Motivating and Quantifying Energy Efficient Behavior among Commercial Building Occupants

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ABSTRACT

The environmental and economic consequences of climate change are severe and are being exacerbated by increased global carbon emissions. In the United States, buildings account for over 40% of all domestic and 7.4% of all global CO_2 emissions and therefore represent an important target for energy conservation initiatives. Even marginal energy savings across all buildings could have a profound effect on carbon emission mitigation. In order to realize the full potential of energy savings in the building sector, it is essential to maximize the energy efficiency of both buildings and the behavior of occupants who occupy them. In this vein, systems that collect and communicate building energy-use information to occupants (i.e. eco-feedback systems) have been demonstrated to motivate building occupants to significantly reduce overall building energy consumption. Furthermore, advancements in building sensor technologies and data processing capabilities have enabled the development of advanced eco-feedback systems that also allow building occupants to share energy-use data with one another and to collectively act to reduce energy consumption. In addition to monitoring building occupant energy-use, these systems are capable of collecting data about specific conservation actions taken by occupants and their interactions with different features of the eco-feedback system. However, despite recent advancements in eco-feedback and building sensor technologies, very few systems have been specifically designed to enable research on the effectiveness of different behavior-based energy conservation strategies in commercial buildings. Consequently, very little research has been conducted on how access to such systems impacts the energy-use behavior of building occupants. In this dissertation, I describe how my research over the past three years has advanced an understanding of how eco-feedback systems can impact the energy-use behavior of commercial building occupants. First, I present a novel eco-feedback system that I developed to connect building occupants over energy-use data and empower them to conserve energy while also collecting data that enables controlled studies to quantify the impacts of a wide variety of energy conservation strategies. Next, I present a commercial building study in which this eco-feedback system was used to investigate the effects of organizational network dynamics on the energy-use of individuals. I then introduce a new set of metrics based on individual energy-use data that enables the classification of individuals and building occupant networks based on their energy-use efficiency and predictability. I describe the principles behind the construction of these metrics and demonstrate how these quantitative measures can be used to increase the efficacy of behavior-based conservation campaigns by enabling targeted interventions. I conclude the dissertation with a discussion about the limitations of my research and the new research avenues that it has enabled.

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CHAPTER 1: INTRODUCTION

A Global Focus on Sustainability

The mounting demands on the natural environment to support continual societal development and global economic expansion have begun to yield serious adverse consequences: all-time high levels of air pollution in many regions are severely impacting human health and life expectancy [Pope 2013], rising atmospheric carbon dioxide levels are causing a rise in ocean acidity that affects underwater eco-systems [Doney 2009], and global warming is causing steady glacier retreat that is expected to significantly impact global sea water levels [Cook 2005, Raper 2006, Solomon 2008]. Climate change linked to anthropogenic greenhouse gas emissions has also played a key role in the increased frequency of destructive global weather events and projections consistently predict that global warming will likely cause an increase in the intensity of tropical storms [Knutson 2010] and irreversible reductions of dry-season rainfall in several regions [Solomon 2008].

It is becoming increasingly clear that unchecked societal and economic development can significantly disrupt and destabilize natural systems and many countries around the world are taking steps to address the challenge of mitigating environmental impacts associated with development. International commitments such as the Kyoto Protocol and Copenhagen Accord, which set goals for anthropogenic emissions reductions according to the United Nations Framework Convention on Climate Change [UNFCCC 2013], have been adopted by many major emitting countries. Independently, the United States has set a federal target of reducing domestics greenhouse gas emissions by 80% by 2050 [US White House 2012], China has updated its ‘Five-Year Plan’ sustainable growth program for 2011-2015 [Lo 2013], and the European Union has established the ‘‘2020 by 2020’’ initiative, committing to reduce its overall emissions to at least 20% below 1990 levels and to increase its share of renewable energy production to 20% by 2020 [EU 2010]. To achieve these ambitious targets, it is necessary to develop a comprehensive understanding of the complex interactions between humans (and society) and nature to inform strategies that promote a sustainable balance between social and economic development, health, and the environment.

Sustainability in the Built Environment

The environmental and economic consequences of climate change are severe and are being exacerbated by increased global carbon emissions. The challenge of reducing carbon emissions for the purpose of climate change mitigation requires that both supply-side and demand-side energy efficiency and conservation initiatives be developed. On the demand-side, commercial and residential buildings account for a significant portion of US electricity. In total, U.S. buildings account for over 40% of all domestic, and 7.4% of all global CO_2 emissions [EIA 2009]. In the United States, total building sector CO_2 emissions are expected to increase faster than any other sector over the next two decades, with commercial building emissions projected to grow the fastest at 1.8% each year through 2030 [EPA 2013]. Therefore, the building sector represents an important target for energy conservation initiatives, where even marginal energy savings across all buildings could have a profound effect on carbon emission mitigation.

The Role of Eco-Feedback in Energy Conservation

Strategies for reducing the energy consumption of buildings typically fall into three categories [Gulbinas 2014]: retrofits and equipment upgrades, building system automation, and behavior modifications. Each category has its own advantages and disadvantages. Research has shown that while retrofits and equipment upgrades (e.g. better insulation, more efficient boilers and water heaters) can significantly improve the energy efficiency of buildings, they are capital intensive and *sometimes* result in a take-back effect [Haas 1998], in which mechanical efficiency gains are offset by more inefficient behavior of building occupants[1]. Furthermore, in commercial buildings, investments in upgrades and retrofits have been shown to fall short due to an unaligned incentive structure in which building owners often cover the initial investment costs while tenants benefit from reduced operating costs [Randazzo 2011]. In a similar vein, purchasers have been shown to assign high short-term discount rates to equipment upgrades and other physical energy efficiency investments [Wilson 2007], which translates to a weaker willingness to spend capital upfront for lower energy operating costs in the future. For these reasons, the barriers to adoption of such technologies are relatively high compared to other less capitally intensive strategies, as owners demand a more abbreviated return on investment period. Building automation solutions, enabled by advanced building energy management systems (BEMS**)**, have traditionally been subjected to similar constraints. In addition to being costly and proprietary, BEMS often fail to engage building occupants, who play a significant role in the energy consumption of buildings [Azar 2012]. Furthermore, centralized automation systems have also been shown to adversely impact occupant comfort [Krioukov 2011], thus reducing their overall appeal.

[1] The take-back effect has only been observed in some instances and is not always present. Therefore, while it has been observed, it should not be expected to present with every physical building modification.

A relatively unobtrusive and economical strategy for achieving energy savings in residential and commercial buildings is to motivate energy-conscious behavior among building occupants. Carrico [2011] found that, based on the commercial retail price of electricity in 2009, for every dollar spent in a low-cost energy-use feedback intervention, $32 dollars in energy related savings were realized. While this may represent an extreme case in savings, it indeed demonstrates that behavior-based interventions can be very cost-effective, with a very short-term payback period. Other early studies in residential settings [Seligman 1978, Becker 1978, Ueno 2006, Petersen 2007, Schultz 2007, Nolan 2008, Allcott 2011] have shown that significant energy savings can be realized by motivating occupants to conserve energy by providing them with information about their energy usage. However, there is little understood about how sustainable and persistent behavior-based energy reduction strategies are or how such strategies can be designed to motivate long-term, sustained energy efficient behavior. While short-term response-relapse patterns have been observed in initial residential building behavior-based eco-feedback studies [Peschiera 2010], little effort has been made to understand how such effects can be mitigated. Positive results from early studies, however, have shown that energy savings are positively correlated with building occupant engagement with energy-use feedback. This suggests that if engagement levels can be sustained, longer-term efficient energy-use behaviors may be able to be formed. However, because of the relative lack of conclusive evidence about the lasting effects on energy-use behavior change, commercial buildings have been slower to adopt behavior-based conservation strategies.

Behavior-based energy conservation strategies have traditionally suffered from a lack of data granularity and the inability to track the progress of energy reductions. However, as building sensing technologies continue to fall in price and become more modular, new conservation strategies and research studies that combine the advantages of BEMS and behavior-based campaigns are emerging. New web-based systems that communicate high resolution, real-time energy-use data (i.e. eco-feedback systems) can also collect occupant interaction data that enable more impactful, targeted behavior-based energy efficiency campaigns [Gulbinas 2014]. These combined solutions, which simultaneously target the efficiency of building systems and occupant behavior, enable the full potential of energy-savings to be realized. Equally important, they will enable research into the temporal sensitivity of behavior-based campaigns, thus providing insights into how such campaigns can be best designed to motivate sustained energy efficient behavior.

Eco-Feedback System Research

Systems that engage building occupants by communicating energy feedback or collecting user-generated feedback make use of valuable, under-utilized human resources to increase building energy efficiency and occupant comfort and productivity. These systems also serve to convince users that they can influence their surroundings, thereby motivating increased levels of user-system engagement [Wilson 2003, Fischer 2008], which has been shown to positively correlate with energy-use reductions [Jain 2012]. In addition to motivating building occupants to conserve energy, eco-feedback systems have also progressed research into the effects of various building energy conservation strategies. Eco-feedback system enabled studies represent a significant improvement over traditional behavior-based intervention studies by facilitating analysis of energy-use data at a much higher temporal and spatial resolution. Improved data resolution enables building occupant energy-use trends and system interactions to be analyzed over different temporal durations. In this way, a better understanding of the sensitivity of various energy conservation interventions to time can be developed, enabling the design of more sustainable interventions. Furthermore, eco-feedback systems can facilitate controlled studies in which the effects of different conservation strategies are tested by limiting the exposure of building occupants to certain types of energy-use information and system features. Such integrated flexibility enables the utilization of a single eco-feedback system to study several different conservation interventions. In residential settings, eco-feedback systems have enabled high resolution studies on the effects of feedback granularity [Ueno 2006], social comparisons [Foster 2010, Petkov 2011], competitions [Petersen 2007], and public commitment [Abrahamse 2007, Grevet 2010] on energy consumption. However, despite several studies that have demonstrated significant energy savings can be achieved through the use of eco-feedback systems in residential settings [Jain 2013, Peschiera 2010, Ueno 2006], there is relatively little known about the effects of such systems in commercial buildings.

Impact of Social and Organizational Networks on Energy Conservation

Eco-feedback systems that connect building occupants through building information also enable the collection of data related to peer network connections and user-interactions [Gulbinas 2014], thereby facilitating research on building occupant networks and the role that they play in building energy consumption. Inspired by early research on the social effects of energy-use data [Seligman 1978, Nolan 2008, Petersen 2007], Peschiera and Taylor [2010] developed the first web-based eco-feedback system specifically designed to study the effects of human network dynamics on energy consumption in residential buildings. Multiple studies enabled by this social eco-feedback system, which connected building occupants through their energy-use information, demonstrated that individuals who interacted with network-level feedback conserved significantly more energy than those exposed only to individual-level feedback [Peschiera 2010]. Further analysis of the data collected from these studies also revealed that network size and degree centrality were positively correlated with energy savings, suggesting the more connected occupants are, the more they are socially influenced [Peschiera 2011]. These findings also informed the development of simulation models that corroborated empirical results at different network scales and also showed that the size of peer networks has little influence on the ultimate energy savings of residential buildings [Chen 2012].

While an initial understanding of the effects of peer networks on energy-use in residential buildings has begun to evolve, due to the relative lack of eco-feedback research in commercial buildings, much less is understood about the effects of organizational networks on energy conservation. All of the research on the potential effects of such networks on energy conservation in commercial buildings has thus far been limited to simulation studies, which have shown that network type and structure may significantly impact the time for conservation initiatives to yield significant energy savings [Anderson 2012, 2014]. Through my research, I aim to expand an understanding of how commercial building occupant behavior impacts energy-use. Furthermore, I hope to demonstrate that high resolution, occupant-level energy-use data can be used to help estimate other building related parameters that may be analyzed to increase building-level energy efficiency through non-behavior based interventions. Examples of such analysis include:

- Estimating occupancy levels of building areas in order to inform building system operation schedules
    - *Significant energy-use reductions can be realized by tuning HVAC and lighting system operations to actual, rather than assumed, building occupant schedules.*
- Quantifying the spatial energy efficiency and utilizations rates of localized building spaces
    - *By identifying underutilized building spaces and areas of high energy-use, shared-use areas can be designated to accommodate individuals who are consistently absent. In this way, buildings space can be more efficiently utilized. This is especially useful in a highly mobile economy where business travel and telecommuting are increasingly common.*

Commercial Building Study Site

My research focuses specifically on the energy-use of occupants in commercial buildings. In 2010, commercial buildings accounted for 18.6% of all U.S. primary energy consumption (45.3% of all building related energy consumption) and 35% of all U.S. electricity consumption (EIA 2010). The EIA divides commercial buildings among 6 main categories: 1) Administrative/Professional 2) Bank/Financial 3) Government 4) Medical (Non-Diagnostic) 5) Mixed Use 6) Other Office. The Alliance for Sustainable Colorado building, the primary site of my research, is an administrative office building located in the Mountain West region. The typical breakdown of electricity use – non-electrical loads are excluded since it is currently very difficult to track these loads in single commercial building research studies – across a sample of administrative office building analyzed by the EIA can be viewed in Figure 1.

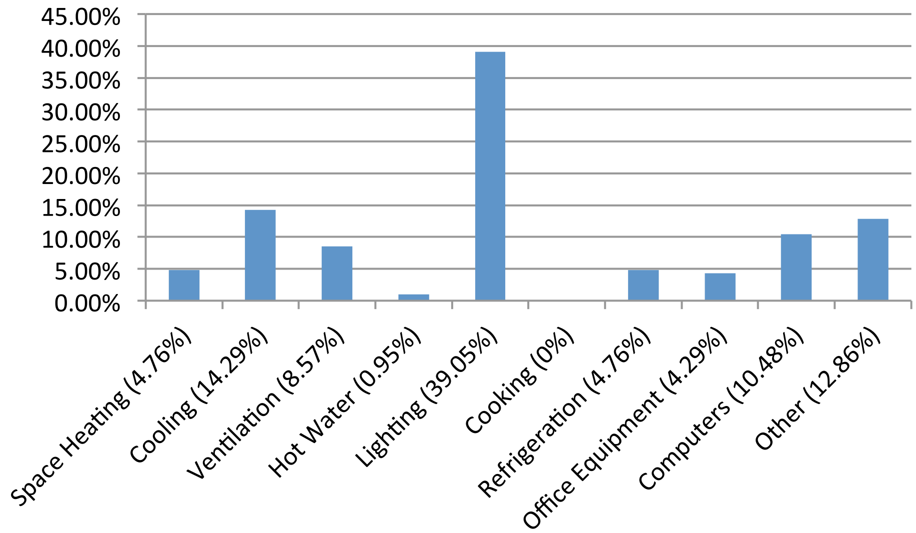

Figure 1: Electricity Consumption by End-Use in Office Buildings (DOE 2010)

In my study, aggregated desk-level plug-loads associated with office equipment, computers, and 'other' devices such as computer monitors, desk lightning, and cell phone chargers were directly monitored and energy feedback was communicated to individual users responsible for their control. These desk-loads account for about 27% of the electricity consumed in typical office buildings. A breakdown of electricity consumption specific to the Denver Alliance Center, which according to a recently installed electricity sub-metering system consumed 57,932 kilowatt-hours of electricity in February 2013, is found in Table 1.

Table 1: Denver Alliance Center Electricity Breakdown

Denver Alliance Center	Proportion of all Alliance Electricity Use (%)	Electricity Use (kWh)	Amount of Potential* Energy Savings due to 10% Reduction in Electricity Use (kWh)
Est. Monthly Total Controllable Electricity Use	90.49	52,422	5,242

Est. Monthly Direct Desk-load Electricity Use	27.63	16,006	1,600
Est. Monthly Indirect Shared Resource Electricity Use	62.86	36,416	3,642
*More savings can be achieved from gas related energy use reductions – primarily heating			

If behavior-based conservation initiatives could be designed to effectively yield 10% electricity savings at the Alliance building, a reasonable goal drawn from an extensive literature review [Gulbinas 2014], then over 5,000 kilowatt-hours of electricity could be conserved each month. Office buildings represent approximately 17% of all commercial building floor space and 19% of all primary commercial building energy consumption in the United States [DOE 2003]. If a 10% savings rate could eventually be generalized to the rest of these commercial office buildings, significant energy-use and carbon emission reductions could potentially be realized. However, it should be noted once again that only plug-load electricity usage was monitored and communicated in my primary research study introduced in chapter 2, and that this study only represents an initial effort for spurring additional studies designed to improve energy saving rates.

Research Methodology and Dissertation Structure

Recent technological advancements have enabled a new generation of eco-feedback systems to collect and communicate increasingly high resolution, high frequency energy-use data, facilitating analysis of individual building occupant energy-use patterns on a minute-by-minute time scale. Such unprecedented data granularity has enabled more insightful research on the impacts of various approaches (goal-setting, competitions, comparisons, etc…) on energy conservation and allows the study of how the effects of these interventions vary over shorter and longer time scales. As observed in Fig. 2, these advancements have thus enabled building energy efficiency study analysis to move beyond whole building and/or floor level energy-use granularity [Petersen 2007]. However, in spite of all the positive trends in the technical development of eco-feedback systems, there is still a dearth of research on how such systems, and more generally behavior-based conservation campaigns, motivate energy efficiency among occupants in commercial buildings.

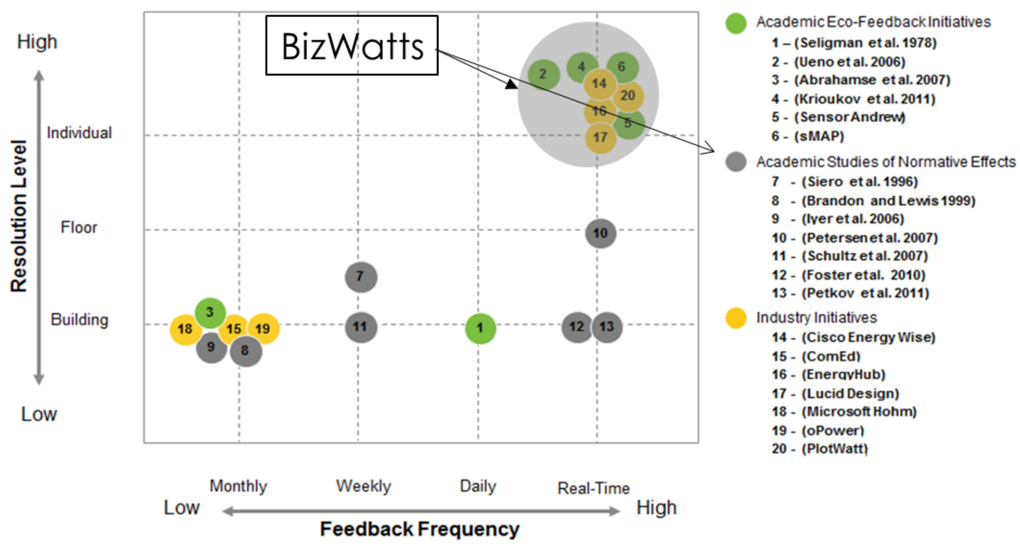

Figure 2: Eco-Feedback Data Resolution and Frequency Trends

Through my research, I have addressed this gap in understanding by developing a new type of modular, eco-feedback system specially designed to enable highly granular behavior-based research in commercial buildings. I have tested and utilized this novel system to extend the empirical study of the effects of peer network dynamics on energy consumption to the commercial building domain and to collect data in order to develop new methods for defining and identifying efficient and inefficient commercial building occupants. The structure of my dissertation research is illustrated in Fig. 3. Given the relative lack of understanding of how eco-feedback systems and commercial building occupants can interact to reduce commercial building energy consumption, it was important to build a system around an iterative research and development strategy to allow periodic system updates and expansions. In this way, valuable lessons from each research study can be used to update a base software platform that is fundamentally structured to support individual and group-

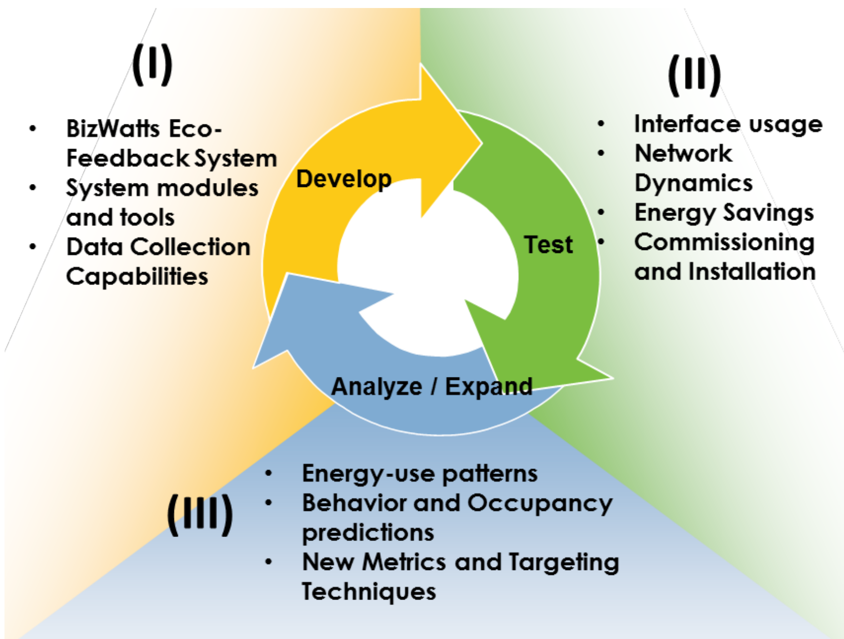

Figure 3: Dissertation Research Structure

based energy efficiency studies that investigate the impacts of a variety of conservation strategies (e.g. goal setting, public commitment, rankings, and comparisons). My dissertation research represents the first complete iteration of the three main steps illustrated in Fig. 3. More specifically, my research was based on the following goals:

1. Develop a modular and expandable, high resolution commercial building eco-feedback system that allows building occupants to share energy-use information and collaborate while also enabling impactful, next-generation energy efficiency studies
2. Conduct a novel commercial building research study to investigate the potential effects of organizational network dynamics on building occupant energy-use (i.e. test the validity of the fundamental peer network principles upon which the eco-feedback system was built)
3. Develop new methodologies and metrics that utilize high resolution energy-use data to effectively classify building occupants and networks according to energy-use efficiency and predictability in order to improve the efficacy of energy conservation programs

This dissertation structure follows a three-paper format. In Chapter 2, I describe the development of a novel commercial building eco-feedback system, *BizWatts.* The system enables controlled studies on the effects of energy efficiency interventions (e.g. goal-setting, conservation competitions, incentives) on building occupants by allowing researchers to restrict user access to specific system features and to control which groups of users are exposed to interventions. Chapter 2 includes a description of the system's technical architecture, the principles behind its design, and the types of energy efficiency studies that it enables. The article in Chapter 2 is under review in the *Journal of Applied Energy* and was co-authored by me and Professor John E. Taylor.

Next, Chapter 3 includes a journal article that describes a novel study designed to measure the impacts of eco-feedback and organizational network dynamics on commercial building occupant energy-use. In the study, building occupants were provided varying access to individual and network-level energy-use data through the eco-feedback system described in Chapter 2, and all interactions between users and the eco-feedback system (e.g. logins, energy-use comparisons, shared communications) were recorded in the form of clickstream data. After combining information about the structure of each user's organizational network with clickstream and energy-use data, statistical analysis was conducted to better understand how organizational networks impact energy-use at the workplace. The study, which was conducted over 3 months in the tradition of previous residential building behavior-based studies, was the first step in understanding how commercial building occupants interact with individualized and network-based eco-feedback. As such, it paves the way for future research into how energy efficient behavior can be sustained in the long term and how such behaviors may influence the utilization of energy intensive shared-resources such as lighting and HVAC that extend beyond plug-loads. In the future, these expanded studies can help motivate larger scale behavior-based efficiency strategies, which large institutions have been slower to adopt without more evidence regarding their efficacy. This chapter is under review in *Energy and Buildings* and was co-authored by me, Dr. Rishee K. Jain and Professor John E. Taylor.

In Chapter 4, I describe the methodology behind the construction of a new set of metrics that serve as quantitative measures of building occupant energy efficiency and energy-use predictability. Recognizing the inability of behavior-based efficiency programs to effectively target the most inefficient energy consumers, I used the data from the study in Chapter 3 to develop these new energy-use metrics to enable classification of building occupants and networks based on their energy-use patterns. The article presented in this chapter is under review at *IEEE Transactions on Smart Grid*. The article is co-authored by me, Ardalan Khosrowpour, and Professor John E. Taylor.

Chapter 5 contains a discussion of how my research has impacted commercial building energy efficiency research and I conclude my dissertation with a discussion of the current limitations of commercial building energy efficiency research and what future research avenues my research has enabled. References cited throughout the dissertation can be found at the end.

A Cautious Word about Behavior

While my research was influenced by many studies rooted in behavior change and organizational psychology, my intended contributions are in the areas of:

1) Eco-feedback system design, development, and utilization
2) Organizational network effects on commercial building occupant energy-use
3) Metrics development based on individual occupant energy-use data

As such, my contributions should not be interpreted as directly impacting any specific theories of behavior. The usage of terms related to behavior, behavior change, and socio-technical systems in my dissertation are applied in the same way as other literature in the field of eco-feedback research, and are not necessarily consistent with more strict definitions in the fields of behavior and psychology. Behavior change in my research is specifically characterized by changes in individual and group energy consumption patterns and is a dependent variable that is influenced by specific interventions that are all applied and investigated through the lens of energy-use and/or network analysis (not psychology or sociology). For example, goal-setting may be introduced in my study, but the analysis will focus on the difference in goal-setting effects on user energy consumption when controlling for network structure (organizational, social, combined, decentralized, etc…) rather than other potential psychological factors. I am not investigating intrinsic/extrinsic motivations and trying to understand why individuals may act to conserve energy; my research seeks to discover the effects on energy consumption when relevant feedback information connects users across social and organizational networks with different structural properties. Instead of asking 'why' individuals behave the way that they do, my research is concerned with 'how' network connections formed over a software platform may impact collaboration, competition, group-identity, and the effects of goal-setting and organizational directives on individual and group-level energy consumption. Furthermore, my research investigates the effect of network connections on the rate of building occupant engagement with eco-feedback systems. In summary, my research deals with statistical analysis of energy-use patterns.

CHAPTER 2: A MODULAR SOCIO-TECHNICAL ENERGY MANAGEMENT SYSTEM FOR EMPOWERING COMMERCIAL BUILDING OCCUPANTS TO CONSERVE ENERGY[2]

Abstract

Commercial buildings represent a significant portion of energy consumption and environmental emissions worldwide. To address this issue, integrated automation systems aimed at reducing energy consumption are becoming increasingly popular. Such systems allow facility operators to identify opportunities for increasing building energy efficiency by providing high resolution energy-use data visualizations and enabling control of mechanical and electrical systems. Concurrently, many commercial organizations are taking an alternative approach to increasing energy efficiency by instituting behavior-based programs aimed at empowering individuals to save energy and reduce operational costs. In this paper, we describe the development of a modular socio-technical energy management system, *BizWatts,* which combines the two approaches by providing real-time, appliance-level power management and socially-contextualized energy consumption feedback. By designing a system that engages both building occupants and facility managers, the system simultaneously empowers occupants to adopt more efficient energy consumption behaviors and collects data that can be used by facility managers to optimize building systems around energy conservation. The system can integrate feedback and goal setting with a variety of organizational structures in order to facilitate cooperation and

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[2] This paper was co-authored by Rishee Jain and Prof. John Taylor and is under review to be published in the Journal of Applied Energy.

Keywords: Behavior Change; Energy Efficiency; Energy Management; Social Networks

competition between individuals and workgroups and encourage the adoption of sustainable practices. Furthermore, all user interactions with the system are captured in the form of clickstream data to allow researchers to conduct robust statistical and network analysis on how individuals interact with the user-interface and how social connections impact energy conservation in commercial settings. We describe in detail the physical and virtual architecture of the system as well as the main principles behind the interface design and component functionalities. A discussion regarding data collection methods and applications of data-driven network analysis and building system optimization is also included. We conclude by commenting on the validation of the system, identifying current system limitations and introducing a number of new research avenues that the development and deployment of a socio-technical energy management system like *BizWatts* could enable.

Introduction

Buildings are inexorably linked to the environment and economy. In the United States, they are responsible for approximately 41% (DOE 2012) of all energy consumed and 40% [EIA 2009] of all carbon emitted. Furthermore, CO_2 emissions from US buildings are expected to increase faster than any other sector over the next two decades with commercial building emissions projected to grow the fastest, at 1.8% each year through 2030 [USGBC 2007]. The United States has joined other countries in recognizing the global importance of emission reductions and has set a federal target of reducing national greenhouse gas emissions by 80% by 2050 [US White House 2012]. To achieve this ambitious target, myriad public and private initiatives to improve building energy efficiency through technological and regulatory means have emerged. Such initiatives initially focused on efficiency rating and certification programs for buildings [USGBC 2013, RESNET 2013] and appliances [EPA, 2013], but have since expanded to include the establishment of energy data repositories [Green Button, 2013], neutral smart building automation protocols [ASHRAE 2013], and Building Energy Management System (BEMS) development standards [ISO 2013]. These new initiatives are designed to facilitate the widespread development and adoption of energy efficiency technologies, which will play a critical role in achieving national energy efficiency goals.

Background

Commercial Building Sector Energy Efficiency

Researchers have developed numerous strategies for improving the energy efficiency of commercial buildings and each approach is dependent on economic, organizational, and structural factors. Building retrofits and equipment upgrades, e.g. the installation of more efficient boilers, can significantly improve the energy efficiency of buildings, but are often capital intensive. In addition, purchasing decision-makers often associate high opportunity costs and disproportionately high short-term discount rates with such investments [Wilson 2007], which often fall short due to a split incentive structure in which building owners bear the initial investment costs while commercial tenants benefit from reduced operating costs [Randazzo 2011]. Investments in automation solutions, e.g., programmable facility ambient controls, can also improve the efficiency of building systems. However integrated automation strategies can also be cost-prohibitive and have been shown to compromise building occupant comfort [Krioukov 2011]. Similar constraints apply to many integrated BEMS, which provide building operators with information and data visualizations of building system operations and energy consumption. Many of these advanced systems facilitate energy efficiency fault detection by monitoring and processing a range of independent building data-streams, e.g. temperature, energy consumption, weather, solar radiation, lightning, etc., [Costa 2013]. However, the lack of monitoring hardware interoperability often necessitates the development of custom software interfaces [Swords 2008, Marinakis 2013] that require significant domain specific knowledge of building systems to comprehend and analyze. Such systems are therefore difficult to design for casual users and costly to customize and implement in new buildings.

A relatively unobtrusive and economically viable energy conservation strategy for commercial buildings is to motivate energy-conscious behavior among building occupants [Carrico 2011]. Modeling and simulation of energy use in commercial buildings [Azar 2011, 2012] has found that occupants can have a significant impact on energy-use; a finding which has been supported by the success of several behavior-based academic studies [Carrico 2011, Siero 1996] and industry sponsored energy efficiency initiatives [USPS 2012, Starbucks 2012]. In some cases, substantial economic benefits have been realized. In an internal group-oriented energy conservation campaign, the United States Postal Service reduced annual operating costs by $22 million dollars across 33,000 buildings in 2011. In a separate behavior intervention program, Carrico and Riemer [2011] estimated that for every dollar invested in the program, $32 dollars in energy costs were saved. Such behavior-based strategies also appeal to small firms, of which there are 23 million in the United States - representing up to 34 billion sq. ft. of commercial real estate [SBA 2013]. Cagno et al. [2013] investigated the drivers for adopting energy efficiency technologies and services among small business owners and found that many rated ‘information on practices’ as more important than ‘information on technologies’, demonstrating a willingness to adopt low-cost practical solutions that do not require significant financial or technological investment. In order to realize large-scale energy savings, cost-effective systems that help translate 'information on practices' to 'actions that save energy' should be designed for firms and buildings of all sizes.

Behavior-based Eco-Feedback Systems

Behavior based energy efficiency initiatives represent an effective method for achieving significant energy savings but often lack the ability to monitor energy consumption trends at a granular level. Conversely, advanced commercial BEMS tend to monitor energy consumption at a high-resolution but often fail to engage and motivate energy-conscious behavior among building occupants [Costa 2013, Swords 2008, Marinakis 2013]. Reconciling the two approaches, research conducted on feedback designed to influence behavior by providing building occupants with various forms of energy consumption feedback (i.e. eco-feedback systems) in residential [Abrahamse 2007, Allcott 2011, Fischer 2008, Jain 2012, Nolan 2008, Peschiera 2010, Petersen 2007, Seligman 1978, Ueno 2006] and institutional settings [Krioukov 2011, Jiang 2009] has shown that such systems typically yield energy savings ranging from 5-55% [Dietz 2009]. In this paper, we introduce *BizWatts*, a socio-technical energy management system for commercial buildings that combines proven social principles of behavior-based energy efficiency initiatives (goal-setting, social comparisons, team-identity) with high-resolution monitoring and feedback technologies. Our system avoids aforementioned constraints associated with integrated building management solutions by utilizing a modular plug-load energy monitoring hardware system. This simplifies and adds important flexibility to the system commissioning and decommissioning process and enables a flexible software architecture that can accommodate buildings and organizations of all types and sizes. In addition, *BizWatts* is designed to simultaneously empower building occupants to save energy and utilize them as sources of building information (e.g. occupancy levels), thus reducing the need to rely on disjoint building system monitoring hardware. In 2013, Marinakis et al. [2013] stated that, "a system which also includes remote control technology to enable energy end-users to monitor the energy consumption and control the operation of buildings' appliances, as well as optimization functions for the reduction of the energy consumption is required [for better reducing energy consumption]… such an integrated system is not present in the international scientific literature." *BizWatts* addresses this call by combining near real-time plug load energy data visualization and remote power management at the appliance level with social energy consumption information. It is also designed to extend eco-feedback research to the commercial domain by tracking relevant user-interface and user-user interaction statistics in the form of clickstream data that can be used for analyzing social effects on individual and group energy consumption. The system's architecture, interface features, and design principles are introduced in the following section.

BIZWATTS Commercial Eco-feedback System

The *BizWatts* system is designed to foster a culture of energy efficiency and collaborative engagement in energy conservation activities at the workplace by providing users with various representations of personal and group level energy consumption data. In this section, we provide specifics regarding the system's architecture, visualizations, data-mining techniques and analysis methods.

BizWatts System Architecture

BizWatts is a web-browser accessed application built on an Apache/PHP/MySQL platform. As a social energy feedback application, its overall system design is similar to that of its residential predecessor, Watt's Watts [Gulbinas 2013], and can be summarized by the simplified feedback loop in Fig 4(a). From a high level perspective, energy data collected by plug-load energy monitors is pushed to a server where it is processed and fed to the *BizWatts* application. The

BizWatts application is accessed by building occupants who interact with one another by comparing energy consumption information and actions and discussing conservation strategies over the application. This network level feedback has proven to motivate [Peschiera 30] building occupants to conserve energy and is intended to encourage closer monitoring of plug-load (and potentially shared resource, e.g. lighting, HVAC) energy consumption. Changes in behavior are then reflected by updated energy consumption data visualization, thereby closing the feedback loop and allowing building occupants to continue the collaborative learning and conservation process.

Energy data is captured by commercially available wireless plug load power monitors manufactured by Monster Cable Incorporated, which also enable users to remotely turn on/off assigned appliances. Each power monitor wirelessly communicates an appliance's power information via 900 MHz RF signal to an edge router that uploads data to a database via Ethernet connection. Time, location, device identification, real power (W), current (A), voltage (V), and power factor data are pushed through the router every 15 minutes to a database hosted on an Amazon Web Services server and managed by the People Power Company. The *BizWatts* system allows up to 12 standard North American 120V appliances (computers, fans, space heaters, etc…) to be assigned to individual users and collects energy data for each appliance independently. With open-API access to the People Power server, *BizWatts* performs nightly migrations of user energy data to an independent database where the data is stored and parsed to optimize the load times of historical energy consumption visualizations over days, weeks, and months. While aggregated historical energy information is retrieved from the *BizWatts* server, to decrease load times same day power and energy information is retrieved directly from the People

Power server. In addition to collecting, processing, and communicating high-resolution energy-use feedback, *BizWatts* also monitors user interactions with the software interface as well as with other users. This clickstream data is used for analyzing several topics of interest, including: when and which users login to the system, which interface components are used the most often, and what actions users are adopting to conserve energy. Collecting this information enables a quantitative approach to system interface improvement that will be discussed later in this paper. A detailed schematic representing the system's design and data flow can be viewed in Fig. 4(b).

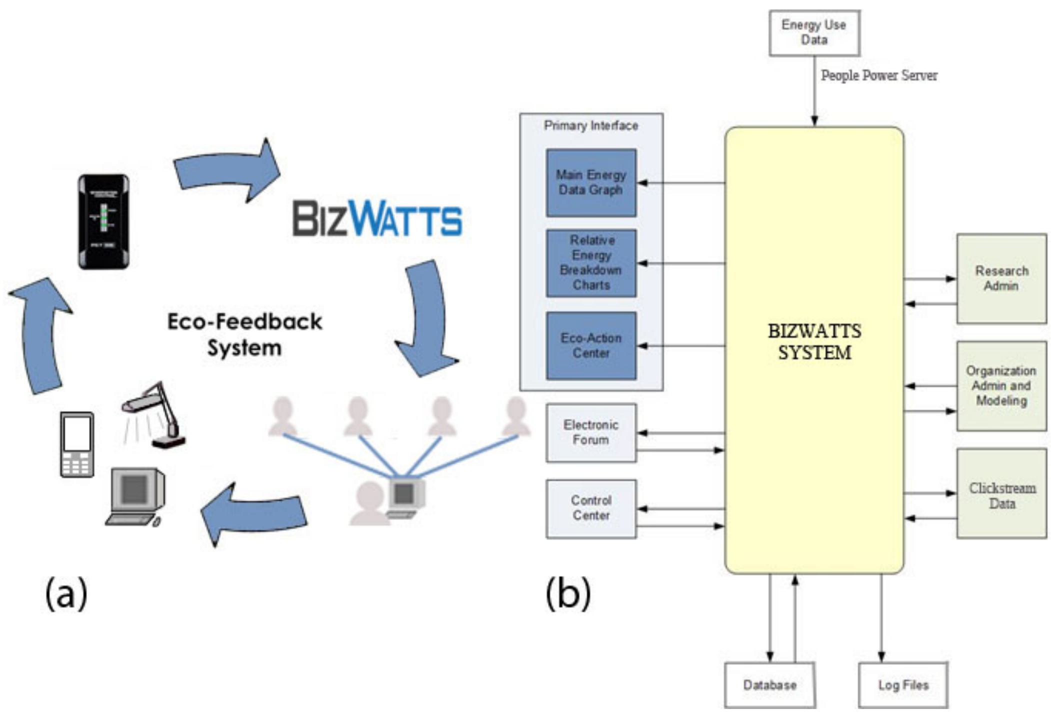

Figure 4: BizWatts Feedback Loop and System Map

System Initialization

To maximize its applicability to various organizational structures and commercial buildings, *BizWatts* was designed to support flexible group configurations that can evolve over time. Once individuals are registered in the database and assigned to specific plug-load monitoring devices, system administrators can create organizational groups to which individuals may be added. When an individual is assigned to a group, a series of group-spanning metrics are calculated, such as the group's total and per capita energy consumption over various time periods and appliance types, in order to facilitate meaningful group energy use comparisons. If an individual changes groups, the system recalculates these metrics and updates group statistics in order to eliminate potential data redundancy. *BizWatts* supports large organizations with multiple layers of groups (e.g. groups within a department, departments within a corporation) in a child-parent structure as seen in the bottom-right of Fig. 5, as well as smaller firms with flat organizational structures. System administrators define group settings and manage the overall organizational structure using the group management screen presented in Fig. 5.

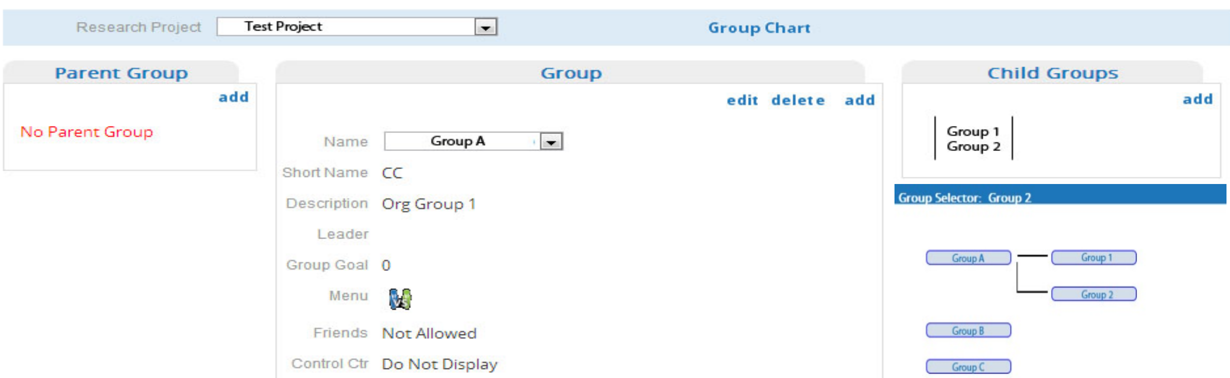

Figure 5: Group Creation and Organizational Structure Screen

Visualizations

BizWatts was designed as a social energy feedback system that facilities individual and collaborative learning around high-resolution, high-frequency feedback. A central navigation bar located in the header of the user-interface controls the core visualization tool and enables users to toggle between combinations of individual, group, social, and appliance-based representations of energy consumption. In addition to toggling between the feedback representations presented in

Table 2, users can select the time unit (e.g. ‘Today’, ‘Weekly’, and ‘Monthly’) over which they would like their appliance, individual or group-level energy data to be aggregated.

Table 2: Available graphical representations of energy consumption

	Appliance Breakdown	Comparisons
Individual View	Relative energy-use of appliances assigned to user	User energy-use comparisons over time with members within group or with friends
Group View	Relative energy-use of each appliance type summed across all members of group	Per capita energy-use comparisons over time of user's group with other groups

Energy-use Comparisons

The ability to share energy information among building occupants was proven to significantly impact network-level energy conservation behavior in residential studies [Peschiera 2010, 2012]. *BizWatts* was designed to leverage such observed social dynamics by encouraging users to share as much energy related information as possible over a simple, intuitive interface. In the comparison graph tool in Fig 6(a), users are able to simultaneously overlay the energy consumption data of up to 8 users over various time intervals. In addition to being able to make energy-use comparisons with others in their organizational networks, users are can also manage an ad-hoc social group consisting of personally selected ‘friends’ from across their entire organization.

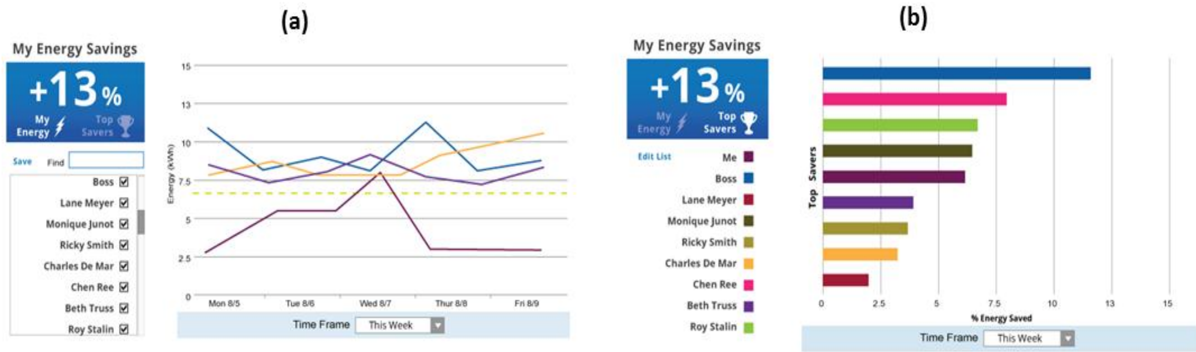

Figure 6: (a) Network Energy Comparison Plot and (b) Energy Savings Rankings

The checklist below the 'My Energy Savings' box in Fig. 6(a) contains a list separating individuals in a user's organizational and social groups, from which users can select other users with whom to compare energy-use. Users can also choose to compare historical data by selecting past time intervals in the 'Time Frame' dropdown below the comparison plot. The dotted line in Fig. 6(a) reflects a performance goal set by a system administrator that is based on a percent reduction applied to the user's average baseline performance[3]. The blue 'My Energy Savings' box in the top left corner of Fig. 6(a) represents the actual percent difference between the total consumption of the user over the selected time frame relative to average baseline levels, as determined by **Equation 1**:

$$\delta_{period} = (E_{baseline} - E_{period}) / E_{baseline} \qquad \textbf{(1)}$$

where (E_{period}) is the total energy consumption of a user or group over the selected day, week, or monthly period and ($E_{baseline}$) is the average daily energy consumption of a user or group over a

[3] A user's baseline performance is defined as a user's average energy use during a period before the BizWatts system was initiated.

baseline period multiplied by the number of days in the user-selected time period. These tracking features allow users to assess their performance relative to a defined goal, which White [1977] showed to have a positive impact on employee productivity. Furthermore, users can compare energy efficiency savings with other users in the ranking view in Fig. 6(b) that is initialized by toggling to the 'Top Savers' mode in the blue 'My Energy Savings' box. Ranking boards have been observed to be the most popular features in other social systems designed to motivate conservation [Foster 2012]. *BizWatts* incorporates a ranking board to allow users to benchmark themselves against others in their network relative to their respective baseline usage.

In organizations that consist of multiple groups, users can toggle to group-based representations of feedback. The ability to compare performance at a group-level was demonstrated by Siero et al. [1996] to help build team identity and foster collaboration, ultimately leading to increased levels of energy conservation. In the *BizWatts* group comparison view, users can track and compare their group's per capita energy-use over time with the per capita energy-use of other groups, facilitating meaningful comparisons between groups of varying sizes. In addition to these group-level energy-use comparisons, the 'My Energy Savings' box changes to reflect the group's performance relative to its baseline consumption levels and the ranking board displays energy savings for each group, rather than each individual. In this way, the entire core visualization tool is updated to reflect a group-level perspective.

Appliance Energy-Use Breakdowns

To complement energy-use comparisons between individuals and groups, we developed an appliance breakdown tool that allows users to independently learn the relative consumption levels of appliances under their control. The development of this tool was motivated by several energy efficiency program studies that demonstrated the utility of appliance-level feedback [Foster 2012, Petkov 2011], as well as Fischer's review of eco-feedback studies [Fischer 2008] that affirmed the importance of interface tools that draw a direct link between specific actions and consumption. The appliance breakdown tool, observed in Fig. 7, shows the relative energy consumption of all appliances assigned to a user over a time period selected by the user**.** If the

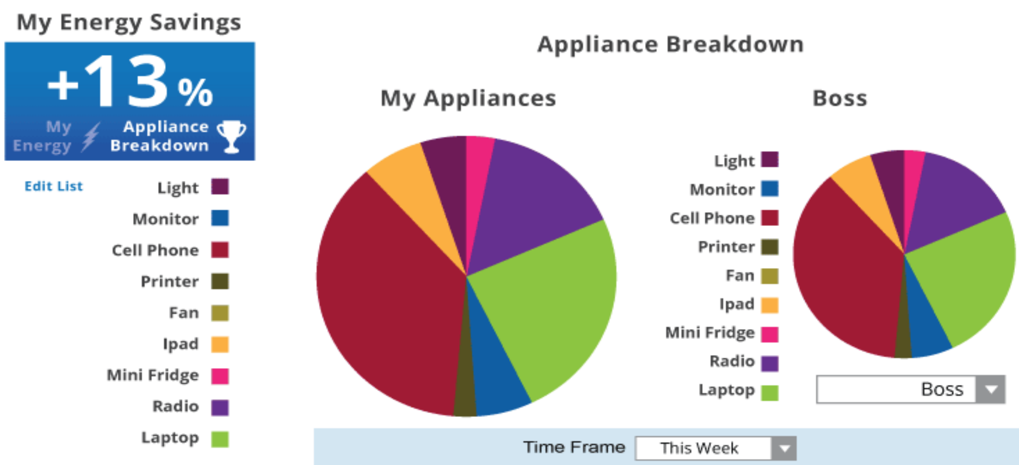

Figure 7: Appliance Breakdown Visualization

group-view appliance breakdown is selected, the relative aggregate energy consumption of all appliance types assigned to members of the group is displayed. The tool helps individuals and groups identify appliances that may be being left powered on or used inefficiently, enabling conservation actions to be targeted to specific appliance types. It also allows users to compare appliance energy breakdowns with other users and groups to learn how top energy savers in their network consume energy.

Eco-Action Center

In order to encourage collaborative conservation strategies, an Eco-Action Center was designed that allows users to share and discuss sustainable practices and to report conservation actions that are not captured by the plug-load energy monitors. The Eco-Action Center, the condensed version of which can be viewed in Fig. 8(a), complements the aforementioned feedback visualizations with a forum where users can explicitly establish and adopt energy efficiency strategies around sustainability-oriented actions. he Eco-Action Center allows organizations to discover the most popular energy efficiency actions among their employees. Conservation action posts created by users are displayed across the entire organizational network where others can ‘like’, ‘comment’, or ‘check’ them. Individuals click the thumbs-up symbol next to a post to express that they ‘like’ the post, the text bubble if they would like to leave a comment regarding the post, and the checkmark symbol to self-report when they complete a specific conservation action. The default view of the Eco-Action Center lists posts according to when they were most recently engaged (‘liked’, ‘commented’, or ‘checked’) by users in the organization but users can also filter posts according to popularity, which is determined by an algorithm that assigns weights to the number of likes, comments, and checks that each action receives. New post creation and popularity growth are monitored by the system and allow system administrators to identify the most regular actions taken by employees. As the number of self-reported ‘checks’ is tracked, users can also compare their activity with others in their network by using the action comparison tool in Fig. 8(b). The static list of actions in Fig. 8(b) is managed by a system administrator, who can select the most relevant set of actions for a specific group and prioritize actions that are more relevant to the organization’s sustainability goals. The user-generated nature of the conservation posts ensures their relevancy to the physical setting of the users, which Grevet et al. [2012] showed to be important for motivating behavior change.

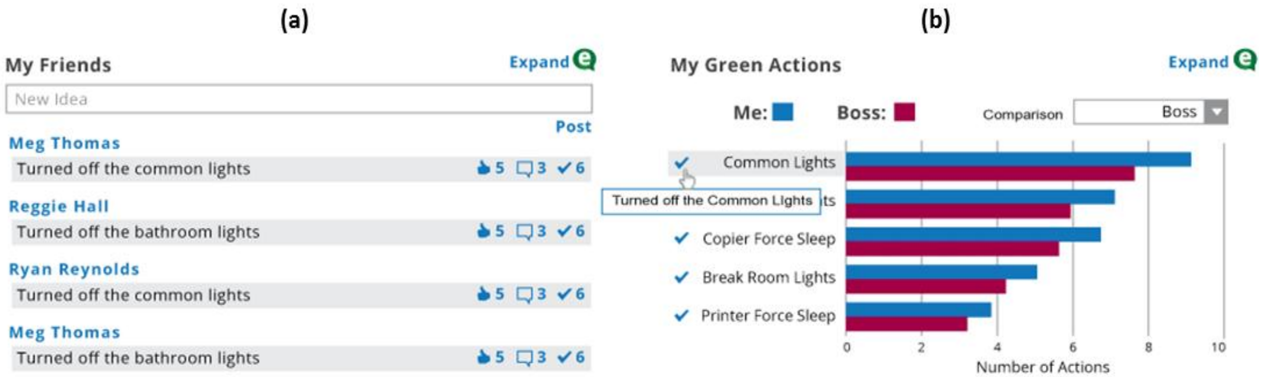

Figure 8: (a) Eco-Action Center Idea Forum (b) Green Action Rankings

When groups are established, a host of additional user and administrative features become available:

1) Members gain access to visualizations of other groups' normalized energy consumption data in addition to their own. This facilitates competition between groups through meaningful group vs. group comparisons.
2) Each group can be assigned a specific energy-use reduction goal relative to a baseline period average, which is displayed on each group member's energy plots. This helps establish group identity and motivates cooperation to achieve the conservation goal.
3) Each group can be assigned a leader, whose energy consumption is overlaid on members' energy graphs. This encourages group leaders to motivate members through their own conservation actions.
4) System administrators can manage the ability of members to remotely control the power states of their appliances at the group level. This prevents accidental power disruptions of sensitive equipment.

The settings of each group, as managed by a system administrator, also define the types of visualizations that are made available to users.

Data Mining and Analysis

BizWatts was designed to collect data from a range of sources that could be used to form rich insights into building occupant behavior and energy-use patterns. These insights can in turn inform the design of more engaging eco-feedback interfaces and provide a better understanding of organizational network dynamics in energy conservation initiatives.

Clickstream Data

Clickstream data can be used to quantitatively assess levels of user engagement with software interface components [Benevenuto 2009, Das 2009, Srivastava 2005]. As user engagement with eco-feedback software systems has been found to be positively correlated with energy savings [Jain 2012], it is important to design such systems to maximize user engagement. To enable an iterative design improvement process, *BizWatts* collects clickstream data pertaining to user interactions with a number of interface components**.** This clickstream data is stored in a database that is continually updated with new activity and can be queried to facilitate clickstream data analysis for identifying underutilized components for redesign or replacement. The clickstream data points collected by *BizWatts*, along with all the other types of data collected by the system, are listed in **Table 3.**

Table 3: List of Collected System Data

Data Point	Details
User Logins	Timestamp of Login and User
Energy Visualization Preferences	Which plots were viewed in what time frame
Added Friends	Timestamp when user adds friend and friend's name
Energy Ranking View Instances	Timestamp when user views energy ranking
Eco-Action Center New Posts	Timestamp and text of post
Eco-Action Center Likes, Comments, Checks	Timestamp and text of associated post
Exposure to Goal	Boolean if user's group has an admin set goal
Ability to Add 'Friends'	Boolean if a user's group can add friends
Leader Presence	Boolean if user's group has leader assigned
Appliance Energy-Consumption	Appliance type and historical energy-use
Building Occupant Energy-Consumption	User's assigned appliances and total energy-use
User Organizational and Social Network Links	Number of network connections and user id's
Overall Organizational Structure	Group relationships and hierarchies

Beyond being used to quantify levels of user engagement with interface components, clickstream data can be combined with other data types to provide additional insights. Time-stamped clickstream data can be matched with plug-load energy-use data to investigate temporal relationships between interface interactions and actual energy conservation. By further combining this matched data with information on organizational network structure, analysis can be extended to quantify the level of influence a user has on a network's energy consumption behavior [Jain 2013] and the impacts of organizational network connections on energy conservation. As *BizWatts* was initially designed as a research tool, a range of administrative group management functions were built into the system to facilitate controlled studies designed to isolate the effects of user engagement and organizational network dynamics. These functions, combined with clickstream and energy-use data, enable scientific research into the impact of different energy conservation strategies (e.g. goal-setting, hierarchical comparisons, network collaboration, user-rankings) in commercial buildings.

Discussion

An Eco-Feedback System for Building Occupants

The *BizWatts* system represents a novel approach to energy management in commercial buildings that complements existing commercial BEMS by monitoring and communicating individual and appliance-level energy-use data that often falls beyond the scope of traditional BEMS. Building off previous research involving the development of residential building social eco-feedback systems [Gulbinas 2013], *BizWatts* connects building occupants through organizational and social networks to facilitate collaboration and competition to achieve energy efficiency goals. This approach, coupled with the modularity of the system's monitoring architecture, allows *BizWatts* to directly incorporate building occupants into the building energy-use feedback loop. The engagement of building occupants is a novel approach enabled by the *BizWatts* system that has traditionally fallen outside the scope of commercial BEMS [Costa 2013, Swords 2008, Marinakis 2013, Cisco 2013, JouleX 2013], due to technological and organizational constraints. Answering the call by Marinakis et al. [2013] to enable user remote control and optimization functions, *BizWatts* provides a platform that simultaneously enables user remote control of connected appliances and captures high-resolution energy consumption data that can inform behavior-based energy efficiency strategies. Furthermore, the flexibility of the system architecture allows *BizWatts* to support a wide range of organizational structures, from small businesses to large, multi-department organizations. Organizational structures vary substantially across businesses and the *BizWatts* system was designed to accommodate such variability.

In addition to facilitating a bottom-up organizational approach to commercial building energy efficiency, *BizWatts* contributes to dialogue regarding eco-feedback design [Jain 2012, Froehlich 2010] and feedback efficacy [Allcott 2011, Fischer 2008] due to its ability to collect data that enables internal design and external impact validation. Collected clickstream data enables a continuous interface improvement process aimed at maximizing user engagement, thus facilitating internal design validation. In addition, collected energy-use data for a predefined baseline period can be compared with consumption patterns after users are given access to the system in order to determine the effectiveness of the system in driving energy conservation. By combining energy-use data with clickstream and organizational network data, the impacts of group collaboration and competition can also be evaluated. This also enables *BizWatts* to extend modeling and simulation research in the area of building occupant energy consumption behavior in commercial buildings [Azar 2011, 2012, Chen 2013] by facilitating validation and calibration of network models.

Pilot Study and System Validation

Unlike existing commercial building energy management systems, *BizWatts* helps commercial building occupants and operators save energy by presenting engaging energy feedback visualizations that motivate and inform conservation behavior. Simultaneously, *BizWatts* also collects a range of data that facilitates interface design improvements and scientific research into the impacts of various energy efficiency strategies. This combined applied and research-oriented approach allows *BizWatts* to go beyond what can be achieved by traditional energy efficiency measures. In an initial pilot study designed to validate the design principles around which the *BizWatts* system was built, organizationally connected building occupants each conserved approximately 50 Wh/day in plug-load electricity relative to a control group (no exposure to feedback) and their own baseline levels, at a statistically significant level of $p=0.05$. Furthermore, over 600 clickstream data points reflecting user interactions with interface components were collected, which have been analyzed to determine which components of the system were underutilized and can be improved. Of these data points, 124 were self-reported conservation actions from occupants who actively engaged in the management of energy intensive shared resources that were not captured in the electricity data collected by the *BizWatts* system. Examples of reported actions include: taking the stairs instead of the elevator, turning off common and bathroom lights, and taking a bike or public transportation to work. *BizWatts* is designed to establish and leverage a link between individual action and energy conservation in order to motivate increased shared resource management, translating into significantly more energy savings than can be achieved by managing plug-loads alone. While the system will evolve to monitor energy-use of shared resources, the pilot study confirmed that individuals who interact with the system are indeed inclined to save energy and engage the interface to self-report active conservation actions– a positive indication that including additional shared resource monitoring will provide value to building occupants.

Limitations

BizWatts is designed to motivate behavior change by leveraging the power of social norms, appliance-specific feedback, and collaborative learning. However, the system is currently limited by its physical capacity to monitor only appliance plug loads. As such, energy consumption data related to shared resources such as overhead lightning, central heating and cooling, and hot water is not captured. While correlations between floor level energy consumption and user engagement with the Eco-Action Center can be investigated, disaggregation of the energy data by specific resource is not possible without the utilization of additional sub-metering equipment. This limitation makes it difficult to disaggregate the total energy savings due to behavior change and to tie specific Eco-Action Center interactions to these savings. However, eco-action center data can be used to determine which conservation actions were the most popular among users, which can be used to indirectly estimate the proportion of total energy savings attributed to each type of action when conducting analysis on total shared resource energy consumption change.

Future Development

Pilot studies are currently being conducted using the *BizWatts* system in several commercial buildings across the United States. Results of initial pilot studies [Gulbinas 2013] indicate that *BizWatts* successfully reduces energy consumption of occupants and in turn, validates the impacts of the system on occupant energy consumption. However, as part of a continuous improvement process the researchers are working to identify several interface components that are consistently underutilized using clickstream data analysis methods described earlier in this paper. Future development of the system will begin with the redesign of some of these underutilized components. These pilot studies have also enabled the authors to identify opportunities to use the high resolution energy-use data that is collected by the *BizWatts* system for more than just communicating individual and group-level feedback.

Large, instantaneous changes in individual energy consumption can reflect occupancy levels, allowing the *BizWatts* system to detect when an individual arrives to their desk. The ability to detect, and with enough data points, predict occupancy levels in specific physical locations of a commercial building with a high degree of accuracy can lead to multiple energy efficiency improvements. The information can be used to optimize the operation of HVAC systems, which account for nearly 43% of the energy consumption of commercial buildings [DOE 2010].

Machine learning algorithms to predict what time of day individuals arrive to a building based on their individual energy-use patterns, which are currently being developed by the authors, can inform the ideal operation schedules of HVAC systems. Furthermore, derived occupancy data can also be used to optimize spatial utilization in commercial buildings. By identifying areas in a building that are underutilized (or over-utilized), office spaces can be reconfigured to provide a more efficient work environment based on an organization's needs. The authors plan to integrate the ability to predict occupancy levels and communicate this information to relevant users in future versions of *BizWatts*.

Future Research Avenues

The results of a *BizWatts* system pilot study [Gulbinas 2013] have indicated that organizational networks can have a tangible impact on energy conservation. As *BizWatts* evolves to support much larger and more complexly structured organizations, it will become possible to investigate hierarchical pressures on network-level energy consumption and differences in network effects that may arise at varying organizational sizes. It will also be possible to install *BizWatts* across multiple organizations to study how influence may extend across networks of independent organizations of various types and sizes, thus helping inform large-scale regional load shedding strategies.

Beyond the organizational network dynamics and eco-feedback interface studies, the *BizWatts* system could be used to investigate the diffusion of energy conservation actions through organizational networks and the effects of combining advanced eco-feedback with goal-setting and hierarchical influences. These studies stand to contribute significantly to research efforts on the design of the most effective organizational energy efficiency policies.

Conclusion

BizWatts was developed to enable research into how organizational and social networks at the workplace behave when goal-setting, normative comparisons and user rankings are combined with high-resolution, high-frequency energy feedback. It is a unique system that is designed to integrate with existing organizational structures to collect a range of clickstream data that allows for the quantification of user, network, and hierarchical influences on individual energy use. Furthermore, it provides a rich environment for users to exchange conservation tips and to collaborate to reduce group energy consumption. The findings from studies enabled by *BizWatts* will impact the design of organizational energy efficiency policies and may provide unique insights related to the effectiveness of different energy management strategies. The development of the *BizWatts* system represents an integral step towards deepening our understanding of the dynamics at the intersection of the human and built environment anecessary for realizing substantial energy consumption reductions in commercial buildings.

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CHAPTER 3: EFFECTS OF REAL-TIME ECO-FEEDBACK AND ORGANIZATIONAL NETWORK DYNAMICS ON ENERGY EFFICIENT BEHAVIOR IN COMMERCIAL BUILDINGS[4]

Abstract

Commercial buildings account for a significant portion of energy consumption and associated carbon emissions around the world. Consequently, many countries are instituting building energy efficiency policies to mitigate the negative environmental impacts of building operations. As building owners and operators act to address the challenge of increasing energy efficiency, occupant behavior modification programs are growing increasingly popular. Recent advances in energy monitoring and control technologies have enabled the development of eco-feedback systems that collect, process, and relay high resolution, real-time energy consumption information to help building occupants control their energy-use. These systems have extended research into the effects of high resolution eco-feedback on building occupant behavior and energy efficiency from residential to commercial building settings. However, little is understood about how organizational network dynamics impact user-engagement levels with such systems and how these network connections may impact the energy conservation behavior of individuals inside commercial buildings. In this paper, results are presented from a novel 9-week eco-feedback system study which demonstrates that organizational network dynamics can significantly impact energy conservation among commercial building occupants. Furthermore, it

[4] This paper was co-authored by Prof. John Taylor and is under review to be published in Energy and Buildings.

Keywords: Behavior; Commercial Buildings; Eco-feedback; Energy Management; Organizational Networks; Social Networks

is shown that exposure to eco-feedback impacts building occupant energy conservation differently in commercial office buildings than it does in residential buildings.

Introduction

Buildings represent a major link between society and the environment and are an essential element in any strategy designed to promote environmental sustainability. In the United States, where humans spend nearly 90% of their time indoors [EPA 2013], buildings are responsible for roughly 41% of all carbon emissions [EIA 2009]. Without significant interventions, CO_2 emissions from US buildings are expected to increase faster than any other sector over the next two decades with commercial building emissions projected to grow the fastest, at 1.8% each year through 2030 [USGBC 2007]. To combat this alarming projection, the United States has set a federal target of reducing total national greenhouse gas emissions by 80% by 2050 [US White Hourse 2012]. As buildings account for approximately 40% of all US energy consumption [5], one strategy for achieving this ambitious emissions reduction goal is to motivate widespread building-sector energy conservation. This approach has spurred numerous initiatives that promote energy efficiency, including: efficiency rating and certification programs for buildings [USGBC 2013, RESNET 2013] and appliances [EPA 2013], the establishment of energy data standards and repositories [Green Button 2013], and the development of Building Energy Management System (BEMS) standards [ISO 2013].

Background

Acknowledging emissions reduction targets and energy conservation initiatives, researchers have increased efforts to improve building energy efficiency by focusing on the development of technological innovations (insulation, lighting, heating, cooling systems) as well as effective behavioral modification strategies (feedback, goal-setting, information campaigns). However, while technological advancements have benefited both residential and commercial buildings, behavior-based energy conservation research has traditionally focused on residential buildings.

Advances in computing capabilities and data analysis techniques have enabled the development of energy efficiency programs and research studies of unprecedented scale. Following the example of seminal residential energy feedback studies dating back to the late 1970's [Seligman 1978, Becker 1978], recent studies have investigated the effects of goal-setting [McCalley 2002, Abrahamse 2007], normative comparisons [Nolan 2008, Iyer 2006], and descriptive and injunctive norms [Schultz 2007] on energy conservation. The results of these studies have spurred the development of utility-scale residential energy feedback programs [OPower 2011, ComEd 2011] that have resulted in significant energy savings that have been externally verified with large data sets of size [Allcott 2011]. Furthermore, technological advances have also enabled the development of web-enabled eco-feedback systems that communicate increasingly high-resolution and high-frequency energy-use feedback [Gulbinas 2013] that building occupants can learn from in order to take action to conserve energy [Froehlich 2008].

Eco-feedback systems have facilitated behavior-based energy efficiency studies in single-family buildings as well as multi-tenant complexes and have contributed many insights into how feedback granularity [Ueno 2006, Fischer 2008], social comparisons and rankings [Foster 2012, Petkov 2011, Peschiera 2010], competitions [Petersen 2007], and data representation [Jain 2013] all impact energy efficient behavior. Furthermore, interactions between users over such systems have also revealed that social network dynamics significantly impact energy conservation [Peschiera 2012] and users directly influence one another's energy conservation behavior [Jain

2013]. Studies enabled by the application of eco-feedback systems, which have even been the focus of usability studies [Grevet 2010, Jain 2012, Chen 2014, Wood 2007], continue to garner behavioral, sociological, and psychological insights related to energy conservation. However, despite the quantity of behavior-based research in residential buildings and the fact that eco-systems have been observed to yield significant building-level energy savings ranging from 5-55% [Dietz 2009], commercial buildings have more slowly adopted eco-feedback technologies as they have become more cost-effective.

Advanced eco-feedback systems stand to benefit commercial buildings by empowering building occupants to conserve energy, an effective strategy for achieving significant energy-use reductions as demonstrated by simulation models [Azar 2011, 2012], academic research studies [Carrico 2011, Siero 1996] and industry sponsored energy efficiency initiatives [USPS 2012, Starbucks 2012]. Furthermore, modular eco-feedback systems [Gulbinas 2012] allow commercial buildings to realize potential energy savings without necessitating intrusive physical building retrofits and equipment upgrades, which are often capital intensive and subject to a split incentive structure in which building owners bear the initial investment costs while commercial tenants benefit from resulting reduced operating costs [Randazzo 2011]. As eco-feedback systems have only recently begun to be designed for and utilized in commercial buildings, it is essential to understand how individuals interact with these systems in the presence of organizational and social forces that are often absent in residential settings. Through targeted studies, it is possible to determine the potential of eco-feedback systems to drive energy conservation in commercial buildings and to understand how to optimize the design of such systems to maximize energy savings through behavior-based interventions.

An important first step for determining the energy-savings potential of eco-feedback systems in commercial buildings is to understand how energy feedback can impact behavior in an environment where individuals have no direct financial responsibility regarding their energy-use. Utilizing advanced eco-feedback systems, recent studies have been able to engage commercial building occupants with real-time energy-use feedback while also monitoring changes in their actual energy consumption. One of the first attempts to quantify the effects of individual eco-feedback on conservation behavior in commercial buildings found that such feedback does not necessarily result in sustained energy savings [Murtagh 2013]. It should be noted, however, that this study was conducted in a university building in which occupants were comprised of students, researchers, and lecturers. It is therefore necessary to extend eco-feedback research to commercial buildings in a more representative non-university setting where organizational and cultural forces may be more prevalent, as these have been shown to significantly influence individual conservation behavior and attitudes [Zhang 2013].

In this paper, results are presented from an empirical eco-feedback study conducted in a non-university affiliated commercial office building where building occupants were provided with access to energy-use feedback through an advanced eco-feedback system that connects individuals over organizational networks [Gulbinas 2014]. The study was designed to investigate whether: 1) exposure to individual energy-use feedback leads to a reduction in personal energy-use among commercial building occupants, and 2) organizational network dynamics, e.g. normative pressures, impact commercial building occupant energy consumption. The second research question aims to expand on the results of two prior studies. The first study, in which information about energy saving actions was collected and communicated manually, found that employees exposed to comparative group-based feedback adopted more energy saving actions than groups who only received feedback about their own actions [Siero 1996]. The second study, in which an advanced eco-feedback system was used, found that occupants in a multi-tenant residential building who received social network energy data in addition to their own conserved more energy than individuals who were exposed only to personal energy-use feedback [Peschiera 2010]. It is therefore important to understand if the same network and normative effects are observed among commercial building occupants exposed to real-time energy-use feedback. An understanding of how eco-feedback and organizational network dynamics impact energy-use behavior among commercial building occupants can be used to increase the effectiveness of future eco-feedback system designs to realize maximum energy saving potential.

Methodology

To determine how individual energy feedback and organizational network dynamics may impact energy-efficient behavior among commercial building occupants, a controlled 9 week study (following a 3 week baseline period) involving 98 employees in a non-university affiliated commercial office building was conducted.

Study Building

The study was conducted in a 6-story multi-tenant commercial office building (Fig. 11) located in downtown Denver, CO. The 40,000 square-foot LEED certified building, owned and operated by the Alliance for Sustainable Colorado, was originally built c. 1908. Since then, it has gone through numerous rebuilds and renovations, the most recent of which was completed in 2004 when it underwent major energy-efficiency upgrades. During the period of the study, approximately 115 full-time employees spanning 27 non-profit organizations occupied the building. The majority of organizations in the building possessed an environmental focus and were already committed to sustainable practices prior to the start of the study. Employees typically occupied the building during regular working hours, from 9:00am to 5:00pm from Monday to Friday. Outside of these regular working hours, the building doors were locked to the general public. Power monitors were installed at each assigned workstation/desk in the building and recorded the total electricity consumption of all connected appliances. Typically connected

Figure 9: Alliance for Sustainable Colorado

appliances included computers, monitors, space heaters, and electronics chargers. Furthermore, each floor in the building had electrical sub-meters installed, which were present prior to the start of the study.

Study Design and Hypotheses

In order to isolate the impacts of exposure to individual energy-use feedback and organizational network dynamics on energy conservation behavior, participants were placed in groups with different levels of access to energy feedback (additional recruitment details are provided in the following section):

- *The Individual Feedback group (Group A - 47 people)*: participants in this group received access only to their own current and historical energy-use feedback. Unlike *Study Group B,* individuals could not view the energy-use information of others in their organization and therefore could not make direct comparisons over the eco-feedback system.
- *The Organizational Network group (Group B - 29 people)*: participants in this group received access to individual and group-level current and historical energy-use feedback as well as the energy-use information and self-reported conservation actions of other employees in their organization. Energy data sharing permissions and network connections were pre-populated into the eco-feedback system before the start of the study.
- *The Control group (22 people)*: individuals in this group received no access to energy-use feedback and could not access the eco-feedback system. Energy-use information was still recorded for individuals in this group.

To control for the possibility of social interactions that could potentially confound study results (e.g. sharing energy-use information with participants in other study groups), participants were assigned to groups according to their physical location within the study building and the size of their respective organizations. *Study Group A* consisted of individuals working for several independent organizations consisting of 1-9 employees, which were distributed over four floors. *Study Group B* included the two largest organizations in the building, which spanned two floors.

Finally, the *Control Group* consisted of individuals who opted out of receiving feedback and were physically distributed over all floors, in order to mitigate potential energy-use idiosyncrasies related to physical location within the building.

Data collected for individuals in the three groups were used to test two hypotheses:

Hypothesis 1: Individuals with access to only their own, personal energy consumption feedback (*Group A)* will reduce their average daily energy-use relative to their baseline values and the control group.

Hypothesis 2: Individuals with access to personal energy consumption feedback and that of others in their organizational networks (*Group B)* will reduce their average daily energy-use relative to their baseline values and the control group.

Recruitment

Approval for a human subjects experiment was obtained from Virginia Tech's Institutional Review Board prior to the recruitment process. During the recruitment period, announcements about the study were made through email messages and in-person interactions with researchers. Participants could sign up in-person or on a Virginia Tech hosted website that also contained detailed information about the study. Recruitment materials emphasized that study participation was optional and that participants could potentially access their own energy-use feedback as well as that of their colleagues, and that their energy-use data might be reciprocally shared among colleagues. Potential environmental benefits associated with study participation were not included in recruitment materials. In total, 76 out of approximately 115 full-time employees agreed to participate in the study by receiving and/or sharing energy-use information. Employees who opted-out of the study cited a lack of time, an inability to commit, and concerns over privacy, which have also been raised in other energy feedback studies [Coleman 2013]. Study participants consisted of employees of varying ages, with a higher concentration of young professionals between the ages of 25 and 35. Slightly more women (62%) elected to participate than men.

Eco-Feedback System Architecture

The study was enabled by the development of a novel eco-feedback system, BizWatts [Gulbinas 2014], which collects energy-use data through commercially available plug load power monitors. Each power monitor connects to standard North American 120V outlets and wirelessly communicates a connected appliance's power information via 900 MHz RF signal to an edge router that uploads data to a database via Ethernet connection. Time, location, real power (W), current (A), voltage (V), and power factor data were pushed through the router every 15 minutes to a database hosted on an Amazon Web Services server and managed by the People Power Company. BizWatts retrieved the energy-use information from the People Power server and periodically moved data to an independently hosted database, where it was stored and parsed to expedite data visualization loading. To minimize these load times, same day power and energy information was retrieved directly from the People Power server, while aggregated and pre-processed historical energy information was retrieved from the BizWatts server. While up to 12 appliances (e.g. computers, fans, space heaters) can be independently monitored for each user, in the study only the total energy-use of all connected appliances for each study participant was monitored – future studies will investigate if appliance data granularity impacts conservation behavior.

Study Procedure

Once energy monitors were installed at each workstation, baseline energy-use data was collected for 3 weeks from April 17th to May 8th. The study commenced on May 9th, 2013 following an email to participants in *Groups A and B*. The email announced the official launch of the study and included BizWatts login information as well as a link to a video tutorial describing how to use specific system features.

The study lasted for 9 weeks from May 9th to July 9th, during which energy-use and clickstream data were collected for each participant. Additional emails were sent to participants in *Groups A and B* on May 28th, June 17th, and June 30th to update them about the energy saving actions that they can take and to remind them to visit the BizWatts web-based eco-feedback system. In these emails, participants in *Group B* also received information about energy conservation behavior and sustainability-oriented actions reported by other individuals in their organization. In addition to the emails, printed reminders to use the BizWatts system were also posted in hallways and common areas throughout the building. These reminders remained until the end of the study, when a final email was sent to announce the completion of the study.

A total of ten individuals (one in *Group A,* nine in *Group B*) were removed from the analysis. Several individuals in *Group* B were removed due to an isolated network disruption which caused an edge router to stop reporting energy data for the majority of the study period. As individuals were assigned groups according to organizational and physical proximity, the disruption was locally contained and only impacted a subset of *Group B*. In addition, other individuals quit their organizations or relocated outside the study building during the course of the study and had to be removed.

Data Analysis

To control for externalities (e.g., weather, schedule variations, power outages) that could impact individual energy consumption trends over the duration of the study, all data analysis was conducted using a percent difference measure relative to the consumption of the control group, as defined in the equation (2):

$$\delta_{period} = (P_{period} - C_{period}) / C_{period} \qquad \textbf{(2)}$$

The subscript 'period' specifies the range of days over which δ is calculated, (P) is the average daily power draw of a user over the period and (C) is the average per capita daily power draw of the control group over the period. To determine if a study group's average level of energy consumption changed after gaining access to energy feedback, δ was calculated for each user's baseline and study periods. The distributions of δ values for each group's users were then tested for normality, after which appropriate statistical tests were selected to compare means between baseline and study periods. For normal distributions, a student paired t-test was used; otherwise, a Wilcoxon signed-rank test was used. A student paired t-test is a method for testing if two data sets that are each normally distributed are statistically distinct. If either of the data sets does not follow a normal distribution, then a more general non-parametric statistical test (Wilcoxon signed-rank test) must be used to determine if the means of the two data sets are statistically distinct. In the case of this energy efficiency study, if the distribution means are statistically distinct at a 95% confidence level, it could be inferred that the feedback intervention may have changed the level of energy consumption for the target group.

In addition to monitoring individual and group-based energy-use data for analysis, BizWatts collected time-stamped user clickstream data to facilitate analysis of the frequency and types of interactions that users have with the system. Over the course of the study, clickstream data related to logins, page visits, graph views, and posts on the system were collected for each user. More detailed information about the full range of clickstream data collected by the BizWatts system can be found in [Gulbinas 2014]. General differences in the level of interaction among users in different groups were observed and are described in the following section.

Results

Fig. 10 graphs the differences in energy consumption between participants in *Groups A and B* relative to the control group for each day from the start of the baseline period to the end of the study. During the first 4 weeks of data collection (including the baseline period), there is little discernable separation between the energy consumption of *Study Groups A and B.* However, about 3 weeks after access to energy feedback was provided, a general trend in which *Group B* begins to consistently consume less than *Group A* relative to the control group can be observed.

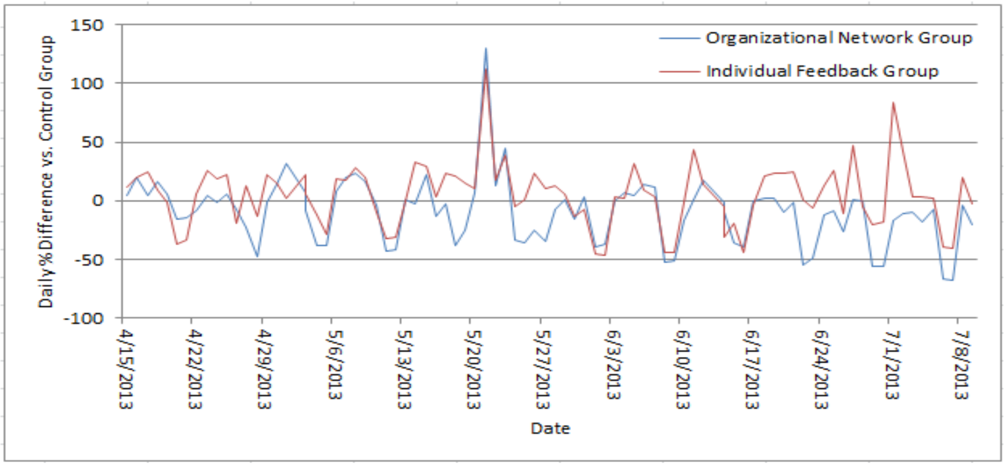

Figure 10: Percent difference values for Network Feedback and Individual Feedback Group

On average, individuals in the organizational network group consumed 13% less energy than the control group for each day after the start of the study. In addition to the observed trending separation, there was sudden spike in energy-use for both groups relative to the control group on May 21st 2013. It was confirmed that an unusually large number of individuals in the control group were absent on that day, resulting in the spike.

After calculating δ values for users in each group over baseline and study periods, Kolmogorov-Smirnov tests were used to test for normality. The Kolmogorov-Smirnov test is a standard goodness-of-fit test that compares an empirical data set to any given statistical distribution. In this case, the set of δ values for each study group was compared to a normal distribution and tests revealed that the distributions of each group's δ values over baseline and study periods were not distinct from a normal distribution at a 95% confidence level. As a result, student paired t-tests were used to test for statistically significant differences between each group's baseline and study period energy consumption levels. Results from these tests are presented in Table 4.

Table 4: Group A and B performance during study period relative to baseline period

Baseline to Study Period				
Study Group	95% Confidence Interval		Mean of Differences	p
	Lower Bound	Upper Bound		
Organizational Network Feedback	1.053	12.793	6.923	0.02266*
Individual Feedback	-7.61	30.34	11.3656	0.2324

*Statistically significant (p<0.05)

At a 95% confidence level, there was not enough evidence to reject the null hypothesis for Hypothesis 1 that there was no change in *Group A's* average individual energy consumption from the baseline to the study period, though the p-value of 0.2324 may suggest weak evidence of an intervention effect that should be examined in future research with a larger number of participants. Alternately, the difference in the mean energy consumption from baseline to study period for *Group B* was statistically significant (p-value=0.02266) enabling the rejection of the null hypothesis associated with Hypothesis 2. This difference suggests that the ability to directly compare personal energy-use feedback with that of others may indeed motivate significant energy conservation among individuals. It should also be noted that although the difference in means for the individual feedback group is greater than for the organizational network feedback group, the variance of energy-use among members in the individual group was also greater, which explains why this larger difference was not statistically significant.

The results from the study are consistent with findings by Siero et al. [1996], who found that comparative energy-use feedback between groups is more effective than individual feedback for motivating energy conservation actions. They also expand on the primary findings of Peschiera et al. [Peschiera 2010], who observed similar impacts on energy-use among individuals exposed to social network energy-use data in a residential building. However, while these results are consistent with previous studies, the increasingly consistent separation of energy-use trends between the two study groups relative to the control group observed in Fig. 10 suggests that the effects of feedback on energy-use differs between commercial and residential building occupants. Peschiera et al. found that residential building occupant energy-use was very elastic and would drastically decrease in the short-term following email notifications sent to study participants; Fig. 10 suggests that energy conservation among commercial building occupants may be less elastic and more sustained in the long-term. To address this observation, post-hoc data analysis was conducted to determine if commercial building occupants exhibited any statistically significant short-term energy-use response-relapse patterns. To facilitate comparative analysis, the short-term response measurement periods were chosen to match those used in the study by Peschiera et al. [2010], and include the first two weeks following the launch of the study and the 3 day periods following each email notification sent to participants. Results of this response analysis are presented in Table 5.

Table 5: Responses to notification emails relative to baseline periods

Organizational Network Group				
Period	95% Confidence Interval		Mean of Differences	p
	Lower Bound	Upper Bound		
Whole Study	1.053	12.793	6.923	0.02266*
Launch (2 Weeks)	-11.153	10.086	-0.533	0.9186
5/29 Email (3 days)	-5.641	29.96	12.16	0.1721
6/18 Email (3 Days)	-16.833	12.477	-2.178	0.7621
7/1 Email (3 Days)	-17.59	43.408	12.908	0.3917

Individual Feedback Group				
Period	95% Confidence Interval		Mean of Differences	p
	Lower Bound	Upper Bound		
Whole Study	-7.61	30.34	11.3656	0.2324
Launch (2 Weeks)	-3.432	20.125	8.346	0.1593
5/29 Email (3 days)	3.506	40.319	21.912	0.02097*
6/18 Email (3 Days)	-15.511	11.831	-1.84	0.7861
7/1 Email (3 Days)	-60.01	16.838	-21.584	0.2618

*Statistically significant ($p<0.05$)

In contrast to the residential building study by Peschiera et al. [2010], there were no consistent short-term energy conservation responses following email notifications among individuals with access to energy-use information of others in their organizational networks. While the organizational network group achieved significant energy-use reductions relative to baseline levels over the course of the entire study, the only short-term period in which a statistically significant reduction in energy-use was observed was the 3-day period following the second email notification, and this was only observed for the individual feedback group. This difference suggests that energy conservation habits form more easily among commercial building occupants exposed to organizational network feedback than among residential building occupants exposed to social network feedback, as energy-use behavior is less elastic in short-term periods following email based reminders.

In addition to monitoring the energy-use patterns of commercial building occupants, the BizWatts system allows individuals to self-report energy conservation and general sustainability-oriented actions, enabling them to track their progress in adopting certain conservation strategies. With this additional information, initial energy-use analysis can be complemented by further investigating how the formation and adoption of energy conservation habits and interaction patterns with the eco-feedback system may differ between commercial and residential building occupants.

The number of reported actions by users in each study group, broken down by type of action, is presented in Table 6. The list of actions from which users could choose to report was decided on by building managers, who selected the specific actions to reflect what they believed to be

Table 6: Self-Reported Conservation Actions

Actions By Type	
Individual Only	*# Actions*
No Meat	3
Stairs	5
Bath Lights	6
Commute	7
Equipment Off	10
Common Lights	12
Organizational Network	*# Actions*
Common Lights	7
No Meat	9
Bath Lights	9
Equipment Off	17
Stairs	19
Commute	20

relevant to building tenants. Over the course of the study, individuals in *Study Group A* reported a total of 43 actions, while those in *Study Group B* reported 81 actions. Total actions reported among individuals in *Study Group B* were significantly more for each category except for 'Common Lights', which referred to turning off overhead lighting when exiting a room. Turning off common overhead lighting and office equipment were the most popular self-reported actions among *Study Group A* individuals, while taking public transportation and using the stairs (instead of the elevator) were the most popular actions among *Study Group B* individuals.

A graphical representation of the number of actions reported over time can be observed in Fig. 11. In contrast to individual energy-use patterns which did not exhibit significant short-term changes in response to email notifications, the number of self-reported actions seemed to spike following reminders.

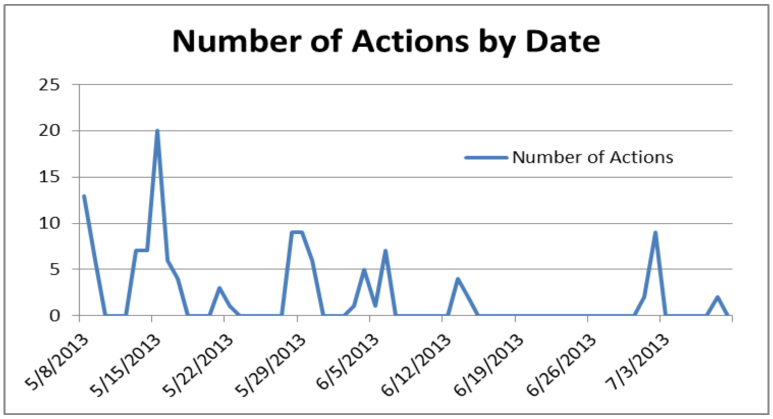

Figure 11: Number of Actions by Date

Users reported the most number of actions in the first two weeks of the study launch, with local maxima observed on dates following email notifications sent on May 29th and July 1st. These patterns suggest that email notifications are useful for reminding commercial building occupants to interact with eco-feedback systems and to report conservation actions.

Further evidence that email notifications effectively spurred increased user interaction with the eco-feedback system can be observed in Fig. 12, where user logins over time are plotted.

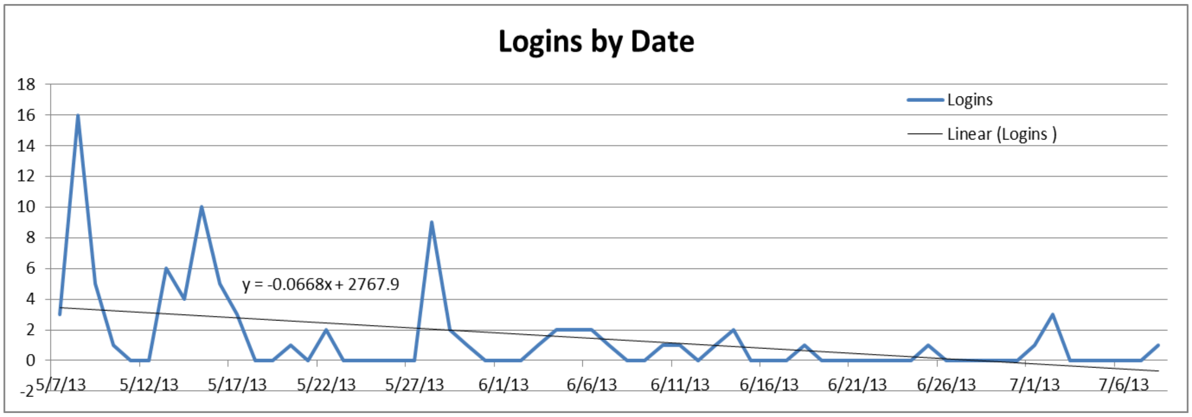

Figure 12: System Logins By Date

Exhibiting a similar pattern to the number of reported actions over time, users logged into the eco-feedback system with decreasing frequency over the course of the study. Furthermore, the system experienced the largest number of logins in the first 2 weeks of the study launch, with short-term spikes in usage corresponding to email notifications sent on May 29th and July 1st. Among all study participants, 42% interacted with the eco-feedback system: approximately 40% of participants in *Study Group A* and 45% in *Study Group B*. *Study Group B* participants who logged into the system averaged about 4.23 logins per person, while those in *Study Group A* only averaged about 1.74 logins per person, suggesting that connecting individuals over organizational networks within an eco-feedback system can motivate them to use the system for frequently and report more actions than if they could only access personal information.

Discussion

Findings from this commercial building energy efficiency study provide many new insights that expand an understanding of how commercial building occupants utilize personalized individual and group-based energy feedback. Consistent with previous research studies in settings where building occupants had no direct financial incentive to conserve energy [Peschiera 2010], it was observed that commercial building occupants who could directly compare current and historical energy-use patterns with others conserved a statistically significant amount of energy relative to a control group and baseline period. In this study, the ability to compare energy-use information with others was limited to the structure of pre-existing organizational networks within the commercial building, thus providing empirical support for previous survey-based findings that organizational culture is an important factor for motivating energy conservation [Zhang 2013]. However, while organizationally connected commercial building occupants did conserve statistically significant amounts of energy, they did not exhibit the same response-relapse patterns as residential building occupants. Energy savings were steady through the duration of the study with no sudden significant short-term decreases in energy consumption following email notifications, suggesting that energy conservation behavior in commercial buildings may be more steady and persistent than in residential buildings.

Also consistent with previous building eco-feedback studies [Peschiera 2011, Murtagh 2013], it was observed that isolated personal energy-use feedback was not sufficient to significantly impact energy conservation behavior. The inability for users to interact with others in their organizational networks also directly impacted the frequency with which users logged into the eco-feedback system and reported conservation actions. Individuals in the organizational network group logged in about 2.5 times more often than those in the individual feedback group, supporting results from another residential eco-feedback study, in which users with access to normative energy-use comparisons interacted with the feedback system nearly 5 times more than users with access only to personal feedback [Foster 2012]. Large differences in the number of reported conservation actions, which represent significant energy saving opportunities beyond desktop appliance management, were also observed. Individuals in the organizational network feedback group reported nearly twice as many conservation actions as participants in the individual feedback group, thereby supporting findings by Siero et al. [1996]. Furthermore, one of the most frequently reported actions by the organizational network group was taking the stairs instead of the elevator. As individuals in this group were located on the 4th and 5th floors of the study building, this represents the adoption and/or reporting of an action that requires non-trivial physical effort and corresponds to potentially significant energy savings not captured by the energy monitoring system.

On a general level, this study confirms that when presented with socially and organizationally contextualized energy-use information, commercial building occupants are capable of reducing energy waste attributed to appliances that are often left powered on in non-residential buildings [Marans 2010] and achieving the potential energy-savings predicted by previous simulation models through behavioral means [Azar 2011]. These findings are especially relevant considering that our study was conducted in a LEED certified building, thus demonstrating that significant energy savings can be achieved through behavioral means in already energy efficient buildings. By empowering employees and commercial building occupants with energy-use feedback, significant energy savings can be achieved without significant financial expenditures. Modular, low-cost eco-feedback systems therefore stand to significantly benefit small businesses that aspire to cost-effectively reduce operational costs through behavior based campaigns. As small businesses represent approximately 34 billion sq. ft. of commercial real estate in the United States [SBA 2013], large-scale energy savings and emissions reductions can be achieved by developing and disseminating customizable, low-cost eco-feedback technologies.

Limitations

While a statistically significant reduction in energy consumption among individuals exposed to organizational network energy feedback was observed, the study was limited to a single, multi-tenant commercial building and could have benefitted from a larger sample size. Commercial building occupants who all belong to a single, large corporation may interact differently than those in multiple, smaller organizations. Furthermore, this study was limited in its sample size and data collection was constrained to a 12 week period. While statistically significant results indicated that organizational feedback can indeed impact energy consumption in a commercial building, future studies should include an expanded sample size and be conducted over a longer period. In this way, longitudinal effects in various contexts can be better understood.

In our study, all organizations in our study possessed an environmental focus and therefore results may not translate to organizations that lack an explicit pro-environmental culture. Nonetheless, the results of the study show that even organizations with pre-existing pro-environmental cultures can benefit from energy feedback. While the system was able to monitor individual level energy-use, the study could have benefited from the added capability of confirming the conservation actions reported by users that fell beyond the scope of the monitoring system. In this way, additional energy savings could be quantified.

Future Research

A natural extension of this study would be to examine how various organization network structures (hierarchical, flat, distribution) impact energy conservation. In this study, no organizational roles were defined or emphasized in the system, and so it was not possible to track how the effect of energy-use information varies with organizational role or position.

Furthermore, as individuals in organizations often form informal social networks independent of their organizational networks, future research should examine how individuals connected to friends rather than co-workers might change their energy consumption behavior. Once it is better understood how various network effects impact energy conservation, eco-feedback systems can be better designed to accommodate these effects in order to maximize potential energy savings among users.

Conclusion

It has been demonstrated that providing commercial building occupants with individual energy feedback does not necessarily motivate them to conserve energy. However, providing individuals with access to energy-use information of others in their organizational network can result in significant energy savings. In addition, while the number of interactions with the eco-feedback system decreased over the course of the study, connected commercial building occupants maintained energy efficient behavior and did not exhibit the same response-relapse patterns as residential building occupants after receiving email notifications. Building occupants connected over the eco-feedback system also logged in more frequently and reported more conservation actions than individuals who could only access their own energy-use information, resulting in additional energy savings that the system could not directly capture. The study results imply that future commercial building eco-feedback systems should be designed to connect individuals and groups in organizations, in order to benefit from increased user-system interactions and to realize significant energy savings. As an understanding of how network connections impact energy conservation continues to develop, eco-feedback system designs should continue to be improved to maximize their potential to induce energy savings among commercial building occupants.

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CHAPTER 4: CLASSIFYING AND TARGETING INEFFICIENT ENERGY-USE IN COMMERCIAL BUILDINGS[5]

Abstract

Drawing inspiration from utility-scale customer segmentation research initiatives, a new set of metrics is introduced that serve as quantitative measures of building occupant energy efficiency and energy-use predictability. Building occupant energy-use data is segmented to facilitate the construction of independent energy-use profiles for workdays, non-workdays, work hours, and non-work hours, which in turn enable further classification of building occupants according to their energy-use patterns. The new metrics enable the design of more effective, targeted energy conservation campaigns and improved assessments of spatial efficiency (energy/occupancy). Furthermore, they can be used to improve the accuracy of energy-use prediction algorithms. We present the methodology behind the construction of the metrics and demonstrate how they can be applied to classify commercial building occupants based on their energy-use.

[5] This paper was co-authored by Ardalan Khosrowpour amd Prof. John Taylor and is under review to be published in IEEE Transactions on Smart Grid.

Keywords: Behavior, classification, clustering, commercial, building, efficiency

Introduction

Buildings account for approximately 40% of all energy consumed and 41% [EIA 2013] of all carbon emitted in the United States, where humans spend nearly 90% of their time indoors [EPA 2009]. Furthermore, CO_2 emissions from US buildings are expected to increase faster than any other sector over the next two decades with commercial building emissions projected to grow the fastest, at 1.8% each year through 2030 [USGBC 2007]. To combat these trends, myriad public and private initiatives have emerged to help spur development of new technologies to improve the energy efficiency of the US building stock [USGBC 2013, RESNET 2013, EnergyStar 2013, GreenButton 2013]. Concurrently, building sensing and automation technologies have become increasingly economical and programs designed to motivate energy efficient behavior among building occupants have become more ubiquitous [Starbucks 2012, USPS 2012, Siero 1996]. However, technology and behavior-based energy efficiency strategies in the commercial building sector have largely been designed and applied independently. Advanced commercial building management systems (BMS) that utilize increasingly extensive sensor networks often fail to engage building occupants [Marinakis 2013] and do not effectively leverage energy-use data as a proxy measure of occupancy and behavior patterns. Alternately, most behavior-based energy efficiency programs are limited in their ability to quantitatively classify building occupants by their energy-use behavior. These limitations prevent the design of more impactful resource conservation campaigns that target specific groups of inefficient energy consumers and also create a confounded incentive system where consistently efficient resource consumers are overlooked. In this paper, we introduce a new set of metrics that enable the design of more impactful behavior-based conservation strategies that leverage newly available sensing technologies; collecting data that can be simultaneously used to optimize BMS to improve efficiency and target specific building occupants for behavior interventions.

Background

Strategies for promoting energy conservation through behavioral interventions date back to the late 1970's [Seligman 1978, Becker 1978], when the effects of goal setting and feedback on energy-use in the residential building sector were first studied. Following these seminal studies, behavior-based programs and research initiatives were expanded to investigate the impacts of normative comparisons [Nolan 2008, Iyer 2006], descriptive and injunctive norms [Schultz 2007], and education on energy conservation. As a better understanding of how different approaches could motivate energy conservation was developed, energy metering technologies also evolved. The broad deployment of advanced metering infrastructure (AMI), combined with the evolution of web-enabled technologies and big data analytics, facilitated the development of a new class of scalable energy efficiency campaigns. Based on previous research [Froelich 2010, Fischer 2008, Nolan 2008, Schultz 2007], many of these campaigns enable energy consumers to learn the breakdown of their own energy-use, compare their energy-use to that of others, and to set personal conservation goals. Furthermore, these social energy-use feedback programs have been deployed and studied at different scales, ranging from single multi-tenant residential buildings [Petersen 2007, Jain 2013, Peschiera 2011] to utility-scale customer bases [ComEd 2013, OPower 2013]. At each scale, they have been shown to yield significant energy savings and have contributed to a reduction of residential building sector energy emissions [Allcott 2011, Dietz 2009].

Behavior-based interventions are also effective tools for realizing energy savings in commercial buildings. Corroborating energy-use simulation models that have shown the potential for significant energy savings through behavior modifications [Azar 2011, 2012], early empirical studies [Carrico 2011, Siero 1996] and industry conservation campaigns [Starbuck 2012, USPS 2012] have demonstrated the positive impacts of behavior-based conservation campaigns. However, despite the proven benefits of behavior-based strategies, the inability to effectively and economically monitor commercial building occupant energy-use behavior has resulted in slower adoption of such strategies by the commercial sector. This inability has made it difficult to identify and reward consistent or progressively efficient behavior among building occupants resulting in diminished incentives to conserve energy. As a result, commercial buildings have largely adopted a more technological approach for improving energy efficiency.

Advancements in sensing and monitoring technologies have enabled the development of increasingly integrated BMS that facilitate centralized monitoring and control of a number of building systems and parameters, such as: lighting, temperature, HVAC, and energy [Costa 2013, Marinakis 2013, Swords 2008]. The emergence of these sensing technologies represents a new opportunity to economically monitor energy-use of individual plug-loads and building occupants [Gulbinas 2013]. Such high resolution energy-use data enables new methods for estimating building occupant presence and behavior [Kleiminger 2013, Milenkovic 2013], which can be used to optimize building systems to run efficiently without compromising building occupant comfort. Other approaches to estimating and predicting building occupant behavioral parameters have also been attempted, including the use of motion control sensors [Agarwal 2010], light sensors [Delaney 2009], and wireless cameras [Erickson 2010]. However, individual energy-use monitoring has indirect benefits that extend beyond enabling the prediction of occupant presence and behavior; such data also enables new methods for quantitatively classifying occupants according to their energy-use patterns. The ability to identify building occupants by their energy-use efficiency allows the design of new behavioral programs that complement, rather than replace, existing BMS solutions. By combining these traditionally distinct approaches, the full potential of commercial building energy savings can be realized.

In this paper, we introduce a new set of behavioral metrics that are enabled by the collection of energy-use data that can be associated with an individual building occupant. Drawing inspiration from utility-scale customer segmentation strategies [Albert 2013, Kwac 2014, Smith 2012], these metrics enable the classification of individual building occupants based on their energy-use efficiency and consistency. The ability to classify occupants based on efficiency allows consistently energy efficient building occupants to be recognized and rewarded. Alternately, inefficient energy consumers can be identified and targeted for interventions, which may include a resource conservation short-course and/or a setting of efficiency goals. In addition, the entropy-based consistency metrics will enable improved predictions of building occupancy and occupant energy-use, thus informing HVAC system operation schedules and leading to improved responsiveness to future demand-response programs. We introduce the methodology behind the construction of the metric in the following section.

Methodology

The classification of commercial building occupants based on their energy efficiency and energy-use entropy consists of three major processing stages, as represented in Fig. 13.

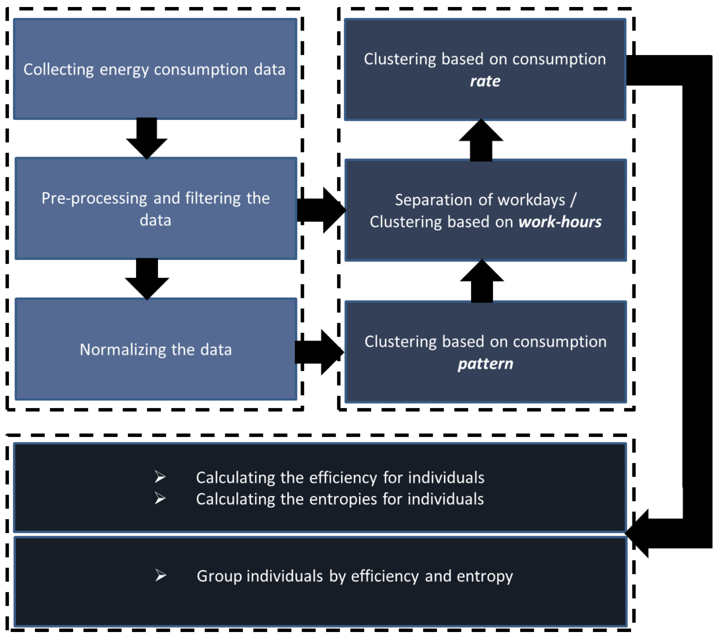

Figure 13: Building Occupant Classification Flow

Pre-processing and Organization

The first stage begins by pre-processing the data by correcting any corrupted values due to lost network connections during data collection. Prolonged durations of corrupted or missing data are identified and appropriately filtered in order to prevent biased classification results; techniques for pre-processing vary with application. Next, two base matrices for each building occupant are constructed, which are referenced throughout the subsequent clustering and classification stages. The first matrix, mat_A, contains non-normalized energy-use or power data (from here-in only energy-use data will be referenced for the sake of simplicity), indexed by day and sub-indexed by time interval. The second matrix, mat_B, shares a similar structure as mat_A and consists of energy-use data normalized over each day, where:

$$mat_B(i,d) = \frac{mat_A\,(i,d)}{max_e(d)} \qquad (1)$$

$mat_A(i,d)$ is the energy consumed over time interval i of day d and $max_e(d)$ is the maximum energy accumulated over any single time interval of day d. In order to facilitate usable clustering results, it is recommended that time intervals be set at a maximum of 1 hour.

Clustering and Separation

The second stage is defined by three sequential clustering phases with intermediate filtering processes that effectively separate a building occupant's workdays, non-workdays, work hours, and non-work hours.

Workday Separation

The aim of the initial clustering phase is to enable the separation of workdays from non-workdays, which are defined as days that a building occupant does not come to the building. For each cluster phase, we employ a slightly modified version of the classical K-means algorithm, which has been successfully applied to day-based time-series energy-use data in several prior

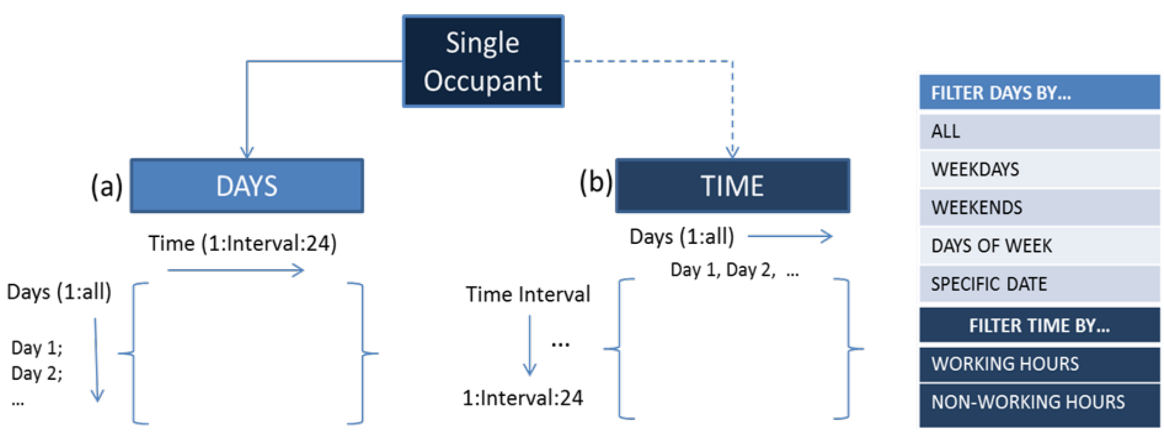

Figure 14: Matrix structuring for subsequent clustering stages

studies [Albert 2013, Green 2014, Kwac 2014, Mutanen 2010]. As the first clustering phase aims to separate daily load profiles by shape for workday classification, the normalized mat_B is utilized. In preparation for clustering, mat_B is reshaped according the structure in Fig. 14. In order to effectively create workable sets of workdays and non-workdays based on daily energy-use load profiles, it is essential to obtain a sufficiently representative set of clusters while minimizing sparse clusters with relatively few members.[6]. To this aim, we employ a distributed K-means algorithm that seeks to maximize the number of representative clusters while maintaining a minimum percentage of total members in each cluster, as outlined in Algorithm 1. Once the initial set of clusters has been established using algorithm 1, it is necessary to classify the cluster centers and respective members as workdays or non-workdays, as described in Algorithm 2. The first filtering pass compares the range of each normalized cluster center against a minimum threshold ($0 \leq threshold \leq 1$) with the assumption that workdays are defined by relatively large variations in daily energy-use profiles. The second filtering pass is designed to check against low energy-use signal noise by comparing the non-normalized energy-use range of each day in each workday cluster against a minimum non-negative threshold of energy, as observed in Fig.16. The two step process effectively separates workdays from non-workdays first by shape and then by absolute levels of energy-use.

[6] The initial clustering phase is also required for subsequent energy and occupancy prediction applications, which are based on the shape of the daily load profiles and are not discussed in this paper.

Algorithm 1 Distributed Day K-means algorithm

Require: Normalized daily load shapes for single user (mat_B) over minimum number of days (Typically more than 20 Days)
Set K = minimum % of total days in each cluster
Set N = Initial number of clusters (15% of total days)
_pass = False
while _pass = False **do**
  _check = True
  Run K-means with N initial centers
  for all clusters **do**
    Check if % of days in cluster (# days in cluster / # total days) $\geq$ K
    if % days in cluster $<$ K **then**
      _check = False
    end if
  end for
  N = N - 1
  if _check = True or N = 1 **then**
    _pass = True
  end if
end while
return N clusters

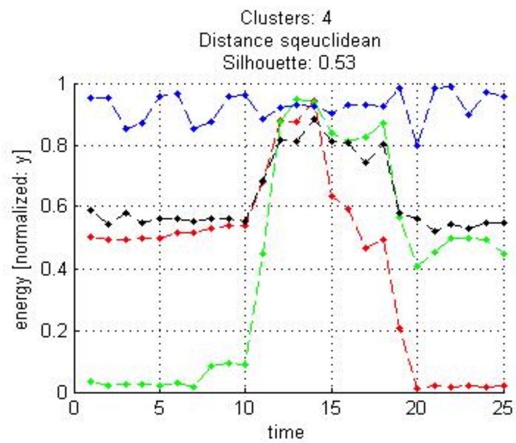

Figure 15: Initial Distributed Clustering Phase Results using Algorithm 1

Algorithm 2 Workday separation algorithm

Require: Distributed Day K-means Results
C_i: Cluster center i $\in$ (1,.....,N)
$D_{j,i}$: Day j $\in$ (1,.....,n_i) in cluster i
Set n_thr = minimum normalized range difference threshold
Set non_thr = minimum non-normalized range difference threshold
Workdays = []
NonWorkdays = []
for all C_i **do**
  Check if normalized center range is above threshold
  if max(C_i) - min(C_i) $<$ n_thr **then**
    for all $D_{j,i}$ **do**
      Check if day range is above non_norm threshold
      if max($D_{j,i}$) - min($D_{j,i}$) $<$ non_thr **then**
        add $D_{j,i}$ to Workdays
      else
        add $D_{j,i}$ to NonWorkdays
      end if
    end for
  else
    add $D_{j,i}$ to NonWorkdays
  end if
end for
return Workdays, NonWorkdays

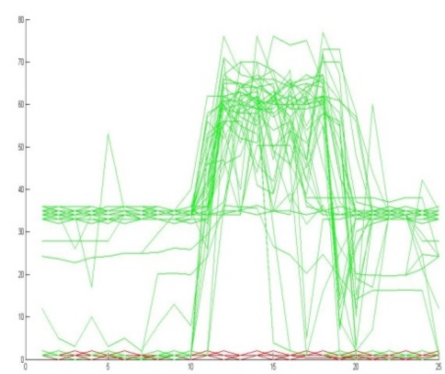

Figure 16: Second Pass Non-normalized Workday Detection and Separation

Work hour Separation

Following the separation of workdays and non-workdays, it is necessary to further decompose the workdays into work hours and non-work hours. By decomposing an individual building occupant's workdays, we are able to further analyze their energy-use behavior at different times of the day. As behavior-based energy efficiency is primarily a function of the frequency at which an individual unnecessarily consumes energy, it is critical to separate necessary energy usage from unnecessary usage. We define work hours as the range of time intervals on workdays during which a building occupant exhibits a consistently high-level of energy consumption relative to other hours of the work day.

We independently determine separate sets of work hours and non-work hours for each occupant as observed in Fig. 17, where two non-work hour ranges ([1-11],[19-24]) are distinguish ed from one work hour range ([12-18]). This separation is accomplished by first combining all

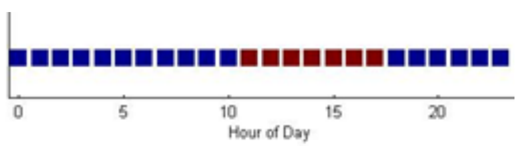

Figure 17: Work hour Range

days in each workday cluster into a single super workday cluster. Next, the mean non-normalized energy level for each time interval across all workdays in the super-cluster is calculated. Standard k-means clustering is then used to separate the array of mean values into two clusters, representing work hours and non-work hours, and the resulting ranges are then used in the third clustering phase.

Workday and Non-Workday Clustering

The final clustering phase enables the classification of sufficiently distinct levels of energy consumption for each separate temporal range (non-workdays, workday work hours, and workday non-work hours) across all days for a single building occupant. In order to enable such classification, the final clustering phase combines algorithm 1 with a secondary separation sequence, described in algorithm 3. Algorithm 3 guarantees that the mean of each cluster center is at least a minimum Euclidian distance away from all other cluster centers, thus enabling

Algorithm 3: Minimum Cluster Separation

Require: Distributed Day K-means Result
- C_i: Cluster center i ∈ (1,….,N)
- $D_{j,i}$: Day j ∈ (1,…..,n_i) in cluster i
- Set non_thr = minimum non-normalized range difference
- Find the 2 closest cluster centers C_i and C_j
- **if mean(C_i) – mean(C_k) < n_thr**
  - **if** N > 2
    - re-cluster with N–1 centers
    - re-run Minimum Cluster Separation with…
      N-1 center results
  - **else**
    - $C_i = (n_iC_i + n_kC_k)/(n_i + n_k)$
  - **end if**
- **end if**

categorical classification of clusters based on ranges of energy-use levels (low/medium/high). Fig. 18 displays the end result of algorithm 3 for a single building occupant over each temporal range. Each non-work range is effectively separated into two distinct clusters, while the work

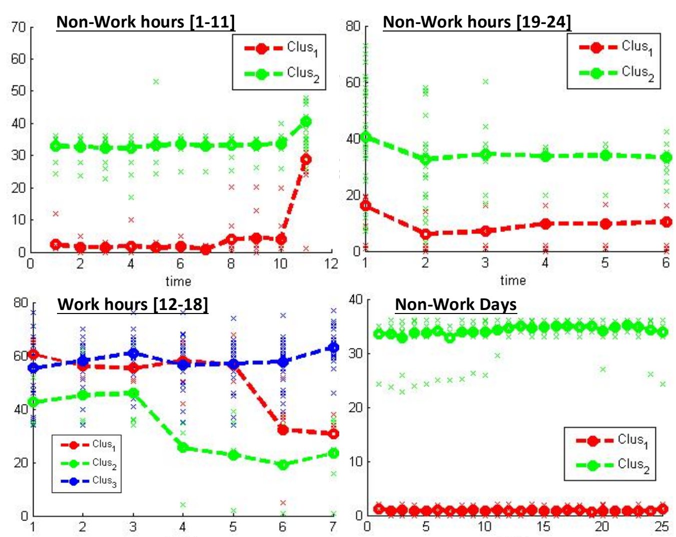

Figure 18: Work Day and Work Hour Minimum Cluster Separation

hour range is best separated into three distinct clusters. The results observed in Fig. 18 are used to determine energy efficiency and energy-use entropy of the occupant in the final processing stage.

Occupant Efficiency and Entropy Calculation

Once time across all analyzed days has been effectively decomposed into non-work day, work day work hour, and work day non-work hour segments, and the energy-use for each segment has been separated into distinct clusters, it is possible to calculate values representative of a building occupant's energy efficiency and energy-use entropy.

We define an individual building occupant's energy efficiency, EE_i, as the percentage of time spent in low energy level clusters (i.e. energy clusters centers with mean values that fall below a predefined maximum threshold). In our examples this threshold was set to 7Wh of energy consumed per hour to reflect estimates of average power consumed by connected appliances in the off state. However, this threshold could vary greatly according to different applications. Energy efficiency as a metric is summarized by equation 3:

$$EE_i = \frac{\sum_1^r h_k \times p(LC_k) \times WD + 24 \times p(LC_n) \times NWD}{\sum_1^r h_k \times WD + 24 \times NWD} \qquad (3)$$

where r is the number of workday non-work hour ranges, h_k is the number of hours in each non-work hour range, k, and $p(LC_k)$ is the probability that the workday non-work hour range is assigned to a low energy cluster. *WD* and *NWD* are the number of workdays and non-workdays as determined by the first clustering phase, and $p(LC_n)$ is the probability that a non-workday is assigned to low energy clusters. Equation (3) represents a weighted average of the amount of time spent in low energy clusters during non-work hours across all days processed for a single building occupant. *EE* values range from 0 to 1, with 1 representing the most energy efficient case in which a building occupant always turns off all appliances during non-work times. Alternately, lower EE values are indicative of more time spent in non-low energy clusters, and occupants with relatively low EE values could be categorized as inefficient. The threshold between 0 and 1 for categorizing building occupants can be manually determined as there is no set definition in literature for individual building occupant efficiency.

Unlike energy efficiency, energy-use entropy is simply a function of the number of distinct clusters over each temporal range, independent of the level of energy-use. The weighted calculation of a building occupant's energy-use entropy, S_i, is described by equations (4a) and (4b):

$$s_l = -\sum_{i=1}^{L} p(C_i)\, log_{10}\, p(C_i) \qquad (4a)$$

$$S_i = \frac{\sum_1^T h_l * s_l}{\sum_1^T h_l} \qquad (4b)$$

where s_l is the entropy of any temporal range, l, that is defined by h_l hours and over which energy-use patterns fall into a total of L clusters using algorithm 3. T is the total number of temporal ranges for which entropy is calculated and can be selectively chosen to include a combination of non-workdays, work hours, and workday non-work hours. In this way, the sensitivity of a building occupant's energy-use entropy to different temporal parameters can be investigated. In addition, specific sets of days and time intervals (listed in Fig. 14) can be filtered to facilitate more targeted analysis. A different application may combine energy-use entropy with the magnitude of work hour energy-use. Building occupants defined by low entropy and a high rate of energy-use during work hours may be targeted for equipment replacement. These consistent, high energy level consumers would benefit the most from more energy efficient equipment, which would reduce otherwise unavoidable, relatively high energy intensity work hour operations.

Experimental Data Analysis and Classification

The data used to demonstrate the classification results of the algorithms and equations presented in the previous section were collected during an energy-use feedback study (Gulbinas) conducted in Denver, Colorado between April 17th and July 9th in 2013. The data represent continuously monitored desk-load electricity use for 87 commercial building occupants over a total of 83 days (59 weekdays, 24 weekend days). Time, location, real power (W), current (A), voltage (V), and power factor data were recorded by each building occupant's energy monitoring device every 5 minutes and uploaded to a central server every 15 minutes. The building occupants were distributed over six floors and were full-time employees who typically occupied the building during regular working hours, from 9:00am to 5:00pm from Monday to Friday. Building occupants had different sets of electrical appliances connected to their energy monitoring devices, and therefore baseline energy-use levels varied from one occupant to the next. Typically connected appliances included computers, monitors, space heaters, and electronics chargers.

The results of the initial clustering phase when applied to an aggregation of all weekdays and building occupants are presented in Figs. 19 (a) and (b) to demonstrate the effects of algorithm 1. In 19 (b), each cluster represents at least 10% of all analyzed days, confirming the effectiveness of the algorithm in selecting the largest number of representative non-trivial clusters. It should be noted that the distribution of clusters for each device (i.e. building occupant) in Fig. 19 (b) may not represent each cluster to the same relative degree as in the aggregate. However, when the algorithm is applied to a single occupant at a time, as is required for the efficiency and entropy analysis, the distribution requirement is upheld.

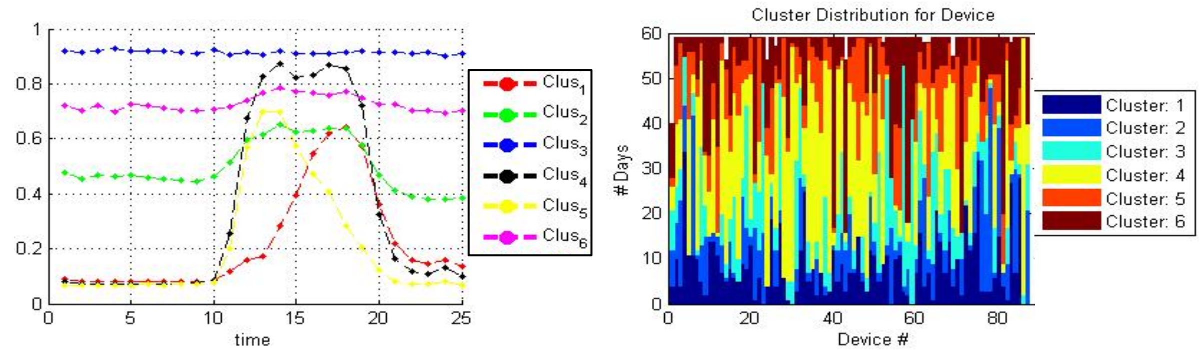

Figure 19: (a) Group Energy-Use Clusters and (b) Cluster Distributions

Workday Schedule Analysis

Results of the second clustering phase, in which workdays, work hours, and non-work hours are separated for each building occupant are presented in Figs. 20 and 21. Fig. 20 shows the ratio of workdays to non-workdays for each occupant as separated by the Algorithm 2. Red points to the far left represent occupants with very few identified workdays, for which efficiency and entropy analysis is limited to non-workdays. At the other extreme are occupants with few non-workdays,

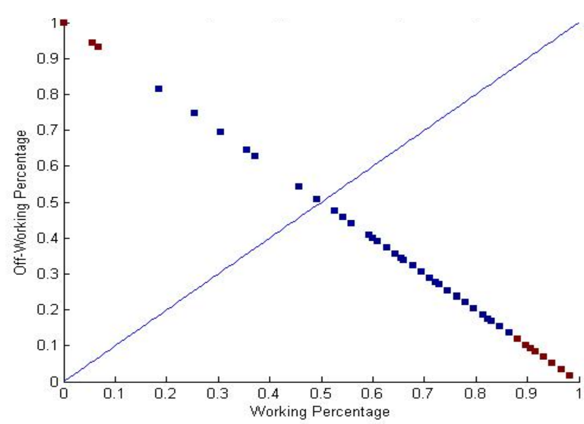

Figure 20: Workday / Non-Workday Balance for Each Building Occupant

represented by the red points to the far right, for which analysis excludes non-workdays. The workday ratio complements data on typical workday schedules by providing insights into which occupants come to the office most consistently. Building spatial energy efficiency may then be improved by co-locating groups of occupants with similar workday schedules.

Fig. 21 displays the work hour schedules as determined by the second clustering phase for each building occupant. Each row corresponds to a single building occupant's average workday

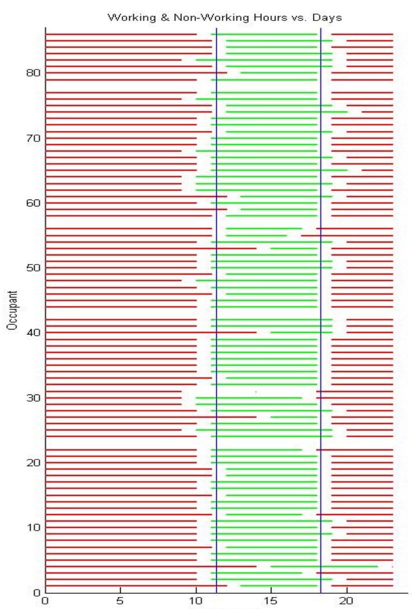

Figure 21: Work hour / Non-Work Hour Range Separation for All Building Occupants

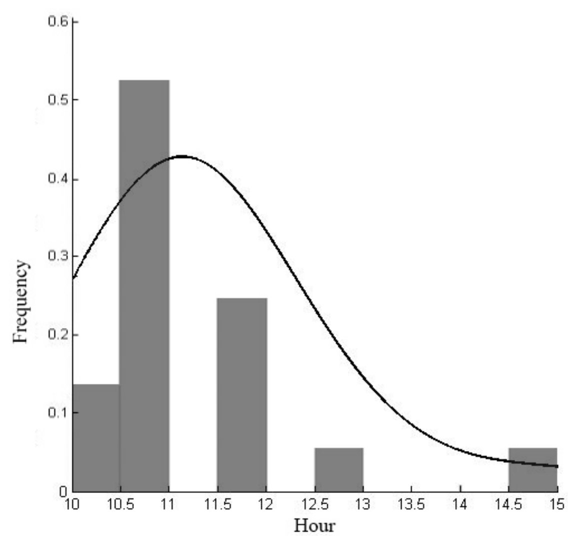

Figure 22: Start Work Hour Probability Distribution

schedule, with green bars representing work hour ranges and red bars representing non-work hour ranges. Missing rows represent individuals for whom too few workdays were detected to enable meaningful analysis, indicating either a disconnected energy monitoring device or an individual who came to work fewer than eight times (our specific workday minimum threshold) over the course of data collection. As can be observed in Fig. 21, our typical 8 hour work schedule assumption was upheld for the majority of occupants. Interestingly, the workday begins after 10am and ends after 6pm for most of the building occupants, as observed in Fig. 22. Such schedule- based statistics could be used to inform building system run-time operations.

Efficiency and Entropy Analysis

The work hour and non-work hour ranges observed in Fig. 21 are next utilized in the third clustering phase for each building occupant, which provides distinct energy-use level clusters for each hour range as well as for non-workdays. An example output for a single building occupant can be observed in Fig. 18. The results of the third clustering phase are finally used to determine energy efficiency and energy-use entropy for each building occupant using equations (3), (4a), and (4b). Figs. 21 (a)[7] and (b) display building occupant energy efficiency for non-work days (when more than 8 non-workdays are detected for an occupant) and non-work hours respectively. From Fig. 23(a) it is observed that ten building occupants never occupy low energy level clusters

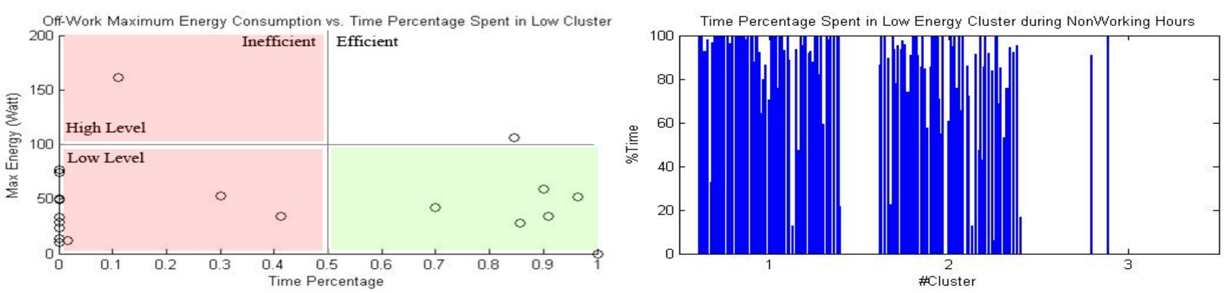

Figure 23: (a) NWD Efficiency vs. Max Energy Level (b) Non-Work Hour Efficiency

during non-workdays (points on y-axis) and only one inefficient occupant has a non-work day energy-use level greater than 100 Watts. The workday non-work hour energy efficiency of building occupants can be observed in fig. 23 (b), where each cluster corresponds to a different

[7] To stay consistent with the rest of the plots, Fig. 11(a) excludes weekend days. Including weekdays would sincrease the number of non-workdays for each occupant, and therefore the number of points in Fig. 11(a).

non-work hour range (e.g. morning and evening ranges). The more workdays for which a building occupant's non-work hour energy-use falls into low energy-level clusters, the more efficient that they are by our definition. Combining non-work hour and non-workday efficiency information further enables the identification of both the most inefficient high-energy and the most efficient low-energy building occupants. Such segmentation can positively inform the design and impact the potential success of behavior-based programs by facilitating a dual incentive system that does not penalize initially efficient occupants. From the probability distributions for morning and evening work hour range efficiency in Fig. 24, it is observed that there are relatively large numbers of occupants who are either very efficient or inefficient, enabling well defined groupings of users based on efficiency. Individuals in groups with high efficiency (far right columns in Fig. 24) can be evaluated on how well they maintain their high level of efficiency, with minimal changes in behavior. Alternately, inefficient occupants (far left columns in Fig. 24) may be evaluated based on how much they improve their efficiency over time, by changing their energy-use behavior.

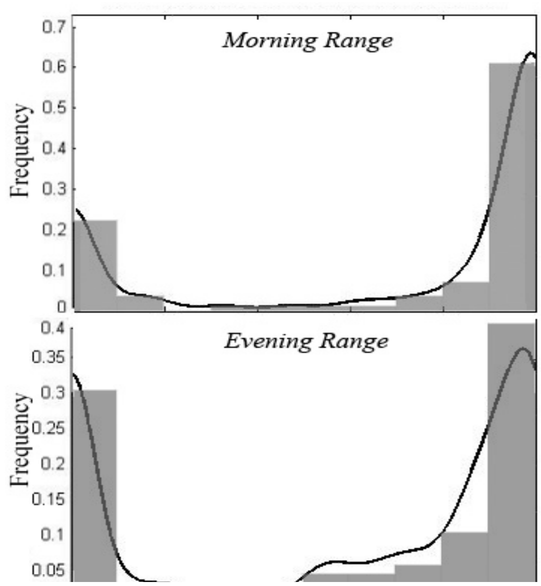

Figure 24: Non-Work Hour Efficiency Probability Distribution

Fig. 25 plots occupants according to their maximum rate of energy consumption during work hours and the amount of time that they spend in this high energy intensity cluster. In contrast to non-work hour efficiency levels, work hour energy-use levels are less sensitive to occupant behavior and are more a function of equipment type; therefore they are not included in efficiency calculations. In Fig. 25, occupants represented by points in the upper-right quadrant consistently operate at high energy intensity during work hours and therefore represent the best candidates for equipment upgrades.

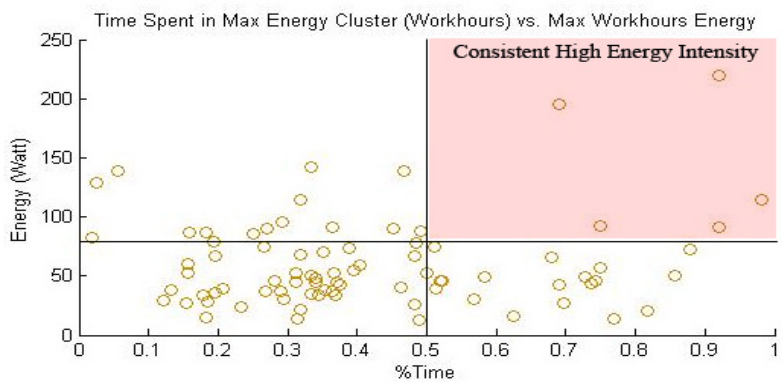

Figure 25: Max Work Hour Energy vs.Time in Max Energy Cluster

Figs. 26 (a) and (b) display the breakdown of energy-use entropy among the building occupants. As observed in Fig. 26 (a), a large number of occupants have zero-valued non-workday entropies, indicating that their non-workday energy-use is best represented by a single cluster and that further separation by algorithm 3 is not practical. This suggests that the non-workday energy-use levels of many building occupants can be predicted with a relatively high degree of accuracy, as their energy-use consistently follows the same cluster pattern. However, there is much more variability in building occupants' workday entropy values, which is a weighted combination of the work hour and non-work hour entropy values represented in Fig. 26 (b).

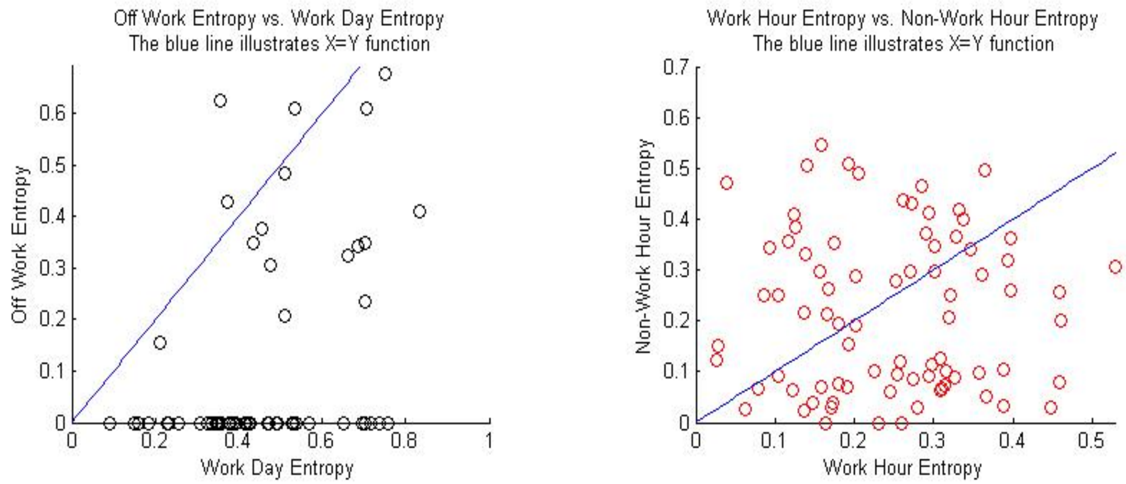

Figure 26: Energy-Use Entropy over Work and (a) Non-work days (b) Non-work hours

Building occupants with relatively low workday energy-use entropies, as observed in the probability distribution in Fig. 27, may be grouped to increase the accuracy of workday energy-use predictions. The ability to group individuals by their workday entropy facilitates

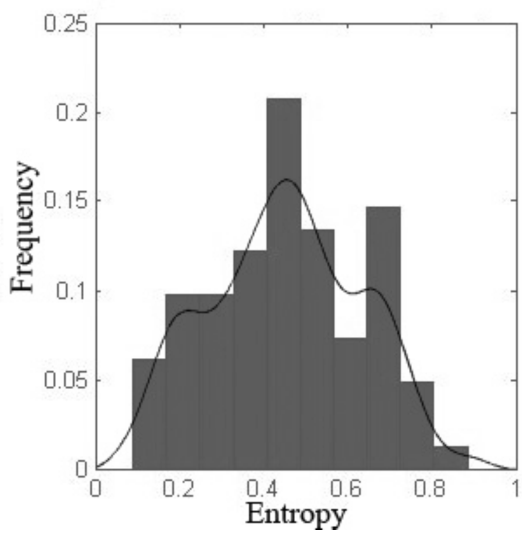

Figure 27: Occupant Total Workday Entropy Probability Distribution

better short-term building energy-use forecasts that take into account end user consumption, a capability that most current forecasting models lack. Furthermore, entropy groupings also enable more impactful behavior-based interventions. For example, high entropy values may suggest that a user has various appliances that are only used intermittently (e.g. printer, space heater, microwave). These appliances can be identified, shared among multiple building occupants and associated with a separate plug-load to reduce user variability, conserve space, and centralize operations. Another example, similar to targeting the same users based on efficiency, includes targeting users with low entropy and high energy-usage for equipment upgrades to conserve energy associated less variable work operations. The distribution of energy-use entropy values can be analyzed for temporal ranges (workday, work hour, and non-work hour) separately or in combination depending on the specific energy-use forecasting or behavioral program application.

Discussion of Impacts

The methodology can be used to effectively classify building occupants according to their typical workday schedules, energy-use levels, efficiency, and predictability. By initially separating sets of workdays, non-workdays, work hours and non-work hours for each building occupant, a number of insights can be gleaned about the behavior of individuals and groups of occupants. First, an approximation of the time that occupants arrive and leave the building, in combination with predictions of which days occupants are likely to come to the building, can be used to determine overall occupancy levels of the building. This information can be used to inform building system operating schedules around actual, rather than predefined, occupancy parameters. Next, a number of behavioral metrics based on energy-use patterns during work and non-work hours can be determined for individuals. Such metrics enable the design of more effective, targeted conservation campaigns in commercial buildings. Such campaigns can be designed to set tailored energy conservation goals for different groups of building occupants, depending on their energy efficiency and energy-use entropy measures. Also, Individuals who consistently consume high-levels of energy during work hours can be identified and targeted for equipment upgrades, in order to reduce unavoidable operating costs and energy consumption. Finally, building occupants can be grouped according to energy-use entropy to enable improved building energy-use forecasting models. Such improvement can positively impact short-term energy management programs by taking into account the predictability of energy-use levels for groups of building occupants.

Limitations and Future Research

The dataset on which the segmentation and classification methods were applied for demonstration purposes was limited to the plug-load electricity consumption of commercial building occupants. Future applications should investigate the possibility of integrating energy end-uses that extend beyond plug-loads, such as: taking elevators, wearing warmer clothes in the winter, and turning off shared lighting resources. Such actions could be self-reported by building occupants and incorporating them into a more comprehensive energy efficiency calculation could be of value to behavioral-based conservation campaigns. In addition, the clustering methods introduced yield approximations of individual occupancy states based on energy-use patterns and were not validated with any external ground truth data. Nonetheless, the occupancy patterns were consistent with observations and interviews with building occupants. Future research should investigate the precision of these approximations to determine typical error rates. Lastly, the effects on energy-use prediction accuracy of separating users by entropy and temporal ranges by work and non-work distinctions should be investigated. Improving short-term energy-use prediction capabilities may improve the effectiveness of demand response programs.

Conclusion

Building sensing technologies will become increasingly ubiquitous as they continue to drop in price and become more modular and easy to install. Concurrently, more building data streams will become available to building management systems and human operators. As these technologies exist in order to balance occupant comfort with resource consumption, it is essential to develop methods to interpret these newly available data streams in order to make building systems more responsive to actual occupant needs and behaviors. As buildings become increasingly efficient, the relative importance of occupant behavior in achieving the full potential of energy savings will increase and behavior-based conservation campaigns will likely become more widespread. As we have demonstrated in this paper, more granular sensing technologies have the potential to improve the ultimate impact of behavioral-based campaigns by enabling targeted interventions, tailored goals and incentives. Therefore, as building technologies continue to evolve, so will the sophistication and efficacy of behavior-based conservation strategies. When applied in combination, the two approaches can realize the full potential of energy savings in the built environment.

in this paper.

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CHAPTER 5: CONTRIBUTIONS

For my doctoral research, I led initiatives aimed at advancing an understanding of how commercial building occupants consume energy and how they can be motivated to increase the efficiency of their energy-use. I approached these goals by first developing expertise in designing and deploying systems that enable quantitative research and analysis of social and organizational network effects on energy efficient behavior. I applied lessons learned from studying previous residential building eco-feedback systems to design and develop a novel, plug-load energy-use feedback system, which I subsequently utilized in 9-week commercial building energy efficiency study involving over 100 participants. The positive results and wealth of data from this study further prompted me to develop a new set of metrics for classifying building occupants by their energy-use patterns, to improve the potential effectiveness of resource conservation campaigns and accuracy of energy-use prediction algorithms. Lessons and contributions associated with these three research initiatives are presented in the following sections.

The Design of Commercial Building Eco-Feedback Systems

In the first stage of my dissertation, I conducted a full review of existing eco-feedback systems and the behavior-based research studies that they enabled. At the time, building sensor technologies (and consequently eco-feedback systems) were beginning to drop in cost, thus enabling higher resolutions of energy-data to be collected and processed. With the increased data resolution, new research opportunities to investigate the effects of behavior-based energy conservation campaigns in commercial buildings emerged. To this effect, I developed *BizWatts*, a novel eco-feedback system that directly incorporates building occupants into the building energy-use feedback loop and connects them through organizational and social networks to facilitate collaboration and competition. While the design of the *BizWatts* system was influenced by earlier eco-feedback systems, several novel concepts were integrated into its design to facilitate new, network-based research studies.

BizWatts was designed to emphasize modularity in hardware commissioning, data collection and processing, and building occupant group management. Unlike other eco-feedback systems, *BizWatts* is based on portable, wireless plug-load energy monitoring technology that offers several advantages over traditional circuit-integrated systems. First, the flexibility associated with the installation of the plug-load monitors allows them to be assigned to specific plugs and individuals in a building. They can be easily reassigned to other occupants and their installation does not interfere with other building systems. Another novel feature is that hardware around which *BizWatts* is built enables users to remotely control connected appliances [Marinakis 2013] while collecting high-resolution (up to 1-minute intervals) energy-use data. The high resolution data enables the determination and prediction of additional proxy measures, such as building occupancy and occupant energy-use efficiency.

Beyond supporting a modular energy-monitoring network, the software architecture was also designed to be highly flexible in order to support a wide range of organizational structures, which can vary highly from small businesses to large, multi-department organizations. Through *BizWatts,* individuals can share and compare energy-use and reported conservation action information. Sharing capabilities are determined by system administrators who can set software permissions that follow flat, hierarchical, and distributed organizational structures.

By combining a high-resolution modular hardware network with flexible software architecture, customizable, unobtrusive energy efficiency campaigns are enabled for a wide variety of commercial (and residential) building environments. To aid in energy-use and user-interface interaction analysis, extensive clickstream data collection capabilities were incorporated into the underlying *BizWatts* architecture. Collected clickstream data enables a continuous interface improvement process for maximizing user engagement and facilitates analysis related to how building occupants interact with one another over the system, as described in Chapter 2.

The novel hardware and software architecture upon which *BizWatts* was developed, in combination with its integrated clickstream and energy-use data monitoring, represent a one-of-a-kind eco-feedback system that was designed to maximize energy-use behavior efficiency and enable new commercial building energy-use studies.

Effects of Organizational Network Dynamics on Commercial Building Energy-Use

In the second stage of my dissertation, I utilized my *BizWatts* eco-feedback system to conduct a novel study to investigate the impacts of organizational network dynamics on energy conservation among commercial building occupants. Due to difficulties associated with collection of high resolution building occupant energy-use and action data, there have been very few empirical research studies on the effects of eco-feedback and network dynamics on building occupant energy-use. Before my study, occupant network effects on energy-use were only investigated in residential settings where energy-use data resolution was still limited to whole residential units (not individual occupants). In addition, even while simulation models indicated that network dynamics may significantly influence the impact of energy conservation initiatives in commercial buildings (Anderson 2014), no empirical occupant network-oriented studies had ever been conducted to test these effects in non-university affiliated commercial buildings.

My *BizWatts* system enabled the extension of high resolution energy-use studies to commercial buildings and was instrumental in the completion of the first empirical study that corroborated simulation model findings by demonstrating that occupants can indeed significantly impact commercial building energy efficiency through behavioral modifications. Data from the study showed that exposure to individual eco-feedback may not result in significant energy savings. However, exposure to network level eco-feedback can significantly impact building occupant energy-use and the level of interaction that individuals have with eco-feedback systems. These results supported previous research that demonstrated a positive correlation between energy conservation and levels of interaction with residential eco-feedback systems (Jain 2012).

In addition to isolating the effects of organizational network dynamics on commercial building occupant energy-use, in the study I was able to statistically demonstrate that exposure to eco-feedback impacts energy-use behavior differently for commercial building occupants than for residential building occupants. The short-term response-relapse patterns of residential building occupants exposed to peer network energy-use information, in which individuals reverted to inefficient energy-use behavior after a short period following feedback exposure (Peschiera 2010), were not observed among commercial building occupants connected over organizational networks. Energy savings were more consistent through the duration of the study with no sudden significant short-term decreases in energy consumption, suggesting that efficient energy-use behavior changes in commercial buildings may be more persistent than in residential buildings.

Quantification of Commercial Building Occupant Energy Efficiency and Entropy

After demonstrating that building occupants can be effectively connected through eco-feedback systems and that these connections positively impact energy conservation, I identified an opportunity to develop new methods for classifying and grouping occupants according to energy-use patterns. In this way, building occupants can be connected over networks that combine efficient and inefficient individuals, thereby enabling positive conservation behaviors to be more effectively spread. Furthermore, inspired by utility scale customer segmentation initiatives, I recognized the potential of classifying individuals by energy efficiency and energy-use predictability to increase the efficacy of commercial building energy conservation campaigns. Most existing behavior-based energy efficiency programs are limited in their ability to objectively identify the most energy inefficient building occupants. These limitations create a confounded incentive system where consistently efficient resource consumers are overlooked and prevent the design of potentially more impactful resource conservation campaigns that target specific groups of inefficient energy consumers.

The final chapter of my PhD research therefore focused on defining and creating a new set of metrics for classifying building occupants according to individual energy efficiency and energy-use predictability. I envisioned and developed a multi-level data clustering technique to effectively separate building occupant workday and non-workday load profiles and demonstrated how multiple measures of a building occupant's energy efficiency can be calculated. By defining independent non-work and work day efficiencies for building occupants, energy conservation interventions can be tailored to specific individuals over specific time frames. In addition, the novel clustering application enables more accurate efficiency metrics to be calculated that account for variations in individual workday schedules. Each efficiency measure is independently calculated and does not assume uniform schedules among all building occupants, thus enabling further identification of individuals who have high energy-use rates during various temporal ranges, such as workday work hours. In contrast to non-work hour efficiency levels, work hour energy-use levels are less sensitive to occupant behavior and are more a function of equipment type. Therefore, occupants who consistently operate at high energy intensity during work hours represent the best potential candidates for equipment upgrades. By identifying these occupants, next steps can be taken to see what kind of equipment that they are using and to explore possibilities for replacing the equipment with more energy efficient versions. This could include high power usage desktop computers, monitors, and desktop lighting with relatively lower power usage laptops, LED monitors, and LED lights.

By classifying all occupants by energy-use efficiency and predictability, individuals can be grouped according to where they fall in the overall probability distributions of these metrics. In addition to enabling targeted interventions, such classification techniques enable new studies that investigate how grouping individuals in efficiency campaigns by properties other than organizational network ties may impact energy conservation. By developing a system that connects building occupants and collects data related to their interactions and energy-use patterns, and defining new methods for classifying occupants according to this collected data, I have enabled a new class of more effective, targeted efficiency campaigns to be developed and studied in the future.

CHAPTER 6: LIMITATIONS & FUTURE RESEARCH

The *BizWatts* eco-feedback systems was designed to connect occupants over peer networks and collect user-generated data in order to enable research on the impacts of feedback, peer networks, and behavior-based interventions on energy conservation. However, it is limited in its ability to collect user-generated feedback regarding indoor environment comfort, which other systems have shown can be used to optimize indoor temperature and humidity levels (Jazizadeh 2013). While each of these approaches uniquely and independently engages building occupants to improve building performance, no system has yet been designed to fully integrate peer network functionality, high resolution energy-use feedback, and occupant generated comfort-related feedback. Another limitation regarding the direct application of the results of my research in setting expectations of other eco-feedback and behavior-based energy conservation initiatives is that I only investigated the effects of eco-feedback and network connections on individual plug-load energy-use behavior. The intention of the research was to investigate if individual energy-use behavior can be influenced by eco-feedback and network-level connections. While this was indeed observed to be the case, my initial research was not designed to see if these individual energy-use (desk-load) behaviors translated into more efficient utilization of shared sources such as lighting and HVAC systems. If such spill-over effects on energy-use behavior can be isolated in future research, the design and adoption of eco-feedback systems could be significantly impacted.

To complement Fig. 10 in Chapter 2, Fig. 28 presents the absolute per capita energy consumption for both study groups and the control group over the course of the eco-feedback intervention. The periodicity in the plot represents the alternation between weekdays and weekends, with low energy-use periods indicative of weekend consumption. The randomized selection of study group members was designed to mitigate any energy-use differences resulting from temporary increased/decreased occupancy levels among groups, which were not directly recorded. Any disruptive weather patterns were assumed to equally affect all building occupants and the Figs. 12 and 28 represent daily per capita group consumption, thus smoothing any disruptions by individual absences. Furthermore, the t-test analysis employed in the study was designed to account for any other potential confounding externalities that could impact certain groups more than others by comparing energy-use levels relative to that of a control group and within-group baseline levels (equation 1). As the control group consists of members randomly distributed through the building, changes in their energy-use levels equally impact all groups, which were also distributed throughout the building.

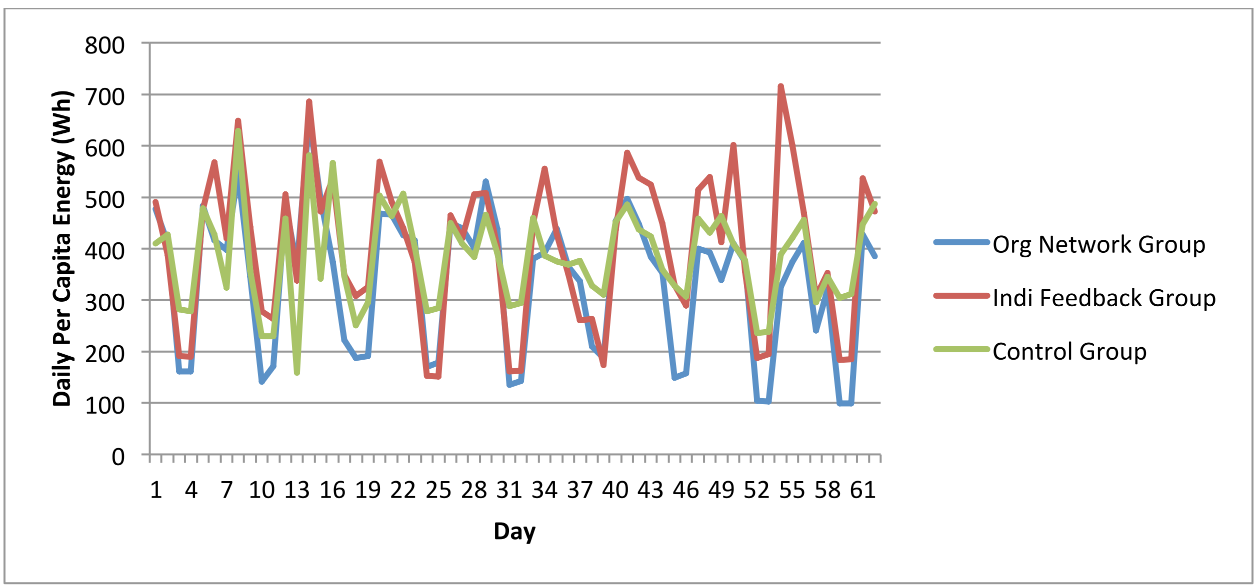

Figure 28: Daily per Capita Energy-Use Levels for each Group

Regarding total energy-use levels, the general patterns for each group in Fig. 28 are visually consistent. However, the absolute per capita consumption of the organizational network feedback group over weekends begins to separate from the individual feedback and control groups after about 40 days. This suggests that the organizational feedback group has increased its weekend energy efficiency by realizing lower rates of energy-use, while the individual feedback and control groups have not. An interesting future study would expand on the methodology presented in Chapter 4 to investigate to what degree energy-use efficiency and predictability increases for each group over time, separated by weekdays and weekends. It could be inferred from Fig. 28 that the weekend efficiency (time spent in low energy clusters on weekends) for building occupants in the organizational network feedback group increased at a faster rate than for the other groups, but this can be empirically tested in the future.

Future research should also investigate how engagement levels for the different study groups correlate with changes in efficiency, as characterized in Chapter 4, and how these engagement levels might be better sustained. Fig. 12 in Chapter 3 shows that general engagement levels across all groups decreased over the course of the study, even though exaggerated energy-use response-relapse patterns (as observed in Peschiera 2010) were not observed. A longer duration study could be conducted to determine if the relatively short-term sustained savings in the 9-week study in Chapter 3 extend to the longer-term. If they are not, then new methods for motivating increased user-system engagement levels might be developed to drive more persistent, long-term energy efficient behavior.

Combined Feedback Systems

A truly integrated smart building system simultaneously empowers building occupants with network and building-level feedback *and* utilizes them as sources of building information related to occupancy, comfort, and maintenance. Future research should therefore continue to build upon recent technological advances to investigate how combined sources of building and occupant feedback could be used in creative, new ways. A system diagram for such a proposed, future system is observed in Fig. 29.

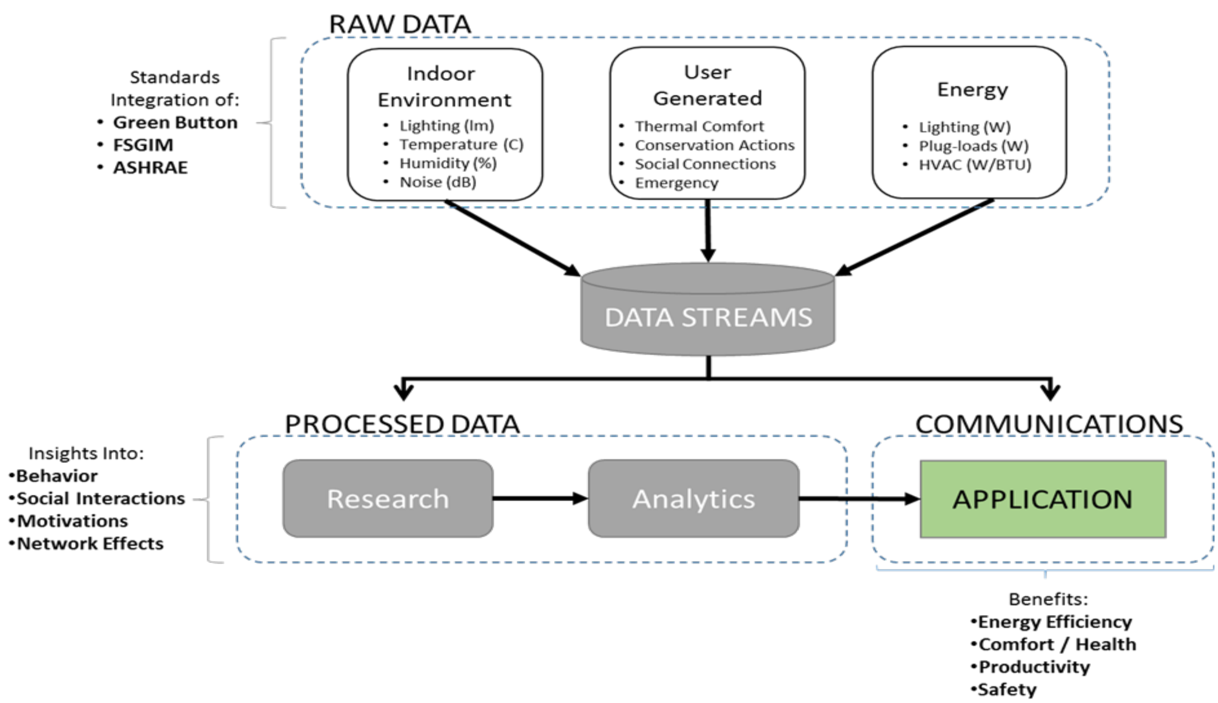

Figure 29: Eco-Feedback System Expansion to Include Building Occupant Comfort Preferences

By integrating additional system monitoring capabilities, occupant preferences related to temperature, lighting, humidity and noise levels can be tracked in order to find an optimal balance between efficiency, comfort, and productivity. A few examples of how the next generation system could utilize combined feedback are listed below:

- Individual energy-use data can be used to predict building occupancy levels which, and when combined with evolving thermal comfort profiles, can be used to optimize not just temperature set points but also operational schedules of HVAC systems to *simultaneously maximize occupant comfort and energy efficiency.*
- When users report thermal discomfort, the system could analyze the occupancy and comfort states of others in the user's organizational network to determine how severe and urgent the discomfort is – and determine whether the system should immediately adjust or delay
- Networks of occupants who experience consistent discomfort can be identified and adjustments can be made to locations of occupants to alleviate the problem
- Energy-use patterns of building areas can reveal if they are being under-utilized or not, which can inform possible reconfigurations to improve spatial efficiency as well as inform schedules related to maintenance and cleaning
- Sensors can automatically detect failures in lighting and mechanical systems while users can provide feedback about optimal lighting and acceptable noise levels for maintenance

Novel algorithms can be developed to process these data to further classify occupants based on individual comfort preferences. In this way, occupant profiles based on energy-use behavior, schedules, and preferences can be selectively analyzed to provide even more targeted interventions. With this information, occupants can be grouped and physically co-located according to preferences and schedules so that building lightning and HVAC systems aren't operated unnecessarily. Furthermore, efficient energy consumers can be selectively grouped with inefficient occupants in conservation campaigns in order to better motivate efficient behavior.

Combined feedback systems should be developed with the ultimate goal of being as low cost as possible, in order to minimize their payback period and maximize their cost-effectiveness. Once such systems are more established, research initiatives should be designed to measure and estimate their overall impacts on building occupant energy-use, comfort, health, and productivity. In this way, their ultimate economic impact could be better estimated and a cost-benefit analysis could be conducted to better compare the economics of physical building retrofits and combined feedback systems. Such a comparative analysis has not yet been conducted.

Additional Organizational Network Energy Efficiency Research

In addition to investigating the potential synergies of combined building sensor indoor environment and user-generated comfort related data, future research can also expand upon the findings from my study in Chapter 3. The fact that organizational network dynamics play a role in commercial building occupant energy-use behavior leads to many more research questions related to how these network effects vary in different settings and conservation approaches. Some research questions that expand upon the findings from the study in Chapter 3 include:

1. How do different organizational structures impact energy-use, user behavior and reporting?
    - *The Chapter 3 study only investigated flat organizational networks*
2. Can network data influence perceptions of comfort and changes in behavior?

- *The Chapter 3 study only investigated impacts on energy-use patterns*

3. How does competition between groups and individuals impact energy-use behavior and user-interface engagement levels?
    - *The Chapter 3 study did not introduce any explicit incentives to conserve energy*

Geographical and Cultural Studies

As climate change is a global problem, it requires a global solution. Building energy efficiency studies should therefore be extended to international locations where the effects of eco-feedback and network dynamics may differ from those observed in US buildings. Several research questions that address cultural differences in energy conservation campaigns are of interest, including:

1. How do geographical and cultural factors impact sustainability strategies?
2. Do cultural differences impact which building data streams and system reporting functionalities users find most valuable and interact with most frequently?
3. Can cross-cultural sustainability campaigns effective engage all users?

While these questions are general in nature, addressing them through research studies would enable the design of web-based eco-feedback systems that more effectively engage users across geographical and cultural boundaries.

CHAPTER 7: CONCLUSION

My dissertation research represents the first step in a very important quest to understanding how people can be engaged and motivated to more efficiently consume the finite natural resources of our planet. On a general level, resource conservation requires a coordinated effort and everyone's participation. Specifically, I have chosen to address the resource conservation puzzle by focusing on energy efficiency in the built environment, where humans spend the majority of their time. I have learned that to promote sustainable behavior in buildings, it is first necessary to establish a conscious link between buildings, occupants, and the environment. In this way, individuals can become mindful of the environmental consequences of their everyday actions and feel empowered to make a positive personal change by adopting more sustainable behaviors. In my research, I have found that connecting individuals to one another within commercial buildings through their energy-use data can help to motivate more efficient energy consumption. Furthermore, I have developed novel ways to classify individual building occupants according to their energy-use efficiency and predictability, enabling more targeted energy conservation campaigns. I hope for others to use my research findings as a stepping stone to further expand our understanding of what motivates us as humans to live more sustainably and lessen our impact on the natural environment.

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