceived as being beneficial for the environment. Cited as less influential were earning points, that the action was fun to do and that they would save money. Coworkers choosing the same action was cited as not influential.

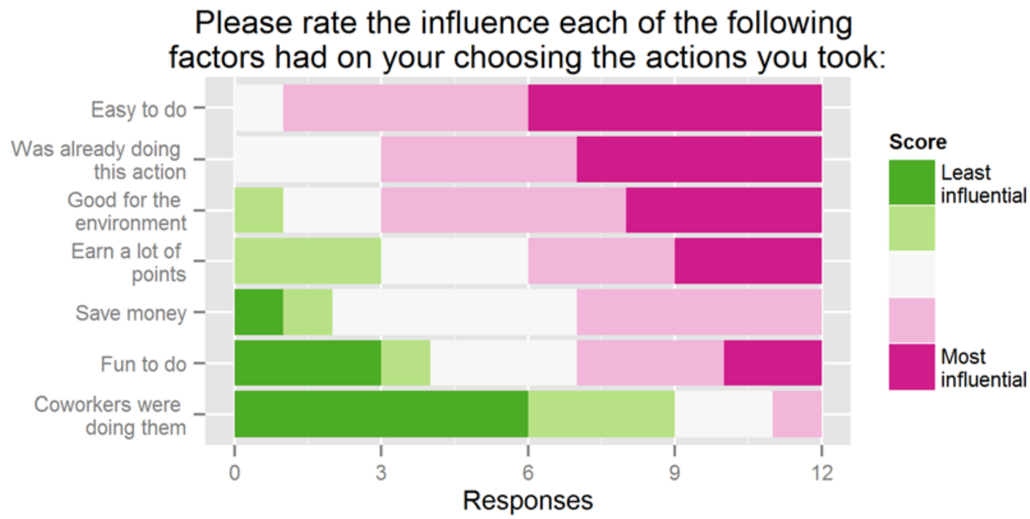


Figure 5.13 Post-game survey questions: reasons to select in-game actions

For Figure 5.14, respondents were asked where they talked about sustainability while the game was active. Most respondents stated that they discussed sustainability at work and at home at least weekly, while half said it was several times a week or more frequently. Interestingly, although this game was initiated at work, players were just as likely to discuss the game at home as they were at work.

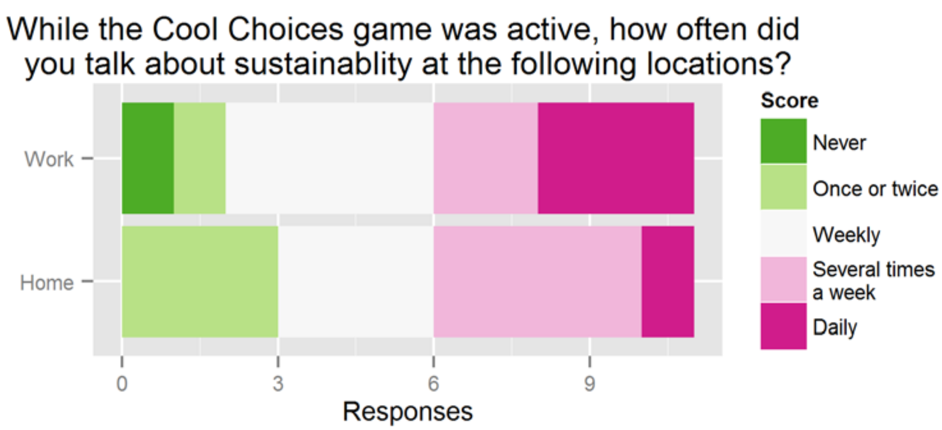


Figure 5.14 Post-game survey question: talking about the game at home and work

The question summarized in Figure 5.15 asked respondents to agree or disagree with statements about how Cool Choices affected them. They stated that the in-game actions were simple to do, and they felt the game was a meaningful part of UCOP's sustainability efforts, and made them more aware of opportunities to save energy. Players reported that they were more likely to turn off equipment or lights when not in use. They also said that their families were enthusiastic about taking Cool Choices actions, further reinforcing the fact that players were engaged in the game outside of the workplace.

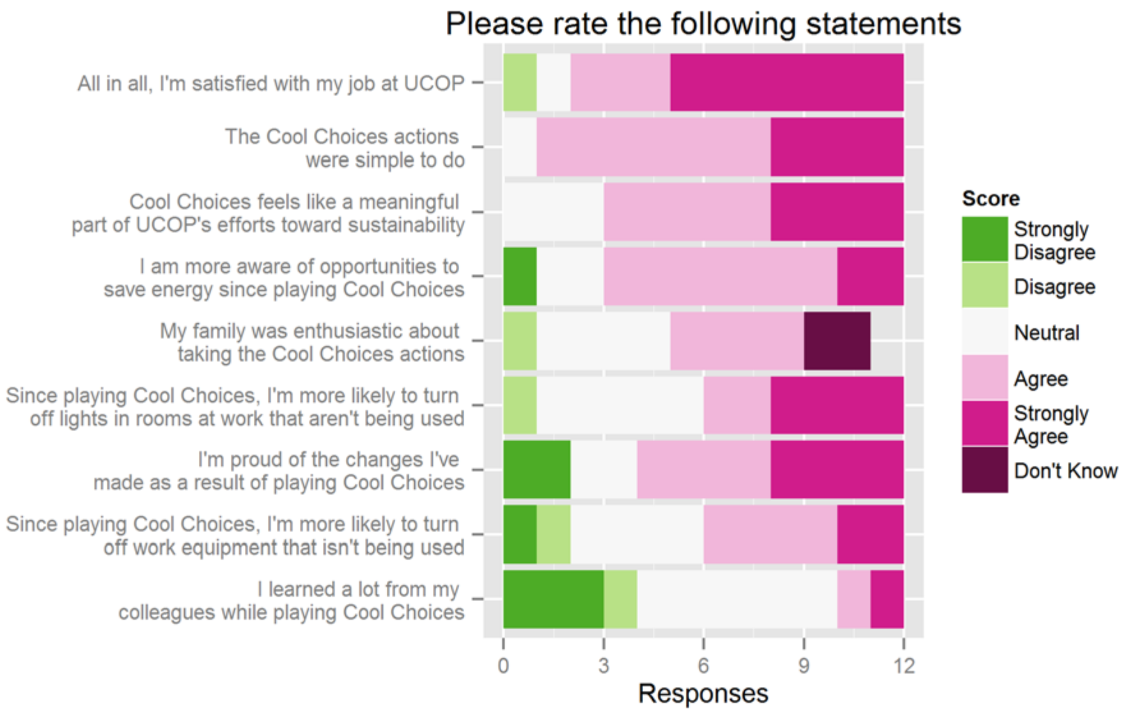


Figure 5.15 Post-game survey question: how Cool Choices affected the players

5.2.3. Before and After

The graphs in this section summarize survey responses that describe players' behaviors before and after the game. For Figure 5.16, players were asked how much they were doing to save energy, gasoline, and water before and after the game. Note that although this question was only asked once, not all surveyed players provided answers for all questions, which explains the different number of responses in the figure. This question was included only in the post-game survey, so players were self-assessing their behaviors before and after the game. In all cases, players reported that they were making efforts to save energy, gasoline, and water (i.e., purple shades correspond to more effort). There was a modest increase in the amount of actions players reported after the game (i.e., in comparing each pair of responses for before vs. after, the purple bars got larger). This is most evident for energy, where four players reported doing little or nothing before the game, but after the game those responses disappeared and all players reported more significant efforts in the top two response categories.

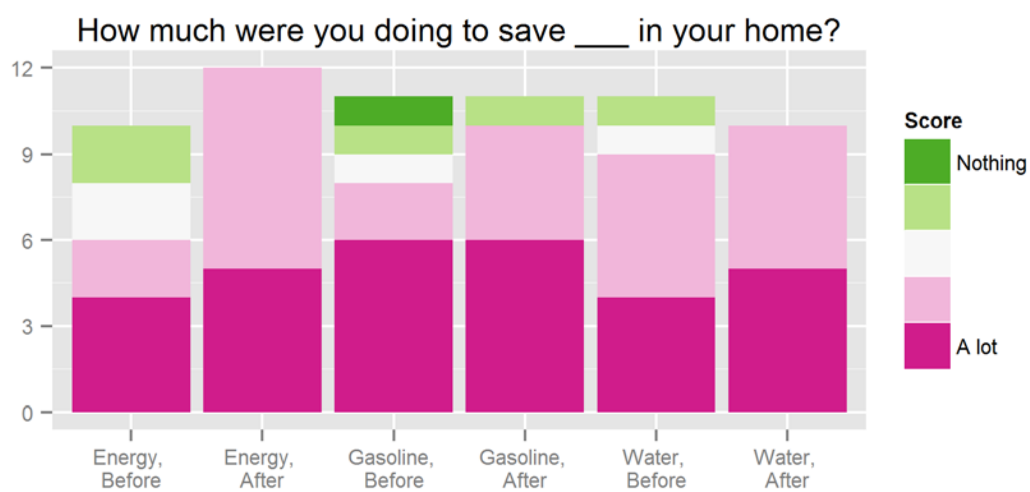


Figure 5.16 Post-game survey question: self-assessment of before and after game actions

In both the pre-game and post-game surveys players were asked to gauge the importance of sustainability to themselves and others around them.   Before the game (Figure 5.17), players generally reported that sustainability was important to themselves, their household, their friends, extended family, coworkers, and UCOP leadership. After the game (Figure 5.18), there was an increase in reporting that sustainability was important to UCOP and coworkers.

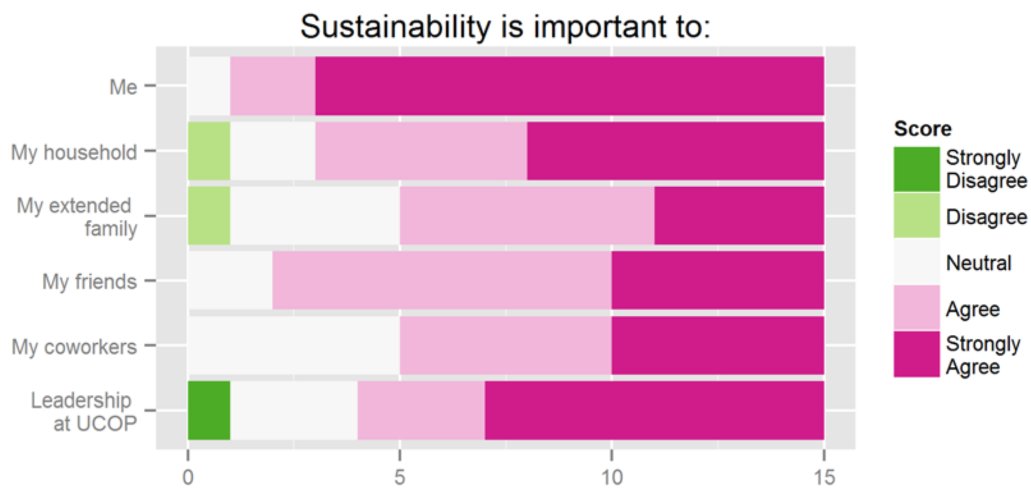


Figure 5.17 Pre-game survey question: importance of sustainability

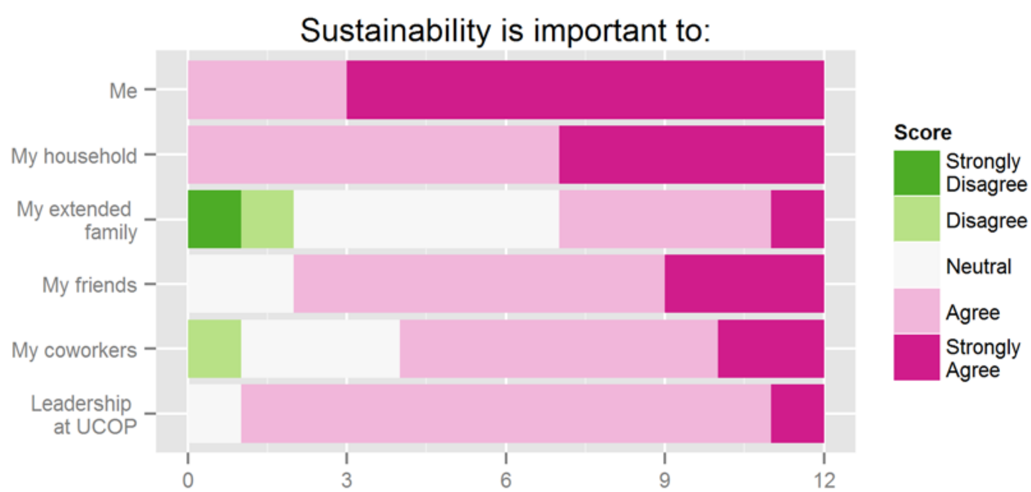


Figure 5.18 Post-game survey question: importance of sustainability

5.3. Cool Choices game: daily actions

The graphs in this section illustrate the daily actions players claimed they took throughout the course of the game. Unless otherwise noted, actions are color-coded by location (Home or Work) and category (Energy, Water, Waste, Transportation, and Knowledge). For example, a "Work, Energy" action might be turning off a work computer at the end of the day, while a "Home, Energy" action might be replacing incandescent light bulbs at home with CFLs or LEDs. Cards categorized as Knowledge include actions like reading the University of California's sustainability policy or uploading a photo of the player recycling.

Figure 5.19 and Figure 5.20 summarize the most popular categories and point values of actions played by all participants throughout the game. Figure 5.19 reveals that the most popular category was Home, Transportation (229 cards), followed by Home, Waste (175) and Home, Energy (168). A total of 136 Work, Energy actions were claimed. Although this is a game administered at work, actions at home were more popular. This could be because occupants were more motivated by potential savings they could achieve at home, as suggested by the post-game survey result indicating that saving money was a motivator for players (Figure 5.12). These results also help to further explain Figure 5.14, which showed that players talked about the game nearly equally at home and at work.

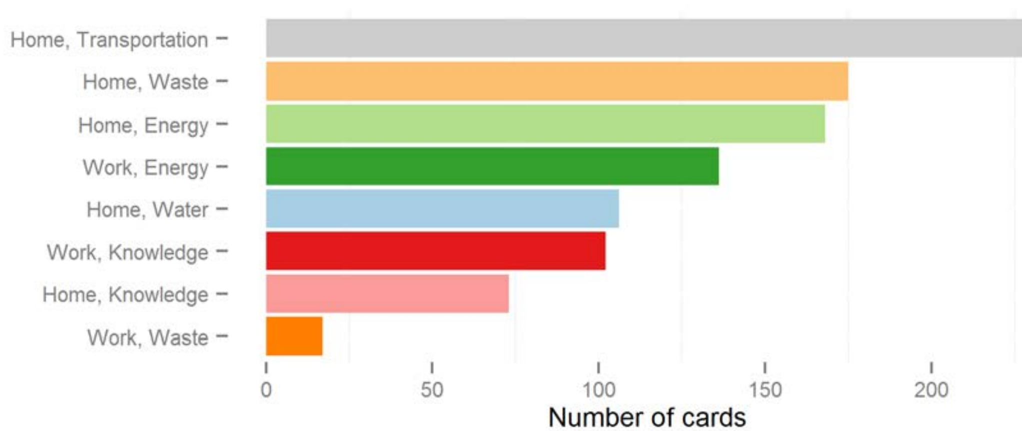


Figure 5.19 Cool Choices: popular card categories

Figure 5.20 reveals which point values were most popular, however considering that 32 of the 42 possible actions were worth 10, 20 or 30 points, it is not surprising that most cards were in this range.

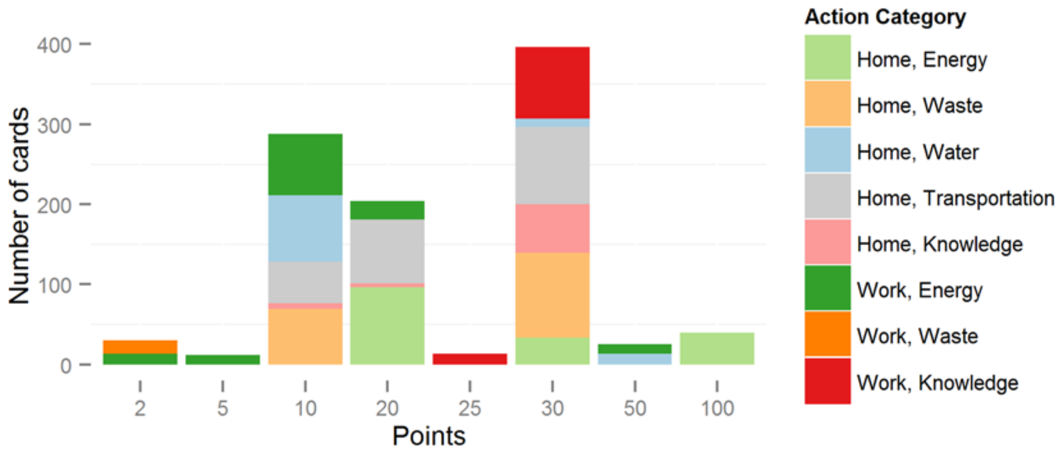


Figure 5.20 Cool Choices: point values of popular cards by category

Figure 5.21 lists all 42 cards, sorted from most frequently to least frequently played for all players. Actions that were claimed most frequently include reducing water use and taking alternative modes of transportation. The most popular Work, Energy actions were turning off computers before leaving work (20), changing monitor settings to turn off after 10 minutes of inactivity (18), and getting rid of personal printers (18).

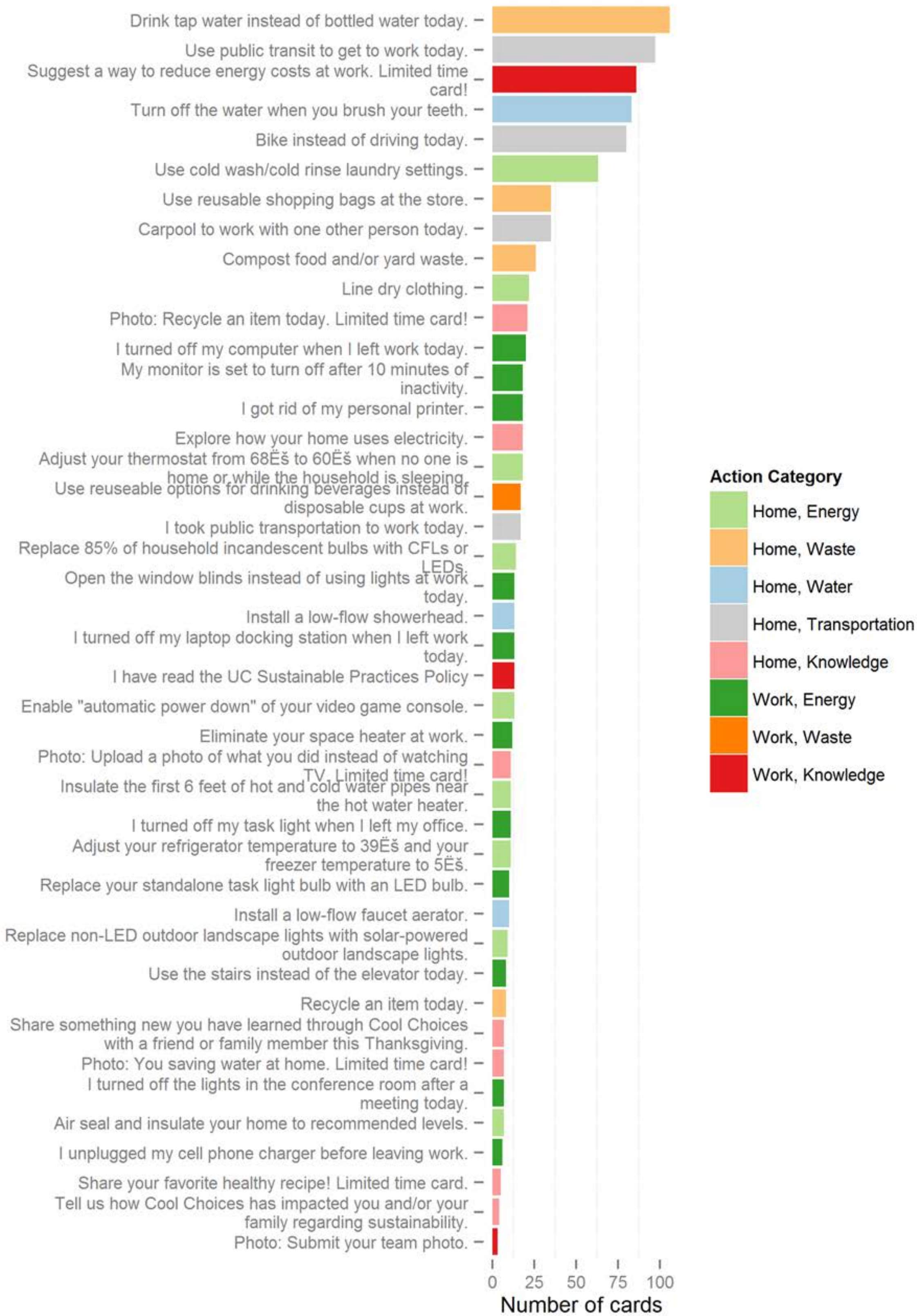


Figure 5.21 Cool Choices: popularity of individual cards

Figure 5.22 illustrates the number of cards played each day by all Cool Choices participants for the 39-day game. Because players were limited by the number of available actions they could claim each day, (starting with two actions the first week and increasing to six actions the last week), Figure 5.23 is provided to illustrate the percentage of possible cards played each day by all players. At least one new action was added to the game each work day, which meant the variety of card categories increased as the game progressed (Figure 5.22). As an online game, players could access Cool Choices from home as well. Figure 5.23 shows that more actions were taken during weekdays (dark blue) than weekends (light blue), however players were still active when not in the office, which means that they were motivated to play even when not receiving the reminder emails, which were only sent during work days. The days with the least activity include the first weekend (days 5 and 6) and Thanksgiving Day (day 24).

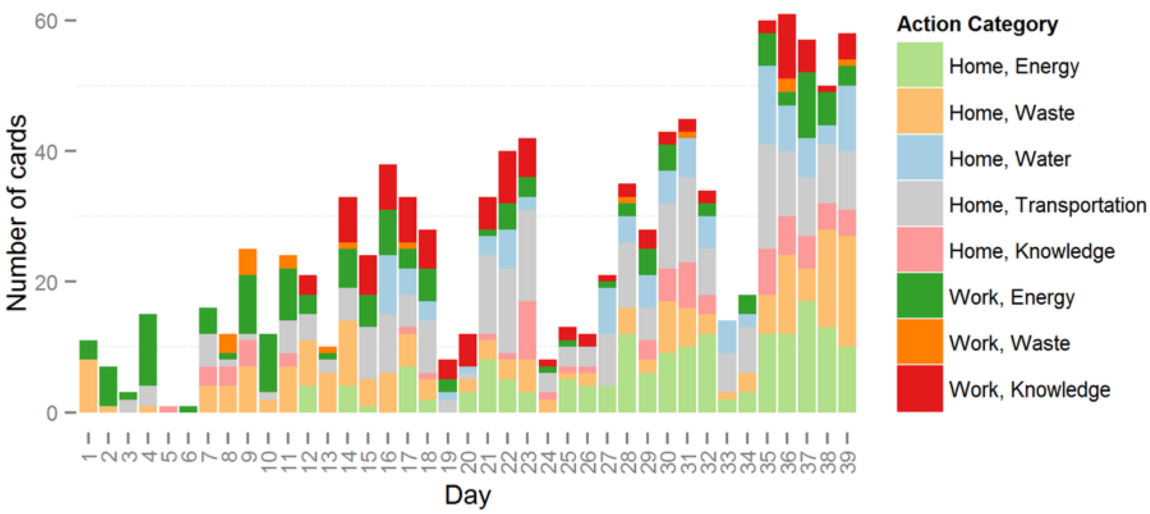


Figure 5.22 Cool Choices: number of cards played each day

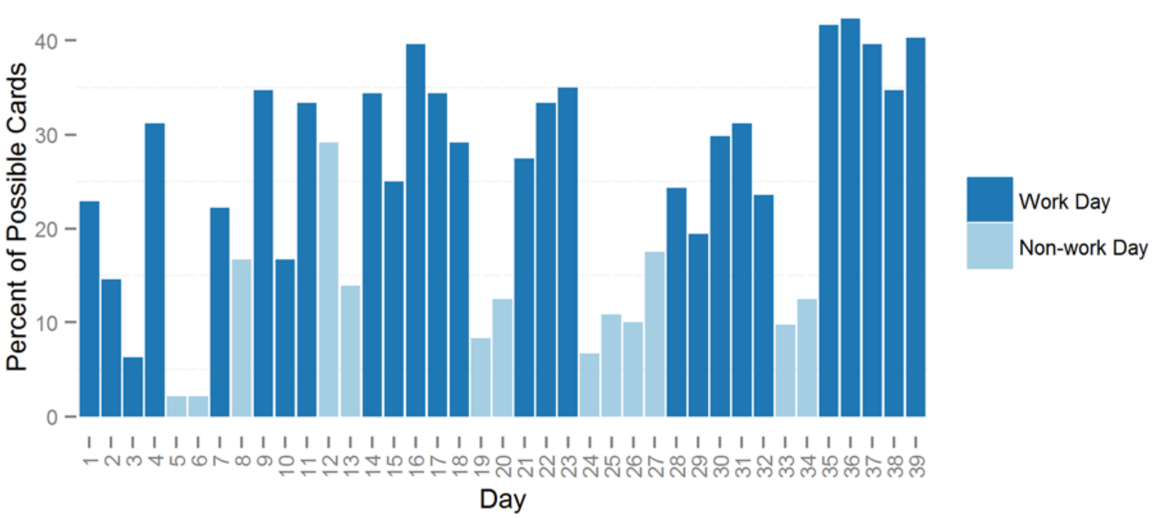


Figure 5.23 Cool Choices: percent of possible cards played each day

Figure 5.24 shows which categories of actions were claimed by each player and the total number of cards each participant played. It is clear that there were different levels of participation, with some players claiming over 80 actions. Figure 5.25 illustrates the percentage of cards each participant played in each category. In general, those who played more cards (top of figure) selected them from a wider variety of cards than those who played fewer cards.

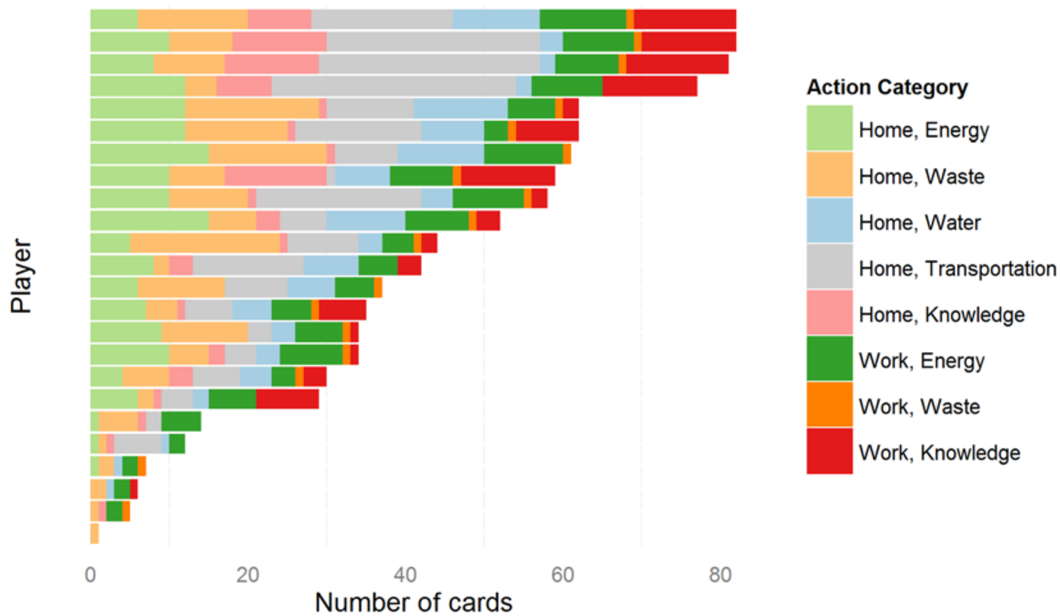


Figure 5.24 Cool Choices: number and category of cards played by each player during the game

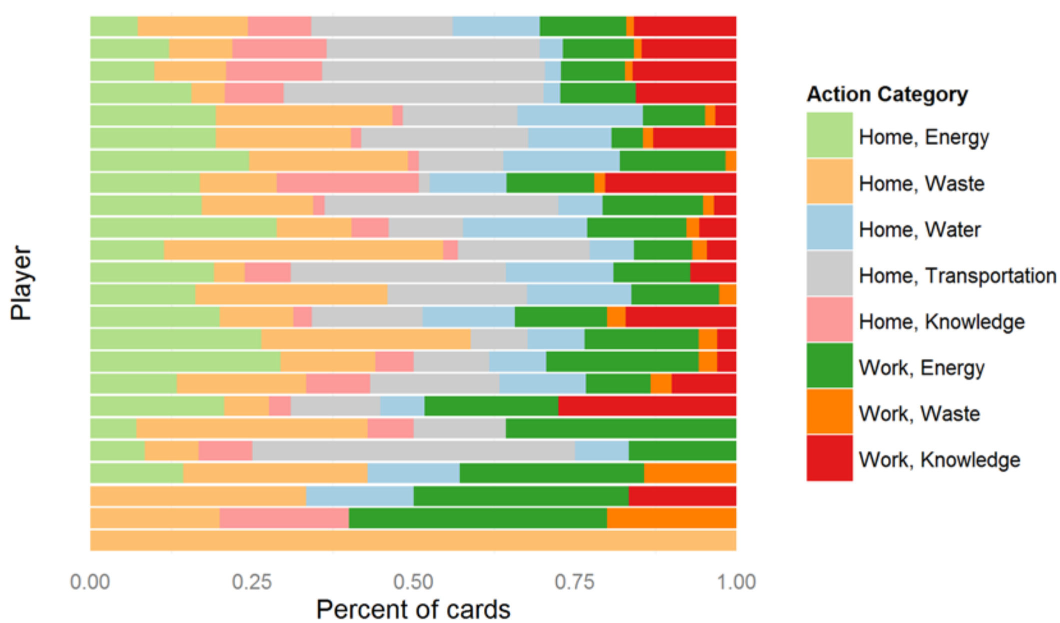


Figure 5.25 Cool Choices: percent and category of cards played by each player during the game

5.4. Cool Choices energy impact

Technical problems with the Enmetric devices and bridges led to an unfortunate loss of data during the game. This mean that, of the submetered devices belonging to Cool Choices players, there were only two monitors and three desktops with sufficient data for analysis. I looked at the chronological use of average power use (heat map), and frequency of average power use (density plot) for each device to analyze game impacts. In the density plot, the area under the curve represents probability, i.e., the area under the curve between two points on the x-axis represents the probability of the device power being between those two values.

5.4.1. Monitors

Figure 5.26 and Figure 5.27 show the power use for Monitor 1 (M1). The heat map in Figure 5.26 shows that M1 is either regularly in use, or completely turned off, suggesting that this occupant spends large amounts of time away from the office, and that the monitor is regularly off when not in use. The data for this device did not include any values for any November during the monitoring period, suggesting that the occupant may be out of the office in November on an annual basis. In fact, UCOP management informed us that this workspace has been occupied by temporary or contract employees in recent years, which explains the large gaps in power consumption. This explains why Figure 5.27's density plot does not include any data during the game. In Figure 5.27 the "before" data have three peaks: 0 W, 19 W and 24 W, while the "after" data have two peaks: 0 W and 19W. This difference in use can be explained by examining April 2014 in the heat map, when there was a clear permanent drop in average power use for this device (perhaps due to a change in device). For M1, the game did not have an effect on power use, however it is not surprising given that the occupant was already engaging in energy saving behaviors, and was not present during the majority of the game.

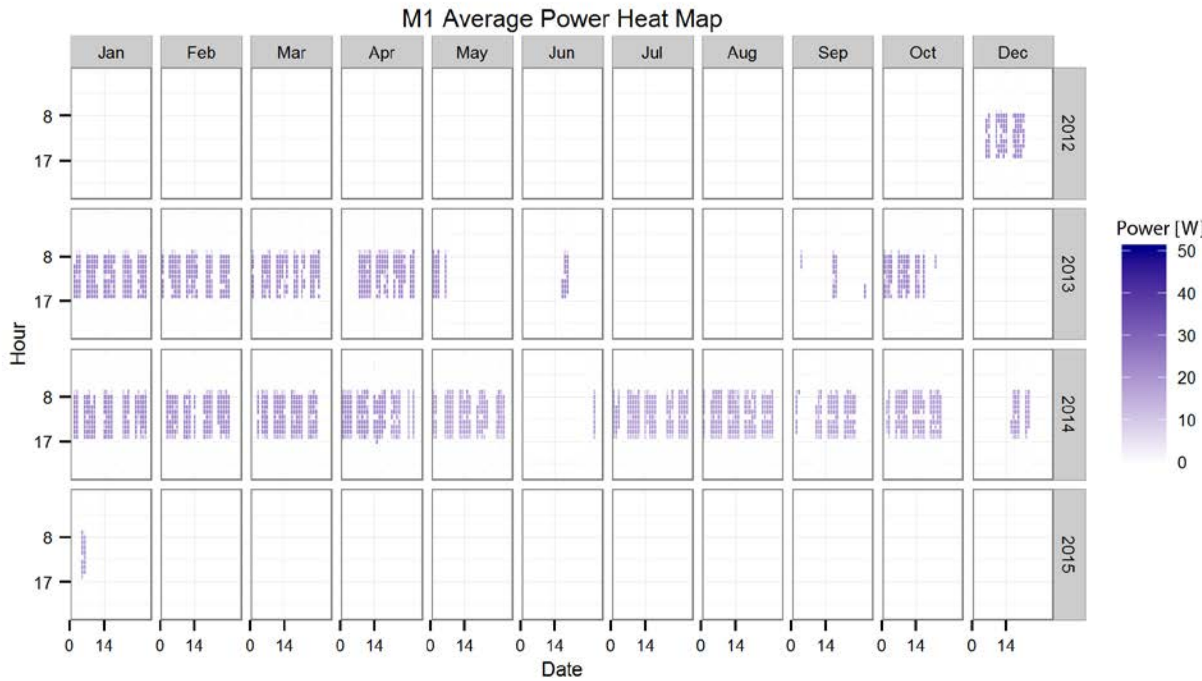


Figure 5.26 Cool Choices: heat map plot for monitor M1 average power use

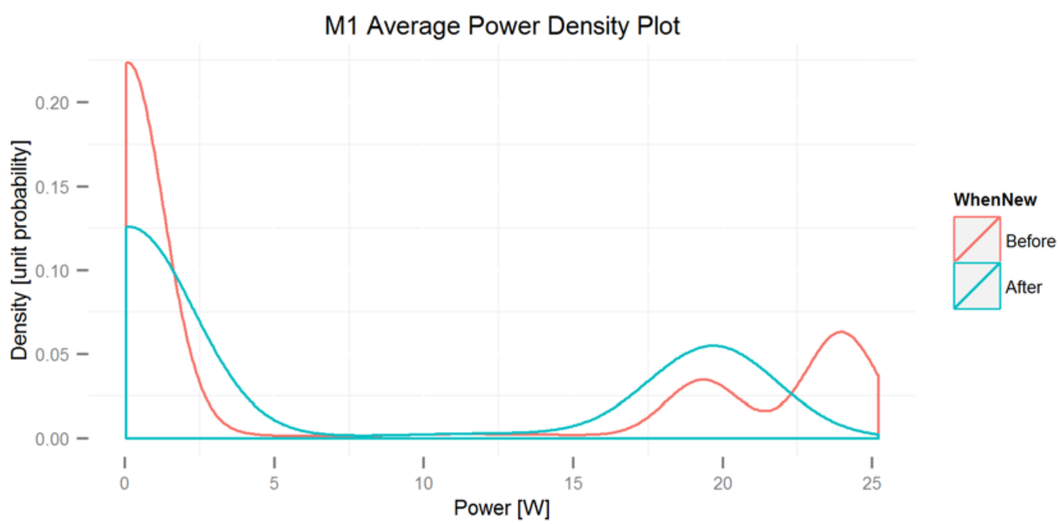


Figure 5.27 Cool Choices: density plot for monitor M1 average power use

Figure 5.28 and Figure 5.29 show power use for Monitor 2 (M2). The heat map in Figure 5.28 shows clearly that this device is regularly turned off during unoccupied periods, which suggests that there are very little additional potential savings to be incurred. The density plot in Figure 5.29 shows clear bimodal behavior: the monitor is either on (37 W) or off (near 0 W). The before, during and after datasets show similar behavior, confirming that energy savings did not occur.

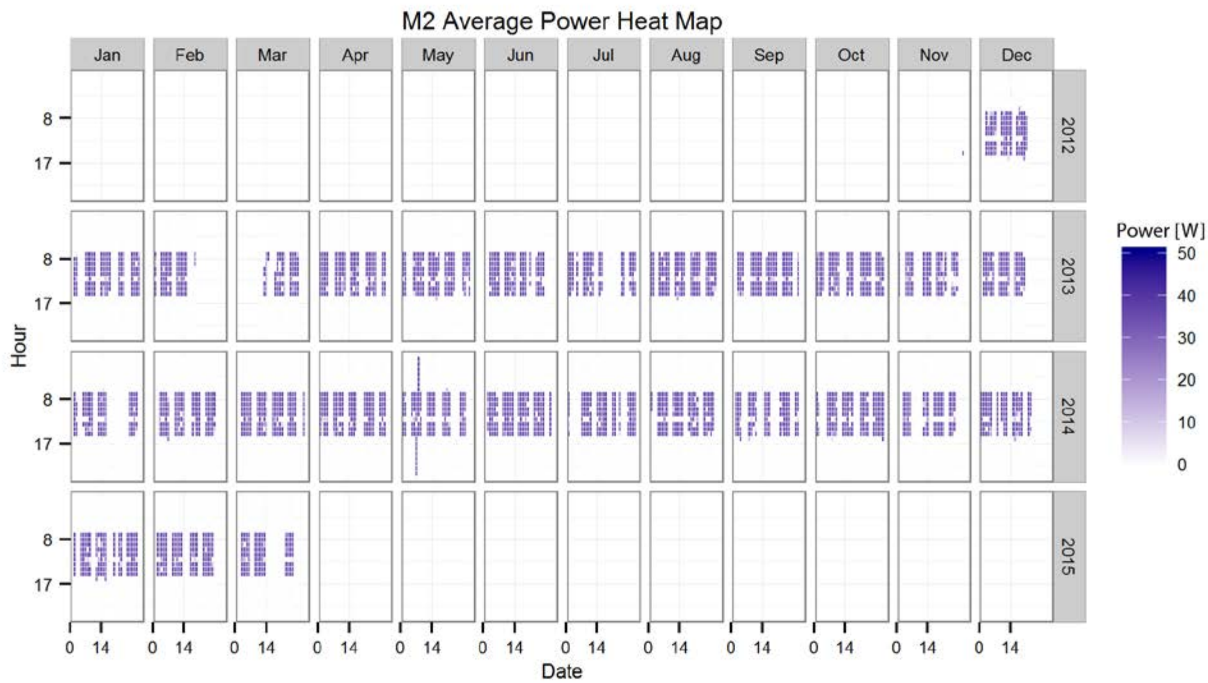


Figure 5.28 Cool Choices: heat map plot for monitor M2 average power use

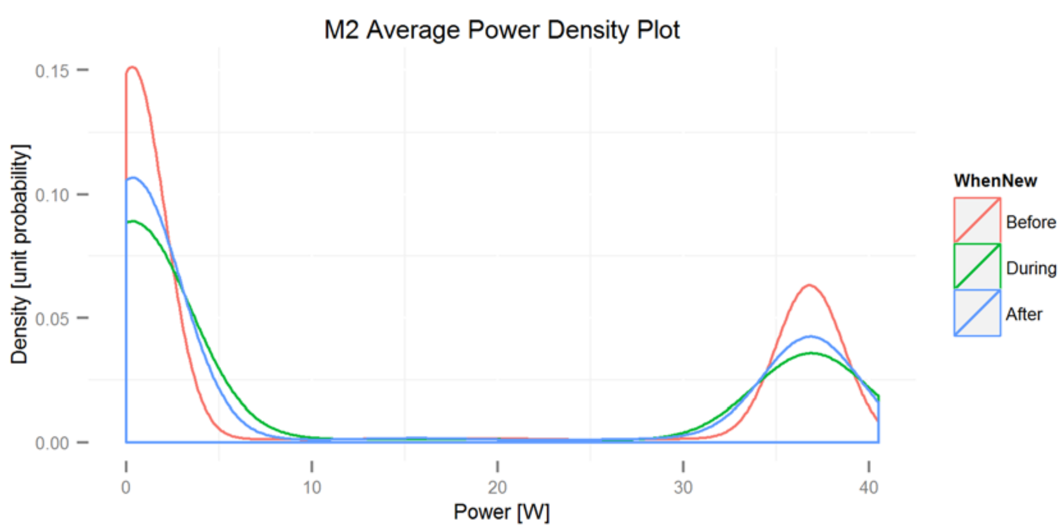


Figure 5.29 Cool Choices: density plot for monitor M2 average power use

5.4.2. Desktops

Figure 5.30 and Figure 5.31 show power use for Desktop 1 (D1), while Figure 5.32 and Figure 5.33 show power use for Desktop 2 (D2). These devices belong to different occupants than device M1 and M2. The heat maps for these devices show infrequent, inconsistent power use, suggesting that these occupants are frequently out of the office. Both heat maps also show that, in general, occupants turn off their devices at the end of the day. The density plots for these devices are shown excluding power below 1 W in order to better understand how the device is used when it is on. The density plot for D1 shows a higher power use after the game when compared to data from before the game. This can be explained with the heat map, which shows that the device was left on overnight more frequently November 2014-March 2015. Given that this appears to be a new behavior, it is possible that there were work-related reasons for leaving their computer on overnight, such as to access their computers remotely from other locations. For D2, the density plot shows a higher peak mode before (160 W), than during and after data (115 W). One possible explanation is that the occupant changed out their device for a more efficient replacement, however the drop coincided with the start of the game, which could also indicate that the occupant changed the computer settings to reduce power consumption, resulting in a permanent reduction in power use. Another explanation comes to us from UCOP management, who explained that this workspace was occupied by temporary or contract employees, which suggests irregular occupancy patterns.

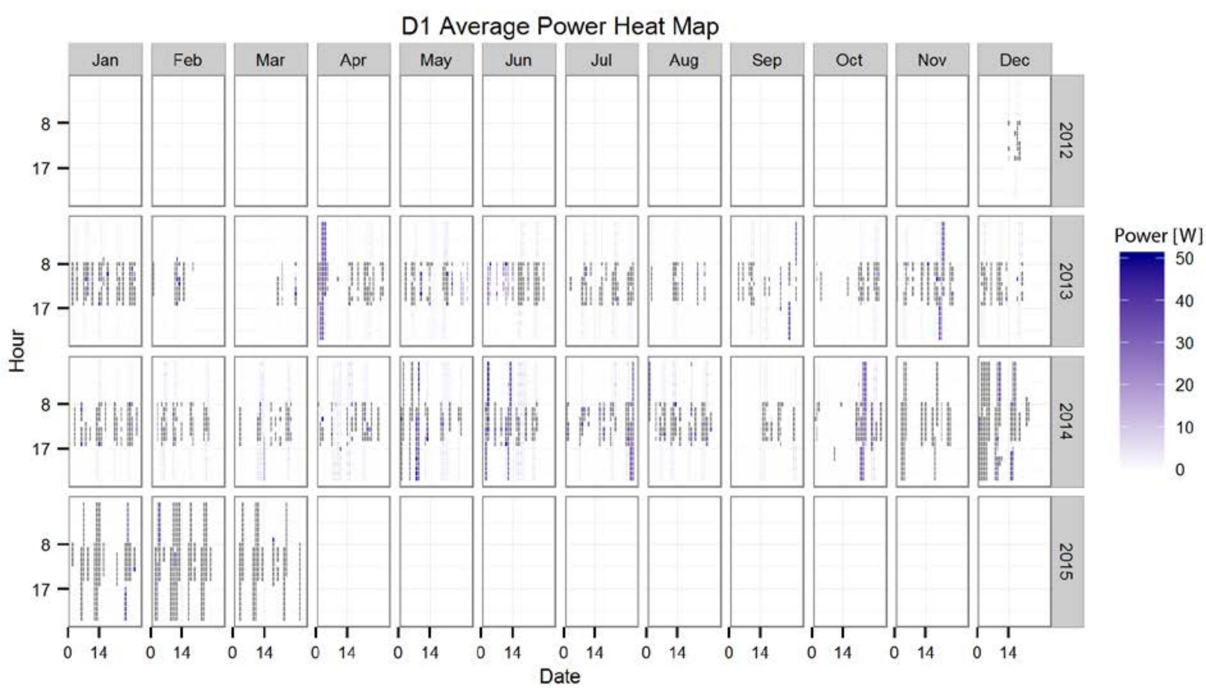


Figure 5.30 Cool Choices: heat map plot for desktop D1 average power use

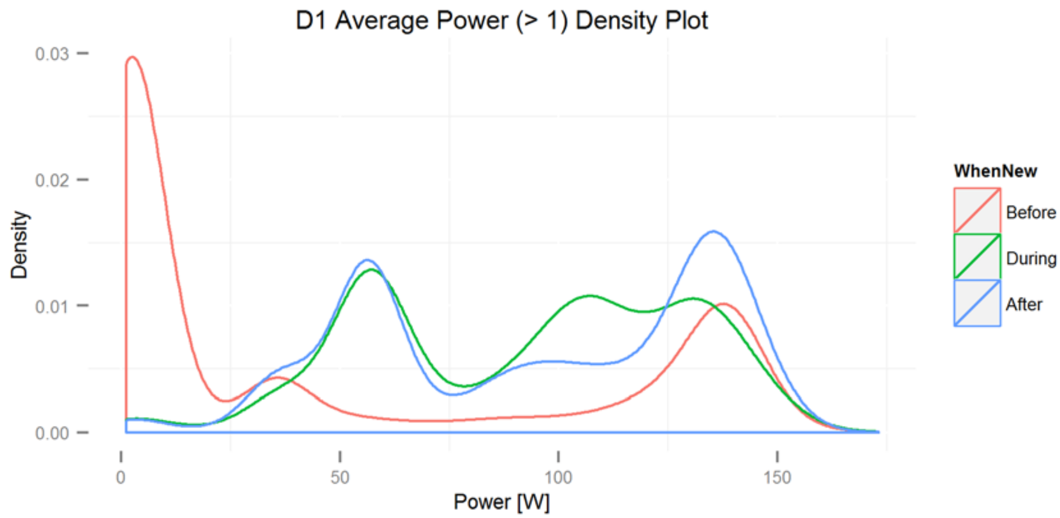


Figure 5.31 Cool Choices: density plot for desktop D1 average power use (greater than 1 W)

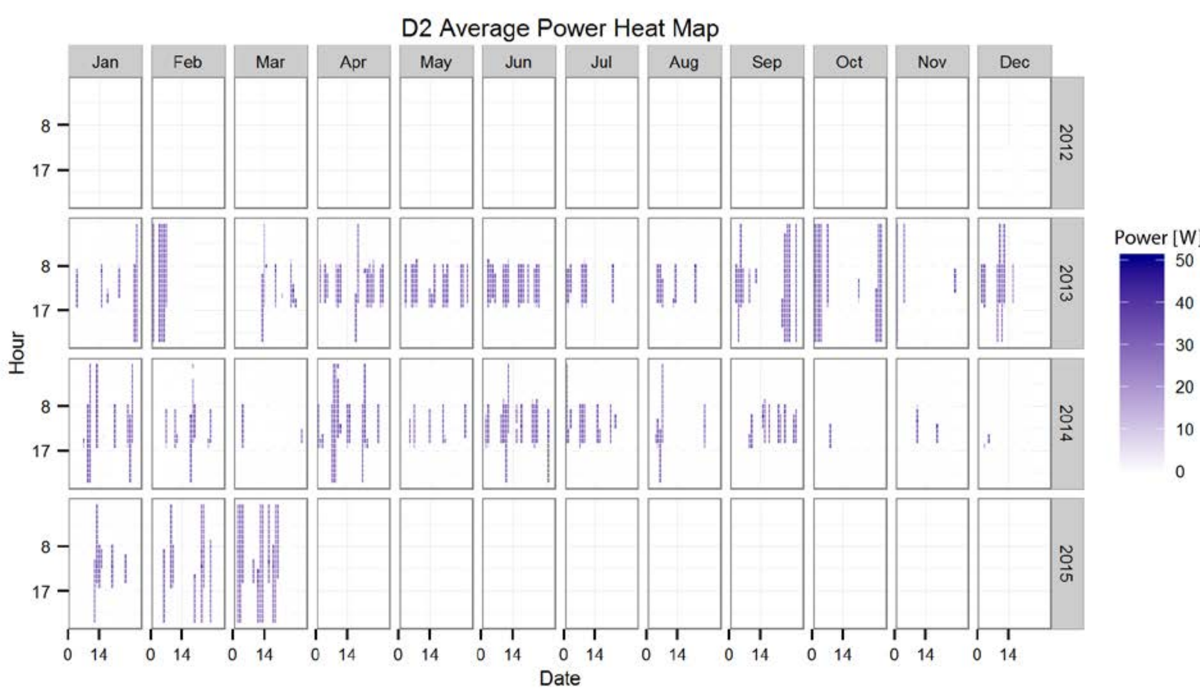


Figure 5.32 Cool Choices: heat map plot for desktop D2 average power use

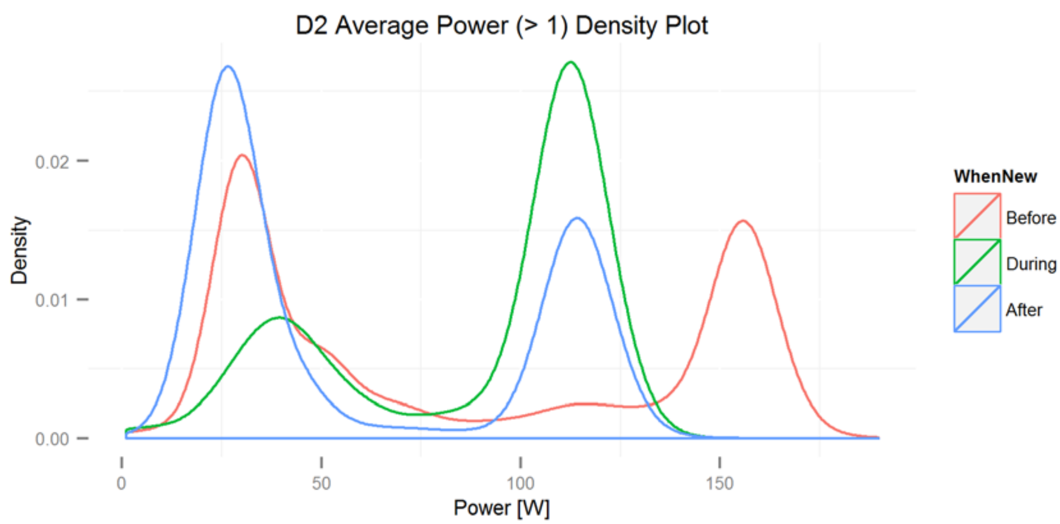


Figure 5.33 Cool Choices: density plot for desktop D2 average power use (greater than 1 W)

Figure 5.34 and Figure 5.35 show power use for Desktop 3 (D3). The heat map in Figure 5.34 shows that D3 was in consistent use throughout the monitoring period. It also shows that since July 2014, the device is not left on overnight, as it was previously. Examining the density plot in Figure 5.35 shows a bimodal trend, and a clear drop in power use after the game. This drop is echoed in the heat map, which shows a permanent drop in average power starting in January 2015. Like D2, this could be explained through equipment replacement or adjusted power settings coinciding with the end of the Cool Choices, game, or the fact that this workspace was occupied by temporary or contract employees.

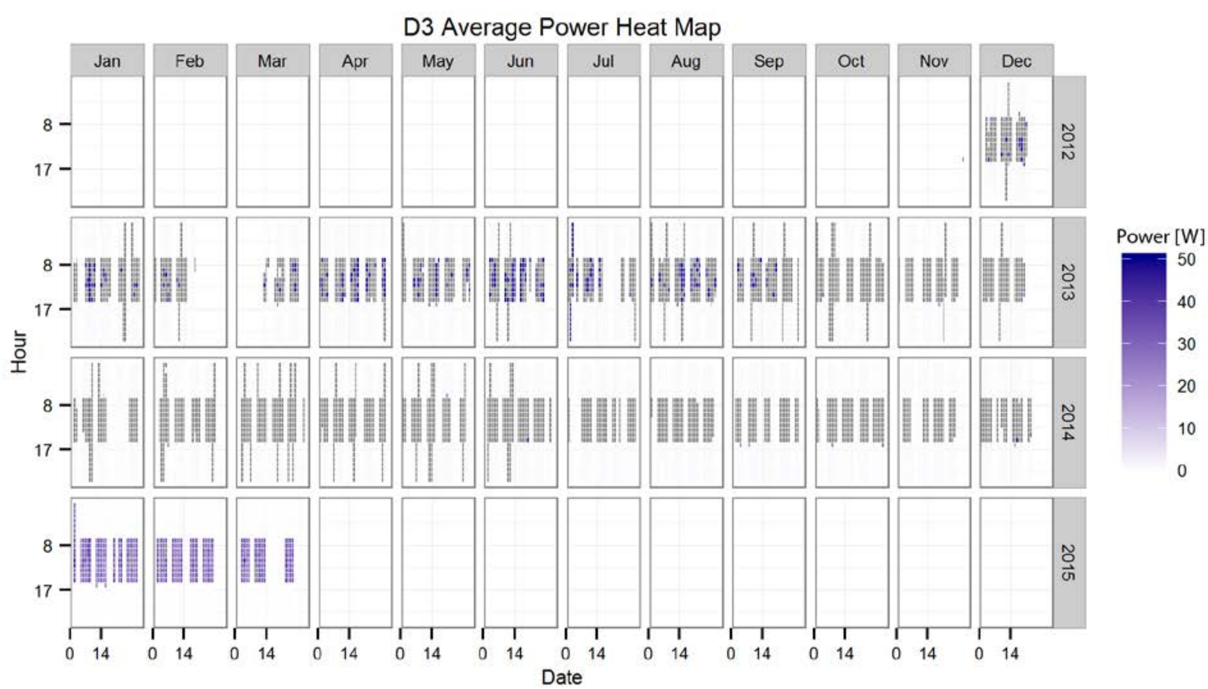


Figure 5.34 Cool Choices: heat map plot for desktop D3 average power use

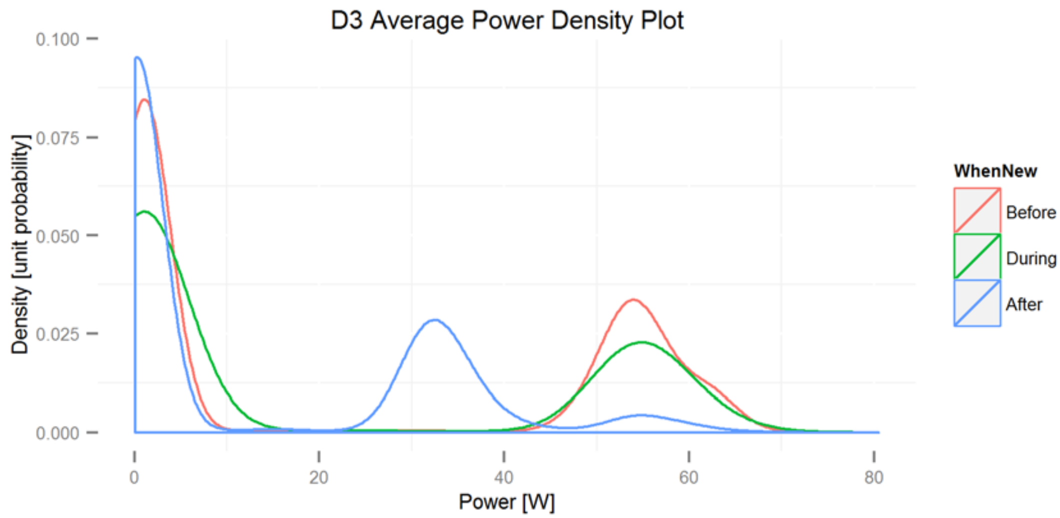


Figure 5.35 Cool Choices: density plot for desktop D3 average power use

5.5. Plug load model

An important application for the trends discovered in the baseline analysis is a predictive model based on collected data. For this plug load model, I created multiple iterations of a Monte Carlo simulation and describe the results of the last two versions here.

$$MCModelv2 = f(D_{start}, D_{end}, qty_d, CDF_{d,t,h})$$
$$MCModelv3 = f(D_{start}, D_{end}, qty_d, CDF_{d,t,h,m})$$

Where subscript *m* means month.

These two models performed differently for each comparison metric (median, variance, NMBE), but one model was not uniformly better than the other. Both are included to demonstrate when the additional complexity of MCModelv3 might be helpful, and when it is not worth it. The two models were executed for each month and for the entire year. Figure 5.36 and Figure 5.37 provide a comparison of the median and variance between the measured data, MCModelv2 data and MCModelv3 data for each timespan. Figure 5.40 illustrates the NMBE for MCModelv2 and MCModelv3.

The points for the measured data are fitted with $\pm$ 10% error bars to indicate the acceptability range established within the Methods section. For the median, MCModelv2 was within 10% of the measured data's median for only seven of the 14 timespans. However, considering that the range is so small (less than 1 W), this is not a significant difference.

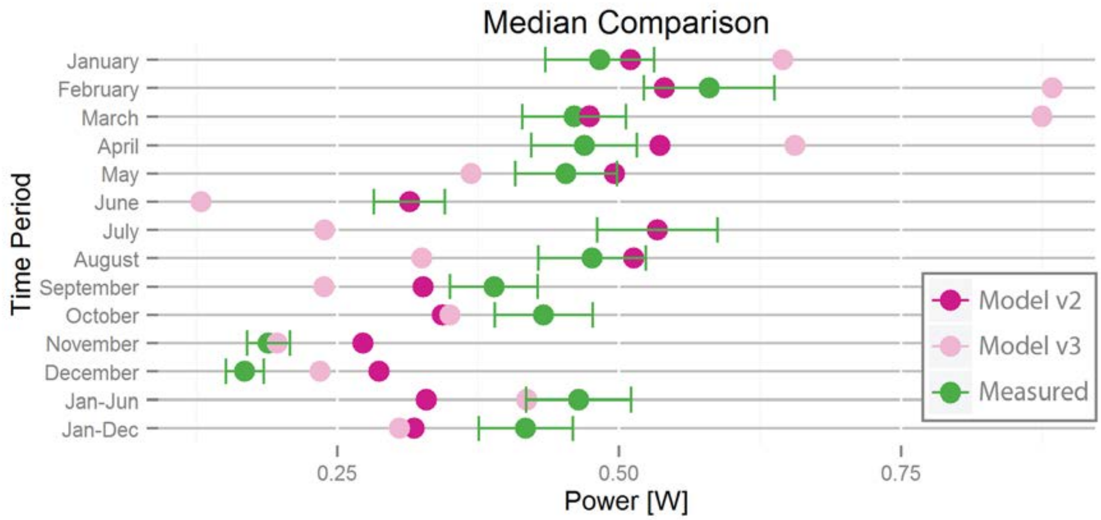


Figure 5.36 Plug load model validation: median power comparison

Figure 5.37 shows the measured data, MCModelv2 and MCModelv3 output. The MCModelv2-predicted variance varies greatly and never falls within 10% of the measured data. In general, both models predict significantly larger variances than the measured variance.

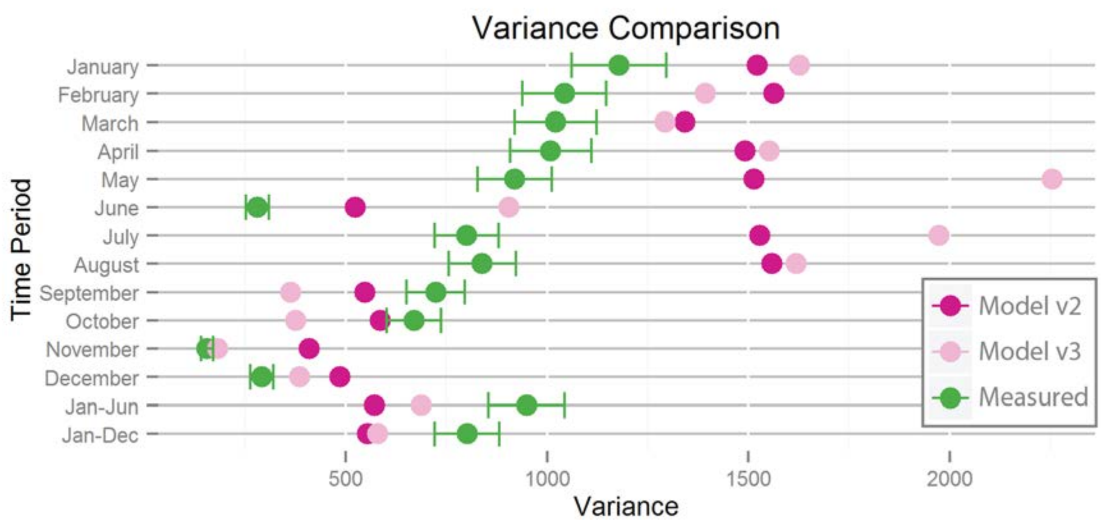


Figure 5.37 Plug load model validation: variance power comparison

Figure 5.38 and Figure 5.39 present two months of plug load power profiles that illustrate the difference in variability between MCModelv2 and the measured data. For clarity, MCModelv3 output is not plotted. Figure 5.38 presents data for October, which had the closest variance (13% difference), while Figure 5.39 presents data for July, which had one of the most inaccurate variances (87% difference). Appendix C includes graphs for the remaining months. Figure 5.38 shows that when the work day/non-work day split is an accurate proxy for occupancy, then the model does a fairly good job of predicting power consumption. However, when occupancy cannot be predicted by this categorization, as in June in Figure 5.39, the model cannot accurately predict power profiles. Please note that we contacted UCOP about the sudden drop in power during the last week of October, but they found no obvious reason for the reduction.

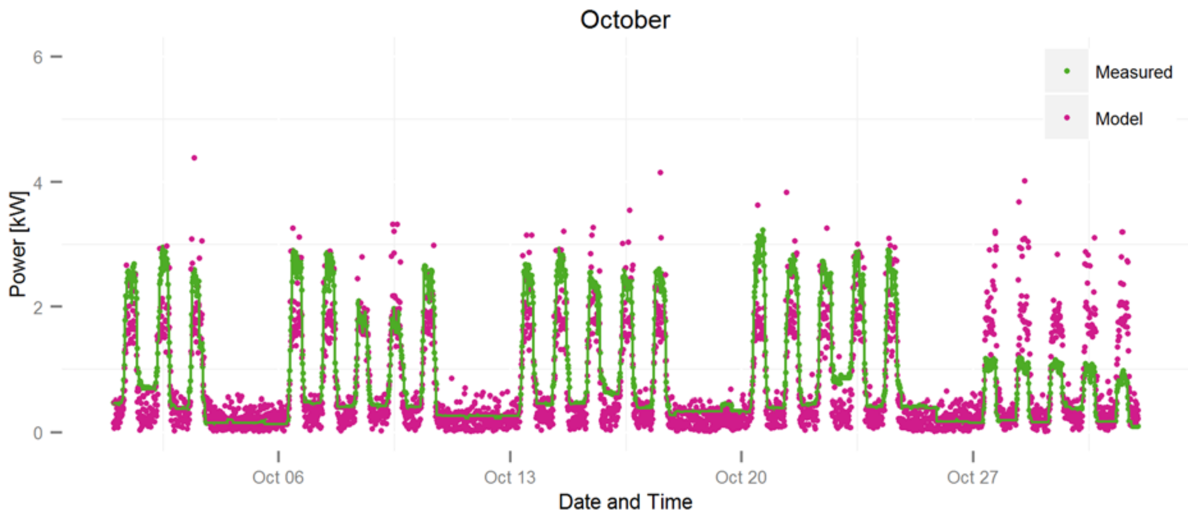


Figure 5.38 Plug load model: October power profile

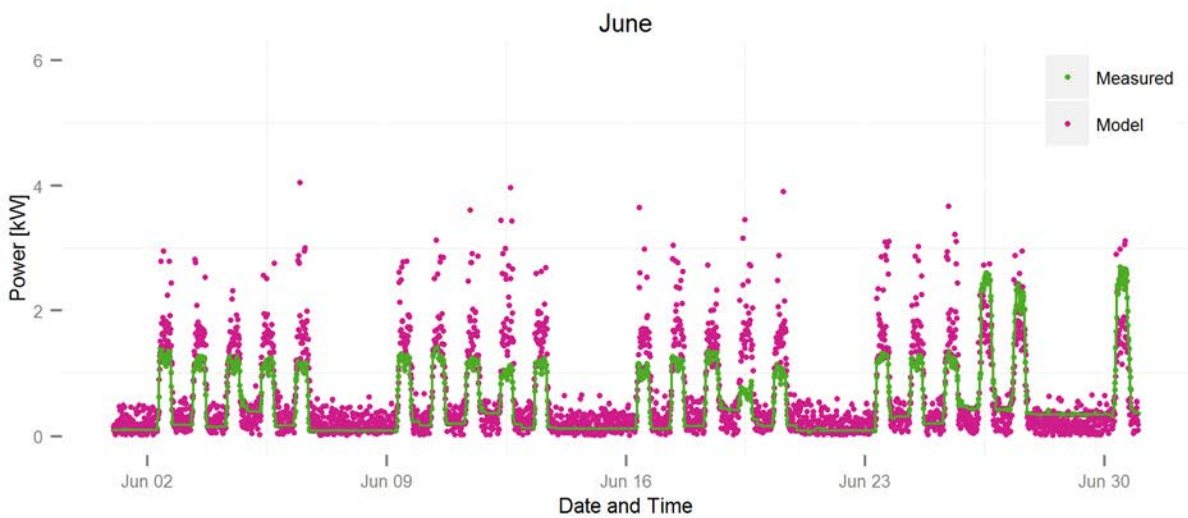


Figure 5.39 Plug load model: June power profile

The last comparison metric I used was the normalized mean bias error (NMBE). Figure 5.40 plots the NMBE for MCModelv2 and MCModelv3 for each timespan (each month individually, January-June, and January-December). The graph also indicates the 10% maximum limit required by ASHRAE Guideline 14. Neither model does particularly well in this metric, with only a few timespans meeting this requirement. The poor performance can be explained by returning to Figure 5.38 and Figure 5.39 and considering the variance. Recall that the NMBE is dependent on the difference between the measured and modeled data at each time step. The NMBE is so high because the modeled data varied so much more than the measured data at each time step.

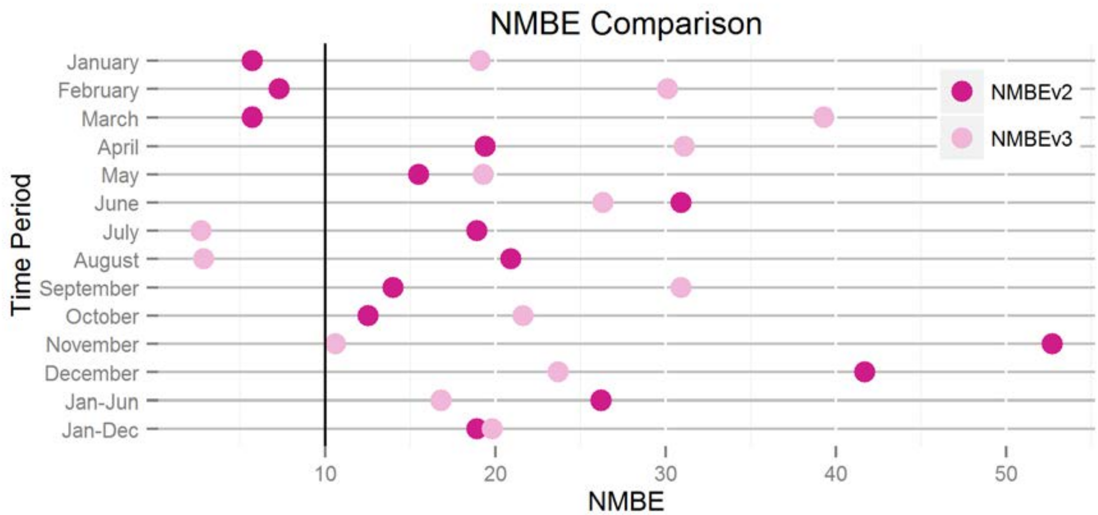


Figure 5.40 Plug load model validation: normalized mean bias error

This comparison shows that including an additional variable (month), as MCModelv3 does, did not result in a plug load prediction which is significantly more accurate than the more simple MCModelv3.

6. Discussion

6.1. Occupancy patterns

The trends from the baseline data analysis illustrate that occupants in the Franklin Building generally have very regular schedules, working from approximately 8:00 am to 5:00 pm during the week (excluding holidays) and not working on weekends. UCOP occupants appear to have an office culture of regular work schedules with minimal overtime in the evenings or on weekends. The daily profiles extracted from the data set illustrate a strong dependence on occupancy rates. Because power consumption during occupied and unoccupied periods on the same day tracked one another, it indicates that when more people are in the office, more power is being consumed, and also that more devices are left running overnight.

Figure 6.1 plots the combined UCOP fractional plug load schedule for work days and non-work days with a selection of published plug load equipment schedules. As described in the literature review, these diversity schedules are often used in energy models to simulate power consumption of plug load devices and peak loads. For clarity of presentation, only the profiles for "medium" size office buildings are included. The published schedules are hourly, while the UCOP schedule is plotted at 15 minute time steps to preserve the nuance within each hour.

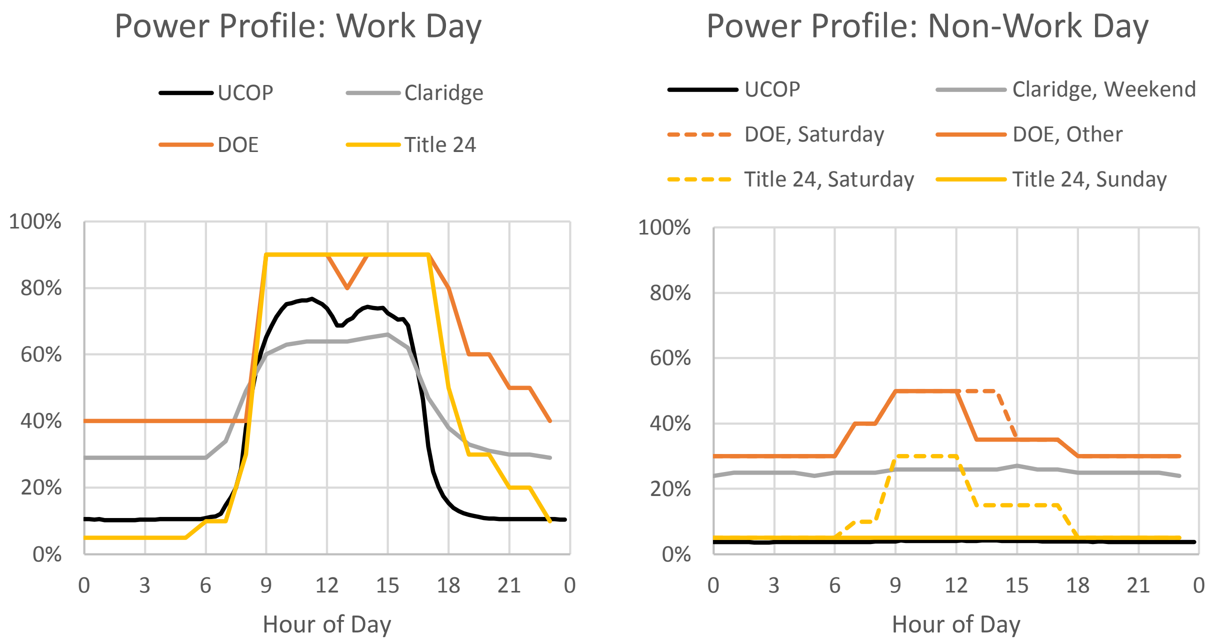


Figure 6.1 Comparison of UCOP daily profiles with published schedules in the literature

This graph illustrates the difference in the published power profiles that were based on all plug load devices, and the UCOP profiles based on monitoring only a selected subset of devices. The difference in workday overnight and non-workday power use indicates that the plug loads responsible for power consumption during unoccupied periods are not personal computing devices. Most likely the elevated power levels during the workday overnight periods in the published schedules are due to shared devices (e.g. printers, servers) that are left on after the workers leave for the day. If a comprehensive plug load study were conducted at UCOP, it would be possible to more completely compare this building to industry standard profiles.

The work/non-work day dichotomy of power consumption evident in the UCOP data is similar to the divisions used in the published sources, although some sources provide different schedules for Saturdays and Sundays, while the UCOP data did not show a distinction between these two days. The power use of the personal computing devices is a strong indicator of occupancy, and that is why I used those trends to inform the plug load model.

The predictive plug load model considers day type and time step key variables in its algorithm. Essentially, the Monte Carlo simulation uses these as stand-ins for occupancy, which is the real predictor of plug load energy consumption. The large discrepancy between the validation data and modeled output indicates that this simplification did not truly capture occupancy patterns.

One of the assumptions of the model is that work days and non-work days (holidays and weekends) are significantly different due to dramatic differences in occupancy on these two types of days. Actual occupancy data was not collected, and therefore occupancy could not be included as a variable in the model. Thus, it follows that there may be periods of time where occupants are out of the office (vacation, working remotely, etc.) that the model does not account for. Indirectly, the model does account for occupants leaving their workstations for periods of time during the day, as this information is captured in the reduced power consumption of devices in sleep mode.

The cumulative distribution functions (CDFs) from the training data might have been able to take out-of-office time into account if these periods were spread out across the year. However, out-of-office events like vacations are likely concentrated during certain times of the year for scheduling reasons. By including month as a variable, MCModelv3 was developed with the intention of picking up on some of these nuances.

For example, Figure 5.3 and Figure 5.4 indicate that there is consistently lower power consumption in November and December for both full years of data, even when excluding holiday periods. This might be because staff takes more holidays or there are more out-of-office events occurring this time of year. MCModelv2 had the highest normalized mean bias error (NMBE) in November and December, 53% and 42%, respectively, while MCModelv3 had much lower numbers, 11% and 24%, respectively. Conversely, when the trends do not repeat themselves, of course MCModelv3 is not be an improvement on MCModelv2, as can be seen with September, where MCModelv2 had an NMBE of 14%, while MCModelv3 had an NMBE of 31%.

Although adding month as a variable in MCModelv3 was an improvement in some months, overall it was not significantly better at predicting the median power and variance of the measured data, and therefore was not providing value commensurate with the additional complexity and computing time a fourth variable added. An improvement on this model would include a different variable to indicate occupancy, such as a minimum power threshold per occupant.

6.2. Energy saving behavior

As the literature review suggested, opportunities for saving energy through behavior hinge primarily on turning unused equipment off, rather than reducing use of equipment during business hours. For monitors, this can be accomplished by using power management settings that put the device into sleep mode after a set period of inactivity (e.g. 10 minutes). Similarly, for desktops, changing power management settings can go a long way towards reducing power use by setting timers to dim the display, turn off the display, and enter sleep mode (e.g. turn down the CPU). The greatest potential savings will occur when occupants do not already have these settings in place, or do not engage in turning devices off when not in use (e.g. overnight, weekends, or just periods when occupants are not at their desk).

As was observed, occupants monitored in this study already engage in plug load energy saving behaviors, which can be seen by the significant drop in overnight and weekend power use. It is highly likely that many of these occupants already have the appropriate power settings on their computers, which means that any potential savings are likely to be small.

However, the data also show less power consumption overnight during the week, than on weekends. This is a consistent trend overnight (i.e., the aggregated power level is close to constant), which suggests that more equipment is being left on during the week, than before a weekend. I interpret this to show that there is a subset of occupants who do know that they should turn off their equipment, but have other reasons for leaving it on (e.g. leaving programs running, or to be able to access their machines remotely). If these occupants need to keep computers on overnight, then potential savings are also likely to be small.

One of the most significant differences in the work day profile comparison (Figure 6.1) is that the UCOP monitored devices have very short ramp up and ramp down periods at the beginning and end of the work day. This kind of behavior indicates that occupants have similar work schedules. And if they have similar work schedules, there are viable options for using timers and occupancy sensors to save energy by turning equipment off when not in use. This can apply to the equipment monitored, as well as other devices that may be switched off when not in use.

For the Cool Choices game, the energy analysis shows that because occupants were already engaging in energy saving behaviors, there was limited opportunity to make additional savings through behavior change alone. For future interventions, it would be helpful to understand the office's culture to better target what energy saving behaviors would be most effective, or if technological interventions might be more promising.

In addition, with a larger sample size, it would be easier to distinguish new behaviors by using the plug load model to predict energy savings after the game. If there had been sufficient energy data associated with Cool Choices participants, the model developed for this study could have been used as a way to evaluate expected energy savings, by comparing actual usage after the game with predicted use that was generated by a model trained with pre-game data.

6.3. Occupant behavior and attitudes

The Cool Choices pre- and post-game surveys provided us with insights into what motivated occupants to play the game, and how they felt about sustainability and saving resources in general.

The responses to the survey questions suggest that players were generally conscious of behaviors that would save and waste energy. In Figure 5.10, respondents generally agreed with statements that would lead towards saving energy or other resources, while disagreeing with statements that would lead towards resource waste, illustrating that they had the knowledge to distinguish different kinds of behaviors. In Figure 5.11, by disagreeing with statements such as "People have the right to use as much energy as they want as long as they pay for it" and "My life is too busy to worry about making energy-related improvements in my home", while agreeing with "It is worth it to me for my household to use less energy, in order to help preserve the environment", it is clear that these respondents feel a sense of responsibility and awareness regarding sustainability and resource conservation. At the same time, Figure 5.9

indicates that approximately half of respondents feel that they use similar amounts of energy, water, and gasoline as comparable households, indicating that while they are aware of what behaviors can save resources, they either do not always engage in them or they feel like most of their peers do engage in these behaviors, which puts them on equal footing. This is in agreement with the findings from the literature review, which report that knowledge and attitudes are not necessarily predictors of energy saving behavior.

The literature review also discussed how occupants might be motivated to save energy without financial incentives. While the actions recommended by the Cool Choices game could result in lowered energy bills (e.g. replacing light bulbs or adding insulation), the post-game survey asked players to describe what motivated them to sign up (Figure 5.12 and Figure 5.13). While saving money was cited by about half of players as a reason to sign up, it is interesting to note what other reasons players had, and to also compare what motivated players to sign up vs. what motivated them to select specific in-game actions.

Two thirds of players stated that they signed up because the game was fun, but less than half reported choosing specific actions in the game because they were fun. About half of players reported that encouragement by colleagues was a reason why they signed up to play, but less than a third stated that they selected actions based on what their coworkers were doing. This suggests that the occupants were motivated by different factors when choosing to sign up for the game, and then choosing specific behaviors. This could be explained in part because the game was not what they expected or, after seeing what types of behaviors were possible, they came to different conclusions. It would be interesting to do a more granular version of this question where players are asked why they chose specific categories or types of actions to understand, more specifically, how they are motivated.

7. Conclusions

7.1. Baseline analysis

The measured plug load data from the monitored work stations exhibit fairly regular power use. There is a clear distinction between work and non-work days, and very regular schedules on work days, indicating that most occupants are at their workstations between 8 AM and 5 PM.

Desktops display the most variety in terms of power consumption, which suggests that their power use is the hardest to predict. Monitors, on the other hand, have very regular power consumption patterns because they are either on or off, with no third power state in between. Laptops show very low power consumption, probably due to the fact that occupants with laptops may be more likely to work at locations other than their assigned workspace. So the monitored data isn't a true representation of total laptop energy use, but rather just the use patterns in the occupant's workstation. Task lights are the most infrequently used monitored device, which could suggest that general lighting is sufficient for most occupants. This could indicate a source of potential energy savings: by reducing ambient lighting in favor of low power task lights, general lighting power could be reduced.

During unoccupied periods (outside of the typical 8 AM to 5 PM work day), desktops draw the most energy, followed by laptops, monitors and task lights (of which the latter two are drawing close to 0 W). This pattern suggests that desktops not only draw more power during the day, but are also drawing more phantom loads when not in use. This could be, in part, because laptop users take their device home at the end of the day and because laptops are more likely to be turned off at the end of the day.

Lastly, in examining power consumption patterns, it is possible to infer occupant behavior in terms of device usage. Desktops are generally used at a constant rate all day, while monitors experience large dips around lunch time, indicating that occupants engage power settings to put their monitor into sleep mode. Laptop power consumption is very low and, as described above, is not necessarily indicative of actual laptop use behavior.

7.2. Cool Choices game

Cool Choices game participants were very conscious of what behaviors could result in energy, water, and waste savings and they self-reported regularly engaging in these behaviors both at work and at home. Game participants were motivated to sign up for Cool Choices in part because the game looked fun and they wanted to win. They were motivated to play because the actions were easy to do, good for the environment, and they could earn points towards winning. Players ranged in engagement level, from playing daily to playing only a handful of days.

Despite the fact that the game was administered from the workplace, occupants played more at home (in terms of actions they claimed) than at work, and reported discussing the game about equally at home and at work. One of the main goals of Cool Choices is to reinforce conservation behavior in all parts of a player's life to encourage long-term habit formation. The survey responses suggest that the players do think about Cool Choices outside of the workplace, but to fully evaluate long-term habit formation would require monitoring behaviors at home, which this study did not do.

The Cool Choices players not only reported engaging in conservation behavior, but actively exhibited energy saving behavior in how they used their plug load devices. For the five devices we monitored, the power use analysis showed either no change, or a small reduction in power consumption. However, due to limited data, it's not possible to conclude that the game had a meaningful impact on plug load usage. In addition, analysis of the data before the game suggests that some players were, in fact, turning their devices off when out of the office, meaning that there was limited potential for demonstrating energy savings as users were already engaging in energy saving behaviors.

7.3. Plug load model

Using a Monte Carlo simulation, I created a simplified plug load model to predict power consumption based on device type, day type (work day or non-work day) and time step using a Monte Carlo simulation. Per the baseline analysis, these variables were identified as most influential in determining power use.

The model (MCModelv2) was underfit as it was not able to fully capture the power consumption behavior. It did a reasonable job of predicting median power use, but vastly overestimated the plug loads' variability (i.e., variance). When occupancy was not well predicted by the work day/non-work day dichotomy, the model was increasingly unreliable. Even after adding an additional variable (month), the model was still not able to predict power consumption to an acceptable degree of accuracy per industry standard (NMBE $\leq$ 10% per ASHRAE Guideline 14). To improve this type of model, a new, more accurate proxy for occupancy would be needed.

8. Future Work

Based on the lessons learned through this study, there are several recommendations for future work in this field.

8.1. Baseline analysis

Collect data from a wider range of plug load devices, including all of the other devices that an occupant may have and shared devices like high volume printers and severs. This will provide a well-rounded view of plug load usage and more accurately illustrate power use during unoccupied periods when shared devices are most likely to be left on.

8.2. Cool Choices

To better understand why players were motivated, I recommend incorporating more detailed questions in the post-game survey to ask participants why they chose specific actions and action categories. This would help understand if there were different reasons for picking various categories of actions, and what other motivations players had.

In addition, for future interventions it would be helpful to survey office occupants to understand their current behaviors and attitudes, and then more fully tailor an intervention to target the behaviors that would be most instrumental in reducing energy consumption.

8.3. Plug Load

The Monte Carlo simulation could be improved in multiple ways. The first is to establish a new proxy variable for occupancy, e.g. analyze individual device data by occupant and establish an individual threshold for “occupied” based on a minimum power or which devices are in use. This method would require modeling individuals, rather than the aggregated approach described in this study. The second improvement would require that the baseline data collection include monitoring for occupancy. This would allow the model to use actual occupancy, rather than a proxy for occupancy, to predict plug load power consumption.

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10. Appendices

10.1. Appendix A. Enmetric

10.1.1. Enmetric website interface

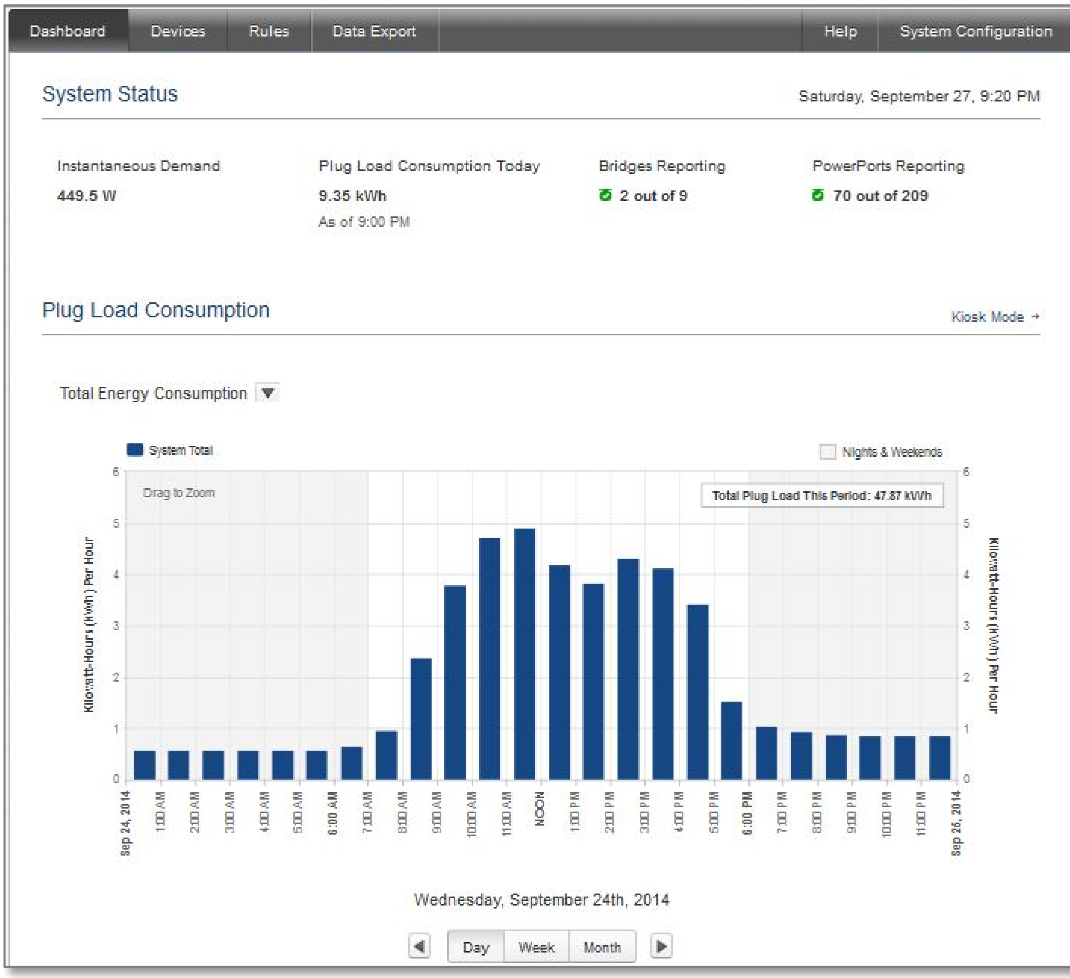


Figure 10.1 Enmetric home page view with system status and power graph

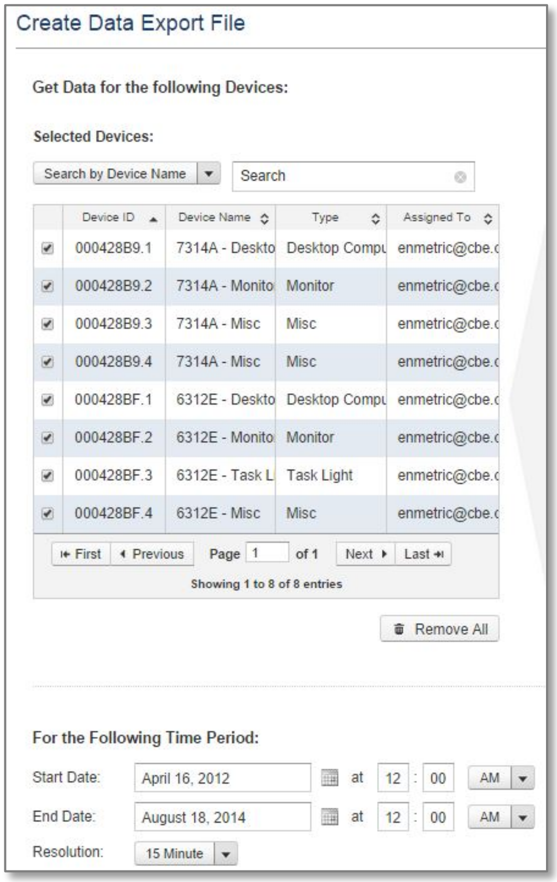


Figure 10.2 Enmetric website data export page example

10.1.2. Data export file header

Table 10.1 Enmetric data export file header description

Column name	**Description**
Account ID	Identifier for CBE's Enmetric account
Node Hid	Identifier for CBE's Enmetric account
Node Description	Name of monitoring equipment (e.g. powerport)
Channel Number	Port number {1,2,3,4}
Description	Workspace identifier and device category
Interval Start Time	Date and time in UTC
Average Power (W)	Over 15 minute period
Minimum Power (W)	Over 15 minute period
Maximum Power (W)	Over 15 minute period
Energy Used (W Hours)	Over 15 minute period
Average Frequency	Over 15 minute period
Average Voltage	Over 15 minute period
Average Current	Over 15 minute period
Average Power Factor	Over 15 minute period
Number of Measurements	Over 15 minute period
Channel On/Off %	1 is ON, 2 is OFF

10.2. Appendix B. Cool Choices

10.2.1. Recruitment flyers

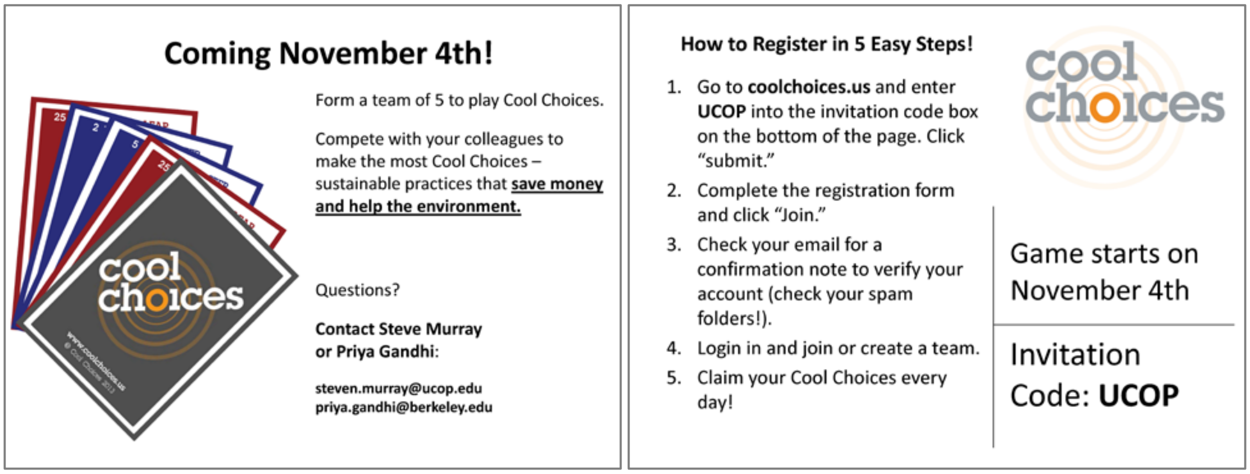


Figure 10.3 Cool Choices recruitment flyers posted at UCOP

10.2.2. Sample daily reminder email

Subject: Your Cool Choices Summary

Hi [first_name]!

Login to play today!

Week 1 Challenge – Claim at least ONE Cool Choice

Now that you're registered it's time to start playing. Did you know that everyone who plays just one card this week has the chance to win a prize? Well, it's true, all you have to do is make a Cool Choice. One player will be randomly selected at the end of this week. Good luck!

Your Cool Choices yesterday:
[actions_yesterday]

Your team, [team name], is making strides because of you!
  [team_total_actions] total actions
  [team_total_points] total points

The following cards are now available:
[cards_released_today]

Way to go and keep up the Cool Choices!
Login to your account to play today!

Thanks!
The Cool Choices Team

10.2.3. Weekly challenge schedule

Week	Theme/Focus - Communications	Engagement Tools*	Recognition/Prizes
Sign-up period		Sign-up challenge/ incentives	4 prizes: - any combination of water bottles or totes
Week 1	"How to play/why play?" Who/What is Cool Choices?	Offer tutorial cards first day, then start releasing 1-2 cards daily – randomly select a winner who fulfills this requirement	2 prizes: - 1 for individual challenge - 1 random player for participation
Week 2	Teamwork – Team Photo card.	Team Photo Challenge – feature top photo submissions; make them fun, wacky, crazy, etc.	2 prizes: - 1 for individual challenge - 1 random player for participation
Week 3		Team Photo Challenge Voting – players vote on their favorite team photo (cannot vote for their own)	1 prize + team prizes: - letter of recognition from President or CEO for winning team(s) - 1 random player for participation
Week 4	Wellness - Share a healthy recipe.	Healthy Recipe Challenge – randomly select a winner who played this card	2 prizes: - 1 for individual challenge - 1 random player for participation
Week 5	Energy – Watch 2 hours less TV today.	Photo Challenge – will ask for photos of the theme card (i.e. watch 2 hours less TV today)	2 prizes: - 1 for individual challenge - 1 random player for participation
Week 6	Final Week – post-game survey and final play	"Tell your story" - get testimonials from players about their experience in Cool Choices game – feature one each day	Quotes can be featured on our social media, public use, on the news feed.

10.2.4. List of game actions and schedule of release

Card Code	Home or Work	Category	Card Type	Points	Point Type	Action	Tips (or Resource titles)?	Resource Title 1	Source	Day Released	Day Removed	Week number
S117C	Home	Wellness	Step	2	Recurring	Use reusable shopping bags	A reusable bag has the potential to offset 20,000 plastic bags over its lifetime. That's a lot of plastic!	Bag Tips	Cool Choices	1	last	1
S145C	Work	Energy	Create	50	Recurring	Suggest a new way to reuse or recycle.			Cool Choices	1	4	1
S150B	Work	Wellness	Step	1	Recurring	Invite a friend to play Cool Choices!			Cool Choices	1	last	1
S168Ba	Work	Energy	Leap	10	One Time	My monitor is set to turn off after 10 minutes of inactivity.	Screen savers are leftovers from old technology and aren't necessary for modern displays. Setting your monitor to turn off after 10 minutes is the new "screen saver."	Screen Savers	UCOP GFC Checklist	1	last	1
S654B	Work	Energy	Leap	10	One Time	I got rid of my personal printer.	Using a network printer saves electricity and resources.	Consolidating printers	UCOP GFC Checklist	2	last	1
S661B	Work	Energy	Step	10	Recurring	I turned off my computer when I left work today.	LBNL reports that only 36% of office workers turn off PCs and monitors after work.	Turning off computers	Priya/UCOP Pledge	2	last	1
S158B	Work	Travel	Step	10	Recurring	I took public transportation to work today.	Want to save money on gas? You can read, safely talk to friends and family on the phone, or even nap on the bus. Try it!	Stress of Driving vs Bus	UCOP Pledge	3	last	1
S143C	Work	Wellness	Step	2	Recurring	Use the stairs instead of an elevator	Get some exercise while you save electricity!	Taking Stairs Saves Time	Cool Choices	4	last	1
S107A	Home	Energy	Focus	25	One Time	Analyze how your home uses electricity	Reduce costs by programming power management settings, unplugging devices not in use, using power strips to turn off electricity entirely, or using timers, etc.	Appliance Energy Usage	I made a Cool Choice: [Short name]	5	last	

Card Code	Home or Work	Category	Card Type	Points	Point Type	Action	Tips (or Resource titles)?	Resource Title 1	Source	Day Released	Day Removed	Week number
S122C	Work	Water	Step	5	Recurring	Drink tap water instead of bottled water today.	You can fill a half-liter bottle 1,740 times from the tap before you use $0.99 of water.	Video on Bottled Water		6	last	1
S149B		Travel	Focus	10	One Time	Photo: Submit your team photo. Make it as crazy, fun or wacky as you can!				7	11	2
S169B	Work	Energy	Leap	10	One Time	Set home computers to "sleep" after 20 minutes.	A typical computer uses around 5 watts of electricity in sleep mode. Many systems use as much as 130 watts of electricity while powered up.	Computer Energy Usage	UCOP GFC Checklist	7	last	2
S660B	Work	Wellness	Step	2	Recurring	Use reuseable options for drinking beverages instead of disposable cups at work.	In America, 6.5 million trees are cut down every year to manufacture paper cups.	Water Bottle Facts	UCOP Pledge	8	last	2
S128Ca	Work	Energy	Step	2	Recurring	I turned off the lights in the conference room after a meeting today.	Rule of thumb: turn off incandescents whenever you leave the room & CFLs if you'll be gone 15 minutes or more.	When to Turn Off Your Lights	UCOP Pledge	9	last	2
S659B	Work	Energy	Step	10	Recurring	I turned off my laptop docking station when I left work today.	LBNL reports that only 36% of office workers turn off PCs and monitors after work.	Energy Vampires		10	last	2
S157C	Work	Travel	Step	10	Recurring	Bike or walk to work today.	Cycling & walking improves your health & reduces your fuel costs.	Walk/Bike to School	Cool Choices	11	last	2
S127A	Home	Energy	Leap	25	One Time	Enable "automatic power down" of video game console at home.	Game consoles come from the factory with the energy saving features turned off.	Game Console Usage	Cool Choices	12	last	2
S119C	Both	Wellness	Step	2	Recurring	Compost food and/or yard waste.	Experts estimate that about 25% of your trash is organic material that can be composted.	EPA Composting Basics		13	last	2

Card Code	Home or Work	Category	Card Type	Points	Point Type	Action	Tips (or Resource titles)?	Resource Title 1	Source	Day Released	Day Removed	Week number
S142C	Home	Energy	Create	50	One Time	Suggest a way to reduce energy use in the office. This card will be available through Friday of this week.	Energy costs can cut into the margins of any organization. Can you imagine ways to save energy and help the environment?		Cool Choices	14	19	3
S658B	Work	Energy	Step	5	Recurring	I turned off my task light when I left my office.	Rule of thumb: turn off incandescents whenever you leave the room & CFLs if you'll be gone 15 minutes or more.	When to Turn Off Your Lights		15	last	3
S112A	Home	Water	Step	5	Recurring	Turn off the water when you brush your teeth	You can save up to 8 gallons of water a day by turning off the tap while you brush your teeth in the morning and at night.	EPA Water Sense	Cool Choices	16	last	3
S147A	Home	Energy	Leap	25	One Time	Insulate pipes near hot water heater.	Insulating hot water pipes allows you to reduce the water heater temperature by several degrees -- a 3-5% energy savings.	Hot Water Tank/Pipe Insulation Options	Cool Choices	17	last	3
S662B	Work	Energy	Step	5	Recurring	I opened the window blinds instead of using lights at work today.	Hanging two curtains over one window creates a tighter air space than one single curtain.	Ways to Save Energy	UCOP Pledge	18	last	3
S158C	Home	Travel	Step	10	Recurring	Use public transit instead of driving.	Want to save money on gas? You can read, safely talk to friends and family on the phone, or even nap on the bus. Try it!	Stress of Driving vs Bus	Cool Choices	19	last	3
S109A	Home	Energy	Step	5	Recurring	Use cold wash/cold rinse laundry settings.	Washing in hot water causes clothes to fade & wear out faster.	Cold Water Washing Video		20	last	3
S137A		Wellness	Leap	10	One Time	Share a healthy recipe.	Sharing recipes that work is a great way to expand your family's culinary options.	Healthy Eating		21	25	4
S657B	Work	Energy	Step	2	Recurring	I unplugged my cell phone charger before leaving work.	Your cell phone charger draws power even when not in use.	Energy Vampires	UCOP Pledge	22	last	4

Card Code	Home or Work	Category	Card Type	Points	Point Type	Action	Tips (or Resource titles)?	Resource Title 1	Source	Day Released	Day Removed	Week number
S663A	Home	Wellness	Focus	10	One Time	Share something new you have learned through Cool Choices with a friend or family member this Thanksgiving.				23	27	4
S160A	Home	Energy	Leap	50	One Time	Adjust your thermostat	Turning the thermostat down 5˚ for 8 hours/day saves 5% of the annual heating costs.	How-To Video	Cool Choices	25	last	4
S153A	Home	Energy	Step	5	Recurring	Line dry clothing.	Line dry clothing.	Line Drying Tips		26	last	4
S115A	Home	Water	Leap	25	One Time	Install a low-flow faucet aerator	Faucet aerators will reduce the water used by 1/3 without compromising water pressure.	How-To Video	Cool Choices	27	last	4
S134A		Energy	Create	25	Recurring	Photo Challenge - Energy Watch 2 hours less TV	Show us what you did instead of watching TV for 2 hours!	Upload a photo of what you did instead of watching TV. For instance, riding your bike, going to a park, playing board games, etc.		28	32	5
S138A	Home	Water	Create	25	Recurring	Photo: You saving water at home. This card will be available through Friday of this week.			Cool Choices	28	32	5
S655B	Work	Energy	Leap	10	One Time	I replaced my standalone task light bulb with an LED bulb.	LED light bulbs use 90% less energy than incandescent bulbs and 60% less energy than CFLs.	Types of Lightbulbs	UCOP GFC Checklist	29	last	5
S162C	Work	Travel	Step	10	Recurring	Carpool to work with one other person today.	In addition to saving money on gas, carpooling lets you reduce wear & tear on your car & provides a break from driving.	Starting a Car Pool	UCOP Pledge	30	last	5
S101A	Home	Energy	Leap	10	One Time	Adjust your refrigerator temperature to 39˚ and your freezer temperature to 5˚.	Your refrigerator & freezer function more efficiently when full.	Setting the Temperature		31	last	5

Card Code	Home or Work	Category	Card Type	Points	Point Type	Action	Tips (or Resource titles)?	Resource Title 1	Source	Day Released	Day Removed	Week number
S129A	Home	Energy	Leap	25	One Time	Replace non-LED outdoor landscape lights with solar-powered outdoor landscape lights.	173,000 terawatts of solar energy strikes the Earth continuously. That's more than 10,000 times the world's total energy use.	Benefits of Solar Outdoor Lighting		32	last	5
S116A	Home	Water	Leap	50	One Time	Install a low-flow showerhead.	Low-flow showerheads use 1.5 gallons of water/minute (gpm) versus 2.5 or more for older models.	How-To Install	Cool Choices	33	last	5
S133C	Work	Wellness	Create	25	Recurring	Photo: You recycling an item today. This card will be available through Friday of this week.			Cool Choices	35	39	6
S148C		Wellness	Focus	5	One Time	Tell us how Cool Choices has impacted your and/or your family regarding sustainaibility.				35	39	6
S652B	Work	Energy	Focus	50	One Time	I have read the UC Sustainable Practices Policy	Did you know that the University has pledged to achieve zero waste and reduce water consumption by 20% by 2020?	UC Sustainable Practices Policy	UCOP Pledge	36	last	6
S653B	Work	Energy	Leap	25	One Time	I got rid of my space heater.			UCOP GFC Checklist	37	last	6
S118C	Both	Wellness	Step	2	Recurring	Recycle an item today.	In 2008, 57.4% of the paper used in the U.S. was recovered for recycling.	Recycling Tips		38	last	6
S100A	Home	Energy	Leap	50	One Time	Replace 85% of household incandescent bulbs with CFLs or LEDs.	Only about 10 - 15% of the electricity that incandescent lights consume results in actual light. The rest is turned into heat.	Lighting Guide		39	last	6
S125A	Home	Energy	Leap	100	One Time	Air seal and insulate your home to recommended levels.	Insulation & air sealing are typically the most cost effective ways to reduce energy usage.	Basics of Insulation		40	last	6

10.2.5. Cool Choices interface

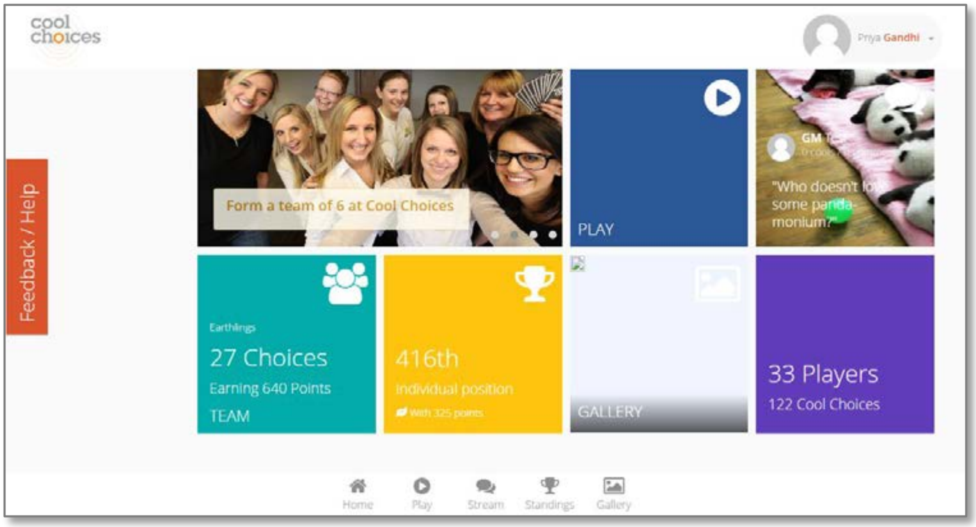


Figure 10.4 Cool Choices home page

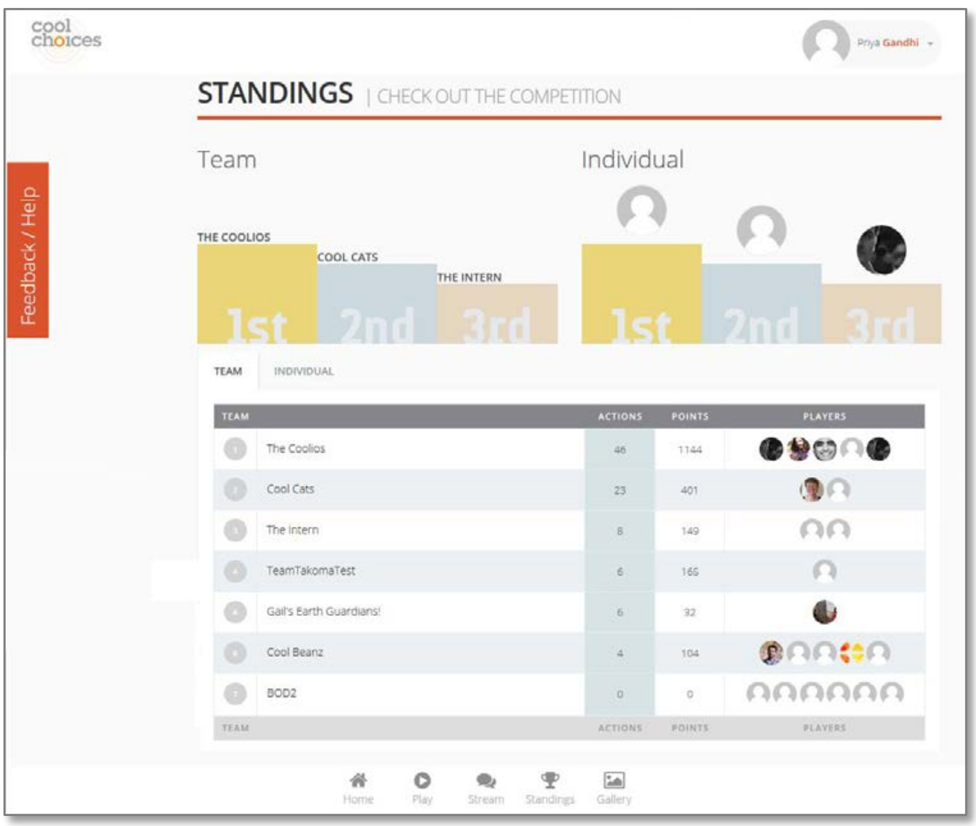


Figure 10.5 Cool Choices team and individual standings page

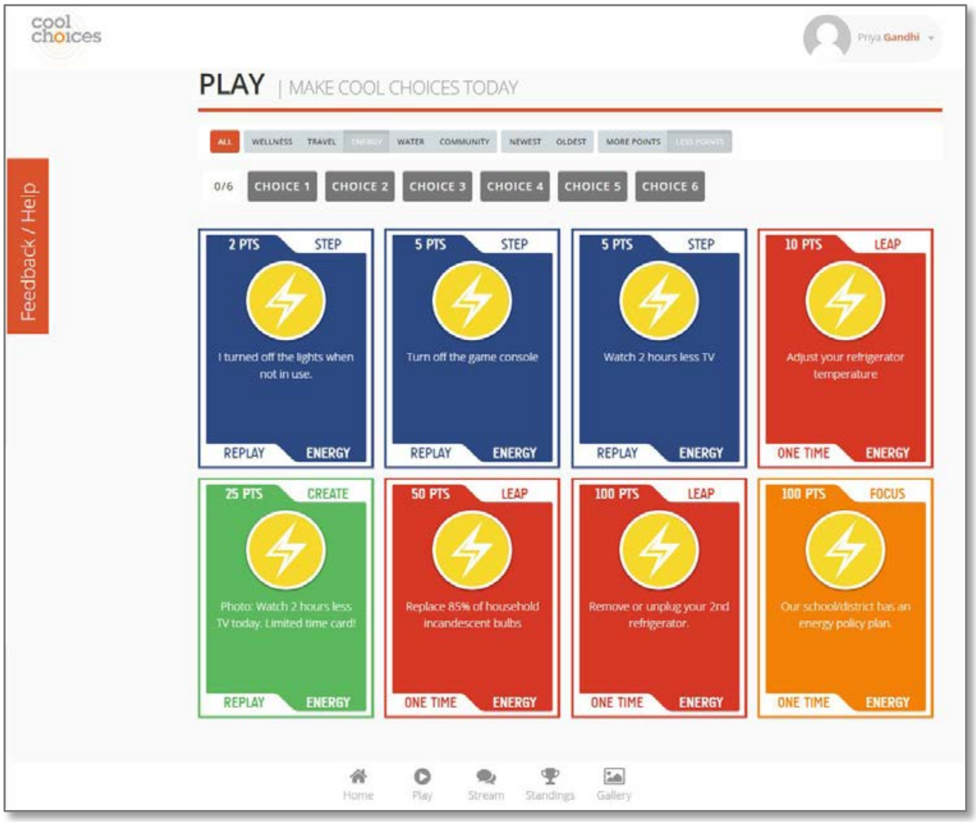


Figure 10.6 Cool Choices game play interface

10.2.6. Pre-game survey

1. How does your household compare to other similar households with regard to...

	We use more than others	We are similar to other households	We use less than other households	I don't know how we compare
Household energy (electricity, natural gas) usage?	○	○	○	○
Gasoline usage for transportation?	○	○	○	○
Water usage?	○	○	○	○
Trash generated? (amount of non-recycled, non-composted garbage)	○	○	○	○

2. About how much did you spend on energy costs for your home during the past 12 months (including electricity and natural gas or any other fuels you use to heat your home)?

Total cost (in dollars)

3. Please indicate how often you do each of the following

	Never	Rarely	Sometimes	Most of the time	All of the time
Leave electronics on when not in use	○	○	○	○	○
Adjust thermostat when away or asleep	○	○	○	○	○
Take 12 minute or longer hot showers	○	○	○	○	○
Take re-usable bags with me to the store	○	○	○	○	○
Leave the car idling for 2 minutes or more	○	○	○	○	○
Turn off unused work equipment	○	○	○	○	○
Drive at or below the speed limit on the highway	○	○	○	○	○

4. At what temperature do you tend to keep your home in winter when people are home and awake?

Temperature

5. Generally, there is a toggle switch on your thermostat that allows you set when a furnace circulates air through the ducts. What is this switch set to?

- ◯ Auto (Your furnace circulates air through the ducts only when actively heating or cooling your home.)
- ◯ On / continuous (Your furnace circulates air through the ducts continuously, whether your heating and central cooling systems are running or not.)
- ◯ Don't have a forced air furnace
- ◯ Don't know

Other (please specify)

6. Which of the following best describes your use of air conditioning in summer?

- ◯ Don't have AC
- ◯ Use little or not at all
- ◯ Use during hot spells only
- ◯ Use much of the summer months

7. How many of the following do you have in your home?

Refrigerators

Stand-alone freezers

TVs

Desktop computers

8. What kinds of light bulbs do you use in your home?

- ◯ Only the traditional incandescent bulbs
- ◯ Mostly incandescent bulbs
- ◯ An equal mix of incandescents and CFLs/LEDs
- ◯ Mostly CFLs/LEDs
- ◯ Only compact fluorescent bulbs (CFLs) or LEDs

9. Sustainability is important...

	Strongly Disagree		Neutral		Strongly Agree	N/A
to me	◯	◯	◯	◯	◯	◯
to my household	◯	◯	◯	◯	◯	◯
to my friends	◯	◯	◯	◯	◯	◯
to my extended family	◯	◯	◯	◯	◯	◯
to my co-workers	◯	◯	◯	◯	◯	◯
to leadership at UCOP	◯	◯	◯	◯	◯	◯

10. People have different opinions about energy and the availability of natural resources. Please tell us how much you disagree or agree with each of the following statements:

	Strongly Disagree		Neutral		Strongly Agree
My life is too busy to worry about making energy related improvements in my home.	○	○	○	○	○
People have the right to use as much energy as they want, as long as they pay for it.	○	○	○	○	○
I try to be knowledgeable about our country's energy policies.	○	○	○	○	○
It is worth it to me for my household to use less energy, in order to help preserve the environment.	○	○	○	○	○
It is worth it to me for my household to use less energy, in order to save money.	○	○	○	○	○
I worry about increases in the cost of resources like gasoline, energy and water.	○	○	○	○	○
My household has already done its part to reduce resource usage.	○	○	○	○	○

11. Please tell us how much you disagree or agree with each of the following statements:

	Strongly Disagree		Neutral		Strongly Agree	Don't Know
When we set goals for our household we usually achieve them.	○	○	○	○	○	○
At work, my opinions seem to count.	○	○	○	○	○	○
This last year, I have had opportunities at work to learn and grow.	○	○	○	○	○	○
I am aware of what my company is doing to be sustainable.	○	○	○	○	○	○
All in all, I'm satisfied with my job here at UCOP.	○	○	○	○	○	○

12. Are you interested in volunteering to help support our upcoming Cool Choices Challenge?

- ◯ Yes, I would like to help promote sustainability at UCOP!
- ◯ Not right now.

Finally, we'd like to know a bit about you and your household.

13. Including yourself, how many people live in your household?

Adults

School-age children (5-18)

Pre-school children (under 5 years of age)

14. Which of the following best describes your house?

- ◯ Single-family home
- ◯ Duplex
- ◯ 3-4 unit apartment building or condominium
- ◯ 5-9 unit apartment building or condominium
- ◯ 10-19 unit apartment building or condominium
- ◯ 20+ unit apartment building or condominium
- ◯ Other (please specify)

15. Do you own or rent your home?

- ◯ own
- ◯ rent

16. When was your home built?

- ◯ Before 1950
- ◯ 1950-1979
- ◯ 1980 or later
- ◯ Don't know

17. Approximately how many square feet of living space does your home have?

Total square feet

18. Which of the following do you use in your home? (Check all that apply.)

- ☐ Electricity
- ☐ Natural gas
- ☐ Propane
- ☐ Fuel oil
- ☐ Wood stove

19. What city do you live in? (Please be specific)

20. What is your gender?

- Male
- Female

21. How old are you?

- Under 25 years of age
- 25-34
- 35-44
- 45-54
- 55-64
- 65 years of age or over

22. What is the highest level of education you have completed?

- Did not complete high school
- High school graduate (includes GED)
- Some college, no degree
- Associates degree
- Bachelor's degree
- Graduate or professional degree

23. Please provide your name, phone number, email (the same one you plan to use for the Cool Choices game) and work title.

Name

Phone

Email (same one you will use for the Cool Choices game)

Work Title

10.2.7. Post-game survey

Cool Choices Post Game Survey

Please complete this survey to help Cool Choices continue to evolve its sustainability game. Please be candid. Your responses will remain anonymous.

This survey will be available through [date] and [prizes] will be given away to [#] random participants.

1. Who encouraged you to play the Cool Choices game? (check all that apply)

- ☐ your team leader
- ☐ other Cool Choices team members
- ☐ other UCOP colleagues
- ☐ UCOP's management
- ☐ someone else (please specify below)
- ☐ no one

Other (please specify)

2. How much were you doing to save energy in your home...

	1=nothing	2	3	4	5=a lot
Before the Cool Choices game started	○	○	○	○	○
Now	○	○	○	○	○

3. How much were you doing to save water in your home....

	1=nothing	2	3	4	5=a lot
Before the Cool Choices game started	○	○	○	○	○
Now	○	○	○	○	○

4. How much were you doing to reduce your gasoline use....

	1=nothing	2	3	4	5=a lot
Before the Cool Choices game started	○	○	○	○	○
Now	○	○	○	○	○

Page 1

5. How influential were each of the following factors in your decision to play the Cool Choices game?

	1=not at all influential	2	3	4	5=very influential
Wanted to win	○	○	○	○	○
Was encouraged by my colleagues	○	○	○	○	○
Liked the lifestyle changes that could come from doing the actions	○	○	○	○	○
It was fun	○	○	○	○	○
Could save money by taking the actions	○	○	○	○	○
Felt obligated as part of my job	○	○	○	○	○
Might win a gift card	○	○	○	○	○
Cool Choices made it seem appealing	○	○	○	○	○

6. What were the lifestyle changes you liked?

7. While the Cool Choices game was active, how often did you talk about sustainability at the following locations?

	daily	several times a week	weekly	once or twice	never
work	○	○	○	○	○
home	○	○	○	○	○

8. Whom did you talk with about sustainability? (check all that apply)

- ☐ teammates
- ☐ other work colleagues
- ☐ spouse
- ☐ kids
- ☐ extended family (parents, brothers or sisters)
- ☐ friends
- ☐ neighbors
- ☐ no one

Page 2

9. What was the most memorable experience or conversation you had playing the game?

Cool Choices cards and actions

10. How frequently were the Cool Choices cards new ideas for you?

- ◯ always
- ◯ often
- ◯ occasionally
- ◯ never

11. Did you look at the stream while playing the game?

- ◯ yes, often
- ◯ yes, a few times
- ◯ no

12. Did you get useful tips from the daily reminder emails?

- ◯ yes, often
- ◯ yes, a few times
- ◯ no
- ◯ did not look at the reminder emails

13. Where did you most often play Cool Choices?

- ◯ on a mobile device (smart phone)
- ◯ on computer
- ◯ used both equally
- ◯ Other (please specify)

14. Please rate the influence each of the following factors had on your choosing the actions you took.

	1=least influential	2	3	4	5=most influential
Was already doing the action	◯	◯	◯	◯	◯
Easy to do	◯	◯	◯	◯	◯
Fun to do	◯	◯	◯	◯	◯
Save money	◯	◯	◯	◯	◯
Good for the environment	◯	◯	◯	◯	◯
Co-workers were doing them	◯	◯	◯	◯	◯
Earn a lot of points	◯	◯	◯	◯	◯

15. What is the most meaningful new action you took as part of the game?

16. While the Cool Choices game was active, did you take any energy saving or sustainability actions that you didn't claim points for?

◯ yes

◯ no

17. What energy saving or sustainability actions did you take that you didn't claim points for?

18. Please rate the following statements:

	strongly disagree	disagree	neutral	agree	strongly agree	don't know
The Cool Choices actions were simple to do.	◯	◯	◯	◯	◯	◯
My family was enthusiastic about taking the Cool Choices actions.	◯	◯	◯	◯	◯	◯
I am more aware of opportunities to save energy since playing Cool Choices.	◯	◯	◯	◯	◯	◯
Since playing Cool Choices, I'm more likely to turn off lights in rooms at work that aren't being used.	◯	◯	◯	◯	◯	◯
I'm proud of the changes I've made as a result of playing Cool Choices.	◯	◯	◯	◯	◯	◯
I learned a lot from my colleagues while playing Cool Choices.	◯	◯	◯	◯	◯	◯
Since playing Cool Choices, I'm more likely to turn off work equipment that isn't being used.	◯	◯	◯	◯	◯	◯
Cool Choices feels like a meaningful part of UCOP's efforts toward sustainability.	◯	◯	◯	◯	◯	◯
All in all, I'm satisfied with my job at UCOP.	◯	◯	◯	◯	◯	◯

19. Sustainability is important...

	strongly disagree	disagree	neutral	agree	strongly agree	n/a
To me	◯	◯	◯	◯	◯	◯
To my household	◯	◯	◯	◯	◯	◯
To my friends	◯	◯	◯	◯	◯	◯
To my extended family	◯	◯	◯	◯	◯	◯
To my co-workers	◯	◯	◯	◯	◯	◯
To leadership at UCOP	◯	◯	◯	◯	◯	◯

20. Do you have any other comments for Cool Choices?

Page 5

21. Please select where you work.

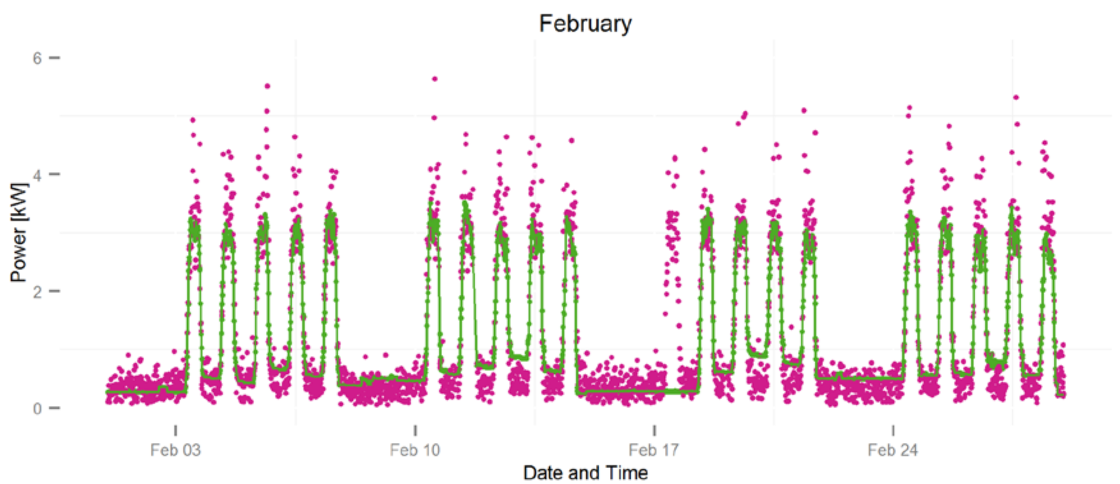
	Floor
Location	

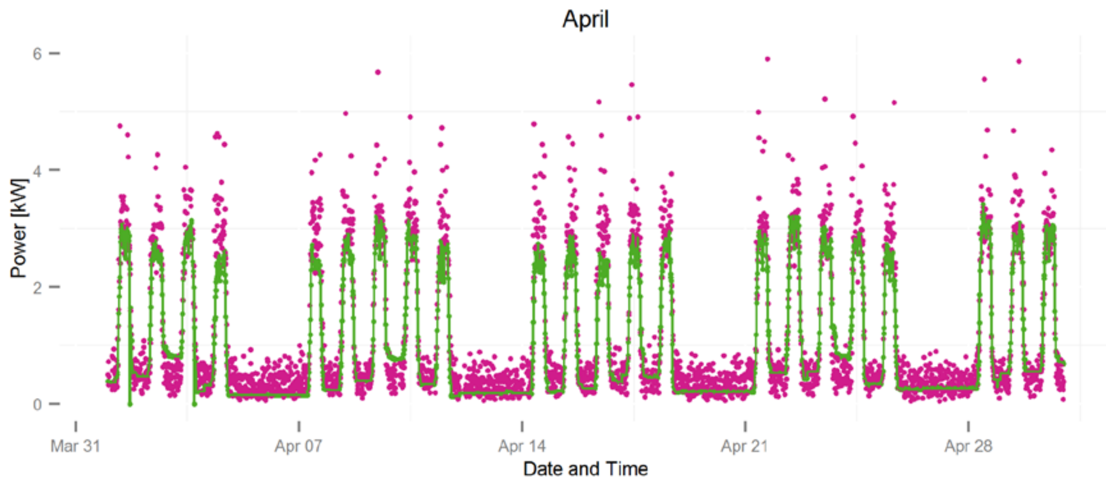
22. To be eligible for the prize drawing, please provide your name and email. (Your responses are completely confidential and have no bearing on the prize drawing)

Name

Email

10.3. Appendix C. Plug load model results

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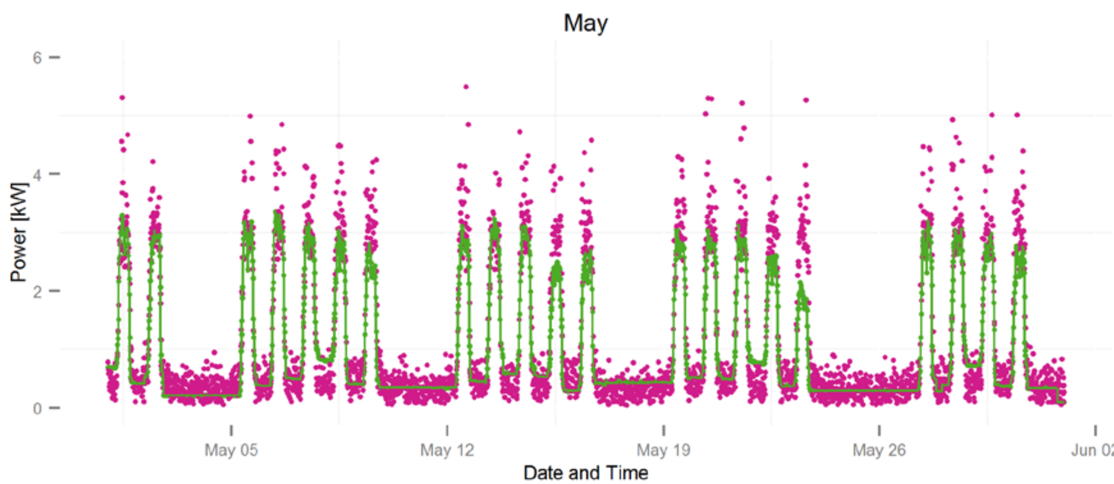
4
2
0
Mar 31
Apr 07
Apr 14
Apr 21
Apr 28
Date and Time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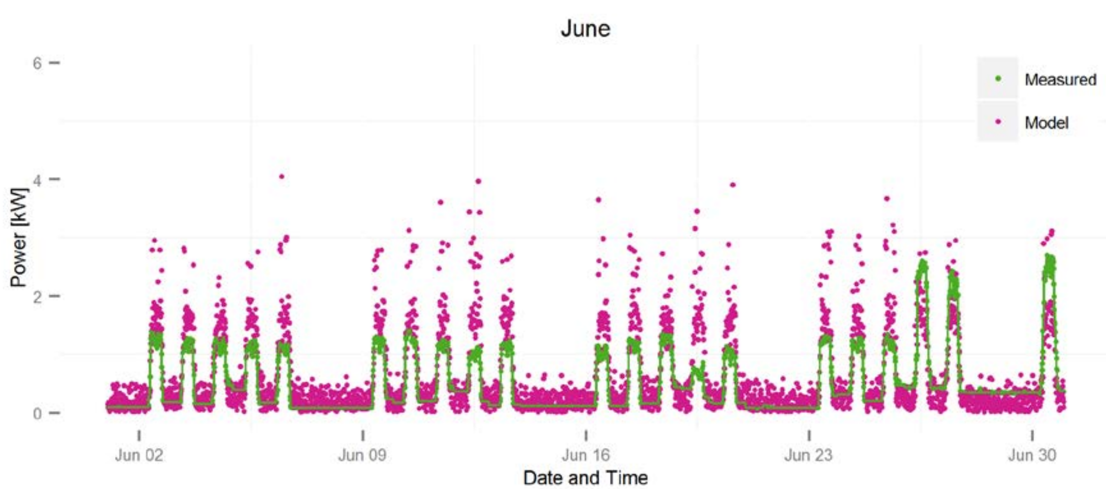
May 05
May 12
May 19
May 26
Jun 02
Date and Time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Measured
Model
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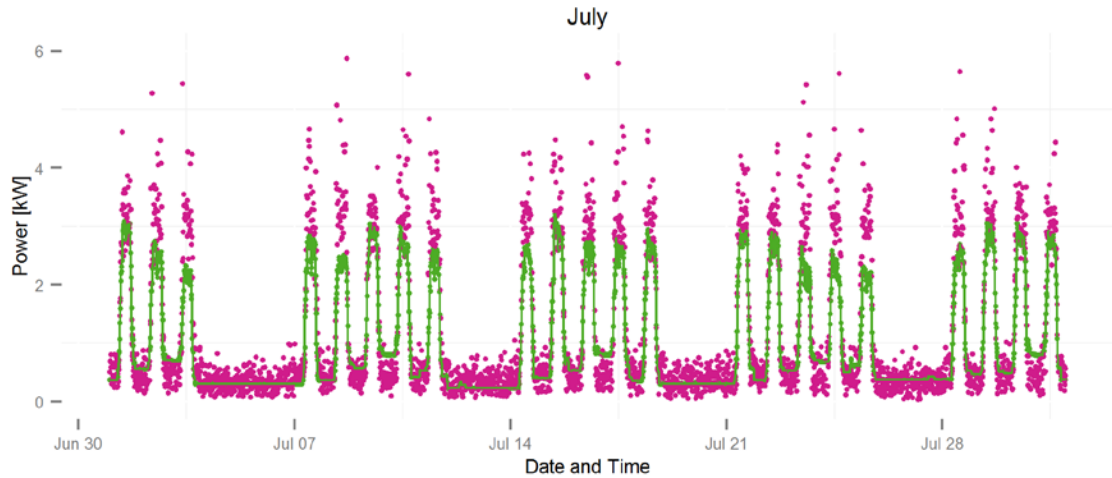
4
2
0
Jun 02
Jun 09
Jun 16
Jun 23
Jun 30
Date and Time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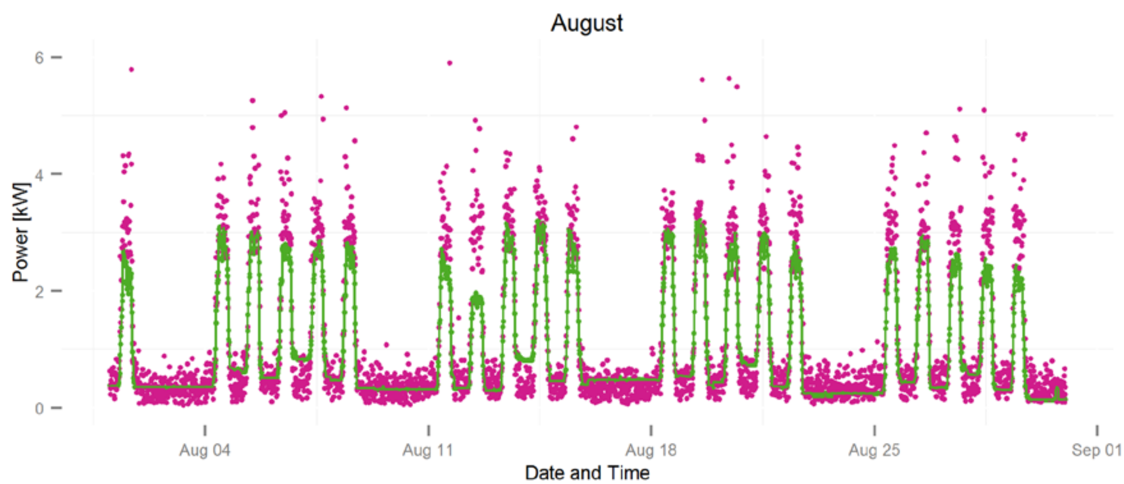
4
2
0
Jun 30
Jul 07
Jul 14
Jul 21
Jul 28
Date and Time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2
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Aug 04
Aug 11
Aug 18
Aug 25
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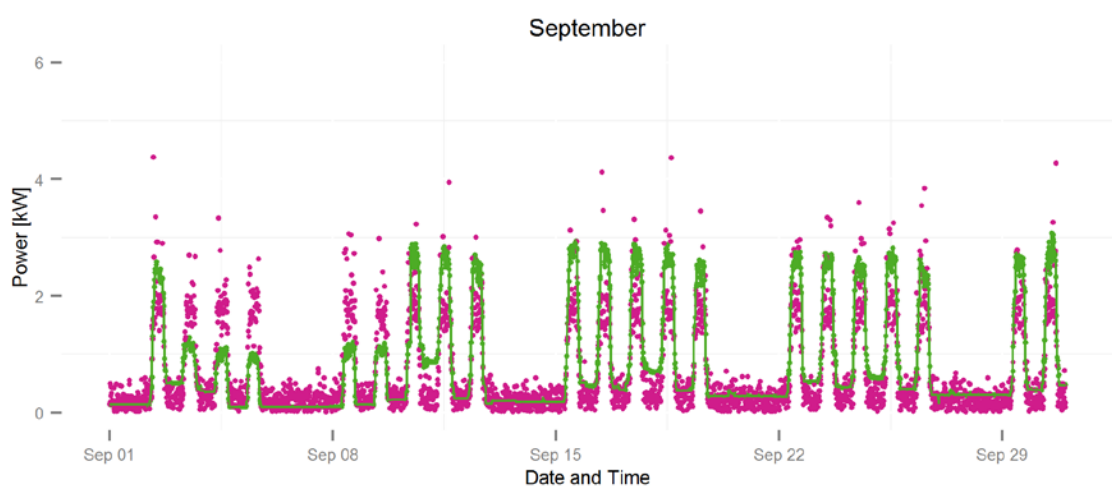
Date and Time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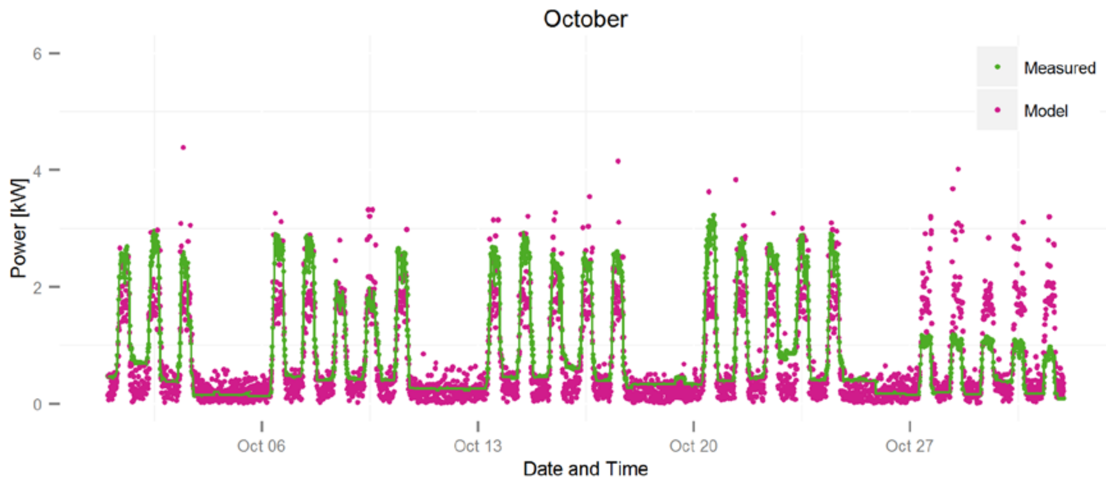
Date and Time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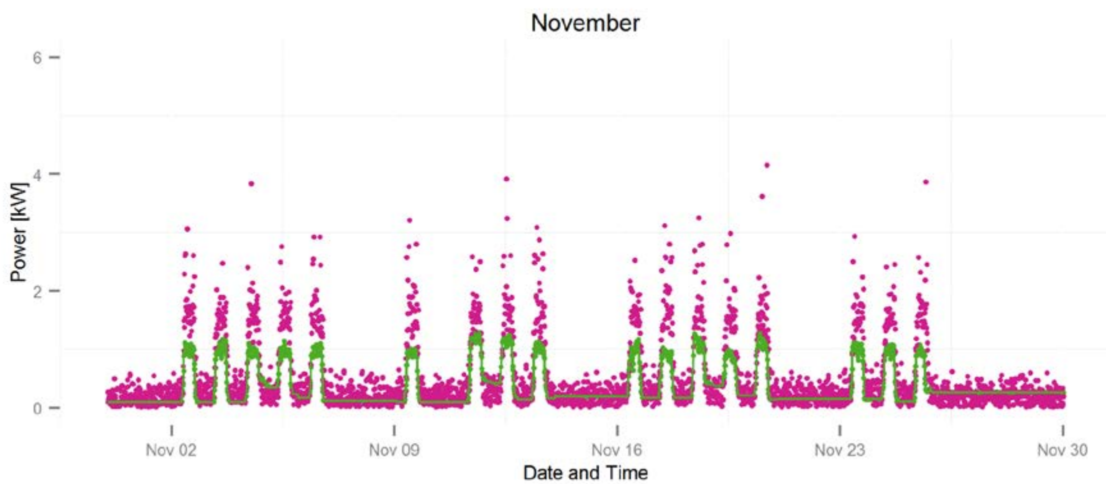
Oct 13
Oct 20
Oct 27
Date and Time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2
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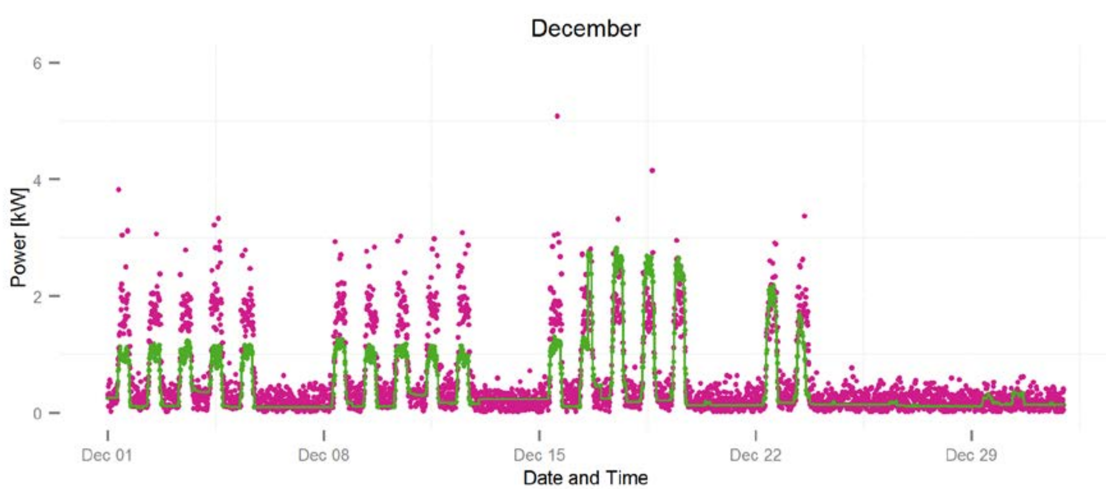
Nov 02
Nov 09
Nov 16
Nov 23
Nov 30
Date and Time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Dec 01
Dec 08
Dec 15
Dec 22
Dec 29
Date and Time