Simulating Network Structure, Layering Multi-layer Network Systems and Developing Network Block Configuration Models to Understand and Improve Energy Conservation in Residential Buildings

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ABSTRACT

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The building sector is a major contributor to total energy consumption in most countries. Traditionally, researchers have focused on leveraging energy efficiency by improving building materials, in-house facilities and transmission equipment. More recently, however, there has been increased focus on research concerning demand-side energy consumption behavior. Current research suggests that energy efficient behavior of a building's occupants can be extensively enhanced through the sharing of energy consumption information among residents in a peer network. However, most of this research relies on experimental tests and does not theorize concepts related to peer network energy efficiency systematically. My dissertation addresses this research gap on two levels. First, I examined if and how the structure of peer networks can impact residents' conservation behaviors through network analysis by employing agent-based simulation techniques. Following confirmation of the impact that network structure has on user behavior, I created a layered network model to integrate information from various network layers and a block configuration model to reconstruct increasingly reliable random networks. In contrast to controlled energy efficiency experiments, real-world networks are large in size, heterogeneous in nature and regularly interact with other networks. By utilizing models developed in this dissertation, we are able to estimate the

contribution of network structural coefficients to the energy consumption performance of peer networks. By comparing the layered network and block configuration model I developed with other conventional models, I prove the efficiency, accuracy and reliability of these improved models. These findings have implications for assessing network performance, creating accurate complex random networks for large-scale research, and developing strategies for network design to improve building energy efficiency. This research establishes a system to study residents' energy efficient behaviors from the perspective of peer networks and proposes some instructive models for further energy feedback system design.

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"Success is a function of persistence and doggedness and the willingness to work hard for twenty-two minutes to make sense of something that most people would give up on after thirty seconds."

-- Malcolm Gladwell, Outliers

In my journey in the pursuit of the Ph.D., I had three simple goals: to learn something new, to try something new and to create something new. However, I found that they are not as simple as I expected; in contrast, they are the most difficult tasks I had ever experienced. Fortunately, there have been so many people who supported me consistently and generously.

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Dedicated to my parents, Meier and Junfang,

who made me an honest person.

Chapter 1

1. INTRODUCTION

"The central act of the coming era is to connect everything to everything. All matter, big and small, will be linked into vast webs of networks at many levels. Without grand meshes there is no life, intelligence, and evolution; with networks there are all of these and more."(Kelly, 1994, p.201)

Kevin Kelly

"The idea is to populate virtual markets with artificially intelligent agents who trade and interact and compete with one another much like real people. These 'agent based' models do not simply proclaim the truth of market equilibrium, as the standard theory complacently does, but let market behavior emerge naturally from the actions of the interacting participants…"(Buchanan, 2008, p.1)

Mark Buchanan

On March 22nd 2012, social game giant Zynga purchased OMGPOP, the creator of the mobile drawing game Draw Something, for $210 million in cash and an employee retention payment. This popular game had been launched only 6 weeks prior, but it was downloaded over 30 million times and users created more than 1 billion drawings. Developed from 2001 to 2006, one of the most famous game series in history, Final Fantasy XIII, cost Square-Enix approximately 35 million USD to develop. Square-Enix had to sell 0.8 million copies of the game in order to cover these high development costs. Unlike traditional video games like Final Fantasy XIII, mobile applications normally only cost \$10k to \$250k and may take only several weeks to develop. This is one major factor that essentially differentiates these two games, and it is also the core idea of this dissertation – How do peer networks make a difference?

During the past few decades, modern society has experienced a tremendous revolution in its "connectedness of…." This revolution has spurred a new trend in scientific research. This trend manifests itself in many incarnations: in research related to the development of the Internet and World Wide Web, the study of global communication, the exploration of information spreading within the financial system, and the epidemics that diffuse within human communities. Through all of these phenomena, we have investigated networks, interactions and the aggregate behavior of groups of people. We have also examined their decisions in a network setting and their consequences based on the links between them and others. In his book *Out Of Control*, Kevin Kelly (1994) predicts that current and future networks will embed themselves even more in our daily life, business and society. Network logic not only shapes our businesses and products, but also affects human behavior profoundly. In this dissertation, I will examine the question of how networks affect people's decision-making in the context of energy conservation.

1.1 Energy Efficiency and Peer Networks

In the presence of alarming climate change trends and dwindling natural energy resources, there is much interest around the world in improving the energy efficiency of buildings. Such interest arises in response to concerns about energy cost, resource scarcity, and environmental deterioration. The building sector is responsible for 41% of the energy use in the US and 36% of the energy related carbon dioxide (CO_2) emissions (US Energy Information Administration 2010). According to the Natural Resources Defense Council, improvements in energy efficiency have the potential to deliver more than 700 billion dollars in savings in the US alone. Studies have also shown that on average, the US consumers spend 6 minutes every year thinking about their energy efficiency. It is essential to enhance building energy efficiency not only to tackle CO_2 emission and climate change but also to balance the energy budget. Energy efficiency related to the goal of reducing energy consumption while maintaining an acceptable level of quality in services and products. An example of a common and effective energy efficiency action is the installation of additional wall insulation, which reduces heating and cooling loads while achieving a similar comfort level as with air conditioning. There are three major approaches to improve energy efficiency: cutting energy demand by using more energy efficient equipment, producing energy locally and reducing transmission wastes, and creating buildings that can self-supply or generate surplus energy (World Business Council for Sustainable Development 2012). However, sometimes buildings are not capable of equipment upgrading or the associated cost is prohibitively high.

As people become more aware of the importance of energy use in buildings, their behavior provides researchers with a relatively untouched domain for energy efficiency research (McMakin et al. 2002; Saelens et al. 2011; Stern 1992). Especially in residential buildings, building occupants have a high degree of control over their energy consumption (e.g. heating, cooling, lightning and plug-loads).

An illuminating study at Oberlin College (Petersen et al. 2007) suggests that providing building occupants with high resolution energy consumption feedback effectively incentivizes residents to substantially reduce their energy consumption. Fischer (Fischer 2008) proposed the idea of eco-feedback systems to distribute energy consumption information to end users as well as their peers, and presents a psychological model to illustrate how and why feedback is an effective tool to encourage households to save energy. Eco-feedback systems can provide building occupants with information regarding their own and their friends' consumption and behaviors in order to encourage adoption of energy efficient behaviors. At the same time, attempts to increase energy conservation through the modification of human behaviors have focused on exploring the rationale behind decisions (Wilson and Dowlatabadi 2007), the process of practice adaptation that influence human behaviors (Dalamagkidis et al. 2007; Haldi and Robinson 2008) and the social-psychological relationship between individuals and their peers. Recent experiments show the effectiveness of eco-feedback systems (Jain et al. 2012) and the importance of peer networks in encouraging energy conservation (Peschiera and Taylor 2012). Despite findings in formal experiments that indicate energy efficiency is related to residents' peer networks, theoretical network analyses have not yet been conducted. This leads me to ask: "If these empirical peer network studies exhibit an impact on building energy efficiency, do other networks also have similar impacts? What traits of networks substantially contribute to these impacts?" In this dissertation, I aim to answer these questions anew by exploring the influences of network structure and its mechanisms in arbitrary networks. Before answering these questions, I will provide a brief introduction about the context of this research.

1.2 Theoretical Background

1.2.1 Network Theory

Network theory treats networked systems as collections of nodes and edges. The nodes within networks can represent individuals or organizations. The edges connect nodes in many ways; they can prepresent physical proximity, friendship or partnership. The research on these network properties allows new modalities for answering social and behavioral science and engineering research questions. Network theory originated from the research of social science research in the 1930s and was systematically developed by pioneers from sociology and social psychology. Early sociometricians such as Moreno, Jennings, Cartwright and Harary (Cartwright and Harary 1956; Moreno and Jennings 1938), advanced network theory through the combination of graph theory and mathematics. A significant advance in network research came in the 1950s and 1960s with the theory of random graphs founded by Erdős and Rényi (Erdős and Rényi 1959; Erdős and Rényi 1960). Statistical models are also used to test theoretical propositions about networks. During 1970s, Davis, Holland, and Leinhardt introduced a wide variety of random directed graph distribution into social network analysis, in order to test hypotheses about various structural tendencies (Davis et al. 1971). In 1998, Watts and Strogatz (Watts and Strogatz 1998) identified the Small-World phenomenon and proposed a mathematical explanation. Combining all of this research and its associated methodologies, network theory "provides a precise way to define important social concepts, a theoretical alternative to the assumption of independent social actors, and a framework for testing theories about structured social relationships" (Wasserman and

Faust 1994, p. 17). The core principles of network theory are relatively straightforward to understand, although most of its models are based on complex mathematical computations. Modern network theory has been widely applied in many different domains, from computer networks, to biological ecosystems, to business management.

One of the most important types of networks is known as the social network, or peer network. Commonly, peer network systems contain the knowledge of connections and interactions between peers. The idea of "peer network" was widely used by scholars for almost a century to connote complex sets of relationships between members within the social network system across all scales of analysis from macro to micro and from local to global. The distinction between peer network research from other network research is the assumption of the importance of relationships among interacting units. Actors within a network and their actions are viewed as interdependent rather than independent; the linkages between actors serve as channels for transferring resources or information. Researchers have studied whether the psychological state of individuals within a group is related to the relationship between group members, which provides validity for the analysis of social networks (Moreno 1953). Since these earlier network studies, networks have been used to study human community (Wellman 1979), diffusion and adoption of innovations (Coleman et al. 1957), corporate interlocking (Levine 1972; Mintz and Schwartz 1981; Mizruchi and Schwartz 1992) and consensus and social influence (Doreian 1980; Friedkin 1986; Friedkin and Cook 1990; Marsden 1990). However, experiments linking peer networks and energy efficiency feedback have only begun to develop in the past decade. This is due, in part, to the fact that data collection is difficult on a large scale because of budgets and time limitation. At the same time, research on network feedback mechanisms calls for a more general and reliable way to extrapolate to data input on larger scales.

1.2.2 Random Networks

In general, a random network is a network generated by some random process with some specific set of parameters. The theory of random networks can be traced back to the random graph theory first defined by Paul Erdős and Alfréd Rényi (Erdős and Rényi 1959) and Gilbert (Gilbert 1959) in 1959. In their model, Erdős and Rényi considered a probability space of graphs and viewed graph invariants as random variables. The Erdős-Rényi model is one of the simplest examples of random graph models. Later, developments in network theory showed that the degree distribution of real-world social networks follow a power law distribution. These networks are called scale-free networks (Barabási and Albert 1999). Following Albert and Barabási, other researchers have proposed models to resolve inconsistencies between random networks and real-world networks. For example, Buckley and Osthus defined the 'LCD model' (Buckley and Osthus 2004); Kumar and colleagues presented the 'copying' model (Kumar et al. 2000) and Cooper and Frieze proposed a mixed model (Cooper and Frieze 2003). Although these researchers resolve some of the structural limitations of the Erdős and Rényi model, some fundamental discrepancies, such as network clustering and network transitivity (Watts and Strogatz 1998), still exist.

A more recent development of random graph theory is the generating function model proposed by Newman and colleagues in 2001 (Newman et al. 2001). The generating function model allows us generate random networks with specified degree distribution.

However, the mode still fails to capture the transitivity and clustering of a network, and is unable to handle large complex muli-layer networks systems. Considering the fact that current random network models only address a piece of the puzzle, in this dissertation I propose a system that combines the multi-layer network model and the block configuration model to explore and construct a more accurate network structure that is specifically designed for research on peer network effects and energy efficiency .

1.2.3 Agent-based Simulation

Agent-based modeling is a computational method that enables creation, analysis, and experimentation with models composed of agents that interact within an environment (Gilbert 2008). In agent-based simulation, each agent individually assesses its situation and makes its own decision based on a set of rules. Agent-based simulation has become increasingly popular in research because it enables one to build models with heterogeneous entities and interactions.

There are three major advantages of agent-based simulation over other models. First, agent-based modeling is simulation that can ensure isolation of the human system and remove ethical problems related to human experimentation. These are not present in virtual or computational systems (Gilbert 2008). Second, derived agent-based simulation models are flexible (Bonabeau 2002). They are able to behave in a given range of inputs, when an analytical solution or experiment is not possible. In other words, agent-based simulation is a cost-effective way to study when an experiment is not practicable or expensive to conduct. For example, it is easy to add more agents to a simulation, but difficult to add additional subjects to real experiments without affecting the environment.

A crucial feature of agent-based simulation is that the agents can interact, or pass information to each other. This feature makes agent-based simulation a powerful tool to study peer networks, whose analysis focuses on node to node interaction.

I will use agent-based simulation models to examine how decisions are made and behavior can spread from one person to another via networks. Examples of such a process include the classical diffusion model and various opinion transmission models (Deffuant 2006; Hegselmann and Krause 2002; Lorenz 2006; Stauffer et al. 2004). I utilize agent-based simulation to study diffusion of energy consumption information and conservation behaviors within peer networks.

1.3 Research Questions and Format of Dissertation

Previous research has established a robust experimental understanding of an eco-feedback system's effectiveness in energy conservation. Eco-feedback systems have three major components which contribute to energy saving behaviors: availability and resolution of feedback, format and content of feedback, and feedback networks. Previous researchers have identified the importance of the first two components (Jain et al. 2012; Petersen et al. 2007). However, little research has investigated networks exposed to eco-feedback systems, which directly carry feedback information. End users only respond to the information they have access to, and that information is shared through network interconnections. At the same time, the topology of networks also varies in terms of their efficiency and the breadth of information pathways through them. Therefore, studies on networks exposed to eco-feedback systems are necessary in order to understand changes in people's energy-use patterns that are evoked by information sharing. To fill this research gap, my dissertation focuses on the study of networks that expedite peer eco-feedback information sharing.

To explore such networks, I follow a decomposing and recomposing process. First, I empirically observe the functions of feedback networks and response patterns of occupants. Second, I propose models to understand the importance of network structures. Lastly, I create a framework to generate and reconstruct random networks, structurally similar to experimental networks but on a larger scale. This dissertation addresses the following research questions:

1. Does peer network structure substantially impact occupants' decisions on energy conservation? If this is true, how do structural parameters contribute to promoting energy efficient behaviors?
2. What impact do networks have on diffusion of energy conservation behavior when multiple layers exist? Can an accurate and efficient method that can quantitatively understand and model this process in multi-layer network systems be developed?
3. Can an accurate method to generate complex random networks be developed to understand energy efficient behaviors in arbitrary networks?

These three questions cover the major impediments to our understanding of eco-feedback systems and the prediction of peer network energy consumption. The resolution of the above questions enables researchers and engineers to: 1) estimate the efficiency of energy feedback systems and the amount of potential energy savings, 2) understand individual energy consumption decision-making mechanisms in complex network systems, and 3) simulate and predict residents' peer network energy consumption.

To answer the above questions, I structure my dissertation as follows:

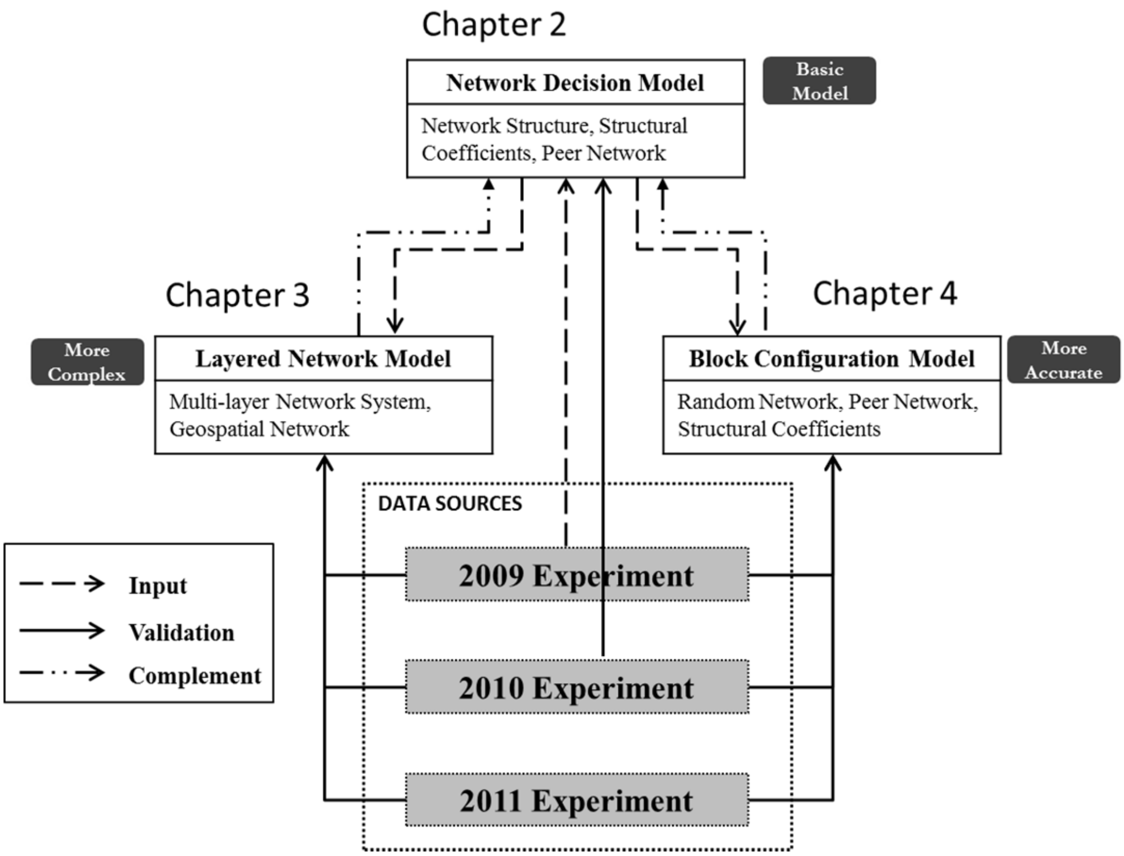


Figure 1 Structure of Peer Network Models in this Dissertation

In order to create and validate peer network models, I utilize data from three Columbia University experiments conducted over three years. Through investigation of the 2009 experiment, I proposed a basic model to understand the mechanism of how a network can promote energy saving behaviors. The 2010 experiment data then served to validate my model quantitatively. I developed a layered network model to complement the network decision model by embedding geospatial network information into the basic model to refine our knowledge on complex network systems. Then I developed a block configuration model aimed at generating more accurate random networks than with the basic model. Both the layered network model and the block configuration model have been validated by experimental data from 2009, 2010 and 2011.

In Chapter 2, I examine the variation in network structures that affect occupant decision making and propose a basic decision model. In Chapter 3, based on the results in Chapter 2, I extend the basic model to general multi-layer systems by considering the impact of geospatial networks. Using random graph theory, Chapter 4 presents an accurate model capable of generating synthetic networks relating to structural requirements. Chapter 5 concludes the dissertation by summarizing the contributions of my research to understanding energy efficiency in peer networks. In Chapter 6, I propose some potential avenues for future research studies. Finally, a reference section is provided with a bibliographic list of the publications cited in this dissertation.

Chapter 2

2. MODELING BUILDING OCCUPANT NETWORK ENERGY CONSUMPTION DECISION-MAKING: THE INTERPLAY BETWEEN NETWORK STRUCTURE AND CONSERVATION

2.1 Abstract

The exposure and diffusion of energy consumption information in building occupant peer networks has been shown to influence an individual's energy consumption decisions. In this paper, we develop an agent-based computational model for individual energy consumption behavior based on data collected during an experiment on residential energy use. We simulate the building occupants' decision making and the information transmission process. By comparing the impact of several parameters in the network level computational model and validating the parameters in a second experimental setting, our research serves to clarify how network relations can be leveraged for modifying energy consumption behavior. Network degree and weight were identified as the major structural parameters that impact building occupants' conservation decisions, while network size was found to have no significant impact. These findings have important implications for the design and effectiveness of residential energy feedback systems designed to promote energy conservation in residential buildings.

2.2 Introduction

Many countries lack sufficient infrastructure to provision domestic energy needs. To address this critical global problem, local, national, and international governing bodies are searching for new energy resources while updating infrastructure to reduce wastes caused by inefficient energy distribution and transmission. At the same time, pressure by governments to reduce and limit greenhouse gas emission is also increasing. According to a 2010 the US Department of Energy report, nearly 41% of energy was consumed by the built environment (US Department of Energy 2010). Nearly 21.2% of energy utilized in the US was allotted to the residential sector for heating, cooling and lighting. In addition, residential energy consumption has increased steadily in the last 20 years, especially in regard to electricity use. According to a recent the US Energy Information Administration report, nearly 38.5% of national total electricity end use was consumed by the residential sector(US Energy Information Administration 2010).

In residential buildings, occupants generally have a high degree of control over their energy consumption. Residential building occupants can control heating, ventilation and air conditioning equipment, kitchen and laundry appliances, and lighting and home electronics equipment, which are the main sources of home energy consumption (US Energy Information Administration 2005). In commercial buildings, simulation research has shown that diverse and dynamic energy use patterns and the interactions among building occupants can result in significant variations in energy consumption (Azar and Menassa 2012). In other words, individuals' energy use behaviors can significantly reduce end use as identified in building simulation studies (Chung and Hui 2009; Richardson et al. 2008) and in survey studies of building occupants (Al-Mumin et al.

2003; Seligman et al. 1978). Hence, an increasing number of scholars are attempting to reduce energy use and encourage conservation behaviors through solutions derived from combinations of social-psychological and technological approaches (Goldstein et al. 2008; Hoes et al. 2009; McMakin et al. 2002; Stern 1992; Yu et al. 2011). Although some scholars have investigated patterns in energy saving behavior by providing energy consumption feedback to users at the social aggregate level, i.e., floor level (Peschiera et al. 2010; Petersen et al. 2007), a more comprehensive study on the relationship between social networks and energy use is still needed. More specifically, research has yet to demonstrate how the structural characteristics of networks affect energy use and how energy-efficient behaviors transmit via a building occupant's social network. The goal of the research presented in this paper is to develop a building occupant network energy consumption decision-making simulation model to explore how patterns of energy consumption relate to the structural properties of peer networks.

2.3 Background

2.3.1 Energy Efficiency Experiments

In residential buildings, residents' personal choices have a strong influence on their energy use (Allcott and Mullainathan 2010). Previous research has determined the amount of energy that individuals can save through behavioral changes (Petersen et al. 2007) and the reasons and motivations behind individual energy saving practices (McMakin et al. 2002; Olsen 1981). In Peterson's experiment (Petersen et al. 2007) a 2 week energy saving competition was run between two dormitory groups in which residents had sufficient control over their own energy use. During the experiment, residents could check their electricity consumption on a website and consumption data were expressed in units of average power consumption (kW) during defined time intervals. Researchers provided two degrees of energy consumption feedback to residents in order to compare the amount of energy saved. In the control group, residents received information on their electricity use updated on a weekly basis. In the study group, residents could view their consumption in real-time (with data updated every 20 seconds). The result of the experiment demonstrated that individuals who received higher-resolution feedback were more effective at conservation. These individuals had a 55 percent consumption reduction compared to a 31 percent reduction for individuals who received low-resolution information.

After the results of this experiment were published, a number of universities built similar systems to provide real-time information feedback to dormitory residents (e.g. Virginia Tech's "Eco-Olympics," U.C.-Berkeley's "Building Energy Dashboard," and MIT's

“Dorm Electricity Competition,” to name only a few campus initiatives). In 2008, a test-bed building was instrumented at Columbia University for the study of peer networks and energy consumption. The building was a six-story residential dormitory building which was coupled with an electricity consumption feedback information system that revealed a participant’s energy usage along with energy usage of others in the individual’s peer network (Peschiera et al. 2010). The experiment involved collecting and disseminating data to participants in three distinct study groups: 1) the individual group, i.e. students who could only view their own consumption, 2) the building average group, i.e. students who could view their own consumption and the average consumption across all members of the building and 3) the network group, i.e. students who could view their own consumption, the consumption of individuals in their peer networks and consumption averaged across all individuals in their building. Forty building residents were not included in the study and were assigned to a non-participating control group in order to account for irregularities in energy consumption.

The Peschiera et al. study found that, on average, the 37 participants consumed a statistically significant 27.3% less electricity than the 40 non-participants over the course of the 5 week study period (Peschiera et al. 2010). In addition, the results showed that the electricity consumption of participants returned to approximately pre-study levels after the experiment was concluded, thus negating the energy use reduction observed during the study period. In other words, the impact of information feedback is consistent with Peterson et. al.’s finding (Petersen et al. 2007), i.e. that when provided with information about their energy use, individual consumers can achieve energy savings. However, the Peschiera et al. study demonstrated that conservation behavior can diminish rapidly. One of the study groups used 70% less electricity than non-participants on average; however, almost all of this conservation behavior decayed by the end of the study period. The only study group to achieve a consistent and statistically robust response pattern was the group that shared energy use data across their occupant peer network. These patterns suggest that providing individuals with energy use information for their peer network helps to sustain energy saving behaviors over time. In this paper we will utilize a simulation algorithm to quantify the energy conservation parameters utilizing data from the Peschiera et al. experiment to predict network level energy consumption and conservation patterns.

2.3.2 The Role of Social Psychology and Social Networks in Motivating Energy Saving Behaviors

Energy conservation can be achieved through both modification to energy infrastructure and through modification of human behavior. For residential buildings, modifications to infrastructure include the installation of energy efficient appliances, modern wall insulation and consumption feedback systems. On the other hand, attempts to increase energy saving through the modification to human behavior have focused both on the role that social networks (Wilson and Dowlatabadi 2007) and practice adaptation (Dalamagkidis et al. 2007) play in influencing human behavior, including the social-psychological relationship between individuals and their peers (DeMeo and Taylor 1984).

Attempts to promote conservation behaviors must take into account the motivations that encourage these types of behaviors. Motivations for energy savings have been explained by two models: 1) the attitude model and 2) the rational-economic model (Archer et al.

1987). The attitude model assumes that conservation behaviors will follow automatically from favorable attitudes toward conservation. The rational-economic model assumes that individuals will perform conservation behaviors that are economically advantageous. However, several studies indicate users fail to adopt currently available conservation techniques even if these techniques are highly cost effective (Ross and Williams 1981; Sjöberg and Engelberg 2005). Individuals are likely to make changes when new behaviors are easy and convenient to perform, when their resources and technologies allow them to conserve, and when their friends and neighbors are taking action to conserve (Costanzo et al. 1986; Stern 1992).

Human behaviors are strongly influenced by peers, especially when peers possess strong relationship ties. This fact has been observed by a number of scholars since the mid-1950s (e.g. (Festinger 1954; Milgram et al. 1969)). For instance, Göckeritz and colleagues (Göckeritz et al. 2010) proposed that the energy conservation behaviors of others have a strong positive correlation with an individual's conservation actions. Nolan and colleagues (Nolan et al. 2008) also showed that a normative message that contains the conservation behavior of the majority of an individual's neighbors is a strong motivator that spurs energy savings. Nolan et al. showed that certain behaviors started by individuals spread throughout a building community and to a larger, societal scale. As the behavior diffused through the peer network, social norms of conservation were established, which promoted individual conservation practices in the home.

2.3.3 Simulating Energy Savings in Peer Networks

Agent-based modeling is a computational method that enables the creation, analysis, and manipulation of models composed of agents that interact within a given environment (Gilbert 2008). Unlike most mathematical models, agent-based models can include agents that are heterogeneous in their features and abilities. Moreover, agent-based models can incorporate situations that are far from equilibrium and can deal directly with the consequences of interaction between agents. Therefore, this model is particularly well-suited for studying topics where understanding processes and their consequences are important.

Agent-based simulation is a widely accepted methodology in the social sciences because it is particularly apt at reflecting the relationship between human behavior and factors present in the environment that can influence human behavior (Epstein 1999; Macy and Willer 2002). Thus, since we are interested in modeling the impact of peer networks on human energy saving behaviors, agent-based simulation is particularly useful for a number of reasons. First, agent-based simulation can predict individuals' behavior based on their personal networks by using computational models. Second, agent-based simulations can also predict how opinions and behavior can be spread from one person to another via peer networks. Two examples of how opinions are modeled using agent-based simulation are the classical diffusion model and various opinion and behavior transmission models (Ahrweiler et al. 2004; Bonabeau 2002). One of the crucial features of agent-based models is that the models can account for the interaction between agents, i.e. they can model the exchange of informational messages between individuals in the network and how this exchange elicits change in behavior. In agent-based simulation, the environment is the virtual world in which the agents act. The environment could link agents together in a network in which the only indication of an agent's relationship to other agents is the list of the agents to which it is connected by network links (Scott 2000). Usually researchers can choose agents at random and create links between these agents. Through these social construction techniques to combine social science and technology together we can bridge the communication gaps at the boundaries between various groups or individuals during their decision-making process (Elle et al. 2010). Moreover, most energy use feedback experiments to date have had relatively short study period durations of only a few weeks, so the long term effects on consumption are difficult to measure. Agent-based simulation is an inexpensive way to estimate longer term consumption patterns (Azar and Menassa 2012).

In this paper, we introduce a set of algorithms to model how network-level information sharing influences energy consumption practices within a peer network. The model is aimed at simulating the conservation process and comparing the impact of network structural properties on conservation. We are interested in exploring how an individual's energy use is influenced by peers and in how peer networks affect individual energy-saving behavior. Moreover, our broad goal is to develop a better understanding of how to encourage more effective energy saving practices through peer network influence.

2.4 Methodology

2.4.1 Data Resource

The simulation input data used in this paper was collected from an experiment published in 2010 (Peschiera et al. 2010). The pilot study allowed us to acquire a rich set of data to construct our simulation model and to incorporate agent decision-making norms based on authentic data collected in an experimental setting. We will describe later how we also use the data collected from a later experiment in 2011 to validate the simulation model we develop in this manuscript. We were able to observe some trends in the data sets we used for our analysis.

Residents' energy consumption can never be negative. At the same time, consumers that use very large and very small amounts of energy are rare and the majority of consumers fall somewhere in between the extremes of energy use. Therefore, it is reasonable to describe individual energy consumption as a restricted distribution. In order to find a suitable distribution for individual energy use, we collected all usage statistics for the non-participant control group, which consisted of data points for 45 building occupants for 46 days, arranged as a 2,070 data point pool of daily individual electricity consumption values. After plotting the histogram and testing goodness of fit, we chose a lognormal distribution as the initial generating distribution for the consumption data. To fit the experimental data, we compared several common distributions and listed the fitting parameters in Table 1.

Table 1 Distribution Fitting Comparison

Distribution	Fitting Tests			Distribution Parameters
	Kolmogorov Smirnov*	Anderson Darling*	Chi-Squared*	
Beta	0.1307	58.596	58.59	α_1=1.5594 α_2=8.8386 a=3.6416 b=1188.1
Exponential	0.2211	158.33	158.33	λ=0.00596
Gamma	0.0939	34.25	34.25	α=1.8986 β=88.434
Lognormal	0.0380	5.75	5.75	σ=0.65468 μ=4.9113
Normal	0.1705	115.58	115.58	σ=121.85 μ=167.9

* Lower Value means Higher Accuracy

The Kolmogorov Smirnov p-value was calculated to be 0.038, which was the parameter used to evaluate goodness of fit. Given that a fitted distribution is statistically meaningful when the p-value is less than 0.05, this result demonstrates that the chosen distribution provides both a reliable and accurate account of the energy consumption observed for the non-participant group. Figure 2 shows the distribution fitting and quantile plot. The vertical straight lines in the quantile plot indicate the 90% (left line) and 95% (right line) confidence interval, respectively. The real data show a fat tail at the extreme values, but since we only concentrate on the general situation and the tail is negatively biased, the lognormal distribution is reliable enough for the simulation. In the following section, we emulate the individual's initial energy consumption based on this distribution.

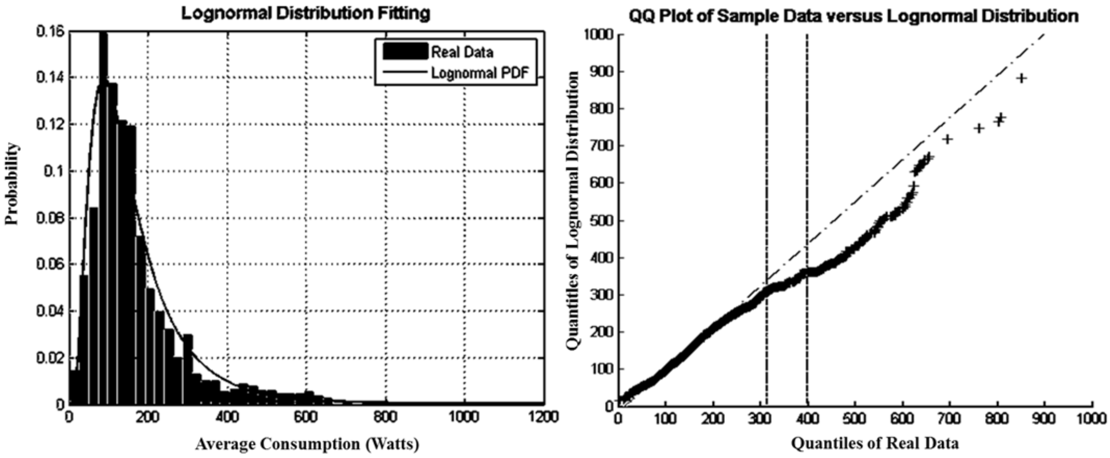


Figure 2 Energy Consumption Data Fitting and Quantile Plot

2.4.2 Network Energy Efficiency Decision Influence Model

Agent Norm

The networks of agents are generated by the computer according to the Erdős-Rényi (ER) model (Erdős and Rényi 1960) and the connectivity is determined by the generated network's adjacency matrix. The agents are assumed to be exposed to all peer consumption in their personal network. Based on the information they receive, an algorithm was constructed for the individual agent norm. When there is a user in the agent's network whose use is less than the agent, they have a probability to take action to reduce electricity use. They will compare their use with each friend and make decisions. If they already use less than others or decide not to take action, even if they use more, they also have a probability to increase their use or remain the same. For each decision making iteration, the probability of whether or not the agents take action to save electricity is correlated with the quality of relationship. Quality of relationship refers to the strength of the relationship, or the weight of the connection between agents in the network. This is determined by how close of friends two agents are in the model. Closer friends have stronger ties, whereas acquaintances have weaker relationship ties.

For the whole decision making process,

$$p = \tau P(\beta_n|\beta_{n-1})P(\beta_{n-1}|\beta_{n-2}) \dots P(\beta_2|\beta_1) = \tau \prod_{i=1}^{n-1} P(\beta_{i+1}|\beta_i) \tag{2.1}$$

Where;

$P(\beta_n)$ is the probability that an individual will take energy-saving action based on the consumption of an individual in their peer network to whom they have the relationship β_n,

n is the index of neighbors in the agent's network, and

τ is a scalar that can convert edge weight to proper probability so that the model output can fit the experiment data.

For the incremental reduction of each agent's energy use, we employed a Geometric Brownian Motion (GBM) process with drift. GBM is a continuous time stochastic process that can vary the quantity of drift following the normal distribution (Revuz and Yor 1999; Ross and MyiLibrary 2003). According to our model and observations from the experiment, residents may increase or decrease their consumption with respect to their peers' consumption. Parameters for the drifting distribution are drawn from the experiment (Table 2):

$$C_{t+1} = C_t \exp(\left[\mu - \frac{1}{2}\sigma^2\right] + \sigma W(T)) \tag{2.2}$$

Where;

C_t is individual's energy consumption at time t,

W(T) is a normal random error with mean equal to 0,

σ is the standard deviation of energy use increment/decrement, and

μ is the mean of energy use increment/decrement.

Table 2 Simulation Setting and Results

		Baseline Network	Expanded Network	Dense Network	Tight Network
Vertex (|V(G)|)		30	50	30	30
Average Degree for edges (deg(G))		3	3	5	3
Simulated Mean of Edge Number		95	160.1	150.9	95
Simulated Vertex Degree		3.17	3.20	5.03	3.17
Weight (Uniform)	Max	1	1	1	1
	Min	0	0	0	0.5
Energy Use (Lognormal)	Mean	167.91 Watts (daily consumption approximately 4.02 kWh)			
	std	122.84 Watts (daily consumption approximately 2.94 kWh)			

In the above agent norm, we applied conditional probability with τ and Geometric Brownian Motion to calibrate the simulation result with the experimental data. Since the direct correlation between the connection weight (relationship β_n) and individual's probability to make decisions is not known, we use τ to calibrate the experimental data with the simulated results. In addition, from the experimental results we know even if individuals decided to conserve energy, it does not necessarily mean they will reduce their energy monotonically. Thus, in order to capture the fluctuation of their energy consumption path, we introduced two types of Geometric Brownian Motion (GBM) in our simulation agent norm—the GBM that has (1) an upward drift (GBMI) or (2) a downward drift (GBMD)—to emulate the consumption increase or decrease. In following algorithm, we define u as threshold of whether an agent will make a decision to increase their energy consumption. This number is the percentage of individuals whose energy consumption drifts upward during the experiment.

Algorithm (Individual decision making process and Agent Norm)
Input: A connected social network with weight and the initialized energy consumption for each agent within the network.

Data Recording Process: Track energy consumption of each agent over a time period and record the energy use within this period.
Output: A matrix that includes the daily energy consumption information of each agent and the network average over the whole simulation period.

[Initialization]

Step 1: Each agent $v_i \in V(G)\ where\ |V(G)| = k$ has an energy consumption of C_{it}. For each agent, find out the neighbors and form as $N(v_{it})$. $v_j \in N(v_{it}), \forall\, j = 1,2, \dots n$ is the neighbor of v_{it} and each v_{jt} also has their own energy consumption C_{jt}.
Step 2: For the total simulation period
While $t \leq T$, record the energy consumption E_{it}
If $t > T$, go to Step 5

Step 3: For j=1: n
If $v_{it} \geq v_{jt}$, generate random number U_1
If $U_1 > \beta_{ij}$, $GBMD_{i,t+1} \rightarrow C_{i,t+1}$
Return $E_{it} = C_{it}$, $t = t + 1$, go to Step 2
Elseif $U_1 \leq \beta_{ij}$, go to Step 4

Step 4:if $v_{it} < v_{jt}$, generate random number U_2
If $U_2 > u$, $C_{it} \rightarrow C_{i,t+1}$
Elseif $U_2 \leq u$, $GBMI_{i,t+1} \rightarrow C_{i,t+1}$
Return $E_{it} = C_{it}$, $t = t + 1$, go to Step 2

Step 5: Return E_{it} and Print Result

Note: i is the index of agents; j is the index of agent i's neighbors; t is the index of time period.
In Step 2, E_{it} comes from Step 3 and Step 4, but for the first iteration, $E_{i1=}C_{i1}$.
Neighbors are the agents that are directly connected with a specific agent according to adjacency matrix.

Some variables and process are explained in following paragraphs. The following flow chart shows the algorithm used to model an individual's decision making process (Figure 3). The decision norm of each agent in the simulation follows this decision algorithm.

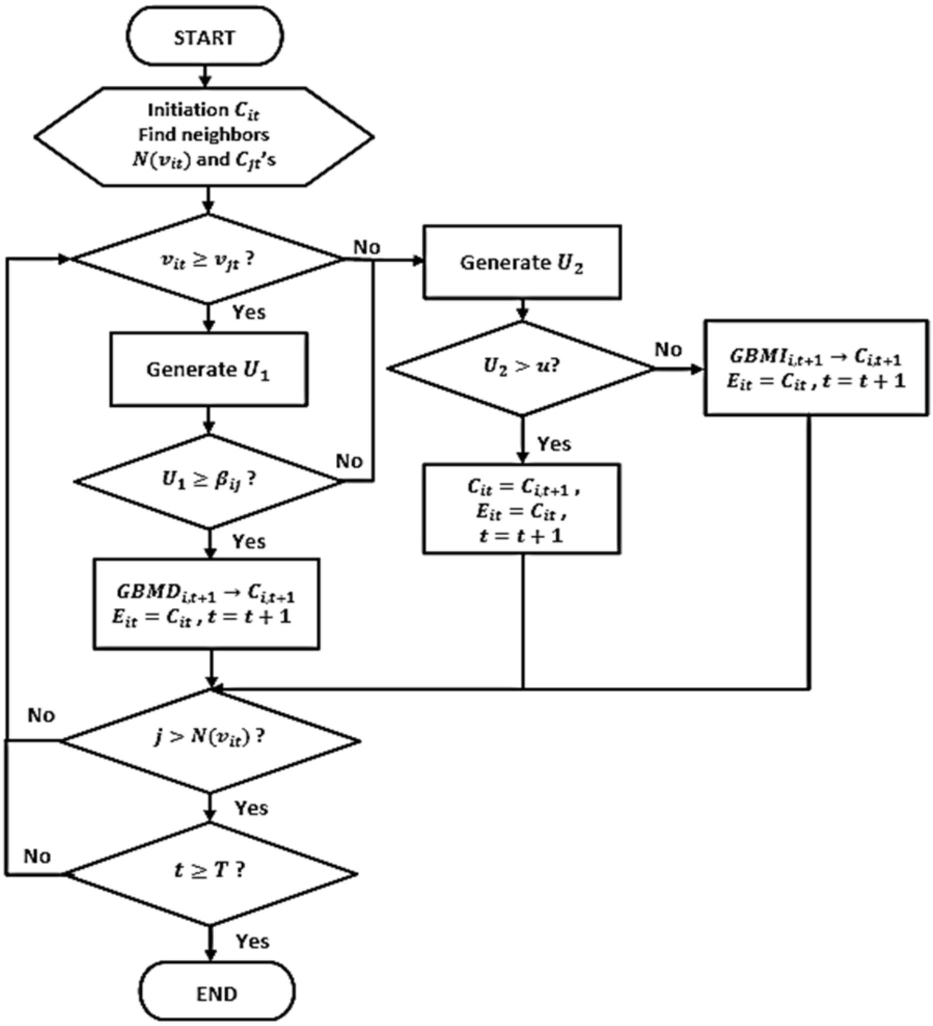


Figure 3 Agent Decision Algorithm Flow Chart

The algorithm simulates the decision making process of each agent. Each agent will compare energy consumption with its connected peers in the network and will have a probability to reduce its consumption according to the conditional probability synchronized from the quality of relationship across all peer network connections. If the agent finds its consumption already less than all of its peers, it will also have a probability to remain the same level of consumption or rebound to a higher level of consumption.

Environment

In this agent-based simulation, the environment in which residents act is their peer network. We assume that one agent's energy use can affect the energy use of other agents with varying degrees of probability. The quantity of consumption by neighbors of an agent's peer network may have a strong influence on modifying a given agent's energy-saving behavior. On one hand, the agent' behaviors can actively change the energy consumption patterns in the whole network, i.e. throughout the environment. On the other hand, once the environment changes, the feedback of changes will inversely affect the agent's decision-making processes. For example, if one agent sees its energy consumption is more than its neighbors, it may take action to reduce energy consumption. Once this change occurs, the effect of its reduced energy consumption will be incorporated into the usage statistics that are viewed by other agents in the network. This new information may provide the catalyst for other network agents to take similar energy-saving action.

Given several basic experiment settings, the primary goal of the analysis presented below is to examine the relationship between network structure and conservation behaviors. Moreover, we aim to qualitatively describe the degree to which various types of network structure influence individual energy-saving behavior. We use four different experimental settings to test how three types of extended network structures impact individual behavior (Table 2):

- *A Baseline Network:* This random network was generated by the Erdős-Rényi model according to the parameters in Table 1. The other three types of networks we will examine are extended from the Baseline Network.
- *An Expanded Network* (i.e. a larger size network with a large number of vertices): The network has more vertices than the baseline case, which indicates a larger network size.
- *A Dense Network* (i.e. a network with a high degree measure): The network has more connections than the baseline case. This indicates a complex relational network.
- *A Tight Network* (i.e. a network with a high weight measure): The network has a higher weight for each edge compared to the baseline case. Networks with high weight measures indicate a closer network.

The above networks can be achieved through three basic network operations (adding vertices, adding edges and increasing weights) to expand a simple network to more complex ones. Our goal is to understand how these operations can impact the average energy consumption of all individuals in the building occupant network. Figure 4 is the sample network plot which is generated randomly for each experimental case. For each simulation run, the network is restructured again. Table 2 contains a summary of the simulation settings we used to construct the network and then model the agents' energy consumption patterns.

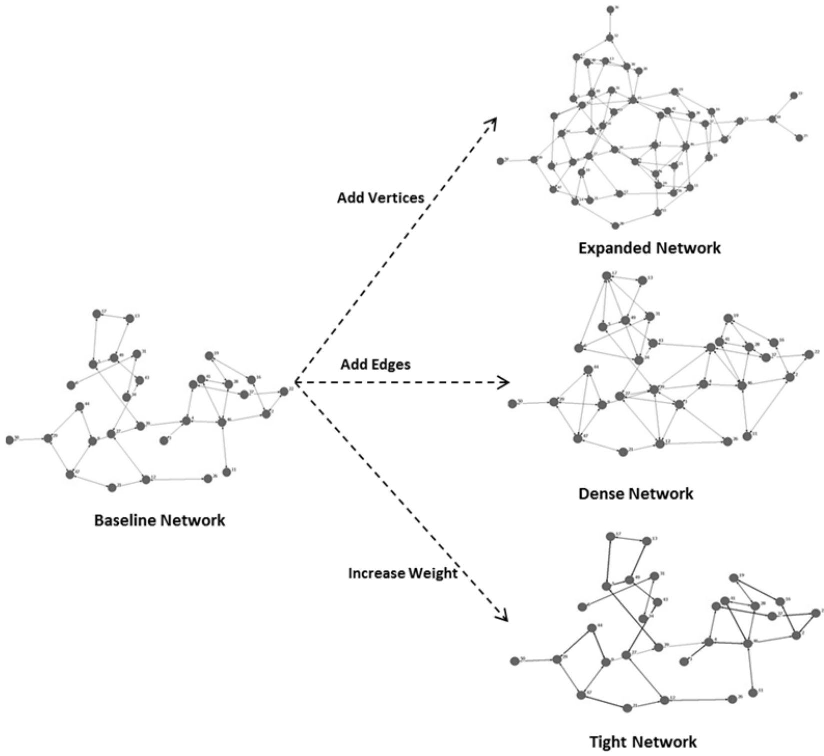


Figure 4 Sample Network for Baseline Network, Expanded Network, Dense Network and Tight Network

(*The thickness of each connecting tie represents the quality of relationship between pairs of individuals.)

2.5 Simulation Results and Validation

2.5.1 Simulation Results

The upper left graph in Fig. 4 reflects a single simulation run of all the network agents' dynamic energy consumption. Each agent can make decisions separately based on its own network connections, although we assume that these decisions will affect decisions made by its neighbors in the peer network. To examine the unique contribution of each network property on conservation behavior, we performed 10,000 simulations of distinct network configurations and 4 sample scenarios. These results, are plotted in Figure 5 in the upper right, lower left and lower right graphs. These graphs indicate the normalized energy use reduction by controlling for network vertex (expanded network), network degree (dense network), and network edge weight (tight network). We also ran the generalized regression on the major predictors to examine their contribution to network energy saving behavior in Table 3, Figure 5 and Figure 6.

Table 3 Summary of Simulated Results

Regression on Simulated Energy Saving (%)			
Predictor	**Coefficient**		
	m1	m2	m3
Vertex	0.00024	0.00024	0.00024*
Degree		0.0569**	0.0569**
Weight			0.1544**
_cons	0.374**	0.147**	0.0419**
R-SQUARE	0.0007	0.7356	0.943
LOG LIKELIHOOD	471.272	680.687	923.285

* p<0.1
** p<0.05

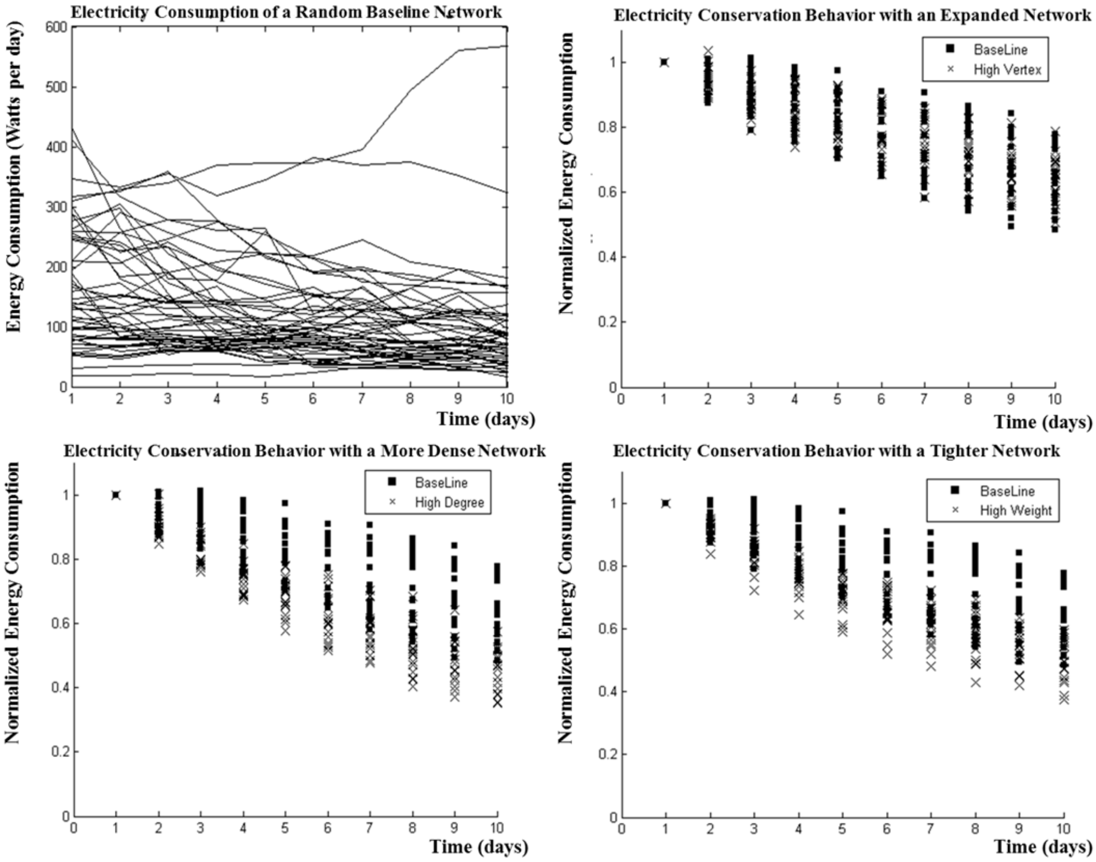


Figure 5 Energy Conservation Performance for Different Cases

(*The top left figure represents the output of a single simulation run)

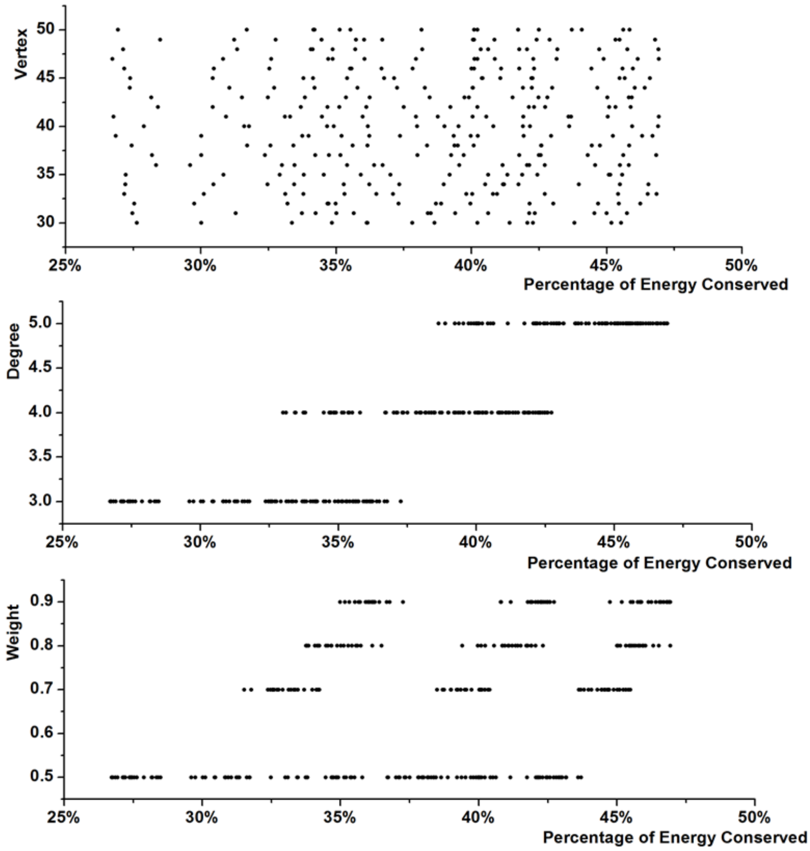


Figure 6 Scatter Plot for the Correlation between Vertex, Degree and Weight, and Percentage of Energy Conservation in the First Week

2.5.2 Observations

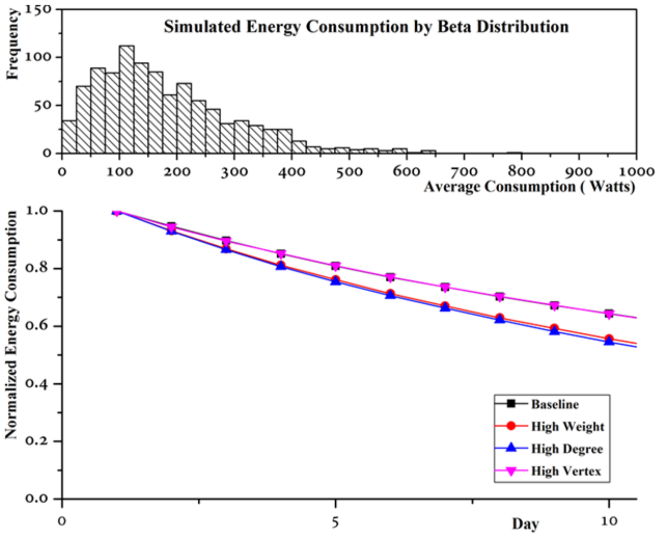
From Table 3, we observe that vertex only achieves its statistical significance in the full model (m3) and has a low R-squared value. The predictors of degree and weight have a statistically significant positive impact on energy saving in the network as well as a high R-squared value. Through the 3 models (m1,m2 and m3) we tested in Table 3 and the scatter plot of Figure 6, the coefficient of regression for vertex and the R-squared value in model 1 (m1) indicate that vertex has limited prediction power for individual energy conservation decisions. Scaling up the network will not provide additional incentive to reduce consumption if we maintain degree and connection weight at the same level. This can be explained by the fractal property of social networks, small networks will repeat the pattern when they are located in larger networks. Connecting small networks in same consumption level cannot efficiently enhance network energy efficiency. *Network energy consumption does not decrease or increase with the expansion of the random network, if the newly added vertices have a similar level of energy consumption.*

In contrast to the weak connection between network size (extended network) and simulated consumption behavior, network degree and weight have a positive relationship with energy conservation. Both the results of the regression and a visual inspection of the scatter plot illustrate that the distribution observed in the simulation is generalizable to larger peer networks. The regression test shows that embedding degree and connection weight significantly increased the model R-squared value and the coefficient is large enough to impact the value of the regressor. The scatter plot suggests a strong correlation between network degree, weight and energy saving. Closer networks are demonstrated to have a higher influence on convincing its members to conserve energy. A network with closer ties, i.e. those networks where members have a tighter connection to other members, can amplify the influence of one member over the decisions made by another member. In a more tightly connected network, the normative behaviors of the peer network as a whole are likely to diffuse to individual members of the network and individuals are more sensitive to aligning their behavior with the behavior of others in their peer network. *Connection degree and strength of relationship between residents each has a positive impact on residents' energy saving.*

In summary, with regard to an agent's simulated energy consumption there are important differences in how different network structural properties impact energy efficiency. Although network size may be expected as one condition that would lead to increasing or decreasing energy saving behavior, the simulation suggests scale of network size does not correspond to higher energy savings. In other words, despite the large size of a network, more local network clusters were more important in stimulating individual energy saving behaviors. Conversely, the simulation results confirm that stronger relationships between network participants (i.e. tighter networks) and more robust associations between members of a network (i.e. denser networks) can serve to improve energy saving behavior.

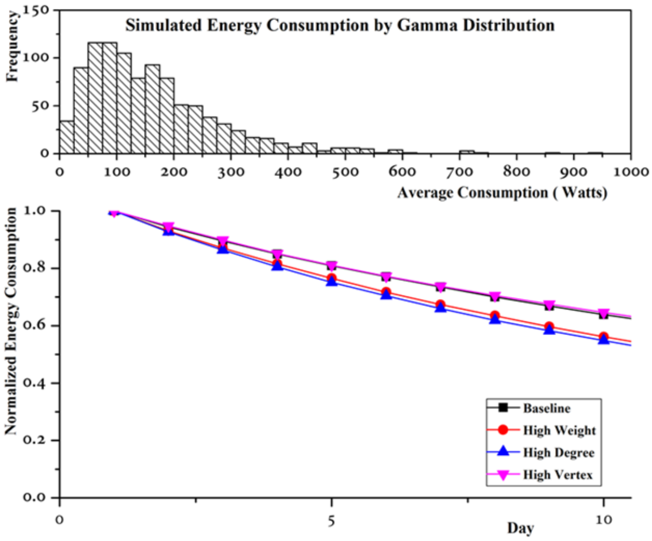
2.5.3 Sensitivity Test for Different Initial Energy Consumption Distributions

Although the lognormal distribution best emulates the pre-experiment energy consumption, it is still worth extrapolating the impact of different distributions. Four additional scenarios were constructed to emulate the initial energy consumption using different common distributions. The shape factors of these distributions are derived from the distribution fitting of the experiment baseline data and control group data.



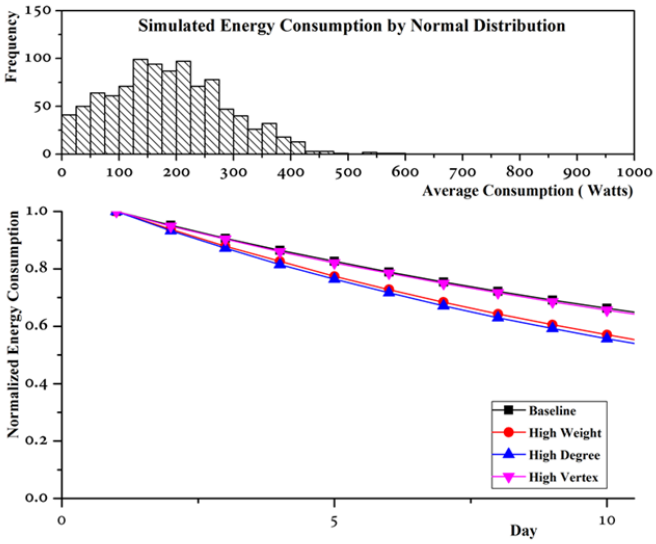
	Estimates	Std Error	t value	Pr(>|t|)
cons	1.0497	0.0461	22.741	<2e-16**
Degree	-0.1228	0.0077	-15.897	<2e-16**
Bond	-0.4929	0.0309	-15.951	<2e-16**
Vertex	-0.0001	0.0003	-0.327	0.744
Adjusted R-square				0.3814
F-statistic				165.4
p-value				<2.2e-16

Figure 7(a) Network Energy Consumption Simulation Based on Beta Distribution



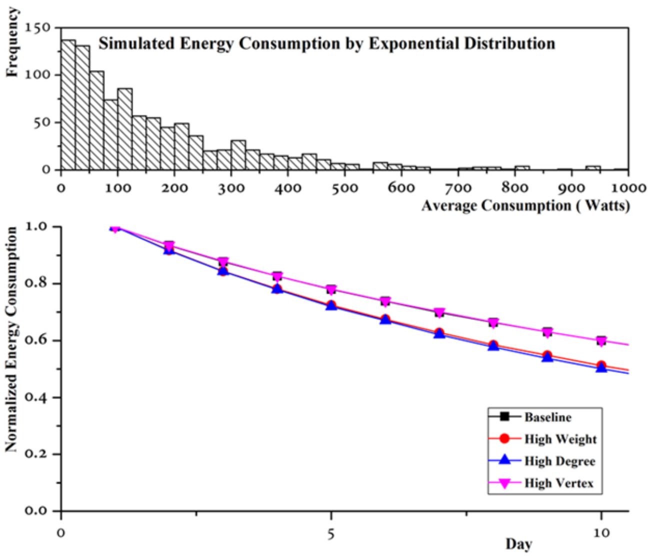
	Estimates	Std Error	t value	Pr(>|t|)
cons	0.9346	0.0471	19.815	<2e-16**
Degree	-0.1126	0.0078	-14.286	<2e-16**
Bond	-0.3691	0.0315	-11.691	<2e-16**
Vertex	0.0002	0.0003	0.522	0.602
Adjusted R-square				0.3068
F-statistic				118.9
p-value				<2.2e-16

Figure 7(b) Network Energy Consumption Simulation Based on Gamma Distribution



	Estimates	Std Error	t value	Pr(>|t|)
cons	1.021	0.004	22.95	<2e-16**
Degree	-0.1184	0.0007	-16.046	<2e-16**
Bond	-0.4346	0.0293	-14.724	<2e-16**
Vertex	-8.46E-05	0.0003	0.229	0.819
Adjusted R-square				0.3674
F-statistic				155.9
p-value				<2.2e-16

Figure 7(c) Network Energy Consumption Simulation Based on Normal Distribution



	Estimates	Std Error	t value	Pr(>|t|)
cons	1.0035	0.0479	20.91	<2e-16**
Degree	-0.1273	0.00803	-15.851	<2e-16**
Bond	-0.4444	0.0321	-13.832	<2e-16**
Vertex	-3.00E-04	0.0004	-0.756	0.45
Adjusted R-square				0.344
F-statistic				140.7
p-value				<2.2e-16

Figure 7(d) Network Energy Consumption Simulation Based on Exponential Distribution

Figure 7 Network Energy Consumption Simulation Based on Different Distributions

Figure 7a through 7d display four energy consumption scenarios utilizing a Beta Distribution, Gamma Distribution, Normal Distribution and Exponential Distribution in order to simulate pre-experiment energy consumption. Based on the data presented in the figure, the normalized energy consumption in these four scenarios is most similar to lognormal simulation results. The regression tests also confirm the findings as discussed in section 2.5.2. Therefore, the fitting distribution selection for the pre-experiment energy consumption will not influence the conclusions of our research.

2.5.4 Validation and Limitations

The purpose of this simulation was to explore the effect of peer network structure on energy saving behavior in residential buildings. In order to achieve this goal, we built an agent-based decision model to estimate the influence of different types of network structure on energy conservation behavior by using controllable input parameters. According to Ziegler, a model's validity is often thought of as the degree to which a model faithfully represents its system counterpart (Zeigler et al. 2000). Zeigler characterizes three types of model validity: 1) *replicative validity* (i.e. whether the model fits the data already acquired from a real system), 2) *predictive validity* (i.e. whether the model fits data before data are acquired from a real system), and 3) *structural validity* (i.e. whether the model completely reflects the way in which the real system operates).

Utilizing data from an experiment to develop the decision influence model for the agent norm provides a level of structural validity to the model. The post-simulation statistical analysis testifies to the replicative validity of model. However, predictive validity is hard to achieve merely through simulation and emulating a single experiment. Therefore, we conducted a replication of the experiment with a second set of building occupants to test whether results from the simulation model have similarity with target systems. The experiment setting is similar to the pilot experiment in 2008, except participants were asked to respond to a survey designed to establish the strength of their relationship to other members of the network, which had not been captured in the earlier experiment.

The second experiment was conducted from October 24, 2009 through March 31, 2010. In this follow-up study, we found similar results to those predicted by the simulation, i.e. that the individuals who were provided with consumption information of their network peers outperformed both the individuals who did not receive peer network energy consumption information and the non-participant control group. Furthermore, we ran a logistic regression on the results to test the statistical properties of the networks' impact on resident energy saving behaviors.

In order to compare the results of the simulation with the results of the follow-up study, a regression analysis was employed to confirm whether the parameters that were statistically significant in the simulation were also significant for the experimental case. In other words, we were interested in whether the results of the simulation were valid for another population in that both network density and tie strength between network participants were meaningful predictors of an increase in individual energy saving behaviors. The results of the regression are presented in Table 4 and are based on a binary outcome of the experimental results that a resident will either improve energy saving (1) or not (0).

Table 4 Summary of Logistic Regression Results

Logistic Regression on Improvement (yes=1, no=0)				
Predictor	Odds Ratio (first week)		Odds Ratio (1 month)	
	m1	m2	m3	m4
Network structure				
Explicit				
Quality of Relationship (Weight)	15.478*		1.06	
Network Size (Vertex)	1.155		1.034	
Network Level (Degree)	1.939*		1.731	
Implicit (Centrality)				
Degree		0.963		0.707
Betweenness		1.044		1.086
Closeness		1.002		0.998
Energy Group				
Green (more than 20% less consumption than average)	0.585	0.469	0.054**	0.043**
Red (more than 20% more consumption than average)	3.013	0.637	0.057*	0.047*
Yellow (neither red nor green)				
LOG LIKELIHOOD	-11.351	-14.159	-9.976	-10.393
PROB > CHI2	0.178	0.849	0.308	0.153

* p<0.1
** p<0.05

In Table 4, we separate network structure parameters into two types: the explicit factors and implicit factors. Explicit factors are basic factors we normally use to generate a random network. The implicit factors are mainly focused on the network centralities which depend on all the vertices in the network and network size. Degree centrality reflects the effect of direct connected vertices without regard to direction; betweenness centrality tells us about the interaction of nonadjacent vertices; closeness centrality interprets how close one vertex is connected or how it interacts with all other vertices. After regressing on the main explicit factors, we used these implicit measures to test whether network size will have a statistically significant impact on improving energy savings. In other words, in addition to directly connected vertex, we wanted to capture the non-adjacent vertices' impacts through the inclusion of these centrality measurements. Group type predictors are utilized as mutually exclusive dummy variables in m2 and m4 to check if the pre-experiment energy consumption pattern will affect their energy utilization in the future.

From the results of the regression, the quality of relationship and network level in the short-term test models (m1, m2) achieved statistically significant levels and had a relatively higher odds ratio than other predictors. For strength of relationship, a one unit increase will have a 15 times escalation effect. However, these patterns do not hold in a long term experiment, this may be caused by the cancellation of negative and positive change during the response-relapse period observed by (Peschiera et al. 2010). The implicit predictors both in the short term and long term tests indicate they do not dramatically affect the probability of agents' energy saving decisions, because the odds ratio is nearly 1. In the long term test, both the green and red group achieved significance and had odds ratios close to 0.05.

Thus the previous assertions derived from the simulation can be supported by the findings from regression results of the second experiment. First, the quality of relationship and connection degree do indeed influence whether individuals modify their behavior to save energy in the short term. In fact, we found that relationship quality and connection degree act as a positive impetus for change to more energy conserving behavior. Second, the size of the network, even for its implicit centrality parameters does not affect the energy saving meaningfully. The previous two findings are also qualitatively consistent with the simulation results.

However, our model also has limitations. First, we simulated the network as regular random graphs (Erdős and Rényi 1960). More recent research shows that real social networks exhibit scale free (Barabási and Albert 1999) and small-world properties (Watts and Strogatz 1998). The reason why we chose regular random graphs is because we had a relatively small and tightly connected local network in the experiment, rather than a multi-clustered network. The network in a single building looks like one cluster in a large scale free network. We built the real social network of the occupants in the experiment and confirmed that they are cluster-less but highly connected. Second, we do not allow the response-relapse saving pattern in our simulation, since we do not fully understand the mechanism of energy use relapse. So, to simplify the model, we assumed the agent behavior was consistent over a relatively short simulated period. Finally, the relational quality is difficult to quantify. Although we asked residents to identify the quality of relationship themselves via survey, people may provide discriminate values through their various knowledge, characters and self-cognition.

2.6 Discussion and Conclusion

The research described in this paper presents an agent-based simulation model that simulates the relationship between peer networks in buildings and energy conservation behaviors of building occupants. Energy efficiency is seldom studied at the peer network level. Experimental research recently has found that sharing energy use information through social networks promotes energy conservation by building occupants (Peschiera et al. 2010; Petersen et al. 2007). However, the shape and character of social networks vary from building to building, which means that the relationship between peer network structure and energy saving behavior is difficult to generalize based solely on experimental data without the aid of simulation. Thus, a model that can quantitatively explain the residents' decision making process under various network configurations is an important contribution to our understanding of how best to leverage the interpersonal relationships in peer networks to encourage energy savings. This model also has practical implications for designers of residential energy feedback systems. The model suggests that feedback should be focused on those residents with stronger relationships rather than more relationships. Providing feedback for residents with more connections to others in their peer network has a limited benefit in terms of enhancing energy efficiency.

Our research expands and builds upon the conceptual model of the relationship between social interaction and individual decision making posited by Wilson and Dowlatabadi (Wilson and Dowlatabadi 2007). In order to formalize Wilson and Dowlatabadi's conceptual model, we established an agent norm for their social interactions, which was based on data collected on the impact of sharing energy consumption information among peer network participants. Our model emulates the distribution of energy consumption and the residents' decision making processes in the experimental setting, such that we can quantitatively explain the relationship between a participant's rationale for their energy consumption behavior and their social interactions with their peer network in the dormitory. Our research extends our current understanding of the impact of network structure on the energy conservation behavior of individual actors within a building peer network to examine networks with more complexity than the experimental case. The resulting simulation model utilizes well-established random graph theory (Erdős and Rényi 1960) to generate a number of different, realistic random network structures to which we have applied the findings from the experimental data collected. Our simulation allows us to test, under heterogeneous network conditions, whether certain network structures promote more or less energy conservation behavior without the cost or time associated with collecting experimental results from a range of buildings. Thus, our strategy utilizes a variety of information structures through which we can study ways that energy saving behavior disperses throughout a peer network, with the ultimate goal of achieving sustained reductions in building energy use.

Our simulation results indicate that network energy consumption does not predictably decrease or increase with the expansion of the random network. At the same time, dense and tight networks outperform the regular and expanded networks. From an individual resident point of view, more information and trustworthy information are more convincing than indirect information, although those indirectly connected residents may eventually affect their decisions through their directly connected peers. This provides a more nuanced understanding of the impact of both explicit factors (i.e. network size, degree and weight) and implicit factors (i.e. network centrality) on energy conservation behaviors of peers within a building occupant network. Our research provides a more comprehensive account of the ties between network participants because we consider more implicit, indirect interactions of non-adjacent vertices between actors. The odds ratio for the logistic regression shows that the interactions between non-adjacent vertices have an insignificant impact on the object vertex during the same period. In other words, residents are highly impacted by people who are connected directly with them rather than by their friends' friends.

Our model could be extended in several ways. In the model we utilized a classic random graph to make networks emulate the network studied in the experiment. However, if the network is widely connected through a larger area, the scale-free property of social networks may impact residents' decision making about energy consumption. A potentially fruitful approach to linking the geographic distribution of individuals in peer networks that may be examined in future research is layered interacting network methods (Kurant and Thiran 2006). Networks are also evolving in response to agents' experiences. Former work on network creation focused on static network structures, but the evolution of networks over time may provide an analytical explanation for the long-term energy conservation performance of dynamic networks.

Chapter 3

3. LAYERING RESIDENTIAL PEER NETWORKS AND GEOSPATIAL BUILDING NETWORKS TO MODEL CHANGE IN ENERGY SAVING BEHAVIORS

3.1 Abstract

Complex human or engineered network systems can be examined as a series of coexisting layers. A variety of dynamic perturbations, such as information flows across computer networks, traffic flows across transportation networks and the spread of energy saving practices across human networks, have been treated separately as single networks in previous research. However, because these phenomena often consist of human networks interacting with engineered networks, analyzing the properties of the multi-layer network systems provides more nuanced insights into the phenomena. In this paper, we examine a multi-layer network system to provide insight into the diffusion of energy consumption practices through peer networks within and across residential buildings. To this end, we introduce a model that treats a residential peer network and a geospatial building network as a single, layered network. We compare this model to a previously published multi-layer interactive network model by simulating diffusion through a real multi-layer network system consisting of a residential peer network and a geospatial building network. We found our model to be more accurate and efficient, hence contributing an efficient mathematical model and set of simulation algorithms that accurately capture the post-perturbation response of a layered, residential peer network and a geospatial building network.

3.2 Introduction

In the United States, nearly 41.3% of all energy consumption is related to the built environment, which is higher than for other sectors (c.f. 30.6% for industry and 28.1% for transportation) (US Energy Information Administration 2010). To reduce building energy consumption, researchers have integrated sensors and information feedback systems into building networks and have used eco-feedback systems to distribute this information to peer networks (Fischer 2008; Peschiera et al. 2010; Petersen et al. 2007). These eco-feedback systems provide building occupants with information regarding their consumption behavior in order to encourage behaviors that lead to energy conservation. In these cases, researchers have shown that digitized feedback is the most effective delivery mechanism for providing information related to energy consumption (Fischer 2008).

Recent research has determined that, through sharing an individual's energy consumption information with that individual and with that individual's peers, energy conservation can be increased in residential buildings (Peschiera et al. 2010; Petersen et al. 2007) and in commercial buildings (Azar and Menassa 2012; Chung and Hui 2009; Hoes et al. 2009). The amount of conservation is highly dependent on the structural position of individuals within their peer network (Chen et al. 2012). A number of energy companies, such as OPOWER, Welectricity and Leafully, are providing peer network feedback to consumers in an effort to capitalize on peer influence to reduce energy consumption. OPOWER, for example, is a leading energy information software company that has set up a platform that enables utilities to provide targeted energy data and advice to each customer.

Beginning in April 2012, users were provided functionality to track and compare their energy consumption and share energy savings accomplishments with their friends.

In most cases, an individual's peer network is not isolated from other networks that may also impact energy saving behaviors, e.g. an individual's ability to adopt energy saving behaviors is simultaneously conditioned by both their peer network and the network of buildings in which an individual's residence is situated. For instance, the diffusion of a particular energy saving practice (e.g. turning off the porch light when not expecting visitors) may be more likely to occur when two individuals live in the same neighborhood because the potential adopter can directly observe the porch light being turned off by a friend who has already adopted the practice. Many scholars have noticed that the spatial development of many innovation and practice diffusion processes is characterized by the adopters clustered around the original nuclei (Brown and Cox 1971; Hagerstrand 1965; Haggett et al. 1977). The geospatial orientation of the two individuals may serve to reinforce the adoption of a practice. The abstract of characteristics of space (for example, distance and accessibility) significantly influence spatial behavior (Morrill 1970). Moreover, temporary and short-distance movements and random communications of people may be also helpful to geospatially facilitate practice diffusion. However, if the two individuals live in different cities, the potential adopter will still have access to information about the energy saving practice (e.g. via telephone) but would not have the reminder triggered by a close geospatial relationship. This simple example demonstrates how both social networks and geospatial networks can contribute to the adoption of energy saving practices, although research to date has treated each network type in isolation. Thus, the major objective of our research is to develop a model capable of analyzing how energy consumption information diffuses through multi-layer network systems and how this diffusion affects the adoption of energy saving behaviors.

The topological properties (e.g. the vertex degree distribution, path length, clustering, robustness and centrality) of social and engineered networks impact how information is transmitted between vertices (Albert and Barabási 2000; Ebel et al. 2002; Faloutsos et al. 1999; Maslov and Sneppen 2002). Although some researchers have used multigraphs to examine multiple types of connections within a network (Flament et al. 1963), most research to date has examined the properties of single networks in isolation. However, in authentic settings, networked individuals are linked through various channels (Kurant and Thiran 2006; Yang et al. 2009). For instance, a computer virus can enter an information technology network via an unsecured web site or via emails. Rumors can be spread though conversations between individuals in physical spaces or through social media applications. Many researchers have observed that network models are heavily affected by the connectivity patterns within and between networks (Burt 1980). When analyzing multi-layer networks, the randomness and complexity of the constituent single networks is increased. In addition, the patterns of diffusion through multi-layer networks will also change because perturbations to a single network may trigger perturbations in the other networks that constitute the multi-layer network.

To date, research has not developed quantitative models capable of capturing the dynamics of multi-layer network systems under perturbation. We developed a model to predict changes in energy saving behaviors in a multi-layer network consisting of a peer social network and a geospatial building occupancy network. Our research serves to fill a gap in our understanding of network dynamics by positing a simulation model based on a novel algorithm that predicts a response pattern in a perturbed, multi-layer network.

3.3 Background

3.3.1 Studying the Diffusion of Energy Saving Behaviors in Multi-Layer Networks

Previous research has investigated how much energy individuals can save through behavioral changes (Petersen et al. 2007) in addition to the reasons and motivations behind the adoption of individual energy saving practices(McMakin et al. 2002; Olsen 1981; Yu et al. 2011). Recent energy experiments have discovered that, through sharing energy consumption information through a peer network, we can promote energy conservation behaviors (Peschiera et al. 2010; Petersen et al. 2007). However, this research did not consider the geospatial aspects of the building, which, as we noted above, can be an important contributor to multi-layer network dynamics. Previous research has shown that the geospatial properties of networks can significantly impact diffusion (Hagerstrand 1968; Ryan and Gross 1943; Xu and Harriss 2008). For instance, Moon and Carley extended the research on geospatial effects to demonstrate that there is an important relationship between social networks and geospatial networks in their study of terrorist networks (Moon and Carley 2007). Our work builds on the research of Moon and Carley as we incorporate both geospatial and social networks into a single, multi-layer network to study the diffusion of energy saving practices through networks in residential buildings.

In order to analyze, simulate, and validate the resulting models, we utilized data collected from several experiments between 2009 and 2011 from a building occupant network in a six story multi-family residential building in New York City. The 2009 experiment was run from April 1 to May 7, 2009 with the first 10 days (April 1 to April 10) as the pre-test baseline energy consumption measurement period. For this experiment, 19 residents participated in the experimental study group and another 46 residents comprised the control group. A second experiment which took place in 2010 also provided data for our analysis. That experiment included 23 residents in the experimental study group and 20 in the control group. The experiment was run from November 17, 2009 to February 4, 2010 with a pre-study baseline period from October 29 to November 17, 2009. Finally, a third set of experimental data was also used from a 2011 experiment which includes the energy consumption information of 38 residents in a control group and 22 individuals who were part of the experimental study group. The study period was from March 23 through May 8, 2011. These three research data sets included both peer network and geospatial network data. During the experimental data collection period for all three experiments, residents who participated in the experimental study group had access to their own energy consumption and the consumption of their peers. The control group was formed as a baseline for comparison, they were not provided with any energy consumption information.

Prior to the experiments, residents in the experimental study group were asked to identify their friends. The peer network for the experimental study group was constructed based on these responses. The residents in the experimental group were located on 6 different floors, which allowed us to incorporate geospatial data into our multi-layer network analysis and modeling. During each day of the experimental period, we collected energy consumption information for each resident, which contributed to our analytical, simulation, and validation procedures.

3.3.2 Network Theory and Random Networks

One of the major limitations of collecting experimental data on energy use in buildings is that data collection can only occur on a small scale due to budget, time and privacy concerns. When we collect socio-spatial data (e.g. friend relationships for residents in different buildings), each building will have a unique peer network structure. Thus, in order to overcome these types of limitations, we utilized simulation models based on (random) network theory in order to theorize how our relatively small, observed networks scale to larger, similarly complex networks.

The research that has contributed to network theory has grown substantially over the past few decades. Research on networks has enabled theoretical advancements in sociology (Mullins 1973; Scott 1988; Wellman 1997), organizational theory (Tichy et al. 1979), epidemiology (Bailey 1975; Pastor-Satorras and Vespignani 2002), computer network security (Bellovin 1993) and energy efficiency (Chen et al. 2012). As a product of this work, random network theory (Erdős and Rényi 1959) emerged as an approach that posited a probability space for graphs and that viewed the graph invariants as random variables. This theoretical work was further developed to account for differences between the theoretical network models and complex, real-world networks. This development has revealed that the degree distribution of real-world social networks follows a power-law distribution (Barabási and Albert 1999) in what has been termed a scale-free network (Barabási et al. 1999). This type of model applies numerical simulation to generate networks with growth and preferential attachment, which allows expansion of network degrees in a power-law distribution. Because random networks more accurately reflect real-world social network dynamics, we chose to base our simulation of energy conservation behavior in a multi-layer network on random network theory.

3.3.3 Energy Efficient Behavior and the SIS Model

In order to analyze how feedback information and energy conservation behaviors perturb the network, we employ an analogy between energy saving behavior and the spread of disease so that we can adopt a susceptible-infected-susceptible (SIS) model to simulate the perturbation process. In our analogy, we make an analogy between the adoption of energy efficient behavior as a “disease”. According to Peschiera et al.’s research (Peschiera et al. 2010), residents show a response-relapse pattern in their energy conservation behavior. In their study, residents who conserved energy did not maintain their conservation behaviors. Rather, conservation behaviors that were initially adopted were later disadopted and then adopted again. Similarly, within epidemic models, when an individual is in a position to repeatedly infect others, they are susceptible to being repeatedly infected. Thus, the SIS model is the most suitable model to mathematically describe the spread of epidemics (Anderson and May 1991; Heesterbeek 2000). In the SIS model, there are two states for each potentially infected candidate, namely, infected and susceptible. In terms of energy saving behavior, individuals are considered “infected” if they adopt energy saving behaviors, while they are “susceptible” when they do not adopt energy saving behaviors, because they have the potential to adopt these behaviors. At every step, every candidate is either susceptible or infected, with an infection rate ν and cured rate δ. Therefore, we define a spreading rate λ as:

$$\lambda = \nu/\delta \tag{3.1}$$

ν is the probability that a susceptible vertex exhibits energy saving behavior when it is connected to one or more vertices that exhibit energy saving behavior;

δ is the probability that a vertex, which has exhibited energy saving behavior, will revert to non-saving state and will thus become a candidate for adopting energy saving behavior again (i.e. that the vertex will exhibit an SIS pattern);

λ is defined as the spreading rate of the energy saving behavior.

This type of epidemic model is commonly used to mimic the spreading of human diseases or computer viruses. It also potentially applies to behavior adaption within social networks (Pastor-Satorras and Vespignani 2001). In this paper, this model is applied to emulate the diffusion of energy efficient behaviors. The epidemic threshold λ_c can be represented as the edge between an adoption phase and a disadoption phase, where a spreading rate of less than λ_c indicates that the adoption of energy saving behaviors will not affect the network at equilibrium. The energy saving behaviors within the adoption phase have a certain level of prevalence and can potentially spread through the whole network while the energy saving behaviors will be distinct when the network is at equilibrium (i.e. when the network is in the "disadoption phase") over time. Previous studies of this epidemic threshold for SIS models mostly focus on single networks, such as on homogenous, lattice and scale-free networks (Pastor-Satorras and Vespignani 2001). However, there is a lack of research that applies SIS models to multi-spreading channels in layered networks. To expand the basic SIS model, we applied the overlap and convolution method in order to analyze the spreading pattern of energy saving behaviors in complex multi-layer networks.

3.4 Analytical Model for Layered Networks

3.4.1 Multi-Layer Network Systems

A ***Multi-layer network system*** is a system that contains multiple network layers. In a multi-layer system, we assume that every layer: 1) can be independent or dependent of the other layers, 2) can be heterogeneous in structure, and 3) can be composed of nodes with various connection types. Each layer can differentiate the network in many ways. First, by analyzing multi-layer network systems, we can model how energy saving behaviors spread through multiple channels, which may or may not interact with each other. Second, we can model the emergence of energy saving behaviors in some network communities that are not directly connected to the energy consumption feedback information in other layers or areas of the network. This uncertainty makes the diffusion of energy efficient practices hard to predict. Thus, by modeling a multi-layer network system, we are able to account for the complex properties that occur due to the interaction between the various networks layers that cannot be observed in single networks Many scholars have utilized multi-layer network systems to study various research issues, for example research has investigated the competitive relationship and rivalry between industrial markets (Yang et al. 2009) in addition to the design of computer and transportation systems (Kurant and Thiran 2006). In the domain of energy efficiency, researchers have studied how providing peer network-level energy consumption feedback can enhance residential building energy efficiency, but there is currently no research on energy saving behaviors that treats residential buildings and occupants as a multi-layer network system that reflects both social and geospatial network properties.

For the computation of the topological properties of a multi-layer network, scholars have applied different mathematical frameworks. In their research, Leicht and D'Souza view a layered network as a correlated, interconnected and interacting network (Leicht and D'Souza 2009). Kurant and Thiran (Kurant and Thiran 2006) apply this view of a layered network in their work on overlapped, multi-layer transportation networks in order to find a more accurate load estimator by comparing the results of their multi-layer approach to results generated from a single-layer approach.

The approach we adopt in this paper processes a multi-layer network system into a complex, single network (i.e. a layered network) through weighted overlapping and the application of mean-field theory. In our approach, each layer shares the same vertices but has different connectivity properties. When vertices only exist on one layer of the network, they will be represented as isolated vertices on the other layer. Thus, the size of each network is not necessarily the same for different layers, although each layer has the same scale on a connectivity adjacency matrix. Figure 8 provides an illustration for how we process a multi-layer network system into a single, layered network.

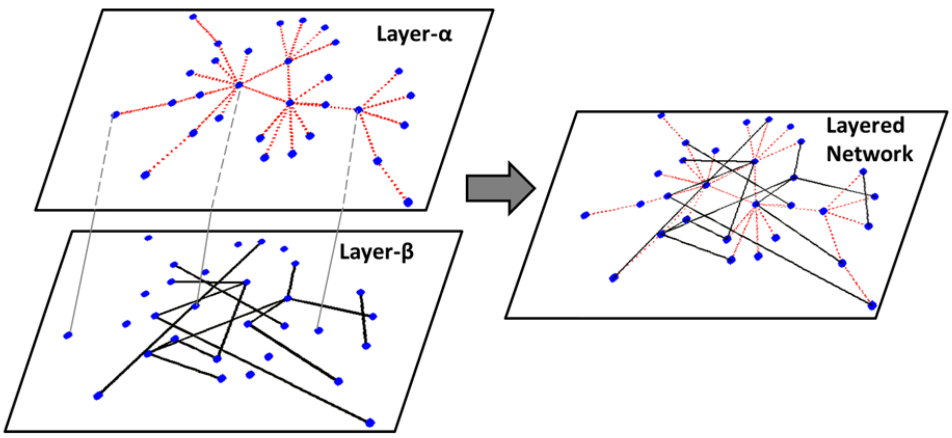


Figure 8 A Sample of Multi-Layer Network System and Layered Network

3.4.2 Generating the Function of Random Networks

The most common configuration for a social network is called a *scale-free network*, which, as we discussed in Section 3.3.2, is based on a power-law distribution. As we note, these types of networks are widely used in random network theory to simulate real-world networks. However, to account for the possibility that not all social networks follow a power-law distribution, we also adopt *Newman's generating function algorithm* (Newman et al. 2001) to model the properties of arbitrary networks.

This arbitrary random network generating method is based on a generating function, which we define with the following equation, given a known degree distribution:

$$G(x) = \sum_{k=0}^{\infty} P(k)X^{k} \qquad (3.2.a)$$

In equation (3.2.a), $P(k)$ is the probability that a node will have a degree of k, and X is a random variable.

For graphs where we do not know the closed form of its degree distribution but know the exact number n_k of vertices having degree k (e.g. if we have access to experimental data), we can create the actual degree function as follows:

$$G(x) = \frac{\sum_k n_k X^k}{\sum_k n_k} \qquad (3.2.b)$$

Equation (3.2.b) is only suitable for cases where the distribution can be written explicitly. For example, in cases where we have access to experimental data, we can calibrate the resulting distribution based on the experimental data for the purpose of more accurate generalization.

To find the quantitative form of a layered network, we overlap weighted, multiple layers into a single-layer network through the following equation:

$$S_n(x) = \sum_{i=1}^{n} a_i X_i \tag{3.3}$$

S_n is the random variable for the overlapped, layered network.

a_i is the coefficient of weight we used to adjust the biased overlapping process.

X_i is the random variable of node degree for the ith layer.

3.4.3 Mean-field Theory

It is difficult to explicitly calculate the interaction between large numbers of network vertices because it is impossible to incorporate all connectivity and interactivity information into a single analytical model. Thus, we adopt the mean-field theory to simplify and convert the networks into a computable system. Mean-field theory is a method that analyzes a physical system with multiple bodies, which allows us to replace all the interactions within the system with their averages or effective interactions (Weiss 1907). According to Barabási and colleagues (Barabási et al. 1999) and Pastor-Satorras and Vespignani (Pastor-Satorras and Vespignani 2001; Pastor-Satorras and Vespignani 2001), the mean-field equation for a network system is captured in the following equation and is explained in terms relative to the context of energy saving behavior in multi-layer networks:

$$\frac{d\rho_k(t)}{dt} = -\rho_k(t) + \lambda k\big(1 - \rho_k(t)\big)\Theta(\rho_k(t)) \tag{3.4}$$

$\rho_k(t)$ is the relative density of residents who are exhibiting energy saving behaviors. In other words, it represents the probability of one node having energy saving behavior when the node is connected to k other vertices;

$\Theta(\rho_k(t))$ is the probability that a link is connected to a node that exhibits energy saving behavior;

k is the number of connections that link to a single node.

λ can be refer to equation (3.1).

Through equation (3.4), we can convert all the rates of each path of the diffusion of energy saving behaviors to a weighted average diffusion rate. From equation (3.4), we assume the energy saving behavior network reaches equilibrium when $d\rho_k(t)/dt = 0$, which leads to;

$$\rho_k = \frac{k\lambda\Theta(\lambda)}{1 + k\lambda\Theta(\lambda)} \tag{3.5}$$

Then,
The probability that a link connects to a node with k connections is equal to $kP(k)/\langle k\rangle$. We can then determine;

$$\Theta(\lambda) = \frac{1}{\langle k\rangle}\sum_{k} kP(k)\rho_k \tag{3.6}$$

And $\langle k\rangle = G'(1)$

Where from equation (3.2.b), $\langle k \rangle$ is the average degree for vertices.

Finally, we can estimate the steady state of the network by

$$\rho = \sum_{k} P(k)\rho_k \tag{3.7}$$

ρ is the prevalence rate of energy efficient behaviors within a network at equilibrium. More specifically, ρ is the portion of residents who have energy efficient behaviors at equilibrium.

3.4.4 An Analytical Solution for Layered Networks

If we assume that the random variables for each layer are independent but not necessarily identical or equally weighted, then the moment generating function for the overlapped layered network is,

$$G_{s_n}(x) = \prod_{i=1}^{n} G\,(a_i x_i) \tag{3.8}$$

To find the probability density distribution, we can apply an Inverse Laplace Transform, which we denote as

$$P(k) = L^{-1}\left(G_{s_n}(x)\right) = \frac{1}{2\pi i} \lim_{T\to\infty} \int_{\gamma - iT}^{\gamma + iT} e^{kt}\, G_{s_n}(x)\, dt \tag{3.9.a}$$

However, an Inverse Laplace Transform can only find the analytical solution when the denominator of $G_{s_n}(x)$ is polynomial and the distribution is continuous. To address these constraints, we can determine the polynomial form of $G_{s_n}(x)$ through a Taylor expansion for the discrete and non-polynomial denominator case.

Thus, the probability p_k is given by the kth derivative of G according to

$$P(k) = \left.\frac{d^k G_{Sn}(x)}{k!\, dx^k}\right|_{x=0} \tag{3.9.b}$$

After we solve for $\Theta(\lambda)$ through (3.3), (3.4) and (3.8)

$$\Theta(\lambda) = \frac{1}{\langle k \rangle} \sum_k \frac{k\lambda\Theta(\lambda)}{1 + k\lambda\Theta(\lambda)} \cdot \left(\left.\frac{d^k G_{Sn}(x)}{(k-1)!\, dx^k}\right|_{x=0} \right) \tag{3.10}$$

We can evaluate ρ

$$\rho = \sum_k \left(\left.\frac{d^k G_{Sn}(x)}{(k-1)!\, dx^k}\right|_{x=0} \right) \cdot \frac{\lambda\Theta(\lambda)}{1 + k\lambda\Theta(\lambda)} \tag{3.11}$$

3.5 Computing the Layered Networks

In order to estimate the properties of the discrete system, we propose a new model. Then, in order to operationalize the model, we use a double-layer network system with the same structural settings as the data collected from the multi-family residential building energy experiments executed in New York City from 2009 to 2011, which we described in Section 3.3.1. We then validate the model by comparing simulation results of our new model, an existing validated model and the experimental data. This is described in more detail in Section 3.6.2.

To simulate this double layer network system, we assume the first layer of the network (i.e. the peer network of residential building occupants) follows a Zeta distribution, which is a more specific type of power-law distribution. The power-law distribution is a series of non-negative distributions with a long tail on the right and which is dominated by a low value on the left. The second layer (i.e. the geospatial network composed of occupants' residential floors) follows a Poisson distribution, which assumes that occupants uniformly fall into each geospatial component. Both Poisson and power-law are discrete distributions. To calculate their generating function, we use the following equations:

$$G_{\alpha}(x) = \sum_{k=0}^{N} k^{-\tau} e^{-\frac{k}{m}} x^{k} = \frac{\mathrm{Li}_{\tau}\left(xe^{-\frac{1}{m}}\right)}{\mathrm{Li}_{\tau}\left(e^{-\frac{1}{m}}\right)} \tag{3.12}$$

$$G_\beta(x) = \sum_{k=0}^{N} \binom{N}{k} p^k (1-p)^{N-k} x^k = (1-p+px)^N = e^{\lambda(x-1)} \tag{3.13}$$

$Li_n(x)$ is the nth polylogarithm of x.

Therefore, the probability function of the scale-free social network has the relationship of

$$P\,(k; \tau, m) \sim k^{-\tau}$$

In general, when γ ranges from 2 to 3, networks are resilient to random break-downs (Cohen et al. 2002). Thus, we take the Zeta distribution, i.e. the prototypical discrete power-law distribution, as an example of a social network. We assume $\tau = 2$ in the following calculation and $m \to \infty$; $\zeta(s)$ as the Zeta function. We can also calculate the probability mass function of the Zeta distribution as

$$P_\alpha(k) = \frac{\frac{1}{k^s}}{\zeta(s)} \tag{3.14}$$

And we can find its probability generating function as

$$G_\alpha(x) = \frac{Li_\tau(x)}{\zeta(\tau)} \tag{3.15}$$

If we elaborate on the assumption that both layers are equally weighted, then we can compute the generating function of the layered network as

$$G_{s_n}(x) = \prod\nolimits_{i=1}^{n} G\,(a_i x_i) = \frac{Li_2(x)}{\zeta(2)} e^{\lambda(x-1)} \tag{3.16}$$

Since we cannot find the closed form of the probability distribution function through an inverse Laplace transform, we use a Taylor expansion of $G_{s_n}(x)$.

$$G_{s_n}(x) = \frac{1}{1.645}\left[e^{-\lambda}x + \frac{1}{4}e^{-\lambda}(4\lambda + 1)x^2 + \frac{1}{36}e^{-\lambda}(18\lambda^2 + 9\lambda + 4)x^3 + O(x^4)\right] \quad (3.17)$$

Finally, we can find the probability mass function by calculating the derivatives of the generating function and estimate the relative density function of vertices through equation (3.17). Although we cannot find the closed form of the density function, we can still solve the equations numerically through equations (3.10) and (3.11), which produces the following results.

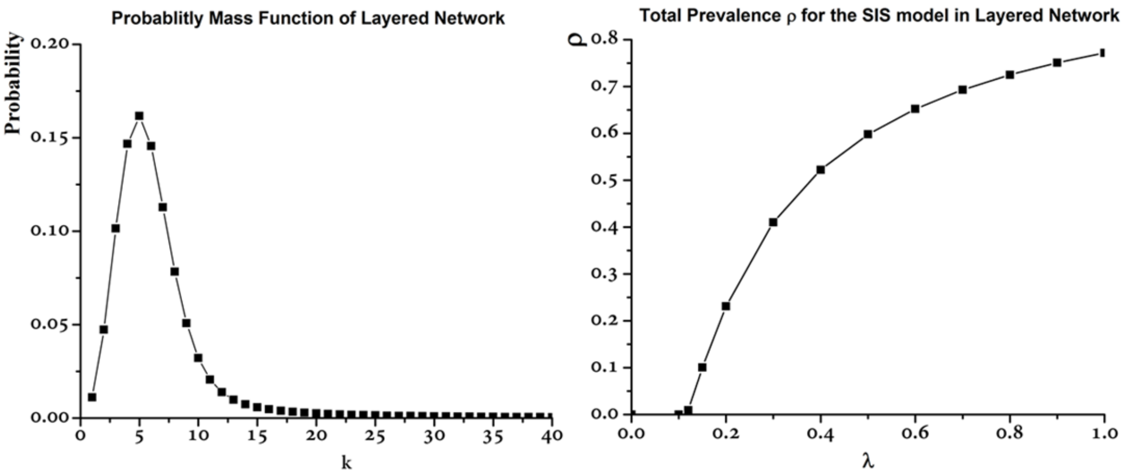


Figure 9 Probability Mass Function and Prevalence of ρ within the SIS Model

From the 40th order Taylor Expansion in equation (3.17), we constructed the probability mass function for the simulation in Figure 9. The shape of the layered network distribution is completely different from Poisson distribution and the Zeta distribution, which validates our assumption that a layered network would have a significant impact on network structure for the multi-layer network. The probability mass function is also useful to verify the simulated networks that we will present in the next section.

We can also observe the prevalence of perturbation within the layered network in Figure 8. In Figure 8, we see the epidemic threshold at equilibrium, which means that the energy saving behavior can spread in the layered network only if the spreading rate λ is greater than 0.12. In addition, the results displayed in Figure 8 indicate that the spreading rate of energy saving behaviors is cannot be determined directly from the experimental data. For the purpose of estimating the diffusion of energy efficient behaviors, ν and ρ are necessary. However, these two critical parameters are impracticable to collect from experiment directly. Therefore, we need to find an analytical solution first. If we assume that energy consumption data collected during the experiment achieves equilibrium, then we can use the prevalence rate (ρ) of the experimental energy saving behaviors to identify the spreading rate (λ). The prevalence rate we used is the average of the percentage of residents who have energy efficient behaviors during the experimental periods. We will discuss this process more fully in following section.

In order to clarify the terms in the analytical model, we define the important terms in Table 5.

Table 5 Network Structure and SIS Model Key Terms

TERM	DEFINITION
Vertices	Points in a network graph that represent a single entity
Edge	A connection between two vertices
Degree	The total number of edges connected to a vertex
Degree Distribution	The probability distribution for all vertices' degrees in a network
Spreading Rate (λ)	The ratio of the probability that people adopt energy saving practices divided by the probability that people disadopt energy saving practices
Prevalence Rate (ρ)	The relative density of residents who have energy saving behaviors. The percentage of people who possess energy saving practices. For example, a Prevalence Rate = 1 means everyone contributes to energy savings.

3.6 Simulating the Networks

Although we have presented a computational model that captures how energy saving behaviors can spread through a layered network at the macro level, a micro level analysis is still necessary because our model to this point has been based on mean-field theory, which can only capture interactions between vertices as a whole. Thus our model to this point incorporates the properties of a multi-layer network in which energy saving behavior can spread, but we have not investigated the spread of behavior at the level of the individual network node.

In order to understand how energy saving behavior can spread from node to node (i.e. from building occupant to building occupant), we must investigate the interactional patterns between vertices. Therefore, we performed simulations for a sample layered network based on two different algorithms. We also validated and compared the simulated output for the two models to experimental data which will be described in section 3.6.2 and 3.6.3.

3.6.1 Degree Distribution of Multi-layer Network System

In the study of graphs and networks, degree distribution is an important concept because it carries a large amount of information about networks, e.g. their density and connectivity patterns. For our simulation, we developed random networks by randomizing the degree distribution and then rebuilt the vertices into connected graphs.

In order to verify our simulation models, we constructed and simulated random, multi-layer network systems with one layer based on a scale-free network (to reflect the peer network) and a second layer based on a clustered network (to reflect the geospatial network of the residential floors). The settings for the simulation are the same as for the energy efficiency experiment we introduced in Section 3.3.1 and for the analytical model that we described in Section 3.5.

Figure 10 shows an example of the output for this random, multi-layer network generation process. Figure 10(a) shows an example of a random layout for the peer network layer, while Figure 10(b) shows an example of random network structure for the geospatial network layer. Figure 10(c) shows the simulated degree distribution for the multi-layer networks created by overlapping Figure 10(a) and Figure 10(b). The example networks in Figure 10(a) and Figure 10(b) are relatively small for the purpose of illustration, but through the simulation, we were able to model a similar multi-layer network with 1000 nodes. Note that the layered network distribution in Figure 10(c) has the same probability mass function as the analytical models presented in Figure 9.

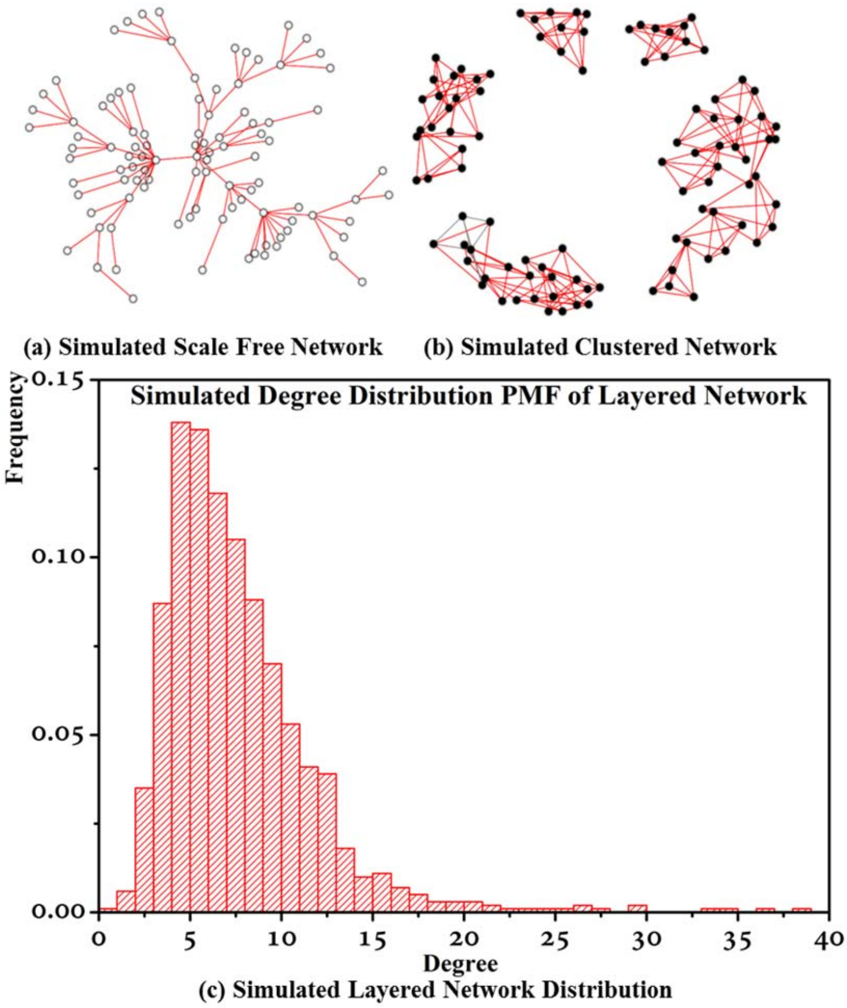


Figure 10 Simulated Multi-layer Network System

3.6.2 Simulation Models

Our simulation approach utilized two models to simulate the perturbing process, which reflects the change in energy saving behavior in the multi-layer network. We used a Layered Network model (which we will refer to as Model 1) and a Multi-Layer Interactive Network model (which we will refer to as Model 2). The Layered Network model is the model we have introduced in this paper. It is the analytical model we developed in Section 3.4.3 to emulate the multi-layer system. For this Layered Network model, we converted the multi-layer networks from our analytical model into single-layer networks.

The Multi-Layer Interactive Network model is the conventional algorithm which has been used in previous research (Alam et al. 2009) to simulate multi-layer network systems and has been used to validate analytical interactive multi-layer models (Leicht and D'Souza 2009). The Multi-Layer Interactive Network model simulates the adoption of energy saving behaviors within the network system separately and in parallel for each layer.

The simulation of both Model 1 and Model 2 predicts whether a building occupant will adopt energy saving behaviors and captures whether the adoption of energy saving behaviors by one occupant influences the adoption by other occupants to whom they are connected. Figure 11 shows the mechanisms for the simulation algorithms underlying each model.

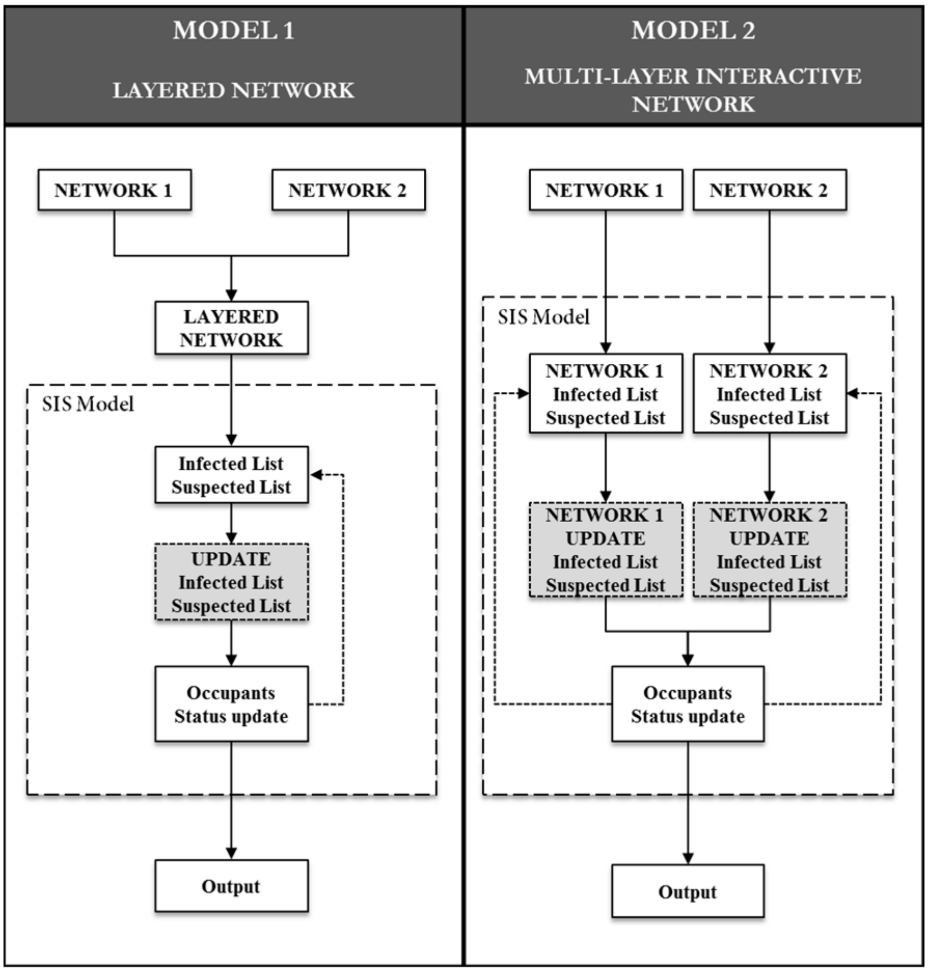


Figure 11 Comparison of Two Simulation Algorithms

3.6.3 Validating the Simulated Model

The parameters used to run the simulations come from data collected as part of the energy efficiency experiments conducted in New York City from 2009 to 2011 as discussed in Section 3.3.1.

In these experiments, residents of a multi-family residential building were exposed to an energy feedback system that provided information on their own energy use as well as the energy use of their peers located in other apartments in the building. The introduction of this energy feedback system acts as the system level perturbation in our model from which we examine the diffusion of energy conservation. For each resident, if they consumed less energy than the baseline, we assumed that they increased their energy conservation behavior. In analogy to the SIS model, we assumed that they are "infected" with energy saving behaviors. In Peschiera's (Peschiera et al. 2010) terms, we conceptualized their energy savings as the "response". If their energy consumption is higher than the baseline, we assumed that they did not adopt energy saving behaviors. In Peschiera's (Peschiera et al. 2010) terms, this state is considered to be a "relapse", while we consider it as an "uninfected" state in analogy to the SIS literature. Because our simulations are based on the experimental data, we are able to determine the average prevalence rate of energy saving behaviors as well as the corresponding rate of spread through the analytical solution of multi-layer network.

The input for the simulation is: 1) the network structure, 2) the interconnection between layers, and 3) the spreading rate λ, which we derived from our analytical model. After the simulation process, we calculated the efficiency and accuracy for both models by comparing the prevalence rate of energy efficient behaviors in order to assess their theoretical value.

Accuracy

Since the input parameter of our SIS model is derived from three separate experimental data-sets from 2009 to 2011, we are able to compare the experimental data with the results of the simulation for each year. From Figure 12, we can determine visually that the Layered Network model (Model 1) is more accurate than the Multi-Layer Interactive

Network model (Model 2). The Multi-Layer Interactive Networks Model has a higher error and underestimates the prevalence of the energy saving behaviors across all three experimental data-sets. The top of Figure 12 is the comparison of energy efficient behavior prevalence rate at equilibrium for both models. The bottom of Figure 12 includes sample simulations of energy efficient behavior prevalence rate. We only plotted 10 scenarios for each model, but in our simulation we recorded 1,000 scenarios.

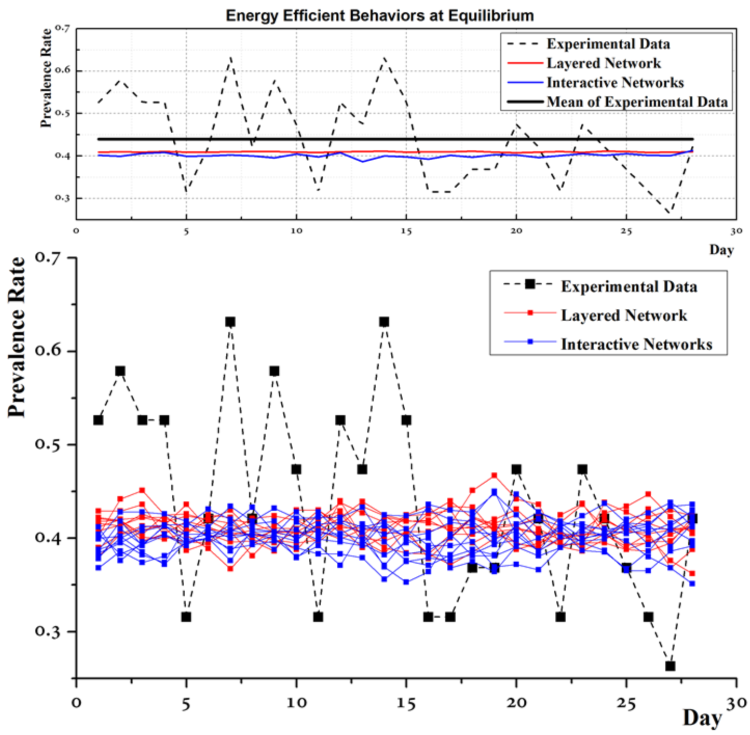


Figure 12 (a) Comparison of Model Accuracy (2009 Experiment)

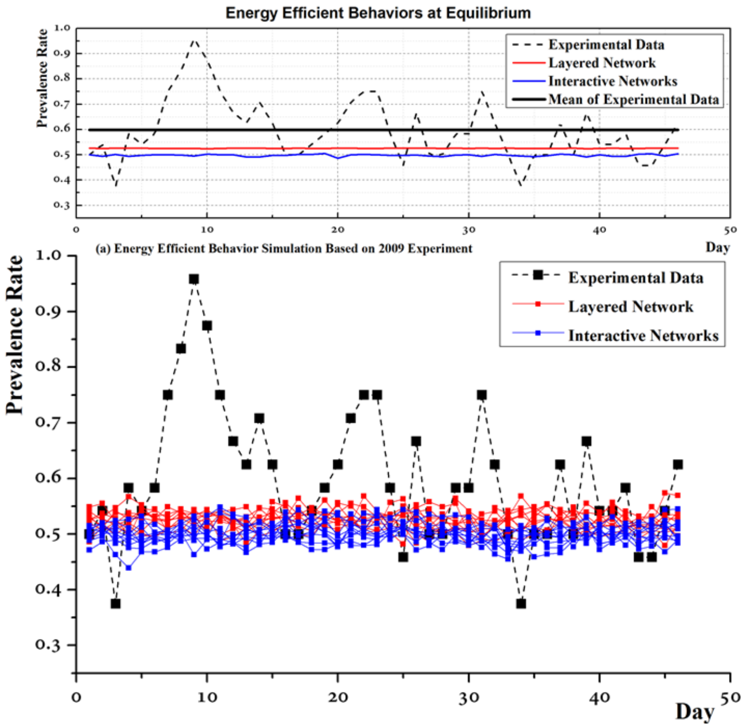


Figure 12 (b) Comparison of Model Accuracy (2010 Experiment)

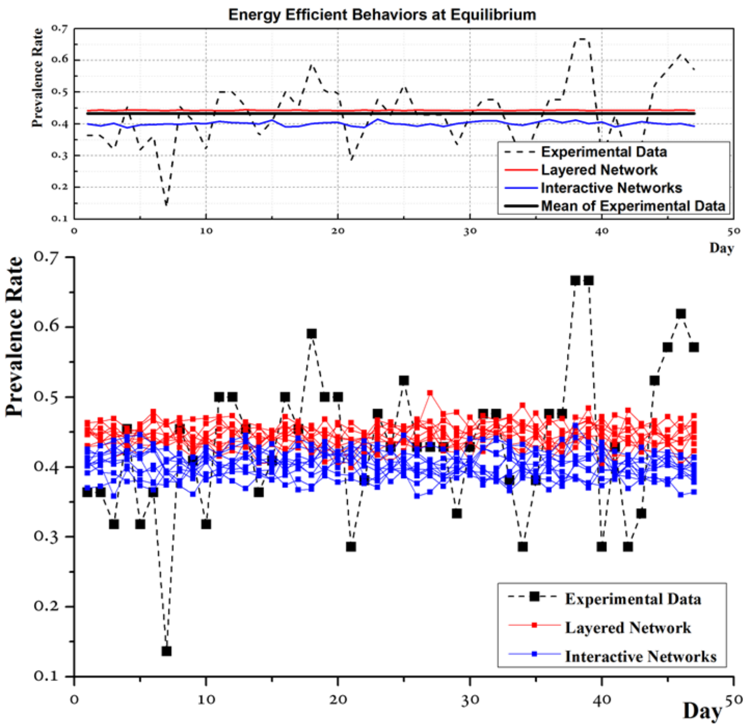


Figure 12 (c) Comparison of Model Accuracy (2011 Experiment)

Figure 12 Comparison of Model Accuracy (2009-2011 Experiment)

Efficiency

One of the major concerns for simulation is its efficiency, i.e. the "cost" of the simulation in terms of how long a particular simulation process takes to run. Complex simulations can take weeks. If two simulations produce similar results and one takes half as long to run, the shorter-running simulation is said to be more efficient. In this section, we compare the efficiency of our model (Layered Network Model) to that of the previously published model (Multi-Layer Interactive Network Model).

Simulation differs from solving numerical systems in that the asymptotic properties for simulation (particularly for agent-based simulations) are difficult to analytically estimate because of the uncertainty between two (or more) given agents. Thus, we ran the simulations repetitively in order to directly record the time for construction of the network and the time to execute the SIS simulation for a network with 1000 vertices.

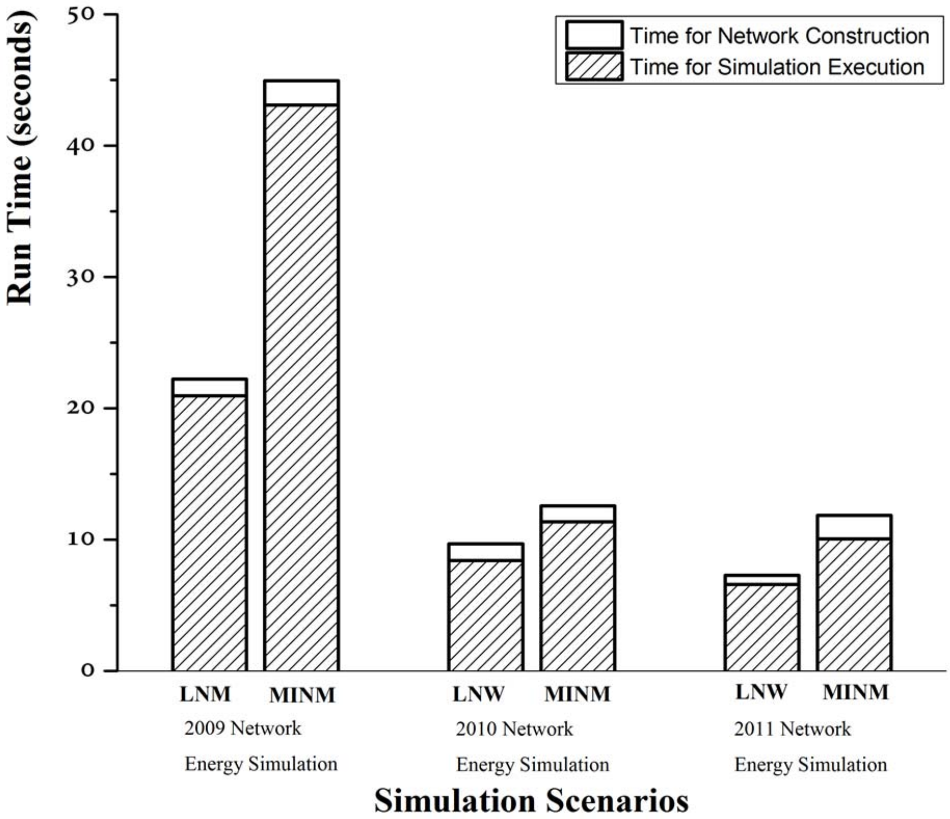


Figure 13 Efficiency Test of Simulation Models for Average Simulation Run

*Note: LNM = Layered Network Model; MINM = Multi-layer Interactive Network Model

From Figure 13, we observe that the total simulation time for the Layered Network Model is less than the Multi-layered Network Model for each of the three data-sets tested. On average, the Layered Network Model took 37.59% less total simulation time than the Multi-layered Network Model across the experimental data-sets. The time devoted to constructing the networks and executing the SIS simulation also suggests the Layered Network Model is more efficient than the previously published Multi-layered Interactive Network Model in that it takes less time to construct the networks across all three data-sets.

Summary of Model Accuracy and Efficiency Comparison

Table 6 summarizes our comparison of Model 1 and Model 2 in terms of their accuracy and efficiency. In terms of accuracy, we found our proposed model (Layered Network Model) to achieve better accuracy across all three experimental data sets compared to the previously published Multi-Layer Interactive Network Model. Moreover, obtaining this greater accuracy was not achieved by sacrificing efficiency. Our model also took on average 37.58% less total simulation time as the Multi-Layer Network Model to run 1000 simulation runs for a 1000 node network. Based on these simulation outcomes which are summarized in Table 6, we conclude that the Layered Network Model we propose in this paper is more efficient and accurate than the Multi-layer Interactive Network Model and, hence, a valid approach to examining multi-layer network systems.

Table 6 Comparison of a Layered Network and a Multi-Layer Interactive Network Model in Simulating the Spread of Energy Saving Behaviors in a Multi-Layer Network

EFFICIENCY (Seconds)						
	2009 Experimental Data		**2010 Experimental Data**		**2011 Experimental Data**	
	Network Construction	Simulation Execution	Network Construction	Simulation Execution	Network Construction	Simulation Execution
Layered Network Model	1.27	20.94	1.21	8.40	0.67	6.59
Multi-layer Interactive Network Model	1.86	43.08	1.22	11.34	1.80	10.05
ACCURACY (Percentage Error)						
	2009 Experimental Data		**2010 Experimental Data**		**2011 Experimental Data**	
	Compared to Real Data from Experiment	Compared to Energy Efficient Behaviors at Equilibrium	Compared to Real Data from Experiment	Compared to Energy Efficient Behaviors at Equilibrium	Compared to Real Data from Experiment	Compared to Energy Efficient Behaviors at Equilibrium
Layered Network Model	8.66%	3.03%	10.51%	7.32%	8.23%	1.03%
Multi-layer Interactive Network Model	9.15%	3.88%	11.71%	10.08%	8.67%	3.18%

3.6.4 Limitations

As for all simulations, our models have limitations. First, we simulated the randomized network structure based solely on degree distribution. Although degree distribution is an essential component of network structure, other attributes (e.g. network coherence, clusterability and transitivity) also contribute to the overall interpretation of a network's structural properties. Our research suggests that the Layered Network model is more appropriate for incorporating additional attributes because it has a relatively low construction time, which allows for the construction of larger networks with more constrains at relatively low cost.

A second limitation is based on our assumption that each layer equally impacts the output. In real contexts, each layer would likely exhibit a different weight on the output. Because it is often difficult to determine the contributing weight of each layer, a scenario analysis (by combining network layers at different weight combinations) would be required to increase the accuracy of our model and would be a fruitful topic for future research.

A final limitation is based on our assumption that the networks are static during the simulation period. Real-world building occupancy networks are typically dynamic in terms of the connections between residents. For example, if a resident moves to another location, he or she will lose or alter geospatial ties in addition to potentially losing some or all of their social ties. Creating open system models that enable new connections to form and existing connections to dissipate is an interesting model extension for future research.

3.6.5 Model Application

The simulation can be based on the observed data from experiments or given data source. The major network inputs are the peer network connection and geospatial location information. These data can be obtained from social network media and geospatial information database or pilot experiments. Then, the Layered Network model will process this information and derive input parameters for SIS simulation. The SIS simulation will predict the energy efficient behaviors diffusion based on the multiple networks' structures. Finally, a prevalence rate at equilibrium and a prevalence curve are constructed for energy consumption forecast. Given various spreading rates of all energy saving practices, our model is able to predict the corresponding prevalence rates. Incorporated the energy savings from each practice, our model enables engineers to estimate the saving amount of energy efficient behaviors through sharing energy consumption information via peer network and geospatial network. Our model also provides an accurate and efficient algorithm for the energy feedback system designers to optimize their efficiency of systems. For example, companies like OPWER and Welectricity can benefit from our model by providing selective information through multiple coexisting networks.

3.7 Discussion and Conclusion

The purpose of our research was to develop an accurate and efficient model to examine energy conservation in layered peer and geospatial networks. The model we introduced in this paper is capable of developing a quantitative account of the diffusion of energy saving behaviors resulting from the implementation of an energy consumption feedback system in a multi-layer network system. To achieve this goal, we utilized random network theory and mean field theory to implement an analytical model that converts a complex multi-layer network into a single-layer network. We then compared the simulated output of two models and found that our model was more efficient and accurate than a previously published model.

Our analytical model expands on Mean Field Theory and a SIS models (Pastor-Satorras and Vespignani 2001; Pastor-Satorras and Vespignani 2001) by applying them in the context of a layered network. Moreover, we expanded Kurant and Thiran's (Kurant and Thiran 2006) research by generalizing their model to layered networks. The result introduces a new method to convert a multi-layer networks system to an equivalent single-layer network system, based on a previously established generating function method (Newman et al. 2001).

Compared to current research on energy conservation behavior in peer networks, which narrowly focuses on social networks (Peschiera et al. 2010), our layered network model adds geospatial networks into the analysis. Our model not only analyzes the properties of networks, but it also simulates the residents' energy saving response to energy information feedback through the two network layers, even given arbitrary degree distributions. Our work provides a new method for predicting energy saving behavior resulting from energy consumption feedback that incorporates these two network layers. Crucially, the method is also scalable to larger simulated, multi-layer networks that may exist in real multi-layer network systems. For example, in addition to peer networks and geospatial networks we might consider other forms of human networks such as communities of practice and hierarchical networks in commercial buildings. We might also model the potential physical infrastructure network interactions such as in residential, office, and schools, as well as across public transportation. A large number of network types may provide explanatory power on energy conservation practice diffusion which requires a scalable methodology to examine.

We utilized random network theory to generate a number of realistic random network structures to which we have applied the findings from the experimental data we collected. This type of experimental research has recently found that sharing energy consumption information through social networks promotes energy conservation by building occupants (Chen et al. 2012; Jain et al. 2012; Peschiera et al. 2010). However, the structure and characteristics of social networks vary from building to building, and the adoption of energy saving behaviors by residents may be conditioned by their geospatial location in particular buildings or on particular floors. This means that predicting the spread of energy saving behaviors through both social networks and geospatial networks is necessary if we want to develop an accurate account of energy conservation dynamics in and across buildings. Our simulation models allow us to test the impact of changes in the behaviors of residents in socio-geospatial networks, even in cases where the networks are heterogeneous or arbitrary.

Moreover, our model allows us to estimate energy saving at the building level as energy saving behaviors diffuse through the multi-layer network system. Thus, our models not only quantitatively emulate the diffusion of behavior under various network configurations and through multiple networks in general, but they also specifically contribute to our understanding of how energy saving behaviors diffuse through peer networks and geospatial networks to encourage energy savings.

Our comparison of simulation models indicates that the method we propose for converting multi-layer networks into a single, layered network is a valid approach. The simulation tests indicate that our proposed layered network model is more efficient and accurate than the previously published multi-layer interaction algorithm. Thus, our research provides a more comprehensive account of changes in residents' energy saving behaviors when they are exposed to real-time energy consumption feedback information through multiple networks.

The model we develop in this paper can be extended in several ways by future researchers. For instance, our model is based on degree distribution to differentiate network structures. However, future research can increase the accuracy of the model further by capturing the attributes of real-life networks. These attributes would include, for example, network coherence, clusterability and transitivity. Another potential extension for this research is to develop a methodology capable of identifying each influential channel or layer and determining their weight when overlapped in a layered network. Finally, future research to expand the layered network model should account for the dynamic evolution of relationships between network actors in response to changes in their experience, e.g. as building occupants move or have a change in friendship status in their peer network. Thus, while our model has laid the groundwork for understanding the diffusion of energy saving behaviors in layered social and geospatial networks, expansion on our model will allow for accurate long-term, quantitative prediction of how energy feedback can change behavior in large-scale geospatially situated peer networks.

Chapter 4

4. BLOCK CONFIGURATION MODELING: A NOVEL SIMULATION MODEL TO EMULATE BUILDING OCCUPANT PEER NETWORKS AND THEIR IMPACT ON BUILDING ENERGY CONSUMPTION

4.1 Abstract

Recent research has shown that providing building occupants with eco-feedback regarding their own energy consumption and the consumption of others in their peer network can lead to substantial energy savings. While empirical eco-feedback studies have provided valuable insights into the dynamics of energy consumption behavior and building occupant peer networks, such studies have faced challenges in examining consumption behavior in larger and more complex peer networks. Computer simulation and random network models offer a solution to this scalability issue, but current random network models are limited in their ability to mimic real world building occupant networks. In this paper, we propose a refined random network model, the Block Configuration Model, and utilize it in an agent-based energy consumption simulation. Results indicate that the Block Configuration Model outperforms conventional models when compared to empirical data from three different eco-feedback experiments. The Block Configuration Model advances our understanding of the dynamics of occupant energy consumption and provides a tool to reduce energy consumption and associated emissions.

4.2 Introduction

Energy has become an expensive commodity both economically and environmentally. The building sector is one of the largest consumers of energy and accounts for 41.3% of consumption and 36% of related CO_2 emissions (US Energy Information Administration 2010). Traditionally, research regarding building energy efficiency has mainly focused on capital intensive physical improvements and retrofits. Recently researchers have begun to explore ways to engage building occupants to encourage energy efficient behavior by providing them access to eco-feedback systems. An eco-feedback system is a system that provides residents with detailed information regarding their energy consumption. Research has shown eco-feedback systems to be an effective method to reduce consumption (Fischer 2008) and systems are now being expanded to include normative comparison features that enable residents to share their energy consumption information with peers in the building (Jain et al. 2012; Peschiera et al. 2010; Petersen et al. 2007).

The emergence of such normative comparison tools in eco-feedback systems has led researchers to examine the impact that connections between users have on energy consumption. Such connections can be thought to describe or form a peer or social network between users. Recent empirical research has shown that reductions in energy consumption are a function of network structure (Chen et al. 2012; Peschiera and Taylor 2012). This empirical work provided insight into the impact peer networks have on energy consumption, but were restricted to studying small scale networks due to the cost limitations of collecting additional data. By combining energy consumption simulation and computer generated random networks, researchers can examine the dynamics of energy consumption beyond small scales. Current models to generate random networks are limited in their applicability and do not accurately reflect the observed clustering and transitive properties of real building occupant peer networks. Therefore, to accurately simulate the energy consumption of users in building occupant peer networks exposed to eco-feedback systems, a new model to generate more accurate random networks is needed.

In this paper, we develop a new random network model, the *Block Configuration Model*, and utilize it in an agent-based simulation to emulate the energy consumption behavior of users in peer networks exposed to eco-feedback.

4.3 Background

4.3.1 Constraints of Peer Network Eco-feedback System Experiments

Empirical eco-feedback experiments have been successful in eliciting energy savings from building occupants. Observed savings in numerous empirical studies have ranged from 2% to 32% (Allcott 2011; Petersen et al. 2007; Spagnolli et al. 2011; Ueno et al. 2006). Normative comparison features have been recently added to eco-feedback systems (Jain et al. 2012; Peschiera et al. 2010; Petersen et al. 2007) to provide users with socially contextualized feedback. Specifically, a recent empirical eco-feedback experiment (Peschiera and Taylor 2012), examined the impact a user's position in his/her peer network has on their energy consumption and found that the more central and connected a user was the less he/she consumed. While this study (Peschiera and Taylor 2012) provided some insight regarding the impact peer networks have on energy consumption, data collection occurred on a small scale due to budget, time and privacy concerns. Moreover, a building occupant peer network may have multifarious connections as a result of various attributes of residents, community culture and geographic location that are difficult to capture in an empirical experiment. Computer simulation and generated random networks offer a solution to examine beyond the inherent limitations of these empirical studies. Utilizing simulation and generated random networks, we aim to quantify the possible savings that can be achieved from larger scale implementations of eco-feedback systems.

4.3.2 Energy Consumption Simulation

Unlike many empirical energy consumption experiments, energy consumption simulation allows researchers to quantify consumption savings on a large scale. Simulation models are not significantly constrained by size. Input parameters of a simulation can be easily modified to reflect different scenarios. For this reason, simulation has become a valuable tool for predicting and forecasting energy consumption. Previous simulations have aimed to predict and optimize energy consumption on a facility and appliance level (Hermes et al. 2009; Negrão and Hermes 2011) and in regards to the thermodynamic conditions of a building (Pisello et al. 2012). While such simulations offer valuable insight into energy consumption patterns and optimization techniques, they do not incorporate mechanisms to account for variation in occupant behavior. Recent data has shown that occupant behavior is an important part of energy consumption(Vassileva et al. 2012) since more than 55% of total energy consumption in households can be attributed to occupant controlled actions (US Department of Energy 2010). Hoes et al. (Hoes et al. 2009) made strides towards incorporating occupant behavior and proposed an energy consumption simulation that allows a building's design to be optimized to actual user characteristics. Olofsson and Mahlia (Olofsson and Mahlia 2012) developed an energy simulation to model residents' energy consumption behavior in response to changes in climate. Similar work has utilized agent-based simulation to model occupant consumption on an individual level to characterize energy consumption patterns in commercial buildings (Azar and Menassa 2012). However, none of these studies incorporate the impact that both eco-feedback and building occupant peer networks have on occupant energy consumption and decision making. A recent simulation (Chen et al. 2012) that incorporated eco-feedback and peer networks found that denser and tighter networks can cause reductions in energy consumption. While this study provided insight into the impact that peer network typology has on energy consumption, the simulation was limited by the accuracy and applicability of existing random network algorithms utilized (discussed further in section 4.3.4). Therefore, novel random network models that more accurately reflect real building occupant peer networks are necessary to refine and expand simulations at the intersection of energy consumption behavior and building occupant peer networks.

4.3.3 Parameters of Network Structure

This paper seeks to introduce the *Block Configuration Model*, a refined random network model that more accurately reflects observed building occupant networks. By definition, a network consists of vertices connected together by edges. These vertices or nodes can be categorized through the use of metrics such as degree distribution, clustering coefficient, and centrality measures. To understand the limitations of current random network generation models, we first introduce and define a few network structure key terms in Table 7.

Table 7 Network Structure Key Terms

TERM	DEFINITION
Vertices	Points in a network graph that represent a single entity
Edge	A connection between two vertices
Degree	The total number of edges connected to a vertex
Degree Distribution	The probability distribution for all vertices' degrees in a network
Clustering Coefficient	The probability that two vertices (*a*, *b*) are connected to each other given that both vertices (*a*, *b*) are connected to a neighboring vertex (*c*)
Degree Centrality	The normalized degree of a vertex
Betweenness Centrality	The extent to which a vertex lies on a path between two other vertices
Closeness Centrality	The normalized distance between vertices

4.3.4 Random Network Algorithms

The idea of creating randomly generated networks that mimic real world networks was introduced by Paul Erdös and Alfréd Rényi in the 1950s and 1960s (Erdős and Rényi 1959; Erdős and Rényi 1960) and came to be known as the *EA Model*. The seminal work of Erdös and Rényi was expanded by Barabási and Albert with their analysis of the theoretical network models and real world networks. Barabási and Albert revealed that the degree distribution of real-world social networks follows a power-law distribution (Barabási and Albert 1999) in what has been termed a scale-free network (Barabási et al. 1999). The scale-free network became the basis for a second random network algorithm, the *Preferential Attachment Model*. More recently, Newman et al. (Cohen et al. 2002) proposed a general model that can create random graphs with arbitrary degree distribution known as the *Configuration Model*. We describe each of these random network algorithms in detail below.

EA Model

The *EA Model* creates a random network by randomly choosing edges between vertices. Because each edge exists with an independent probability *p*, there is not a constraint degree distribution across a network created by the *EA Model*. In practice, the value of *p* is derived from experimental data. Unfortunately, because edges in the *EA Model* are chosen with a constant probability, an *EA Model* generated random network fails to capture properties observed in real world networks such as the scale-free property (Cohen et al. 2002) .

Preferential Attachment Model

The *Preferential Attachment Model* relies on the scale-free property of real world networks and therefore operates on the premise that there is a higher probability that a vertex will be linked to another vertex that already has a large number of connections. Simon (Simon 1955) mathematically demonstrated this "rich-get-richer" effect and found that the effect gives rise to a power-law distribution. Barabási and Albert (Barabási and Albert 1999) termed this mechanism *preferential attachment* and many real-world networks have been observed to follow this pattern. For example, researchers have been observed to be more likely to cite papers that are already highly cited (Redner 1998).

The *Preferential Attachment Model* has two major constraints that limit its effectiveness to generate networks that mimic real world networks. The first is that the model can only generate a purely connected network, one that is completely connected and therefore has only one component. This assumption of a singular component does not reflect real world networks. The second is that the degree distribution cannot be controlled, therefore leading to degree distributions that do not mimic real world conditions.

Configuration Model

The *Configuration Model* was created in response to the degree distribution constraint of the *Preferential Attachment Model* and creates a network with constant degree distribution. The *Configuration Model* algorithm begins by specifying the degree distribution for the network and assigns a degree for each vertex based on that distribution. Then, it gives each vertex *k stubs, k* is the degree randomly generated according to an arbitrary distribution. A *stub* is half an edge that is only connected to one vertex. Next, the algorithm chooses two *stubs* uniformly at random and connects these two *stubs* to form an edge between the two vertices. The algorithm then reduces the degree of two vertices by one, and repeats this process until all vertices are assembled together and no stubs are left.

The *Configuration Model* is also constrained in that it only specifies degree distribution and does not set any limits on the other structural parameters of a generated network. Specifically, the model is not flexible enough to generate networks with structure similar to those observed in building occupant peer networks. One major assumption of the *Configuration Model* is that the vertices are drawn uniformly when selecting vertices randomly to reconstruct the network. This assumption is likely to result in the model missing important structural features of the network. For example, the network can be compacted tightly like a fish net or be spread widely like a chain. Furthermore, real-world networks show strong clustering and transitivity, where configuration models do not (Newman 2003).

In this paper, we aim to build an improved *Configuration Model* to generate more accurate and realistic networks. We develop a refined model, the *Block Configuration Model* by building a degree correlated block model, separating the adjacency matrix into blocks according to connectivity, and then reconstructing the network. To validate the *Block Configuration Model,* we utilize it in an agent-based simulation of peer network energy consumption and compare the results against the *EA Model*, the *Preferential Attachment Model* and the *Configuration Model*.

4.4 Methodology

4.4.1 The Block Configuration Model Algorithm

Due to the constraints of existing simulation algorithms and empirical eco-feedback experiments, the *Block Configuration Model* algorithm is specifically designed to simulate building occupant peer networks. The occupant peer networks during experimental periods are small in size, disconnected in components and complex in structure. Therefore, the *Block Configuration Model* aims to create simulated networks that mimic the structural traits of the networks observed in empirical eco-feedback experiments.

The basic idea of the proposed *Block Configuration Model* is to generate a random network in blocks so that the generated network is consistent with structural properties of an observed network. The simulation process consists of three steps and is shown in Figure 14. The first step collects the simulation inputs by parsing an observed network for structural information. We adopt the block model from the field of social network analysis theory to separate a network into blocks and components. The second step simulates the network block by block and then assembles the blocks together. The third step functions as a filter to reject networks that do not meet the structural parameters collected from the first step.

Through the network parsing process the following information is determined from the observed network: (a) Proportion of the network that is part of the small components and giant component, (b) Size distribution of the small components and degree distribution of the giant component, (c) Block model and density matrix of the giant component, and (d)

Cluster coefficient and centrality coefficients for the entire network. (a), (b) and (c) are collected as simulation inputs for the second step; (d) is utilized in the selection of qualified networks.

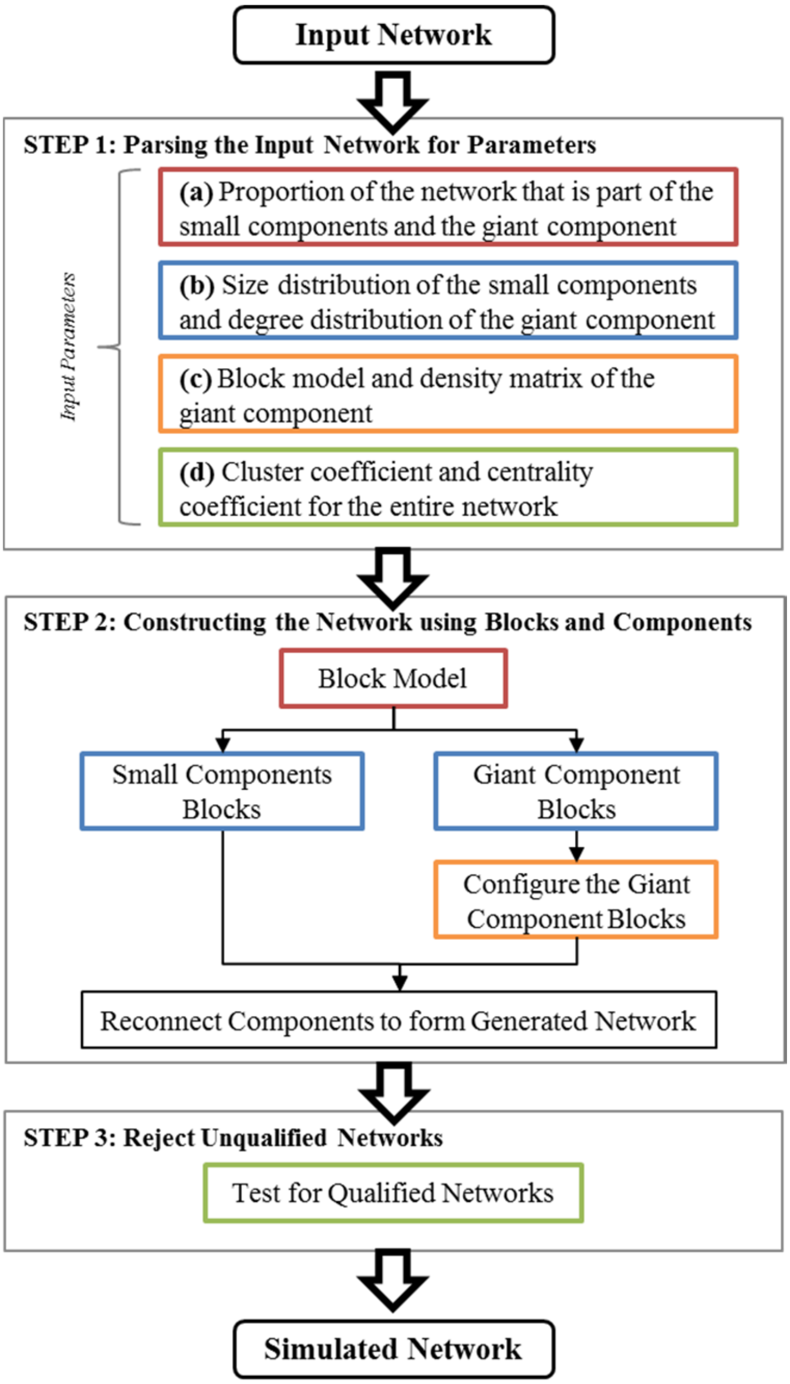


Figure 14 Constructing Networks Using Block Configuration Model

4.4.2 Parsing the Input Network for Parameters (Step 1)

The main objective of a block model is to separate the network into blocks and use connections between blocks instead of connections between vertices to describe the network. The graph of connections between blocks is called a reduced graph. To separate the network into blocks, the idea of structural equivalence was introduced by researchers (Everett and Borgatti 1994). Two vertices are structurally equivalent if they have identical ties to and from the same vertices. We use the established factions partitioning method (de Amorim et al. 1992) to arrange network vertices into blocks. The factions partitioning approach divides a dichotomous network (only have 1 or 0 in adjacency matrix) into *n* groups, then counts the number of missing ties within each group summed with the ties between the groups and takes that as measure of the extent to which the groups form separate clique like structures. In other words, within one particular faction, vertices are more tightly connected to one another than they are to members of other factions. The algorithm can form any number of groups that the user inputs by seeking to maximize connections within the groups, and minimize connections between the factions. As an example, Figure 15 shows the construction of a block model using the faction partitioning method for a peer network collected in a previous empirical energy experiment.

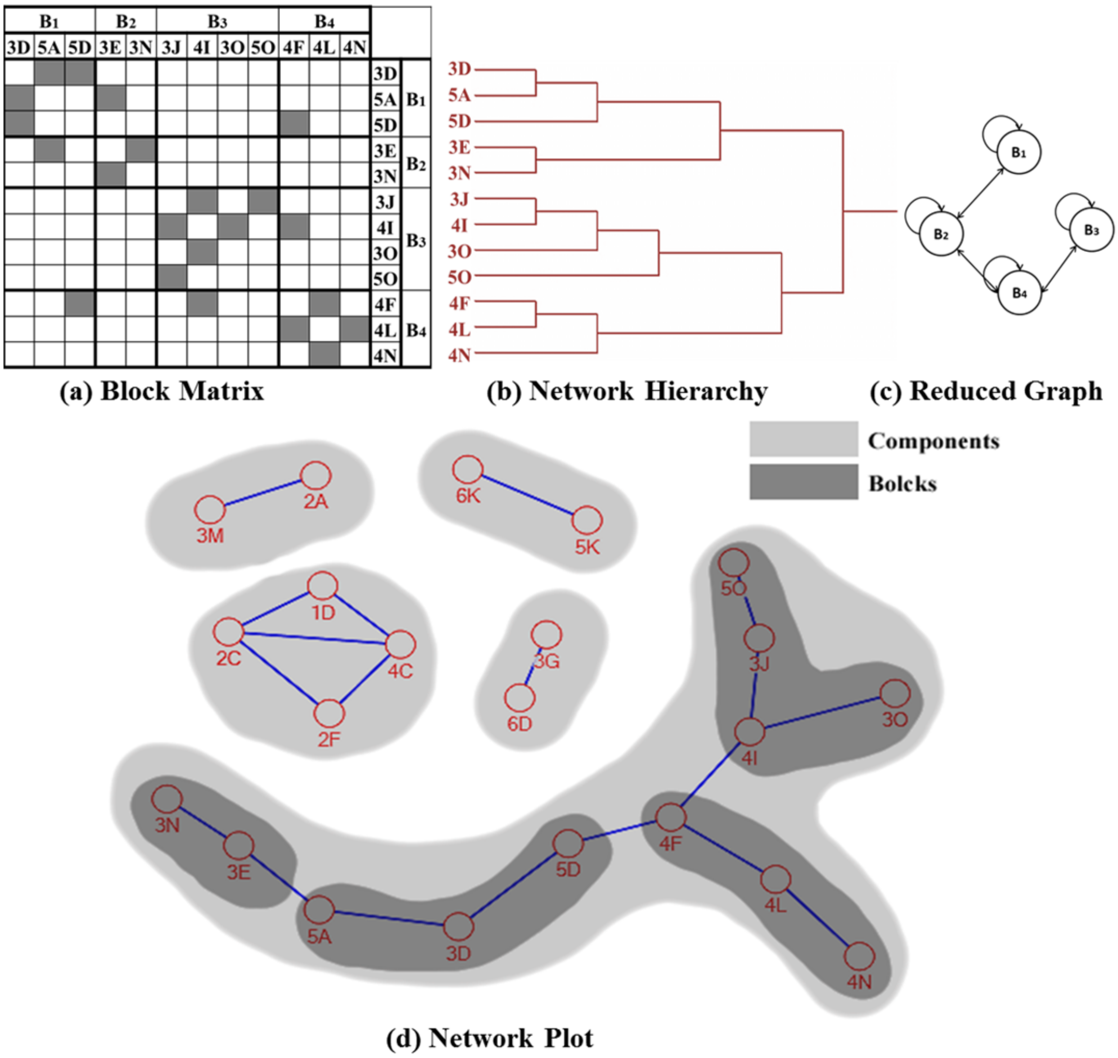


Figure 15 Block Model for a Sample Experiment Peer Network

4.4.3 Constructing the Network using Blocks and Components (Step 2)

The *Block Configuration Model* generates and constructs networks by components and blocks. In the real world, a network can be any combination of small components and giant components and the giant components can be divided into multiple blocks. The size of the giant component increases with the expansion of networks, but the size of small components remains same and follows a certain distribution. The heterogeneity in their behavior requires us to simulate the giant components and small components separately.

Small Components Blocks

In order to generate the small components of a network, we need to determine the expression for the distribution of components size. Let p_k be the probability that a vertex has degree k and let q_k be the probability that a vertex has excess degree k. Excess degree is the number of *stubs* that are not connected to the existing generated network (Newman 2010).

Excess degree is a function of degree and probability that a vertex has a certain number of degrees. The formula to calculate excess degree is:

$$q_k = \frac{(k+1)p_{k+1}}{\langle k \rangle} \tag{4.1}$$

q_k is the probability a vertex has k excess degree;

p_{k+1} is the probability a vertex has $k+1$ degree

As a result, the probability generating functions for p_k and q_k are:

$$g_0(x) = \sum_{k=0}^{\infty} p_k x^k \quad , \qquad g_1(x) = \sum_{k=0}^{\infty} q_k x^k \tag{4.2.a}$$

For these equations, we know the exact number n_k of vertices having degree k for each degree k from the network's adjacency matrix. Therefore, we can write the probability generating functions in terms of n_k as the following:

$$g_0(x) = \frac{\sum_k n_k\, x^k}{\sum_k n_k}, \qquad g_1(x) = \frac{\sum_k (n_k - 1) x^k}{\sum_k (n_k - 1)} \tag{4.2.b}$$

As noted earlier in Equation (4.1), there is a direct relationship between degree distribution and excess degree distribution, utilizing this relationship we can derive the following:

$$g_1(x) = \frac{g_0'(x)}{g_0'(1)} \tag{4.3}$$

It is not always possible to find the closed form of $g_1(x)$ under some conditions, so we have to approximate its form numerically.

In the end, we aim to quantify the probability that a randomly chosen vertex belongs to a small component of size s defined as π_s. Doing so will allow us to find the explicit expression of component size distributions and implement accurate simulation for small components. The small component distribution (π_s) given by Newman (Barabási et al. 1999) is defined as:

$$\begin{cases} \pi_s = p_0, & s = 1 \\ \pi_s = \dfrac{\langle k \rangle}{(s-1)!}\left[\dfrac{d^{s-2}}{dx^{s-2}}[g_1(x)]^s\right]_{x=0}, & s > 1 \end{cases} \tag{4.4}$$

Giant Component Block

A giant component in a network is a component whose size grows as the size of the network increases. Giant components differ from small components whose size is deterministic in that giant components can expand in size dynamically. While it is common for networks to have a giant component, it is not always the case. The existence of a giant component depends on the parameters of the degree distribution of the network.

In order to create a more accurate random network, our model permutes the giant component's adjacency matrix in order to rearrange the adjacency matrix into blocks according to each block's density. The *density* of a block is the proportion of ties in the block divided by the total of number of possible ties. A density matrix is then formed by summing the densities for each block. The density matrix enables us to construct networks block-by-block rather than uniformly picking connections as is the case in the *ER Model* and *Configuration Model*.

Assembling Blocks and Components

The next step is to calculate a probability for each block by normalizing the vertex degree across the block. According to this probability, stubs are selected and connected to form the giant component. The giant component is then combined with the small components to create the complete generated network.

4.4.4 Reject Unqualified Networks (Step 3)

In order to determine which randomly generated networks most accurately represent the observed real network, we need to compare the clustering coefficient and centralities of the simulated network and the observed network. The clustering coefficient is the parameter to quantify transitivity, which is a network structural parameter we introduced in section 4.3.2. After step 2, the clustering coefficients and centralities will be calculated for each newly generated network. Generated networks that do not meet the coefficient criteria derived from observed networks will be rejected. However, a direct comparison of the clustering coefficients of the generated networks and the observed network cannot be made because the networks are of different sizes. If we assume a vertex v has at least two neighbors, which we will denote *i* and *j* and *i* and *j* are both extended from *v*, then the degree of *i* and *j*, denoted as k_i and k_j, both follow the excess degree distribution of the network. Then, the probability that there exists an edge between *i* and *j* is $\frac{k_i k_j}{2m}$. Based on the law of total probability, we can formulate:

$$C = \sum_{k_i, k_j = 0}^{\infty} q_{k_i} q_{k_j} \frac{k_i k_j}{2m} = \frac{1}{2m} \left[\sum_{k=0}^{\infty} k q_k \right]^2 \tag{4.5}$$

If we substitute Equation (4.4) into Equation (4.5), we can formulate:

$$\begin{aligned} C &= \frac{1}{2m\langle k \rangle^2} \left[\sum_{k=0}^{\infty} k(k+1) p_{k+1} \right]^2 = \frac{1}{2m\langle k \rangle^2} \left[\sum_{k=0}^{\infty} k(k-1) p_k \right]^2 \\ &= \frac{1}{n} \frac{[\langle k^2 \rangle - \langle k \rangle]^2}{\langle k \rangle^3} \end{aligned} \tag{4.6}$$

From Equation (4.6), we observe that C is a function of *n* (the network size and degree distribution). Even if the simulated and observed network have the same degree distribution, the value of C can still vary with network size. C is a random output for each simulated network. In our model, we calculate C from experimental data as a benchmark to determine qualified networks from erroneous randomly generated networks. To make this comparison, we use an adjusted clustering coefficient to account for the variance in network size:

$$C_c = C_e \frac{n_s}{n_e} \tag{4.7}$$

C_e is the clustering coefficient derived from experimental or observed network. n_e is the number of vertices in an experimental or objective network. n_s is the size of the network we are going to simulate. C_c is the calibrated clustering coefficient we use as a benchmark to select qualified networks in our *Block Configuration Model.*

4.4.5 Sample Simulated Network

The computational algorithm developed from the model process and a sample network constructed from the algorithm is shown in Figure 16.

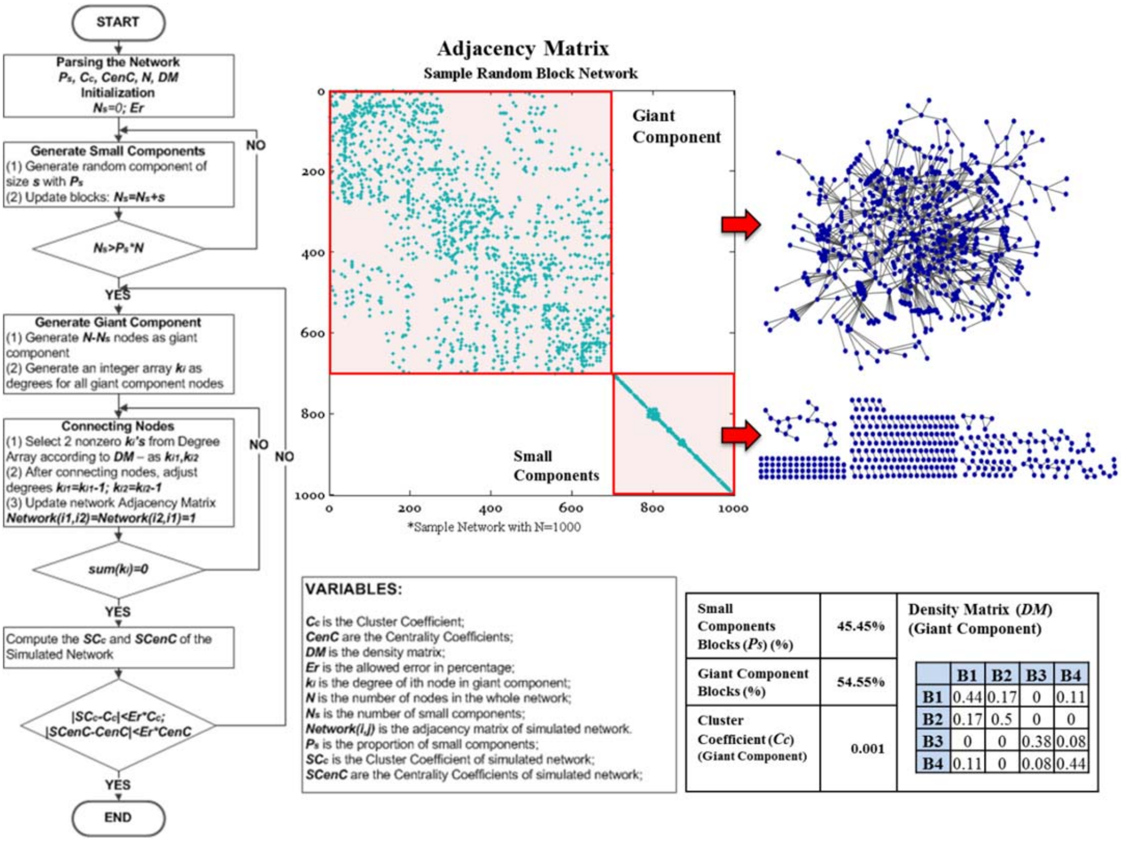


Figure 16 Block Configuration Model Algorithm

4.5 Simulating and Validating the Block Configuration Model

4.5.1 Eco-feedback Empirical Experiments

Previous research has studied how much energy individuals can conserve through the use of a normative eco-feedback system. The amount of energy conserved has been observed to be highly dependent on the structural position of individuals within their peer network (Peschiera and Taylor 2012; Peschiera et al. 2010). The *Block Configuration Model* is utilized to simulate the behavior of networked building occupants when they are exposed to eco-feedback. The occupant peer network data used as an input to the simulation was collected as part of multiple energy efficiency experiments conducted in a multi-floor building in New York City from 2009 to 2011. In the experiments, residents of a multi-family residential building were exposed to an eco-feedback system that provided information on their own energy use as well as the energy use of their peers located in other apartments in the building. Prior to the experiments, residents in the experimental study group were asked to self-identify their friends so that a peer network for the building could be constructed. The experimental data set includes data collected from three different studies conducted in a test-bed building between 2009 and 2011.

4.5.2 Simulating the Networks from the Empirical Experiments

We executed an agent-based simulation to emulate the energy consumption patterns of residents for each of the three experimental data sets. The inputs for the simulation are the connectivity and structural information of the observed peer network from each experiment.

In order to compare the performance of the *Block Configuration Model* against conventional random network generation models we simulated a series of networks using four different algorithms (*ER Model*, *Preferential Attachment Model*, *Configuration Model* and the *Block Configuration Model* we introduce in this paper). The simulation process of *Block Configuration Model* follows the process displayed in Figure 16. The process begins by deriving and scaling the basic structural information from the peer networks observed in the energy efficiency experiment as input for the network simulation. Then, by using this information as input, the simulation algorithm is used to generate a series of random networks. During the simulation, we generated 1,000 qualified random networks, each with 1,000 vertices for each random network model. Each of the random network models is compared to the energy simulation of the observed real network to determine relative performance.

There are two primary considerations in comparing our random network model with conventional models. The first is how close the coefficients of our synthetic networks are to the observed network. The second is how these generated networks perform in simulating residents' energy consumption.

Table 8 Comparison of Network Structural Parameters between Random Network Simulation Models (2011 Experiment)

Mean Values	Observed Network	ER Model	Preferential Attachment Model	Configuration Model	Block Configuration Model
Proportion of small components	45.45%	0%	0%	74.96%	45.45%
Proportion of giant component	54.55%	100%	100%	25.04%	54.55%
Adjusted Clustering Coefficient*	6.6E-3	7.3E-2	1.7E-3	1.4E-3	6.5E-3
Degree Centrality	1.72	69.59	2.00	1.71	1.70
Betweenness Centrality	3.6E-2	1.5E-3	5.4E-2	1.7E-1	2.4E-2

* Adjusted Clustering Coefficient is a scale factor that adjusts the clustering coefficient based on the network size in accordance with Equation (4.5).

As can be observed from Table 8, one of the most important advantages of the *Block Configuration Model* is that it generates a random network with structural parameters (i.e., proportion of small and giant components) consistent with the observed network. Since the *Block Configuration Model* takes the proportion values as a control variable and simulates each block separately, it can more accurately represent the combination of component blocks compared to the conventional models. The *Block Configuration Model* also has a higher accuracy for the transitivity property as evidenced by the close alignment with the observed network's adjusted clustering coefficient. This is due that fact that the *Block Configuration Model* rejects unqualified networks that do not meet the clustering coefficient criteria relative to the experimental data. While the *Block Configuration Model* is observed here to be more accurate than the conventional models on all metrics, it is still unknown at this point if this improvement will translate into a more accurate prediction of energy consumption.

4.5.3 Simulating Energy Consumption

Although we have confirmed the structural consistency of the *Block Configuration Model* with the real-world experimental network, it is still necessary to determine how the *Block Configuration Model* performs relative to conventional models in an energy consumption simulation. To determine this, we created an agent-based simulation model to emulate the energy consumption patterns derived from each of the experimental data sets. In addition to simulating the energy consumption in the real experimental network, we also executed the simulation using the networks generated by the *Block Configuration Model* and the other three conventional algorithms.

Based on the observed behaviors of residents in the experiment, we created a decision model for all agents as shown in Figure 17. Each agent in the simulation can interact with other agents to whom the agent is directly connected to within the peer network. The decision flow is based on the comparison of the agents' energy consumption. We differentiate a given agent on the basis of whether the given agent is connected to another agent that uses less energy than itself. This assumption is based upon the observation of Peschiera and Taylor (Peschiera et al. 2010) that people have a higher probability to take actions to save energy when they are connected to a person who uses less energy. Once the agents make their decision to save or not save energy, the decrease and increase to the amount of energy used follows a Geometric Brownian Motion process. Since the Geometric Brownian Motion process is a percentage drift, it is not only able to simulate the increase and decrease amount as random variables, but also assures the energy consumption is non-negative value.

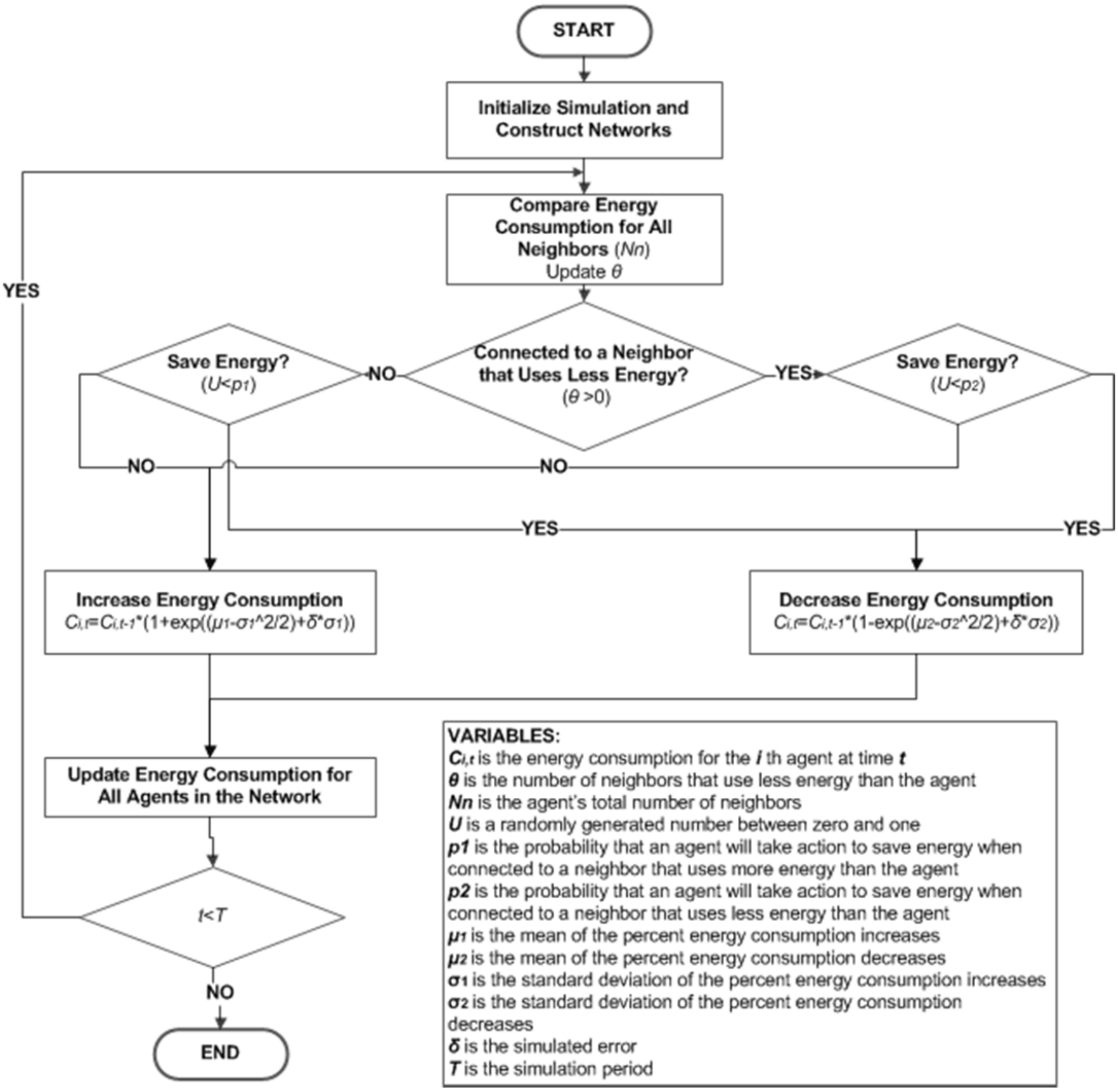


Figure 17 Decision Model (Agent-Norm) for Agent-based Simulation

The simulation inputs are derived from three experiments separately and displayed in following Table 9.

Table 9 Agent-based Simulation Inputs

Probabilities for Decision Making

2009 Experiment	Probability to Decrease Energy Consumption	Probability to Increase Energy Consumption
Connected to a Neighbor Using Less Energy	0.40	0.60
Not Connected to a Neighbor Using Less Energy	0.65	0.35

2010 Experiment	Probability to Decrease Energy Consumption	Probability to Increase Energy Consumption
Connected to a Neighbor Using Less Energy	0.64	0.36
Not Connected to a Neighbor Using Less Energy	0.40	0.60

2011 Experiment	Probability to Decrease Energy Consumption	Probability to Increase Energy Consumption
Connected to a Neighbor Using Less Energy	0.59	0.41
Not Connected to a Neighbor Using Less Energy	0.37	0.63

Parameters for the Geometric Brownian Motion process

	2009 Experiment		*2010 Experiment*		*2011 Experiment*	
	% Increase	% Decrease	% Increase	% Decrease	% Increase	% Decrease
Mean	45.05	18.18	26.99	18.58	23.78	17.21
STD	72.65	16.95	38.91	15.23	30.42	13.13

Parameters for Lognormal Distribution

	2009 Experiment		*2010 Experiment*		*2011 Experiment*	
	Mean	STD	Mean	STD	Mean	STD
Lognormal Distribution	1.55	1.17	0.79	0.58	0.59	0.27

4.5.4 Comparison of Models

Observed peer networks from the 2009, 2010 and 2011 experiments have a small number of vertices and are assumed to remain stable during the study period. To maintain consistency, the networks generated by the *Block Configuration Model* and the other three conventional algorithms all contain the same number vertices for each simulation run. The simulation duration is set to 60 days and the initial energy consumption of agents is simulated based on the control groups' energy consumption in each experiment. Each simulation algorithm is tested for 1,000 runs and each run rebuilds another random network using the same algorithm. One single simulation run simulates all agents' energy consumption and interaction through the whole 60 day period. The normalized simulation results are summarized in Figure 18.

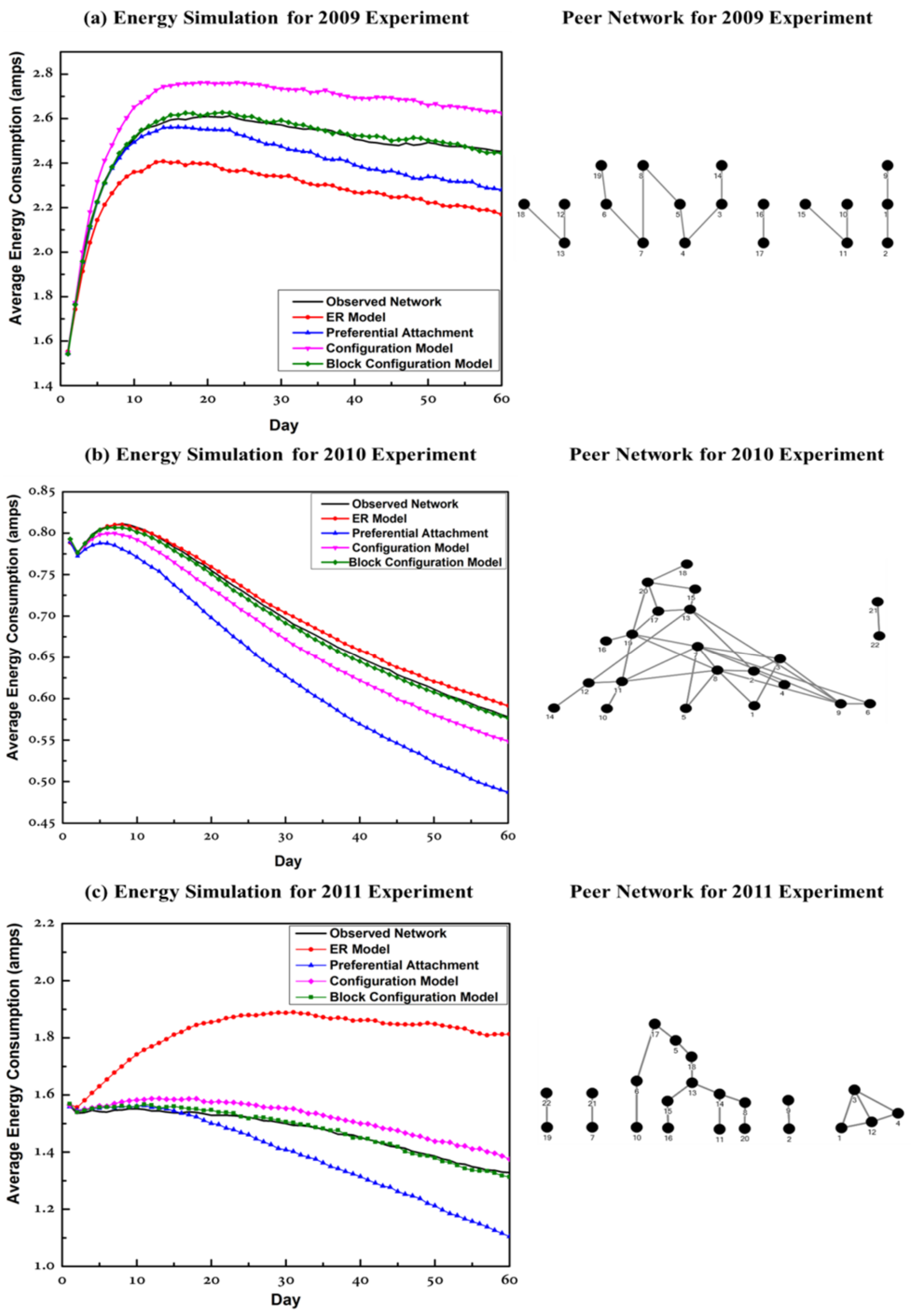


Figure 18 Energy Consumption Simulation to Compare Models across Three Experimental Data-sets

Figure 18 shows that the *EA Model* is the least accurate random network model and that the *Block Configuration Model* and *Configuration Model* are relatively reliable compared to the other two algorithms. While the *Configuration Model* is stable, it is clearly visible that the average energy consumption simulated by the *Block Configuration Model* is closest to the observed network energy consumption and therefore, performs better than the other conventional models in terms of accuracy. Detailed error comparisons for each random network model are provided in Table 10. For each of the three experimental data-sets, the *Block Configuration Model* resulted in the lowest percentage error of the four models investigated.

Table 10 Average Errors Compared to the Observed Network

	ER Model	Preferential Attachment Model	Configuration Model	Block Configuration Model
	Error (%)	Error (%)	Error (%)	Error (%)
2009 Experiment	21.05	8.85	15.59	1.39
2010 Experiment	0.99	9.53	3.40	0.56
2011 Experiment	12.88	3.53	1.74	0.34

4.6 Discussion

The goal of this research was to develop an accurate and reliable simulation to emulate energy consumption behavior when occupants are exposed to eco-feedback. To do so, we introduced the *Block Configuration Model*, a new model for generating more accurate random networks used in energy consumption simulation. The *Block Configuration Model* expands on the conventional *Preferential Attachment Model* and *Configuration Model* (Newman et al. 2001) by separating the observed network into blocks and reassembling them using the density matrix. The giant components' structures in the observed network (Figure 15(d)) are similar to those generated by the *Preferential Attachment Model*, but because the *Preferential Attachment Model* does not incorporate the disconnectivity in small components it overestimates the network's potential energy savings. At the same time, although the *Configuration Model* may be capable of generating disconnected components, researchers lack the control over the size and connectivity of network components. The *Block Configuration Model* allows researchers to control the network size and connectivity thus ensuring that the resulting generated network is consistent with each observed network's clustering and transitivity properties. Specifically, in the three observed building occupant networks we can see that connectivity and clustering of occupants varies greatly across the three data sets. We postulate that this variance can be attributed to the multifarious connections of a building occupant network related to geo-spatial, social and community issues. Therefore, when simulating building occupant networks the freedom to control network size and connectivity are crucial to generating networks that mimic real life networks. When compared with the conventional random network generation models (*ER Model,* *Preferential Attachment Model* and *Configuration Model*), the *Block Configuration Model* is most consistent with the structural properties of the observed network. This consistency is highlighted the most by the fact that the ratio of small components to giant components is almost identical to the observed network (Table 8) and is a direct reflection of the *Block Configuration Model's* flexibility in controlling connectivity parameters.

The agent-based energy behavior simulation results indicate that the *Block Configuration Model* is the most accurate in predicting the energy consumption of building occupants exposed to eco-feedback. The *Block Configuration Model* is shown to outperform the conventional models for all three experimental data sets. While one would expect the performance of the conventional models to be consistent across each experimental case, further analysis of the results in Figure 18 shows this not to be the case. The simulation results for the 2009 experiment indicate the *Preferential Attachment Model* to be the second most accurate at simulating the occupant network's energy consumption behavior, while for the 2010 experiment it was the *ER Model*. In the 2011 experiment, the *Configuration Model* is the second most accurate at simulating the consumption behavior. This variance in the results further highlights the ability of the *Block Configuration Model* to adapt to different types of building occupant networks and, in turn, yield more accurate simulations of occupant energy consumption behavior.

This research extends current energy efficient behavior simulation literature by developing a model that is able to integrate the impact of eco-feedback systems and occupant peer networks. Energy consumption simulation allows researchers to quantify consumption savings on a large scale, which is not easily implemented in empirical experiments (Azar and Menassa 2012; Hoes et al. 2009). Current behavior simulation research (Azar and Menassa 2012; Haas et al. 1998; Hoes et al. 2009) has been limited to modeling individual energy consumption behavior by residents and not how the interactions between residents impacts consumption behavior. Models that incorporate peer network interactions allow us investigate the behavior patterns of people who are socially connected to each other. While these models increase the understanding of individual consumption behavior, they do not reflect real world conditions in that a person's conservation decision making is highly dependent on social norms (Goldstein et al. 2008). Therefore, our simulation model extends current energy consumption behavior research by introducing network theory to account for interactions between residents. Rather than simulating each resident's behavior separately, we model that residents in a building are connected to each other and form an occupant peer network. Doing so enables us to simulate the energy consumption decision making process on an occupant-by-occupant basis, which is more robust than previous simulations and simultaneously incorporates the impact of socially contextualized eco-feedback. Results of this simulation and the introduction of the *Block Configuration Model* open up several pathways in the field of energy behavior simulation. In our simulation we assume that the network we are going to simulate is a single complex network. However, networks in the real world can be much more complex. A single-layer network may actually be composed of a network system with multiple layers. Future energy behavior simulations can expand upon this work by adding additional layers to the network modeling process using the *Block Configuration Model*. Such an extension of energy behavior simulations will also enable researchers to further account for other sociotechnical interactions of building occupant networks and eco-feedback systems and increase the predictive power of energy behavior simulations. Moreover, more sophisticated and predictive network based energy behavior simulations can be utilized to extend empirical experiments to the city scale and yield a deeper understanding of large scale energy consumption patterns. Findings from such large scale energy behavior models could have important implications on the planning and design of energy policy and infrastructure systems.

4.7 Limitations

While the *Block Configuration Model* is more accurate than its conventional counterparts, it is not without limitations. Similar to the *Configuration Model*, the generated network may contain either loops or multi-edges. When randomly connecting the generated vertices, if one vertex cannot find a counterpart to connect, it may connect to itself (loop) or connect to a counterpart already connected (multi-edge). However, the average number of loops and multi-edges in the configuration model remains constant even when the networks grows, which means that the density of loops and multi-edges trends to zero when the network is large enough (Itzkovitz et al. 2004). A second limitation of our agent-based energy consumption simulation is the assumption that building occupants' energy consumption is dependent on consumption information sharing. While this may not be the case in all sample populations, previous research (Jain et al. 2012; Peschiera and Taylor 2012; Peschiera et al. 2010) has provided statistically significant evidence of such dependence in several experiments. Moreover, to further ensure our simulation reflects real life conditions and consumption behavior we utilized inputs derived from three different empirical experiments.

4.8 Conclusion

In this paper we proposed a refined model to simulate random networks, the *Block Configuration Model*, and implemented it in an agent-based energy consumption simulation. The results of the simulation indicated that the *Block Configuration Model* outperforms the conventional random network generation models in predicting the energy consumption of networked users exposed to eco-feedback across three separate experimental data-sets. Specifically, the *Block Configuration Model* was found to be more accurate in replicating the structural parameters of an observed real world building occupant network by incorporating inputs of transitivity, clustering and centrality information.

The introduction of normative eco-feedback systems has allowed researchers to collect data regarding the impact a building occupant peer network has on consumption. However, empirical studies that aimed to examine the dynamics of occupant consumption behavior in these systems have been limited in their ability to assess such dynamics at large scales. Research at the intersection of energy consumption simulation and building occupant peer networks can fill this gap by utilizing the flexibility and generalizability of computer simulation techniques and random network models. By gaining a deeper understanding of the dynamics occurring between occupants in large networks, researchers may be able to formulate behavioral interventions that leverage peer networks and maximize energy savings. Because buildings account for a substantial portion of CO_2 emissions, such interventions could provide significant and sustainable reductions in emissions and help to realize more energy efficient buildings and cities.

Chapter 5

5. CONTRIBUTIONS

5.1 Theoretical Contributions

I began this dissertation by pointing out the significance of the role of peer networks in our modern society. Later, I outlined the major components of peer network structure that impact energy efficiency in residential buildings. I proposed an occupant network decision model to emulate the process of information diffusing through peer networks. To refine this decision model, I conducted research on multi-layered network systems to layer peer networks and research on random networks to develop a block configuration model. In its entirety, the contributions of this research develop a deeper understand and build theory regarding Peer Network Energy Efficiency. The findings presented in this dissertation provide new knowledge on how networks affect occupant decisions and extend the experimental efforts to more general networks that empirical studies have not covered before. The theoretical and academic contributions of Chapter 2 through 4 can be found in following subsections.

Chapter 2: Modeling Building Occupant Network Energy Consumption Decision-Making: The Interplay between Network Structure and Conservation

Earlier experimental research had found that sharing energy use information through peer network promotes energy conservation by building occupants (Fischer 2008; Peschiera et al. 2010; Petersen et al. 2007). However, the topology of networks can be different from building to building. If researchers want to predict the energy saving behaviors in buildings where experimentation is not possible, simulation would be an appropriate choice. However, before simulation can be used we need an understanding of a network structure's impact on energy conservation behavior.

In Chapter 2, I proposed an agent-based model and confirmed the validity of peer network's impact on energy saving behavior. The model suggests that feedback should focus on those residents with stronger connections rather than more connections. More connections have a limited benefit in terms of enhancing energy efficiency. The odds ratios of logistic regression in validation test also indicate that non-adjacent vertices have an insignificant impact on the object vertex during the same period. In other words, people who are directly connected to residents have higher impact. In all, the goal of Chapter 2 was achieved both in the agent-based simulation model and the regression test; these models confirmed that the structure of network had a substantial impact on energy efficient behaviors. This conclusion is consistent with experimental networks by other researchers' work (Peschiera and Taylor 2012), but may now be applied more broadly to other buildings.

Chapter 3: Layering Residential Peer Networks and Geospatial Building Networks to Model Change in Energy Saving Behaviors

The purpose of Chapter 3 was to build upon the work in Chapter 2 to develop an accurate and efficient model to examine energy conservation behaviors in layered peer and geospatial networks. In most cases, an individual's peer network is not isolated from other networks and these networks also impact energy saving behavior simultaneously. One potential channel for energy efficient behavior adaptation is from neighborhoods.

Geospatial networks may co-influence energy efficient practices spreading within peer networks. However, previous research in energy efficiency and network theory study networks independently and exclusively. My research developed an efficient and accurate quantitative model that is able to capture the dynamics of multi-layered network systems under perturbation. Expanding the Mean-Field Theory and SIS model (Pastor-Satorras and Vespignani 2001, 2002), the model simulates the energy efficient behaviors as diseases spreading through multiple channels. The findings in Chapter 3 complement the basic model in Chapter 2. The method is also scalable to larger and more complex simulated, multi-layer networks. For example, the networks of communities of practices, the hierarchical networks in commercial building, transportation networks and internet-connected networks.

Chapter 4: Block Configuration Modeling: A Novel Simulation Model to Emulate Building Occupant Peer Networks and Their Impact on Building Energy Consumption

In this chapter I developed an accurate and reliable model that can emulate energy efficient peer networks so that the randomly generated networks possess similar attributes to the target network. Superior to the Configuration Model (Newman 2010), the Block Configuration Model is able to reflect the target network's clustering and transitivity profile. To achieve this goal, we utilized random network theory and block models to implement the conventional configuration model, which can construct arbitrary degree distribution networks. The comparison between the parameters of the simulated output for all three models (the Preference Attached Model (Barabási and Albert 1999), Configuration Model (Newman 2010), and Block Configuration Model) to experimental data found that the Block Configuration Model I developed is more accurate than the other models. Therefore, my model allows researchers to generate arbitrary random networks with a controllable structural coefficient. This effort makes it possible to more accurately evaluate the performance of energy efficient feedback systems deployed to peer networks.

5.2 Practical Contributions

The models in this dissertation serve as a wind tunnel test for energy feedback system design in various networks. The basic decision model in Chapter 2 identifies the most significant structural parameters in networks that can help designers of eco-feedback systems to find out what information is important and how to distribute this information to residents. The layered network model helps designers to create and evaluate multiple network feedback channels. The block configuration model assists designers in building desired networks for testing energy efficiency interventions in certain peer groups.

The introduction of network theories allows engineers to collect meaningful and selective information that impact building occupants' energy consumption. However, studies that aimed to examine the dynamics of occupant consumption behavior in these systems have been limited by their ability to scale. Research at the intersection of energy consumption simulation and building occupant peer networks may fill this gap by combining computer simulation techniques with network models. With a deeper understanding of peer network dynamics, researchers may be able to formulate behavioral interventions that optimize energy savings. Buildings account for a considerable portion of CO_2 emissions in our society, such interventions could enable significant and sustainable reductions in emissions. Multilayer network system modeling and block configuration modeling will allow engineers to quantify the savings resulting from energy efficient behaviors through sharing energy consumption information via peer networks and geospatial networks. These models are also quantitatively accurate and efficient to develop.

One potential specific application for my research is the improvement of social media energy efficiency applications. Many energy companies are working hard to provide more feedback to their consumers. For example, OPOWER, one of the leading energy information software companies, set up a platform that enables utilities to provide targeted energy data and advice to each customer. Sixty-five utilities partner with OPOWER to improve their energy-efficiency feedback system and motivate their customers to become more energy efficient. Starting from April 3rd 2012, people can access a social media app on Facebook to directly connect with their utility account and track their energy consumption and share energy savings accomplishments with their friends. The social app can compare energy use to similar homes and among friends and automatically import energy data for their providers. Although these companies introduce the idea of peer networks into their products and services, we still have limited understanding of the role of networks in energy conservation behaviors. In addition, the benefits of connecting multiple layers of residency networks (for example, geospatial networks and peer networks) may potentially be a new approach to promote energy savings. Therefore, our models are able to provide theoretical support for further practical development of these feedback systems.

Chapter 6

6. FUTURE RESEARCH

Although the topic of energy efficiency has been studied for decades, little research has been based on the theory of human and spatial networks. At the same time, the development of communication and transportation technologies enables more profound connections between energy users and significantly influences their daily energy consumption. My dissertation has pointed out the importance of the structural topology of networks in modeling energy efficient behavior and has proposed a set of numerical and simulation models to understand peer network mechanisms. However, this approach only addresses a small piece of a very complex puzzle. Thus, future research is still necessary on following topics:

1. *Develop geospatial networks research to promote energy efficient behavior diffusion*

   Many researchers have realized that physical closeness is an important factor with the potential to change human behavior. For example, the "neighborhood effect" servers as an efficient channel through which to facilitate the diffusion of practices and innovations (Cartigny et al. 2004; Hagerstrand 1968; Haggett et al. 1977; Roberts et al. 2004). However, these empirical studies do not consider the geospatial locations of interconnected networks. The concept of "neighborhood" in this line of research is too broadly and ambiguously defined to quantify its distance and accessibility. In addition, to enable research on a larger scale, it is appropriate to model neighborhood relationships as an interconnected geospatial network for computational convenience. Therefore, eco-feedback strategies based on geospatial network research can make potential contributions to our understanding of the diffusion of energy efficient behavior.

2. *Optimize energy efficient practice diffusion in multiple networks*

   Building occupants are connected by heterogeneous networks, which are characterized by their social status, physical locations and shared activities. Energy-saving practices can be transmitted via these networks at various rates. Similar to other efforts at network flow optimization, researchers can optimize behavior diffusion through selecting, incorporating and manipulating networks by their types, structures and breadth. Management of the itemized practices diffusion through multiple networks can be a novel practical strategy to promote energy efficiency.

3. *Conduct experiments and simulations on multiple buildings*

   As with building occupants, buildings are also members of network. Measuring and sharing the building energy consumption profiles in a building network perspective can expand the range and scope of eco-feedback system research from the building level to the community level. Moreover, in addition to information sharing, buildings may have more complicated physical interactions with each other in a network, for instance due to mutual shading and the resultant thermal exchange. Studying buildings in networks could increase our knowledge on inter-building energy consumption relationships.

4. *Provide customized feedback by community*

Another potential research opportunity is to anticipate the whole building response to eco-feedback systems according to local community features (e.g. the educational background, income level and culture diversity of the communities' residents). Community features could differentiate residents' response to eco-feedback. Through the research on community features, researchers will be able to identify and estimate the role of different types of feedback. In other words, customized feedback based on community features is a potential approach to enhance energy efficiency at the level of the local community.

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