INVESTIGATING THE ROLE OF OCCUPANTS, COMPLEX CONTEXTUAL FACTORS, AND NORMS ON RESIDENTIAL ENERGY CONSUMPTION

by

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DEDICATION

To my family

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ABSTRACT

INVESTIGATING THE ROLE OF OCCUPANTS, COMPLEX CONTEXTUAL FACTORS, AND NORMS ON RESIDENTIAL ENERGY CONSUMPTION

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Human behavior in the built environment has repeatedly been found to have significant meaningful impact on energy consumption. As a consequence researchers have spent considerable efforts investigating various approaches to induce improved occupant behavior, with much recent attention on the use of normative approaches. However, it still remains unclear as to how occupants behave in buildings, how complex factors influence behavioral interventions, and what the long term effects of intervening are. With this background in mind, there are three broad goals in this research: (1) to improve our understanding of the impact of occupant decision making in residential energy consumption, (2) to enhance our understanding of how individual characteristics and complex contextual factors influence change in individual behavior and its diffusion through communities when subjected to normative intervention, and (3) to identify more effective normative behavioral strategies for reducing energy consumption in the built environment. In order to achieve these diverse research objectives, I conducted four interrelated studies based on an iterative research framework that applies an interdisciplinary research approach integrating field experiments with computational modeling. Through these studies it was found that: (1) vast quantities of energy are spent in unoccupied residences and that the percentage of energy consumed while unoccupied in a residence is unrelated to total use; (2) when applying behavior interventions social network structure can meaningfully affect how behavior diffuses and intervention outcome; (3) normative messaging duration positively influenced the durability of behavior change; (4) not all individuals were equally influenced by normative messaging with high norm individuals reducing energy consumption and low norm individuals increasing consumption; (5) by exploiting behavioral responses to normative messaging significant reductions in energy consumption could conceptually be achieved. These findings improve our understanding of occupant behavior, how occupants are influenced by social forces in the built environment, and how complex contextual factors moderate the diffusion of behavior. Further, the findings provide insight into how to improve the environmental sustainability of buildings through behavioral approaches.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Globally, concerns over unsustainable consumption of energy resources and the emission of greenhouse gases continue to grow. It is predicted that continued increases in the atmospheric concentrations of carbon dioxide caused by anthropogenic emissions will lead to significant changes in climate with serious consequences (Houghton et al. 2001; Thomas et al. 2004).

In the US and other developed countries, buildings are the largest consumers of energy, accounting for approximately 40% of all primary energy use (EIA 2014; Perez-Lombard et al. 2008). Within the building sector households account for slightly over 21% of all energy use in the US and over 26% across the EU-28 countries (EIA 2014; European Commission 2013). This makes buildings the largest single contributor to energy consumption and a major contributor to climate change. In the US alone, household fuel consumption results in the emission of nearly 1.2 billion metric tons of CO2 equivalent emissions annually (EPA 2012). Given the vast importance of the building sector on anthropogenic greenhouse emissions, many countries are taking significant steps to reduce carbon emissions from the built environment (US Congress 2007; Poel et al 2007).

Efforts to reduce the impact of building energy consumption and emissions have historically taken two forms, design improvements and behavioral improvements. Design improvements focus on improving the efficiency of building systems and include everything from how to strategically place trees (Simpson and McPherson 1990) to renewable energy systems (Hepbasli and Akdemir 2004) and advanced building control systems (Foley 2012). The alternative approach to this focuses on occupant behavior and methods to promote environmentally preferable behavior from occupants.

While both methods for reducing carbon emissions from the built environment are crucially important, in the end all buildings are operated by humans and how occupants chose to behave in buildings will, to a great extent, determine how much energy is consumed in buildings. This is evident in the significant impact of occupant behavior on energy consumption which often creates differences in consumption between 5% and 25% (Bahaj et al. 2007; Emery and Kippenhan 2006; Santin et al. 2009; Yu et al. 2011; Yun et al. 2011)—and even differences in consumption greater than 100% in identical buildings (Gill et al. 2010). It is also frequently evident after technological improvements have been implemented as expected reductions in energy use are often not achieved as a result of changes in occupant behavior (Druckman et al. 2011; Sorrell et al. 2009). In addition, as buildings become more efficient and passive in design, the influence of occupant behavior on energy consumption is expected to become even more pronounced (Robinson and Haldi 2011). When considered in the aggregate, improving human behavior in the built environment has substantial potential to reduce carbon emissions and achieve national energy reduction goals (Dietz et al. 2009; Gardner and Stern 2008).

1.2 PRO-ENVIRONMENTAL BEHAVIOR INTERVENTIONS

Given the importance of human behavior on energy consumption, since the 1970's researchers have put forth models and examined numerous variables to enhance our understanding of what prompts one to engage in pro-environmental behaviors and which variables make good predictors as to whether or not an individual will partake in environmentally preferable behaviors (De Young 1993; Hines et al. 1987; Kaplan and Kaplan 2009; Osbaldiston and Schott 2012; Stern 2000; Stern 2011; Wilson and Dowlatabadi 2007). Many of these studies have been dedicated to encouraging environmentally responsible energy use in buildings and most have focused on attempting to change repetitive, or curtailment, behaviors such as turning off the lights when leaving a room. Repetitive behaviors, as opposed to one time behaviors such as purchasing new more efficient heating systems, have been the main focus of most intervention studies. The extensive focus on curtailment behaviors is partially because they typical have no financial or logistical barriers which is not true of many one-time behaviors (McKenzie-Mohr 2000) and are applicable to a larger population base including renters which make up over a third of all US households (Census Bureau 2013a).

To promote improved occupant behavior many diverse intervention techniques have been applied including environmental education, information, social modeling, intervention agents, incentives, disincentives, competitions, goal setting, commitments, individual or group feedback, rewards, and penalties. Of these various strategies, substantial work has been focused on providing individuals with feedback of their behavior (Darby 2006). Early feedback studies were mainly performed by psychologists and largely presented participants with feedback on previous behavior only. In these studies occupants have been provided with daily, weekly, monthly or continuous feedback (Abrahamse et al. 2005); the results of the studies have varied substantially. Several studies reported positive effects on energy consumption between roughly 5 and 15% (Bittle et al. 1979a; Hutton et al. 1986; McClelland and Cook 1979; Van Houwelingen and Van Raaij 1989; Wilhite and Ling 1995), but others have also reported no significant change in consumption (Katzev et al. 1981; Sexton et al. 1987). In addition, feedback has also been reported to have undesired effects where high energy consumers will decrease consumption, but low and midlevel consumers increase their use as a result of feedback (Bittle et al. 1979b; Schultz et al. 2007).

More recently, researchers have begun employing the use of comparative feedback which presents individuals with feedback on their own behavior as well as social norms of a reference group. Social norms, although often underappreciated through self-appraisal, have repeatedly been found to be a significant predictor of how one behaves (Nolan et al. 2008) and have been successfully applied in energy use behavior interventions. The most common application to date is the use of descriptive norm messaging; consumers are provided mean energy use data of other households in their locality (Schultz et al. 2007). These interventions may also attach injunctive norm messages, messages expressing approval or disapproval of the consumer’s use. Large-scale experiments across the US using normative messages containing both descriptive and injunctive norm messages on monthly and quarterly energy bills have reduced residential energy consumption by around 2% (Allcott 2010; Allcott and Rodgers 2012; Ayres et al. 2013). Norm-centric interventions, as opposed to financially focused interventions, have the advantage of being applicable in situations where the target population has no financial incentive to change behavior. This includes rental properties, offices, hotels, and dormitories. Appealing to occupants through the use of social norms has been shown effective in these types of buildings (Nolan et al. 2008; Goldstein et al. 2008; Peschiera et al. 2010).

With intervention strategies that focus on comparative information to elicit behavioral change such as normative feedback messaging interventions, system and individual behavior change dynamically during and after the implementation of the intervention. Considering the dynamic nature of these interventions, understanding how behavior spreads and changes over time would allow interveners to develop more favorable intervention strategies. Regrettably, collecting data necessary to explore these interactions through field experiments can be cost prohibitive and face privacy challenges. Therefore, researchers have begun developing simulation models to analyze the potential effect of implementing normative feedback interventions in building communities (Anderson et al. 2012; Anderson and Lee 2013; Anderson et al. 2013; Azar and Menassa 2012a; Chen et al. 2012; Zhang et al. 2011). These efforts have applied computer modeling methodologies to simulate human interactions and the spread of behavior. The use of simulation experiments, in contrast to field experiments which have traditionally been conducted in this field, offer a cost-effective and expedient means to assess potential success and failure of interventions. These virtual experiments can provide insight to decision makers as to the potential outcomes and the distributions of outcomes of the tested intervention strategies. Further, these virtual experiments provide researchers a new method to explore how specific complex contextual factors and behavior setting characteristics, such as social network structure, contribute to the diffusion of behavior in building and residential communities.

1.3 PROBLEM STATEMENT

Unfortunately, despite the large body of research on energy use feedback interventions, several key limitations exist throughout much of the literature. First, while previous research efforts have made significant contributions to our understanding of behavior interventions many studies have suffered from limited sample sizes, variable measurement, and have used mixed intervention designs (Abrahamse et al. 2005). Often studies will measure only behavioral determinants (i.e., predictor variables to behavior such as environmental attitudes or knowledge) or behavioral outputs (e.g., energy use) (Abrahamse et al. 2005). In doing so, limited knowledge is gained into causal relations between the two. For instance, although a study might find that individuals increased their knowledge about environmental issues or identified with norms, if no data is collected on energy use over the same period no insight is gained as to whether or not behavior actually changed as a result of the intervention. In other words, it is critically important to identify both whether the intervention was truly successful and the reasons why it was or was not. This limitation of much of the previous research greatly restricts the usefulness of many previous findings.

Additionally, almost all studies to date have focused only on short-term behavior change. Many interventions have been shown to result in substantial energy savings due to changes in behavior, often between 5% and 15% and sometimes upward of 20%. Unfortunately, the changes in energy use behavior are rarely measured over significant durations (i.e., a year or more) to see if they are maintained or if behavior relapses to baseline levels upon withdrawal or with continued intervening. In the limited studies where intervention effects have been measured over more substantial durations, they have often not proved durable after intervention withdrawal or provide much smaller energy use reductions than shorter term studies (Abrahamse et al. 2005; Allcott and Rodgers 2012; Darby 2006; Geller 2002; Osbaldiston and Schott 2012). Until recently, very few norm-based feedback studies had given any consideration to the durability of the behavior change induced through intervention. The durability of an intervention is assessed by whether or not treatment effects persist after intervention withdrawal. In a rare study that investigated longer-term effects of normative energy use feedback, Allcott and Rodgers (2012) found that households never fully habituated to receiving monthly messages. Comparing groups that had interventions withdrawn after one year with groups that had interventions withdrawn after two years, they found that effects were much more persistent with the group that had received messages for two years. However, it remained less clear why the additional duration of messaging resulted in more persistent behavior change.

Further, relatively little is currently known as to how complex factors influence the outcomes of these normative interventions and the state-of-the-art in intervention modeling has not nearly advanced to the point of being useful for predictive purposes. More specifically relating to the first limitation, how the specific building or residential community social networks affect the spread and diffusion of energy use behaviors is not well understood. To date computational models that simulate behavior interventions have not considered the influence that social network structure exerts on simulation results. This is critical because from one study to the next different social networks structures are implemented (Azar and Menassa 2012a; Chen et al. 2012; Zhang et. al 2011). Using different social network structures and not understanding the role they play in determining intervention outcomes dramatically reduces the generalizability of the findings from these studies. Identifying common social network structures in target populations and exploring their effect on interventions remains a critical prerequisite to modeling interventions if they are to eventually be used for predictive modeling and 'what if' scenario evaluations. Further, despite the state-of-the-art in intervention modeling advancing rapidly over the last few years most models have lacked strong theoretical foundations and empirical evidence for behaviors rules which limits model usefulness to highly conceptual exploratory analyses. In order to advance beyond this level of analysis and mature towards predictive modeling it is necessary to develop conceptually sound and theoretically robust models to simulate human behavior. These models then in turn must be validated and calibrated with empirical findings from longitudinal field experiments in the populations they are attempting to model.

1.4 RESEARCH OBJECTIVES AND APPROACH

With this background in mind, there are three broad goals in this research: (1) to improve our understanding of the impact of occupant decision making in residential energy consumption, (2) to enhance our understanding of how individual characteristics and complex contextual factors influence change in individual behavior and its diffusion through communities when subjected to normative intervention, and (3) to identify more effective normative behavioral strategies for reducing energy consumption in the built environment. The following are more specific objectives of this research:

1. **To measure the operational efficiency of residences**: Despite the large body of work attempting to improve occupant energy behavior and vast research efforts quantifying energy consumption, a poor understanding of the operational efficiency of residences remains. Quantifying the operational efficiency of residences will provide a target for energy intervention programs

2. **To explore the relationship between social network structure and pro-environmental behavior intervention outcomes**: It is not clear at this time how complex factors contribute to the outcome of normative based behavior interventions. Since normative interventions focus on the spread of behavior through social networks understanding how social network structure influences diffusion of behavior has significant implications for developing improved intervention strategies as well as for the application of predictive intervention modeling.

3. **To identify and measure relationships between behavioral determinants and normative feedback intervention effectiveness in both the short and long term**: Although research on pro-environmental behavior interventions began over forty years ago there has been extremely limited study of the long term effects of most intervention techniques. Understanding whether or not normative feedback programs induce sustainable long term behavioral improvements and under what circumstances these methods are more effective has significant policy implications.

4. **To create a formal behavior model for occupant behavior in order to predictively model normative feedback interventions**: A formal model of how occupants respond to normative feedback will allow interveners the opportunity to conduct hypothetical experiments and test alternative intervention strategies. The outcomes from these experiments can provide estimates into expected intervention outcomes and risks.

In order to achieve these diverse research objectives I have developed an iterative research framework that applies an interdisciplinary research approach (Figure 1.1). This framework integrates the use of: 1) longitudinal field experiments which consist of exploratory data analysis, survey data collection, behavior interventions, and statistical analysis; and 2) formalized behavior modeling and computational modeling and simulation techniques. The first half of the framework, the use of field experiments, has been widely used in the social sciences. This approach allows researchers to test causal relationships between variables of interest and provides invaluable real world data. The second half of the research framework, computational modeling and simulation, has been extensively used in the study of complex systems. Simulation and modeling permits researchers to test hypotheses that are often cost prohibitive or very difficult to test in the field in virtual laboratories.

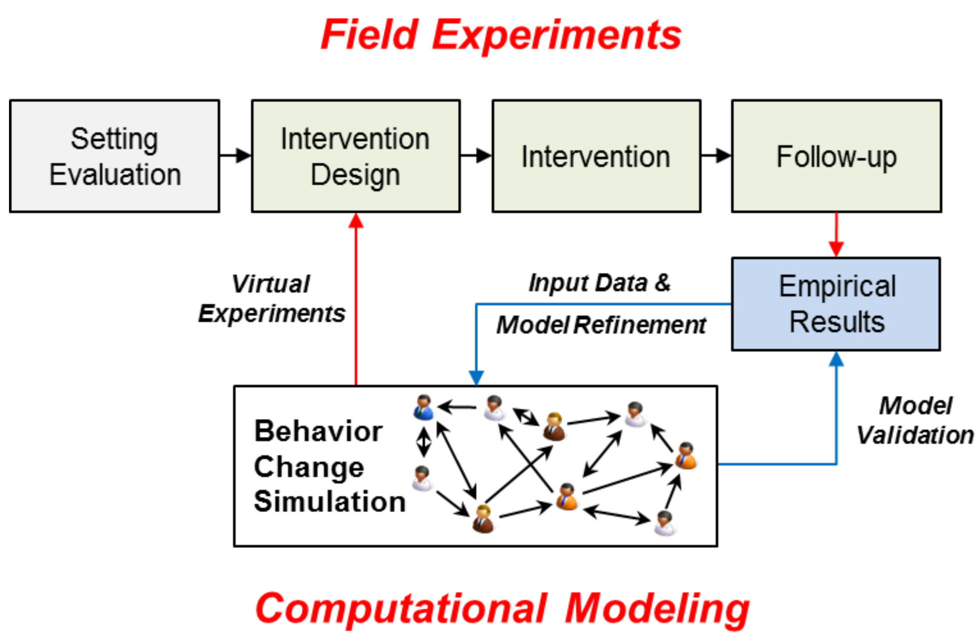


Figure 1.1: Iterative research framework.

The key element of this research framework is its iterative structure. Data and findings collected from the field experiments will feed into and guide the modeling research. This will provide a strong empirical foundation for the behavior models and a means by which to validate and calibrate the simulation models. Through this process it will improve model validity and credibility. With more refined and calibrated models new hypotheses can be tested in a virtual building community before being implemented in the field. This provides a very cost efficient and quick method for identifying novel intervention strategies which are more likely to be successful when deployed into live populations. Further, findings from the simulation work can also be used to direct the work done in the field in several respects. First it can identify areas to focus on and collect additional data. Second, modeling work can propose new hypotheses as to the mechanisms by which occupants behave.

1.5 DISSERTATION STRUCTURE

The organizational structure of this dissertation is reflects the iterative framework presented above. The dissertation is composed of six Chapters. Chapter 1 and 6 provide the introduction and conclusion to this work and the interior Chapters each introduce a study which corresponds to a stage in the aforementioned research framework. The following is a list of the chapters.

Chapter 1: Introduction. This chapter introduces the background, problem statements, objectives, and approaches of the entire research effort.

Chapter 2: Opportunities for Improvement: Energy Use in Unoccupied Dormitory Residences. This chapter presents an exploratory analysis of energy consumption in dormitory residences. The study focuses primarily on quantifying the amount of energy consumed during periods of non-occupancy and its implications for meeting energy reduction goals through behavioral interventions.

Chapter 3: Exploring the Role of Social Network Characteristics on Normative Behavior Interventions. This chapter details a study that models the diffusion of behavior through social networks which investigates the effect and role of social network structure on normative feedback interventions using a bottom-up modeling approach.

Chapter 4: A Longitudinal Investigation of the Effect of Normative Energy Use Feedback. This chapter presents a field study that combines the use of survey and weekly messaging to test the effectiveness of normative feedback, the durability of behavior change upon intervention withdrawal, and enhance our understanding of which behavioral determinants are critical for inducing behavior change.

Chapter 5: An Empirically Grounded Model for Simulating Normative Feedback Intervention Strategies. This chapter presents the culminating work of this dissertation, a study that details the creation and development of a refined behavior model grounded in the empirical findings from the previous chapter. This model is then used to test novel normative feedback intervention strategies.

Chapter 6: Conclusions and Recommendations. This chapter summarizes the findings and main conclusions from the previous chapters. Recommendations for future work are also provided and outlined.

CHAPTER 2

OPPORTUNITIES FOR IMPROVEMENT: ENERGY USE IN UNOCCUPIED DORMITORY RESIDENCES[1]

2.1 INTRODUCTION

Within buildings there are numerous opportunities for energy reduction and recently researchers have attempted to identify the amount of energy used in buildings during periods of non-occupancy (Brown et al. 2010; Masaoso and Grobler 2010; Lindelof and Morel 2006; Mahdavi et al. 2008; Yun et al. 2012). Quantifying the amount of energy that is consumed in buildings while unoccupied is important since it helps provide insight into the operational efficiency of buildings. When considering residences, it offers an approximation of the amount of energy that could be saved from improvements in occupant behavior without occupants having to make changes to their behavior in a manner that potentially could negatively affect his/her comfort (e.g., raising or lowering thermostat settings). This quantity, depending on the climate where the building is situated, is a slight overestimation of what could be considered waste since the vast majority of this energy could be reduced without affecting comfort[2]. The amount of energy spent on useful services (e.g., refrigeration) would vary by building type, size, and several other factors. Identifying the quantity of energy consumed in unoccupied buildings still offers a reasonable target for energy reduction programs and identifies a high end estimate

[1] This chapter is adapted from Anderson, K., Song, K., Lee, S., Lee, H., and Park, M. "Energy Consumption in Households While Unoccupied: Evidence from Dormitories." *Energy and Buildings*, Elsevier, 87(1), 335-341.

[2] Not all energy spent in unoccupied residences is or should be considered wasted energy as some is used to perform important services such as food refrigeration, heating to maintain minimum temperatures in cold weather to avoid building damage. This amount of energy however is quite minimal for most climates as it mainly consists of food refrigeration which is less than eight percent of all electrical energy consumption in the home (EIA 2014).

of potential savings from behavioral improvements before occupants might feel as if he/she has to sacrifice in order to achieve energy conservation goals.

In a study of 160 non-domestic buildings, over 20% left on heating equipment during periods of vacancy (Brown et al. 2010). Such behavior can have an extremely detrimental effect on reducing energy consumption in the built environment and can amount to substantial proportions of the total energy demand of a building. Masoso and Grobler (2010) found that across six buildings in South Africa and Botswana more energy was used during non-working hours than working hours, 56% to 44%. This was largely a result of occupants failing to turn off lighting and equipment when leaving. Over half of the consumed energy in these buildings was spent because of poor occupant behavior. Other studies have highlighted the amount of energy consumed in vacant offices during working hours in commercial buildings as a result of leaving on equipment and lighting when not present, which can be up to 50% of the work day (Lindelof and Morel 2006; Mahdavi et al. 2008; Yun et al. 2012). In all cases, this represents a tremendous amount of energy being spent in empty buildings and is of greater quantity than national energy use reduction goals in the US seek to achieve through design improvements (U.S. Congress 2007). Despite this unfavorable data, there is a silver-lining. Behavioral improvements, unlike technological improvements, can potentially be achieved at almost no cost. Further, improving many behaviors that can lead to energy consumption in unoccupied buildings (e.g., not turning off lights when leaving rooms, leaving on devices such as TVs and computers, not turning air conditioners) can dramatically reduce building energy consumption without impairing occupant comfort.

Unfortunately, to the best of my knowledge, studies to date using field-collected data have only investigated energy consumed during periods of non-occupancy in non-domestic buildings and little is known regarding this quantity of energy in households. Current approximations of energy spent in vacant households have relied on self-reported data along with assumptions regarding occupancy and occupant behavior to generate estimates (Meyers et al 2010). The work presented in this chapter attempts to bridge this information gap and contributes to the literature by presenting a first look into the amount and percentage of energy that is consumed in households while unoccupied using field-collected data. The chapter proceeds with a description of the research methodology. This is followed by the study's results and discussion, and then ends with concluding remarks.

2.2 METHODOLOGY

Advanced metering equipment was used to collect electrical energy consumption data for over 1,000 rooms in seven mid-rise dormitory buildings in Seoul, South Korea. These seven buildings include single occupancy and double occupancy rooms housing both graduate and undergraduate students. Utilities are paid for indirectly and are included in the cost of housing, a common practice for many rental properties (one in seven rental units in the US (US Census Bureau 2013b)). All buildings are newly constructed, nearly identical in design, and have identical room floor plans for each type of room. Rooms do not have kitchens but have mini-refrigerators. Each room has an electric ceiling mounted air conditioning unit (2.6 kW max capacity) with three functions: on/off, temperature up, and temperature down. Further, all rooms have an under-floor electric heating system, a commonplace heating system in Korea, with a max power rating of 4 kW. The heaters have the same control options as the air conditioning units: on/off, temperature up, and temperatures down. In every room electrical energy use is collected hourly. This data accounts for electricity consumed by plug-loads as well as electricity consumed as a result of lighting, heating, and cooling.

In addition to electrical energy use, data is collected on the occupancy status of each individual resident for the whole year by card entry and exit readers installed in every room. This provides an unparalleled level of detail of occupancy data relative to previous studies which have relied on work hours and water consumption data as a proxy for occupancy (Brown et al. 2010; Masoso and Grobler 2010). In this study, occupancy data is unique to the individual, not the room, and is recorded on an hourly basis. In order for an occupant to enter his/her room he/she must use a key card. Once he/she enters the room he/she places the key card in a card reader on the inside of the door. Having the key card in the reader enables the lights in the room to be operated as well as the ceiling mounted air conditioning unit; however, the key card reader does not affect the room's heating system or outlets. From observation and discussions with occupants in the dorms, all residents place his/her card in the reader upon entry and rarely neglect to do so.

Each time the occupant enters or leaves the room, the key card is either placed in or removed from the reader, the time is recorded as well as the action, entering or leaving. The system records and stores these events and logs on an hourly basis and reports the final action of each hour for each occupant.

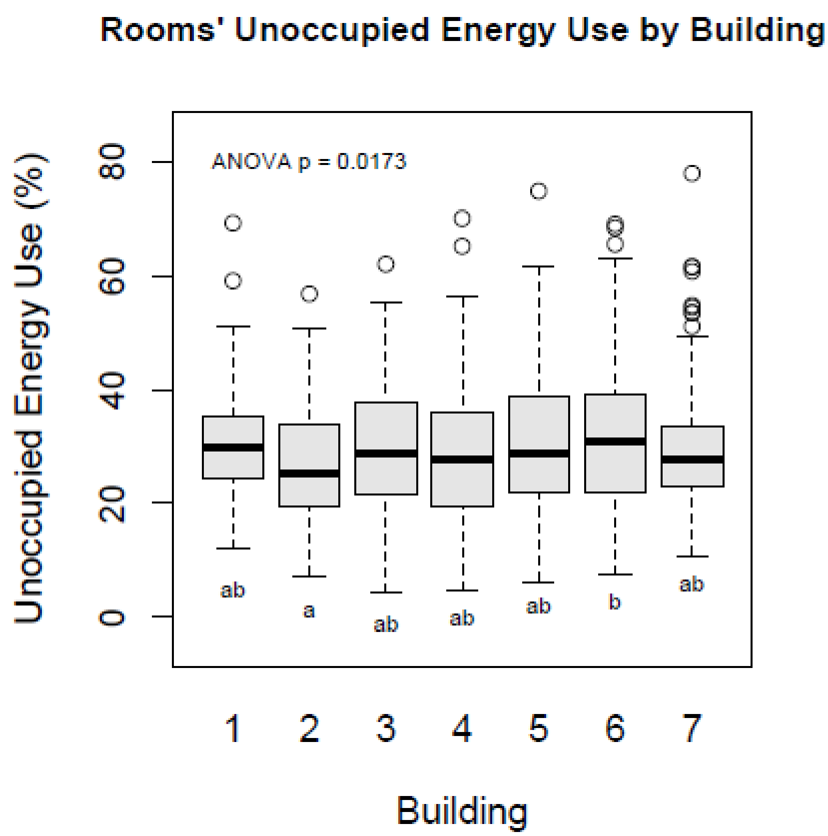


Figure 2.1: Room's unoccupied energy use by building. Each of the seven buildings had very meaningful amounts of energy consumed during periods of non-occupancy over the course of the year. This quantity for the seven dormitory buildings varied significantly ($F_{6, 952} = 2.583$, $p = 0.0173$, $n = 959$). Subscripts indicate statistical differences between buildings.

Data for both individual occupancy and room electrical consumption was collected from January 1, 2013 through December 31, 2013. However, from April 24 to May 3 no data was gathered due to a system wide malfunction with the electrical metering system. In addition, some rooms had to be removed from analysis due to errors and inconsistences in occupancy data as a result of individual card reader malfunction and remaining tenantless for substantial portions of the year. In total 959 rooms are included in the analysis. This includes 152 single occupancy units and 807 double occupancy units. The total number of units in each of the seven buildings (single, double) are 67 (9s, 58d), 93 (21s, 72d), 110 (19s, 91d), 106 (16s, 90d), 218 (36s, 182d), 224 (46s, 178d), and 141 (5s, 136d) respectively.

Analysis of the results is conducted using multiple techniques. Analysis of variance (ANOVA) is used to test for statistical differences in annual energy consumption as well as percentage of consumption while vacant across buildings. In order to meet the normality assumptions of ANOVA the percentage of annual energy use while unoccupied has undergone an arcsine square root transformation and annual energy consumption has undergone a square root transformation. When significant results are found the Tukey honest significant difference test is applied to identify which means significantly differ. Additionally, Welch Two Sample t-tests are used to test the significance of room type on annual percentage energy consumed in unoccupied rooms and net energy consumption. Correlation analyses are also run to identify relationships between several variables.

2.3 RESULTS AND DISCUSSION

2.3.1 Annual Energy Consumption

Each of the seven dormitory buildings had substantial amounts of energy spent in vacant rooms (Figure 2.1). This amount differed significantly between the seven buildings over the course of the year ($F_{6, 952} = 2.583$, $p = 0.0173$, $n = 959$). Building 2 had the lowest mean percentage among the buildings at 26.9% while building 6 had the highest mean percentage at 31.9% (Table 2.1). Across the seven buildings the average room spent 869 kWh a year, or 30.2%, of all energy while vacant. Taken in aggregate, only including rooms in the analysis–959 rooms, over 833 mWh of site energy was consumed during periods of vacancy in slightly less than one year. Of this use it should be noted that roughly four percent is spent on useful services such as the operation of the mini-fridge in each room.

Table 2.1: Mean Annual Room Energy Use by Building and Room Type

	No. of Rooms (% Singles)	Mean Energy Use per Room (kWh) While Vacant	While Occupied	Total	Mean Use While Vacant (%)
Building 1	67	893.6	2070.3	2963.9	30.6
	(13.4)	(393.5)	(738.9)	(898.4)	(10.6)
Building 2	93	789.2	2152.2	2941.3	26.9
	(22.6)	(396.7)	(686.2)	(848.6)	(10.4)
Building 3	110	896.2	2124.9	3021.1	29.3
	(17.3)	(458.9)	(733.5)	(955.9)	(11.3)
Building 4	106	833.2	2079.4	2912.6	28.7
	(15.1)	(446.4)	(786.9)	(997.3)	(11.8)
Building 5	218	896.0	1973.6	2869.6	30.9
	(16.5)	(467.2)	(660.2)	(871.2)	(11.9)
Building 6	224	929.2	1953.4	2882.6	31.9
	(20.5)	(469.9)	(630.6)	(817.1)	(12.5)
Building 7	141	775.7	1793.5	2569.2	30.0
	(3.5)	(382.1)	(612.9)	(787.4)	(11.0)
Across all buildings		**868.6**	**1995.5**	**2864.1**	**30.2**
		(443.8)	(685.6)	(879.1)	(11.7)
Single Occupancy Rooms	152	899.8	1446.0	2345.8	37.7
		(425.3)	(461.5)	(646.0)	(12.7)
Double Occupancy Rooms	807	862.8	2099.0	2961.8	28.7
		(447.2)	(671.7)	(883.3)	(10.9)

With the exception of values in the Number of Rooms column, all values in parentheses are standard deviations.

Within the buildings the percentage of energy spent in unoccupied rooms varied substantially from one room to another. The number of hours a rooms was unoccupied and their respective percentage of energy consumed while vacant was highly correlated (Pearson's r = 0.63, t = 25.1507, df = 957, p-value < 2.2e-16). Naturally this is to be expected; however, this did not explain all, or even half, the variation in the percentage of energy consumption while vacant across rooms. Poor occupant behavior, e.g., leaving on heaters and appliances while away from home, is one explanation for the wide variance between rooms. Rooms that had occupants who were home frequently and exhibited better behavior (i.e., those that turn off appliances and equipment when leaving) had very small percentages of energy consumed while vacant, as low as 4%. On the other end of the spectrum, rooms where occupants were frequently away from home and left equipment on had over 70% of total energy consumed while unoccupied. In between the two extremes, a quarter of all rooms spent less than 22% and a quarter of all rooms spent more than 37% of all electricity in unoccupied rooms over the course of the year. In the building with the lowest average quantity of energy spent in empty rooms, building 2, rooms consumed on average just over a quarter, 26.9%, of all their energy during periods of vacancy. In building 6, the worst performing building, residents spent on average almost one-third of their total electrical consumption for the year, 31.9%, while away from home.

When comparing the effect of room type on energy consumption patterns it can be seen that single occupancy rooms average statistically significant less annual energy use than double occupancy rooms at 2,346 kWh compared to 2,962 kWh (Welch's t-test $t = -10.1104$, $df = 269.832$, $p\text{-value} < 2.2e\text{-}16$), but have significantly higher percentages of energy consumed while unoccupied at 37.7% versus 28.7% (Welch's t-test $t=8.0988$, $df = 195.164$, $p\text{-value} = 5.896e\text{-}14$) (Figure 2.2). The increased energy consumption in double rooms is to be expected considering that the rooms have slightly larger living quarters and would have additional electronic devices since there are two occupants. It is also fitting that with more occupants in the room the percentage of energy spent while no one home is decreased. The higher percentage of energy use while unoccupied in single rooms can largely be attributed to more periods of vacancy. Since two occupants reside in the double rooms the periods of vacancy are lower. This restricts the total potential vacant energy use in double rooms beyond that of single occupancy rooms even if occupants exhibit similar behavioral practices in each room type. So even when occupants in each room type have uniform behavior the percentage of energy consumption while away from home should be lower in higher occupancy rooms. Despite this, and the fact that single rooms use more energy while unoccupied on average than double rooms, both in absolute terms and percentage, there is no relationship between the average amount of energy spent in empty rooms in each building and its percentage of single rooms (Table 2.1). This implies that the number of single rooms in each building is not the cause of the differences in consumption in unoccupied rooms in each building, but rather that occupant energy use practices with regards to turning off equipment and devices when leaving his/her residence vary from building to building.

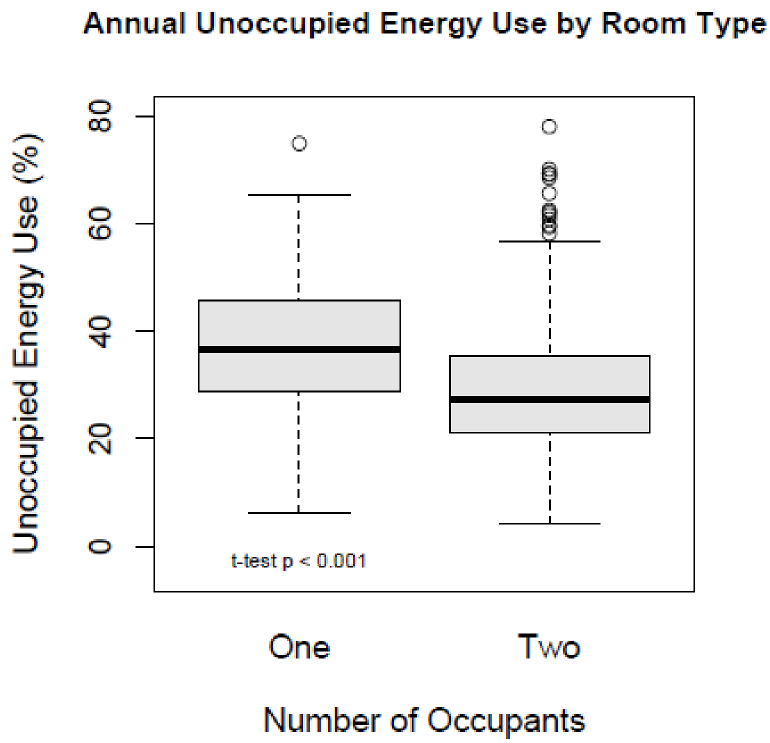


Figure 2.2: Annual unoccupied energy use by room type. Single occupant rooms spent a significantly higher percentage of their total energy consumption over the course of the year while unoccupied when compared with double occupancy rooms (Welch's t-test t=8.0988, df = 195.164, p-value = 5.896e-14).

Beyond looking at average amounts of energy spent in unoccupied rooms, understanding which rooms tend to consume more energy while away from home would be beneficial. Examining total energy consumption against the percentage of energy spent while away from home I find that there is no meaningful relationship between the two variables (Pearson's r = 0.048, t = 1.4721, df = 957, p-value = 0.1413, n.s.). High and low energy consuming rooms both tended to spend similar percentages of energy while away from home. This suggests that while most occupants tend to leave on devices and equipment when leaving their rooms an equal amount, the difference between the high and low energy users is the quantity and intensity of the devices and equipment he/she leaves on. For instance, a low energy user might not use the heater on mildly cool days in the fall, but they tend to leave on their desktop when going out. On the other hand, a high energy user would use both devices and tend to leave both on when going out.

This finding has positive implications for behavioral interventions. The uniformity in behavior between both high and low energy users permits the deployment of non-particular, or generic, interventions. In other words, interventions focusing on mitigating energy use while away from home will likely be applicable to the entire population and not just specific sub-populations.

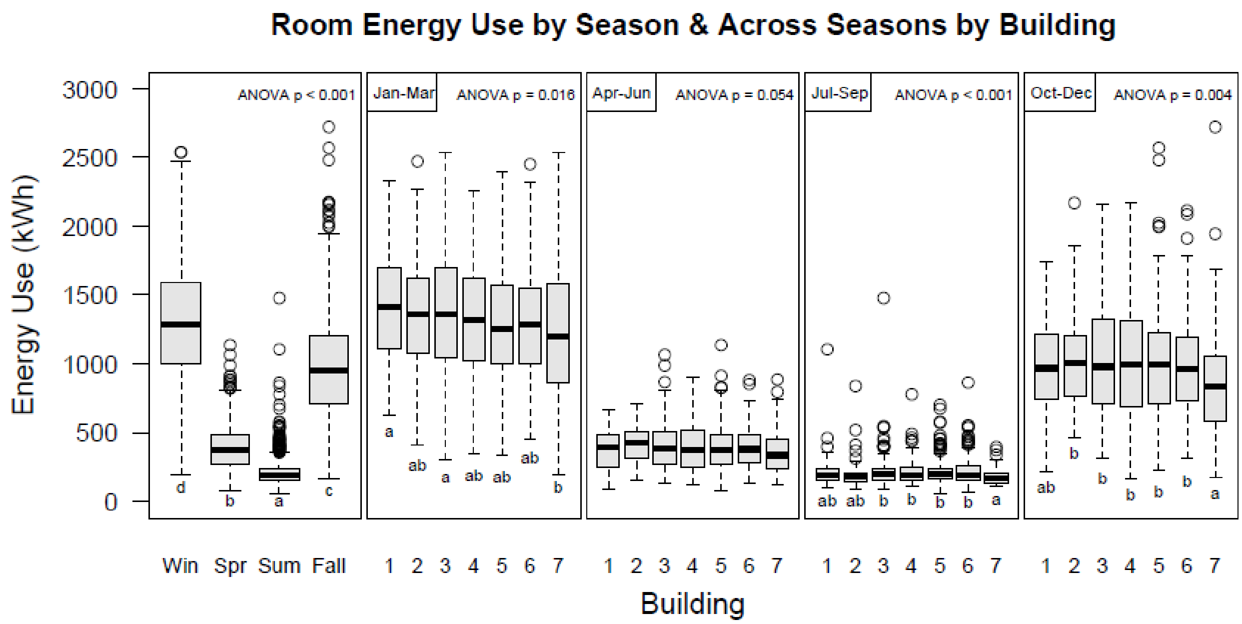


Figure 2.3: Room energy use by season and across seasons by building. The average amount of electrical energy use in kWh per room varies significantly and meaningfully by season ($F_{3, 3775}$ = 2707, p = 2e-16, n = 3779). Energy use differed significantly among buildings in all seasons except spring (winter: $F_{6, 927}$ = 2.613, p = 0.0162, n = 934; spring: $F_{6, 951}$ = 2.07, p = 0.0543, n.s., n = 958; summer: $F_{6, 930}$ = 4.177, p = 0.0003, n = 937; fall: $F_{6, 943}$ = 3.205, p = 0.0040, n = 950).Winter is January through March, spring is April through June, summer is July through September, and fall is October through December. Letters on the plots indicate significant differences between buildings.

2.3.2 Energy Consumption by Season

Seoul is situated in a climate which requires significant heating during the colder months and limited cooling in the summer months; the seasonal energy use by residents in the seven dormitory buildings reflects this (Figure 2.3). In 2013, Seoul had 5,814 heating degree days (HDD) and 1,392 cooling degree days (CDD) (Weather Underground 2014). Electrical energy consumption differed significantly by season ($F_{3, 3775} = 2707$, $p < 2e\text{-}16$, $n = 3779$) and peaked in the winter months. In 2013, January was the coldest month followed by December and February with 1300, 1116, and 1047 HDD respectively (Weather Underground 2014). Alternatively, July and August were the hottest months. Overall energy consumption during the summer months was depressed relative to the others for two reasons. First, some students were away from his/her rooms more than in previous months due to school being in recess. Second, it was not possible for residents to leave on air conditioners while away from home which reduced the amount of energy that was consumed during periods of non-occupancy. Looking closely at the energy consumption across the seasons by buildings, certain buildings consumed more energy on average than others, with the exception of during spring, where there were no significant differences in consumption (winter: $F_{6, 927} = 2.613$, $p = 0.0162$, $n = 934$; spring: $F_{6, 951} = 2.07$, $p = 0.0543$, n.s., $n = 958$; summer: $F_{6, 930} = 4.177$, $p = 0.0003$, $n = 937$; fall: $F_{6, 943} = 3.205$, $p = 0.0040$, $n = 950$). Given that these buildings are identical in construction, these results further highlight the importance of individual behavior on energy consumption.

When considering energy use in unoccupied rooms from a seasonal perspective I find that the percentage energy consumed while away from home is fairly consistent in magnitude throughout the year despite energy use varying with changes in seasonal weather patterns. Mean energy use while vacant did statistically significantly differed by season though ($F_{3, 3775} = 23.61$, $p = 3.93e\text{-}15$, $n = 3779$). Net energy use in unoccupied residences increased in roughly an equal proportion to net energy use as consumption changed with the seasons (Figure 2.4). Mean values ranged from 27.5% in the fall to 31.5% in the summer (Table 2.2). Investigating this at the building level it can be seen that energy spent in vacant rooms varied significantly by building in each of the four seasons (winter: $F_{6, 927} = 2.356$, $p = 0.029$, $n = 934$; spring: $F_{6, 951} = 3.245$, $p = 0.00366$, $n = 958$; summer: $F_{6, 930} = 5.603$, $p = 1.01e\text{-}5$, $n = 937$; fall: $F_{6, 943} = 3.232$, $p = 0.00379$, $n = 950$). Within each season most buildings did not statistically differ, but rather only two of three of the buildings did. In the colder seasons, fall and winter, we see a slight peak in the percentage of energy consumed in vacant rooms. This is expected since air conditions cannot run in unoccupied rooms. Some extreme households consumed over 80% of its total energy while away from home, and eight percent of all rooms spent over 50% of all electrical expenditures while away from home. These results reinforce the previous finding from the annual time scale that the quantity of energy spent in empty rooms scale with the total amount of energy consumed. As an individual consumes more electricity he/she also consumes more while away from home in a comparable ratio to when his/her consumption was lower. This finding, in spite of the negative connotations associated with it, can be viewed in a positive light. If occupants can be induced to lower his/her total energy consumption the amount of energy spent while vacant should decline proportionally as well (Figure 2.5).

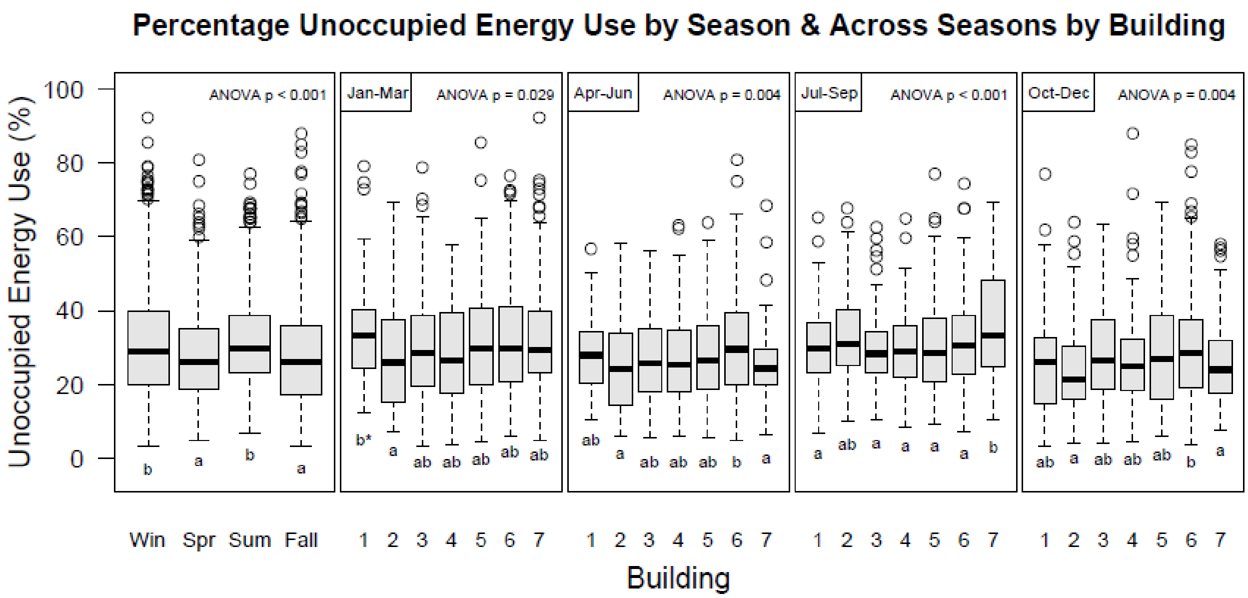


Figure 2.4: Percentage unoccupied energy use by season and across seasons by building. The percentage of energy used in vacant residences remains relatively consistent in magnitude across the seasons, but does significantly differ ($F_{3, 3775}$ = 23.61, p = 3.93e-15, n = 3779). In addition, it differs significantly among buildings in all seasons (winter: $F_{6, 927}$ = 2.356, p = 0.029, n = 934; spring: $F_{6, 951}$ = 3.245, p = 0.00366, n = 958; summer: $F_{6, 930}$ = 5.603, p = 1.01e-5, n = 937; fall: $F_{6, 943}$ = 3.232, p = 0.00379, n = 950). Letters on the plots indicate significant differences between buildings (* indicates p < 0.1, all others are p < 0.05).

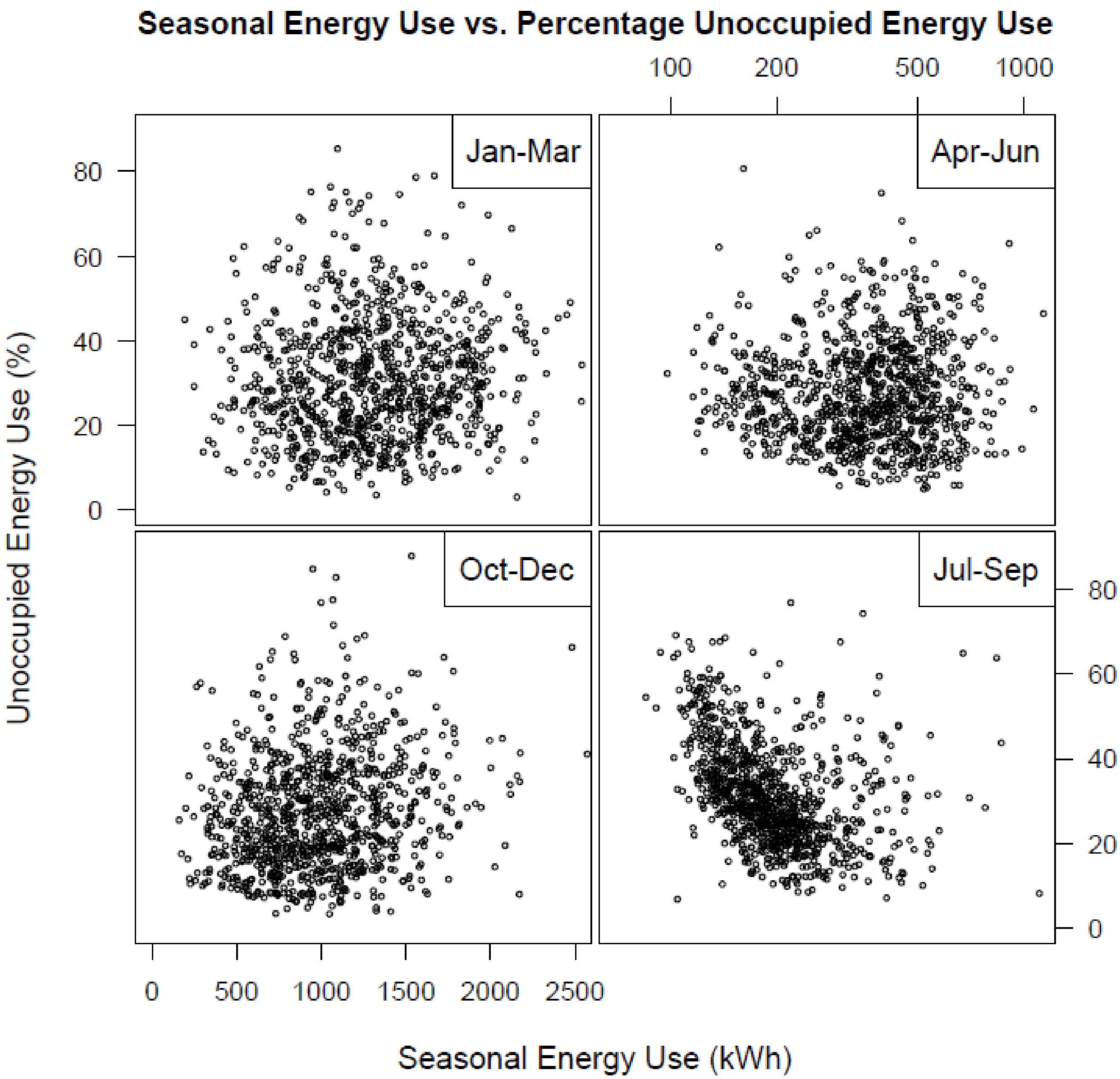


Figure 2.5: Seasonal energy use versus percentage unoccupied energy use. Over the course of the year there is largely no relationship between the amount of energy used in a given room and its percentage of energy consumed while unoccupied (note the change in scales on the x-axis, the right two most plots also use a log scale x-axis).

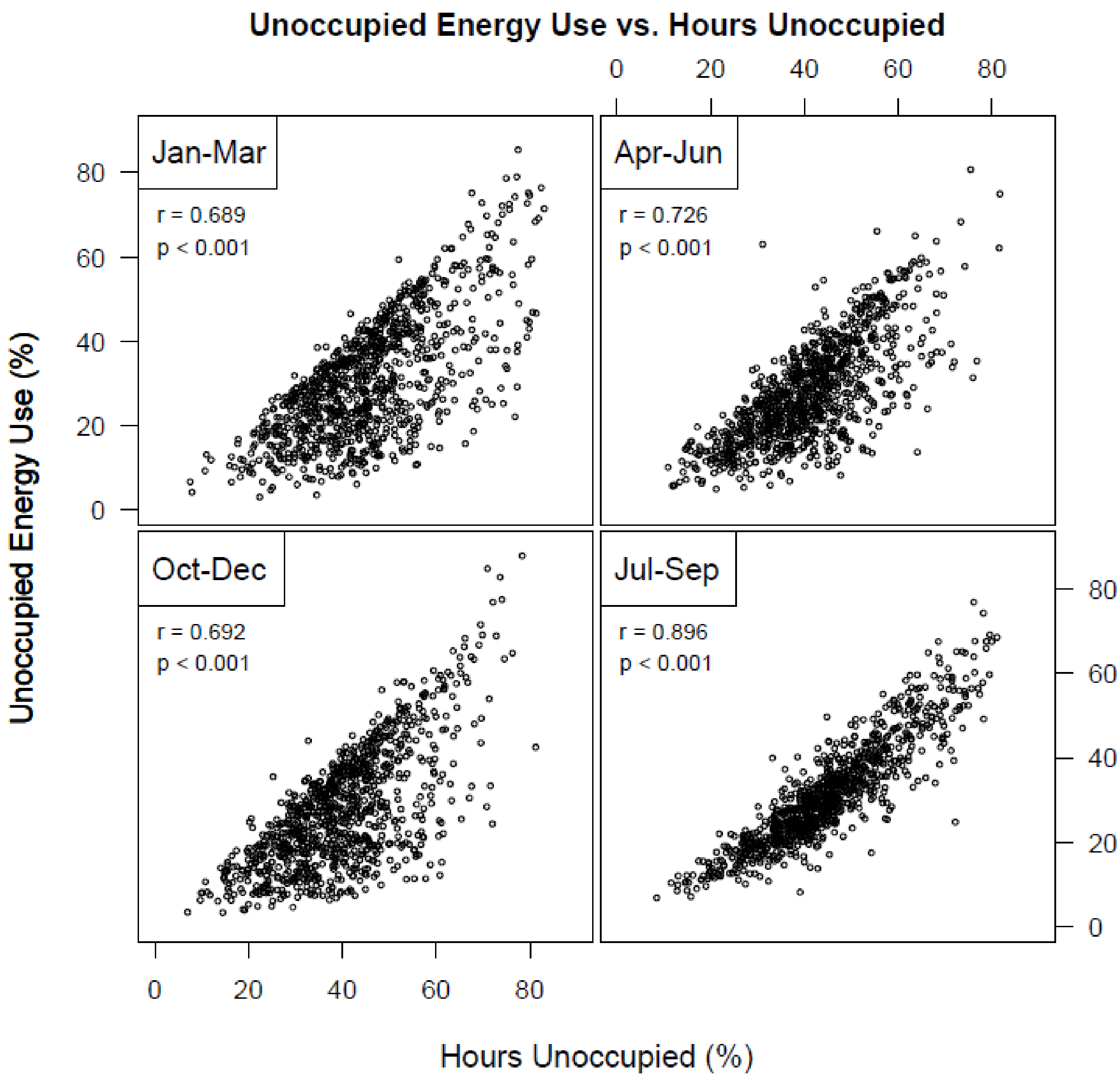


Figure 2.6: Unoccupied energy use versus hours unoccupied. The percentage of energy a household consumed while unoccupied is highly correlated with the number of hours the dwelling was unoccupied; however, this does not completely explain all the variance in the percentage of energy consumed while vacant. Occupant behavior can help explain the remainder. Many households left on equipment while away from home, but many others turned off equipment when leaving home.

Table 2.2: Mean Room Energy Use by Season

Season (Months)	Mean Energy Use per Room (kWh)			Mean Use While Vacant (%)
	While Vacant	While Occupied	Total	
Winter (Jan-Mar)	406.7	894.9	1301.6	31.0
	(239.8)	(339.2)	(424.5)	(14.5)
Spring (Apr-Jun)	107.6	278.1	385.7	27.8
	(70.4)	(124.9)	(160.6)	(12.0)
Summer (Jul-Sep)	62.8	147.1	209.9	31.5
	(39.0)	(83.1)	(103.4)	(12.2)
Fall (Oct-Dec)	279.0	702.0	981.0	27.5
	(199.0)	(286.2)	(380.2)	(13.8)

Standard deviations are shown in parentheses.

In addition, once again the amount of time rooms remain unoccupied is highly correlated with percentage of energy that is consumed during periods of non-occupancy (winter: Pearson's $r = 0.689$, $t = 28.99$, $df = 932$, p-value $< 2.2e-16$; spring: Pearson's $r = 0.726$, $t = 32.56$, $df = 956$, p-value $< 2.2e-16$; summer: Pearson's $r = 0.896$, $t = 61.52$, $df = 935$, p-value $< 2.2e-16$; fall: Pearson's $r = 0.692$, $t = 29.55$, $df = 948$, p-value $< 2.2e-16$). These correlations do not completely explain all the variance in the percentage of energy consumed while vacant though (Figure 2.6). It can be seen that there is minimum amount of energy consumed during periods of non-occupancy, around 4%, even in the rooms with very low levels of energy use while unoccupied relative to their percentage of hours unoccupied. This energy is believed to stem from powering the mini-refrigerator in each room, which through experimentation has been found to have a functional power rating between 25 and 33 watts. Differences in occupant behavior among the households can help explain the remaining variance. In all seasons except summer, many households consume approximate the same amount of energy while home as while away from home. Occupants appear to leave on heating equipment, and possibly other appliances, regardless of whether anyone is home or not. This is not true of all households though. A fair number of households consume substantially less energy on a percentage basis when away from home relative to the percentage of hours the unit is unoccupied (e.g., unoccupied 40% of the time but only consumes 10% of energy while vacant). This suggests that these households exhibit environmentally preferable behavior and turn off equipment when leaving home. This pattern, a lower ratio of consumption while vacant relative to hours of vacancy, is found in almost all households in the summer since the largest consumer of electricity, the air conditioner, can only be run while occupants are home.

2.4 CONCLUSIONS

In commercial buildings the amount of energy spent in building during non-working hours has been found to be in excess of 50% of all energy use, but to the best of my knowledge little is known as to the quantity of energy use in vacant households. In this study I conducted an investigation into the quantity of energy spent in unoccupied households, focusing specifically on dormitories. Electrical energy consumption and occupancy data has been collected on an hourly basis for seven dormitory buildings housing over 1000 individual residences in Seoul, South Korea from January 1, 2013 to December, 31, 2013. During this period using hourly occupancy and electricity consumption data it has been found that over 30% of all electrical energy consumption (which accounts for plug loads, lighting, heating, and cooling) took place in unoccupied residences. This quantity represents an overestimation of the amount of energy that could be reduced by improvement in occupant behavior before requiring lifestyle changes (e.g., wearing a sweater rather than turning on the heaters), since not all energy spent in unoccupied residences is wasted energy use (e.g., refrigeration). In these dormitories, roughly four percent of all energy used while away is spent on useful services and should be detracted from the following values in order to estimate realistic targets for reduction. Through the seasons the percentage of energy consumed in vacant rooms across the seven buildings ranged from 27.5% to 31.5% while individual rooms fluctuated from around 4% to over 80%. It is reasonable to expect that similar magnitudes of energy expenditures while unoccupied, when conditioned on number of occupants, would be found in more traditional residential dwellings as well (i.e., single family apartments), since these dormitories are essentially studio apartments without kitchens and energy consumption related to food storage and preparation represents less than eight percent of total site energy use in the home (EIA 2014). The amount of energy consumed in unoccupied households, while highly correlated with how often the household is vacant, is also strongly influenced by occupant behavior. In addition to the aforementioned findings, no meaningful relationship was found between total a residences total energy consumption and the percentage of energy that was used while unoccupied. High and low energy users both spent energy while away from home in proportion to his/her consumption.

These findings, which could be perceived as discouraging can alternatively be viewed as a significant opportunity to improve the sustainability of households at little to no cost through behavioral approaches. Energy behavior interventions can offer a low cost and effective means to reduce building energy consumption (Abrahamse et al. 2005; Osbaldiston and Schott 2011; Wilson and Dowlatabadi 2007). Recently, normative behavior interventions have shown considerable promise in inducing environmentally significant behavior in a variety of settings (Goldstein et al. 2008; Schultz et al. 2007). Using these techniques in conjunction with prompts at the point of behavior could be particularly apt at addressing behaviors which lead to energy expenditures in unoccupied buildings. A very favorable quality of energy use in unoccupied spaces, with respect to eliciting behavior change in occupants, is that it is mostly energy that can be saved without occupants having to sacrifice his/her comfort. In addition, since the percentage of energy that is spent in unoccupied households is found to be proportional to total consumption, behavior interventions aimed at reducing this quantity of energy do not necessarily have to be tailored to the target group. Interventions can be highly non-particular which places less demands on interveners (De Young 1993), since energy consumption while away from the home is largely the culmination of a very specific set of behaviors common to all individuals, such as not turning off devices and equipment prior to exiting the residence. Such behavioral efforts specifically focusing on targeting these behaviors, given the large quantity of energy consumed in vacant households found in this study, have the potential to meaningfully improve the environmental sustainability of the built environment.

CHAPTER 3

EXPLORING THE ROLE OF SOCIAL NETWORK CHARACTERISTICS ON NORMATIVE BEHAVIOR INTERVENTIONS[3]

3.1 INTRODUCTION

The previous chapter highlighted the substantial role individual behavior can have on energy consumption in the home. Understanding the importance of behavior it is critical to develop and implement sound methods for promoting pro-environmental behaviors. Ideally to study the effectiveness and consequences of pro-environmental intervention strategies robust large scale randomized field experiments should be employed. Unfortunately, conducting field experiments to test new intervention strategies is very time consuming and costly. Therefore, researchers have begun developing models to simulate the effect of behavioral interventions, but very limited work in this area has been done to date[4]. The ability to model and simulate interventions aimed at changing occupant behavior is of particular interest and importance as it creates a means to experiment, test and in turn identify favorable interventions in a cost effective and timely manner prior to implementation. Being able to accurately identify effective interventions for specific buildings or communities of buildings based on local conditions has significant implications for reducing energy consumption and demand in buildings.

The limited intervention modeling efforts to date have focused on modeling intervention techniques where social norms, social influence/pressure, are exploited to induce behavior change (Azar and Menassa 2012a; Chen et al. 2012; Zhang et. al 2011). Social norms can be

[3] This chapter is adapted from Anderson, K., Lee, S., and Menassa, C. (2013). "Impact of Social Network Type and Structure on Modeling Normative Energy Use Behavior Interventions." *Journal of Computing in Civil Engineering*, ASCE, 28(1), 30-39.
[4] This is not to be confused with public policy modeling which has received considerable attention (Mundaca et al. 2010) or the development of theoretical behavior models which has been extensive.

thought of as general codes of conduct, i.e., shared understandings of what is and what is not acceptable behavior for a group (Bendor and Swistak 2001). In the models, as in the real world, the transmission of social norms occurs through social networks. Results from these studies suggest that normative based interventions can have significant impact on energy use. However, in these previous modeling efforts minimal attention has been given to the impact of social network type (e.g., random graphs, small-world networks) and social network structure (e.g., number of people, number of relationships per person). If these models are to be used for predictive purposes understanding the importance of social network type and structure (SNTS) is necessary since SNTS are likely not identical across various residential communities or in different types of communities. This brings into question whether or not SNTS is an important determinant in simulation results. Therefore, further effort needs to be extended to quantify the impact that SNTS have on normative based interventions. In order to address this shortcoming in the literature I will use agent-based modeling to simulate behavior interventions across an array of different social network structures.

3.2 COMPUTATIONAL MODELING: AGENT-BASED MODELING

Agent-based modeling (ABM) is an analytical method that allows the modeling of heterogeneous agents in various types of environments with explicit decision rules (Gilbert 2008). This form of modeling permits adaption and learning which can be difficult to model using alternative methods (e.g. variable-based approaches). These attributes make ABM particularly well suited for modeling and understanding complex adaptive systems (Miller and Page 2007). In buildings, agents, i.e. occupants, are not homogeneous, are adaptive, and communicate through a complex system of social relationships. For that reason ABM is quite appropriate for exploratory studies on how individual behavior changes in social networks due to social influence. Several studies have used ABM in conjunction with energy interventions; these include Zhang et al. (2011), Azar and Menassa (2012a), Chen et al. (2012). The aforementioned modeling efforts, have attempted to model the dynamics of social influence caused by energy interventions.

However in the previous work, little attention has been given to the role of SNTS. Zhang et al. (2011) used small-world networks in their study, but mainly focused on calculating the effectiveness of automated lighting sensors and little on the dynamics of social interactions and influence. Azar and Menassa (2012a) consider a given social network type or structure, but rather modeled a network where all occupants interact. In this study the authors focused on attempting to integrate energy simulations with ABM of occupant behavior changes due to social norm diffusion and education. Lastly, Chen et al. (2012) evaluated the importance of social network structures within the context of normative energy interventions. Here the authors also developed a set of behavioral rules for how occupants change their behavior. In this work, social network structure was only evaluated within the context of random graphs.

While each study has its own merits, if models are to be used to provide intervention design selection guidance, i.e. to predict actual behavioral change due to interventions, modeling assumptions must be rigorously reviewed (Law and Kelton 2000). Cowan and Jonard (2004) found that within single network types differences in architecture can lead to different conclusions when investigating diffusion. Further, social science research has shown that social networks likely are either defined by scale free properties or are small-world networks which feature high amounts of clustering and short path lengths (Barabasi and Albert 1999; Liljeros et al. 2001; Watts and Strogatz 1998). In buildings, scale free networks could represent buildings with hierarchal social structures. For example, workers are likely to know the CEO or students to know the resident advisor in a dormitory, but not all people in other departments or all other residents. Small world networks on the other hand could be thought of as a society where occupants form clusters or groups with loose ties to other groups. This can be thought of as people on a given floor are likely to know each other and have a few ties to people on other floors. These are compared to random graphs which can be thought of as randomly knowing individuals in the building. Since SNTS are likely not consistent from building to building it is important that the impact of SNTS on energy interventions is better understood. Thus, a better understanding of SNTS on normative interventions is required to add confidence and validity to modeling attempts which aim to accurately model intervention outcomes. Additionally, greater emphasis needs to be placed on developing models built on sound theories and evidence of how individuals interact and influence each other.

In this chapter I develop an integrated model which combines established social-psychological principles of social influence and cultural norm diffusion with building social network profiles to examine the effect of energy interventions aimed at reducing energy consumption across multiple building environments. The main objectives of the research are to: (1) to test the impact of SNTS on behavioral energy interventions and (2) evaluate the effectiveness of the proposed interventions, providing occupants with peer data and inserting intervening agents into the building, in different scales of buildings. In order to achieve these goals, agent-based modeling and statistical analysis is utilized to simulate and measure the interactions of heterogeneous building occupants in social networks. Two separate interventions are used to examine the effect SNTS, increasing social connectivity and implementing an intervention agent, from here on referred to as an environmental champions (EC), a person who demonstrates strong pro-environmental behavior and is unsusceptible to negative influence and can significantly influence others in his/her network.

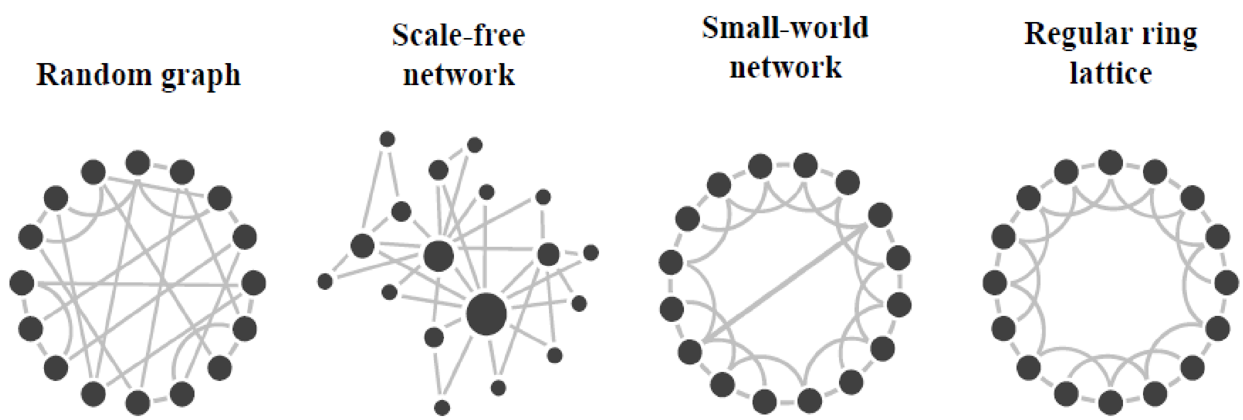


Figure 3.1: Illustration of the four social network types being investigated (Anderson et al. 2012).

3.3 MODEL DEVELOPMENT

I will describe the model using the Overview, Design concepts, Details (ODD) protocol for describing agent-based models (Grimm et al. 2006; Grimm et al. 2010). This is to improve the clarity, completeness and reproducibility of the model. The choice of the experimental model is guided by my previous work (Anderson et al. 2012) but model assumptions have been reevaluated; details on changes will be provided in the following subsections. The model has been programed in Java using Repast J v 3.0 (Repast 2012).

3.3.1 Purpose

The purpose of this model is to understand the impact of SNTS on modeling energy interventions. Specifically investigating four types of social networks random graphs (RND), regular ring lattices (REG), small-world networks (SWN) and scale-free networks (SFN) (Figure 3.1). Additionally, to examine the effect of the social network structural variables: number of degrees (K) (i.e. average number of relationships per occupant) and social network size (N) (i.e. number of persons in the network).

3.3.2 Entities, State Variables, and Scales

In this model the entities, agents, are the building occupants. These occupants have several attributes: energy use standard (EUS), relationships with other occupants stored as a list, and a value representing their susceptibility to external influence, this is referred from here on as susceptibility. The primary attribute of interest is the EUS which is dynamic and changes based on an influence calculation which will be detailed in the submodel section. Relationships between occupants are undirected, i.e. reciprocal. The number of relationships in the model can vary slightly between the SFN and the others due to how it must be constructed, but differences are quite minimal (for example, in the large network, N=441 with K=6, the SFN has 2634 total relationships and the others have 2646). The social network, regardless of which type it is, is always continuous. In other words, the social network is one component and does not have any individuals in it who are not connected to the giant component. Lastly, time steps in the model do not represent actual time units and are used relatively as measures.

3.3.3 Process Overview and Scheduling

The model begins by creating occupants. The model then takes the occupants and assigns them relationships dependent on which SNTS has been selected. This is described in further detail under network generation in the submodels section. After all occupants have been placed into the social network, during each time step, occupants compare their EUS with the group norm of the members with whom they have relationships (direct or indirect) as detailed in the influence calculations provided in the submodel section. Agent processing order does not have a bearing on the outcome as agents alter their EUS using the observed EUS of their peers from the previous time step. Once all agents have calculated their new EUS, they update synchronously. Model operations end once equilibrium conditions are met as detailed further in the submodels section. The process flowchart can be seen in Figure 3.2.

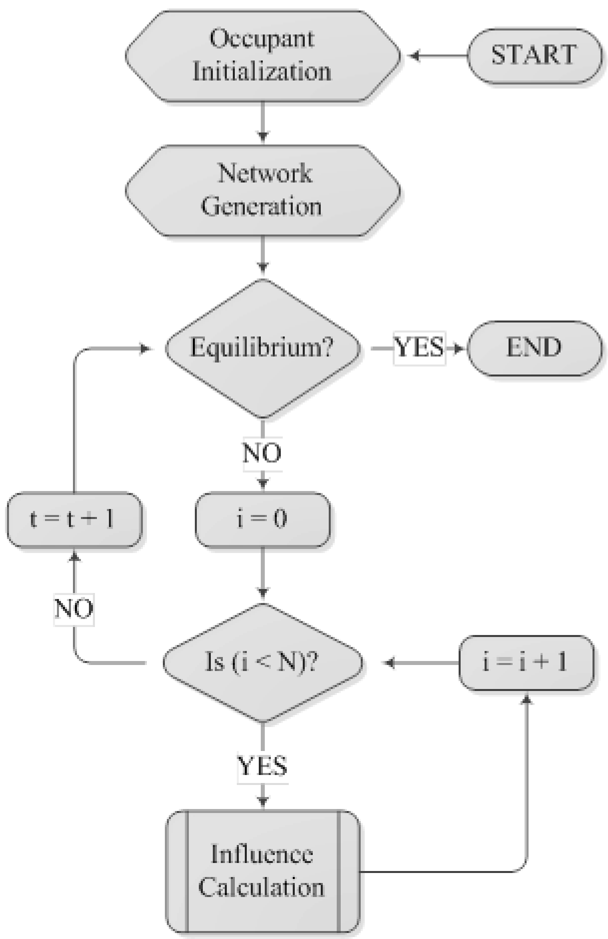


Figure 3.2: Model process flowchart. *i* is the occupant id of the occupant being evaluated and N is the total number of occupants in the simulation.

3.3.4 Design Concepts

The basis for the model rests in findings from the social sciences that people modify their behavior to conform to social norms on many issues, including energy use (Nolan et al. 2008). Two very basic assumptions are made in the model: 1) an energy intervention which provides occupants with feedback of their own energy use and peer energy use data is being installed in a building where previously there was no such feedback, and 2) energy use behavior and practices are not such a polarizing topic that occupants of different practices would be unable to have relationships with each other. Additionally, not all occupants are equally susceptible to influence from others. Susceptibility to influence from others has been shown to be correlated with individual intelligence (presented in Bearden, Netemeyer, and Teel 1989 from Petty and Cacioppo 1981, pp. 80-84), self-confidence (Cox and Bauer 1964), self-esteem (Janis 1954), and interpersonal confidence (Berkowitz and Lundy 1957). It should also be noted that the model assumes that behavior moves with equal ease both upward (increasing energy use) and downward (decreasing energy use). This is in contrast the previous agent-based models which have tended to place a downward bias on the direction of movement in behavior.

In the previous iteration of this model (Anderson et al. 2012), rate of change of occupant behavior, EUS change per time step, had been constrained for a given time period (Anderson et al. 2012). This modeling assumption has been reevaluated and reworked to not limit the rate at which occupants are allowed to change their behavior practices. This represents a substantial difference in model behavior and philosophy. Previously, behavior had been thought of as a continuous variable, one which gradually moves along a spectrum. This assumption was based on the idea that one does not make radical leaps in behavior instantly. However, based on findings from my previous work and further review of the literature I have determined that behavior should be considered as present or not present, i.e., one turns off the lights when they leave home or they do not (Franz and Nunn 2009). This means that when considering behavior, intent of performing a behavior is not considered, but rather, only if a behavior has been performed or not. The model adopts stochasticity at several stages: initializing susceptibility, initial EUS, and relationships for occupants. One hundred simulations are run for each configuration of input parameters. From and during the simulation runs I observe and keep statistics on net change in mean system EUS from initialization to equilibrium, time to reach equilibrium, and the standard deviation in EUS of all occupants at equilibrium.

3.3.5 Initialization

Each network initializes with 35 occupants which represents a medium sized building with an average of six relationships per occupant. The EUS of each occupant is generated from a log-normal distribution (μ=163 watts and σ=123 watts) based on observations from buildings where occupants are not responsible for energy costs (Chen et al. 2012). Occupant susceptibility is normally distributed with a mean of 0.92 and a standard deviation of 0.01. These values range between 0 and 1 (truncated at 0 and 1), where 0 means the occupant is never influenced by others and 1 indicates their behavior decisions are completely influence by others. These values express that people usually conform to social pressure and norms but have different rates of adaption (Friedkin 2001). Each input value derived from previous studies, EUS and susceptibility, were subjected to sensitivity analysis and found to demonstrate only relative changes in system behavior (e.g. lowering susceptibility would make the simulation times larger across all network types a comparable amount).

3.3.6 Submodels

As mentioned previously the model has three separate submodels to generate the social network, calculate how occupants determine their EUS and how the model determines when the simulation has reached equilibrium.

3.3.6.1 Social Network Generation

Three of the social network types are generated based on ideas presented Watts and Strogatz (1998). A regular ring lattice is created where an occupant (node) *n* is connected to the K/2 (K is degrees or number of connections to other occupants, K must be even) to the right of the occupant and repeated for each node. Right is expressed as a larger number node, determined by occupant Id number, until it reaches the last node then starts over at the first one thus creating a ring. Occupants are counted as *n* (their Id), so if the max number of degrees was set to 4, occupant 5 would make a connection with occupant 6 and 7. This procedure then repeats for occupant 6, then 7. Once completed, occupant 7 would be connected to occupant 5, 6, 8, and 9, (K=4) thus representing the configuration of a regular ring lattice. To make this a small-world network while creating each connections there is a chance, *p*, which ranges from 0 to 1, to not connect to the intended node and instead randomly connect to another that does not fall within the range n±K/2. To make a random network p is set to 1 and to make a regular lattice *p* is set to 0; *p* is set to 0.1 to create the small-world network.

The forth network type, the scale-free network, is generated based on ideas presented in Barabasi and Albert (1999). Here the maximum number of degrees each occupant is created with is set, *K*, and initially *K+1* occupants are made and each is connected to the other. Next a new occupant is added and *K* connections are made to the already created nodes. The new node connects to the already created node *n*, with probability equal to $C_n/\Sigma C$, where C_n is the number of edges node n has, i.e. relationships, and ΣC is the sum of the number of connections of all nodes. When checking to make connections, the new node searches through the list of all nodes until the max number of connections has been made. If it goes through the whole list and not enough connections have been made it repeats this process again. Before searching through the list for the first time and each subsequent time, the list of existing nodes is shuffled so there is no bias in creating connections. This repeats until all occupants have been connected to the network.

3.3.6.2 Influence Calculations

This submodel computes occupants' EUS for the next time step. Every time step occupants make groupwise comparisons to see how their EUS compares to that of other members in the social network. All other members in the social network do not influence the occupant evenly but are instead weighted as given in (1) (Friedkin 1998; Friedkin 2001):

$$w_{ij} = \frac{s_i c_{ij}}{\sum_k c_{ik}} \tag{1}$$

where w_{ij} is the weight of influence of occupant j on occupant i, s_i is the susceptibility value of occupant *i*, c_{ik} is a measure of closeness between occupant *i* and *k* (i.e., probability of interpersonal attachment), $i \neq \{j, k\}$, $0<w_{ij}<1$, $\Sigma_j w_{ij}=1$ (thus $w_{ii}=0$), and $0<s_i<1$. Since all relationships in this model are undirected, closeness is determined by considering whether there is a direct relationship between occupant *i* and *j* and if occupant *i* and *j* share interpersonal connections, both have relationships with occupant *k*. The amount an occupant changes their EUS in a time step is then calculated by (2) based on Friedkin (2001):

$$y_{i,t+1} = (1 - s_i) y_{i,t} + s_i (w_{i1} y_{1,t} + w_{i2} y_{2,t} + \ldots + w_{iN} y_{N,t}) \qquad (2)$$

where t is the current time step, $y_{i,t}$ is the EUS of occupant i at time t, N is the total number of occupants in the social network, and w_{iN} is occupant N's weight of influence on occupant's i behavior. Naturally this formula allows for occupants to increase or decrease their energy use from one time step to another based on the influence of others.

Table 3.1: Simulation Experiment Settings

	EX. 1	EX. 2	EX. 3
Level of Connectivity (K)	2, 4, 6, 8, 10, 12	4	6
Size (N)	35	7, 35, 441	35
Environmental Champions (EC)	0	0	1
Occupant Energy Use			
Mean	168 W	168 W	168 W
Std Dev	123 W	123 W	123 W

3.3.6.3 Equilibrium Determination

Two methods determine whether the system has reached equilibrium. The first checks for convergence of behavior of all occupants. This is done by checking the standard deviation between all occupants' EUS and if it returns a value less than or equal to 1 watt the behavior of occupants has converged. The second method measures rate of change in the mean and standard deviation of occupant EUS in the system. When these values have slowed down beyond a certain threshold the simulation run is said to have reached equilibrium by grouping of behavior. This represents that there are different pockets of people who express different energy use practices. These pockets can vary widely or even be close to what I term system convergence, but with a standard deviation of all occupants' EUS greater than one. To determine whether or not the system has converged the current mean EUS and standard deviation are compared against a weighted average of these values over the last 50 time steps. Grouping happens when the difference between the weighted and current mean EUS is less than 0.25 watt and the difference between the weighted and current standard deviation of energy use behavior is less than 0.12.

These values were set based on observations from numerous simulation runs considering all different combinations of potential input parameters and have been refined from my previous work, since simulation runs now behave differently due to changes in modeling assumptions (Anderson et al. 2012).

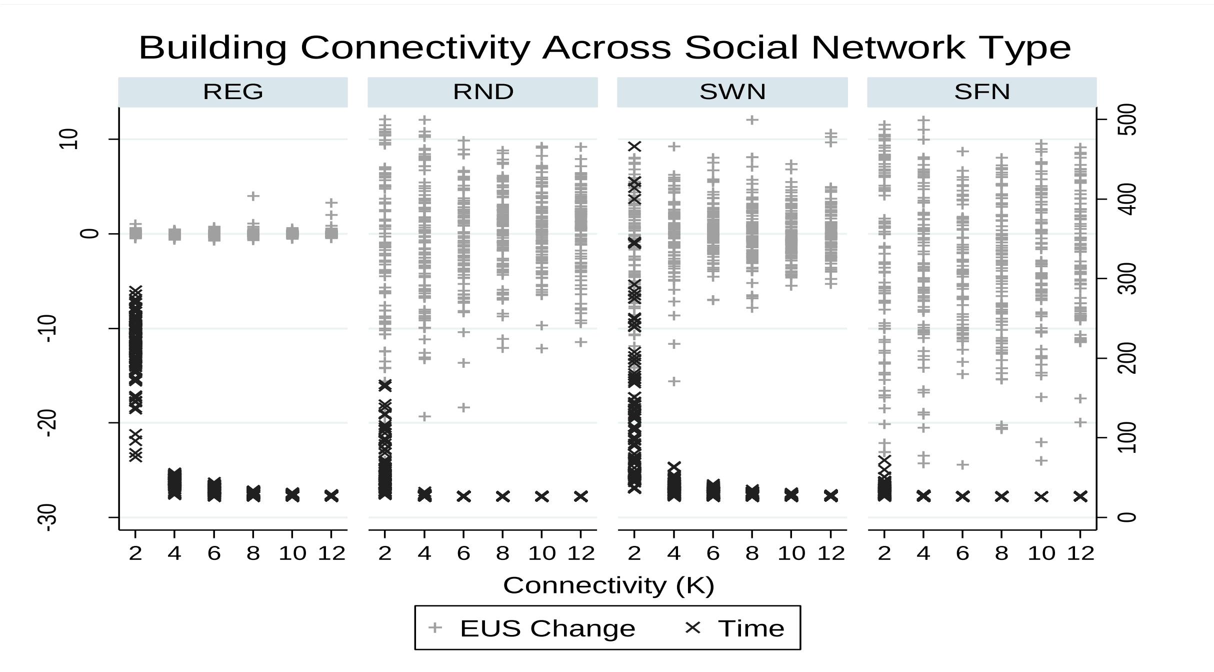


Figure 3.3: Combined scatter plot of average EUS change per occupant and time to reach equilibrium.

3.3.7 Experiments

To test the significance of SNTS during energy interventions, an analysis of the effect of enacting one of two interventions in buildings with different network structural properties, connectivity levels and size, across social network types was performed (Table 3.1). The first intervention involves installing a contextualized peer feedback system. The second, adds an intervening agent in addition to the feedback system. The first experiment (i.e., EX #1) investigates the effect that the social network structure property connectivity has on determining simulation outcomes across social networks types. To evaluate social network structure I expand the four baseline networks, one for each network type, by increasing and decreasing levels of social connectivity. In this experiment connectivity ranges from two average relationships per occupant, a less social building, to twelve, a much more social building, by twos. The second experiment (i.e., EX #2) examines the effect of social network size on the feedback intervention. Two additional building sizes, a very small social network (N=7) and a sufficiently large network (N=441) are added in addition to the baseline value (N=35) and tested (Azar and Menassa 2012b). The final experiment (i.e. EX #3) inspects the importance of social network type on building intervention outcomes. Here, one EC is inserted into the building system along with the feedback system. Only one EC is added based on the results my previous work that showed that the addition of more than one EC did not affect EUS change and only contributed to reducing time to reach equilibrium in specific scenarios. The EC is created by selecting the occupant with the lowest EUS and making them unsusceptible to negative influence. This is done by setting their s_i is set to zero.

3.4 RESULTS

EX #1 tested building connectivity. The baseline networks (N=35, K=6) were expanded to include five additional values of connectivity, two, four, eight, ten and twelve. Each set of conditions was simulated over 90 times to produce sufficiently large sample sizes, resulting in over 2000 simulation runs. I ran ordinary least squares dummy variable regressions with interactions to see how each categorical variable and interaction terms are related to the outcome of interest (EUS change, time to reach equilibrium, and standard deviation of EUS). Network type is a dummy variable with 0 for REG, 1 for RND, 2 for SWN, and 3 for SFN. Network connectivity, K, is a covariate. Network size is a dummy variable with 0 for small, 1 for medium, and 2 for large networks. Simulation results and behavior varied considerably across the four social network types and different levels of connectivity (Figure 3.3).

Table 3.2: Regression of network type and connectivity level on time with interactions

	Time	
VARIABLES	Coefficient	Standard Error
RND	-150.4***	3.618
SWN	-74.88***	3.446
SFN	-180.9***	3.581
K 4	-169.2***	3.411
K 6	-180.2***	3.411
K 8	-184.9***	3.419
K 10	-186.8***	3.411
K 12	-188.1***	3.411
RND x K 4	132.0***	5.003
RND x K 6	142.1***	5.009
RND x K 8	146.6***	4.984
RND x K 10	148.5***	4.978
RND x K 12	149.7***	4.972
SWN x K 4	65.50***	4.849
SWN x K 6	70.82***	4.849
SWN x K 8	73.33***	4.855
SWN x K 10	73.92***	4.849
SWN x K 12	74.69***	4.849
SFN x K 4	161.9***	5.065
SFN x K 6	172.5***	5.073
SFN x K 8	177.1***	5.024
SFN x K 10	179.0***	5.040
SFN x K 12	180.3***	5.065
Constant	214.7***	2.412
Observations	2,268	
R-squared	0.768	

*** p<0.01, ** p<0.05, * p<0.1

Each social network type resulted in different distributions of energy use change over time, with comparable means of roughly zero energy use change at equilibrium. This is significantly different from our previous work where energy use actually tended to increase due to the limited allowable rate of change (Anderson et al. 2012). Time to reach equilibrium on the other hand was found to depend on level of social connectivity and network type (Table 3.2). With fewer relationships, lower values of K, the interventions took more time to reach to equilibrium and experienced the emergence of grouping of behaviors. Beyond the lowest connectivity level, K=2, grouping of behavior happened rarely as almost all simulation runs resulted in system convergence of behavior. This convergence happened more and more quickly as the number of relationships increased. Across network types these behavioral observations are fairly consistent; however, time to reach equilibrium differs significantly when few relationships exist and the range of potential outcomes in EUS change can fluctuate dramatically from one network type to another. These observations are in contrast to my previous work where grouping had continued well beyond the lowest levels of connectivity depending on the rate of allowable change, and time to reach equilibrium could be several factors of time longer (Anderson et al. 2012). Further, previously due to assumptions about rate of change EUS would increase in all scenarios, but here all scenarios concluded with no change in mean EUS.

Table 3.3: Regression of network type and network size on time with interactions

	Time	
VARIABLES	Coefficient	Standard Error
RND	3.943	4.513
SWN	-0.0591	4.462
SFN	0.108	4.425
N 35	19.37***	4.369
N 441	320.1***	4.369
RND x N 35	-22.27***	6.298
RND x N 441	-322.3***	6.259
SWN x N 35	-9.321	6.221
SWN x N 441	-273.8***	6.221
SFN x N 35	-19.07***	6.349
SFN x N 441	-318.9***	6.203
Constant	26.11***	3.113
Observations	1,149	
R-squared	0.895	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

EX #2 investigated the effect of social network size. For this experiment the baseline networks (N=35 and K=4) were expanded to model the effect of increasing and decreasing building size across network type. The level of social connectivity for this experiment was reduced from six to four since when the network is only seven people since a connectivity of six would make all occupants in the network connected to each other. Again each configuration was simulated over 90 times. Mean EUS change for each scenario remained around zero, but again the range of potential outcomes depended on network type and network size (Figure 3.4). Method of reaching equilibrium only varied for one scenario, REG in the large network, where it grouped regularly. Outside of this scenario, all networks exclusively reach conclusion through the convergence of behavior. Time to reaching equilibrium was found to not be significant the network type alone but was for the interaction terms between network type and building size, expect for in one instance (Table 3.3).

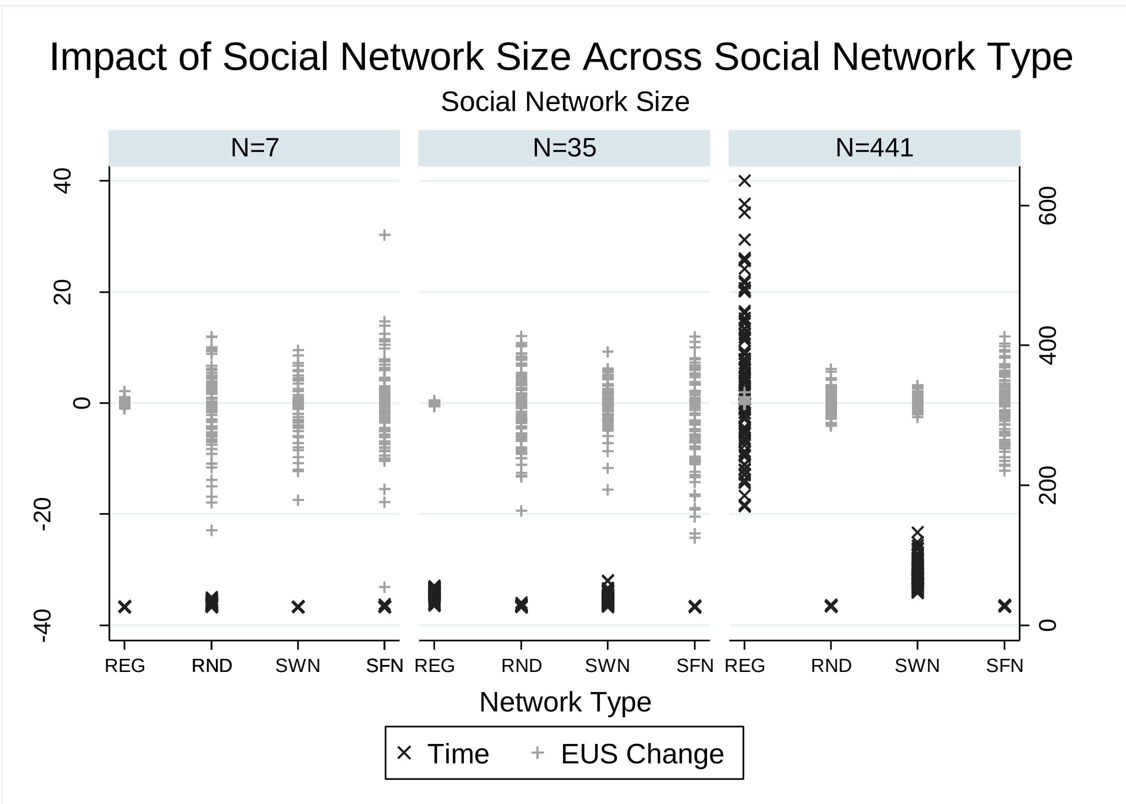


Figure 3.4: Average EUS change per occupant at equilibrium and time to reach equilibrium by social network size and type.

EX #3 examined the impact of inserting an EC into the building; this experiment took the baseline networks (K=6 and N=35) add an EC. Unlike the intervention with only providing feedback, adding the EC resulted in substantial declines in energy use upon reaching equilibrium

(Figure 3.5). Here similar distributions of energy use change are observed between network types in contrast to when no EC is present. During individual simulation runs, behavior followed similar patterns as simulations without EC, but when the system would previous stall and stop experiencing behavior change the EC would slowly reduce all other members in the network behavior. Naturally by prolonging the simulations, the time required to achieve this reduction in energy use increased by an order of magnitude (Figure 3.6). All simulation runs for all network types concluded by reaching convergence of behavior.

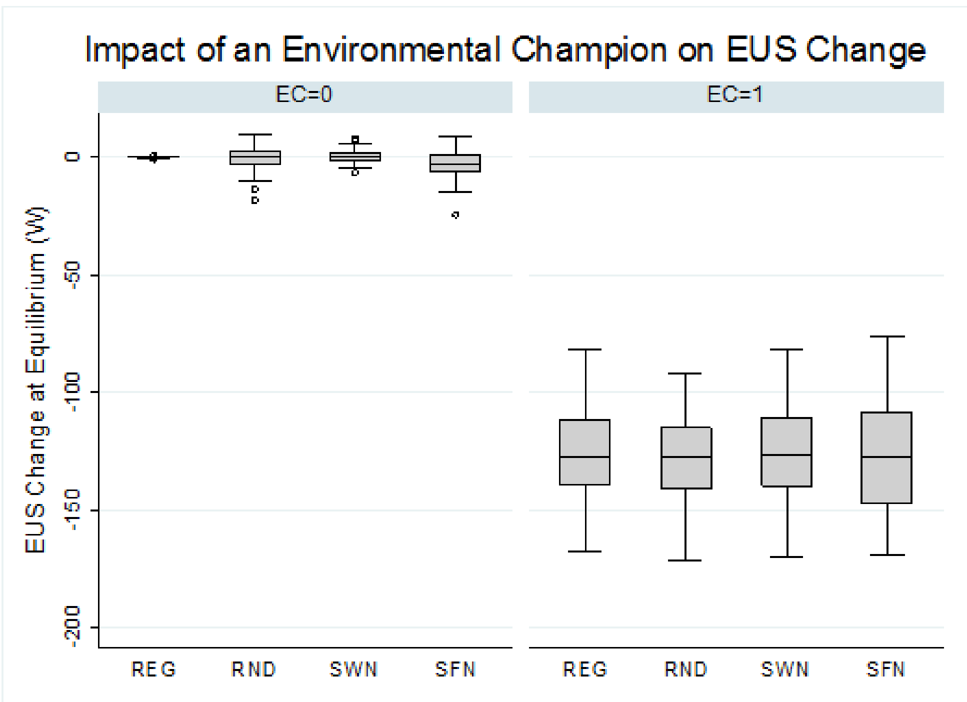


Figure 3.5: Change in average EUS per occupant caused by inserting an EC across network type.

3.5 MODEL VALIDATION

One of the most difficult problems when creating and working with simulation models is in determining whether or not the simulated model is actually representative of the system being modeled, or in other words if the model is valid. Validation is critical because if a model is not deemed valid the results and findings it produces are not useful. Therefore, it is of paramount importance to keep in mind the objective of the model when considering which criteria to judge the model by for whether or not it has met the burden to be considered validated (Law and Kelton 2000). For model based research, validity can be demonstrated in a number of forms. According to Zeigler et al. (2000), model validity can be shown in three ways, 1) the model has replicative validity, or that it is able to replicate data acquired from a real system, 2) the model possess predictive validity, the model is able to generate data that fits data from real world systems prior to being created, and 3) the model can have structural validity, the model accurately reflects how the real system operates. Analogous to structural validity, one can consider the conceptual validity of a model (Robinson 1999).

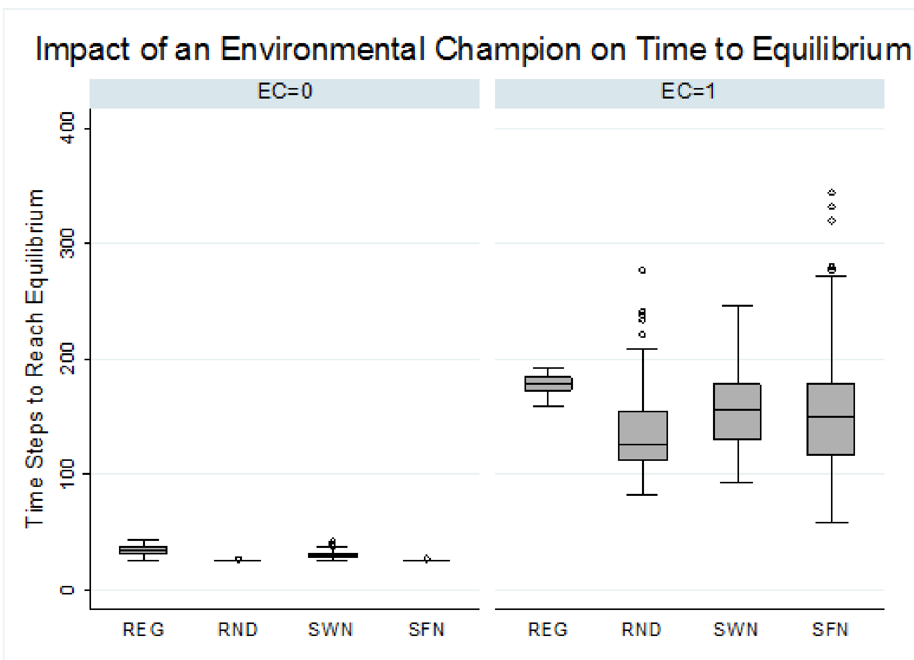


Figure 3.6: Effect of adding an EC on time to reach equilibrium across network type.

To validate this model efforts have been focused on conceptual model validation to align with the objectives of the model. This model aims to provide insight into the impact of SNTS modeling assumptions on intervention outcomes, and not to make accurate predictions of the interventions itself, making conceptual validation appropriate and meaningful. I employed several techniques to enhance conceptual model validity. First the model and submodels were verified by using extreme value testing and unit testing during development. Next the construction of the model relied on the application of established and validated theories from social psychological research to properly describe how interventions that target behavior change, through the use of social norms, propagate through social networks. More specifically, submodels used to calculate how occupants changed their energy use, via social influence and learning, depending on their social network, were based on work from various researchers in the field, in particular from Noah Friedkin (Marsden and Friedkin 1993; Friedkin 1998; Friedkin 2001). Although these theories have been previously validated, it is important to be aware of the inherent difficulties in modeling human behavior. This is why it is crucial must evaluate the validity of the model considering its purpose, a comparative analysis of SNTS as opposed to making detailed and definitive predictions of intervention outcomes.

In addition, input parameters for the model were based on observations and results from previous studies and further subjected to sensitivity analysis. Furthermore, to improve the validity of the modeling assumptions and in turn the model itself, conversations were held with a subject matter expert in the field of complex system for their input in modeling group behavior dynamics. The aforementioned techniques are all established and recognized methods to enhance model validity (Law and Kelton 2000). Lastly, the model has limited replicative validity as the results found from the first two simulation experiments, low energy users increasing their use and high energy users decreasing their use, are consistent with findings from previous field studies that employed comparative feedback to modify household energy use (Bittle et al. 1979b; Brandon and Lewis 1999; Schultz et al. 2007).

3.6 DISCUSSION

In this chapter, impact on behavioral interventions were measured using three metrics, network energy use change, time for this change to occur, and what network behavior was observed when change concluded. Although EUS change in all scenarios showed no mean differences for different SNTS, range of outcome distributions in EUS change varied substantially across different network types and to a lesser extent with level of social connectivity. The range of potential energy use change was the most dramatic in the SFN. Such wide ranges in outcomes are believed to be caused by highly central people with low susceptibility exerting disproportionate amount of influence through the network on other occupants. This explains why there is such low variance in the REG, since all members are roughly equivalently central. From a building management perspective, this implies that it would be worthwhile for managers to attempt to determine social network type prior to implementing specific additional interventions. In the case of the SFN, identifying who central persuasive personalities are in the building social network would be useful as these individuals should be targeted and efforts focused on them to alter their energy use behavior as such changes in their energy use are likely to have meaningful impacts on building energy use and time to achieve changes in behavior. However, as seen that central figures are of less importance in other network types, such strategies as individually targeting key people would likely be a less effective intervention strategy.

Beyond differences in ranges of energy use change, time to grouping or convergence showed significant differences over levels of social connectivity as expected. With few relationships in networks occupants only have a few friends, except possibly in the SFN, and each time step they evaluate their energy EUS against their peers at the previous time step. When occupants look at their peer's EUS they will change to be in line with them and their peers will do the same. This creates, in a sense, a switching of EUS practices that slowly move towards each other. At low levels of connectivity the occupants were prone to stalling and grouping of behavior. This explains why when they compare with larger number of peers they do not just emulate the behavior of one or two people but instead many which lessens the oscillation of behavior for an individual each time step leading to faster system convergence. Additionally, it describes why changes in time to reach equilibrium with increases in connectivity and grouping behavior are much less pronounced in the SFN, since in the SFN relationships per individual are not evenly distributed so less oscillation of behaviors take place and grouping occurs less frequently.

Contrary to Chen et al. (2012) the simulations suggest that only adding peer feedback into a building that previously did not have it will not necessarily result in the desired outcome, lower mean energy use in the building. This finding, that net energy use in the building did not result in the desired behavior, is consistent with several studies that employed social norm comparisons which found that social-norm marketing campaigns either resulted in undesired effects or none at all (Wechsler et al. 2003; Werch et al. 2000). As can be seen in the first two experiments, the mean EUS change, considering all simulations for each scenario, does not change. This does not imply that nothing is happening in the system but rather that the high energy users move closer to the system mean and that occupants who are already exhibiting desired behavior are subject to what is referred to as the boomerang effect where their energy use increases (Schultz et al. 2007). This implies that building managers and intervention designers should look to design interventions that can minimize negative consequences of normative feedback. This can be accomplished by combining multiple intervention methods. One such intervention which was demonstrated to have potential to combat this is the use of intervening agents. Adding the intervening agent to the network had a substantial impact on combating this boomerang effect and served as a means to slowly decrease the system mean EUS. By slowly decreasing the system mean EUS, occupants who previously might have been below the mean might now be above the mean and alter their behavior to conform to group standards. Changing one of the occupants into an environmental champion could be practically applied in many building environments where a central authority is responsible for energy costs. Individual occupants can be elected to act as an EC and incentivized or rewarded to promote conservation behavior in a manner similar to targeting influential persons to reduce their energy use. Alternative intervention strategies could also be tested and employed to combat the boomerang effect such as the use of injunctive messages (Schultz et al. 2007). Rather than informing well behaving occupants specifically how well they perform and the mean performance, individual feedback can be supplement with an injunctive message that indicates desired or undesired behavior.

3.7 LIMITATIONS

The model and experiments are not without some limitations. First time steps represent an arbitrary unit of time, could represent an hour or a month, since it is not known at what actual rate energy use behavior changes. Change is assumed to be based on viewing and altering ones behavior to align themselves with social norms, but further work is needed to determine what frequency people view and adapt to feedback information to identify the rate of behavior change.

Accurately identifying rate of behavioral change would have large implications on whether or not intervention methods would achieve expected results in feasible amounts of time given a particular SNTS since time steps required to reach equilibrium varied significantly based on the network properties. In addition, work needs to be conducted measuring and identifying what SNTS are most prevalent across different building types (e.g. dormitories, commercial office buildings, affordable housing projects). Field experiments that identify these parameters, rate of behavioral change, frequency of interaction with feedback interfaces, and common network structures in various building types would substantially enhance the model's predictive validity. Knowing these values would also allow us to make more definitive predictions about the effect of interventions without relegating to relative analysis. The model is also limited in replicative validity as it relies on result comparisons with previous studies alone. These previous studies did not consider network structure but instead only evaluated comparative feedback. The replicative validity of the model could benefit from small scale field experiments that test how energy use behavior diffuses across social networks through the use of general social influence formulas to model this propagation.

3.8 CONCLUSIONS

This chapter contributes to the body of knowledge on modeling energy use interventions by systematically testing the importance of social network modeling assumptions for use in predicting energy intervention outcomes. Previous modeling efforts have given little attention to social network structure and even less to social network type when modeling interventions. Findings indicate that while different network types and structure over many trials result in similar mean net changes in system energy use, the process of achieving the final outcome (time to reach and method of reaching) and the distributions of potential outcomes depend on SNTS. This is of importance when attempting to generalize conclusions about findings particular to one building to another, as distributions of outcomes and time to achieve behavior change vary widely depending on SNTS. Therefore, when selecting and designing social norm based interventions, expected interventions outcomes should not be assumed based solely on previous outcomes, but consideration should also be given to the uncertainty of potential outcomes based upon specific social network properties in which they were found.

CHAPTER 4

LONGITUDINAL ANALYSIS OF NORMATIVE FEEDBACK EXPERIMENTS ON DORMITORY OCCUPANTS

4.1 INTRODUCTION

Simulation models, such as the model presented in the previous chapter, can be a very useful tool to explore and better understand behavior interventions. However, to enhance the credibility of the models, calibrate the models, and validate assumptions used in these models as well as model performance it is necessary to conduct experiments in the field in the actual target populations. In addition, field experiments are often necessary to test new fundamental hypotheses which cannot be tested in virtual environments, e.g., do behavior changes persist in the longer term.

In the extensive literature testing pro-environmental behavior interventions very few studies have investigated anything beyond the short-term effects of intervening and only a handful of studies have given any consideration to treatment effects in the longer term (Abrahamse et al. 2005; Geller 2002; Osbaldiston and Schott 2012). In a rare study which investigated the longer term effects of behavior interventions Staats et al. (2004) found that the Eco-team approach, an intensive and in-depth intervention methodology which combines many intervention techniques, produced durable behavior change. However, most studies apply an intervention and measure change in behavior only over a short period, usually less than three months (De Young 2013). Then the intervention is withdrawn and no more measurements are taken. No data is collected and no insight is gained into whether or not treatment effects persist over time or what contributes to the persistence of treatment effects. Current carbon emission goals require approximately 2% reductions annually (Wolske 2011), so if curtailment behavior interventions are going to be used to achieve this goal behavioral improvements must be sustained over time. Thus it is imperative that we explore the long term effects of behavior interventions.

The long term effects of feedback messages, in particular normative feedback, remain unclear despite the substantial amount of recent research work investigating these intervention methodologies (Darby 2006). Further, the relative benefit of adding normative elements to individual feedback messages remains debated. Therefore this chapter focuses on investigating the durability of feedback interventions and specifically addresses the relative impact of normative feedback relative to generic individual feedback.

To date only a few studies have been conducted which have investigated normative feedback in the longer term, and to the best of my knowledge all have relied on data from the company oPower (e.g.., Allcott (2012), Allcott and Rodgers (2013), and Ayres et al. (2013)). oPower conducted opt-out messaging experiments on a monthly and quarterly feedback cycles. While these studies provide a great foundation for exploring the durability of normative feedback they are not without limitation and several key research questions remain unanswered. First the oPower studies do not isolate the effect of normative messaging but rather confound the effect of the normative messages with individual energy use feedback as well as education and information making the relative effect of the normative elements of the intervention ambiguous. Second, the studies attempt to induce households through financial information/education to engage in capital improvements. This makes it impossible to determine how much energy improvements are a result of behavioral improvements versus capital improvements. Lastly, and perhaps most importantly, the studies only collect energy data. Without data on the behavioral determinants (e.g., environmental attitudes) of the households it is not possible to gain significant insight into understanding what drives the effectiveness of the intervention (i.e., identify with what type of individuals the intervention is successful and with whom it is not) (Abrahamse et al. 2005).

Therefore in this chapter I conduct and analyze two separate year-long field experiments testing the durability and effect of normative feedback messaging on energy consumption. In the study I specifically aim to answer the follow questions: 1) how do energy use behavioral determinants relate to each other as well as energy consumption, 2) does adding normative elements to individual energy use feedback messaging improve energy use behavior, 3) what type of person is affected by normative messaging, 4) does normative messaging promote more durable behavior change, and 5) does the duration of normative messaging contribute to the durability of behavior change?

This chapter will proceed with an overview of the experiment. This is followed by the empirical strategies employed for analysis along with the results. Then I present a discussion of the results and end the chapter with conclusions from the work.

4.2 EXPERIMENT OVERVIEW

4.2.1 Site and Population Overview

The experiment site is the same as that of the study detailed in Chapter 2, a dormitory complex on a university in Seoul, South Korea. Seoul is a heating dominated climate; annually heating is the largest energy expenditure. As mentioned previously, the site consists of seven mid-rise dormitories up to eight stories tall and features single occupancy as well as double occupancy rooms (Figure 4.1). Each room has a built in radiant floor heating system and air conditioning system in the ceiling. All rooms also have a bathroom and shower as well as mini-fridge. Six of the buildings mainly consist of graduate students and one building almost exclusively houses undergraduate students.

Undergraduate student presence in the dormitories often revolves around the academic calendar whereas graduate students tend to remain in the buildings year round. The academic year for schools in South Korea begins the first week of March and concludes the last week in December. The school has two semesters, spring and fall. The spring semester commences in March and ends the last week of June. From this time until the fall semester begins, the first week of September, undergraduate students do not reside in the dormitories. When the fall semester starts the undergraduate students move back into their previously occupied rooms. Alternatively, graduate students move into their units the first week of March and live continuously in the same room until their contract expires, if they do not extend it, until the last week of February the following year. Both undergraduate and graduate students may live in the same unit for more than one year.

Figure 4.1: Dormitory buildings located in Seoul, South Korea (Top). The bottom image shows a typical interior of a single occupancy room.

4.2.2 Feedback Messages

The energy use feedback messages were delivered in both English and Korea and were sent based on the language participants selected for their intake survey. One of two different messages was sent to each participant during the course of the intervention, a control (Figure 4.2a) or treatment message (Figure 4.2b). Both the control and treatment messages feature common energy use feedback information including how much energy in kWh was consumed during the last reporting period, the previous week, along with a few energy conservation tips. The treatment message adds a descriptive norm message and an injunctive norm message. The descriptive norm message informs the participant of the mean energy use of other similar residents and the mean use of efficient residents, the top 10% of users, which provides a target for participant behavior. Complementing the descriptive norm messages is the injunctive norm message which comments on social desirability of the participant's current behavior (e.g., Best! Good job!). The top 10% of users receive the top rating "Best! Good job!/최상! 참 잘 했어요!" and two stars. The next 40% of users who have energy use below the median receive the rating "Good, keep working at it!/상, 계속 노력하세요!" and one star. Finally, participants who use more energy use than the median user receive the message "Poor, but keep working at it!/하, 조금 더 노력하세요!" and a frowning emoticon. Lastly, since all participants are renters, energy conservation tips provide suggestions for ways to improve energy consumption through behavioral improvement.

Table 4.1: Study timeline

	Study Phase		
	Baseline Data Collection	Intervention	Follow-up Data Collection
Dates	3/3/14 thru 4/20/14	4/21/14 thru 9/28/14	9/29/14 thru 2/22/15
Duration	7 Weeks	16 Weeks	21 Weeks

4.2.3 Experimental Design

The graduate and undergraduate student samples are divided into two separate experiments due to differences in occupancy throughout the year in addition to being physically segregated into different buildings. The graduate students are dispersed across six buildings and the undergraduate population is almost exclusively contained in a single building. Initially across the six graduate buildings 220 rooms participated with a total of 276 individual participants. In the undergraduate building 152 rooms signed up to participate with a total of 219 individual participants.

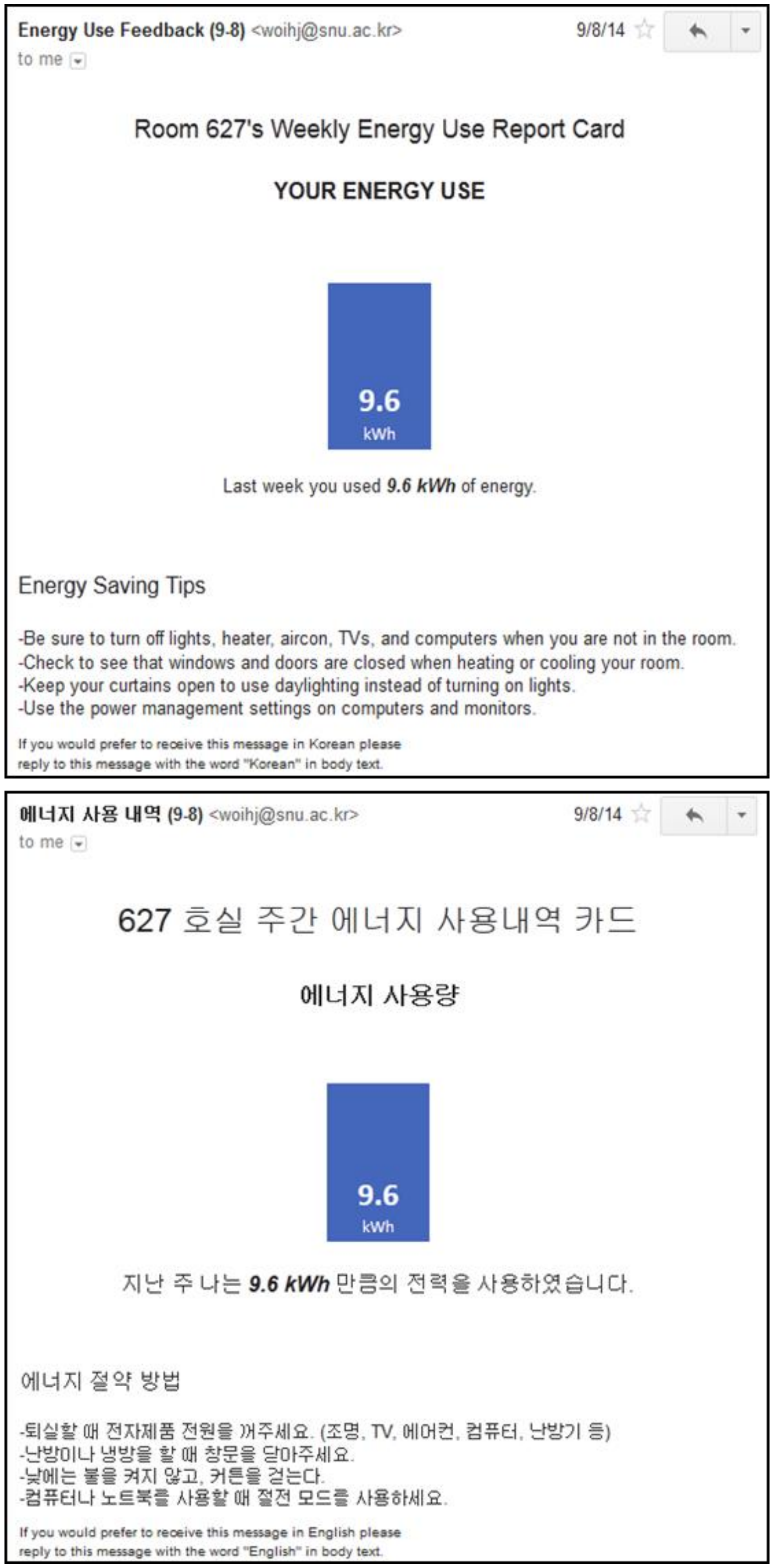


Figure 4.2a: Control message with individual feedback and conservation tips in English and Korean.

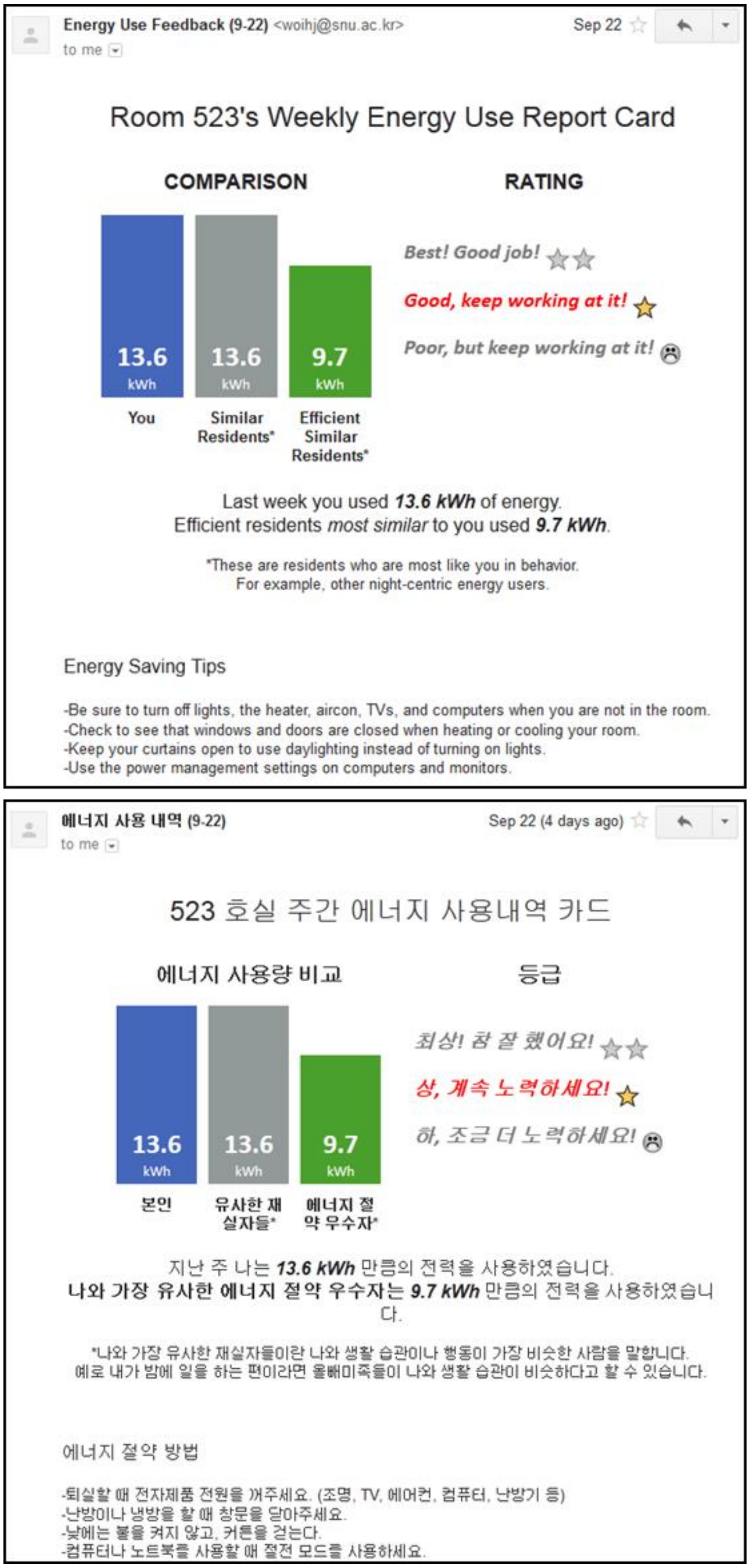


Figure 4.2b: Treatment message in English and Korean. The treatment message adds a descriptive and injunctive normative message.

For both the undergraduate and graduate student experimental groups' data collection began on March 3, 2014 and concluded on February 22, 2015 (Table 4.2). Pre-intervention baseline data was collected for seven weeks from March 3 through April 20. For 16 weeks from April 21 through September 28 both experiments conducted their respective the feedback interventions. After September 29 the interventions were stopped. Post-intervention data was collected for 21 weeks until February 22, 2015 for both experiments in order to examine the durability of the methods.

Three surveys were conducted during the course of the experiment. An intake survey was distributed to participants during a dormitory move in orientation held by the university which took place between March 3 and March 28. Surveys were handed out and collected in person. The second and third surveys were conducted electronically and sent out via email. The second survey was sent out upon withdrawal of the intervention on October 6, 2014. The final survey was sent out upon the conclusion of the follow-up period on March 1, 2015.

In the undergraduate building experimental treatments were randomly assigned resulting in 76 rooms in both the treatment and control groups. Treatment and control rooms are randomly assigned throughout the building and not separated by floor level. The use of random assignment allows me to clearly isolate treatment effects. Previous normative energy use feedback studies have suggested that it is not necessary to physically segregate treatment and control samples based off of concerns for geographic spillover, i.e., people talking with their neighbors about the reports, and random assignment at the household has become standard practice for such studies (Allcott and Rodgers 2012). Feedback messages were sent weekly to participants for seven weeks from April 21 to June 8. Messaging was halted after this data until students returned from the summer recess on September 1 after which time messaging resumed for three more weeks.

Unlike the undergraduate student population, the graduate student population remained in their units throughout the year and was dispersed across six buildings. For this experiment with the graduate student population treatment groups were assigned by building resulting in six treatment groups. As mentioned previously, the graduate student population followed the same pre-intervention and post-intervention as the undergraduate student population; however, the intervention schedule differed substantially. In contrast to the undergraduate student experiment where the treatment and control groups continuously received the same message throughout the entire intervention period, the graduate student treatment groups received both the control and treatment feedback messages. Upon the start of the intervention all treatment groups received the control message for the first three weeks. Every three weeks thereafter a new treatment group received the treatment message (Figure 4.3). Phasing in a new treatment group every three weeks allowed me to test the effect of messaging duration of normative messaging on behavior change durability. This experimental design has many benefits. First it allows me to control for building effects which may be present. Second, and most importantly, it permits me to test the effect of the intensity of messaging on both immediate behavior change and long term behavior change; this is also referred to as messaging duration throughout this section.

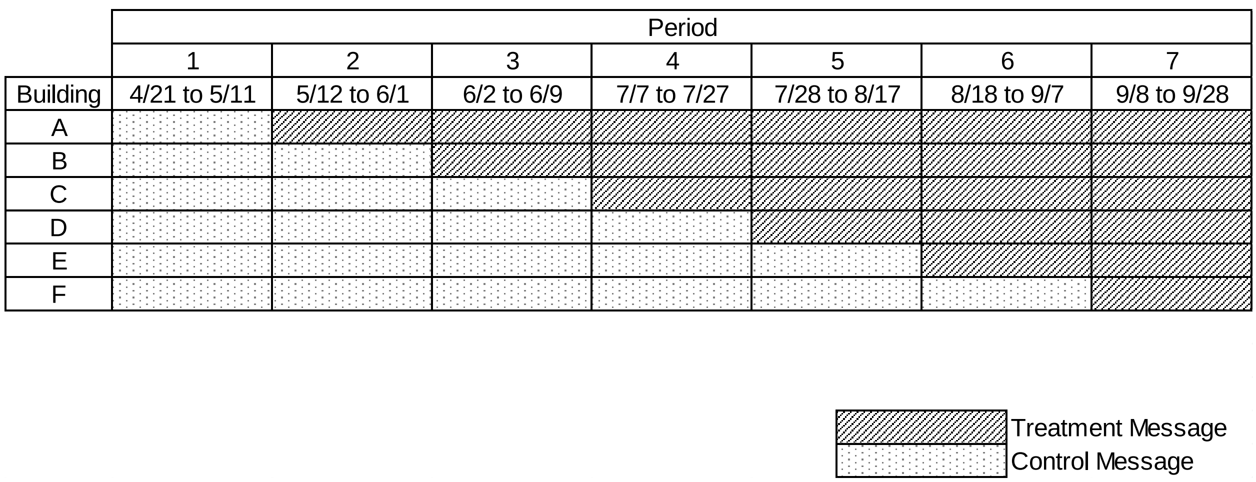


Figure 4.3: Graduate student experiment messaging schedule by treatment group.

4.2.4 Data

Data on each room's electricity consumption was collected on an hourly basis. The electricity energy use data includes all plug loads as well as heating, cooling, and lighting electricity usage. During the course of the intervention this data was aggregated weekly and used in the feedback messages. For analysis purposes for both the graduate and undergraduate population this data has been aggregated into four values to smooth out the significant hour to hour and week to week fluctuations in energy use. The four values are: pre-intervention mean weekly energy use (this is also termed baseline energy use), mean weekly energy use during the intervention period, mean short-term follow-up weekly energy use, and mean full-term follow-up weekly energy use. Follow-up energy use value has been decomposed into two periods, short-term and full-term. The short-term period consists of only the first 12 of the 21 weeks of the follow-up period. The reason for this separation is that a significant portion of the undergraduate student population, 85% (185 out of 219) vacated their rooms beginning during the twelfth week of the follow-up period. For the graduate student experiment the weekly energy use during the intervention is also aggregated into blocks to match the treatment schedule presented in Figure 4.3.

Table 4.2: Undergraduate students' pre-intervention Spearman Rank correlation coefficients between behavioral determinants and baseline energy used

	Variable	(1)	(2)	(3)	(4)	(5)
(1)	Baseline Energy Use	1.000				
(2)	Attitude	0.000	1.000			
(3)	Subjective Norm	0.005	-0.022	1.000		
(4)	Perceived Behavioral Control	-0.133'	0.363*	0.034	1.000	
(5)	Behavioral Intention	0.078	-0.474*	0.078	-0.357*	1.000

Notes: A lower attitude value indicates that one has negative attitudes toward energy conservation in the home. A lower subjective norm value indicates a higher level of concern and motivation to comply with the norm. A lower perceived behavioral control value indicates a low level of perceived control over one's energy consumption. The sample size is 219. Significant results at the .01 and .05 levels are respectively marked * and '.

Three surveys were also conducted over the course of the study. The first survey, the intake survey, had 495 respondents and is the main source of data for occupant behavioral determinants (Appendix A). The survey was based off of the Theory of Planned Behavior and was designed to elicit occupant behavioral beliefs, normative beliefs, control beliefs, and behavior intention related to energy conservation in their home (Ajzen 1991; Ajzen 2015). Questions were asked using multiple bi-polar Likert items and transformed into Likert scale values which represent the individuals' attitude, subjective norm, and perceived behavioral control towards energy conservation in the home (Ajzen 1991). Table 4.2 and 4.3 present the initial correlations between these behavioral determinants and baseline energy consumption for the undergraduate and graduate student samples. The correlations for the undergraduate and graduate student samples are highly similar and highlight some surprising relationships. Interestingly one's behavior intention, a direct measure of one's intention to conserve energy or not, is not correlated with actual energy use. However, all the behavioral determinants, with the exception of the subjective norm, are significantly and meaningfully correlated with each other for both samples.

In addition to gathering information on behavioral determinants the survey's collected data on self-reported pro-environmental behaviors which will be used in my future work. Questions also attempted to solicit social network information, but unfortunately proved to be unusable due to excessive missing data. The latter two surveys replicated the questions presented in the intake survey and had 173 and 144 responses respectively. Beyond asking the same questions, these surveys added a few questions for use in my subsequent modeling work and for data verification (Appendices B and C).

Table 4.3: Graduate students' pre-intervention Spearman Rank correlation coefficients between behavioral determinants and baseline energy used

	Variable	(1)	(2)	(3)	(4)	(5)
(1)	Baseline Energy Use	1.000				
(2)	Attitude	-0.112	1.000			
(3)	Subjective Norm	0.058	-0.134'	1.000		
(4)	Perceived Behavioral Control	-0.150'	0.356*	-0.104	1.000	
(5)	Behavioral Intention	0.071	-0.554*	0.133'	-0.351*	1.000

Notes: A lower attitude value indicates that one has negative attitudes toward energy conservation in the home. A lower subjective norm value indicates a higher level of concern and motivation to comply with the norm. A lower perceived behavioral control value indicates a low level of perceived control over one's energy consumption. The sample size is 276. Significant results at the .01 and .05 levels are respectively marked * and '.

Over the course of the study rooms were lost to attrition and error. From the two samples 74 graduate rooms and 34 undergraduate rooms (15 treatment group rooms and 19 control group rooms) had to be removed. Of these room 102 have been removed due to occupancy changes (i.e., occupants moved out or changed rooms), one due to a data recording malfunction, and five were identified as outliers–energy use more than three standard deviations away from the mean in any of the four periods being analyzed. No participants elected to opt out of the study. I am not concerned that the dropped data could bias the results as in both samples the baseline energy consumption of the dropped rooms does not significantly vary from the rooms included in the analysis (undergraduate population: Welch t-test t=0.7045, df=41.578, p-value=0.485; graduate population: Welch t-test t=-1.4848, df=116.237, p-value=0.1403). Further, there is no reason to suspect that moving is related to the behavioral characteristics of the occupants which are of interest for energy conservation. In addition to the data lost from the dropped rooms, lightning struck the building complex on June 9 and caused the site's data recording system malfunction. No data was collected between June 9 and June 23. This malfunction had no effect on the undergraduate student study; however, it slightly interrupted the graduate student experiment. As a result, no messages were sent out for the week of June 16, June 23, or June 30. Data was collected for the week of June 30 though and used as the input data for the July 7 messages.

Table 4.4: Graduate student mean energy use in kWh per week by floor and period

	Floor								
Time Period	First	Second	Third	Forth	Fifth	Sixth	Seventh	Eighth	All
Baseline	59.2	43.8	30.8	31.5	31.2	24.1	28.2	30.0	33.4
	(18.3)	(29.0)	(18.0)	(22.9)	(20.3)	(10.7)	(16.2)	(15.3)	
Intervention	22.4	16.7	15.1	16.1	15.2	14.8	16.6	15.3	16.2
	(6.8)	(5.0)	(4.7)	(4.3)	(4.8)	(4.7)	(6.5)	(5.1)	
Short-term Follow-up	86.1	71.4	67.4	64.2	59.1	58.7	63.0	75.6	66.5
	(20.3)	(23.7)	(31.6)	(22.9)	(17.5)	(14.1)	(19.5)	(24.2)	
Full-term Follow-up	105.4	92.5	85.2	82.6	74.4	76.1	77.7	94.5	84.3
	(18.4)	(25.4)	(32.8)	(26.6)	(19.8)	(14.9)	(20.6)	(25.8)	
Mean	62.3	51.0	43.7	43.4	40.3	38.3	40.8	46.6	45.8
Rooms	9	24	13	22	21	21	21	15	146

Note: Standard deviations are shown in parentheses.

Looking at room energy use, energy consumption was highly affected by seasonality and weather as well as by room floor level (Table 4.4). Energy use varies substantially by floor due to how heat flows through buildings, e.g., heating in the ground level floor diffuses to the second level which reduces the required heating load for the second floor[5]. As a result interior floors in buildings require less space conditioning. The baseline period is at the end of the winter months and occupants use substantially more energy for space conditioning than they do during the intervention which takes place in spring and summer. The follow-up period extends from fall through winter and units use considerably more electricity during this period for space heating. This increase in heating demand is clearly evident in the large difference in weekly energy

[5] Ground temperatures have a similar effect on the first floor.

consumption between the short-term and full-term follow-up periods. In addition as mentioned in Chapter 2, room occupancy type, single or double occupancy, also contributes to room energy consumption. The graduate student population has both single and double occupancy rooms, but the undergraduate population only has double occupancy rooms.

4.3 EMPERICAL STRATEGIES & RESULTS

4.3.1 Graduate Student Experiment

4.3.1.1 Room Level Analysis

I begin the analysis of the graduate student experiment by estimating the following regression:

$$BaselineEnergyUse_{rft} = \beta_0 + \beta_1 Duration_{rft} + \alpha_f + \alpha_t + \varepsilon_{rft} \quad (1)$$

where *BaselineEnergyUse*$_{rft}$ is the mean weekly energy use of room r during baseline period and *Duration*$_{rft}$ is the duration in weeks that room r received normative feedback. Two separate dummy variables are also added to absorb fixed effects for each room floor level, α_f, and room type, α_t. The equation, and all others presented in this chapter are estimated using Ordinary Least Squares (OLS) unless otherwise specified. This analysis is run as a check to test and see if initial differences exist between the assigned treatment groups prior to intervention.

Table 4.5: Graduate room baseline energy use comparisons by group selection

Explanatory Variable	(1)	(2)	(3)
Duration of Normative Messaging (weeks)	-0.008	-0.001	-0.002
	(0.012)	(0.012)	(0.012)
Floor Fixed Effects	No	Yes	Yes
Room Type Fixed Effects	No	No	Yes
Adjusted R^2	.000	.092	.095

Notes: OLS on log transformed baseline mean weekly energy use (kWh/week). Significance at the 0.05, 0.01, and 0.001 levels are designated by *, **, *** respectively. Standard error terms are in parentheses. The sample size is 146. Data is transformed to meet normality assumptions. Duration of messaging ranged from three to sixteen weeks.

Regression results are presented in Table 4.5. To meet normality assumptions mean weekly energy consumption during the baseline period was log transformed. Column 1 omits the addition of floor and room type dummies; columns 2 and 3 add in the dummies. Results indicate there are no differences in energy use behavior prior to intervention by group selection.

Findings from the literature suggest that the addition of normative feedback to weekly messages should be more effective at inducing improvements in energy behavior. Therefore I used difference-in-difference estimations to test the relative effect of a receiving normative feedback compared to individual feedback. For each pair of consecutive periods, e.g., period 1 to 2 (see Figure 4.3), mean difference in energy use between treatment and control groups was tested. No significant mean differences were found between any pair of periods. These results are likely a consequence of the high variance in energy use behavior among rooms and the limited sample size.

While effects were not present using higher frequency energy consumption data, it is possible the effects may be present when the variance in behavior is less. To reduce the variance in energy use behavior all energy consumption data during the intervention is aggregated. The literature suggests that since normative feedback is more effective than individual feedback alone, the duration for which rooms received normative messages would be hypothesizes to have lower levels of energy consumption. To test the effect of the duration of normative messaging on energy consumption during the course of the intervention I use the following model specification:

$$IntEngUse_{rft} = \beta_0 + \beta_1 Duration_{rft} + \beta_2 BaseEngUse_{rft} + \alpha_f + \alpha_t + \varepsilon_{rft} \qquad (2)$$

where $IntEngUse_{rft}$ is the mean weekly energy use of room r during the course of the intervention and $BaseEngUse_{rft}$ is the mean weekly energy use of room r during baseline period. The remaining variables are the same as in model specification (1).

Results from the regressions are presented in Table 4.6. Once again to meet normality assumptions all energy use values are log transformed. Column 1 omits fixed effects dummies and the covariate for baseline energy consumption. Column 2 adds a covariate for room baseline energy use and columns 3 and 4 add in fixed effect dummies for floor and room type respectively. Here, much like with the difference-in-difference estimations, normative messaging is found to have no effect on energy consumption. Previous energy use behavior is the most significant predictor of current energy use behavior.

Table 4.6: Effect of duration of normative messaging on energy use during the intervention

Explanatory Variable	(1)	(2)	(3)	(4)
Duration of Normative Messaging (weeks)	-0.004	-0.002	0.001	0.001
	(0.006)	(0.005)	(0.005)	(0.006)
Log Baseline Energy Use (kWh/week)	---	0.246***	0.227***	0.227***
		(0.036)	(0.040)	(0.040)
Floor Fixed Effects	No	No	Yes	Yes
Room Type Fixed Effects	No	No	No	Yes
Adjusted R^2	.000	.233	.225	.219

Notes: OLS on log transformed energy use during the intervention (kWh/week). Significance at the 0.05, 0.01, and 0.001 levels are designated by *, **, *** respectively. Standard error terms are in parentheses. The sample size is 146. Data is transformed to meet normality assumptions. Duration of messaging ranged from three to sixteen weeks.

The results so far suggest that normative messaging in this sample had no significant effect on energy use behavior during the intervention. However, it is possible that differences could not be identified due to limitations of the study, e.g., sample size, and that receiving normative messages for longer durations had a positive effect the durability behavior change after the intervention was withdrawn. To test the effect of duration of normative messaging on energy use during the post-intervention the following modeling specification was used:

$$PostIntEngUse_{rft} = \beta_0 + \beta_1 Duration_{rft} + \beta_2 BaseEngUse_{rft} + \alpha_f + \alpha_t + \varepsilon_{rft} \qquad (3)$$

where $PostIntEng_{rft}$ is the mean energy use of a room in the post-intervention follow-up period.

Regression results are shown in Table 4.7 and the columns present the same regressions as the columns in Table 4.6. In contrast to the previous results, during the post-intervention follow-up period the duration of normative messaging significant affected energy use. For each week a room received the normative message they used on average 0.85 kWh of energy less per week. To put this quantity into perspective rooms that received normative messages for between three and sixteen weeks and mean weekly energy use during the follow-up period across all rooms was 84 kWh. The explanatory power of the duration of messaging however is quite low as would be expected since it is unlikely that the addition of normative message would cause very large swings in behavior. Once again previous behavior has the greatest explanatory power as would be expected.

Table 4.7: Effect of duration of normative messaging on energy use in the post-intervention follow-up period

Explanatory Variable	(1)	(2)	(3)	(4)
Duration of Normative Messaging (weeks)	-0.818'	-0.760*	-0.790*	-0.849*
	(0.471)	(0.374)	(0.378)	(0.355)
Baseline Energy Use (kWh/week)	---	0.687***	0.681***	0.631***
		(0.074)	(0.080)	(0.076)
Floor Fixed Effects	No	No	Yes	Yes
Room Type Fixed Effects	No	No	No	Yes
Adjusted R^2	.014	.378	.400	.470

Notes: OLS on energy use after intervention withdrawal (kWh/week). Significance at the 0.1, 0.05, 0.01, and 0.001 levels are designated by ', *, **, *** respectively. Standard error terms are in parentheses. The sample size is 146. Duration of messaging ranged from three to sixteen weeks.

4.3.1.2 Individual Level Analysis

The previous section analyzed the effects of the intervention on the total sample and provided insight into system level outcomes and behavior. To enhance our understanding of who changed their energy use behavior as a result of the intervention it is necessary to jointly consider intervention outcomes and individual behavioral determinants.

It is unlikely that the entire sample of participants would be equally affected by the addition of the normative element of the feedback message. It is reasonable to hypothesize that individuals who perceive pressure to conform to group norms and who possess a high motivation to comply with social norms would be more likely to be affected by normative messaging. Also individuals who have a high intention to conserve energy use may receive more benefit from the additional normative information in the messages which could improve behavior. On the other hand given the normative nature of the intervention there is little reason to suspect individual attitudes and perceived behavioral control toward energy conservation in the home would predict normative messaging effectiveness.

To begin this analysis I cut the data into subsets conditional on occupant behavioral characteristics. For each behavioral determinant, I cut the data to only leave occupants with extreme values, approximately the top and bottom 25% of occupants for the given behavioral determinant under investigation. For instance, I took the occupants who identified themselves as being highly influenceable by social norms and the occupants who identified themselves as being highly un-influenceable by social norms. This process was repeated all four behavioral determinants (attitudes, social norms, perceived behavioral control, and intention).

Using theses subsets I estimated the following regressions:

$$IntEngUse_{ift} = \beta_0 + \beta_1 Duration_{ift} + \beta_2 BaseEngUse_{ift} + \alpha_f + \alpha_t + \varepsilon_{ift} \tag{4}$$

$$PostIntEngUse_{ift} = \beta_0 + \beta_1 Duration_{ift} + \beta_2 BaseEngUse_{ift} + \alpha_f + \alpha_t + \varepsilon_{ift} \tag{5}$$

These regressions are slightly different from model (2) and (3) as they are run on the individual response level, i, and not the room level, r. In addition standard errors are robust and clustered at the room level to control for correlations for rooms with multiple participants. All regressions using the sub-samples on mean participant energy consumption during the intervention, model (4), resulted in no significant differences between treatment groups once again. However, during the post-intervention follow-up, model (5), some sub-samples were significantly affected by the duration of normative messaging (Table 4.8).

Columns 1 through 3 include the entire population and sequentially add fixed effect dummies for floor and room type. Column 4 uses the same model specifications as column 3 except is run using only individuals who are highly influenceable by social norms. The effect of normative messaging duration is meaningfully larger than for the entire population at -2.084 compared to -0.942. This suggests that highly influenceable individuals receive additional benefit from receiving normative message for a longer duration. These equate to a treatment effects of 1.2% less energy use per week of messaging for the entire population and 2.4% per week of messaging for highly influenceable individuals. Column 5 uses the sub-population of individuals who have low motivation to comply with social norms and perceive little social pressure to conform to norms. As could be expected, longer exposure to normative messaging had no significant effect on these individuals. Column 6 shows the results using individuals who self-identified as high intention to conserve. Most occupants in the study stated they have a fairly high intention to use less energy in the home so this sub-population includes two-thirds of the entire population. For this group the duration of treatment was significant but the effect is not meaningfully different from that of the entire population (column 1). Lastly, subsets based on attitudes towards conserving and perceived behavior control had no significant effects. The lack of significance considering that the entire population (column 1) had a significant result is not meaningful, but rather a consequences of the smaller sample size as the non-significant treatment effects are approximately -1.0.

Table 4.8: Effect of duration of normative messaging on energy use in the post-intervention follow-up period conditional on occupant behavioral determinants

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Duration of Normative Messaging (weeks)	-0.942**	-0.953**	-1.008**	-2.084*	-0.900	-1.052*
	(0.335)	(0.334)	(0.317)	(1.010)	(0.595)	(0.407)
Baseline Energy Use (kWh/week)	0.790***	0.764***	0.727***	0.473*	0.786***	0.733***
	(0.071)	(0.075)	(0.072)	(0.177)	(0.124)	(0.091)
Floor Fixed Effects		Yes	Yes	Yes	Yes	Yes
Room Type Fixed Effects			Yes	Yes	Yes	Yes
Highly Influenceable by Norms				Yes		
Highly Un-influenceable by Norms					Yes	
High Intention to Conserve						Yes
Adjusted R^2	.417	.457	.512	.392	.570	.482
Observations	183	183	183	47	52	118

Notes: OLS on energy use after intervention withdrawal (kWh/week). Significance at the 0.1, 0.05, 0.01, and 0.001 levels are designated by ', *, **, *** respectively. Standard error terms are clustered at the room level and shown in parentheses. Duration of messaging ranged from three to sixteen weeks.

4.3.2 Undergraduate Student Experiment

4.3.2.1 Room Level Analysis

The analysis of the undergraduate student experiment follows the same form as the graduate student experiment. Analysis of this experiment differs in three regards. First, this experiment used random assignment of treatment and control and the message that was sent to each room and participant remained constant. Second, the post-intervention follow-up period is shorter. Third, the undergraduate population only has double occupancy rooms so there is no fixed effect dummy for room type. To begin the analysis of this experiment I estimate the following regressions:

$$BaselineEnergyUse_{rf} = \beta_0 + \beta_1 T_{rf} + \alpha_f + \varepsilon_{rf} \tag{6}$$

$$IntEngUse_{rf} = \beta_0 + \beta_1 T_{rf} + \beta_2 BaseEngUse_{rf} + \alpha_f + \varepsilon_{rf} \tag{7}$$

$$PostIntEngUse_{rf} = \beta_0 + \beta_1 T_{rf} + \beta_2 BaseEngUse_{rf} + \alpha_f + \varepsilon_{rf} \tag{8}$$

where T_{rf} is a dummy variable which takes a value of 0 for control group rooms and 1 for treatment group rooms, and $PostIntEng_{rf}$ is the mean energy use of a room in the post-intervention follow-up period. The remaining terms are identical to those used in model (1) and model (2). Model (6) tests whether or not there are initial differences in the randomly assigned groups prior to intervention. Model (7) tests the effect of adding normative messages to the individual feedback on energy consumption during the intervention. Finally, model (8) tests this effect during the follow-up period.

Table 4.9: Undergraduate room OLS regressions on energy consumption by treatment group

Explanatory Variable	(1)	(2)	(3)
Treatment Group	0.075	-0.298	2.095
	(0.077)	(1.012)	(3.151)
Baseline Energy Use (kWh/week)	---	0.211***	0.527***
		(0.022)	(0.067)
Floor Fixed Effects	Yes	Yes	Yes
Adjusted R^2	.153	.495	.463

Notes: OLS on energy use (kWh/week). Significance at the 0.05, 0.01, and 0.001 levels are designated by *, **, *** respectively. Standard error terms are in parentheses. The sample size is 118. (1) is on mean baseline energy use and is log transformed to meet normality assumptions. (2) is on mean weekly energy use during the intervention. (3) is on mean weekly energy use during the post intervention follow-up period. There are two groups, treatment and control.

Regression results are presented in Table 4.9. To meet normality assumptions for model (6) mean weekly energy consumption during the baseline period was log transformed. The other two models use untransformed data. Column 1 shows the results for model (6). The random room assignment resulted in both treatment groups not differing statistically when controlling for floor fixed effects. Model (7) results are presented in column 2. In contrast to previous studies, likely partially due to the limited sample size, no statistical differences in energy use are found between the two groups. During this period the room's floor level and previous energy use have significant explanatory power and explain roughly 50% of the variance in energy use. In the post-intervention follow-up period, Model (8) and column 3, the treatment groups once again do not statistically differ and room floor level and previous behavior retain their high explanatory power.

4.3.2.2 Individual Level Analysis

To investigate the effect of normative messaging on sub-samples the same procedure of regressing subset samples based on behavioral determinants that was used in the graduate student study is used again here. For this analysis I re-use the basic models from the room level analysis, models (6) through (8), except now the analysis is run using individual level data, i, instead of room level data, r. Once again standard errors are robust and clustered at the room level to control for correlations for rooms with multiple participants. In this investigation in addition to creating subset with the top and bottom 25% of each behavioral determinants I also look at very extreme users, the top and bottom 10% to see if more extreme behavioral values results in stronger treatment effects.

Running the regression model on mean baseline energy use for each sub-sample did not result with any statistical differences for any of the sub-samples based on treatment group assignment. This suggests that the randomization worked as intended.

Next I estimated model (7) with the changes as noted above. Regression results are presented in Table 4.10. Of all the behavioral determinants treatment only differed in the sub-samples for level of normative influencability. Column 1 shows the base model for the entire sample with the room floor dummy omitted. Column 2 adds in the room floor dummy. Floor effects explain approximately 3% of the total variance in energy use. Columns 3 through 6 present the results for the sub-samples based on level of social norm influencability. During the intervention the treatment had a significant and meaningful effect on energy consumption conditional on occupant self-identified influencability to social norms. Across the continuum of influencability to social norms the most extreme occupant, both high and low, had the most dramatic treatment effects. These results should be seen with some caution given the very limited sample sizes; however, steps were taken to check the robustness of the results against the influence of highly influential data points[6]. Extremely influenceable occupants who receive the normative message used on average 8.5 kWh less per week relative to their counterparts who received the control message. At the other end of the influencability spectrum the opposite effect is seen where recipients of the normative message actually used 5 kWh per week more than recipients of the control message. These two changes represent significant treatment effects of approximately 25% and 50% reductions. Looking at the larger sub-samples, top 25% of each end of the continuum, the same direction of behavior is seen but with smaller treatment effects.

Table 4.10: Effect of normative messaging on energy use during the intervention conditional on occupant behavioral determinants in the undergraduate experiment

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Group	-0.746	-0.799	-8.450**	-1.247	4.096*	5.070*
	(0.808)	(0.805)	(2.467)	(1.563)	(1.532)	(2.073)
Baseline Energy Use (kWh/week)	0.199***	0.201***	0.083	0.205***	0.125**	0.097*
	(0.016)	(0.017)	(0.056)	(0.037)	(0.039)	(0.043)
Floor Fixed Effects		Yes	Yes	Yes	Yes	Yes
Highly Influenceable by Norms (top 10%)			Yes			
Highly Influenceable by Norms (top 25%)				Yes		
Highly Un-influenceable by Norms (top 25%)					Yes	
Highly Un-influenceable by Norms (top 10%)						Yes
Adjusted R^2	.461	.490	.511	.441	.438	.686
Observations	181	181	18	47	45	21

Notes: OLS on energy use during the intervention. Significance at the 0.1, 0.05, 0.01, and 0.001 levels are designated by ', *, **, *** respectively. Standard error terms are clustered at the room level and shown in parentheses.

[6] Since the sample size in the extreme samples is so limited the possibility of results being driven by a few highly influential data points is increased. Therefore, I used Cook's distance to identify highly influential data points (Cook 1977). If data points were identified as being highly influential they were removed and the regressions re-run. The results from the re-run regressions are presented in Table 4.9. In both cases, treatment effects matched significance levels and were in the same direction suggesting that the results are robust to influential data points.

This same procedure was used to test the effect of normative messaging on energy consumption in the post-intervention follow-up period conditional on behavioral determinants using the modified model (8). In contrast to the results just described, in the follow-up period the energy use of individuals based on treatment group did not statistically differ in any of the sub-samples. The social norm sub-samples did exhibit similar trends in treatment effects though where highly influenceable individuals who received the normative messages continued to use less energy and high un-influenceable individuals used more (Table 4.11). To put these values in perspective, the mean energy use in the follow-up period for the undergraduate students was approximately 66 kWh.

Table 4.11: Effect of normative messaging on energy use in the post-intervention follow-up period conditional on occupant behavioral determinants in the undergraduate experiment

Explanatory Variable	(1)	(2)	(3)	(4)
Treatment Group	-3.513	-0.312	5.850	4.005
	(5.797)	(5.676)	(5.569)	(4.873)
Baseline Energy Use (kWh/week)	1.172***	0.627***	0.623***	0.306*
	(0.132)	(0.136)	(0.142)	(0.102)
Floor Fixed Effects	Yes	Yes	Yes	Yes
Highly Influenceable by Norms (top 10%)	Yes			
Highly Influenceable by Norms (top 25%)		Yes		
Highly Un-influenceable by Norms (top 25%)			Yes	
Highly Un-influenceable by Norms (top 10%)				Yes
Adjusted R^2	.903	.339	.530	.817
Observations	18	47	45	21

Notes: OLS on energy use during the intervention. Significance at the 0.1, 0.05, 0.01, and 0.001 levels are designated by ', *, **, *** respectively. Standard error terms are clustered at the room level and shown in parentheses.

4.4 DISCUSSION & CONCLUSION

The two longitudinal field experiments detailed in this chapter aimed to address several important gaps in the literature on normative feedback interventions. The first question of interest is how the suspected behavioral determinants (behavior intention, attitude, social norms, and perceived behavioral control) of energy consumption relate to each other and how do they relate to actual energy consumption. Attitude toward conserving and intention to conserve in the home had the highest correlation at -0.55 (a more favorable attitude correlated with higher intention). Interestingly though, positive attitudes towards conserving and behavior intention were not significantly correlated with energy. The Theory of Planned Behavior postulates that behavior intention is usually fairly correlated and predictive of behavior when subjects have sufficient degrees of actual behavioral control and this has been found to be true in numerous studies (Ajzen 1991). This was not found to be true in this study in either of the experiments as intention was neither correlated with energy use prior to intervention. I suspect the reason for the lack of correlation between these two variables has to do with the nature of the question which solicited the occupant's behavioral intention to conserve energy. The question that directly measured behavior intention asked participants to what degree do they "plan to conserve more energy in the home." The responses to this question were heavily skewed towards strongly agree (Mean 2.37 on a bipolar scale from 1 to 7 with 1 being 'strongly agree') with only 3.8% of responses indicating no intention or negative intention to conserve. This could suggest that although occupants intend to conserve they lack the tools (e.g., procedural knowledge) or sufficient motivation necessary to translate this intention into action.

In the undergraduate study on the whole adding normative elements to the feedback messages did not result in statistically significant less energy consumption relative to the individual feedback only messages either during the intervention or during the post-intervention follow-up period. This finding conceptually conflicts with the previous research which suggests that normative messages with both descriptive and injunctive norms will improve the effectiveness of energy use feedback messages (Schultz et al. 2007). In Schultz et al. (2007) it was found that feedback messages with both the injunctive and descriptive norm elements reduced energy consumption in high energy users and reduced the 'boomerang effect' of low energy users increasing their consumption to be in line with group norms. The combination of these two phenomena should in turn result in net energy reductions for rooms receiving normative messages relative to individual feedback only. This was not found in the undergraduate study.

Many potential reasons exist which could explain this divergence in results. First, the Schultz et al. (2007) study intervened on a different demographic of occupants households where occupants were responsible for energy expenditures whereas participants in the experiments in this chapter are indirectly billed for their energy expenditures The additional inherent financial incentives to reduce energy consumption could have contributed to the effectiveness of the messages in the Schultz et al. (2007) study. Second, feedback in their study was hand delivered, incorporated hand written elements, and placed on their front doors. These characteristics could make the messages seem more personal and consequently make the participants feel a greater sense of social pressure and concern for the messages. Emails can be seen as distant and impersonal relative to hand written notes. The handwritten notes were also publicly visible as they were place on front doors to homes which could further enhance the perceived social pressure to comply.

Additionally, it is possible that weather contributed to the lack of system level treatment effects in both the graduate and undergraduate studies during the intervention. During the intervention the weather in Seoul was relatively mild and required almost no heating and cooling as evident by a mean weekly energy use rate of approximately 16 kWh per room. With limited space conditioning requirements the relative control occupants have over their energy consumption is greatly reduced. Reducing energy consumption through behavioral changes related turning on and off lights in a single room dwelling are quite limited. This could explain why in the graduate student experiment differences in energy consumption based on the duration of normative messaging became apparent in the post-intervention follow-up period when energy consumption demand was much greater.

The graduate experiment found that normative messaging duration had a significant effect on energy consumption in the longer term. Given this finding one would suspect that the same pattern would be present in the undergraduate experiment but it was not. The difference in intervention messaging schedule could potentially explain this discrepancy. The graduate students received continuous normative feedback for up to sixteen weeks. The undergraduate treatment group received messaging for seven week then had a three month hiatus from living in the facility and receiving feedback before returning and receiving three more feedback messages. The long break could have nullified the effect of the previous seven weeks of messaging and made the intervention essentially equivocal to just the last three weeks of treatment. This would then imply that residents did not have enough time to develop and reinforce the perceived social norm and behavioral changes necessary to see improvements in the post-intervention period. The need for longer periods of continuous messaging is consistent with the finding from the graduate population where groups that received normative feedback for longer used less energy in the follow-up period. Findings from Allcott and Rogers (2012) support this hypothesis.

The experiments also attempted to unearth information as to the prerequisite individual behavioral characters that moderate the effectiveness of normative feedback messages. In both experiments it was found that only individuals who had a high motivation to comply with social norms and perceived positive social norms exhibited statistically and meaningfully improved behavior as a result of receiving normative messages. While this finding is intuitive it had not yet been found in the field to the best of my knowledge. It was also found that individuals who reported having little to no motivation to comply with social norms and perceived no social pressure increased their energy consumption when they received the normative message. Since these individuals reported essentially not caring about social norms it is interesting that they responded negative to receiving them. Lastly, the fact that only individual social norm levels influenced the effectiveness of the treatment provides important insight into the role of the other behavioral determinants, particularly about attitude. Specifically, that it is not beneficial to attempt to change individual attitudes when conducting normative based feedback interventions and that effort would be better spent attempting to persuade occupants that a positive norm of energy conservation exists.

In conclusion, the studies presented in this chapter found that the normative messaging duration positively influences in the durability of behavior change. Further, not all individuals are equally influenced by normative messaging. High norm individuals were found to be positively induced to change their energy use behavior whereas low norm individuals had the opposite effect. Developing and testing interventions to take advantage of this finding has the potential to reduce cost of intervention by limiting the population which should receive normative feedback. It also has the potential to improve the effectiveness of such programs by avoiding undesirable behavior change in large subsets of the population.

CHAPTER 5

AN EMPIRICALLY GROUNDED MODEL FOR SIMULATING NORMATIVE FEEDBACK INTERVENTION STRATEGIES

5.1 INTRODUCTION

Behavior intervention simulation models to date can be classified into one of two categories: 1) highly conceptual exploratory models that intend to provide insight into how complex factors affect intervention strategies (Anderson et al. 2012; Anderson and Lee 2013; Anderson et al. 2013; Chen et al. 2012; or 2) models which aim to estimate the impact of changes in occupant behavior on energy consumption (Azar and Menassa 2012a; Azar and Menassa 2015; Zhang et al. 2011). While these models have provided unique insights into potential energy savings as a result of improved occupant behavior and how complex factors can affect intervention success, these models have not yet reached the capability to be used for predictive modeling purposes.

According to Axtell and Epstein (1994), the performance of an agent-based model can be assessed and categorized by how accurately it represents reality. Their classification focuses on accurately, both qualitatively and quantitatively, reflecting both macro level structures (e.g., group level behavior) and micro level structures (e.g., individual occupant behavior). Their tiers of modeling performance build upon each of the previous. The lowest level of modeling performance and accuracy is present when the agent behavior rules are in qualitative agreement with the micro behavior. The second tier is achieved when the model's behavior is in qualitative agreement with empirical macro structures. The third tier is achieved when the model's behavior is in quantitative agreement with empirical macro level structures. Lastly, the highest level of modeling performance is achieved when the model's behavior exhibits quantitative agreement with micro level structures.

In the previous studies most models have only achieved the first tier of performance, model performance is in qualitative agreement with micro level structures, and a few could be argued to have not even achieved even the lowest tier of performance. If these behavior models are to be used for predictive modeling purposes and "what if" scenario analysis it is crucial that higher performance models are developed which are grounded in sound conceptual theories on human behavior as well as empirical data. Therefore, this chapter builds on the model presented in Chapter 3 and develops a refined empirically and conceptually grounded occupant behavior model for simulating normative feedback interventions. This model aims to be capable of qualitatively and quantitatively exhibiting agreement in both macro- and micro-level structure behavior found in the field. This model will then in turn be used to conduct "what if" analyses testing several novel normative messaging feedback intervention strategies.

5.2 METHODS

In this section I detail the new model once again using the ODD (Overview, Design concepts, Details) protocol for describing agent-based models (Grimm et al. 2006; Grimm et al. 2010). This protocol is applied to help improve the clarity, completeness and reproducibility of the model. The model has been in Java using Repast J v 3.0 (North et al. 2006).

5.2.1 Purpose

The model detailed below has been developed to provide a means to test new and alterative normative feedback intervention strategies which attempt to reduce energy consumption for the building community studied in Chapter 4. Given the uncertainty of the social network structure in building communities this model also compares how these interventions are affected by the classification of social network in which they take place, specifically how they propagate in block configuration networks (BCN) (Chen et al. 2013) and small world networks (SWN) (Watts and Strogatz 1998).

5.2.2 Entities, State Variables, and Scales

The agents in this model are the building occupants. Each building occupant has multiple attributes. Every building occupant is assumed to have a unique set of energy use practices which are summarized into a single variable that represents their power rating, or energy use behavior (EUB). Individual energy use behaviors, such as constantly using the heater or leaving on the television while away from home, are reflected in this one rating to match the aggregated level of the collected energy use data from the field experiment (Chapter 4).

Agents are also stochastically provided a value which combines their motivation to comply with subjective norms and their perceived social pressure to or not to conserve energy in their dwelling. Alternatively stated, this value represents the agent's susceptibility or lack of susceptibility to social influence. Additionally, each occupant is assigned a likelihood of checking their email in a given week and reading their feedback message.

Agents can also have relationships with other agents in the model. These relationships are expressed through the models of social network where occupants connect to each other. All relationships between occupants are reciprocal to match modeling assumptions that will be detailed in Section 5.2.4. Lastly, each time step in the simulation represents one week to match the frequency at which feedback messages were distributed in the field experiment. The simulations run for 50 time steps, or a simulated 50 weeks.

5.2.3 Process Overview and Scheduling

When the model is initialized it first creates all occupants present in the simulated housing community and sets, and stores, their initial EUB and likelihood of checking their feedback report during the week. Agents are also assigned a value representing their susceptibility to social influence; this is unlike the previous model detailed in Chapter 3 where an occupant's susceptibility to social influence stemmed solely from their location in social network. Following the assignment of these variables, the model creates the building community's social network and assigns social relationships to the occupants. How this is done is contingent on which type of social network is being created. Specifically how the social connections amongst occupants are created is detailed completely in Section 5.2.6.1.

Next the model begins to progress forward in time and collects initial descriptive statistics regarding the EUB of all occupants and social network properties. During each time step, every occupant has a chance to check their email for their feedback message. Occupants also have a chance to talk with their friends, social network connections, about their feedback messages and how much energy they consumed over the last observation period. Whether or not an occupant checks their energy use feedback message, and/or talks with their peer or friends about their behavior, determines how the occupant's EUB changes. Specifically how their new EUB is calculated is explained in further detail in Section 5.2.6.2. If the occupant did not receive any new external input, be it through reading their feedback message or gaining new insight into the energy behavior of their social connections, their behavior remains constant at what it was during the last period. Once the occupant's EUB has been calculated, this value is subjected to a degree of random noise.

After all occupants have had the opportunity to change their behavior the model updates synchronously and data is collected about energy used during that time step. The simulation run terminates after two years of simulated time. The complete model flow of logic in the model is depicted in Figure 5.1.

5.2.4 Design Concepts

The premise for this model is based on a combination of theories and concepts from social science research as well as from the findings and observations of the field study I conducted which was detailed in Chapter 4. The first concept incorporated into this model relies on the observation that people will adjust their behavior to conform to group norms (Epstein 2001; Schultz et al. 2007). The second concept incorporated into the model comes from the literature on social impact and asserts that the impact of social sources on behavior is a multiplicative function of the number of sources and is subject to diminishing returns with each additional source (Latane 1981). The third concept built into the model reflects from the findings of the field experiment presented in Chapter 4; when presented with the group norm, occupants with a strong motivation to comply with social norms wish to be at or below the norm more whereas those with the least motivation to comply behave in the opposite manner. The study in Chapter 4 was based in part on the Theory of Planned Behavior which includes attitude and perceived behavioral control as two key variables in the model. These variables have not been included in this model though as it was found that they had no predictive power on behavior in the study in Chapter 4.

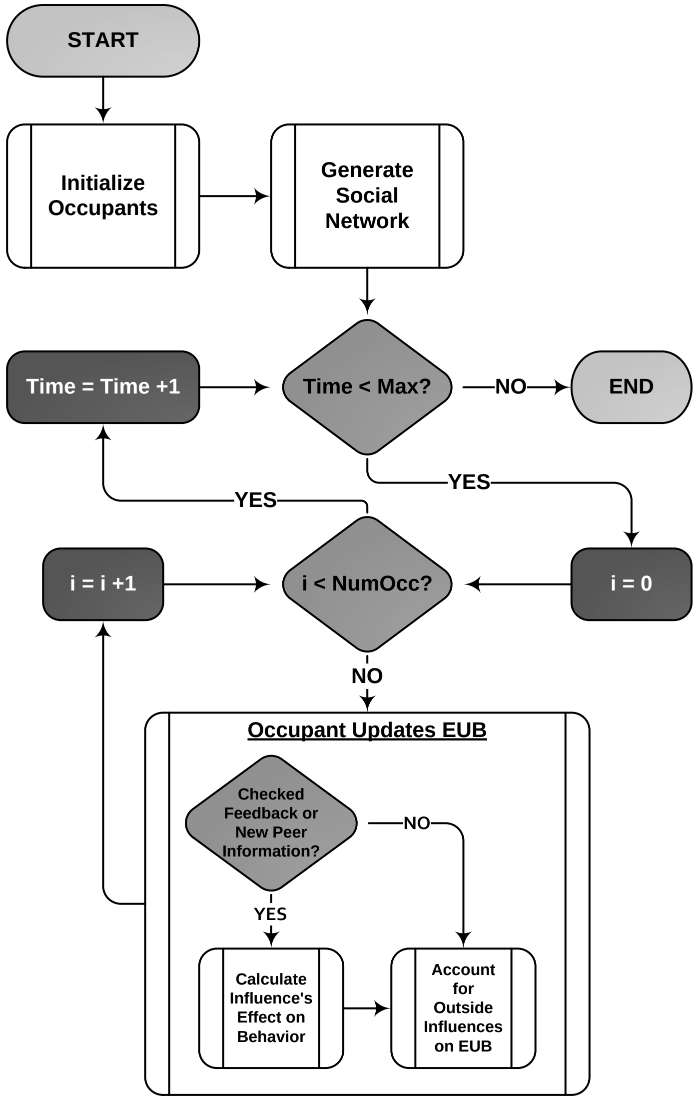


Figure 5.1: A high level flowchart of the model's operation. Please note that 'NumOcc' is the number of occupants in the simulation.

In this model, similar to the model presented in Chapter 3, model occupants are provided with feedback regarding their energy use, however, unlike the previous model occupants are not directly presented with feedback of their peers' energy use through the feedback system. In this model occupants receive one of two types of feedback messages that replicate the types of messages used in the field experiment in the previous chapter: 1) individual energy use feedback or 2) individual energy use feedback along with the mean use of the entire community (descriptive norm). If the occupants read their feedback they can be influenced by it in one of two ways. They can be influenced by the normative aspect of the message (if they received normative feedback) to positively or negatively alter their energy use to be more in line with the group norm (Schultz et al. 2007). Occupants can also be influence by learning of the energy use of their friends which is assumed to occur through direct conversation which happens infrequently. In the model it is assumed that occupants do not try to adjust their behavior to match their peers through observing their friend's behavior, but instead only adjust their behavior to their peer's after they are explicitly told it (i.e., energy use comes up in a conversation the two individuals have). There are two primary reasons for this assumption: 1) the physical structure and layout of the housing community being model makes it impossible to directly observe the energy use of another from the outside their residence, and 2) even from inside the residence it is difficult to accurately estimate an individual's energy use through observation giving the numerous sources that contribute to energy consumption (e.g., heater, air conditioner, lighting, plug loads) and few individuals have the expertise required to estimate such values.

An important aspect of occupant behavior in the model is that behavior remains relatively stable when not subjected to external sources of influence. This is because people often develop automated responses to stimuli in their behavior setting, or habits, which are persistent. However, the model does account for 'unexplained' behavior changes by incorporating in stochasticity in behavior change. Allowing for factors beyond the feedback messages to change an occupants' energy use is required to make agent behavior more realistic. It is well known that how humans determine to make decisions regarding behavior is extremely complex and subject to numerous determinants. It is also possible that residents make physical or structural changes to their home which would influence their energy consumption (e.g., purchased a new TV or computer).

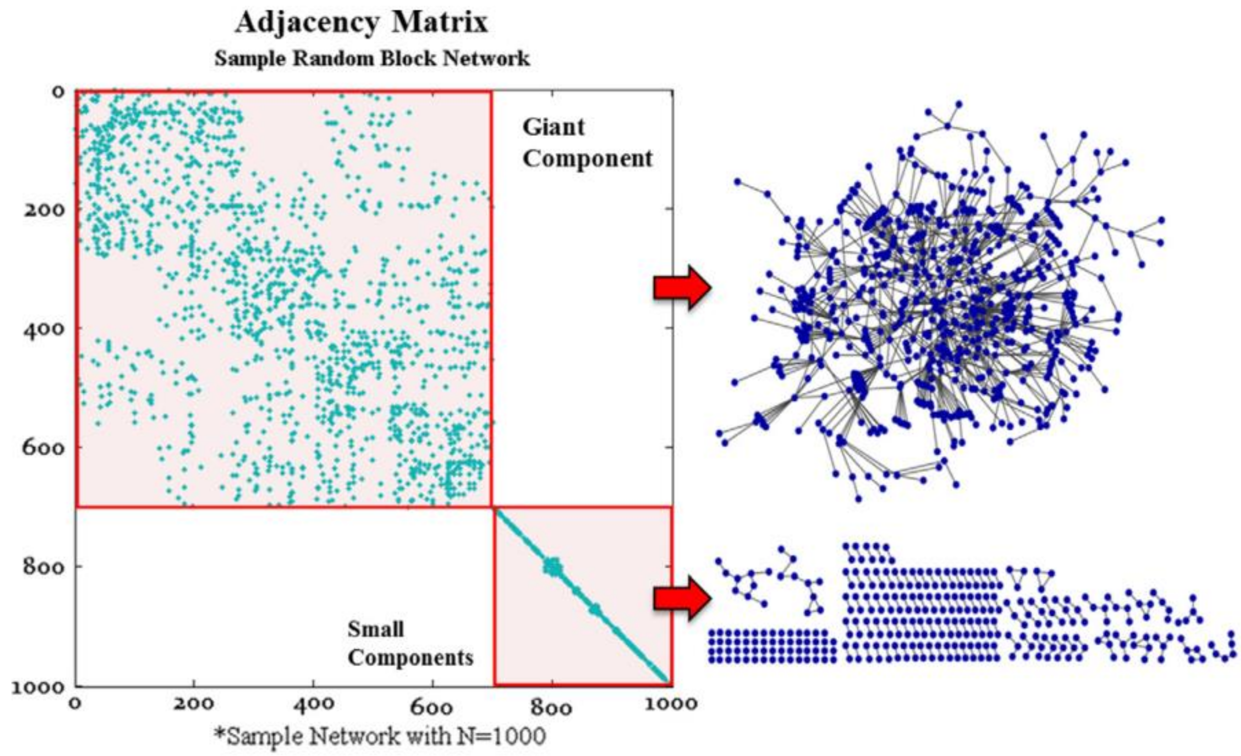


Figure 5.2a: A graphical illustration of block configuration network which is comprised of giant component and small components of various sizes (Chen et al. 2013).

Lastly, the social network in which the occupants reside is assumed to be one of two varieties, a block configuration network or a small world network (Figure 5.2a and Figure 5.2b). Unfortunately, the data collected regarding the social network structure in the field experiment was unusable due to missing data; therefore, the model relies on observations from other studies which suggest that these two networks structures are likely to be present in the dormitory community. The block configuration network is based off of observations of the social network structure in American dormitories. The network features a giant component which includes approximately 55% of all occupants and small components that account for the remainder. This network is detailed further in section 5.2.6.1. The small world network on the other hand features many of the same properties, such as many tightly connected groups of individuals, i.e. clichés. However, the network differs in that all occupants are loosely connected together.

In the model stochasticity is used when setting social ties among occupants, computing the size of small components in the block configuration network, determining the rate at which an occupant checks their feedback messages, checking if an occupant converses with friends about energy use, checking whether or not an occupant reads their feedback message in a given week, and whether to change their energy use as a consequence of factors not accounted for directly in the model.

Figure 5.2b: A graphical illustration of a small world network with an average degree peer node of two. Here it can be seen that all nodes are connected and part of the same component (Galan et al. 2011).

5.2.5 Initialization

The model initializes with 1,225 occupants to approximate the size of the dormitory community that was invested in Chapter 4. The initial energy use behavior of the occupants is generated from a normal distribution with a mean of 63 kWh per week and standard deviation of

25 kWh per week to match data from the baseline period in the field study. Occupants who are given extreme values for their energy use, both high and low, have their energy use bound to match high and low observations. A minimum value of 15 kWh per week and a maximum value of 125 kWh per week are enforced. In the same fashion occupants are given a value to represent their susceptibility and motivation to comply with social influence which represents the Likert scale norm value calculated using data collected in the field experiment intake survey. These values are generated from a normal distribution with a mean of four and standard deviation of one to match observations. Extreme values are once again bound with a minimum of one and a maximum of seven to properly correspond with the input data.

Social network properties for the block configuration network are based off observations from Chen et al. 2013 and statistics of configuration network properties from Newman 2010. The percentage of occupants in the giant component is set at approximately 58%. Based off the size of the giant component the mean degree per node is 1.5 (Newman 2010). For the small world networks to approximately match the properties of the block configuration networks I use the smallest available mean degree per node valuable possible, 2. The probability of randomly re-wiring a connection in the small world network, p, is 0.1. Specifically how these networks are generated is discussed in Section 5.2.6.1.

Additional model input variables including the weight of normative influence on an occupant's decision making, the multiplicative factor for the impact of multiple sources of information on behavior, probability to check feedback messages, and probability of conversing about energy use among friends have been configured based off a combination of literature, observations, informal survey, and sensitivity analyses. These values have been calibrated so the model replicates both macro- and micro-level behavior observed in the field experiment for individuals whom received only individual feedback and individuals who received individual and normative feedback. The weight of normative influence w_n, is set at 0.35. The multiplicative factor, m, is 1.9 if the occupant receives normative information from peers and the feedback message, else it is 1. Probabilities to check feedback messages have been set using data collected in the second survey from the field experiment. One percent of occupants never check their feedback, 16% of all occupants have a 40% probability to read their feedback in a given week, 28% have an 80% chance to check, and 55% read their feedback every week (Table 5.1). Lastly, occupants have a 1% chance to talk with each friend weekly about their energy consumption data.

Table 5.1: Distribution of feedback reading rates for occupants

Percentage of Occupants	Probability to Check Feedback
1	0%
16	40%
28	80%
55	100%

Using these calibrated values, the micro-level behavior of the shift in energy use discussed in Chapter 4 of high norm occupants reducing their energy use and low norm occupants increasing their energy use when a the normative feedback is added to the weekly message is evident in the simulation while retaining a good approximation of the overall distribution of behavior of all occupants relative to the field observations (Figure 5.3). In this figure it can be seen that occupants with high motivation to comply use less energy when the normative message is added to the feedback in both the field experiment and simulation experiment. The opposite effect is seen for occupants at the other end of the norm spectrum. This effect is once again seen for both the field collected data and simulation data. It should be noted that the experiment scatterplots in Figure 5.3 differ in scale from the simulation plots with regard to energy use due the fact that the simulations are based off of baseline energy use and do not model changes in weather and or model differences in energy use by location in the building. The change in weather from the baseline period through the intervention reduced energy consumption and altered the distribution of energy use among occupants. These factors which affect energy consumption, occupant floor in the building and weather, are not modeled in the simulation model so it is not possible to make quantitative comparisons between collected data and simulated data.

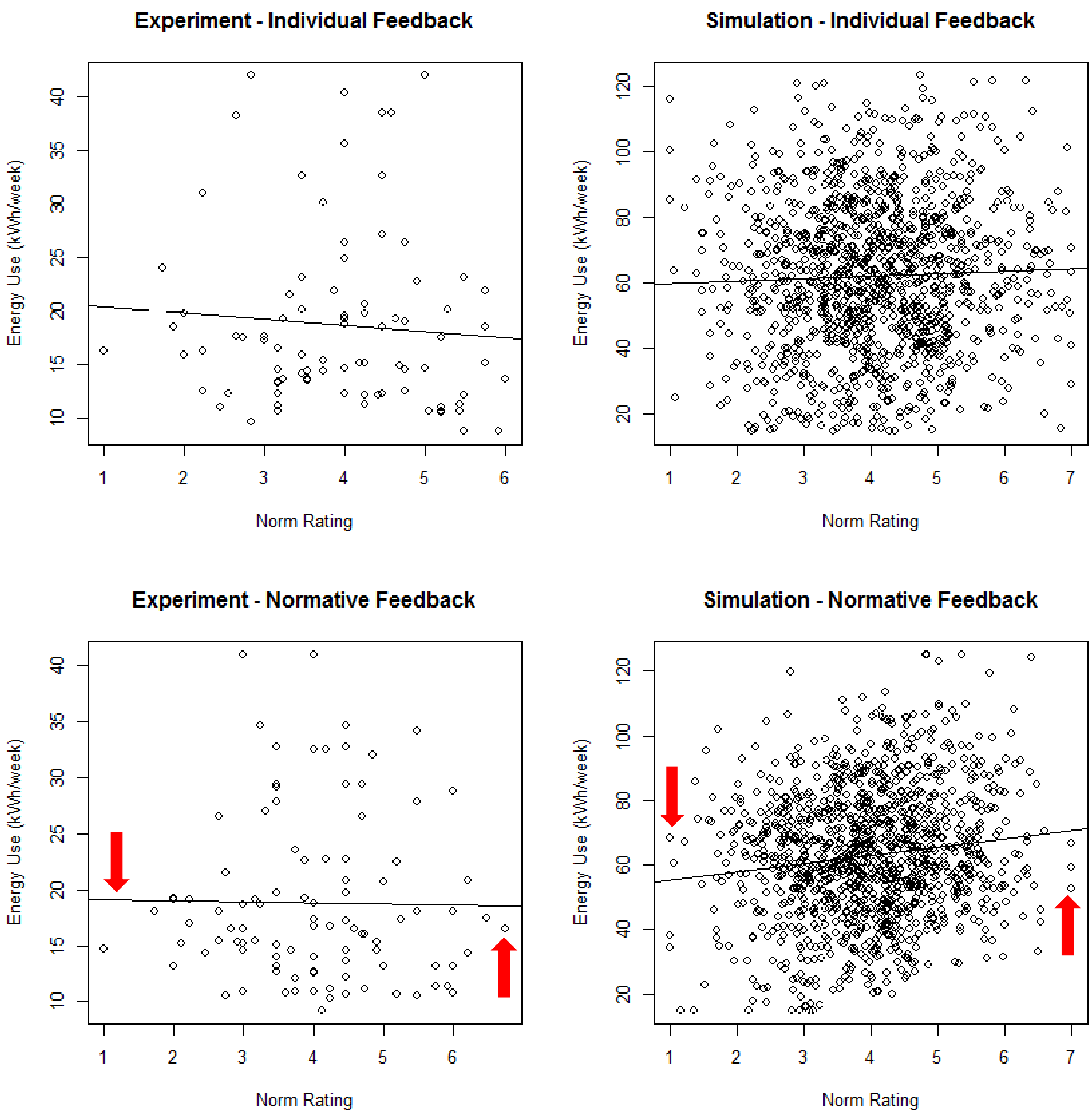


Figure 6.3: Plots of experimental and simulated data. These plots show the observed and simulated average weekly energy use of occupants by their norm rating at the end of the intervention (a lower norm rating value indicates a higher concern and motivation to comply with the norm). The simulation model accurately models the shift downward in energy use when normative feedback is added to the weekly message. Lines are least squared lines. The upper left plot has 86 observations; the bottom left plot 99, and each of the simulation plots have 1225.

5.2.6 Submodels

5.2.6.1 Social Network Generation

Two different social network structures are being created and evaluated with this model, small world networks and block configuration networks. The process to generate these two social network structures varies considerably. The method of construction for the small world network is identical to the method previous presented in Chapter 3 Section 3.6.1 so it will not be reiterated here. It should be noted though that in this study only one specific small world network is considered. This is a network with an average node degree of two and a probability of reconnection of 10%.

The block configuration network on the other hand has not been previously detailed and will be here. The configuration network stems from a model for generating random networks by Newman (2003) which was modified by Chen et al. (2013) to match the observed properties of networks from a small sample of dormitories in the US. This network is created based on observed properties reported in Chen et al. (2013) and is conceptually very different from the small world network. In this network not all occupants are connected to each other and many have a chance of no other social connections within the building community. This can clearly be seen in Figure 5.2a. As can be seen in this imagine there is one giant component with over half of the occupants and many smaller components with a range of sizes running from approximately 1 to 15. Observations from Chen et al. (2013) suggest that the giant component should consist of approximately 58% of all the occupants.

To generate this model 58% of all the occupants, 710 in total, are randomly selected to be part of the giant component and the remaining 42% will comprise the small components. The giant component is constructed first, but the order of construction is unimportant. The size of the giant component is a function of the average degree, therefore in order to generate a network with the appropriate size of the giant component to match observations one must use the corresponding average degree, which is 1.5 (Newman 2010). Using these values the giant component is constructed in a manner very similar to how the scale free, or preferential attachment, network is generated in Chapter 3 Section 3.6.1. First two occupants are randomly selected and connected to each other. Next a randomly selected occupant from the remaining 708 occupants is added. In order to match the desired average node degree of the network the current occupant only adds one connection and connects to the existing occupants already in the network with the probability of that node's number of connections divided by the total number of connections in the network at the current time. For example, if there are currently four nodes in the network and node A has three connections and each of the other nodes only have one connection (to node A), the probability if tested that the new node would connect to node A would be 50% (3/6). To ensure there is no bias in generating these connections the list of all nodes currently in the giant component is randomly shuffled before each new node attempts to join and the connecting node cycles through this list until it connects to another node. This process is repeated until all remaining nodes destined for the giant component have been added to it.

The small components are generated in a similar fashion. The size of small components do not scale as the size of the network increases and the probability that a node belongs to a small component of size *s* is given by the following formula (Newman et al. 2010),

$$\pi_s = \frac{e^{-sc}(sc)^{s-1}}{s!}$$

where c is the mean degree of the network (1.5) and s is the size of the randomly selected small component. The probabilities associated with small component sizes given an average degree of 1.5 are shown in Table 5.2. I have limited the maximum size of the small components to fifteen since the probabilities associated with each size larger rapidly decreases and all remaining sizes occur only two percent of the time (only 1% are larger than 25). While generating the small components the model first randomly draws a number and using the probabilities in Table 5.2 determines the size of the new small component. If the random draw between 0 and 1 falls above .9791 a size of fifteen is used. Once the size has been determined a check is conducted to ensure there are enough occupants still available to construct the new small component. If there are it is constructed, if there are not enough remaining occupants the process repeats. After the size has been determined the occupants are added and connected using the same procedure that is used to construct the giant component.

Table 5.2: Probabilities for the small component sizes with an average degree of 1.5

Small Component Size	Probability	Cumulative Probability
1	53.13%	53.13%
2	17.78%	70.91%
3	8.93%	79.83%
4	5.31%	85.15%
5	3.47%	88.62%
6	2.41%	91.03%
7	1.74%	92.77%
8	1.30%	94.07%
9	0.99%	95.06%
10	0.77%	95.84%
11	0.61%	96.44%
12	0.49%	96.93%
13	0.39%	97.32%
14	0.32%	97.64%
15	0.26%	97.91%

5.2.6.2 Energy Use Calculations

When occupants check their weekly normative feedback or discuss energy consumption with their friends they adjust their energy use behavior to conform to the mean of these outside influences. At the same time occupants remember and consider their initial behavioral preferences and partially remain true to their original behavior as well. If the occupants do not receive any new normative information during a given week their behavior remains the same as it was during the previous period but is subjected to random change as a result of influences beyond the scope of the behavior rules.

The method of calculating peer influence in this model is based on the social network influence work of Friedkin (2001) in conjunction with observations and findings from the field study I conducted. I borrow his equations for calculating the effect of social influence on behavior change and simplify them by making each peer of the occupant being evaluated have equal weight of influence. An occupants energy use for a given time step if they either spoke with at least one peer or read their normative feedback message is calculated using the following equation,

$$EUB_{i,t+1} = (1 - m * w_n)EUB_{i,0} + (m * w_n)\frac{\left(f * \frac{\sum_j^{F_i} EUB_{j,t}}{F_i} + g * \frac{\sum_k^n EUB_{k,t}}{n}\right)}{f + g} + \varepsilon$$

where $EUB_{i,t+1}$ is the EUB of occupant i at time $t+1$, $EUB_{i,0}$ is the initial EUB of occupant i, m is the multiplicative effect of receiving influence from multiple sources, w_n is the weight of normative influence towards determining an occupant's energy use behavior, F_i is the number of friends occupant i has which he has received energy use information from, $EUB_{j,t}$ is the EUB of the *j-th* friend of occupant i at time t, $EUB_{k,t}$ is the EUB of the *k-th* person in the building community at time t, n is the total number of occupants in the housing community, f and g are binary values for whether or not the occupant received information from at least one friend or read their normative feedback message, and $\mathcal{E}$ represents the random movement of energy use behavior due to outside influences. The norm of one's peers is $\frac{\sum_j^{F_i} EUB_{j,t}}{F_i}$ and the group norm of the community is $\frac{\sum_k^n EUB_{k,t}}{n}$. Let the average of these two values for occupant i at time t be termed $Norm_{i,t}$. When an occupant receives information from both sources the weight of normative influence is multiplied by the factor m. When only one source of information is received m is set to one.

From the study I conducted in Chapter 4 I found that the effect and direction of change in energy use based on receiving the normative feedback message is conditional on the occupant's concern and motivation to comply with the norm. Therefore, the value w_n is assigned using two conditional step functions (Figure 5.4). When the occupant has a low norm rating value, high concern, they are induced to reduce their energy use until they are below the weighted norm of their friends and the building community. On the other hand, those with high norm rating values, low motivation to comply, respond in the opposite manner increasing their energy use when they are below the mean. Individuals between the two extremes tend to move towards the mean regardless if they are above or below it.

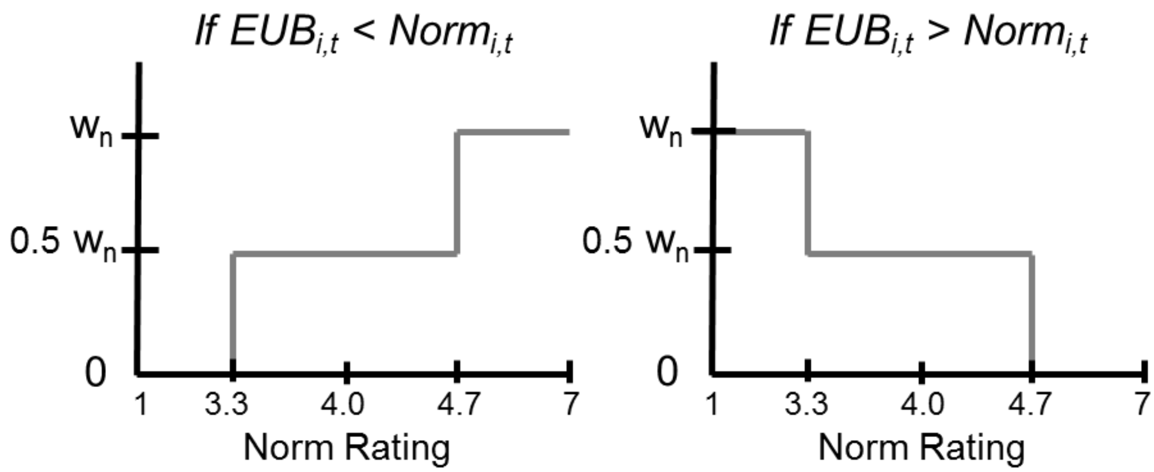


Figure 5.4: Condition step functions for the weight of normative influence on occupant energy use behavior.

The formula presented above is used to calculate the energy use behavior of an occupant for the following time period except when a) the occupant has no peers and only receives their individual feedback with no descriptive norm, or b) the occupant receives no new information by not talking to peers and not reading their normative feedback. In both cases since the occupant is not subject to any social influence they continue to behave as they did in the previous step but once again are subjected to random fluctuations in their behavior.

5.2.7 Experiments

This model simulates five different intervention strategies across the two network structures. To calibrate and assess the model the first two intervention strategies match those that were applied in the student population in the field experiment. The first strategy sends only individual feedback to all occupants and can be considered the baseline scenario since a scenario where no intervention is applied would simply result in random movement of the occupants. The second strategy sends individual and normative feedback to all occupants. The next three intervention strategies are new and previously untested messaging strategies.

The third strategy and first new strategy sends normative messages only to occupants who have been identified as highly susceptible to normative influence. Conceptually the motivation for testing such a strategy is very straightforward given the findings from the field experiment since these individuals responded favorably to receiving normative information in addition to their individual feedback.

The fourth strategy, and second alternative strategy, being evaluated is sending normative information to individuals based on their consumption relative to the community norm, or the mean energy use of all the occupants in the dormitory community. Occupants who use more energy than the average occupant will receive a normative feedback message in addition to their individual feedback and occupants who use less than the group norm will only receive their individual energy use feedback. The literature, and specifically the theory of social influence, assert and provide evidence that individuals conform to the norm. Therefore, in an attempt to mitigate the boomerang effect of low consuming individuals moving in the undesired direction up towards the norm one would only provide the normative information to those who presumably would adjust their behavior as desired. This strategy, unlike the previous would also be very easy to apply in the field. Since this strategy relies only on knowing the individuals energy use along with the group norm and no self-reported information it could readily be implemented.

For the fifth strategy and last alternative strategy I use a variant of the third intervention strategy where only the highly susceptible individuals receive any sort of feedback. In this scenario the high norm individuals receive normative and individual feedback messages. All other individuals receive no feedback and therefore only alter their behavior through random change. This scenario acts to a degree as a barometer for the maximum possible reduction that could be expected using the aforementioned behavior rules.

Each of these five intervention strategies are tested using both network structures to explore the effect that social network structure has on their outcomes. Every specification is run five hundred times using the same initialization values for all but those which are being evaluated.

Several dependent variables are being collected from each simulation for statistical analysis: total energy use consumption during the intervention, change in mean EUB from initial to the end of the intervention, the standard deviation in EUB at the end of the intervention, mean energy use of high norm rating individuals, and mean energy use of low norm rating individuals. Monitoring total energy use permits us to see differences in the net outcome of implementing the different messaging strategies. Tracking the energy use behavior of the individuals based on their norm rating is a means to validate the behavior of the model against collected data from the field experiment. Lastly, the standard deviation of EUB helps identify what sort of dynamics are taking place within the model, i.e., do occupants tend to converge to a common norm or do other patterns of EUB emerge?

5.3 RESULTS

In total five thousand simulations were run to explore the effect of the five intervention strategies given the two different social network structures. Statistical differences between the variables of interest are tested using simple t-tests and the Kruskal-Wallis test since normality assumptions for non-parametric tests could not be met even after applying various data transformations. Complete descriptive statistics of the output variables of interest are shown in Table 5.3.

From Table 5.3 it can be seen that in both network structures the mean energy use change of the average occupant in the building only marginally differs from zero for the first two strategies. This result matches the findings from the field experiment where energy use change at the system level showed no difference in energy use due to adding a normative element to the feedback messages. However, looking closer at the difference in energy use of occupants based on their susceptibility to influence it can be seen that the addition of the normative message causes a 5% reduction ($\frac{61.26-58.00}{61.26}$) and a 5% increase ($\frac{65.46-68.82}{65.46}$) in energy use for highly susceptible and highly unsusceptible individuals respectively. These counter balancing changes mimic the results found in the field experiment and cause the system level behavior to remain essentially unchanged.

Table 5.3: Descriptive statistics of simulation results

Network Structure	Messaging Strategy	Mean EUB Change	Mean Occupant EUB	EUB Standard Deviation	Mean EUB of High Norm Occupants	Mean EUB of Low Norm Occupants	Total Energy Consumed (mWh)
BCN							
	One	0.10	63.31	23.24	61.26	65.46	3875.7
		(0.29)	(0.74)	(0.43)	(1.34)	(1.39)	(43.25)
	Two	0.09	63.29	19.22	58.00	68.82	3873.9
		(0.26)	(0.75)	(0.39)	(1.17)	(1.21)	(44.31)
	Three	-0.68	62.51	22.43	58.38	65.45	3824.5
		(0.28)	(0.75)	(0.42)	(1.24)	(1.34)	(43.93)
	Four	-1.29	61.95	21.08	59.83	65.10	3781.9
		(0.31)	(0.75)	(0.41)	(1.19)	(1.42)	(43.08)
	Five	-1.43	61.79	23.08	57.64	63.37	3799.6
		(0.17)	(0.72)	(0.43)	(1.16)	(1.40)	(43.58)
SWN							
	One	0.09	63.34	22.53	60.19	66.58	3878.4
		(0.21)	(0.75)	(0.43)	(1.34)	(1.37)	(44.73)
	Two	0.16	63.36	18.69	57.32	69.73	3876.6
		(0.24)	(0.73)	(0.40)	(1.16)	(1.14)	(43.60)
	Three	-0.54	62.65	21.80	58.07	66.37	3829.4
		(0.22)	(0.70)	(0.41)	(1.18)	(1.34)	(42.37)
	Four	-0.89	62.32	20.46	60.22	65.75	3792.3
		(0.21)	(0.74)	(0.41)	(1.11)	(1.36)	(44.26)
	Five	-1.67	61.56	23.01	56.68	63.47	3791.7
		(0.18)	(0.70)	(0.44)	(1.15)	(1.41)	(42.66)

Notes: Intervention strategies are as follows: One - individual feedback to all occupants, Two - normative feedback to all occupants, Three - normative feedback to occupants with a norm rating less than 3.3 and individual feedback to all others, Four - normative feedback to all individuals with energy use above the group norm and users below the norm receive individual feedback, and Five - occupants with a norm rating less than 3.3 receive a normative message and all other occupants receive no feedback. Standard deviations are in parentheses. All values are in kWh per week unless otherwise stated. Each intervention strategy has a sample size of 500. All values are in kWh per week.

The effectiveness of the alternative strategies can clearly be seen in Figure 5.5. In both the block configuration network and the small world network the each alternative intervention strategies have a statistically significant effect on reducing energy consumption (H = 2070.861, p < 2.2e-16, df = 4; H = 2204.33, p < 2.2e-16, df = 4). Using the block configuration network there is no difference between intervention strategies one and two, but when using the small world network structure they statistically differ although not meaningfully. For both network structures the three new intervention strategies made a marked improvement on system level energy consumption. Sending normative messages only to highly susceptible individuals reduced mean occupant energy use by roughly 0.7 kWh per week relative to the previous strategies. Intervention strategies four and five produced even larger reductions at approximately 1.2 and 1.65kWh per week per occupant each respectively. These reductions amount to system level reductions in energy consumption of 1.1%, 1.9% and 2.6% relative to the first two intervention strategies. Over the course of the intervention the reductions in individual energy consumption in aggregate amount to tangle savings ranging from roughly 48 to 88 mWh over the fifty weeks.

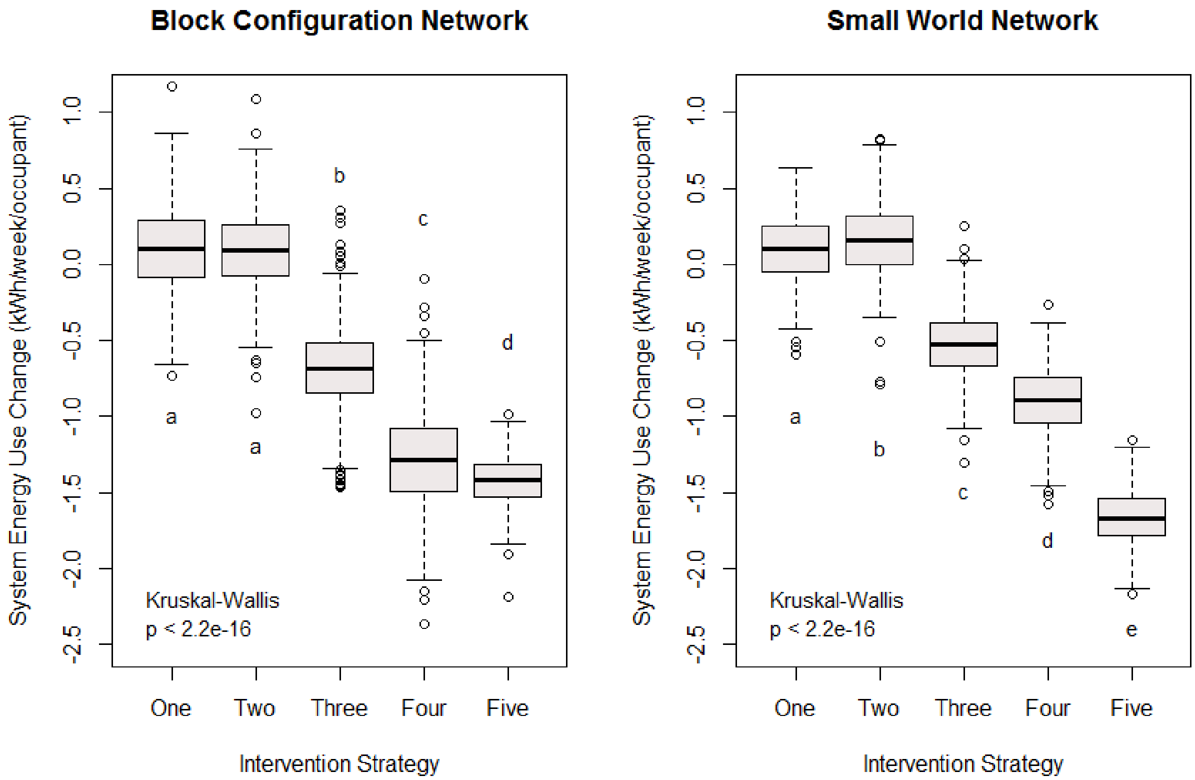


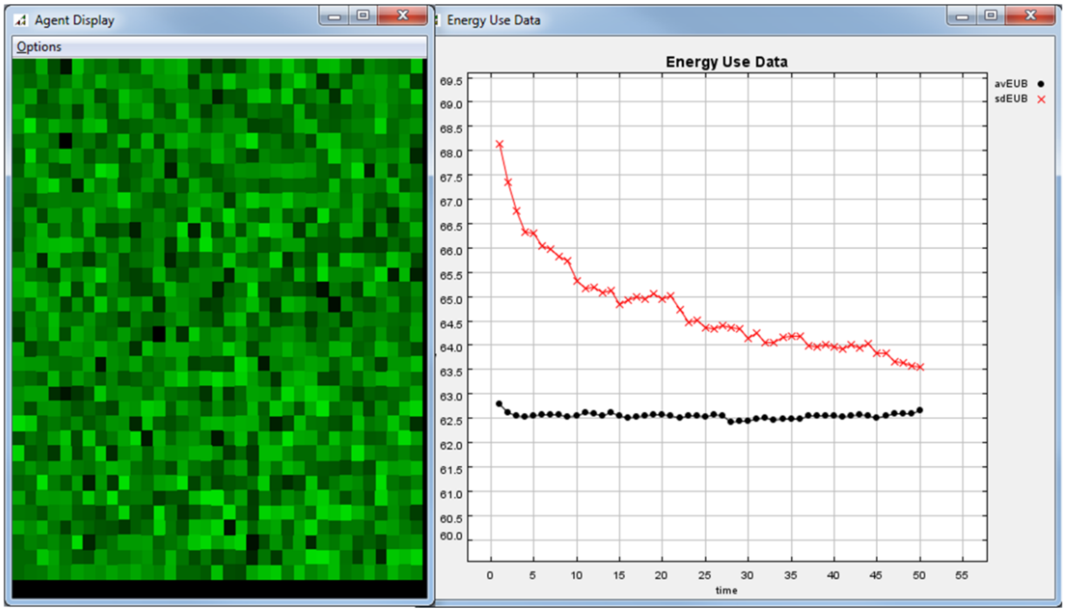
Figure 5.5:Boxplots of simulation results by network structure. Left – Mean energy use change by intervention strategy in the block configuration network. Right – Mean energy use change by intervention strategy in the small world network. Change values are in kWh per week per occupant. Letters indicate statistical differences between intervention strategies.

Of the new strategies at the end of the fifty simulated weeks, strategy five clearly produces the largest average occupant reduction in energy use at -1.67 kWh a week, but over the course of the intervention is not the most effective at reducing total energy consumption (Table 5.3). Intervention strategy four actually reduces net energy consumption more during the fifty weeks of the simulated intervention. This result stems from the difference in dynamics of how the interventions affect the population. Individual runs of intervention four and five using the same random seed are shown in Figure 5.6.

The social network structure did affect the average net energy use change per occupant for all of the intervention strategies with the exception of providing occupants only with individual feedback (One - $H = 0.0251$, $p = 0.8741$, df =1;Two - $H = 22.3436$, $p = 2.28\text{e-}6$, df = 1;Three - $H = 100.1531$, $p < 2.2\text{e-}16$, df = 1;Four - $H = 374.2755$, $p < 2.2\text{e-}16$, df = 1;Five - $H = 340.5062$, $p < 2.2\text{e-}16$, df = 1). Despite having statistically different outcomes for the second intervention method, the difference between the two is not meaningfully different at 0.09 to 0.16 kWh per week per occupant. The same is true for strategy three and five. However, a more meaningful difference between the two social network structures appears when applying the fourth messaging strategy. The difference is 0.4 kWh per week per occupant, almost 45%. The fifth scenario also exhibits a modest difference between the two structures at 0.24 kWh per week per occupant. As note previously, these differences in mean occupant change in the final time step of the model due to network structure do not translate into differences in the overall effectiveness of the interventions between the two as measured by net energy consumption.

The network structure also affects the change in use of the high and low norm rating users. The small world network's structure tends to exacerbate the behavior change of these two groups beyond what is seen in the block configuration network by approximately one percent. Upon conclusion of intervention, the standard deviation of energy use behavior is also slightly lower in every intervention scenario for the small world network as well.

Intervention Four: Normative Messaging to All Occupants with Use Above Group Norm



Intervention Five: Normative Messaging to Low Norm Rating Occupants Only

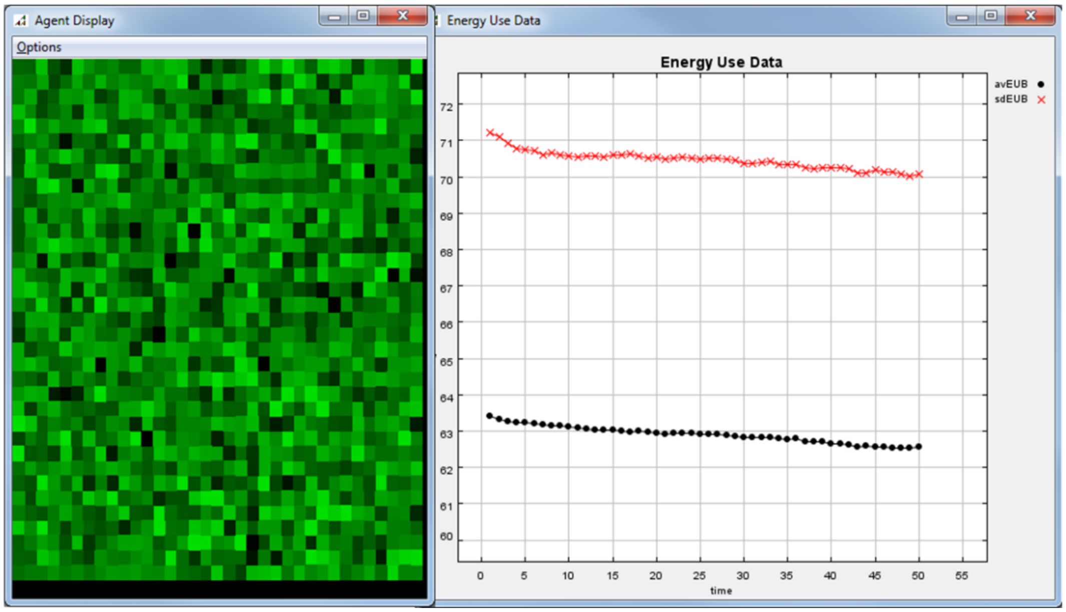


Figure 5.6: Single run mean energy use (black line) and the standard deviation of mean energy use (red line) for strategy four (top) and five (bottom) in the block configuration network using the same random generator seed. Please note that standard deviation values are multiplied by 3 to be able to be shown on the same scale. The x-axis in the plot is time steps and the y-axis is kWh per week. The images on the left graphically show the energy use behavior of every occupant in the network. The brighter the color the lower the energy use of the occupant (e.g., black occupants use near 125 kWh per week).

5.4 DISCUSSION

The model presented in this chapter simulated applying various feedback intervention strategies in a college dormitory community using theories from the literature and observations from the field study that was conducted in Chapter 4. When simulating the application of the intervention methods applied in the field study the model is able to accurately reflect both the macro level outcomes as well as the micro level behavior of the occupants to match field observations. When individual feedback or normative is sent to all the occupants in the network at the macro level we see no reduction in energy use, the same as found in the field experiment and other normative feedback studies (Schultz et al. 2007). The reason for the lack of system level change is that some occupants increase their energy consumption as a result of the normative feedback and move toward the mean, the boomerang effect, whereas others reduce their energy consumption as desired. This is reflected in the model at the micro level where we see a shift in the energy use behavior of individuals who are highly susceptible and unsusceptible to normative influence. With both the macro level and micro level behavior of the model reflecting real world observations it provides confidence in the agent behavioral rules.

With the model calibrated and validated against field data it was used to test the effectiveness of three new feedback intervention strategies on the effect of social network structure on intervention outcomes and to test the effectiveness of these strategies. The three alternative intervention scenarios include sending normative messages to only highly susceptible individuals (third scenario), sending the normative message only to individuals who use more energy than the group norm (fourth scenario), and sending normative feedback only to high norm individuals and no feedback to any other occupants (fifth scenario). Of these strategies the fifth proved to be the most effective at changing the average occupant's energy use behavior upon the conclusion of the intervention as expected, since it essentially only allowed for downward movement in energy use behavior. The forth method was almost equally effective when applied in the block configuration network but performed meaningfully worse when applied in the small world network. However, when considering the net energy used over the course of the two interventions, these methods proved to be equivocal. With the forth intervention method occupants immediately shift their energy use down upon the receipt of the first few feedback messages (Figure 5.6). This immediate downward shift upon receiving feedback is commonly seen in this type of intervention (Allcott and Rogers 2012). Alternatively in the fifth scenario mean occupant energy use slowly drifts lower each time step. If the simulations had run for a longer duration, the fifth scenario would have performed better with regards to net energy consumption.

The social network structure in which the interventions were conducted did affect the outcome in terms of macro level behavior and micro level behavior for all intervention strategies except for when individual only feedback was used. These two network structures despite having comparable average degrees are conceptually very different. While both networks are believed to occur in social systems I believe that the block configuration network better represents the social network structure of residential communities. The small world network can be thought to represent that everyone knows their neighbors immediately adjacent to them and a few individuals may know a person on a different floor of their building or in a different building. This means that everyone knows someone else in the housing community. This does not seem to be a realistic assumption for large scale housing communities, especially in highly transient communities. The survey questionnaires completed by occupants in the dormitory community partially corroborates this, as many individuals when asked where they spend time outside of their residence in the building community provided no answers. While it is unclear if the lack of response is due to not having social ties in the building or respondents simply skipping the question, based off of data in the literature (Chen et al. 2013), it seems reasonable to assume that some respondents do not have social ties within the building community. The block configuration network structure reflects this as approximately 22% of all individuals have no social connections in the housing community. To be clear this does not mean these individuals have no friends or peers, just none that live in the dormitories.

This difference between the two networks' structures, the completely connected small world network versus the segregated small components of the block configuration network, can explain the differences in intervention outcomes caused by the two networks. In the small world network since all individuals are connected the change in behavior in one can eventually propagate to all other individuals in the network, but in the block configuration network this is not possible through peer feedback. The complete connectedness of the network means occupants indirectly influence every other occupant, although very minimally. This is reflected in the slightly lower standard deviation of energy use behavior of the occupants in each intervention scenario except the fifth. This is not found in the fifth scenario since three quarters of the population receive no feedback and simply move about randomly. The variation in structure of the two networks also affects the effectiveness of each intervention method in absolute terms, but not in relative. Therefore, even if the network structure were unknown and one were to simulate new alternative strategies for reducing energy use, expected reductions might vary, but the conclusion as to which intervention to should be applied likely would not.

While these three new intervention methods all improved upon the two tested in the field experiment, there are practical limitations to consider. In the field to implement the third and fifth scenarios the intervener would have to elicit information from the occupants to derive a value for their susceptibility to normative influence which would limit the wide scale application of these methods. On the other hand, scenario four, which was found to be the second most effective intervention strategy, is highly non-particular (De Young 1993) and could be easily applied everywhere as it requires no self-reported data from occupants.

Lastly, while the model achieved a high level of performance in simulating occupant behavior, this does not imply that the model could not be further improved. The model assumes that the influence from the group norm message and peer norms had an equal weight on influencing the occupants behavior. This assumption, while plausible, would benefit from evidence from the field. Secondly, the relative impact of receiving information from multiple sources was assumed based on observations from the literature (Latane 1981). Collecting data on the relative effectiveness of receiving norm messages from these two types of sources would further benefit the model.

5.5 CONCLUSIONS

In this study a novel behavior model was created to test the effectiveness of three behavior interventions and the effect that social network structure has on their outcomes. All three alternative intervention strategies generated marked improvements upon the generic application of individual or normative feedback messaging. Although each method resulted in marked improvements in energy consumption, from an application perspective one strategy is significantly superior to the others, normative messaging based upon energy consumption relative to the group norm. This method resulted in a mean energy use reduction of 1.4 kWh per week per occupant, 2.2%, relative to the two baseline intervention techniques and can readily be applied today.

Lastly, the social network structure in which the interventions took place affected the absolute outcomes of the simulations but not the relative outcomes. This suggests that while accurately modeling the social network structure is important to gauge potential cost and benefits of applying these normative interventions it will likely not influence the selection of which intervention strategies should be applied.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 SUMMARY OF RESEARCH

This research effort started with the following overarching research goals: (1) to improve our understanding of the impact of occupant decision making in residential energy consumption, (2) to enhance our understanding of how individual characteristics and complex contextual factors influence change in individual behavior and its diffusion through communities when subjected to normative intervention, and (3) to identify more effective normative behavioral strategies for reducing energy consumption in the built environment. Considering these goals, the research had these four more specific research objectives: (1) to measure the operational efficiency of residences, (2) to explore the relationship between social network structure and pro-environmental behavior intervention outcomes, (3) to identify and measure relationships between behavioral determinants and normative feedback intervention effectiveness in both the short and long term, and (4) to create a formal behavior model for occupant behavior in order to predictively model normative feedback interventions.

In order to achieve the research goals and objectives an iterative research framework was developed and four studies were conducted. A summary of the results and implications from the studies follows.

1. To measure the operational efficiency of residences: In this study I conducted an investigation into the quantity of energy spent in unoccupied households, focusing specifically on dormitories. It was found that over 30% of all electrical energy consumption (which accounts for plug loads, lighting, heating, and cooling) took place in unoccupied residences. Across the seasons the percentage of energy consumed in vacant rooms ranged from around 3% to over

80%. The amount of energy consumed in unoccupied households, while highly correlated with how often the household is vacant, was also strongly influenced by occupant behavior. In addition no meaningful relationship was found between total a residences total energy consumption and the percentage of energy that was used while unoccupied. These findings suggest that there are significant opportunities to improve the sustainability of households through behavioral approaches.

2. To explore the relationship between social network structure and pro-environmental behavior intervention outcomes: In this study I investigated how social network structure influenced the outcome of normative behavior interventions. It was found that while different network types and structure over many trials result in similar mean net changes in system energy use, the process of achieving the final outcome (time to reach and method of reaching) and the distributions of potential outcomes highly depend on social network properties. This is of importance when attempting to generalize conclusions about intervention results from one building to another, as distributions of outcomes and time to achieve behavior change vary widely depending on network structure. Therefore, when selecting and designing social norm based interventions, expected interventions outcomes should not be assumed based solely on previous outcomes, but consideration should also be given to the uncertainty of potential outcomes based upon specific social network properties in which they were found.

3. To identify and measure relationships between behavioral determinants and normative feedback intervention effectiveness in both the short and long term: In this study conducted and analyzed two separate year-long field experiments testing the durability and effect of normative feedback messaging on energy consumption. It was found that normative messaging duration positively influenced the durability of behavior change. Further, not all individuals were equally influenced by normative messaging. High norm individuals were found to be positively induced to change their energy use behavior whereas low norm individuals had the opposite effect. Developing and testing interventions to take advantage of this finding has the potential to reduce cost of intervention by limiting the population which should receive normative feedback. More importantly, it also has the potential to improve the effectiveness of such programs by avoiding undesirable behavior change in large subsets of the population.

4. To create a formal behavior model for occupant behavior in order to predictively model normative feedback interventions: In this study I created a refined behavior model building on the model presented in Chapter 3 by integrating in new theories on social influence, social network formation in buildings, and empirical data and findings from the studies conducted in Chapter 4. The new behavior model was calibrated and validated against the studies' results from Chapter 4 and conducted 'what if' analysis of three alternative intervention strategies. All three alternative intervention strategies generated marked improvements upon the generic application of individual or normative feedback messaging. Although each method resulted in marked improvements in energy consumption, from an application perspective one strategy is significantly superior to the others, normative messaging based upon energy consumption relative to the group norm. This method resulted in a mean energy use reduction of 1.4 kWh per week per occupant, 2.2%, relative to the two baseline intervention techniques and could readily be applied today. Lastly, the social network structure in which the interventions took place affected the absolute outcomes of the simulations but not the relative outcomes. This suggests that while accurately modeling the social network structure is important to gauge potential cost and benefits of applying these normative interventions it will likely not influence the selection of which intervention strategies should be applied.

6.2 FUTURE RESEARCH

While this work has expanded our understanding of occupant behavior in dormitories and the role social networks play in the diffusion of energy use behavior many questions remain which still warrant further attention in future research efforts. A few such questions follow.

1. Precisely how much of the energy consumed in unoccupied residences is spent on useful services (e.g., refrigeration, maintaining minimum indoor temperatures)? Further, what are the exact distributions of energy consumption by energy source in unoccupied residences?

2. How do social network structures change over time and can this dynamicity be leveraged to encourage the desirable diffusion of pro-environmental behaviors? Also do social networks vary in different building communities (e.g., apartment communities, traditional detached-home neighborhoods, work places)?

3. Is there a particular threshold in terms of time or exposure that must be crossed in order for normative message to have a positive effect on behavior change durability and how does this vary for each individual? Or by what function does this enhancement in durability manifest? Further, do behavioral improvements or deterioration in energy consumption spill-over into other pro-environmental behaviors?

4. Do residents discuss energy consumption and if so how frequently do they discuss it? How much influence do interpersonal communications have on energy use decisions relative to descriptive norms? What at what rate do additional sources of information increase the influence to partake in a behavior and how are conflicting behaviors from sources interpreted?

6.3 FINAL REMARKS

In this research the methodologies and framework that were developed and used focused specifically on energy consumption behavior in the built environment, these methods however, are not conceptually constrained to the study of energy use behavior. It is reasonable to assert that many other pro-environmental behaviors (e.g., water consumption) would be affected by the similar social and psychological mechanisms. Thus, the extension of methods in this research could be of potential benefit to the study of many other pro-environmental behaviors. Additional research efforts investigating alternative pro-environmental behaviors could further enhance the sustainability of the built environment and enhance our general understanding of how these behaviors are influenced by social mechanisms and diffusion through our environment.

APPENDIX A – INTAKE SURVEY

ENGLISH VERSION

MICHIGAN ENGINEERING
UNIVERSITY of MICHIGAN ■ COLLEGE of ENGINEERING

SEOUL NATIONAL UNIVERSITY

OCCUPANT SURVEY

This study is performed by University of Michigan and Seoul National University. The goal of this study is to evaluate energy consumption in the building. The result of this study will help building managers better operate the building.

- Participating in this survey is VOLUNTARY and you may stop at any time.
- All of your answers on this questionnaire will be CONFIDENTIAL.
- Your answers will be used ONLY FOR RESEARCH PURPOSES.

Thank you very much for your participation in this study.
We greatly appreciate it.

Instructions:
Many questions in this survey make use of rating scales with 7 places; you are to circle the number that best describes your opinion. For example, if you were asked to rate "Eating oranges" on such a scale, the 7 places should be interpreted as follows:

Typically, the taste of an orange is

good :	1 :	2 :	3 :	4 :	5 :	6 :	7 : bad
	extremely	quite	slightly	neither	slightly	quite	extremely

If you think that oranges typically taste extremely good, you would circle *number 1*, as indicated below:

good :	(1) :	2 :	3 :	4 :	5 :	6 :	7 : bad
	extremely	quite	slightly	neither	slightly	quite	extremely

If you think that oranges do not either taste good or bad, you would circle *number 4*, as indicated below:

good :	1 :	2 :	3 :	(4) :	5 :	6 :	7 : bad
	extremely	quite	slightly	neither	slightly	quite	extremely

If you think that oranges taste quite bad, you would circle *number 6*, as indicated below:

good :	1 :	2 :	3 :	4 :	5 :	(6) :	7 : bad
	extremely	quite	slightly	neither	slightly	quite	extremely

When answering the questions, remember to:

*Please answer all questions

*Circle only one answer for each question

-1-

Name ___________ Building_____ Room______

Please answer each question by circling the number that best describes your opinion. Although some questions might appear similar, they address slightly different issues, please read each question carefully. There are 31 questions.

For questions 1 to 11, during the past year, how often did you do the following when you had the opportunity?						
1.	Set thermostat to 18 degrees or lower during cool or cold weather?	Never	Rarely	Sometimes	Most of the time	N/A
2.	Set thermostat (air conditioner) to 25 degrees or higher during warm or hot weather?	Never	Rarely	Sometimes	Most of the time	N/A
3.	Turn off lights when I leave the room?	Never	Rarely	Sometimes	Most of the time	N/A
4.	Use a reusable water bottle, coffee cup, travel mug, etc.	Never	Rarely	Sometimes	Most of the time	N/A
5.	Use the power saving settings on my computer?	Never	Rarely	Sometimes	Most of the time	N/A
6.	Turn off my computer when not using it?	Never	Rarely	Sometimes	Most of the time	N/A
7.	Run washer only when I have a full load of clothes?	Never	Rarely	Sometimes	Most of the time	N/A
8.	Limit time in the shower?	Never	Rarely	Sometimes	Most of the time	N/A
9.	Recycle bottles, containers, and paper products	Never	Rarely	Sometimes	Most of the time	N/A
10.	Buy Products (besides food) that carry some type of ecolabel or certification (e.g. lumber, organic cotton clothing, household cleaning products)	Never	Rarely	Sometimes	Most of the time	Don't Know
11.	Buy locally grown or processed, organic, or fair trade food?	Never	Rarely	Sometimes	Most of the time	Don't Know

Circle the corresponding answer or fill in the blank

12. I am a ______ student: First year Sophomore Junior Senior Graduate/Professional Degree

13. List where you are most likely to be found in the SNU dorms (building and room number).
Bld___Rm_____, Bld___Rm_____, Bld___Rm_____, Bld___Rm_____, Bld___Rm_____,
Bld___Rm_____, Bld___Rm_____, Bld___Rm_____, Bld___Rm_____, Bld___Rm_____.

Circle the number that best describes your opinion

14. I plan to conserve more energy in my home
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

15. In general, people should conserve energy, even if it is inconvenient.
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

16. Conserving more energy would negatively affect my comfort
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

17. Using less energy at home will have environmental benefits
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

18. Conserving more energy would be an inconvenience to me
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

19. Negatively affecting my comfort to conserve energy is
very undesirable : 1 : 2 : 3 : 4 : 5 : 6 : 7 : very desirable

20. Behaving in a manner that benefits the environment is good
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

21. My neighbors' think that I should be more environmentally responsible with my energy use
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

22. My close friends' think that I should be environmentally responsible with my energy use
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

23. Generally speaking, how much do you care what your neighbors think you should do
not at all : 1 : 2 : 3 : 4 : 5 : 6 : 7 : very much

24. Generally speaking, how much do you care what your close friends think you should do
not at all : 1 : 2 : 3 : 4 : 5 : 6 : 7 : very much

25. I know what consume energy in the home
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

26. If it is hot or cold, it would make it difficult for me to conserve energy at home
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

27. If I am mentally tired, it would make it more difficult for me to conserve energy at home
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

28. Knowing what consumes energy will enable me to reduce my energy use
strongly agree : 1 : 2 : 3 : 4 : 5 : 6 : 7 : strongly disagree

29. It is either hot or cold in my home
    Very rarely :__1__:__2__:__3__:__4__:__5__:__6__:__7__: very frequently

30. When at home, I am mentally tired
    very rarely :__1__:__2__:__3__:__4__:__5__:__6__:__7__: very frequently

Use the following lines to briefly answer the follow question and add any comments you might have

31. If you currently actively attempt to conserve energy, why do you do so? If you currently do not, why not?
    ____
    ____
    ____
    ____
    ____
    ____
    ____

KOREAN VERSION

MICHIGAN ENGINEERING
UNIVERSITY of MICHIGAN ▪ COLLEGE of ENGINEERING

서울대 기숙사 내 에너지 소비 절약을 위한 설문 조사

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본 설문은 미시간대학교와 서울대학교가 공동으로 수행하는 연구의 일환으로 계획되었습니다. 본 설문의 목적은 응답자의 기숙사 에너지 사용과 관련된 사항을 측정하는 데 있습니다. 이 설문의 결과는 기숙사 에너지 사용 절약을 위하여 활용될 것입니다.

- 본 설문은 자발적인 참여를 통해서만 진행될 것입니다.
- 응답자의 신상에 대한 비밀은 철저히 보장될 것입니다.
- 본 설문은 연구 이외의 목적으로 활용되지 않을 것입니다.

설문 방법 및 주의사항

본 설문를 구성하는 대부분의 문항은 리커트 7 점 척도를 활용하였습니다. 응답자의 의견을 가장 잘 대변하는 숫자에 동그라미 표시를 해주십시오. 예를 들어, 응답자가 느끼는 오렌지의 맛을 답변한다고 할 때 다음과 같은 방법에 따라 응답하십시오.

오렌지의 맛을 7 단계로 구분하면 다음과 같은 형태로 표현이 가능합니다.

좋다 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 나쁘다

매우 꽤 약간 보통 약간 꽤 매우

이때 오렌지의 맛이 아주 좋다고 느꼈다면, 7 번에 표시하면 됩니다.

좋다 :__(1)__:___2___:___3___:___4___:___5___:___6___:___7___: 나쁘다

매우 꽤 약간 보통 약간 꽤 매우

만약 오렌지의 맛이 좋지도 나쁘지도 않았다면, 4 번에 표시하면 됩니다.

좋다 :___1___:___2___:___3___:__(4)__:___5___:___6___:___7___: 나쁘다

매우 꽤 약간 보통 약간 꽤 매우

성 명: ____________________

건물 동번호: ________ 실번호: ________

재실 형태: 1 인실 다인실

본 설문은 총 31 개 문항으로 구성되어 있습니다. 자신의 의견을 가장 잘 대변하고 있다고 생각되는 번호를 동그라미로 표시해 주십시오. 일부 문항이 유사해 보인다고 할지라도 서로 다른 쟁점을 다루고 있으니 주의깊게 답변해주시면 대단히 감사하겠습니다.

첫 열한 문항은 응답자의 과거 생활과 관련이 있습니다. 문항별로 묻는 행위를 얼마나 자주 했는지 답변해주십시오.

1. 시원하거나 서늘한 날씨일 때 실내온도조절장치를 18 도 이하로 설정한 적이 있다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
2. 따뜻하거나 더운 날씨일 때 실내온도조절장치를 25 도 이상으로 설정한 적이 있다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
3. 외출 시 실내조명을 소등한다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
4. 재사용 가능한 물병, 커피잔, 텀블러를 사용한다.	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
5. 컴퓨터의 절전 모드를 사용한다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
6. 컴퓨터를 사용하지 않을 때에는 전원을 차단한다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
7. 세탁물이 가득 차면, 세탁기를 사용한다.	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
8. 샤워 시간을 스스로 제한하고 있다	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
9. 빈병, 플라스틱 용기, 폐신문지를 재활용한다.	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
10. 환경인증마크가 부착된 상품을 구매한다.(예: 유기농 세제).	전혀 아니다 가끔 자주 대부분 그렇다 해당없다
11. 지역에서 생산된 유기농 음식을 구매한다.	전혀 아니다 가끔 자주 대부분 그렇다 해당없다

자신의 의견을 가장 잘 대변하고 있다고 생각되는 번호를 동그라미로 표시해 주십시오.

12. 나는 __________학생이다.

1 학년 2 학년 3 학년 4 학년 대학원생

13. 내가 기숙사에서 내 방에 없을 경우 나는 다음 기숙사 장소에서 찾을 수 있을 것이다.

(동/호): _________(_____) (동/호): _________(_____) (동/호): _________(_____)

(동/호): _________(_____) (동/호): _________(_____) (동/호): _________(_____)

(동/호): _________(_____) (동/호): _________(_____)

14. 나는 기숙사 내 방에서 소비되는 에너지를 절약할 계획이다. (강하게 동의한다면 1 번에 표시)

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

15. 사람들은 불편을 감수하더라도 에너지를 절약해야 한다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

16. 에너지 절약은 나의 쾌적함에 부정적인 영향을 미칠 것이다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

17. 기숙사 내 방에서 에너지 절약은 환경에 긍정적인 효과를 미칠 것이다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

18. 에너지 절약하는 일은 나에게 불편을 야기할 것이다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

19. 에너지 절약이 나의 쾌적함에 부정적으로 영향을 미치는 것은

결코 바람직 하지않다 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 아주 바람직하다.

20. 환경에 이득을 가져다 주는 행동은 좋다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

21. 기숙사 이웃들은 에너지 사용과 관련된 환경적인 책임을 내가 더 가져야 한다고 생각한다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

22. 나의 친한 친구들은 에너지 사용과 관련된 환경적인 책임을 내가 더 가져야 한다고 생각한다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

23. 일반적으로 나는 기숙사 이웃들의 기대에 부응해야 한다고 생각한다.

결코 아니다 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 매우 그렇다

24. 일반적으로 나는 가까운 친구들의 기대에 부응해야 한다고 생각한다.

결코 아니다 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 매우 그렇다

25. 나는 기숙사 내 방에서 무엇이 에너지를 소비하는 지 알고 있다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

26. 더위 또는 추위로 인하여 기숙사 내 방 에너지 절약이 어렵다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

27. 나는 정신적으로 피곤할 때, 기숙사 내 방 에너지 절약이 더 어렵다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

28. 기숙사 내 방에서 무엇이 에너지를 소비하는 지 아는 것은 에너지 절약을 가능하게 한다.

강하게 동의 :___1___:___2___:___3___:___4___:___5___:___6___:___7___: 강하게 부정

29. 내 기숙사 방은 덥거나 춥다.

전혀 아니다:___1___:___2___:___3___:___4___:___5___:___6___:___7___: 자주 그렇다

30. 나는 기숙사 내방 에 있을 때 정신적으로 지친 상태이다.

매우 그렇다:___1___:___2___:___3___:___4___:___5___:___6___:___7___: 전혀 아니다

다음 문항은 주관식 입니다. 마지막 질문에 대한 답변과 본 설문에 관하여 추가적으로 할 말이 있다면 가감없이 부탁드리겠습니다.

31. 현재 본인이 적극적으로 에너지 절약을 시도하고 있다면 그 이유는? 만약 그 반대라면 그 이유는?

____

____

____

____

____

설문에 참여해주셔서 대단히 감사합니다!

APPENDIX B – SECOND SURVEY: ADDITIONAL QUESTIONS

ENGLISH VERSION

English

[한국어로 설문 조사에 참여하고 싶으시다면 오른쪽 상편에서 한국어를 택해 주십시오]

This study is performed by University of Michigan and Seoul National University. The goal of this study is to evaluate energy consumption in the building. The result of this study will help building managers better operate the building.

- Participating in this survey is VOLUNTARY and you may stop at any time.
- All of your answers on this questionnaire will be CONFIDENTIAL.
- Your answers will be used ONLY FOR RESEARCH PURPOSES.

Thank you very much for taking a few minutes to complete this survey.

Please enter the following information:

Name	
Building	
Room	

NEXT

Survey Completion

0% 100%

English

Have you lived in the same dorm room since March 10, 2014 (with the exception of during summer break if you are an undergraduate student)?

- Yes
- No

If you live in a double room, has your roommate changed since March 10, 2014?

- No
- Yes, my roommate changed
- Yes, my roommate moved out
- N/A

How frequently did you receive weekly energy use feedback emails since March 10, 2014 with the exception of June 16 to 30 (undergraduate students excluding summer break, June 16 to September 8)?

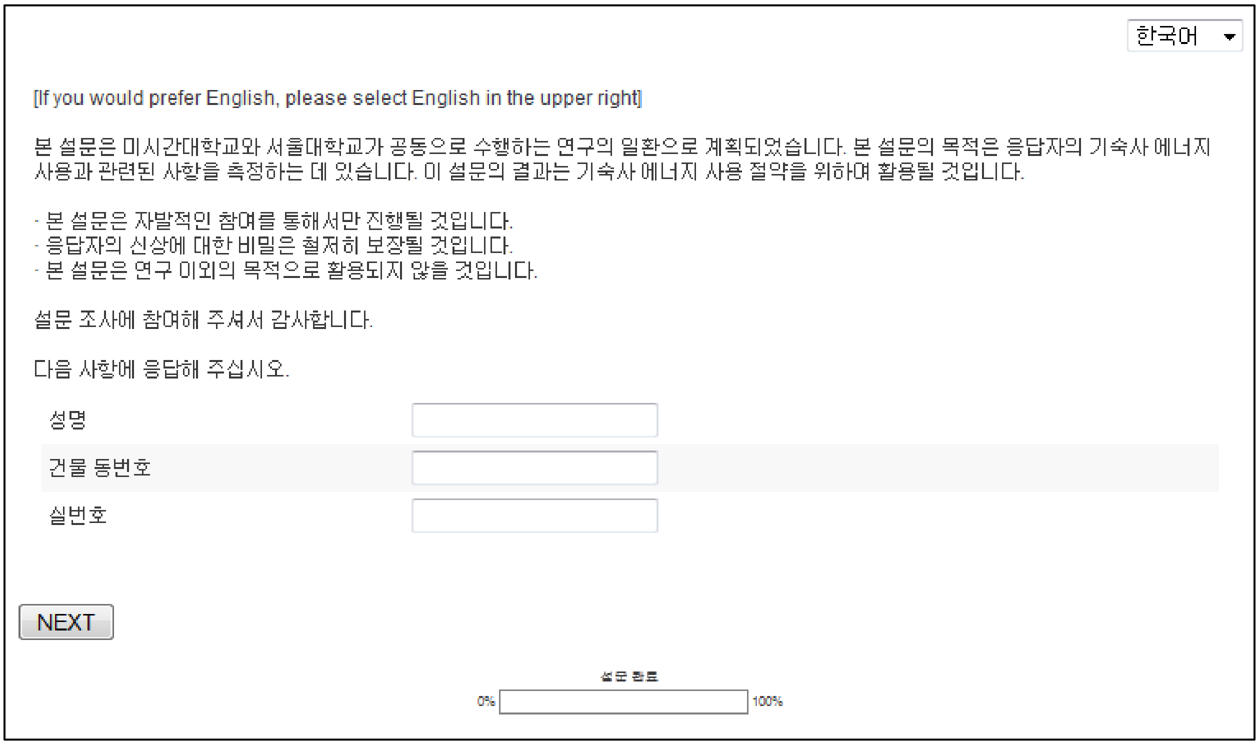
- Every week
- Most weeks
- Some weeks
- Never

How frequently did you read the energy use feedback emails?

- Every week
- Most weeks
- Some weeks
- Never

BACK NEXT

KOREAN VERSION



한국어

[If you would prefer English, please select English in the upper right]

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- 본 설문은 자발적인 참여를 통해서만 진행될 것입니다.
- 응답자의 신상에 대한 비밀은 철저히 보장될 것입니다.
- 본 설문은 연구 이외의 목적으로 활용되지 않을 것입니다.

설문 조사에 참여해 주셔서 감사합니다.

다음 사항에 응답해 주십시오.

성명

건물 동번호

실번호

NEXT

0% 100%

한국어

2014년 3월 10일부터 동일한 기숙사 방에 살고 있습니까 (학부생인 경우 여름 방학 동안 기숙사에 살지 않은 기간은 제외함)?

- 네
- 아니오

2인실을 사용하는 경우 2014년 3 월 10일 이후 룸메이트가 바뀌었습니까?

- 아니오
- 네, 저의 룸메이트가 바뀌었습니다
- 네, 저의 룸메이트가 나가서 혼자 지내고 있습니다
- 해당없다

2014년 3월 10일부터 얼마나 자주 주간 에너지 사용 내역을 담은 이메일을 받으셨습니까 (6월 16일부터 6월 30일 제외, 학부생은 6월 16 일부터 9월 8일 제외)?

- 매주
- 거의 모든 주
- 가끔씩
- 받은 적 없음

얼마나 자주 에너지 소비 절약 결과를 담은 이메일을 읽었습니까?

- 매주
- 거의 모든 주
- 가끔씩
- 받은 적 없음

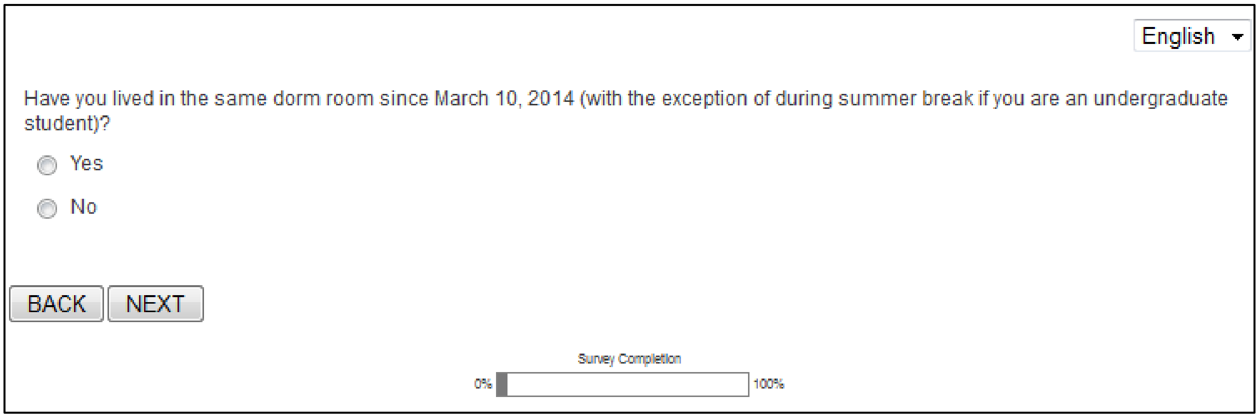
BACK NEXT

설문 완료

0% 100%

APPENDIX C – THIRD SURVEY: ADDITIONAL QUESTIONS

ENGLISH VERSION



English

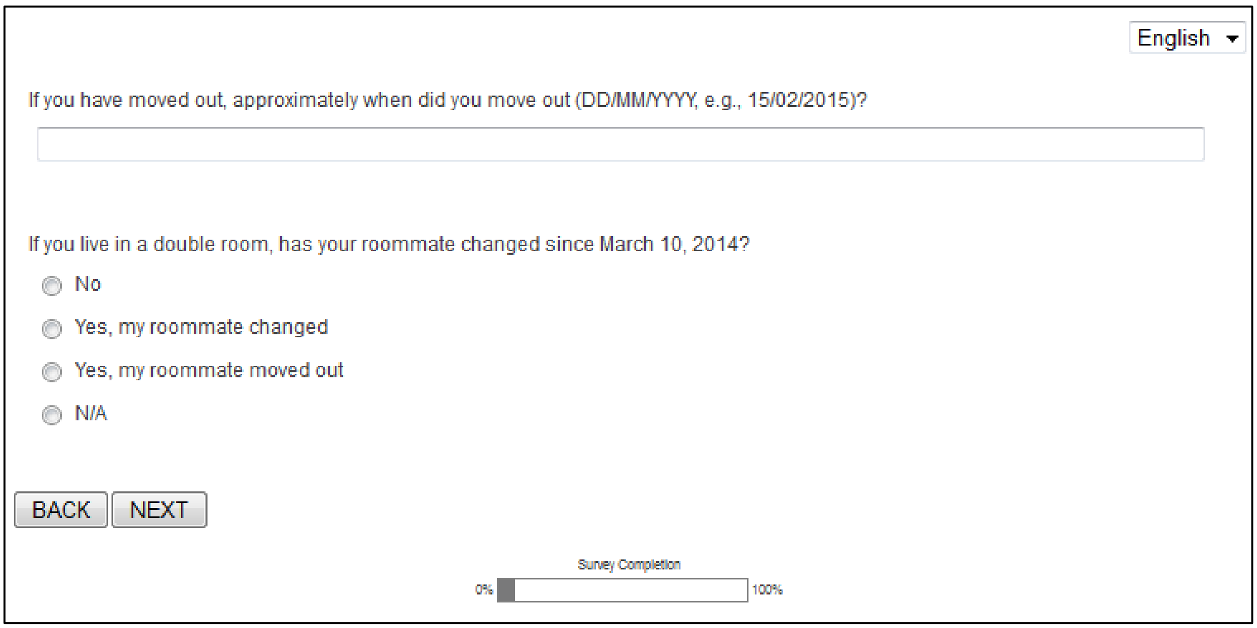
Have you lived in the same dorm room since March 10, 2014 (with the exception of during summer break if you are an undergraduate student)?

- Yes
- No

BACK NEXT

Survey Completion

0% 100%



English

If you have moved out, approximately when did you move out (DD/MM/YYYY, e.g., 15/02/2015)?

If you live in a double room, has your roommate changed since March 10, 2014?

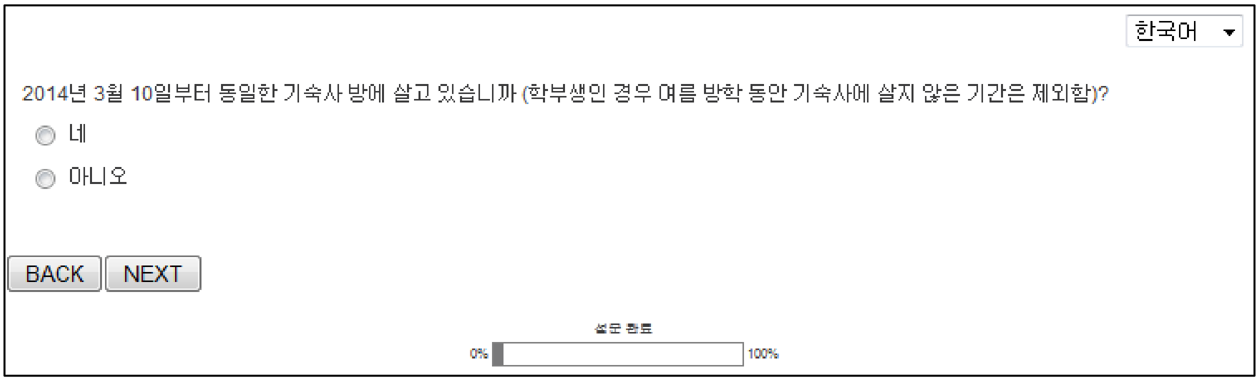
- No
- Yes, my roommate changed
- Yes, my roommate moved out
- N/A

BACK NEXT

Survey Completion

0% 100%

KOREAN VERSION


한국어

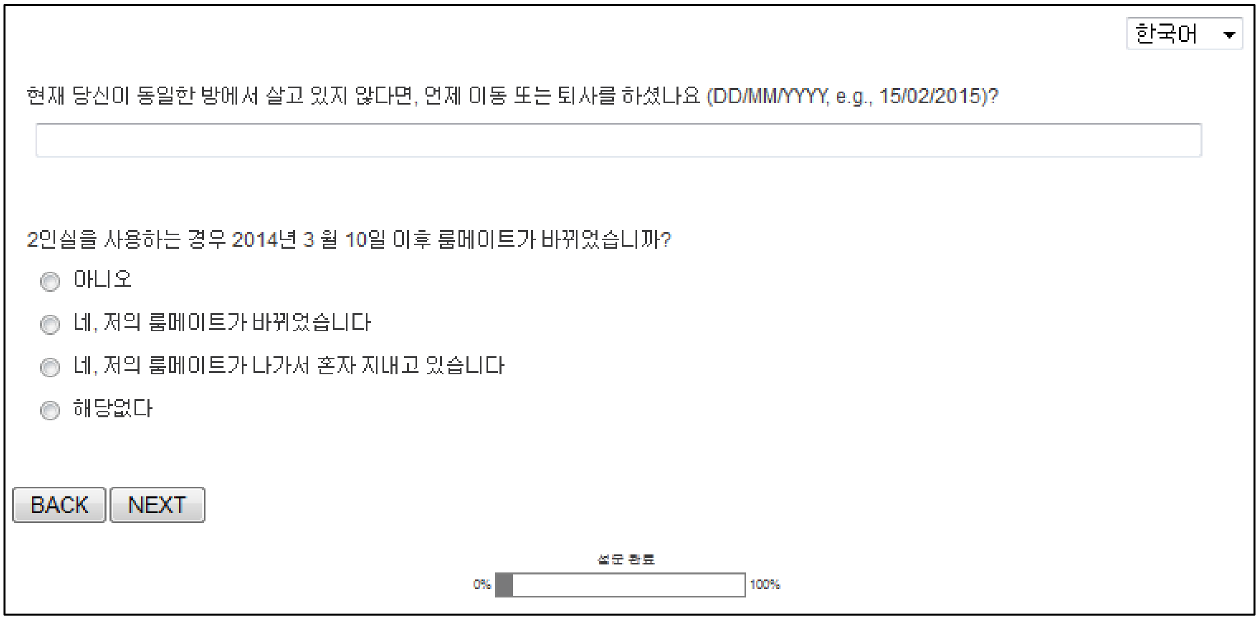
2014년 3월 10일부터 동일한 기숙사 방에 살고 있습니까 (학부생인 경우 여름 방학 동안 기숙사에 살지 않은 기간은 제외함)?

- 네
- 아니오

BACK NEXT

설문 완료

0% 100%


한국어

현재 당신이 동일한 방에서 살고 있지 않다면, 언제 이동 또는 퇴사를 하셨나요 (DD/MM/YYYY, e.g., 15/02/2015)?

2인실을 사용하는 경우 2014년 3 월 10일 이후 룸메이트가 바뀌었습니까?

- 아니오
- 네, 저의 룸메이트가 바뀌었습니다
- 네, 저의 룸메이트가 나가서 혼자 지내고 있습니다
- 해당없다

BACK NEXT

설문 완료

0% 100%

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