

2018

Exploring households' weatherization adoptions: An agent-based approach

Wanyu Huang
Iowa State University

Follow this and additional works at: <https://lib.dr.iastate.edu/etd>

Part of the [Industrial Engineering Commons](#)

Recommended Citation

Huang, Wanyu, "Exploring households' weatherization adoptions: An agent-based approach" (2018). *Graduate Theses and Dissertations*. 16924.
<https://lib.dr.iastate.edu/etd/16924>

This Thesis is brought to you for free and open access by the Iowa State University Capstones, Theses and Dissertations at Iowa State University Digital Repository. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

Exploring households' weatherization adoptions: An agent-based approach

by

Wanyu Huang

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
MASTER OF SCIENCE

Major: Industrial Engineering

Program of Study Committee:
Caroline C. Krejci, Co-major Professor
Michael C. Dorneich, Co-major Professor
Ulrike Passe
Lizhi Wang

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2018

Copyright © Wanyu Huang, 2018. All rights reserved.

DEDICATION

I would like to dedicate this thesis to Prof. Krejci, Prof. Dorneich and Prof. Passe for the guidance and help on the sustainable cities project, and to Prof. Wang who taught me lots of optimization skills and provided useful guidance on the PSERC project. I would also like to thank my fiance Siyuan Qiao for his love and support during my undergraduate and master periods. I am grateful too for the support from my parents, who encourage me spiritually throughout my life. Love you all.

TABLE OF CONTENTS

	Page
LIST OF TABLES	vi
LIST OF FIGURES	vii
ACKNOWLEDGMENTS	ix
ABSTRACT	x
CHAPTER 1. INTRODUCTION	1
1.1 Overview	1
1.2 Weatherization	3
1.3 Social Network Analysis in Energy Behaviors	4
1.4 Agent-Based Model in Energy Behaviors	5
1.5 Thesis Organization	7
CHAPTER 2. ANALYZING RESIDENTIAL WEATHERIZATION DECISIONS USING HYBRID SIMULATION MODELING	9
2.1 Introduction	10
2.2 Modeling Methods	13
2.2.1 Building Energy Simulation	13
2.2.2 Social Network Analysis	14
2.2.3 Agent-Based Modeling	17
2.3 Hybrid Simulation Model Description	19
2.3.1 Building Energy Model Description	19
2.3.2 Social Network Model Description	20
2.3.3 Agent-based Model Description	22

2.4	Experiments	29
2.5	Results	31
2.6	Discussion	37
2.6.1	Encourage Community Connectedness and Engagement	38
2.6.2	Leverage the Influence of Trusted Messengers	39
2.6.3	Invest in Publicizing and Improving the Efficiency of WAPs	40
2.6.4	Periodically Remind Residents about Seasonal Peak Energy Costs	40
2.7	Conclusion	41
CHAPTER 3. WEATHERIZATION ADOPTION IN A MULTILAYER SOCIAL NETWORK: AN AGENT-BASED APPROACH 43		
3.1	Introduction	44
3.2	The Theoretical Framework	47
3.3	Conceptual Model Description	48
3.3.1	Building Energy Simulation	48
3.3.2	Agent-based Model	50
3.4	Experiments and Results	65
3.4.1	Social Network Structure	67
3.4.2	Randomness of The Physical Social Network	67
3.4.3	Selection of Initial Weatherized Household Agents	68
3.4.4	Weatherization Assistance Program Service Probability	70
3.4.5	Media Agents	70
3.5	Conclusion	74

CHAPTER 4. CONCLUSIONS AND FUTURE WORK	76
4.1 Conclusion	76
4.2 Future Work	77
4.3 Contributions	78
BIBLIOGRAPHY	80

LIST OF TABLES

	Page
Table 1.1	Connections and differences between $M1$ and $M2$ 8
Table 2.1	Rules for interaction-based information level increases 27
Table 2.2	Experimental Conditions. — means not applicable 31
Table 2.3	Cohen’s d effect size thresholds 31
Table 2.4	Comparisons of “ $leader: NL$ ” and “ $leader: AL$ ” subjects 34
Table 2.5	Comparisons of “ $leader: NL$ ” and “ $leader: NAL$ ” subjects 34
Table 2.6	Comparisons of “ $L: short$ ” and “ $L: long$ ” subjects 36
Table 2.7	Comparisons of “ $CC: low$ ” and “ $CC: high$ ” subjects 36
Table 3.1	Age of population 18 years and over 51
Table 3.2	Household income 51
Table 3.3	Education attainment (highest level) of population 18 years and over 51
Table 3.4	Race 52
Table 3.5	IL & AL Evolution Rules (Agent $i \rightarrow$ Agent j). — means not applicable. . . 63
Table 3.6	Fixed Experimental Parameters. 66
Table 3.7	Experimental Scenarios. 66

LIST OF FIGURES

	Page
Figure 2.1	Overview of the hybrid simulation model. 13
Figure 2.2	Four Kinds of Network Types (adapted from Anderson et al. (2012)). 16
Figure 2.3	Two networks with the same network size and different closeness constant values. 21
Figure 2.4	An example of the social network generation process. 22
Figure 2.5	umi model: energy consumption visualization of Capitol East neighborhood 30
Figure 2.6	Average number of weatherized households in each time-step for each experimental scenario 32
Figure 2.7	Average and standard error of the total energy consumption in the final time-step (kWh) 33
Figure 2.8	Average number of weatherized households in the final time-step for three levels of community leader presence 33
Figure 2.9	Average number of weatherized households in the final time-step for short and long agent memory lengths 35
Figure 2.10	Average number of weatherized households in the final time-step for low and high closeness constant values 35
Figure 2.11	Number of weatherized households in the final time-step over 20 simulation replications 37
Figure 2.12	An example energy bill form 41
Figure 3.1	Theoretical framework for households' decision-making processes on whether or not to weatherize their homes. 48
Figure 3.2	Overview of the model. 49

Figure 3.3	A visualization of energy consumptions for residential buildings in the Capitol East Neighborhood.	50
Figure 3.4	An example network consisting of 11 agents and 15 connections.	54
Figure 3.5	Sub-models.	59
Figure 3.7	PSN	60
Figure 3.8	OSN	60
Figure 3.9	Overlaps and differences in a multilayer social network	60
Figure 3.10	Multilayer Social Networks.	60
Figure 3.11	A schematic diagram for SEIR model.	62
Figure 3.12	Ability Judgment.	64
Figure 3.13	Flowchart describing the logic for updating household agent state variables. Agents that adopt weatherization will follow the dashed line to update their <i>IS</i> and <i>AL</i> values.	64
Figure 3.14	NetLogo Interface.	65
Figure 3.16	Effects of multilayer social networks on weatherization adoption.	67
Figure 3.18	Effects of PSN randomness on weatherization adoption. <i>MSN @ PSN means the results of PSN part when households have MSN; MSN @ MSN means the results of MSN part when households have MSN; PSN @ PSN means the results of PSN part when households only have PSN.</i>	68
Figure 3.20	Effects of Different Selections of Initial Weatherized Agents on weatherization adoption.	69
Figure 3.22	Effects of increased WAP service probability on weatherization adoption.	70
Figure 3.24	Effects of increased number of media agents on weatherization adoption.	71
Figure 3.26	Effects of media coverage on weatherization adoption.	72
Figure 3.28	Effects of households' susceptibility to media on weatherization adoption.	73
Figure 3.30	Effects of media agents' adding time on weatherization adoption.	74

ACKNOWLEDGMENTS

Foremost, I must express my sincere thanks to my advisor Prof. Caroline C. Krejci. She is a good advisor and has offered me so many useful guidance and help. I really appreciate her time and efforts that she spent on bettering my research. I feel so lucky to have she been my advisor within the two years. I am grateful too for the support and advice of my co-major advisor Prof. Michael C. Dorneich. I have learned a lot from ACSL group. I also appreciate Prof. Ulrike Passe for the opportunity she provided to let me join the Sustainable Cities project.

My appreciations must go to Prof. Lizhi Wang as well. I have learned lots of useful optimization skills from his classes. I also enjoyed the time on the PSERC M-37 project and thank Prof. Wang for offering me so many useful guidance and help. I also very enjoyed the brainstormings in our individual meetings. It is so exciting and delightful to work with Prof. Wang in this year.

Thank all my committee members again for their time and effort in reading this thesis and their helpful comments in improving this work.

I must acknowledge my friend, Minliang Yang. She is a Ph.D. candidate at Department of Agricultural and Biosystems Engineering of Iowa State University. Thanks for her help and advice on my thesis preparation.

ABSTRACT

This thesis consists of one submitted journal paper and one modified conference paper, both on simulating residents' weatherization adoption decisions.

Residential buildings are responsible for a large number of energy consumptions and are therefore a major contributor to climate change. Weatherization is set of approaches that can be used to make buildings more energy-efficient. This yields many benefits for residents, including reduced energy costs and improved health and safety, as well as benefits for the environment, such as reducing greenhouse gas emissions and conserving resources. However, the current adoption rate for such a good practice remains low. The government has been trying to encourage the adoptions, but its efforts have had limited success. Therefore, it is of great practical significance to explore residents' weatherization adoption decisions, and then assist stakeholders in encouraging weatherization.

This thesis proposes two hybrid simulation models of an urban neighborhood populated with autonomous "households" for their weatherization adoption decisions. They both include three modeling techniques: 1) a building energy simulation model, 2) an agent-based model, 3) a social network model. The building energy simulation model is used to calculate monthly energy consumption data of residential buildings under pre- and post- weatherized conditions, which inform households of the potential energy savings that would result from the decisions to weatherize homes. The agent-based model is used to model the detailed decision-making process of households and peer interactions among them about weatherization. The realistic topology of households' social environment, in which peer interactions and information diffusion take place, is captured by the social network model. The hybrid models represent the complex dynamic feedback loop that connects households' weatherization decisions, energy-related decision outcomes, and communication of outcomes among community members, all of which influence future decisions.

The first hybrid model models a block of 29 households and their physical social networks (i.e., the physical neighborhood). The effects of households' and communities' internal attributes on households' weatherization adoption decisions are explored. Experimental results suggest that more households tend to weatherize when there is a self-weatherized leader or they have short memories about energy bills, and especially in a denser social network as it is a self-reinforcing circle where positive information about weatherization can spread more widely. Four corresponding recommended policies to improve the adoptions of weatherization are also discussed.

The second hybrid model develops an agent-based model with household agents and media agents. It is embedded in a multilayer social network, which allows households to interact via both a physical social network (i.e., their neighborhood) and a virtual social network (i.e., online). We evaluate the strength of social interactions based on households' local centrality, spatial location, and social demographics. Opinion dynamics of households are captured by the Susceptible-Exposed-Infected-Recovered epidemic model. This model is used to explore the effects of more characteristics of households, media, and communities, and evaluate different interventions that government and other policy makers could adopt in an effort to promote weatherization adoption in residential buildings. Experimental results demonstrate the necessity of modeling a multilayer social network and the slight usefulness of a higher value of randomness of the physical social network. The results also indicate that selecting the most important (influential) households as early adopters of weatherization could significantly promote the weatherization adoptions. In addition, slightly increasing the probability of an approved applicant being served by WAP (e.g., the current real-life value in Iowa is 2.5%) yields dramatic increases in weatherization adoptions. How to greatly leverage the effects of media on households' weatherization adoption decisions is also discussed.

CHAPTER 1. INTRODUCTION

1.1 Overview

Energy-saving innovations in residential buildings has been a topic of interest in recent years because of their high levels of energy consumption. In 2016, about 27% of total U.S. energy consumption (U.S. Energy Information Administration, 2017b) and 36.5% of U.S. electricity use was consumed by the residential buildings (U.S. Energy Information Administration, 2017a). This is also a major contributor to climate change. Energy-efficient residential buildings offer great potential for reducing greenhouse gas emissions and saving resources, and therefore protecting the environment. It also can help reduce the economic pressure of low-income households, who spend 16.3% of their annual income on residential energy expenditures (U.S. Department of Energy, 2017), by lowering their energy bills.

Weatherization is the set of various practices to increase the energy efficiency of existing residential buildings, like sealing air ducts, upgrading cooling systems, and installing insulation in walls, floors, and ceilings. Weatherization not only benefits households by lowering energy bills and improving air quality, it also contributes to revitalizing the society through producing more weatherization-related job opportunities and reducing negative environmental impact (U.S. EERE, 2018a). However, high up-front investment and the potentially long financial payback period of weatherization may serve as barriers for households to adopt weatherization, especially for low-income households (Krejci et al., 2016). To overcome these barriers, the U.S. Department of Energy provided the Weatherization Assistance Program (WAP) to qualified low-income households. WAP offers households financial and technical support to make weatherization easier (U.S. EERE, 2018a).

While the current administration is pushing for greater efforts on encouraging the adoptions of weatherization, the current adoption rate of weatherization remains low. Some simply have a

general lack of awareness about weatherization or WAPs (Kathleen, 2006), and/or have difficulties in completing the whole process of WAPs. Some may think weatherization has a bad return on investment. A better understanding of households' decision-making process of weatherization adoptions is useful for stakeholders to learn to improve effectiveness of policies and interventions. Models on households' weatherization adoptions are needed.

The decision-making process of adopting weatherization is complex, which will be influenced by various factors when adopting weatherization. Financial incentives, peer interactions and factual knowledge about weatherization play important roles in households' decisions to adopt weatherization (Letendre et al., ; Southwell and Murphy, 2014; Krejci et al., 2016; Jain et al., 2013; Rai and Robinson, 2015). For example, the interactions between households may serve to convey locally relevant knowledge about weatherization and social norms, e.g., "weatherization saved lots of money for me", "weatherization improved the air quality of my house", or "the application to weatherization assistance program is easy to make and you just need to...". However, traditional energy consumption behavior studies typically ignore social relationships among households.

Traditionally, models of household behavior and building energy consumption have been regression-based aggregate estimates of whole-building behavior in response to thermal stimuli. The models typically do not account for heterogeneity in individual households' behavior, nor do they incorporate social influences (Langevin et al., 2015). In fact, theory and knowledge from the social sciences remain underused in existing energy studies (Sovacool, 2014). Therefore, it is necessary to explore households' social dynamics to have a deeper understanding their energy consumption behavior (Southwell and Murphy, 2014).

The importance of social interactions in determining households' weatherization adoptions suggests that agent-based modeling would be an appropriate method for modeling a network of households. Agent-based models (ABMs) allow researchers to model individual decision makers as autonomous agents that are capable of social behaviors and interactions (e.g., information sharing) with other agents. Over time, the effects of these repeated interactions and feedbacks on individuals' decisions may yield system-wide changes that are unexpected and difficult to predict without the

use of computational modeling (Wang et al., 2007). ABM is a promising methodology for capturing consumer behavior in general and energy technology adoption in particular (Wolf et al., 2012; Macy and Willer, 2002; Epstein, 1999; Bonabeau, 2002; Mittal and Krejci, 2017; Mittal et al., 2017; Mittal and Krejci,). ABM facilitates the modeling of opinion dynamics in a social system, which is useful in representing households' socially-motivated decisions to weatherize their homes (Southwell and Murphy, 2014; Rai and Robinson, 2015; Azar and Menassa, 2011). As social context is of great importance, adequate considerations must also be given for the social network of households when modeling their weatherization adoptions.

In the following section, firstly, the background knowledge of weatherization is provided. Afterwards, basic information and literature reviews of the key modeling methods, social network analysis and agent-based model, are presented. Finally, the organizations of the two hybrid simulation models in Chapter 2 and Chapter 3 are elaborated.

1.2 Weatherization

From air sealing to improving ventilation to adding insulation to upgrading inefficient equipment, weatherization (U.S. Department of Energy, 2018) includes a wide variety of measures to make buildings more energy-efficient.

Weatherization can help residents lower energy expenditures. Low-income residents usually carry a larger burden for energy costs, which may cause them to cut back on other expenditures, even other key living expenses. Along with weatherization, lower energy bills enable residents to have more funds to pay for other expenditures, which improve residents' living quality and potentially benefit society. In addition, improved house conditions (e.g., better indoor air quality, safer heating system) result in less out-of-pocket health costs (U.S. Department of Energy, 2017). For the environment, weatherized houses will be more energy-efficient and therefore save resources as well as reduce greenhouse gas emissions (Dietz et al., 2009). It also creates a businesses market with many job opportunities. Weatherization could return \$2.78 in non-energy benefits per \$1.00 invested in the program (Tonn et al., 2014).

To help more households weatherize, the U.S. Department of Energy offers the Weatherization Assistance Program (WAP), which is the nation’s single largest residential whole-house energy efficiency program (U.S. EERE, 2018a). WAP provides core program funding to states, territories, and Native American tribes, which then contract with local governments and nonprofit agencies to provide qualified low-income households (i.e., those with income less than 200% of the federal poverty line) with energy efficiency upgrades, typically at no cost to the household. In 2008, this program provided \$5,000 of energy cost savings per weatherized unit, improved comfort and health, and reduced carbon emissions by two million metric tons (U.S. EERE, 2018b). Despite these successes, few income-eligible households apply for weatherization assistance, and even fewer actually receive it (Fowlie et al., 2015).

1.3 Social Network Analysis in Energy Behaviors

A social network is a structure comprised of entities (i.e., individuals, collective social units) with ties among them. Social network analysis (SNA) identifies underlying patterns of social relations based on the ways entities are connected to each other (Wasserman and Faust, 1994; Scott and Carrington, 2011). SNA has been applied in geography, biology, epidemiology, economics, linguistics, anthropology, and sociology (Sparrow, 1991; Barabási et al., 2002; Wang and Chen, 2003; Christakis and Fowler, 2008). It has been used to analyze the effects of human social behavior on energy-related behaviors. Providing eco-feedback to building occupants about their energy consumption can promote energy-saving behavior (Wilhite and Ling, 1995; Fischer, 2008; Faruqui et al., 2010; Allcott, 2011; Kang et al., 2012). Some of this work assumes that occupants’ behaviors will be influenced by their social networks via a normative comparison element, in which occupants compare their energy consumption with peers and neighbors. For example, a spatial analysis of residential heating, ventilation, and air conditioning (HVAC) systems shows that HVAC adoption is “contagious” or spatially-dependent in adjacent neighborhoods due to social pressures and feedback (Noonan et al., 2013). Jain et al. (2013) demonstrates the potential of SNA to improve

understanding of the social dynamics of energy-efficient behavior and concludes that social influence can drive energy-saving behavior in occupants who receive feedback on energy consumption.

Real-life social networks often contain thousands of individual actors connected via a variety of relationships. Such networks are highly complex, exhibiting non-trivial topological properties (Boccaletti et al., 2006). Therefore, analyzing the structural characteristics of social networks requires the use of graph theory, where a complex network is abstracted as a graph composed of nodes representing actors in the social network, and links representing relationships between actors. Through mathematical analysis, the structural characteristics of the real network can be determined and underlying behavioral rules can be revealed (Ferrara and Fiumara, 2012) to enable a greater understanding of the implications of changes to the social network on outcomes of interest, and the impacts of policy interventions on social behaviors (Moffitt et al., 2001).

1.4 Agent-Based Model in Energy Behaviors

Agent-based modeling (ABM) is a bottom-up approach in which individuals can be represented as discrete heterogeneous agents, which is far more realistic than using a statistical aggregate to model diverse human attributes and behaviors and decentralized decision making (Epstein and Axtell, 1996). It is a type of simulation modeling wherein multiple autonomous agents with intelligence (i.e., internal logic) have the ability to make complex decisions and engage in complex interactions with other agents and objects within their environment to achieve one or more identifiable objectives. Over time, the agents can accumulate information about the outcomes of these interactions and apply this knowledge to future decisions and behaviors (Gilbert and Troitzsch, 2005). Capturing such dynamic agent adaptations is difficult, if not impossible, with other modeling approaches (Macal and North, 2005). ABM also enables humans to be realistically characterized and modeled as boundedly rational agents that are capable of making subjective choices via explicit decision rules (Bonabeau, 2002). This capability distinguishes ABM from rational choice modeling (e.g., game theory), in which human actors are assumed to possess perfect information and infinite

computational capabilities, and always follow an equilibrium strategy to maximize their long-run personal advantage (Farmer and Foley, 2009; Johnson et al., 2014).

The system (macro-level) behavior and properties that are introduced through individual agent (micro-level) interactions and adaptations over time often cannot be predicted simply by examining the behavior of the individual agents (Pathak et al., 2007). Such system behavior and resultant properties, which are often counterintuitive and surprising, are said to be *emergent*. Agents may respond to emergent changes in their environment by adapting accordingly, which will result in new agent interactions and decisions, thereby creating a feedback loop between the micro- and macro-level behaviors (Lebaron, 2008). ABM is well-suited to understanding and predicting emergent behavior in social systems consisting of interdependent actors, e.g., weatherization.

To describe agents' interactions precisely in an ABM, it is critically important that the underlying logic of their connections is clearly defined (Macal and North, 2005). SNA is a particularly useful method for describing the topology of agents' interactions in an ABM. Integrating SNA and ABM enables an analysis of agents' behavior and interactions in simulated networks to determine how/whether certain social network characteristics affect agent behavior, which typically cannot be observed in real-life social networks. To leverage these capabilities, some existing models of building occupants' energy-related behavior have integrated SNA and ABM. Chen et al. (2012) proposed an ABM to study the influence that different social network characteristics have on occupants' energy consumption behavior. Using this model, they determined that while the size of the network was unimportant, networks with more edges tended to exhibit more energy-conserving behavior. However, the basis for this network is a random network, which is very different from the structure of a real-life social network. Anderson et al. (2013) developed an ABM to study how building occupants' social network types and structures influence energy-use interventions. Experimentation with four different types of networks indicated that network type and structure have a major influence on occupants' energy consumption when an energy-use intervention is introduced. Friege et al. (2016) incorporated social and geographic factors into an ABM of individuals' decisions to install insulation in their homes. Their results suggest that the residents' social networks have

a much stronger influence on this decision than financial incentives. We also address the social network context of the ABM in the proposed two hybrid simulation models.

1.5 Thesis Organization

Chapter 2 and Chapter 3 develop two hybrid simulation models, *M1* and *M2*, respectively. Chapter 2 is submitted to *Energy Policy*. Chapter 3 is modified from a paper published in *CSS '17: CSSSA's Annual Conference on Computational Social Science* (Huang et al., 2017).

Table 1.1 shows the connections and differences between the two hybrid simulation models. *M1* and *M2* both incorporate three components, building energy simulation (BES), agent-based model (ABM), and social network (SN). They share the same BES model but have different ABMs and SNs. The ABMs of *M1* and *M2* have different agents and submodels to describe the decision-making process. *M1* only captures the household as the agent while *M2* includes households as well as media agents. The household agents in *M1* and *M2* are also characterized by different parameters. *M2* models the multilayer social network for agents to interact while *M1* focuses on the one-layer physical social network. *M1* and *M2* also explore different attributes of social networks. Based on *M1*, *M2* makes some improvements on its weak parts. For example, *M2* adopts and improves the classic Theory of Planned Behavior (TPB) model (Ajzen, 1991) to describe the logic of households' decision-making process on weatherization, which is more realistic than that in *M1*. *M1* assumes that all households can have interactions while *M2* uses Susceptible-Exposed-Infected-Recovered (SEIR) epidemic model (Li and Muldowney, 1995; Apolloni et al., 2009; Cha et al., 2012) to incorporate households' specific attitudes toward information sharing. Also, the characteristic which has already been explored in *M1*, i.e., network closeness constant (*CC*), has a fixed value in *M2*.

Chapter 4 concludes the work and clarifies its contributions, limitations, and future directions.

Table 1.1: Connections and differences between $M1$ and $M2$.

Characteristic	$M1$	$M2$
BES	✓	✓
ABM	✓	✓
SN-Layer	one-layer	two-layer
SN-Type	physical social network	physical & online social network
Household Agent	✓	✓
Media Agent	—	✓
Number of Agents	29	over 2,000
Behavioral Model	—	improved TPB
Interaction Rule	all agents can interact	SEIR
Weight of Connections	uniform	determined by local centrality, spatial information, social demographics
Quit WAP	allowed	not allowed
Network Randomness (P_{rewire})	$P_{\text{rewire}} = 0.1$	variable
Network Closeness Constant (CC)	variable	$CC = \text{low}$
Households' Memory Length	✓	—

CHAPTER 2. ANALYZING RESIDENTIAL WEATHERIZATION DECISIONS USING HYBRID SIMULATION MODELING

Submitted to *Energy Policy*

Wanyu Huang, Caroline C. Krejci, Michael C. Dorneich, Ulrike Pässe,
Linda Shenk and Jacklin Stonewall

Abstract

Weatherizing residential buildings to make them more energy efficient offers great potential for reducing greenhouse gas emissions and conserving resources in the face of climate change. The adoption rate of such a good practice, however, remains low. The government and planning agencies are trying to make the most effective policies to encourage households to weatherize and conserve energy. Previous research suggests that not only factual knowledge about energy and financial incentives drives households' energy behaviors but also social interactions. We developed a hybrid simulation model, integrating building energy simulation with an agent-based model, which is embedded in social networks, to assist stakeholders in encouraging weatherization. One application of the model to a residential block in Des Moines is presented.

2.1 Introduction

Energy-efficient buildings are critical for increasing the resilience of urban communities in the face of climate change. While there has been considerable focus on reducing energy use in newly-constructed commercial buildings, existing residential buildings provide tremendous opportunities for energy savings. Residential buildings are currently responsible for approximately 21% of all domestic energy use (U.S. Energy Information Association, 2013), and future demand for residential heating and cooling is projected to increase significantly due to climate change (Petri and Caldeira, 2015). Therefore, the U.S. Department of Energy (U.S. Department of Energy, 2016), therefore, has set a goal of reducing energy use in existing single-family homes by 35% by 2025 (U.S. Department of Energys Building Technologies Office, 2017). Many U.S. cities have set community-wide efficiency targets for residential building energy reduction as well (ACEEE, 2018). Achieving these goals will require aggressive implementation of energy-efficient technologies and retrofit strategies (Reyna and Chester, 2017), known as weatherization. Weatherization includes a wide variety of measures that increase the energy efficiency of a residential building's enclosure, heating and cooling systems, and appliances (U.S. EERE, 2018a). Weatherization benefits households by reducing energy bills over a sustained period of time, allowing residents to recuperate an average of 2.2 times the cost of the improvements (U.S. Department of Energy, 2016). Furthermore, as temperatures increase with climate change, weatherization may enable residents to avoid increased energy costs associated with cooling (Jagani and Passe, 2017).

Despite these benefits, weatherization involves up-front investment and potentially lengthy financial payback, which can be barriers to adoption by low-income residents (Hernández and Phillips, 2015). Low-income urban residences have 20% greater median annual utility costs per square foot than non-low-income residences (Drehobl and Ross, 2016). They spend 16.3% of their annual income on residential energy expenditures, compared to 3.5% for non-low-income households, and they have an increased risk of illness and death due to living in buildings not properly heated in winter or insufficiently cooled in summer (Reames, 2016). Thus, improving residential building energy efficiency also has social implications related to equity.

To assist low-income households in weatherizing, the DOE developed the Weatherization Assistance Program (WAP), which has provided subsidized weatherization services to more than seven million low-income households since 1976 (U.S. Department of Energy, 2016). WAP provides grants to states, territories, and Native American tribes, which then contract with local governments and nonprofit agencies to provide qualified low-income households (i.e., those with income less than 200% of the federal poverty line) with energy efficiency upgrades, typically at no cost to the household. In 2008, this program provided \$5,000 of energy cost savings per weatherized unit, improved comfort and health, and reduced carbon emissions by two million metric tons (U.S. EERE, 2018b). Despite these successes, few income-eligible households apply for weatherization assistance, and even fewer actually receive it (Fowlie et al., 2015). Many are simply unaware of the existence of WAPs (Kathleen, 2006) or lack sufficient information about the process and benefits (Reames, 2016), and/or are unwilling or unable to complete the time-intensive process, which involves extensive paperwork to document eligibility, inspections, and retrofit implementation (Fowlie et al., 2015; Hoffman, 2017). All of these factors make involvement even more difficult for non-English-speaking households (Kathleen, 2006).

Social psychology and behavioral science research has shown that the most effective techniques for motivating weatherization adoption involve leveraging social norms to overcome status quo and framing biases (Ashby, 2010). For example, WAP success depends on whether the program is framed as a social policy-oriented program or an energy-related program (Ternes et al., 2007). A national survey found that interacting with others about energy issues was the single largest determinant of weatherization; residents who participated in social interactions were more than twice as likely to have weatherized their homes (Southwell and Murphy, 2014). The interactions likely served to convey locally relevant knowledge about weatherization and social norms, both descriptive (“people like us weatherize”) and injunctive (“it’s good to weatherize”). Marketing WAPs through a community group is one of the best ways to improve participation rates in low-income households (Stern et al., 1986), due to the importance of engaging “trusted messengers” to encourage community members to adopt weatherization (Fuller, 2010). Trusted messengers include

community leaders such as school representatives, politicians, religious leaders, businesspeople, and community organizations representatives. They encourage adoption by providing information, publicity, and outreach, leading by example (upgrading their own homes and businesses), and recruiting participants. These findings suggest that the success of a weatherization program depends on policymakers' understanding of the ways in which social norms and information sharing affect adoption decisions.

In an effort to increase this understanding, a hybrid simulation model of an urban neighborhood populated with autonomous “household” agents has been developed. A preliminary version of this model is described in a proof-of-concept paper (Krejci et al., 2016). The version of the model described in this paper is the next step in the development of a decision support tool that will help city officials, planners, and residents develop policies and programs to increase weatherization adoption among low-income residents. The Capitol East Neighborhood in Des Moines, Iowa, was chosen for a pilot study, primarily because of its social and economic composition. The development of the simulation model described in this paper is one component of a larger research project (Iowa State University, 2018) that aims to develop data-driven methods to improve the energy efficiency, sustainability and resilience of the built environment in low-resource neighborhoods in Des Moines, thereby improving the quality of life of its residents.

The hybrid simulation model integrates three modeling techniques: 1) a building energy simulation model to calculate monthly energy consumption, 2) a social network-generating algorithm to represent social interactions and community influence, and 3) an agent-based model (ABM) to capture household weatherization decisions. The integrated hybrid model represents the complex dynamic feedback loop that connects residents' weatherization decisions, energy-related decision outcomes, and communication of outcomes between community members, all of which influence future decisions.

The paper is organized as follows: Section 2 explains the three modeling techniques used in developing the hybrid model and reviews relevant literature on social behavior models related to energy conservation. Section 3 describes each model component in detail. Section 4 describes a set

of experiments to demonstrate the model's capabilities. Section 5 presents experimental results. Finally, Section 6 explores potential policy implications, based on model outputs and preliminary survey data collected from local residents.

2.2 Modeling Methods

The hybrid simulation model contains three components: building energy simulation, social network analysis, and ABM (Figure 2.1).

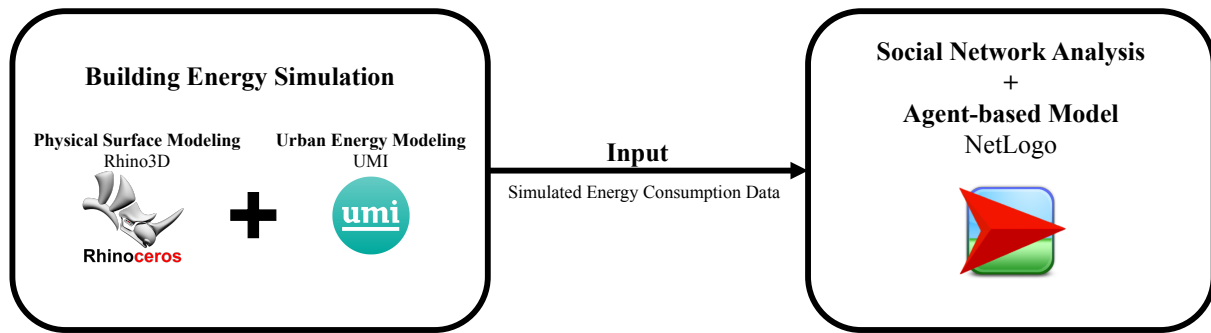


Figure 2.1: Overview of the hybrid simulation model.

2.2.1 Building Energy Simulation

Building energy simulation is of considerable benefit for architects, engineers, and urban planners. With building material and geometry inputs, occupancy schedules, and climate data, energy consumption can be predicted. However, in models currently used to simulate building energy use, interactions between buildings and their environments are oversimplified (Anderson et al., 2015; Moonen et al., 2012), as are the relationships between human energy-related behavior and energy consumption. Recently it has become possible to develop integrated energy models for clusters of urban buildings. One such urban energy simulation workflow, the Urban Modelling Interface (umi) has been developed by MIT's Sustainable Design Lab (Reinhart et al., 2013) as a plugin for Rhinoceros 3D, a Non-Uniform Rational B-Splines (NURBS) modeler (McNeel et al., 2015).

NURBS are mathematical curves, which enable the creation of 3D shapes in a computational design environment. To date, umi has been used to model energy use in in Kuwait City (Cerezo et al., 2015) and the City of Boston, but the input data for occupant schedules was schematic (Davila et al., 2016). One of umi’s strengths is an open data structure that allows for addition of new metrics. umi thus offers the ability to edit the material assembly of individual houses in the neighborhood, such that the potential impact of different weatherization strategies (e.g., re-caulking windows to decrease air infiltration; adding spray insulation in unfinished attics to prevent heat loss during the winter) can be tested.

2.2.2 Social Network Analysis

Research has demonstrated that human social behavior influences energy-related behaviors. For example, providing eco-feedback to building occupants about their energy consumption can promote energy-saving behavior (Allcott, 2011; Faruqui et al., 2010; Fischer, 2008; Kang et al., 2012; Wilhite and Ling, 1995). Some of this research assumes that occupants’ behaviors will be influenced by their social networks via a normative comparison element, in which occupants compare their energy consumption with peers and neighbors. For example, a spatial analysis of residential heating, ventilation, and air conditioning (HVAC) systems shows that HVAC adoption is “contagious” or spatially-dependent in adjacent neighborhoods due to social pressures and feedback (Noonan et al., 2013). Furthermore, social influence can drive energy-saving behavior in occupants who receive feedback on energy consumption (Jain et al., 2013).

Social network analysis (SNA) is a statistical method that has the potential to yield an improved understanding of the social dynamics of energy-efficient behavior. A social network is a structure consisting of entities (i.e., individuals, collective social units) with ties among them. SNA identifies underlying patterns of social relations based on the ways entities are connected to each other (Scott and Carrington, 2011; Wasserman and Faust, 1994). Real-life social networks often contain thousands of individual actors connected via a variety of relationships. Such networks are highly complex, exhibiting non-trivial topological properties (Boccaletti et al., 2006). Therefore,

analyzing the structural characteristics of social networks requires the use of graph theory, where a complex network is abstracted as a graph composed of nodes representing actors in the social network and links representing relationships between actors. Through mathematical analysis, the structural characteristics of the real network can be determined and underlying behavioral rules can be revealed (Ferrara and Fiumara, 2012) This enables a greater understanding of the implications of changes to the social network on outcomes of interest and the impacts of policy interventions on social behaviors (Moffitt et al., 2001).

The most important characteristics of a social network are degree distribution, average path length, clustering coefficient, and density:

Degree distribution: A single node in a social network can be characterized by its degree, where the degree k_i of node i is defined as the number of connections (edges) the node i has to neighboring nodes (Boccaletti et al., 2006). For example, a person socially connected to 20 people has a degree of 20. The overall network can be described in terms of the degrees of its constituent nodes via a probability distribution $P(k)$, which defines the probability that a node randomly selected from the network will have degree k . $P(k)$ is the ratio of the number of nodes with degree k (n_k) to the total number of nodes in the network (N):

$$P(k) = \frac{n_k}{N}. \quad (2.1)$$

Average path length: The shortest path d_{ij} between any two nodes i and j refers to the path that connects them with the fewest edges. Most real networks have a short average path length leading to the “small world” concept, where everyone is connected to everyone else through a short path. The average path length of a network is the average distance between two nodes, calculated by finding the shortest paths between all pairs of nodes, summing the distances of these paths, and then dividing by the total number of pairs (Fronczak et al., 2004).

Clustering coefficient: An individual node i in a network can also be characterized by a clustering coefficient, which is a measure of the connectedness of its neighboring nodes with each other. The clustering coefficient is often referred to as an “all-my-friends-know-each-other” property (Boccaletti et al., 2006). The ratio of the actual number of edges to the maximum number of possible edges

among k neighbors defines the clustering coefficient of node i (Watts and Strogatz, 1998). The clustering coefficient for an entire network is the average of the clustering coefficients of all N nodes in the network.

Density: A network's density is a measure of the closeness of its nodes. For example, the network density of a family reunion would be high, while a public bus would be low. In an undirected network (i.e., having bidirectional edges), the density is the ratio of the actual number of edges in the network to the number of possible edges.

Figure 2.2 illustrates four classic network models: regular ring lattices, random graphs, small-world networks, and scale-free networks. In a regular ring lattice, each node shares an edge with all other nodes, such that the average path length, clustering coefficient, and density equal 1, and all nodes have the same degree ($N - 1$). A random graph has a Poisson degree distribution and randomly connected nodes. By contrast, the clustering coefficients of small-world and scale-free networks are relatively high, with short average path lengths. A small-world network has a Poisson degree distribution, while the degree distribution of a scale-free network follows a power law.

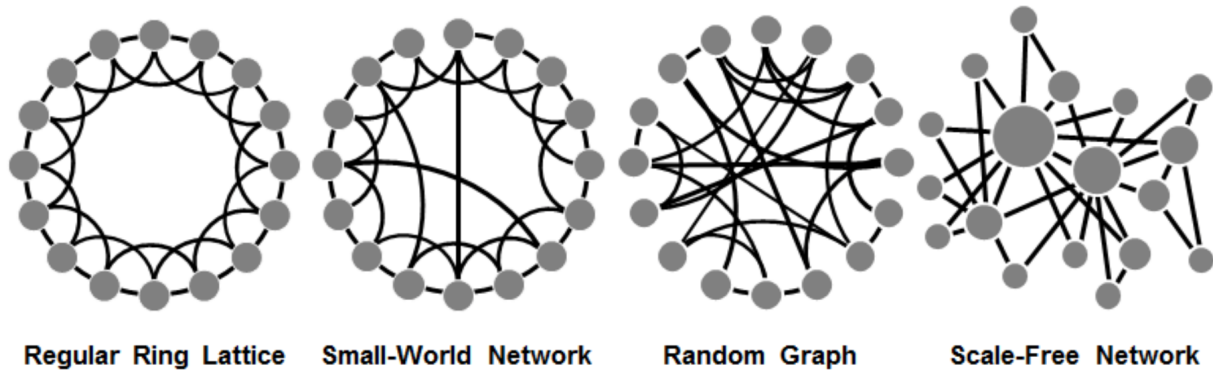


Figure 2.2: Four Kinds of Network Types (adapted from Anderson et al. (2012)).

Increases in computational power have enabled researchers to analyze complex real-world social networks and gain a deeper understanding of their topologies. Results have demonstrated that many real networks are characterized by similar topological properties, such as small average path lengths, high clustering coefficients, and fat-tailed degree distributions (Amaral et al., 2000; Barabási, 2009;

Boccaletti et al., 2006; Camacho et al., 2002; De Castro and Grossman, 1999; Ebel et al., 2002; Grossman and Ion, 1995; He et al., 2010; Jeong et al., 2001, 2000; Johnson et al., 2014; Watts and Strogatz, 1998). Two significant discoveries are the small-world and scale-free properties of most complex networks. The small-world property describes the social connections that exist between strangers via a chain of acquaintances and reflects the abundance of short paths in real social networks. For example, six-degrees-of-separation theory states that any two people are socially connected within a maximum of five intermediaries. An analysis of data from social network platforms such as LiveJournal, YouTube, and Flickr found that the average path lengths of these networks tend to be less than six (Mislove et al., 2007). The scale-free property describes the phenomenon that relatively few nodes (i.e., central nodes) tend to have a degree much larger than the average degree of the network nodes. Thus the degree distribution of the network follows a power-law distribution (Barabási and Albert, 1999), where the probability that a given node will have a degree k is described by:

$$P(k) = ck^{-\lambda}, \quad (2.2)$$

where $2 \leq \lambda \leq 3$. The scale-free property has been observed repeatedly in real-world social networks (Mislove et al., 2007; Willinger et al., 2009).

2.2.3 Agent-Based Modeling

Traditionally, models of building occupant behavior and building energy consumption have used regression-based aggregate estimates of whole-building behavior in response to thermal stimuli (Nicol, 2001; Rijal et al., 2008; Steemers and Yun, 2009). However, this does not account for heterogeneous individual occupant behavior, nor does it incorporate social influences (Langevin et al., 2015). By contrast, agent-based modeling (ABM) is a bottom-up approach in which individuals are represented as discrete heterogeneous agents, which enables diverse human attributes, behaviors, and decentralized decision making to be captured (Epstein and Axtell, 1996). With ABM, multiple autonomous agents with intelligence (i.e., internal logic) can make complex decisions and engage in complex interactions with other agents and objects to achieve one or more

identifiable objectives. Over time, agents accumulate information about the outcomes of these interactions and apply this knowledge to future decisions and behaviors (Gilbert and Troitzsch, 2005). Capturing such dynamic agent adaptations is difficult, if not impossible, with other modeling approaches (Macal and North, 2005). ABM also enables humans to be realistically characterized and modeled as boundedly rational agents that are capable of making subjective choices via explicit decision rules (Bonabeau, 2002). This capability distinguishes ABM from rational choice modeling (e.g., game theory), in which human actors are assumed to possess perfect information and infinite computational capabilities, and always follow an equilibrium strategy to maximize their long-run personal advantage (Farmer and Foley, 2009; Johnson et al., 2014).

Recent models of building occupant behavior and building energy consumption have utilized ABM to capture human behavior. Most models described in the literature focus on the energy-related behaviors of heterogeneous commercial building occupants to reduce energy usage while maintaining adequate occupant thermal comfort. For example, ABM has been used to predict occupants' thermal comfort and related adaptive behaviors (e.g., clothing/thermostat adjustment, opening/closing windows) (Langevin et al., 2015). Some of these models have been linked with building energy simulation models. For example, an ABM linked to EnergyPlus simulated the impacts of commercial office building occupant behaviors on thermal conditions and building energy use (Lee and Malkawi, 2014). The model provided insight into the behaviors (e.g., using blinds) that maximize comfort and minimize energy use. The literature describing ABMs of residential energy applications is sparser. Hicks et al. (2015) developed an ABM that captures the adoption of energy-efficient lighting technologies among individual residents, using survey data to inform agent behavior. Chen et al. (2012) developed an ABM/EnergyPlus model of apartment building residents to assess the impact of different building maintenance schedules on energy consumption and occupant comfort.

SNA can be integrated with ABM to analyze agents' behavior and interactions in simulated networks to determine the effects of social network characteristics on agent behavior. Chen et al. (2012) proposed an ABM to study the influence that different social network characteristics have on

occupants' energy consumption behavior and determined that while network size was unimportant, networks with higher degrees tended to exhibit more energy-conserving behavior. However, a random network was used, which is very different from the structure of a real-life social network. Using SNA and ABM, Anderson et al. (2013) determined that network type and structure have a major influence on occupants' energy consumption when an energy-use intervention is introduced. Experimentation with four different types of networks indicated that network type and structure have a major influence on occupants' energy consumption when an energy-use intervention is introduced. Friege et al. (2016) incorporated social and geographic factors into an ABM of individuals' decisions to install insulation in their homes. Their results suggest that the residents' social networks have a much stronger influence on this decision than financial incentives.

2.3 Hybrid Simulation Model Description

This section describes the hybrid simulation model that was developed to explore the impacts of social interactions on weatherization decisions for households located in the Capitol East Neighborhood under pre- and post-weatherization conditions.

2.3.1 Building Energy Model Description

umi (described in Section 2.1) was used to generate the comparative building energy consumption data that informs the weatherization decisions of the household agents in the ABM. A detailed energy model of a single residential block in the Capitol East Neighborhood was developed to show the potential energy savings that would result from a resident's decision to weatherize their home. The one-block area of the neighborhood was selected because of the similarity of the buildings in both use and construction, while still representing a large range of square footage. The 29 buildings that comprise this block are all residential and built with wood-framed construction.

First, spatial information was extracted from GIS maps that are maintained by the City of Des Moines to model building footprints, streets, sidewalks, and lot boundaries. Rough floor plans that indicate which areas are more than one story high are available for each house, and this

information was used to refine the individual 3D building models. The second step was to use the information available in the Polk County Assessor’s database (Polk County Assessor website, 2015) to extract the building-related data needed to build the umi energy model. Each building’s address, parcel number, number of building stories, date of construction, and number of separate residences contained within were extracted. An identification system for each house was derived from the parcel number of each lot and was used to cross-reference information between the Rhino-umi model and the Assessor’s data. The 3D building models were created by extruding each building’s footprint to the given roof elevation included within the GIS data, and then manually edited later using measurements from the Assessor’s floorplans to more accurately reflect the true size of the house. This step is important, because the umi energy simulation analyzes each structure based on the volume of a given structure, and most multiple-story houses are only “full height” over a certain percentage of their floor area. Lastly wall and roof thermal properties were extracted to generate generalized building characteristics templates and schedules.

2.3.2 Social Network Model Description

The BarabasiAlbert (BA) algorithm was used to generate the topology of a scale-free social network in NetLogo. The BA algorithm starts with a random network model used to incorporate preferential attachment, also known as the “rich-get-richer” effect (Merton, 1968). As a social network is generated, a new edge has a greater probability of attaching to nodes with higher degrees. This reflects a real-life social phenomenon: people are more likely to connect with someone who already has many connections. Networks generated by the BA algorithm have other realistic characteristics. Compared to a random network, BA models have generally significantly higher empirically-determined clustering, systematically shorter average path lengths, and their degree distribution follows a power-law distribution.

The BA algorithm starts with an initial network of m_0 nodes. New nodes are added to the network one at a time. Each new node is connected to CC existing nodes, where $CC \leq m_0$. CC is a “closeness constant”, which determines the connectedness of the network. Intuitively, larger

values of CC increase the number of links presenting in the network, and more links imply more potential paths between node pairs, such that they are “closer”. A new node will connect to an existing node with a probability p_i proportional to the number of links that existing node i already has:

$$p_i = \frac{k_i}{\sum_j k_j}, \quad (2.3)$$

where k_i is the degree of node i .

The BA model was used to generate a scale-free network of 29 agents representing 29 households. Figure 2.3 shows two BA networks with the same network size but different CC values. The network with larger CC value is much denser.

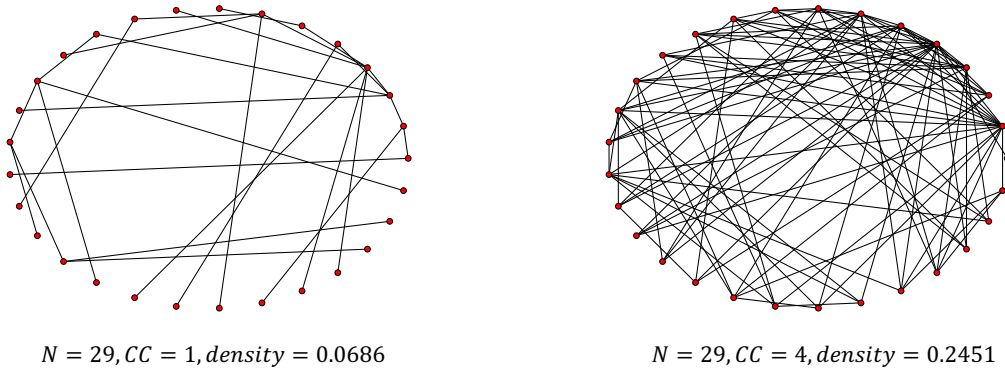


Figure 2.3: Two networks with the same network size and different closeness constant values.

Figure 2.4 shows an example of the output of the network generation process for the 29-node network with $m_0 = 2$ and $CC = 2$. Each node has an influence factor that impacts the degree to which its information level changes when it interacts with another node. For example, a community leader may have relatively greater influence on members of his/her community. The influence factor of node i , denoted as $influence_factor_i$, is positively related to node i 's degree k_i , its clustering coefficient C_i (Chen et al., 2012), and its node type. Node type is a random integer between 0 and 3, where larger values represent greater influence. For example, the 29-household network can

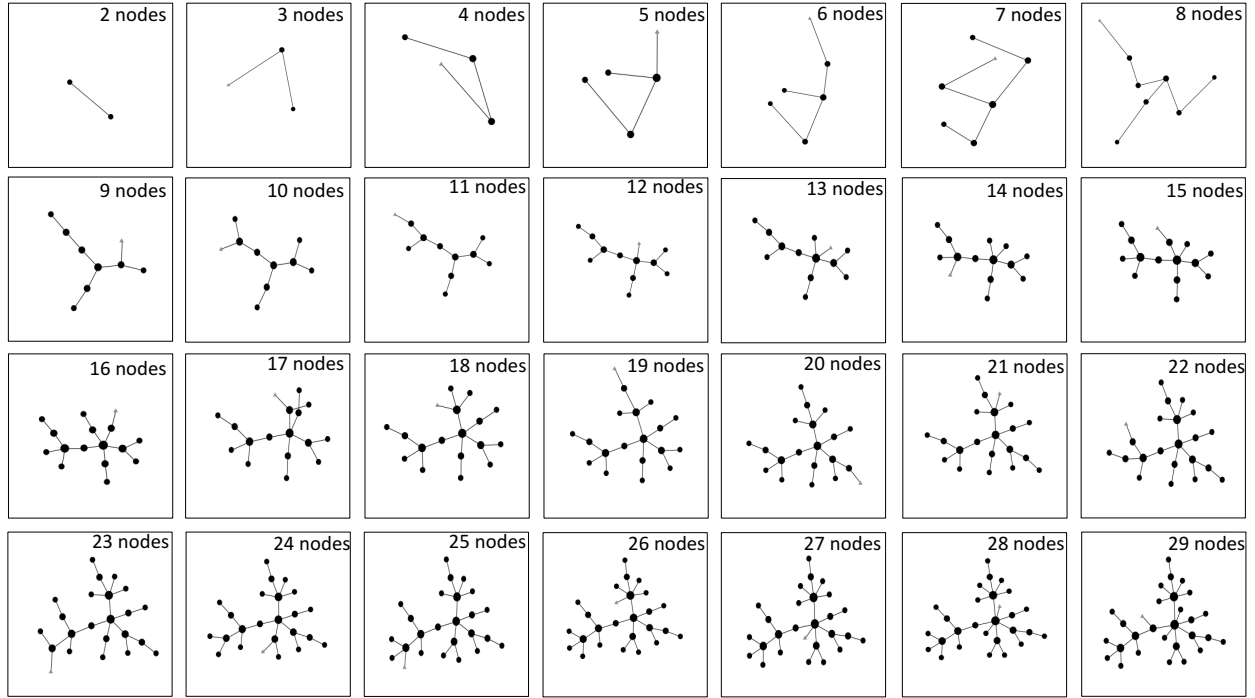


Figure 2.4: An example of the social network generation process.

include a node that represents a community leader (node type 3). The influence factor of node i is:

$$\text{influence_factor}_i = 0.1 \times \frac{k_i}{k_{\max}} + 0.1 \times \frac{C_i}{C_{\max}} + 0.8 \times \text{node_type}_i, \quad (2.4)$$

where k_{\max} and C_{\max} refer to the network's maximum degree and clustering coefficient values.

2.3.3 Agent-based Model Description

2.3.3.1 Agents

Each of the 29 household agents represents a set of residents occupying one of 29 houses on the Capitol East Neighborhood block modeled in the building energy model. Each agent represents a household instead of an individual resident because weatherization decisions are assumed to be made at the household level. Each agent is assumed to qualify for WAP, which provides installation assistance at no cost to the household.

Each household agent has three constant parameters for each 24-month simulation:

- *House ID*: A specific identification number that links the agent to a building in the building energy model.
- *Monthly Energy Consumption*: A vector containing 24 entries representing each agent's monthly energy consumption. The first 12 entries represent the agent's energy consumption in each month of the year under pre-weatherization conditions, and the remaining 12 entries represent monthly consumption under post-weatherization conditions. This data is generated by the building energy model prior to running the ABM.
- *Satisfaction Threshold*: A threshold below which an agent is dissatisfied with its household energy costs, which triggers the agent to consider weatherization. The threshold for all agents is 0.35.

Additionally, each agent has eight state variables that may change in each monthly time-step:

- *Weatherization Level*: A binary variable representing the agents' current weatherization status: weatherized (1) or not (0). An agent's weatherization level can change from 0 to 1, but cannot revert from 1 to 0 (i.e., weatherization is irreversible).
- *Current Utility*: This represents an agent's level of satisfaction, on a scale of 0 to 1 (0 is "least satisfied", 1 is "most satisfied"). Utility is assumed to be a linear function of the agent's energy cost (c) in the current month m . A linear function was chosen for simplicity, since there is currently insufficient empirical data to approximate each household's risk tolerance parameters (Chelst and Canbolat, 2011). The endpoints of each agent's utility function are its maximum and minimum possible monthly energy costs (c_{\max} and c_{\min} , respectively), extracted from the output provided by the building energy model. An agent's current utility $U(m)$ in time-step m is:

$$U(m) = \frac{c_{\max} - c}{c_{\max} - c_{\min}} \quad (2.5)$$

- *Memory Length:* Each agent makes weatherization decisions based on its energy costs in the previous L months (i.e., each agent only stores L months of energy costs in its “memory”).
- *Utility History:* A vector that stores the agent’s utility values from the previous L months.
- *Cost History:* A vector that stores the agent’s energy costs from the previous L months.
- *Weighted Utility:* It is assumed that that recent events will have a stronger influence on an agent’s decision process. To capture this effect, an agent’s energy costs in recent months are weighted more heavily when assessing its current level of satisfaction. For example, if $L = 4$ and $U(m)$ is the agent’s utility in time-step m , in the ninth month the agent’s weighted utility would be:

$$U_w = \frac{4u_9 + 3u_8 + 2u_7 + u_6}{4 + 3 + 2 + 1} \quad (2.6)$$

- *Satisfaction Level:* If the weighted utility of an agent is greater than its satisfaction threshold, its satisfaction level is set to 1, which means the agent is satisfied with its household energy cost; otherwise, its satisfaction level is set to 0.
- *Information Level:* This state variable consists of two components: the agent’s level of information about WAP and its level of information about self-weatherization. Its information level on WAP (i_{wap}) represents the degree to which an agent is informed about WAP (e.g., how to apply, eligibility, benefits), while its information level on self-weatherization (i_{wap}) represents how informed it is about weatherizing its home without assistance (e.g., payback periods, level of difficulty, expected energy cost savings). The variable falls between 0 (i.e., completely uninformed) and 1 (i.e., fully informed). It is assumed that each agent’s level of information will remain the same or increase in each time-step; the agent never becomes less-informed.
- *Self-weatherization Probability:* This represents the probability that an agent will decide to weatherize its house without WAP. The probability increases/decreases with decreasing/increasing payback period length and increasing/decreasing information level about self-

weatherization. The agent estimates the length of the weatherization payback period by dividing the cost of weatherization by the weighted average of the agent's cost history. The cost of weatherization is fixed throughout each simulation run and is assumed to be accurate and identical for each agent.

- *Assistance Status*: This variable represents an agent's WAP status as one of five discrete levels in each time-step:
 - Level 0: Agent has not yet applied for assistance.
 - Level 1: Agent has applied for assistance and is waiting for a response.
 - Level 2: Agent has been approved to receive assistance.
 - Level 3: Agent has made an appointment to receive assistance.
 - Level 4: Agent's home has been weatherized by the agency providing assistance.

An agent's assistance status cannot return to a previous value, unless it decides to cancel its appointment (i.e., its status may revert from Level 3 to Level 2).

2.3.3.2 ABM Submodels

The ABM contains five submodels. The initialization submodel is run once at the beginning of each simulation run. The remaining four submodels are run in sequence in each monthly time-step.

Initialization: Each agent is assigned a unique number corresponding to the location of its house in the building energy model. The agent is initialized to a weatherization level of 0 (i.e., no weatherization), an assistance status of 0 (i.e., not applied), a satisfaction level of 1 (i.e., perfectly satisfied), an information level of 0 (i.e., no information about weatherization), and the entries in their utility and cost history lists are all set to 1 (i.e., perfect utility). The 29 agents are connected via a scale-free social network generated using the BA model. Each agent is assigned its 24 monthly energy consumption values (in kilowatt hours) generated by the building energy model.

Update application and weatherization status: If an agent has applied for assistance and is waiting for a response (level 1) or has made an appointment and is waiting for service (level 3),

and the waiting period for that agent has ended in the current time-step, the agent's status is updated to level 2 (approved for assistance) or level 4 (it has received weatherization assistance), respectively. If the agent is currently at level 4, its current weatherization status is updated from 0 (i.e., not weatherized) to 1 (i.e., weatherized).

Update memory, assess satisfaction, and assess self-weatherization probability: Based on current weatherization level and current month, each household agent determines its total energy cost by multiplying its total monthly energy consumption (in kilowatt hours) by the current cost per kilowatt hour. This value is appended to the agent's cost history list, and the oldest value in this list is removed. The weighted average of this updated list is used to update its self-weatherization probability. The current energy cost value is used to calculate the current utility value, which is appended to its utility history list, and the oldest list value is removed. The agent accesses this list to calculate its weighted average utility value, compare it to its threshold utility value, and update its satisfaction level.

Gather information: In this submodel, the agents acquire information about the WAP and self-weatherization. The increase in an agent's level of information is random and depends upon its interactions with the other 28 agents, as well as its current satisfaction level. If the agent does not interact with other agents, as in the base-case experiment, then the incremental increase in information is simply a uniformly distributed random value between 0 and 0.05 (if the agent is satisfied) or 0 and 0.10 (if the agent is dissatisfied), with an upper bound of 1.00. This logic assumes that a dissatisfied agent will be more motivated to seek out information and more likely to increase its knowledge of the WAP in a given time-step.

In the agents' social network, not every agent has a direct connection with all others. In the experimental cases in which agents are allowed to interact, it is assumed that in each time-step an agent A is guaranteed to interact and share information with all agents with which it has direct connections, while the probability of an interaction with a "stranger" (i.e., no direct connection) is 0.10. It is assumed that "strangers" have less influence on agent A than direct connections. Therefore, for a given influence factor value, the maximum possible increase in agent

A 's information level based on an interaction with a "stranger" is assumed to be half that of a neighbor.

When agent A and agent B interact, and agent B has weatherized its home and is currently satisfied, then agent A 's information level will increase based on agent A 's satisfaction level, agent B 's weatherization approach (i.e., with assistance or self-weatherization), and the connection between A and B (see Table 2.1 for detailed rules).

Table 2.1: Rules for interaction-based information level increases

Agent A Satisfaction Level	Agent B Weatherization Approach	Agent A - Agent B Connection	Increase in Agent A Weatherization Assistance Information Level	Increase in Agent A Self-Weatherization Information Level
1	assistance	connected	$\text{uniform}(0, 0.20) \times \text{influence_factor}_B$	N/A
1	assistance	strangers	$\text{uniform}(0, 0.10) \times \text{influence_factor}_B$	N/A
0	assistance	connected	$\text{uniform}(0, 0.50) \times \text{influence_factor}_B$	N/A
0	assistance	strangers	$\text{uniform}(0, 0.25) \times \text{influence_factor}_B$	N/A
1	self-weatherized	connected	N/A	$\text{uniform}(0, 0.20) \times \text{influence_factor}_B$
1	self-weatherized	strangers	N/A	$\text{uniform}(0, 0.10) \times \text{influence_factor}_B$
0	self-weatherized	connected	N/A	$\text{uniform}(0, 0.50) \times \text{influence_factor}_B$
0	self-weatherized	strangers	N/A	$\text{uniform}(0, 0.25) \times \text{influence_factor}_B$

Deliberate: In this submodel, each agent decides whether it will weatherize its home, either with or without WAP. If an agent is dissatisfied, and its assistance status is at level 0, it must decide whether it will apply for assistance, which depends on its weighted average utility and information level. The lower the utility value U and the higher the information level on WAP i_{wap} , the greater the likelihood the agent will apply, with probability:

$$P_{\text{apply}} = 0.1 - 0.1 \times U + 0.1 \times i_{\text{wap}}. \quad (2.7)$$

If the agent decides to apply, its assistance status is updated to level 1, and it is assigned a randomly selected application waiting period, with a maximum possible wait time of six months. If

the agent decides not to apply, it will subsequently consider whether it will pay for weatherization out of pocket, with a likelihood defined by the agent's self-weatherization probability. If the agent decides to weatherize without assistance, it is assumed that it does not have to wait, and its current weatherization status is updated from 0 to 1 in the current time-step.

If an agent is dissatisfied, and its assistance status is at level 1 (applied), it must decide whether to continue waiting for a response or to pay for weatherization out of pocket. The probability that an agent will decide to pay to weatherize its home increases for longer elapsed wait times. If the agent decides to pay, it is assumed that the agent's home will be weatherized in the current time-step.

If an agent is dissatisfied, and its assistance status is at level 2 (approved), it is assumed that the agent will schedule an appointment for weatherization assistance. Its assistance status is updated to level 3, and it is assigned a randomly selected appointment waiting period, the maximum possible wait time for an appointment is two months. If a dissatisfied agent has previously made an appointment to receive weatherization assistance (i.e., assistance status level 3), it is assumed that the agent will continue to wait for its appointment.

No matter whether an agent is currently satisfied or dissatisfied, the agent may cancel its appointment (i.e., change to its assistance status is from level 3 to level 2). The probability that an agent cancels its appointment increases with increasing overall utility values, based on the assumption that a highly satisfied agent might not want to bother with the inconvenience of following through with the weatherization appointment. If the agent has waited a long time for the appointment, it is more likely to go ahead with the appointment than if it has just recently scheduled (i.e., the agent has a sunk cost bias with respect to waiting time). For an agent, the probability of canceling is:

$$P_{\text{cancel}} = U \times (t_{\text{appointment}} - t_{\text{current}}). \quad (2.8)$$

2.4 Experiments

The hybrid model was used to perform experiments to test the impacts of changes to key parameter values on the number of weatherized households over 24 simulated monthly time-steps. First, the building energy model generated the simulated monthly energy consumption values for each household in each month for pre- and post-weatherization conditions. umi assigned a simulation template to each of the 29 houses in the 3D Rhino building model. This template reflects the construction type and condition of the house. umi translated this information into values of thermal performance and infiltration rate (i.e., the rate at which a given structure allows conditioned air to exchange with unconditioned outdoor air), which has a significant impact on energy consumption. Using infiltration rate and thermal resistance as the target impact areas, the baseline pre-weatherization file used the ASHRAE minimum performance requirement for attic insulation within wood framed attic construction (i.e., a 0.15-meter-thick layer of fiberglass batt insulation and a 0.12-meter-thick layer of polystyrene insulation). The total R-value of the roof assembly was 8.55 m²K/W. The post-weatherization file doubled the thickness of both layers to 0.3 meters and 0.24 meters, respectively, increasing the R-value to 16.04 m²K/W. The assumed air infiltration rate for existing structures in the baseline template was 0.75 ach, and the post-weatherization rate was 0.25 ach.

Combined with a historical weather file (the Typical Meteorological Year 3 data) for the City of Des Moines (Wilcox and Marion, 2008), the model simulated the monthly household energy performance, split into heating, cooling, and lighting. The simulation was run twice: once using the pre-weatherization templates, and then again using the post-weatherization templates. This yielded two comparative data sets, which were exported as text files. The values in these text files were then read into the ABM during its initialization and were stored as each respective household agent's monthly energy consumption parameter values. A color-coded visualization of the pre-weatherized energy consumption for the 29 houses is shown in Figure 2.5.

The values of four parameters in the ABM were experimentally varied over the course of a 24-month simulation run:

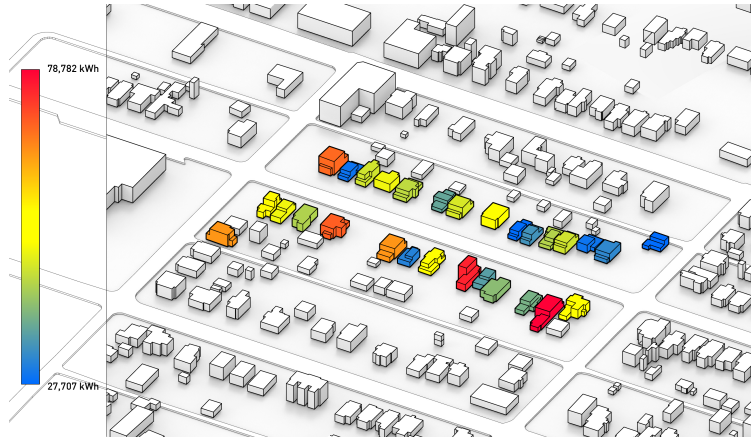


Figure 2.5: umi model: energy consumption visualization of Capitol East neighborhood

- *interact*: This binary system parameter was assigned either a value of 0 or 1, where 0 indicates that the 29 household agents are not allowed to interact, and 1 indicates that interactions are allowed.
- *Network Closeness Constant (CC)*: The closeness constant used in generating the social network, assigned one of two possible values: low (1) or high (4).
- *Agent Memory Length (L)*: The memory length of all 29 agents was assigned one of two values: short (2 months) or long (5 months).
- *leader*: This system parameter determines the presence of a community leader (i.e., node type 3) among the 29 household agents. If present, this leader is assumed to have a strong influence on other agents when they are gathering information about weatherization. The parameter is experimentally assigned one of three different values:
 - NoLeader (NL): There is no community leader agent present in the network.
 - AssistanceLeader (AL): One of the 29 household agents is a community leader that has weatherized its residence using WAP prior to the start of the simulation.
 - NoAssistanceLeader (NAL): One of the 29 household agents is a community leader that has self-weatherized its residence without WAP prior to the start of the simulation.

These parameters were experimentally varied across 14 simulated scenarios, summarized in Table 2.2. Twenty 24-month simulations were run for each scenario. The total number of weatherized buildings N was captured in each monthly time-step and averaged over 20 replications.

Table 2.2: Experimental Conditions. — means not applicable

Experiment	<i>interact</i>	<i>CC</i>	<i>L</i>	<i>leader</i>
E1	1	Low	Short	NAL
E2	1	Low	Short	AL
E3	1	Low	Short	NL
E4	1	Low	Long	NAL
E5	1	Low	Long	AL
E6	1	Low	Long	NL
E7	1	High	Short	NAL
E8	1	High	Short	AL
E9	1	High	Short	NL
E10	1	High	Long	NAL
E11	1	High	Long	AL
E12	1	High	Long	NL
E13	0	—	Short	—
E14	0	—	Long	—

2.5 Results

To gain an understanding of the relationships between the four experimental parameters and the key output metric of interest (i.e., number of weatherized households), t -tests were conducted. Results are reported as significant for $p < 0.05$ and highly significant for $p < 0.001$. Cohen's d was calculated to determine the effect size of each parameter, which indicates the difference between two means in units of standard deviation. Table 2.3 contains descriptors for threshold magnitudes of $d = 0.01$ to 2.0 (Cohen, 1988; Sawilowsky, 2009). The One-Sample Kolmogorov-Smirnov Test was used to confirm the normality of the data.

Table 2.3: Cohen's d effect size thresholds

Effect Size	<i>d</i>	Effect Size	<i>d</i>	Effect Size	<i>d</i>
Very small	0.01	Small	0.20	Medium	0.50
Large	0.80	Very large	1.20	Huge	2.00

Figures 2.6 and 2.7 show the average number of weatherized households in each monthly time-step and the average total energy consumption in the final time-step (kWh), respectively, for all 14 experimental scenarios over 20 replications. The experimental scenarios that yielded the lowest total energy consumption (E7, E1, and E10) had more weatherized households, as would be expected. Weatherization adoption increased markedly in months 2 and 3 (February and March of year 1) and in months 13-15 (January, February, and March of year 2) across all 14 scenarios. This result provides a measure of model verification – the City of Des Moines typically experiences its coldest annual temperatures (with an average high of 33.5°F and low of 16.5°F in January and February, and residents’ energy bills tend to be highest in these months. Weatherization decisions are influenced by energy costs.

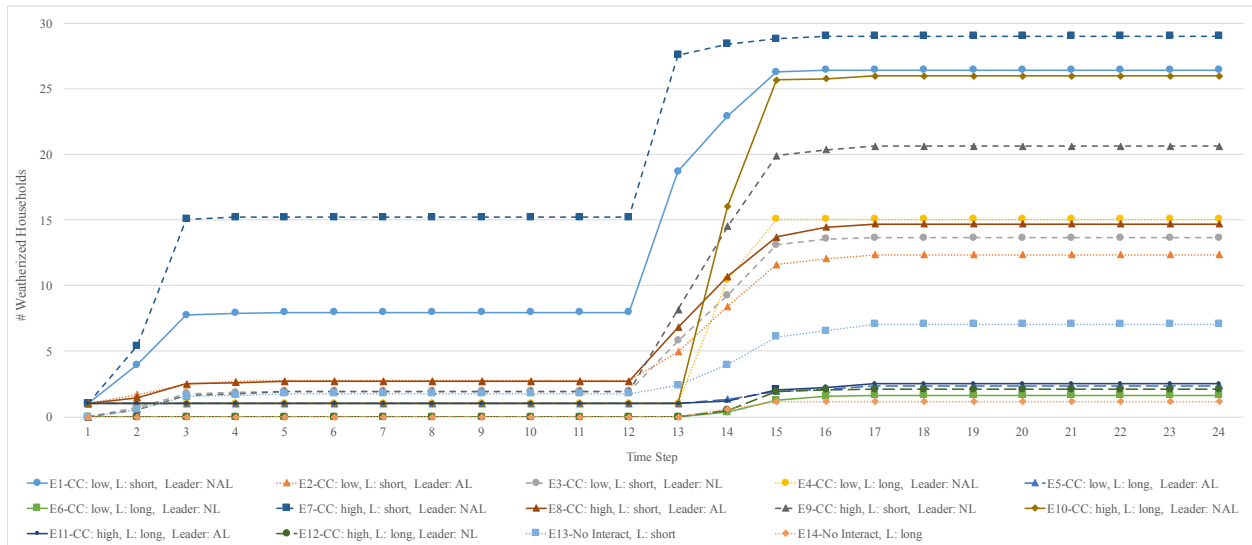


Figure 2.6: Average number of weatherized households in each time-step for each experimental scenario

The total number of weatherized homes varies considerably. To better understand the reasons for these differences, the output data in the final time-step were analyzed with respect to different levels of the key experimental factors. Figure 2.8 shows the average number of weatherized houses in the final time-step for the 12 experimental scenarios in which agents could interact, for three different levels of community leader agent: no community leader (NL), community leader that

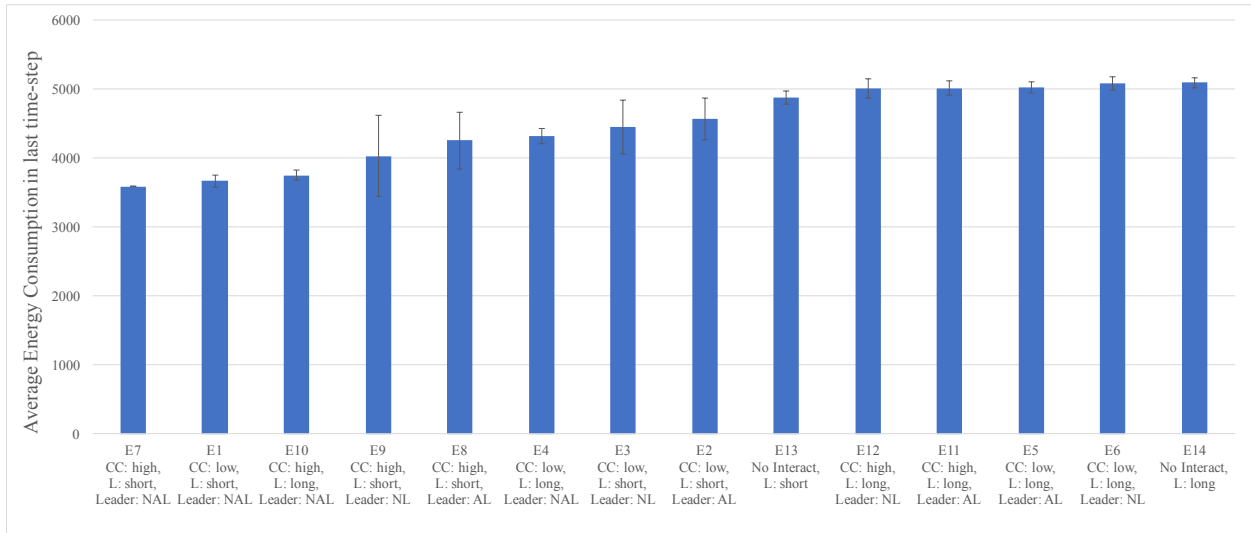


Figure 2.7: Average and standard error of the total energy consumption in the final time-step (kWh)

weatherized with assistance (AL), and a community leader that self-weatherized (NAL). The *t*-test and Cohen’s *d* values are shown in Table 2.4 and Table 2.5. There is no significant difference between the number of weatherized households in the final time-step when incorporating a leader that weatherized with assistance (AL). By contrast, the presence of a self-weatherized leader (NAL) significantly increases the number of weatherized households in all experimental scenarios ($p < .001, d > 1.2$), with all or nearly all 29 household agents adopting weatherization. In addition to

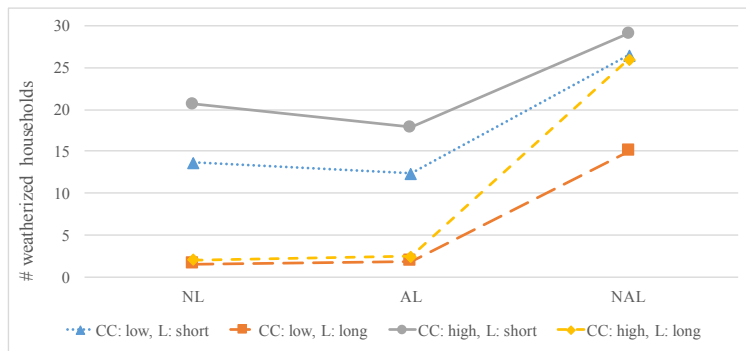


Figure 2.8: Average number of weatherized households in the final time-step for three levels of community leader presence

Table 2.4: Comparisons of “leader: NL” and “leader: AL” subjects

Group	Configuration	Mean	SD	$t(19)$	p
Control	E3-CC: low, L : short, leader: NL	13.7	7.3	0.8	.41
Experimental	E2-CC: low, L : short, leader: AL	12.4	5.0		
Control	E6-CC: low, L : long, leader: NL	1.7	1.0	-0.9	.38
Experimental	E5-CC: low, L : long, leader: AL	2.0	1.1		
Control	E9-CC: high, L : short, leader: NL	20.6	9.1	1.0	.34
Experimental	E8-CC: high, L : short, leader: AL	17.9	7.0		
Control	E12-CC: high, L : long, leader: NL	2.1	2.0	-0.9	.40
Experimental	E11-CC: high, L : long, leader: AL	2.5	1.2		

Table 2.5: Comparisons of “leader: NL” and “leader: NAL” subjects

Group	Configuration	Mean	SD	$t(19)$	p	d
Control	E3-CC: low, L : short, leader: NL	13.7	7.3	-6.6	< .001	2.10
Experimental	E1-CC: low, L : short, leader: NAL	26.4	2.3			
Control	E6-CC: low, L : long, leader: NL	1.7	1.0	-23.2	< .001	7.75
Experimental	E4-CC: low, L : long, leader: NAL	15.1	2.3			
Control	E9-CC: high, L : short, leader: NL	20.6	9.1	-4.1	< .001	1.53
Experimental	E7-CC: high, L : short, leader: NAL	29.0	0.0			
Control	E12-CC: high, L : long, leader: NL	2.1	2.0	-38.7	< .001	11.75
Experimental	E10-CC: high, L : long, leader: NAL	26.0	2.1			

the importance of a self-weatherized leader, the roles of social interactions and connectedness had strongly positive effects, allowing for more household agents to adopt weatherization in scenarios with no leader at all.

Figure 2.9 shows the average number of weatherized houses in the final time-step when the household agents’ memory lengths are either short or long. t -test and Cohen’s d value are shown in Table 2.6. In all cases, significantly more agents weatherize when they have short memories than when they have long memories ($p < .001, d > 2$). Agents with longer memories are relatively insensitive to energy cost increases in winter, whereas agents with a short memory length tend to be highly responsive to changes in energy costs and more influenced to adopt weatherization due to a sudden increase in costs.

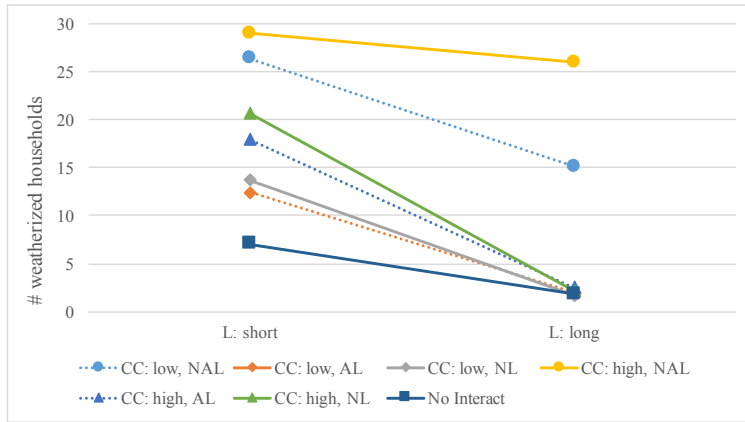


Figure 2.9: Average number of weatherized households in the final time-step for short and long agent memory lengths

Figure 2.10 shows that a high closeness constant (CC) yields more weatherization than a low CC . Table 2.7 summarizes the t-test and Cohen’s d values. The effect is only significant for the scenarios in which a community leader that self-weatherized is present ($p < .001, d > 1.2$), or households have short agent memory length ($p < .05, d > 0.8$). These results demonstrate the importance of density in a social network – greater connectedness can yield a self-reinforcing circle in which information about weatherization (and therefore weatherization adoption behavior) can spread more widely.

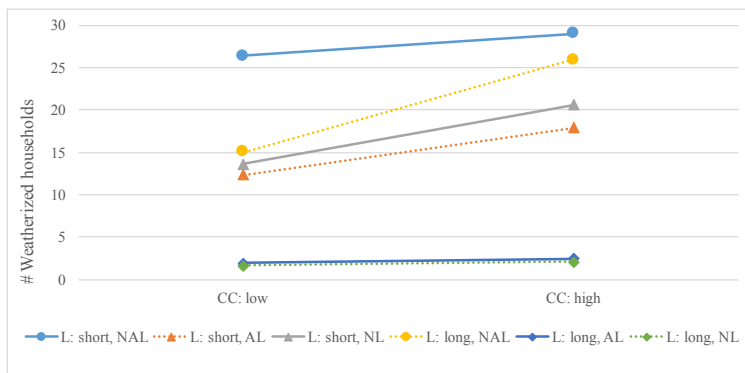


Figure 2.10: Average number of weatherized households in the final time-step for low and high closeness constant values

Table 2.6: Comparisons of “*L*: short” and “*L*: long” subjects

Group	Configuration	Mean	SD	<i>t</i> (19)	<i>p</i>	<i>d</i>
Control	E13-No Interact, <i>L</i>: short	7.1	2.8	7.2	< .001	2.49
Experimental	E14-No Interact, <i>L</i>: long	1.8	1.2			
Control	E3- <i>CC</i> : low, <i>L</i>: short , leader: NL	13.7	7.3	7.6	< .001	2.36
Experimental	E6- <i>CC</i> : low, <i>L</i>: long , leader: NL	1.7	1.0			
Control	E9- <i>CC</i> : high, <i>L</i>: short , leader: NL	20.6	9.1	9.0	< .001	2.87
Experimental	E12- <i>CC</i> : high, <i>L</i>: long , leader: NL	2.1	2.0			
Control	E1- <i>CC</i> : low, <i>L</i>: short , leader: NAL	26.4	2.3	13.5	< .001	5.10
Experimental	E4- <i>CC</i> : low, <i>L</i>: long , leader: NAL	15.1	2.3			
Control	E7- <i>CC</i> : high, <i>L</i>: short , leader: NAL	29.0	0.0	6.5	< .001	2.09
Experimental	E10- <i>CC</i> : high, <i>L</i>: long , leader: NAL	26.0	2.1			
Control	E2- <i>CC</i> : low, <i>L</i>: short , leader: AL	12.4	5.0	9.7	< .001	2.97
Experimental	E5- <i>CC</i> : low, <i>L</i>: long , leader: AL	2.0	1.1			
Control	E8- <i>CC</i> : high, <i>L</i>: short , leader: AL	17.9	7.0	9.5	< .001	3.70
Experimental	E11- <i>CC</i> : high, <i>L</i>: long , leader: AL	2.5	1.2			

Table 2.7: Comparisons of “*CC*: low” and “*CC*: high” subjects

Group	Configuration	Mean	SD	<i>t</i> (19)	<i>p</i>	<i>d</i>
Control	E3- <i>CC</i> : low, <i>L</i> : short, leader: NL	13.7	7.3	-3.5	.003	0.86
Experimental	E9- <i>CC</i> : high, <i>L</i> : short, leader: NL	20.6	9.1			
Control	E6- <i>CC</i> : low, <i>L</i> : long, leader: NL	1.7	1.0	-1.0	.33	
Experimental	E12- <i>CC</i> : high, <i>L</i> : long, leader: NL	2.1	2.0			
Control	E1- <i>CC</i> : low, <i>L</i> : short, leader: NAL	26.4	2.3	-5.2	< .001	1.67
Experimental	E7- <i>CC</i> : high, <i>L</i> : short, leader: NAL	29.0	0.0			
Control	E4- <i>CC</i> : low, <i>L</i> : long, leader: NAL	15.1	2.3	-14.0	< .001	5.06
Experimental	E10- <i>CC</i> : high, <i>L</i> : long, leader: NAL	26.0	2.1			
Control	E2- <i>CC</i> : low, <i>L</i> : short, leader: AL	12.4	5.0	-2.9	.009	0.94
Experimental	E8- <i>CC</i> : high, <i>L</i> : short, leader: AL	17.9	7.0			
Control	E5- <i>CC</i> : low, <i>L</i> : long, leader: AL	2.0	1.1	-1.4	.18	
Experimental	E11- <i>CC</i> : high, <i>L</i> : long, leader: AL	2.5	1.2			

Figure 2.11 illustrates the number of weatherized households in each scenario’s final time-step, where agents were allowed to interact. Results indicate that the presence of a self-weatherized community leader consistently yielded the greatest number of weatherized households. Nearly all weatherization adoptions, across all scenarios, were performed without assistance. Notably, most self-weatherized households did not apply for WAP before weatherization, either because they were uninformed about WAP or because they were dissatisfied with WAP. Some agents did apply for WAP, but finally chose to pay for weatherization out of pocket because of long delays for appointment.

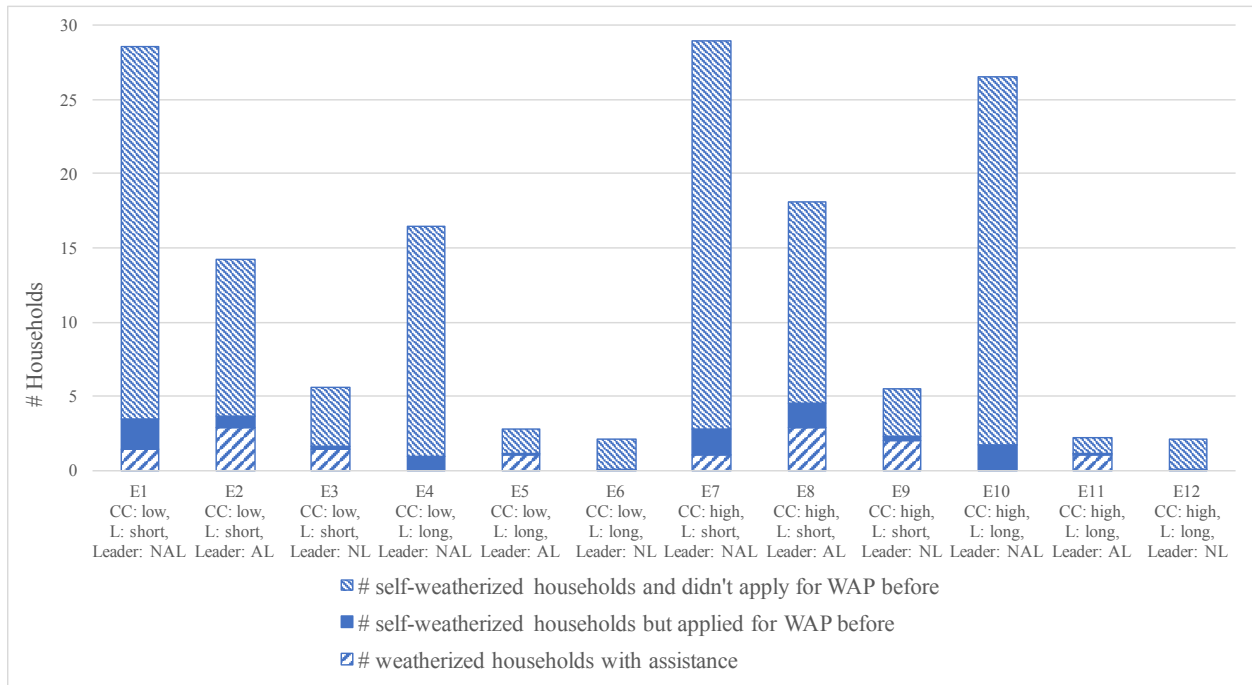


Figure 2.11: Number of weatherized households in the final time-step over 20 simulation replications

2.6 Discussion

This section discusses the experiment results in the context of policies that may have potential for increasing weatherization adoption. Four recommended policies are discussed.

2.6.1 Encourage Community Connectedness and Engagement

Experimental results from the model indicate that social interactions greatly increase weatherization adoption rates. After 24 months, an average of 14.1 household agents had weatherized when agents could interact and share information, whereas only 4.4 households weatherized when no interactions were allowed. The literature supports this result, indicating that information sharing via social interactions is a key influence in weatherization decisions; one study showed that it doubled the likelihood of weatherization (Southwell and Murphy, 2014).

Results also demonstrated that greater connectedness among household agents increased adoption. Using a larger closeness constant increased the network's connectedness and frequency of agent interactions. This significantly increased the rate of weatherization adoption in four of the six experimental scenarios in which a large closeness constant was. These results agree with data from a preliminary survey in which 34 local residents were asked questions related to their attitude, knowledge, and experience with weatherization (Stonewall et al., tted). According to the survey, 71% of respondents would be more likely to make weatherization changes to their home if they saw a neighbor doing the same. These results suggest that promoting connectedness and encouraging community engagement can support increased weatherization adoption. For example, providing opportunities for neighborhood residents to share information about energy conservation techniques (e.g., through community events) could be valuable.

These results emphasize the impact of local residents' sharing their experience on taking tangible action. Such results match research in the social sciences that places social connectedness and action as a crucial combination for creating more resilient communities, particularly for resource-vulnerable populations. This combination, known as social capital, involves the central role of action in the coming together of individuals within groups and then connecting with external partners to form the collaborative ties needed for resilient, adaptive communities (Adger, 2003; Ashwill et al., 2011; Houston et al., 2015; Smith et al., 2012; Wolf et al., 2010). Experimental results support the impact that agents taking their own action (i.e., self-weatherization) and interacting with each other can have on improving the quality of life in a community. Thus, it may be useful for policymakers

working with communities that are not well-connected and that may not have easily identifiable leaders to gather momentum for change first through community engagement where residents can share experiences with each other and then take simple, inexpensive action.

2.6.2 Leverage the Influence of Trusted Messengers

A community leader was important in encouraging weatherization adoption, significantly increasing the number of household agents that weatherized (24.1 households vs. 9.5 households). The literature supports this outcome, emphasizing the importance of trusted messengers in increasing weatherization adoption in a community (Fuller, 2010). Furthermore, the results of a local survey indicated that more than half of respondents (59%) would turn to neighborhood association leaders and/or experts at community events to learn about weatherization (Stonewall et al., tted). These results indicate that policymakers should consider dedicating resources to training community leaders about weatherization techniques. Particularly for low-income neighborhoods where some residents may be un- or under-employed, city officials may also consider offering training that could lead to employment in city-provided weatherization services such as energy audits. These new professionals/leaders could then use their influence to teach others in the community about weatherization practices.

The literature also suggests that a key role for trusted messengers involves explaining to community members how WAPs work and recruiting them to participate (Fuller, 2010). However, when a leader agent was present that had weatherized with assistance, the model results showed no significant impact on the final number of weatherized households. This result reflects the strength of the agents' perception of weatherization assistance as providing less satisfaction (in terms of their utility values) than self-weatherization. The influence of a trusted messenger was unable to overcome this perception.

2.6.3 Invest in Publicizing and Improving the Efficiency of WAPs

In the model, agents' decisions about applying to the WAP were based on their awareness of the program and their beliefs about the process. Nearly all of the agents that weatherized chose to self-weatherize (80%), rather than using the services of the WAP. The literature supports this result, with very few income-eligible households applying for weatherization assistance because of a lack of awareness and perceptions that the application and approval processes are difficult, inconvenient, and lengthy (Fowle et al., 2015; Kathleen, 2006). Similarly, 76% of the local survey respondents indicated that they would be willing to reduce their energy bills via self-weatherization, while only 41% would seek assistance from a weatherization program (Stonewall et al., tted). Of the participants who indicated that they had previously sought assistance to cover the cost of weatherization, 43 % mentioned having a poor experience or long wait time. Of the participants who had not previously applied for assistance, 42% mentioned that they were unaware of the program.

These results suggest that, if WAPs are to be effective in increasing adoption, potential recipients must perceive them as being efficient and convenient. A program's good reputation can then be reinforced and disseminated via trusted messengers and social interactions among community members to increase participation.

2.6.4 Periodically Remind Residents about Seasonal Peak Energy Costs

Significantly more household agents decided to weatherize when they had short memories (18.1 households) than long memories (7.3 households). Shorter memory length made agents more sensitive to the high energy costs experienced in winter months. Social psychology confirms that these kinds of "recency effects" tend to bias human decision making to weigh recent events more heavily than earlier events (Laham and Forgas, 2007).

This suggests that periodically reminding residents about high seasonal energy bills could encourage increased weatherization adoption. For example, the bill (City of Ames, 2017) shown in

Figure 2.12 provides a graph of the resident's energy usage history, which may help to keep high winter heating costs fresh in memory and potentially increase the likelihood of weatherization.

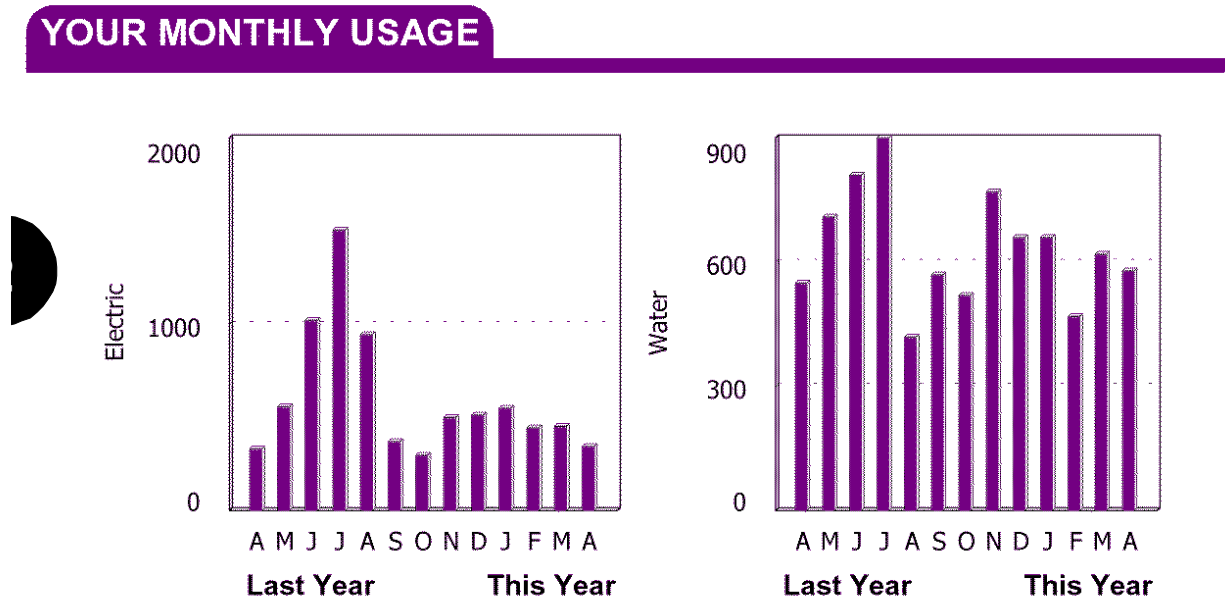


Figure 2.12: An example energy bill form

2.7 Conclusion

Significant amounts of public funds have been allocated to WAPs that are intended to help low-resource residents improve the energy efficiency of their homes, thereby improving the resilience of the community and quality of life. However, they have not been as effective as they could be. Many qualified residents are unaware that such programs exist, or they perceive that the program's potential benefits do not outweigh the struggle with the application and implementation processes. While improving the efficiency of assistance programs is necessary to increase adoption rates, convincing residents to weatherize also requires that common cognitive decision biases (e.g., status quo and framing biases) are overcome by leveraging social norms, community connectedness, and trusted messengers.

The hybrid simulation model presented in this paper can be used to inform the decisions of urban policymakers, enabling them to explore the impacts of different interventions on households' weatherization decisions. The model connects the dynamic social interactions, adaptations, and decision processes of individual and autonomous urban households with the physics of building energy usage. The model allows parameters of interest (e.g., social network density, agents' memories and decision processes, influence of a trusted messenger) to be experimentally varied such that the relationships between these parameters and output metrics of interest (e.g., weatherization adoption, assistance program usage, energy consumption) can be observed and analyzed. Understanding these relationships can help to inform effective policy-related decisions.

The next stage of model development involves empirical validation. A survey is being developed and administered to over 1000 households in three contiguous neighborhoods, on the east side of Des Moines, including Capitol East. This survey will collect relevant data on household demographics, individual and social behaviors related to energy and weatherization, building infrastructure, and previous weatherization efforts. Model outputs will be compared and tuned to the behaviors of the real-life urban neighborhoods via an iterative modeling validation process. The model will be further validated through participatory modeling with key stakeholders and policymakers in Des Moines, such that sufficient "buy-in" is generated to build trust in model outputs, encourage adoption of the model as a decision support tool, and support the creation of data-driven policy for increased energy conservation and long-term community resilience.

CHAPTER 3. WEATHERIZATION ADOPTION IN A MULTILAYER SOCIAL NETWORK: AN AGENT-BASED APPROACH

Modified from a paper published in *CSSSA's Annual Conference on Computational Social Science, 2017*

Wanyu Huang, Caroline C. Krejci, Michael C. Dorneich, Ulrike Passe

Abstract

Energy conservation in residential buildings has been a topic of interest in recent years because of their high levels of energy consumption. Weatherization is set of approaches that can be used to make buildings more energy-efficient, thereby helping residents lower their energy bills and improving environmental sustainability. However, there are two significant challenges associated with weatherization adoption: high upfront investment costs with a long payback period, and minimal awareness of weatherization and its benefits. This paper proposes an agent-based model that will allow researchers to explore residents' socially-motivated energy conservation decisions by providing a realistic social context via a multilayer social network and incorporating opinion dynamics based on the Susceptible-Exposed-Infected-Recovered epidemic model. Several experimental scenarios are run to demonstrate the model's potential to help policymakers determine how to encourage residential weatherization adoption.

3.1 Introduction

The promotion of energy-saving innovations in residential buildings has been an area of significant interest in recent years (Friege et al., 2016; Southwell and Murphy, 2014; Noonan et al., 2013; Anderson et al., 2012; Jain et al., 2013). Residential buildings are responsible for nearly 27% of all energy consumption (U.S. Energy Information Administration, 2017b) and 36.5% of electricity use (U.S. Energy Information Administration, 2017a) in the U.S. and are therefore a major contributor to climate change. Furthermore, low-income households are disproportionately burdened with energy costs, typically spending 16.3% of their total annual income on energy, compared with 3.5% for other households (U.S. Department of Energy, 2017).

Weatherization is the practice of improving the energy efficiency of existing residential buildings through a variety of approaches, such as installing insulation in walls, upgrading inefficient refrigerators, and reducing air leakage. This yields many benefits for residents, including reduced energy costs and improved health and safety, as well as benefits for society through job creation and a reduction in greenhouse gas emissions (Iowa Department of Human Rights,). Despite these benefits, weatherization adoption rates remain low, as a result of high upfront investment costs and long payback periods (Soratana and Marriott, 2010), as well as a general lack of awareness about weatherization techniques and benefits. The government has tried to overcome these barriers through various campaigns aimed at raising awareness of the energy cost savings from weatherization, as well as providing financial assistance to low-income residents to help them weatherize their homes (Jagani and Passe, 2017). However, these efforts have had limited success.

Rather than only relying on financial incentives to convince residents to weatherize, research suggests that policymakers should instead leverage the strength of social influence. Peer interactions have proved to be an important factor in residents' decisions to adopt energy-related behaviors (Jain et al., 2013; Rai and Robinson, 2015; Krejci et al., 2016; McEachern and Hanson, 2008; Noonan et al., 2013; Friege et al., 2016), and the influence of social networks on energy-efficiency innovation diffusion has been demonstrated (McMichael and Shipworth, 2013). In particular, social interaction

regarding energy-related tips and information is a predictor of weatherization behavior (Southwell and Murphy, 2014).

The importance of social interactions in determining residents' energy-related decisions suggests that agent-based modeling would be an appropriate method for modeling a network of residents. Agent-based models (ABMs) allow researchers to model individual decision makers as autonomous agents that are capable of social behaviors and interactions (e.g., information sharing) with other agents. Over time, the effects of these repeated interactions and feedbacks on individuals' decisions (i.e., at the micro level) may yield system-wide changes that are unexpected and difficult to predict without the use of computational modeling (Wang et al., 2007). ABM is a promising methodology for capturing consumer behavior in general and energy technology adoption in particular (Wolf et al., 2012; Macy and Willer, 2002; Epstein, 1999; Bonabeau, 2002; Mittal and Krejci, 2017; Mittal et al., 2017; Mittal and Krejci,). ABM facilitates the modeling of opinion dynamics in a social system, which is useful in representing residents' socially-motivated decisions to weatherize their homes (Southwell and Murphy, 2014; Rai and Robinson, 2015; Azar and Menassa, 2011).

However, when modeling energy-related behaviors, adequate consideration must be given to the agents' social network structure and properties (Anderson et al., 2013). To this end, some modelers have made efforts to incorporate realistic social networks into ABMs (Fontana et al., 2015; Rahmandad and Sterman, 2008; Alam and Geller, 2012; Hamill and Gilbert, 2009). In particular, small-world networks, which have a structure that is an interpolation between regular and random networks, are often used to represent social networks to explore social behavior. Small-world networks have been integrated into ABMs to model the diffusion of solar photovoltaic adoption (Palmer et al., 2015; Rai and Robinson, 2015). The networks in these models are used to represent interactions that occur in a physical space, such as a neighborhood. Furthermore, the agents that populate these models typically interact in the same way with all of their neighbors (Hegselmann et al., 2002; Krejci et al., 2016)), and pairs of agents are randomly selected for interactions (Meadows and Cliff, 2012; Rai and Robinson, 2015). By contrast, Azar and Menassa (2011) developed an ABM of energy use behavior, in which they assumed that only adopters were capable of spreading infor-

mation to non-adopters, since only adopters would have the ability to make realistic and reliable assessments of their adoption decisions. The agents in this model have heterogeneous attitudes toward information sharing; for example, some agents may have no interest in the information and are therefore immune to it, which means that their existing beliefs will not be affected by social interactions. The strength of these interactions may also vary. Chen et al. (2012)) proposed a semi-local centrality measure to identify influential nodes in complex networks. Geographic distances (Scellato et al., 2010; Barthélemy, 2011) and demographic similarities (Diamantopoulos et al., 2003; Islam and Meade, 2013) also known to affect the strength of interactions. Furthermore, interactions between individuals are often multidimensional, occurring in both physical and virtual environments (e.g., via online social networks).

This paper describes a conceptual ABM that is embedded in a multilayer social network to model weatherization adoption among residential households, with a specific focus on low-income residents. The model is based on the Capitol East Neighborhood in Des Moines, Iowa, which is a low-income neighborhood that has a strong neighborhood association and a goal of improving sustainability. The multilayer approach allows the agents to interact via a physical social network (i.e., their neighborhood) and a virtual social network (i.e., online). Small-world networks are used to describe the physical social networks (PSNs), while scale-free networks are used to represent the online social networks (OSNs), since the primary characteristic of many OSNs (e.g., Flickr, YouTube) is the scale-free property (Ahn et al., 2007; Barabási, 2009; Mislove et al., 2007). To incorporate agent' intention to spread information, a Susceptible-Exposed-Infected-Recovered (SEIR) epidemic model (Li and Muldowney, 1995; Apolloni et al., 2009; Cha et al., 2012) is used. The SEIR model provides a framework for defining the rules that determine agent interactions and influence. Agents' local centrality (Chen et al., 2012), spatial location (Scellato et al., 2010) and social demographics (Diamantopoulos et al., 2003) are considered when evaluating the strength of each interaction. The agents' decisions about adopting weatherization are characterized by emotional and economic factors and are based on the theory of planned behavior (Ajzen, 1991), a widely-used theory in studies on energy-related behaviors (Rai and Robinson, 2015; Harland et al.,

1999; Ajzen et al., 2011). The model is used to perform several experiments, in which the influence of randomness in the physical social network, the different choices of initial weatherized agents, the number and coverage of media agents that can spread weatherization information, when to add these media agents, households' susceptibility to media, and the efficiency of the Weatherization Assistance Program are explored. The results of these experiments demonstrate the potential of this modeling framework to inform policymakers' decisions regarding programs for increasing weatherization.

3.2 The Theoretical Framework

Figure 3.1 depicts the theoretical framework that is used to represent a household's decision-making process with respect to weatherization adoption. The theory of planned behavior (TPB) is the basic principle of the theoretical framework (Ajzen, 1991). TPB states that behavioral intention is the best predictor of actual behavior, and intention is determined by three factors: 1) the degree to which a person has a favorable or unfavorable evaluation of the behavior (attitude), 2) the social pressure and the motivation to comply (subjective norm), and 3) the perception of the ease or difficulty of performing the behavior (perceived behavioral control). The TPB has been used to describe a wide variety of behaviors, including electronic commerce adoption (Pavlou and Fygenon, 2006), smoking (Godin and Kok, 1996), and leisure choice (Ajzen and Driver, 1992). It has also been adopted to explain environmentally relevant behaviors (Abrahamse and Steg, 2009; Harland et al., 1999; Friege et al., 2016).

Household weatherization decisions are triggered by behavioral intentions and actual behavioral control (i.e., ability). For example, in the model described in this paper, the household agents evaluate the estimated return on investment for weatherization, which results in positive (e.g. "weatherization will save money over time") or negative (e.g. "the weatherization is too expensive") attitudes toward weatherization. Subjective norms are captured through the agents' socio-demographics and their peer interactions. The ability (e.g. "I have enough money to pay for weatherization") determines whether or not a household can weatherize and also determines

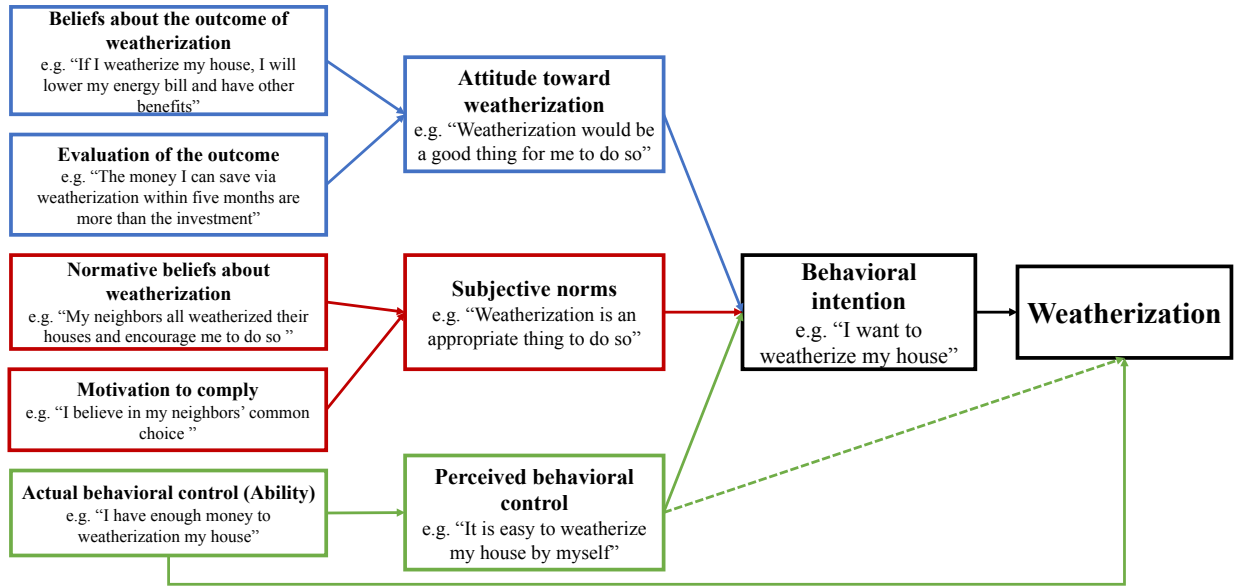


Figure 3.1: Theoretical framework for households' decision-making processes on whether or not to weatherize their homes.

the perceived behavioral control. Intuitively, if behavioral intention and ability both have positive value, a person will conduct the actual behavior.

3.3 Conceptual Model Description

This section describes the building energy simulation model and the ABM, which is implemented in NetLogo 5.3.1 (Wilensky, 1999). The preliminary version of this model is described in a proof-of-concept paper (Huang et al., 2017).

3.3.1 Building Energy Simulation

The building energy model is a digital model of the Capitol East Neighborhood in Des Moines that was built using Rhinoceros 3D and the Urban Modeling Interface (*umi*) plugin from MIT's Sustainable Design Lab (Reinhart et al., 2013). This model was used to create a dataset consisting of the monthly energy consumption values of residential buildings in the neighborhood under

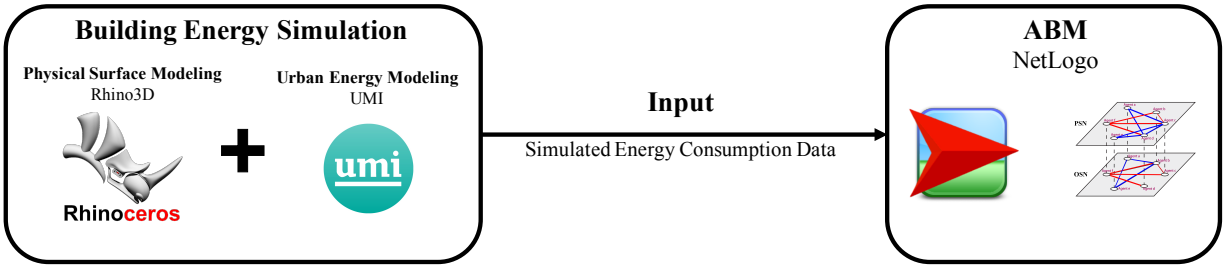


Figure 3.2: Overview of the model.

pre- and post-weatherization conditions (Jagani and Passe, 2017). The Rhino-umi model uses geographic information system (GIS) data obtained from the City of Des Moines to model the physical geometry of the Capitol East Neighborhood. Information available in the Polk County Assessor’s database (Polk County Assessor website, 2015) is then used to refine the Rhino model at the building scale. This database provides detailed information on the each building in the neighborhood, including the parcel number, date of construction, construction materials, number of stories, and number of separate residences contained within. Because regional climate strongly influences residential energy consumption patterns, regional weather data was also included in the simulation. We use typical meteorological year weather data (TMY3) obtained from the Department of Energy (Wilcox and Marion, 2008) and the future typical meteorological year weather data (FTMY) (Patton, 2013) weather datasets to incorporate the climatic impact on energy consumption in residential buildings. TMY3 provides a reasonably sized annual dataset consisting of hourly meteorological values that are intended to typify conditions at a specific location over a longer period of time. Aforementioned data about building footprint, building forms, construction materials and weather conditions served as a basis for the Rhino model. Additional details about the model are available in Jagani and Passe (2017). Figure 3.3 shows a visualization of building energy consumption generated by the Rhino-umi model, where different colors indicate different energy consumption values.

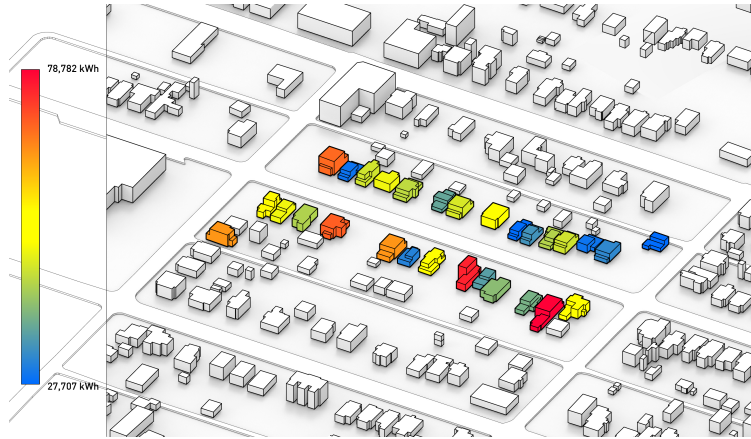


Figure 3.3: A visualization of energy consumptions for residential buildings in the Capitol East Neighborhood.

3.3.2 Agent-based Model

3.3.2.1 Agents

The ABM contains two types of agents: household agents and media agents. Household agents are used to represent each household in the Capitol East Neighborhood as an autonomous agent that is capable of communicating with other agents via its social networks and making decisions about weatherizing its home. Media agents are tools used to store and deliver information for households to learn weatherization-related information and news.

Household Agents Households agents have the ability to adopt weatherization and share weatherization information with other household agents. Each household agent represents an entire household, rather than an individual resident, because weatherization decisions are assumed to occur at the household level. Only single-family residential buildings were included since the energy consumption values for multi-family buildings (e.g., apartments) are difficult to capture with the Rhino-umi model. The model has 1548 household agents, of which 548 are located within the Capitol East Neighborhood and the remaining 1000 are located elsewhere.

Each household agent has been assigned a level for each of four major demographic factors: age, income, education, and race (Mittal et al., 2017; Apolloni et al., 2009), which are used to

determine the similarity of household agents. Based on empirical data for the City of Des Moines, seven levels (0-6) of age (Ag), nine levels (0-8) of income (In), four levels (0-3) of education (Ed) and four levels (0-3) of race (Ra) are defined, as shown in Tables 3.1, 3.2, 3.3, 3.4.

Table 3.1: Age of population 18 years and over

Definition	Level
18 - 24 years	0
25 - 34 years	1
35 - 44 years	2
45 - 54 years	3
55 - 64 years	4
65 - 74 years	5
75 years and over	6

Table 3.2: Household income

Definition	Level
Less than \$10k	0
\$10k - \$15k	1
\$15k - \$25k	2
\$25k - \$35k	3
\$35k - \$45k	4
\$45k - \$55k	5
\$55k - \$60k	6
\$60k - \$65k	7
\$65k - \$70k	8

Table 3.3: Education attainment (highest level) of population 18 years and over

Definition	Level
Less than high school graduate	0
High school graduate	1
Some college or associate's degree	2
Bachelor or higher	3

Each household agent is characterized by 13 key parameters:

- *ID*: Each household agent is assigned a unique identification number.

Table 3.4: Race

Definition	Level
White	0
Black	1
Asian	2
Other	3

- *Poverty level (PL)*: A household agent's poverty level is binary and determines its eligibility for financial assistance. An agent with a poverty level of 1 has a total household income that is at or below 200% of the federal poverty level (IOWA Department of Human Rights, 2017a). This means that the agent is eligible for the Weatherization Assistance Program (WAP), which is a federal grant program that provides financial assistance to help low-income residents to weatherize their homes (IOWA Department of Human Rights, 2017b). A household agent with a poverty level of 0 is not eligible for WAP (i.e., its total household income is too high).
- *Monthly energy consumption (E)*: In each month m , each household agent is assigned two values that represent its monthly energy consumption (in kWh) before and after weatherization (NWE_m and WE_m , respectively). These values are outputs of the building energy simulation.
- *Estimated payback period (P)*: Each household agent is capable of estimating the breakeven point at which the upfront investment in weatherization pays for itself through subsequent energy cost savings. The upfront investment (U_t) (U.S. Department of Energy, 2017) in year t is initialized as \$4,695 (U_0) and increases over time due to inflation:

$$U_t = U_0(1 + R_1)(1 + R_2)\dots(1 + R_t)(1 - F_t), \quad (3.1)$$

where R_t denotes the inflation rate in year t , and F_t refers to the federal income tax credits for energy efficiency, which is assumed to be 30% (Energy Star, 2017). By weatherizing, single-family homes saved an average of \$283 annually on energy costs (U.S. Department of Energy, 2017). Therefore, each agent's annual household energy cost savings in the year in which it

decides to weatherize (S_0) is set to \$283. If an agent weatherizes in year t , its total savings over n years (TS_{t+n}) is calculated as:

$$\begin{aligned} TS_{t+n} &= S_t + S_{t+1} + \dots + S_{t+n} \\ &= S_0((1 + R_t) + (1 + R_t)(1 + R_{t+1}) \\ &\quad + \dots + (1 + R_t)\dots(1 + R_{t+n})). \end{aligned} \quad (3.2)$$

An agent's estimated payback period P is the value of n (in years) for which $U_t = TS_{t+n}$.

- *Budget (B)*: The maximum amount of money (in dollars) that an agent is able to spend on weatherization. Household agents with a poverty level of 0 must pay U_t for weatherization out of pocket. Each agent's budget for weatherization is drawn randomly from a uniform distribution between \$500 and \$5,000.
- *Degree (D)*: The degree (D_a) of agent a is defined as the number of connections (edges) the agent a has to neighboring agents. For example, a person socially connected to 20 people has a degree of 20.
- *Local centrality (LC)*: We adopt the semi-local centrality measure (Chen et al., 2012) to explore influential agents in networks, in which the agent with a larger value of local centrality is more influential. The local centrality Lc_a of agent a is defined as

$$Q_i = \sum_{j \in \Gamma_i} N_j, \quad (3.3)$$

$$LC_a = \sum_{i \in \Gamma_a} Q_i, \quad (3.4)$$

where Γ_a is the set of the nearest neighbors of agent a and N_j is the number of the nearest and the next-nearest neighbors of node j . In Figure 3.4, agent 1 has seven nearest neighbors (agent 2 to 8) and two next-nearest neighbor (agents 9 and 11). Therefore, $N_1 = 9$. The N value of agent 2-8 are calculated in the same manner. Using Eq. 3.3, $Q_1 = \sum_j^{2,3,4,5,6,7,8} N_j = 52$. The local centrality of agent 1 is equal to the sum of Q over all the nearest neighbors of agent 1 (Eq. 3.4), such that $LC_1 = \sum_i^{2,3,4,5,6,7,8} Q_i = 127$.

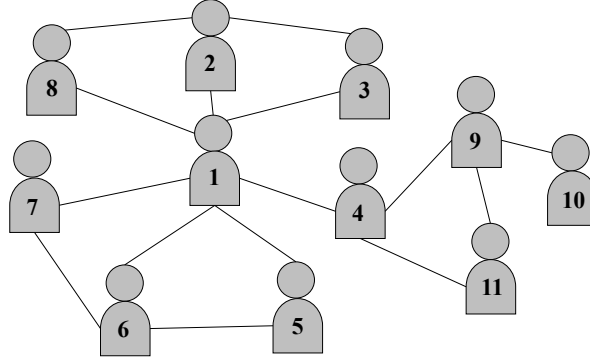


Figure 3.4: An example network consisting of 11 agents and 15 connections.

- *Global influence level (GIL)*: In order to normalize the household agent's local centrality to 0-1 range, the global influence level is defined. A household agent with higher value of global influence level is likely to have higher influence in the network (Chen et al., 2012). The global influence level of agent a is defined as

$$GIL_a = \frac{LC_a - LC_{\min}}{LC_{\max} - LC_{\min}}, \quad (3.5)$$

where LC_{\min} , LC_{\max} refer to the minimum and maximum local centrality among all household agents in the Capitol East Neighborhood, respectively.

- *Distance from others (DS)*: GIS data obtained from the City of Des Moines provides spatial information for the Capitol East Neighborhood, which was used to calculate distances (in meters) between the residential buildings associated with each of the 548 household agents located in Capitol East. Each of these agents therefore has a vector that stores its distance from all 547 other agents in the Capitol East Neighborhood.
- *Similarity ($Simi_{ab}$)*: Household agents are assumed to have heterogeneous characteristics and preferences. However, each pair of agents may also share some similar traits. The four major demographics factors are used to determine the similarity of each pair of household agents (Kwan, 2012; Islam and Meade, 2013; Diamantopoulos et al., 2003; Hughes and Podolefsky, 2015). The similarity ($Simi_{ab}$ or $Simi_{ba}$) of agent a and agent b is assumed to be

indirectly proportional to the differences in their age (Ag), income (In), education (Ed), and race (Ra) levels, with equal weights on each factor. The similarity can be obtained using

$$\text{Simi}_{ab} = \left(\frac{1}{4} - \frac{|\text{Ag}_a - \text{Ag}_b|}{24}\right) + \left(\frac{1}{4} - \frac{|\text{In}_a - \text{In}_b|}{32}\right) + \left(\frac{1}{4} - \frac{|\text{Ed}_a - \text{Ed}_b|}{12}\right) + \left(\frac{1}{4} - \frac{\text{Ra}_{ab}}{4}\right), \quad (3.6)$$

where Ra_{ab} is 0 if the race values of agent a and b are the same; otherwise it is assigned a value of 1.

- *Local influence level (LIL_{ab}):* The local influence level defines agent a 's local influence on agent b , which is assumed to be symmetrical (i.e., $\text{LIL}_{ab} = \text{LIL}_{ba}$). It is assumed that an agent's local influence on another agent, in terms of interactions, information sharing, and knowledge exchange, is determined by their similarity and geographical proximity (McPherson et al., 2001; Boschma, 2005). For agents located in the Capitol East Neighborhood, the local influence level between two agents a and b is defined as follows:

$$\text{LIL}_{ab} = \text{LIL}_{ba} = \frac{\text{DS}_{\max} - \text{DS}_{ab}}{\text{DS}_{\max} - \text{DS}_{\min}} + \frac{\text{Simi}_{ab}}{2}, \quad (3.7)$$

where DS_{ab} denotes the distance from agent a to agent b , and DS_{\min} , DS_{\max} refer to the minimum and maximum distance between all household agents in the Capitol East Neighborhood, respectively. The local influence level values of the 1000 household agents located outside the Capitol East Neighborhood (for which there are no spatial data) are drawn from a uniform distribution between 0 and 1.

- *Influence coefficient (IC_{ab}):* The influence coefficient defines agent a 's influence on agent b in general. Thus each household agent has a set of influence coefficients, with a value assigned to each of its connections. The influence coefficient IC_{ab} is the arithmetic mean of the local (LIL_{ab}) and global (GIL_a) influence levels:

$$\text{IL}_{ab} = \frac{\text{LIL}_{ab} + \text{GIL}_a}{2}. \quad (3.8)$$

- *Media susceptibility (MS):* The media susceptibility of household agent a to media agent i is the degree to which media agent i can influence household agent a . Household agent

a 's susceptibility to media agents is assumed to be a random number drawn from a normal distribution with mean MS_a .

Each household agent also has 10 state variables that may be updated in each monthly time-step:

- *Weatherization status (WS)*: This binary variable represents the agent's state of weatherization adoption, where a value of 1 indicates that the agent has weatherized its home, and a value of 0 indicates that it has not yet weatherized. An agent can only transition from a status of 0 to a status of 1, based on the assumption that weatherization is irreversible.
- *WAP status*: This binary variable represents the agent's state of receiving weatherization assistance, where a value of 1 indicates that it has successfully received assistance, and a value of 0 indicates that it has not been served by the WAP. It is assumed that an agent with a WAP status of 1 cannot return to a status of 0.
- *Current energy consumption (C)*: Based on its weatherization status and the current time-step (i.e., month), a household agent's current monthly energy consumption (in kWh) is obtained from the outputs of the Rhino-umi model (i.e., the agent's NWE_m and WE_m).
- *Monthly savings (M_m)*: The money that a weatherized household agent saves in month m is based on the difference between its energy consumption before and after weatherization (NWE_m and WE_m , respectively). This difference is multiplied by the energy cost per kWh, which includes the current residential electricity rate E , a rate equalization factor REF, an energy adjustment clause EAC, a transmission cost adjustment TCA, and a 1.00% sales tax, according to the electricity bill calculation provided by MidAmerican Energy Company (MidAmerican Energy Company, 2017),

$$M_m = (NWE_m - WE_m)(E + REF + EAC + TCA)(1 + TAX). \quad (3.9)$$

- *Current average saving (AS)*: This variable, which is calculated for household agents that have weatherized, is determined by dividing the agent's total savings by the number of months since it weatherized.
- *Information status (IS)*: This variable is defined based on the epidemic SEIR epidemic model (Apolloni et al., 2009). A household agent can take on one of four different IS values in each time-step:
 - S (Susceptible): An agent that has not received weatherization-related information from another agent but is ready to receive it.
 - E (Exposed): An agent that has received information but is not yet infectious (i.e., cannot transmit information to others).
 - I (Infected): An agent that can spread weatherization-related information to others.
 - R (Recovered): An agent that is immune to weatherization-related information (i.e., it neither receives nor transmits information).

No contractions, an agent's status towards spreading information can potentially be different in its PSN and OSN; however, its status with respect to weatherization awareness must be the same in both networks. In other words, an agent could be in status E in its PSN and status I in its OSN, but if it is in status S in one network and has a non-S status in the other, its information status will be reconciled to the non-S value in both PSN and OSN after the current time-step.

- *Intention level (IL)*: This variable, which takes values between 0 and 1, denotes a non-weatherized agent's intention to adopt weatherization.
- *Intention*: This binary variable may change from 0 to 1 with a probability of IL in each monthly time-step. A value of 1 indicates that the agent intends to adopt weatherization.
- *Assessment level (AL)*: This variable takes a value between 0 and 1 and represents the degree to which a weatherized agent is satisfied with its weatherization adoption. An agent's AL

value is based on its assessment of the perceived value of its weatherization decision and is influenced by social interactions.

- *Ability*: This binary variable takes on a value of 1 for an agent if it has the ability to weatherize and a value of 0 if it does not. Ability can be achieved in two ways:
 - The agent has received assistance through WAP.
 - The agent's budget exceeds the upfront investment required for self-weatherization.

Media Agents The media is a means by which the government can share weatherization-related information to residents. In this model, media agents seek to spread weatherization information to household agents. Each media agent has four parameters, which take on values that remain unchanged throughout the simulation run:

- *Information status (IS)*: All media agents are assumed to have an information status of 1, since they play the role of information providers.
- *Weatherization status (WS)*: The weatherization status of all media agents is assumed to equal 1 (i.e., they have weatherized).
- *Assessment level (AL)*: This value is assumed to be 1 for media agents, since it is assumed that the media is supportive of weatherization adoption.
- *Coverage*: This variable, which takes values between 0 and 1, indicates the degree to which households are able to acquire information from a certain media agent. For example, a media agent with a coverage value of 1 can access all household agents.

3.3.2.2 Sub-models

The ABM contains five sub-models: *Initialization*, *Information Diffusion*, *Intention & Assessment Level Evolution*, *Ability Judgment*, and *Household Weatherization Adoption*. First, the multilayer social network is generated, and the agents' parameter values are initialized. Then, in

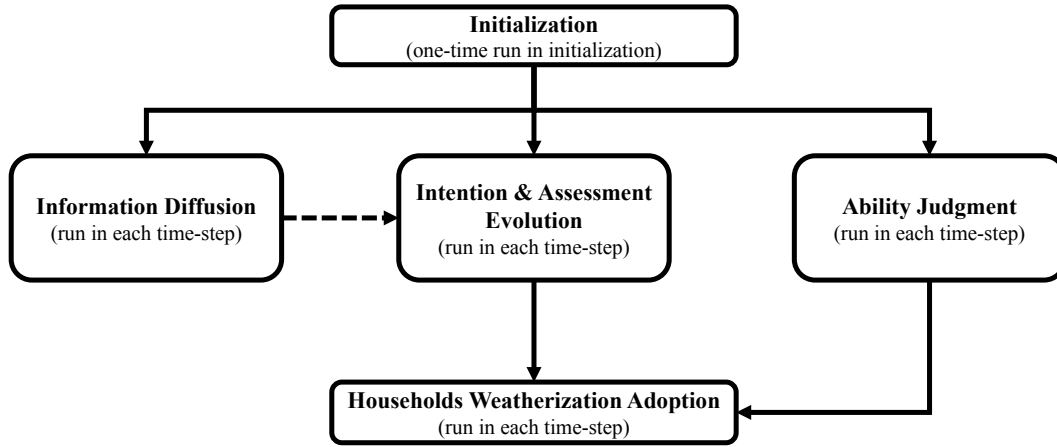


Figure 3.5: Sub-models.

each monthly time-step, agents interact via the multilayer social network, where information diffusion takes place. Based on these interactions, agents' intention and assessment level values evolve, which inform their judgments regarding their weatherization abilities. Finally, at the end of each time-step, each non-weatherized household agent decides whether to adopt weatherization, based on its intention and ability values.

Initialization: Before the first time-step, a multilayer social network is created to allow the agents to interact through both a physical social network (PSN) and an online social network (OSN). There are 548 single-family household agents in the Capitol East Neighborhood. Each node in the PSN (Figure 3.7) represents one of these agents, and each edge represents a connection between the agents it connects, in other words, two connected households know each other and are allowed to have interactions. The PSN is a small-world network that was built using the Watts-Strogatz algorithm (Watts and Strogatz, 1998). This algorithm starts with a regular network, in which each node shares an edge with all other nodes, and “rewires” the edges of this network randomly, based on a probability P_{rewire} . In other words, the small-world network is an interpolation between regular and random networks, and the greater the value of P_{rewire} , the more random the network will be.

The Barabási-Albert (BA) algorithm (Barabási and Albert, 1999) was used to generate a scale-free network for the agents' OSN (shown in Figure 3.8). The OSN consists of the 548 household agents in the Capitol East Neighborhood, as well as 1000 household agents that exist outside the Capitol East Neighborhood, and an experimentally-varied number of media agents. Thus the 548 agents that represent households in the Capitol East Neighborhood exist both in the PSN and the OSN, while the 1000 household agents outside the neighborhood only have virtual connections via the OSN. If no media agents are included, the number of nodes in the OSN is therefore 1548, and the total number of nodes in the multilayer social network (MSN) is 2096. As with individuals in the real world, there are overlaps and differences between the 548 household agents' connections in the PSN and the OSN. Figure 3.9 demonstrates this phenomenon, with red edges indicating overlapping connections and blue edges representing differences.

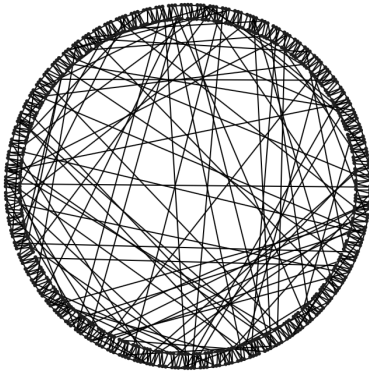


Figure 3.7 PSN

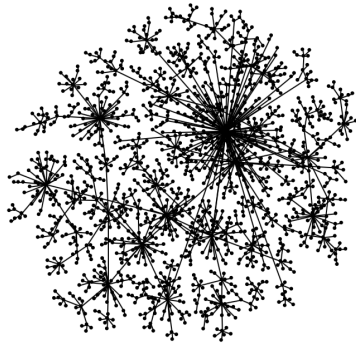


Figure 3.8 OSN

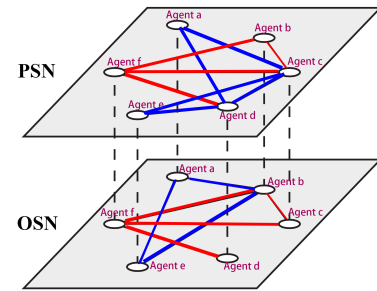


Figure 3.9 Overlaps and differences in a multilayer social network

Figure 3.10: Multilayer Social Networks.

The PSN and OSN are initialized as follows:

- Initially, there are InC weatherized household agents among the 548 agents in the Capitol East Neighborhood and InO weatherized agents outside this neighborhood. In other words, initially, there are InC weatherized agents in the PSN and $InC + InO$ weatherized agents in the OSN.

- The selection of the initial weatherized household agents in the Capitol East Neighborhood can occur in one of the following ways:
 - Random: The *InC* initial weatherized household agents are randomly chosen from the 548 household agents.
 - Important: The *InC* household agents with the largest global influence levels will be selected.
 - One Centroid: The initial weatherized household agents are the *InC* closest ones around the centroid of the neighborhood, as determined by the *k*-means algorithm (MacQueen et al., 1967).
- The information status (*IS*) for all non-weatherized agents is initialized to ‘S’, and for weatherized agents it is initialized to ‘I’.
- The intention level (*IL*) of each non-weatherized household agent is initialized to 0.
- Based on the agent’s upfront investment U and its estimated payback period P , the estimated monthly savings $\frac{U}{12P}$ represents the estimated savings which can pay off U over $12P$ months. The assessment level (*AL*) of each weatherized household agent is based on actual average savings (AS) and estimated monthly savings $\frac{U}{12P}$ due to weatherization using a sigmoid function:

$$AL_0 = \frac{1}{1 + e^{-(AS - \frac{U}{12P})}}. \quad (3.10)$$

Information Diffusion: In this sub-model, the agents interact and then update their information status (*IS*) values accordingly. At the beginning of each time-step, the *IS* value for each agent will have one of four possible values (S/E/I/R). Only infected agents ($IS = I$) can be information senders, while only susceptible, exposed, and infected agents ($IS = S, E, \text{ or } I$) can be information receivers. In each time-step, all infected agents will expose their connected agents (neighbors) with S/E/I status to weatherization-related information. Figure 3.11 shows the transition probabilities associated with changes in an agent’s *IS* value. As an example, if an agent with

information status I is exposed to information, it will transition to status R with probability $P_{I \rightarrow R}$. As discussed previously, an agent's information status value in its PSN and OSN will not always be synchronized to be the same after each time-step.

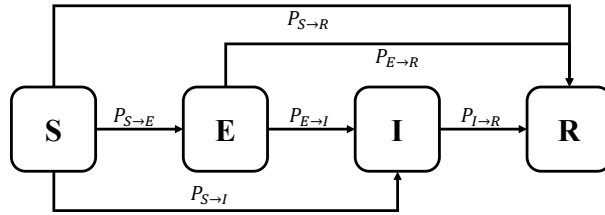


Figure 3.11: A schematic diagram for SEIR model.

Intention & Assessment Level Evolution: A household agent's intention level (IL) is only activated if the agent is in a non-weatherized state, while its assessment level (AL) is only activated if it has weatherized. The values of both IL and AL evolve with interactions.

In each time-step, all agents with information status (IS) equal to I will interact with their connected agents that have $IS = S/E/I$, which will influence the agents' IL or AL values. Table 3.5 summarizes the rules and outcomes when agent i (household or media agents) exposes agent j (household agents) to information. Based on its information status (IS) and weatherization status (WS), each agent falls into a certain category (e.g., I/W). The first letter refers to the agent's IS value, and the second letter represents its WS value, which can be W (weatherized, $WS = 1$) or N (non-weatherized, $WS = 0$). At the beginning of each time-step, the values of IL/AL for the 548 household agents in the Capitol East Neighborhood will be the same in their PSN and OSN. However, over the course of a time-step, the IL/AL values in their PSN and OSN may become different, as a result of the different interactions that may occur in different layers of the social network. The IL/AL of these 548 agents is reconciled to the arithmetic mean of the values in the agent's PSN and OSN at the end of each time-step, thereby ensuring that their IL/AL will have the same value in both layers at the beginning of the next time-step. Each non-weatherized household agent has a probability of IL to change its intention value from 0 to 1. For weatherized agents, the

Table 3.5: IL & AL Evolution Rules (Agent $i \rightarrow$ Agent j). — means not applicable.

Agent i	Agent j	Rules (Agent i is a household agent)	Rules (Agent i is a media agent)
I/W	S/N — E/N	$AL_i = AL_i$ $IL_j = IL_j + IC_{ij}(AL_i - IL_j)$	$AL_i = 1$ $IL_j = IL_j + MS_{ji}(1 - IL_j)$
I/W	I/N	$AL_i = AL_i + IC_{ij}(IL_j - AL_i)$ $IL_j = IL_j + IC_{ij}(AL_i - IL_j)$	$AL_i = 1$ $IL_j = IL_j + MS_{ji}(1 - IL_j)$
I/W	E/W	$AL_i = AL_i$ $AL_j = AL_j + IC_{ij}(AL_i - AL_j)$ $AL_i = AL_i + IC_{ij}(AL_j - AL_i)$	$AL_i = 1$ $AL_j = AL_j + MS_{ji}(1 - AL_j)$ $AL_i = 1$
I/W	I/W	$AL_j = AL_j + IC_{ij}(AL_i - AL_j)$ $AL_j = AL_j + IC_{ij}(AL_i - AL_j)$	$AL_j = AL_j + MS_{ji}(1 - AL_j)$ $AL_j = AL_j + MS_{ji}(1 - AL_j)$
I/N	S/N — E/N	$IL_i = IL_i$ $IL_j = IL_j + IC_{ij}(IL_i - IL_j)$	—
I/N	I/N	$IL_i = IL_i + IC_{ij}(IL_j - IL_i)$ $IL_j = IL_j + IC_{ij}(IL_i - IL_j)$	—
I/N	E/W	$IL_i = IL_i$ $AL_j = AL_j + IC_{ij}(IL_i - AL_j)$	—
I/N	I/W	$IL_i = IL_i + IC_{ij}(AL_j - IL_i)$ $AL_j = AL_j + IC_{ij}(IL_i - AL_j)$	—

value of AL at the beginning of each time-step t following weatherization will be the arithmetic mean of its AL value at the end of time-step $t - 1$ and initialized value $AL_{t(I)}$:

$$AL_t = \frac{AL_{t-1} + AL_{t(I)}}{2}. \quad (3.11)$$

Since each agent's actual savings (AS) is updated at the beginning of each time-step, and agents' AL will be affected by AS , it will have an initialized value $AL_{t(I)} = \frac{1}{1 + e^{-(AS - \frac{U}{12P})}}$.

Ability Judgment: As shown in Figure 3.12, an agent has the ability to weatherize if its WAP status is equal to 1, or if it has a budget that is sufficient to pay for weatherization out of pocket. Only household agents with an income level of 1 qualify for weatherization assistance. In reality, there are many eligible applicants for WAP; however, very few of them receive assistance each year because of limited funding and inefficiencies. For example, in Iowa, 80,000 WAP applicants are approved each year, but only approximately 2,000 applicants can be served (IOWA Department of Human Rights, 2017c). Therefore, the probability P_{wap} that eligible agents receive assistance from WAP in each time-step is assumed to be 2.5%.

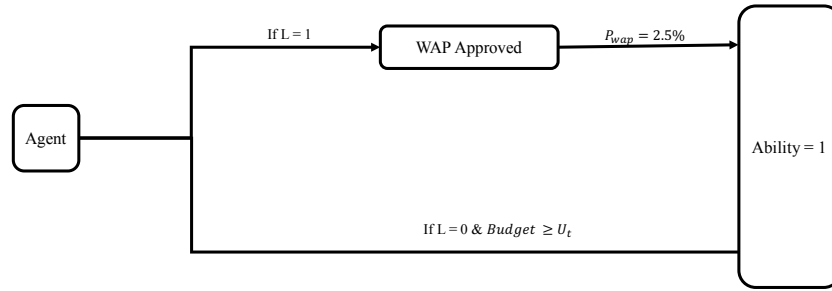


Figure 3.12: Ability Judgment.

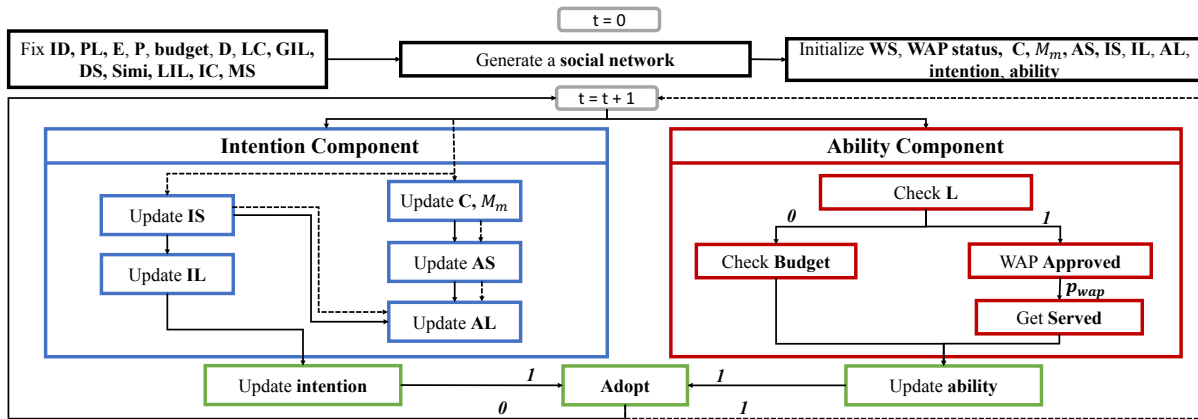


Figure 3.13: Flowchart describing the logic for updating household agent state variables. Agents that adopt weatherization will follow the dashed line to update their *IS* and *AL* values.

Households Weatherization Adoption: The household agents’ weatherization behavior is based on the Theory of Planned Behavior (TPB) (Ajzen, 1991). TPB is a static model which states that intention and perceived behavioral control can result in the actual human behavior. However, this theory does not consider the evolution of these variables with time and interactions (Rai and Robinson, 2015). In this model, the agents’ intention and ability components are used to represent the intention and perceived behavioral control elements of TPB. Each agent’s intention component is dynamic and evolves in the Information Diffusion and Intention and Assessment Level Evolution sub-models in each time-step, and its ability component evolves with the value of the inflation rate in the payback period calculation. In the final decision-making stage, a household agent will weatherize its house if and only if its intention and ability levels are both equal to 1.

3.4 Experiments and Results

The interface developed for the weatherization ABM in NetLogo 5.3.1 (shown in Figure 3.14) allows for the control of multiple experimental variables and provides a visualization of the dynamic social network generation process (left: PSN, right: OSN). To gain a better understanding of how certain factors might influence weatherization adoption, and to provide some potentially useful recommendations to government actors with the City of Des Moines to encourage residents to weatherize, a set of 30 experimental scenarios was developed and run over 180-month replications, which allowed long-run system behavior to be observed. For each scenario, twenty 180-month replications were run. In each replication, the total number of weatherized houses in each monthly time-step and the average adoption timing of weatherization were captured. Table 3.6 shows the values of six parameters that are fixed and constant throughout all experiments, and Table 3.7 provides the experimental variable values for all 30 scenarios. The two key output metrics of interest were the number of household agents that adopted weatherization and the time at which they adopted.

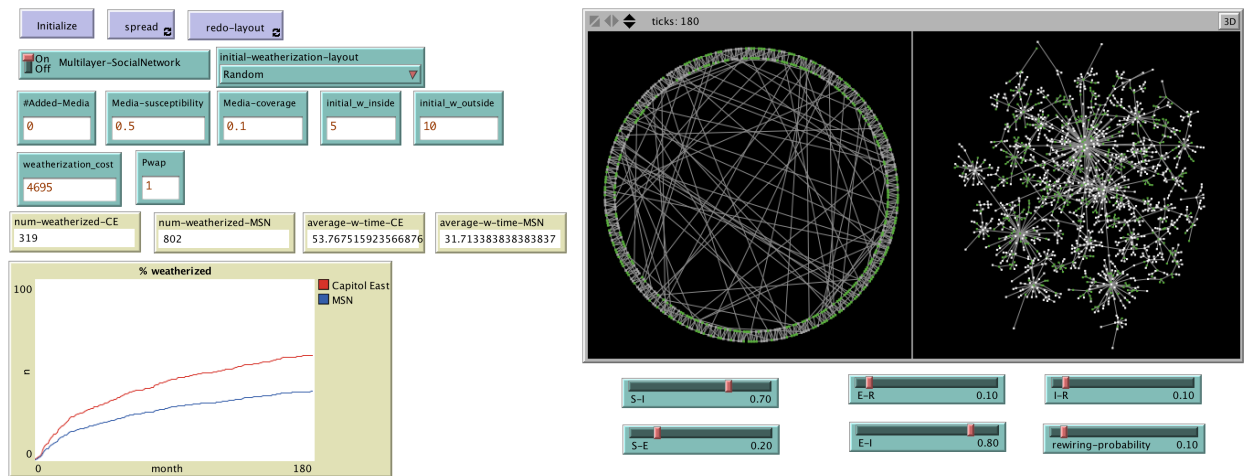


Figure 3.14: NetLogo Interface.

Table 3.6: Fixed Experimental Parameters.

Parameter name	Value	Parameter name	Value	Parameter name	Value
$P_{S \rightarrow E}$	0.20	$P_{S \rightarrow I}$	0.70	$P_{S \rightarrow R}$	0.10
$P_{E \rightarrow I}$	0.80	$P_{E \rightarrow R}$	0.10	$P_{I \rightarrow R}$	0.10

Table 3.7: Experimental Scenarios.

Scenario	SN	P_{rewire}	InC	InO	InLayout	# Media	T_{AddMedia}	Sus _{HtoM}	Cover _M	P_{wap}
Scenario 0	MSN	0.1	5	10	Random	0	—	—	—	2.5%
Scenario 1	PSN	0.1	5	—	Random	0	—	—	—	2.5%
Scenario 2	MSN	0.1	5	0	Random	0	—	—	—	2.5%
Scenario 3	MSN	0.1	5	50	Random	0	—	—	—	2.5%
Scenario 4	MSN	0.1	5	100	Random	0	—	—	—	2.5%
Scenario 5	MSN	0	5	10	Random	0	—	—	—	2.5%
Scenario 6	MSN	0.5	5	10	Random	0	—	—	—	2.5%
Scenario 7	MSN	1	5	10	Random	0	—	—	—	2.5%
Scenario 8	MSN	0.1	5	10	Important	0	—	—	—	2.5%
Scenario 9	MSN	0.1	5	10	One Centroid	0	—	—	—	2.5%
Scenario 10	MSN	0.1	5	10	Random	1	0	0.5	0.1	2.5%
Scenario 11	MSN	0.1	5	10	Random	2	0	0.5	0.1	2.5%
Scenario 12	MSN	0.1	5	10	Random	3	0	0.5	0.1	2.5%
Scenario 13	MSN	0.1	5	10	Random	4	0	0.5	0.1	2.5%
Scenario 14	MSN	0.1	5	10	Random	5	0	0.5	0.1	2.5%
Scenario 15	MSN	0.1	5	10	Random	10	0	0.5	0.1	2.5%
Scenario 16	MSN	0.1	5	10	Random	50	0	0.5	0.1	2.5%
Scenario 17	MSN	0.1	5	10	Random	1	0	0.5	0.5	2.5%
Scenario 18	MSN	0.1	5	10	Random	1	0	0.5	1.0	2.5%
Scenario 19	MSN	0.1	5	10	Random	1	0	0.8	0.1	2.5%
Scenario 20	MSN	0.1	5	10	Random	1	0	1.0	0.1	2.5%
Scenario 21	MSN	0.1	5	10	Random	1	60	0.5	0.1	2.5%
Scenario 22	MSN	0.1	5	10	Random	1	120	0.5	0.1	2.5%
Scenario 23	MSN	0.1	5	10	Random	0	—	—	—	5%
Scenario 24	MSN	0.1	5	10	Random	0	—	—	—	7.5%
Scenario 25	MSN	0.1	5	10	Random	0	—	—	—	10%
Scenario 26	MSN	0.1	5	10	Random	0	—	—	—	50%
Scenario 27	MSN	0.1	5	10	Random	0	—	—	—	100%
Scenario 28	PSN	0.1	5	—	Important	0	—	—	—	100%
Scenario 29	PSN	0.1	5	—	One Centroid	0	—	—	—	100%

3.4.1 Social Network Structure

The differences of weatherization adoption amount and time when 1) agents only have the physical social network or 2) agents have both the physical and online social network (i.e., have the multilayer social network) are explored in $S1$, $S2$. The effect of the amount of initial weatherization household agents outside the Capitol East Neighborhood (InO) was also demonstrated ($S0$, $S2$, $S3$, $S4$). As shown in Figure 3.15a, the weatherization amount is much higher when household agents have the online social network, even there are no initial weatherized household agents outside the neighborhood ($S1$, $S2$). But having more initial weatherized household agents outside the neighborhood still stimuli and accelerate weatherization adoptions (Figure 3.15b). It indicates the necessity of modeling the multilayer social network as households could access information from various channels in real life.

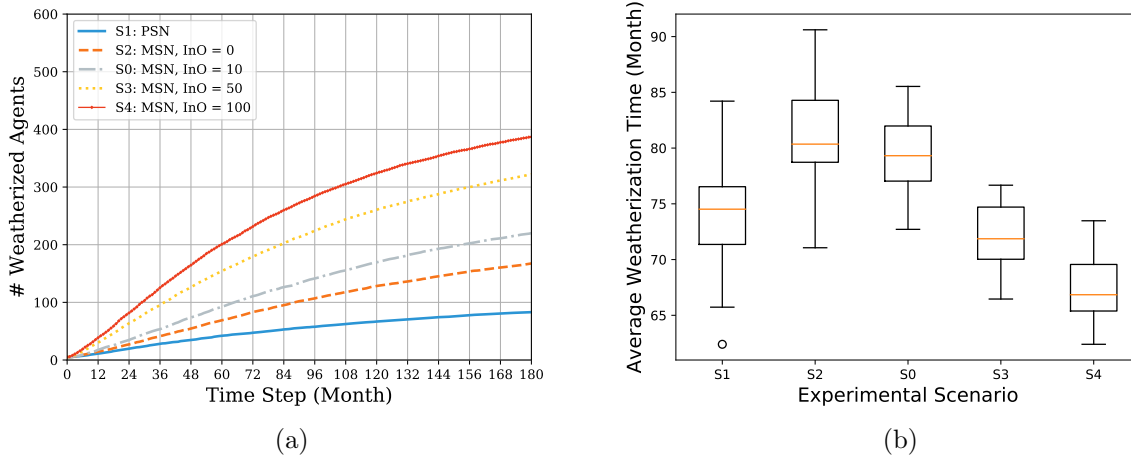


Figure 3.16: Effects of multilayer social networks on weatherization adoption.

3.4.2 Randomness of The Physical Social Network

Then the value of P_{rewire} was experimentally varied to determine how the physical network structure, especially the randomness of the physical network, would affect household agents' decisions to adopt weatherization ($S0$, $S5$, $S6$, $S7$). Figures 3.17a and 3.17b indicate that the weatherization

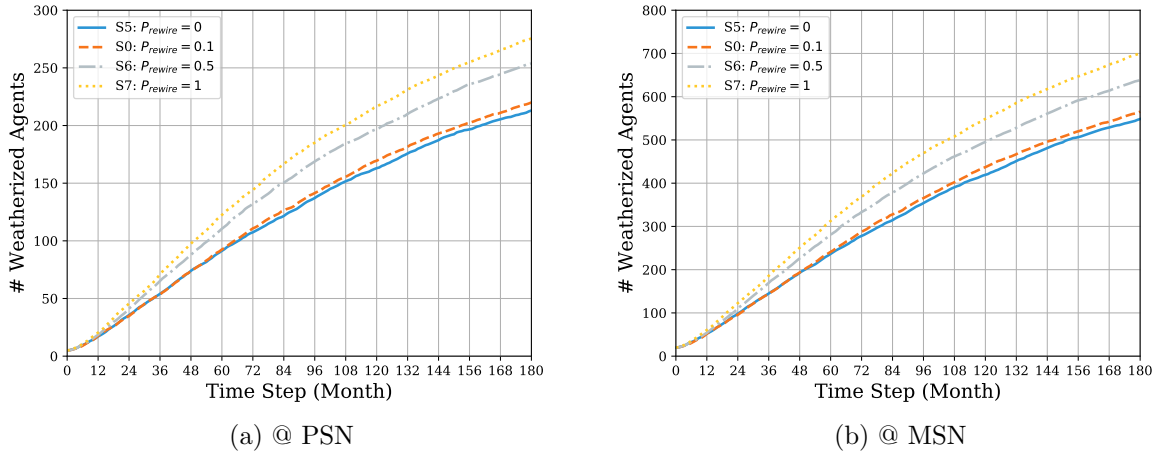
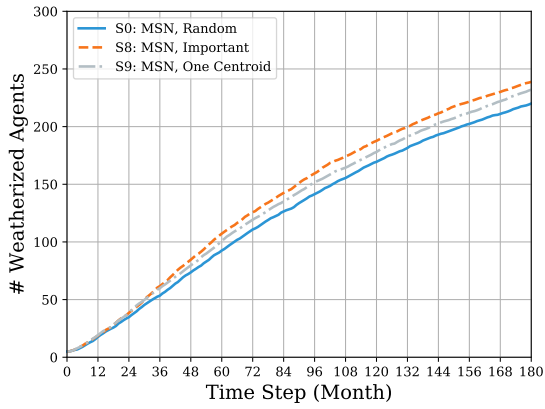


Figure 3.18: Effects of PSN randomness on weatherization adoption. *MSN @ PSN* means the results of PSN part when households have MSN; *MSN @ MSN* means the results of MSN part when households have MSN; *PSN @ PSN* means the results of PSN part when households only have PSN.

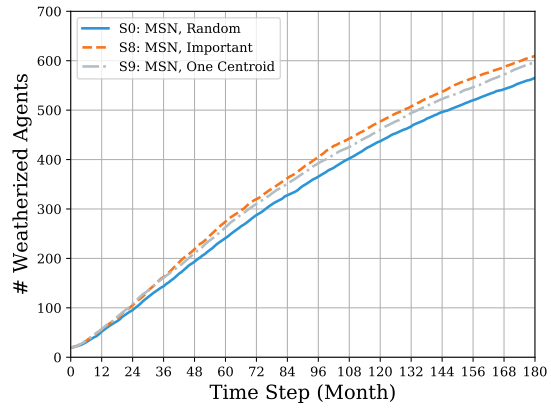
adoption rate is slightly higher in a more random PSN but that it is generally insensitive to changes in P_{rewire} .

3.4.3 Selection of Initial Weatherized Household Agents

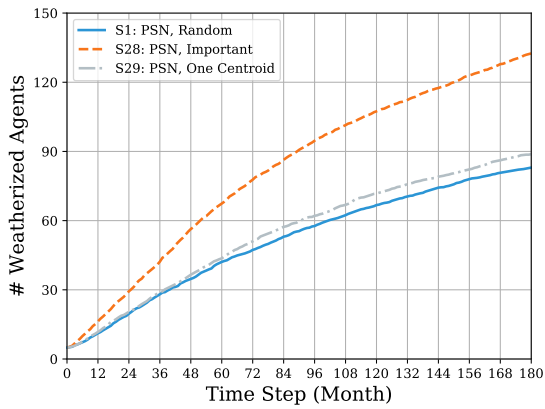
The initial weatherized household agents are the early adopters of weatherization. Finding out who are the most appropriate groups as the target group to be encouraged on weatherization has practical significance. Three ways (*InLayout*) to select the initial weatherized household agents in the Capitol East Neighborhood (i.e., “Random”, “Important”, “One Centroid”) are conducted ($S0, S8, S9 / S1, S28, S29$). Based on the experiment results, selecting the most important households (i.e., households of largest global influence level) shows best performance on encouraging weatherization adoptions (Figures 3.19a, 3.19b, 3.19c), also early adoptions (Figures 3.19d, 3.19e, 3.19f). Compared with random selection, selecting the households which are closet to the centroid of the Capitol East Neighborhood doesn’t show significant effects.



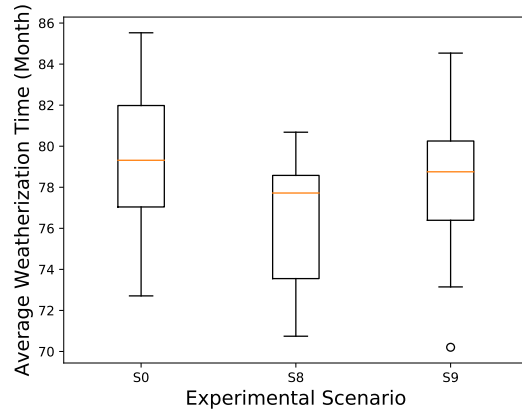
(a) MSN @ PSN



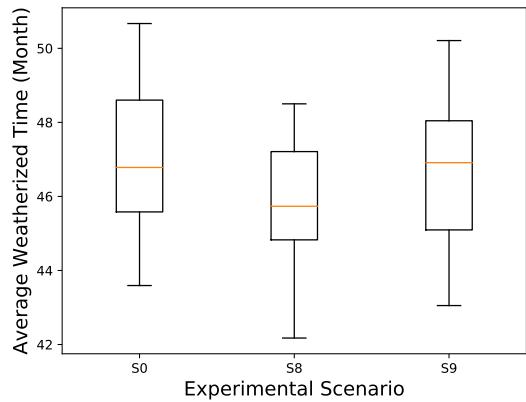
(b) MSN @ MSN



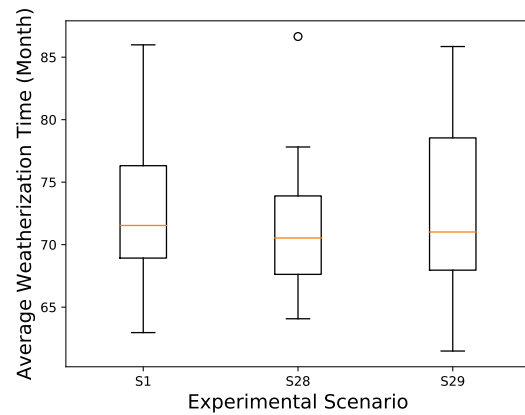
(c) PSN @ PSN



(d) MSN @ PSN



(e) MSN @ MSN



(f) PSN @ PSN

Figure 3.20: Effects of Different Selections of Initial Weatherized Agents on weatherization adoption.

3.4.4 Weatherization Assistance Program Service Probability

The probability of an approved applicant being served by WAP (P_{wap}) was experimentally varied ($S0, S23-27$). The current real-life value of P_{wap} is quite low (2.5%), and it was hypothesized that increased investment by the government could yield greater weatherization adoption rates. Weatherization adoption exhibits noticeable increases with the increases in P_{wap} , as shown in Figures 3.21a and 3.21b. Furthermore, higher values of P_{wap} tend to encourage more households to choose to weatherize in an earlier time-step. While increasing P_{wap} from 2.5% to 5.0% yields dramatic increases in adoption, there are diminishing returns from increasing P_{wap} from 50% to 100%. Similar adoption trends are apparent in PSN and MSN.

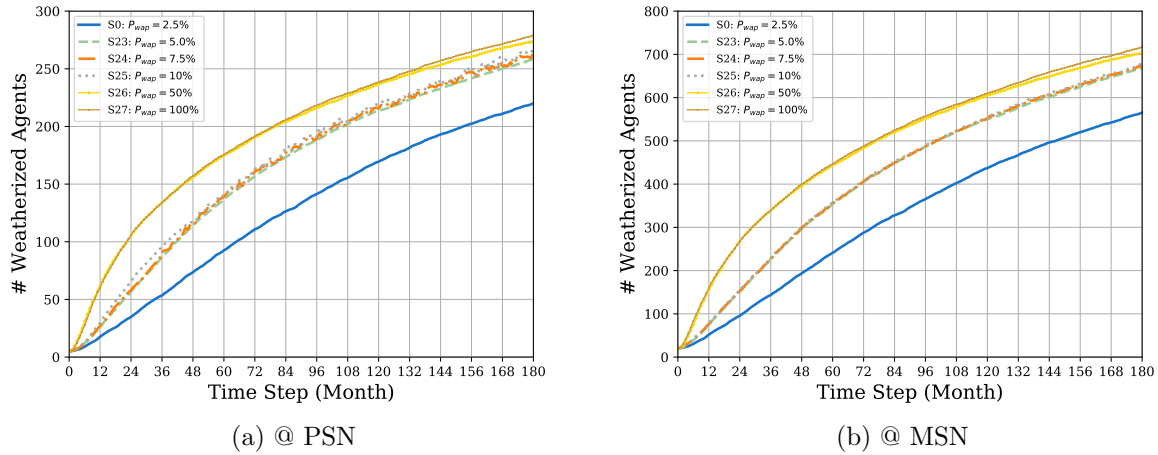


Figure 3.22: Effects of increased WAP service probability on weatherization adoption.

3.4.5 Media Agents

3.4.5.1 Number of Media Agents

As Figures 3.23a and 3.23b show, adding more media agents to spread weatherization information can promote greater weatherization adoption, even when their coverage ($Cover_M = 0.1$) is quite low. Besides, more media agents intend to encourage more early adopters (Figures 3.23c and 3.23d). Interestingly, however, increasing the number of media agents does not increase adoption

proportionally. For example, the increase in adoption that occurs by increasing the number of media agents from 0 to 50 is less than twice as much as that which is gained by increasing the number of media agents from 0 to 1 in the PSN (four times in the MSN).

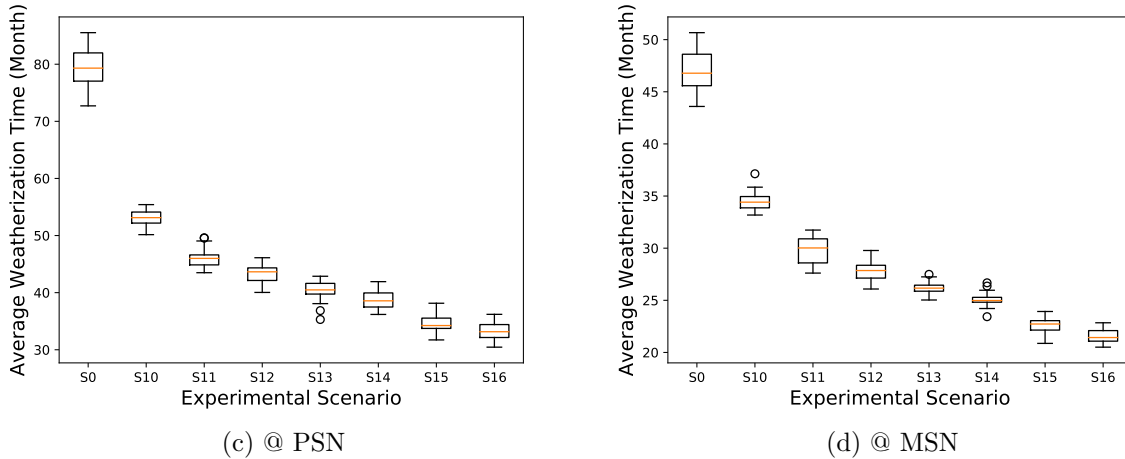
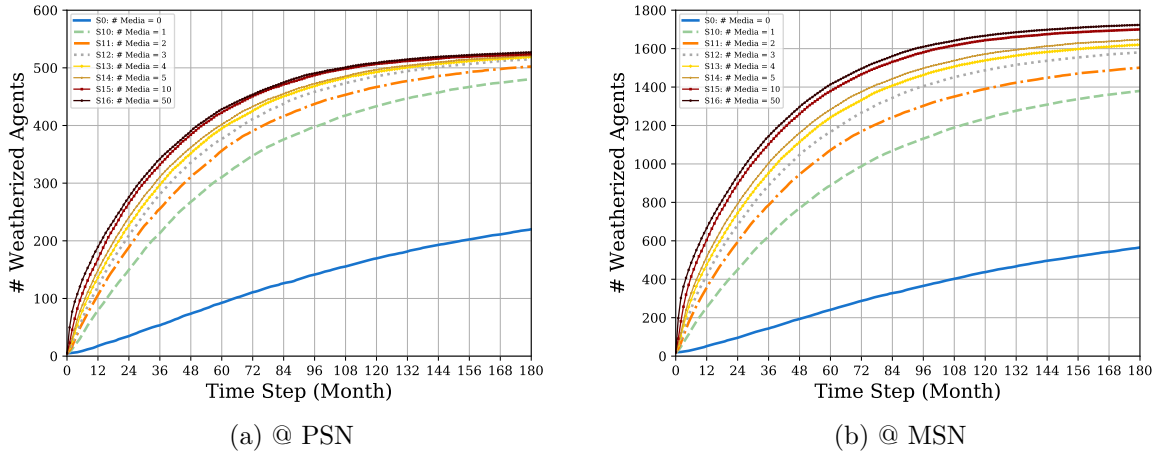


Figure 3.24: Effects of increased number of media agents on weatherization adoption.

3.4.5.2 Media Coverage

Figure 3.26 indicates increasing the chance ($Cover_M$) of household agents being exposed to the weatherization information provided by each media agent, i.e., increasing the number of households

who can access the weatherization information from media agents, slightly promote the weatherization adoptions and greatly encourage more early adopters.

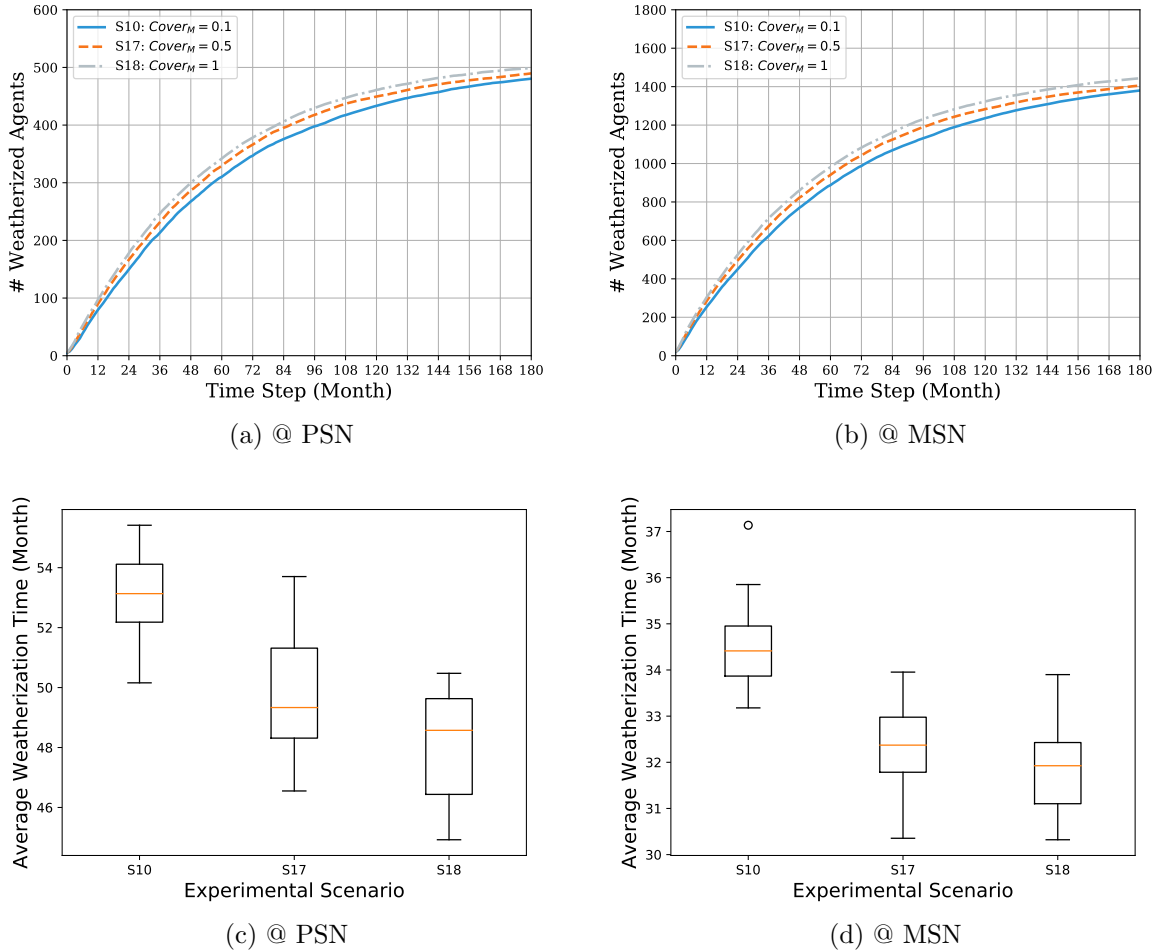
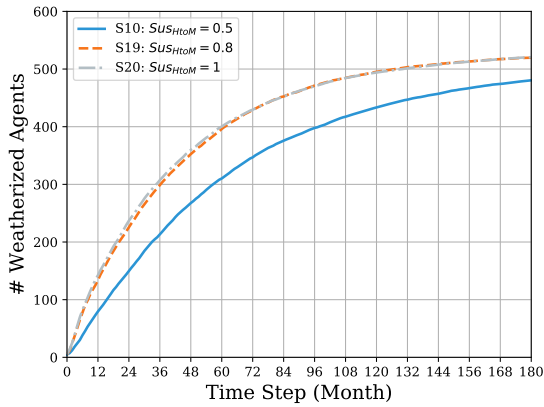


Figure 3.26: Effects of media coverage on weatherization adoption.

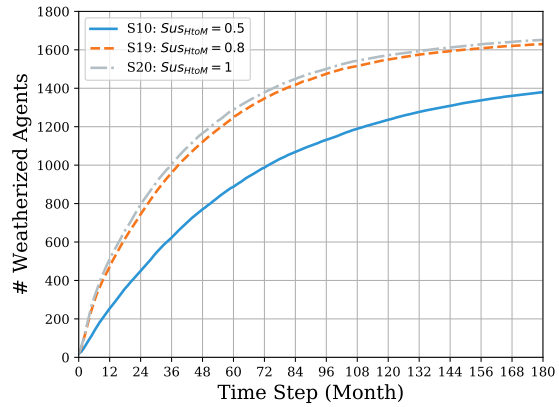
3.4.5.3 Households' Susceptibility to Media Agents

Households have own susceptibility to media (Sus_{HtoM}), maybe strongly trust or is dubious about the information obtained from media agents. Figure 3.28 shows the results when households have different values of susceptibility. Higher Sus_{HtoM} results in more weatherization adoptions

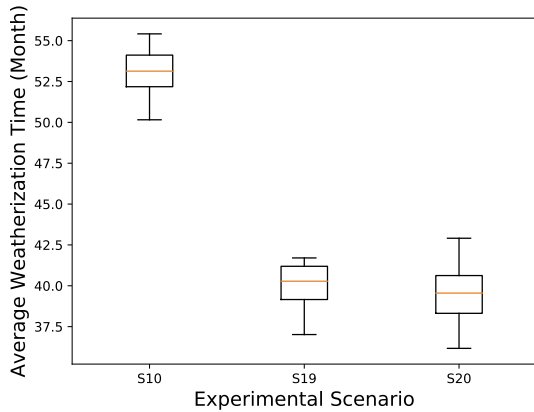
and early adoptions. When Sus_{HtoM} is high enough, increasing its value makes little changes ($S19$, $S20$).



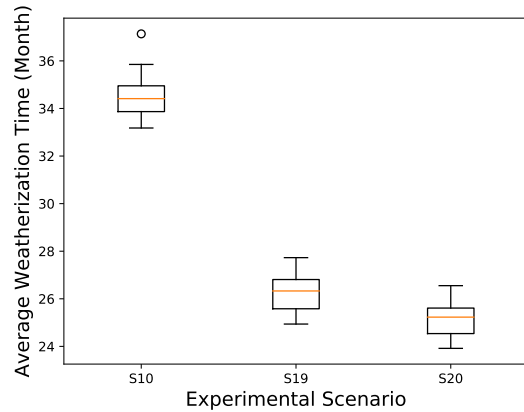
(a) @ PSN



(b) @ MSN



(c) @ PSN



(d) @ MSN

Figure 3.28: Effects of households' susceptibility to media on weatherization adoption.

3.4.5.4 Time of Adding Media Agents

As shown in Figure 3.29a, when to add the media agent (in the initialization time, 60 months later or 120 months later) have little influence on the weatherization adoptions.

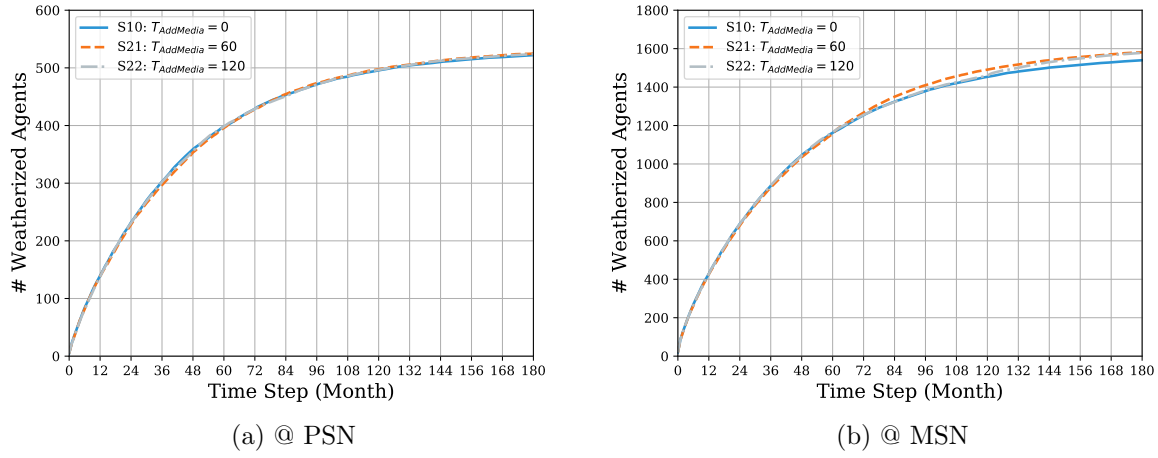


Figure 3.30: Effects of media agents' adding time on weatherization adoption.

3.5 Conclusion

The agent-based model described in this paper incorporates a multilayer social network to explore the effects of information diffusion through different types of social interactions (i.e., physical and online) on households' decisions about adopting weatherization. The Theory of Planned Behavior provides the basis for the household agents' decision process, in which the agents' intention levels are influenced by social interactions with neighbors and media agents, and their ability to weatherize depends on both their available budget for weatherization and their WAP eligibility. The strength of agents' social influence on others is determined by their local centrality, spatial location, and social demographics. The rules of social interactions among agents are determined by their information statuses, which are updated using the logic that is based on the SEIR epidemical model. The model was used to explore the effects of the multilayer social network, increased randomness in the physical social network, different selections of early adopters, increased media exposure on households' weatherization adoption over time, and increased WAP eligibility,

Future work will include the development of a dynamic social network which considers the possibility of population migration in certain areas. Empirical data must be collected to enable model validation, including 1) the number of houses in the Capitol East neighborhood that actually

weatherize in each month, 2) real-time cost of electricity, 3) behavioral data to inform the media agents' impact on households (e.g., how often they read certain newspapers or listen to certain radio stations), 4) households' budgets for weatherization and their income levels, and 5) households' evaluations of the extent to which information from physical and online social networks influence their attitude toward weatherization adoption. An empirically-validated version of the conceptual model described in this paper has the potential to serve as a useful decision support tool for the City of Des Moines to assist them in their efforts to promote residential weatherization adoption, thereby reducing energy consumption.

CHAPTER 4. CONCLUSIONS AND FUTURE WORK

4.1 Conclusion

Weatherization helps households reduce energy consumption and optimize energy efficiency of their residential buildings. It is also an important contributor to reduced greenhouse gas emissions and conserved natural resources. The industry can also produce new jobs and technologies. The government has been trying to encourage the adoption of weatherization. For example, WAPs have been allocated with significant amounts of funds and professional crews to help low-resource residents improve the energy efficiency of their homes while ensuring the resident's health and safety. However, these efforts have had limited success. The adoption rate of weatherization remains low. Therefore, having a deeper understanding of households' weatherization adoptions is of great significance, which is useful to assist stakeholders and policymakers in encouraging weatherization. Households usually consider various factors when making adoption behaviors. They tend to have their own estimates of their investment and payback on weatherization. Also, peer views influence their decisions via social interactions. When they tend to apply for WAP, the policies and efficiency of WAP affected their experience and their final adoption behaviors. As a result, the decision-making processes of households' weatherization adoptions are complex and difficult to model.

To address this problem, two hybrid simulation models of households' weatherization adoptions were developed. The two models can be used to inform the decisions of urban policymakers, enabling them to explore the impacts of different interventions on households' weatherization decisions, and therefore provide some directions or suggestions for future policies.

The hybrid simulation model presented in Chapter 2 (*M1*) explores the effects of social network density, households' memories about energy bills and influential households on weatherization adoptions and energy consumptions. Experimental results from *M1* suggest that, the presence of

a self-weatherized leader significantly increases the number of weatherization adoptions and more households tend to weatherize when they have short memories as agents with a short memory length tend to be highly responsive to changes in energy costs and more influenced to adopt weatherization due to a sudden increase in costs. The results also indicate that a denser social network can yield more weatherization than a sparse one, especially when there is a self-weatherized leader or households have short memories, as a social network is a self-reinforcing circle where information about weatherization can spread more widely.

The model developed in Chapter 3 (*M2*) improves *M1* through adding more rules and submodels supported by theoretical backgrounds. *M2* incorporates a multilayer social network into the agent-based model to explore the effects of information diffusion through different types of social interactions (i.e., physical and online) on households' decisions about adopting weatherization. The formulation of its behavioral model is motivated by the Theory of Planned Behavior, where households' adoption decisions will be determined by intention and ability components. Their intentions toward weatherization are based on their estimates of investment and payback, and influenced by social interactions with neighbors and media. The ability to weatherize depends on both their available budget for weatherization and their WAP eligibility. The rules of social interactions among agents are determined by their information statuses, which are updated based on the SEIR epidemical model. The extent to which each social interaction between households influence their attitudes is evaluated by households' local centrality, spatial location, and social-demographics. In addition, the effects of the multilayer social network, increased randomness in the physical social network, different selections of early adopters, increased media exposure on households' weatherization adoption over time, and increased WAP eligibility are explored in *M2*.

4.2 Future Work

There exist several interesting directions for future work. The most important thing of next step is the empirical validation. As we lack empirical data to support our model, a survey is being developed and administered to over 1000 households in three contiguous neighborhoods, on

the east side of Des Moines, including Capitol East. This survey will collect relevant data on household demographics, individual and social behaviors related to energy and weatherization, building infrastructure, and previous weatherization efforts. Apart from the ongoing survey, more data about the mentioned attributes of media in Chapter 3 is needed. Then, an empirically-validated version of the two hybrid simulation models has the potential to serve as a decision support tool for the City of Des Moines to make more efficient future policies and interventions about weatherization.

4.3 Contributions

This work has proposed two hybrid simulation models on households' weatherization adoption decisions. The overall and outstanding contributions of this work are to 1) create a complex dynamic feedback loop that connects households' weatherization decisions, energy-related decision outcomes, and communication of outcomes among community members, all of which influence future decisions, and 2) develop the realistic social context where households' interactions and actual behaviors take place.

The contributions of each chapter are summarized as follows.

In Chapter 2:

- Connecting the building energy simulation model (Rhino-umi model) and agent-based model is particularly well-suited to capturing this heterogeneity of physical and human entities across the urban landscape, enabling decision makers to tailor their policy approaches appropriately for each neighborhood.
- Through the three components (a building energy simulation model, an agent-based model, a social network model), the hybrid model connects the dynamic social interactions, adaptations, and decision processes of individual and autonomous urban households with the physics of building energy usage. In other words, the building energy simulation model provides the inputs to inform the household agents in the agent-based model, which is embedded in a physical social network generated using the Barabasi-Albert algorithm.

In Chapter 3:

- It is novel to develop a multilayer social network and integrate it to the agent-based model. It provides a realistic social context as interactions between households are often multidimensional, occurring in both physical and virtual environments.
- Households, who can share information and make weatherization adoption decisions, and media, which can store and deliver information to households, are both captured as agents in the proposed agent-based model. Their interactions are explored.
- Susceptible-Exposed-Infected-Recovered epidemic model is used to present households' heterogeneous attitudes toward information sharing.
- The strength of each social interaction between households is captured by households' local centrality, spatial location, and social demographic.
- The behavioral model of households toward weatherization is based on the Theory of Planned Behavior.

BIBLIOGRAPHY

- Abrahamse, W. and Steg, L. (2009). How do socio-demographic and psychological factors relate to households direct and indirect energy use and savings? *Journal of economic psychology*, 30(5):711–720.
- Adger, W. N. (2003). Social capital, collective action, and adaptation to climate change. *Economic geography*, 79(4):387–404.
- Ahn, Y.-Y., Han, S., Kwak, H., Moon, S., and Jeong, H. (2007). Analysis of topological characteristics of huge online social networking services. In *Proceedings of the 16th international conference on World Wide Web*, pages 835–844. ACM.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.
- Ajzen, I. and Driver, B. L. (1992). Application of the theory of planned behavior to leisure choice. *Journal of leisure research*, 24(3):207.
- Ajzen, I., Joyce, N., Sheikh, S., and Cote, N. G. (2011). Knowledge and the prediction of behavior: The role of information accuracy in the theory of planned behavior. *Basic and Applied Social Psychology*, 33(2):101–117.
- Alam, S. J. and Geller, A. (2012). Networks in agent-based social simulation. In *Agent-based models of geographical systems*, pages 199–216. Springer.
- Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics*, 95(9-10):1082–1095.
- Amaral, L. A. N., Scala, A., Barthélemy, M., and Stanley, H. E. (2000). Classes of small-world networks. *Proceedings of the national academy of sciences*, 97(21):11149–11152.

- Anderson, J. E., Wulfhorst, G., and Lang, W. (2015). Energy analysis of the built environment: a review and outlook. *Renewable and Sustainable Energy Reviews*, 44:149–158.
- Anderson, K., Lee, S., and Menassa, C. (2012). Effect of social network type on building occupant energy use. In *Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, pages 17–24. ACM.
- Anderson, K., Lee, S., and Menassa, C. (2013). Impact of social network type and structure on modeling normative energy use behavior interventions. *Journal of computing in civil engineering*, 28(1):30–39.
- Apolloni, A., Channakeshava, K., Durbeck, L., Khan, M., Kuhlman, C., Lewis, B., and Swarup, S. (2009). A study of information diffusion over a realistic social network model. In *Computational Science and Engineering, 2009. CSE'09. International Conference on*, volume 4, pages 675–682. IEEE.
- Ashby, K. (2010). Behavior insights and tools.
- Ashwill, M., Flora, C., and Flora, J. (2011). Building community resilience to climate change: testing the adaptation coalition framework in latin america. *World Bank, Washington, DC Google Scholar*.
- Azar, E. and Menassa, C. C. (2011). Agent-based modeling of occupants and their impact on energy use in commercial buildings. *Journal of Computing in Civil Engineering*, 26(4):506–518.
- Barabási, A.-L. (2009). Scale-free networks: a decade and beyond. *science*, 325(5939):412–413.
- Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *science*, 286(5439):509–512.
- Barabási, A.-L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., and Vicsek, T. (2002). Evolution of the social network of scientific collaborations. *Physica A: Statistical mechanics and its applications*, 311(3-4):590–614.

- Barthélemy, M. (2011). Spatial networks. *Physics Reports*, 499(1-3):1–101.
- Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., and Hwang, D.-U. (2006). Complex networks: Structure and dynamics. *Physics reports*, 424(4-5):175–308.
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3):7280–7287.
- Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional studies*, 39(1):61–74.
- Camacho, J., Guimerà, R., and Amaral, L. A. N. (2002). Robust patterns in food web structure. *Physical Review Letters*, 88(22):228102.
- Cerezo, C., Sokol, J., Reinhart, C., and Al-Mumin, A. (2015). Three methods for characterizing building archetypes in urban energy simulation. a case study in kuwait city.
- Cha, M., Benevenuto, F., Ahn, Y.-Y., and Gummadi, K. P. (2012). Delayed information cascades in flickr: Measurement, analysis, and modeling. *Computer Networks*, 56(3):1066–1076.
- Chelst, K. and Canbolat, Y. B. (2011). *Value-added decision making for managers*. CRC Press.
- Chen, D., Lü, L., Shang, M.-S., Zhang, Y.-C., and Zhou, T. (2012). Identifying influential nodes in complex networks. *Physica a: Statistical mechanics and its applications*, 391(4):1777–1787.
- Christakis, N. A. and Fowler, J. H. (2008). The collective dynamics of smoking in a large social network. *New England journal of medicine*, 358(21):2249–2258.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* lawrence earlbaum associates. *Hillsdale, NJ*, 20:26.
- Davila, C. C., Reinhart, C. F., and Bemis, J. L. (2016). Modeling boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets. *Energy*, 117:237–250.

- De Castro, R. and Grossman, J. W. (1999). Famous trails to paul erdős. *The Mathematical Intelligencer*, 21(3):51–53.
- Diamantopoulos, A., Schlegelmilch, B. B., Sinkovics, R. R., and Bohlen, G. M. (2003). Can socio-demographics still play a role in profiling green consumers? a review of the evidence and an empirical investigation. *Journal of Business research*, 56(6):465–480.
- Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., and Vandenberg, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce us carbon emissions. *Proceedings of the National Academy of Sciences*, 106(44):18452–18456.
- Drehobl, A. and Ross, L. (2016). Lifting the high energy burden in americas largest cities: How energy efficiency can improve low income and underserved communities.
- Ebel, H., Mielsch, L.-I., and Bornholdt, S. (2002). Scale-free topology of e-mail networks. *Physical review E*, 66(3):035103.
- Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, 4(5):41–60.
- Epstein, J. M. and Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*. Brookings Institution Press.
- Farmer, J. D. and Foley, D. (2009). The economy needs agent-based modelling. *Nature*, 460(7256):685.
- Faruqui, A., Sergici, S., and Sharif, A. (2010). The impact of informational feedback on energy consumption: a survey of the experimental evidence. *Energy*, 35(4):1598–1608.
- Ferrara, E. and Fiumara, G. (2012). Topological features of online social networks. *arXiv preprint arXiv:1202.0331*.
- Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy? *Energy efficiency*, 1(1):79–104.

- Fontana, M., Terna, P., et al. (2015). From agent-based models to network analysis (and return): the policy-making perspective. *University of Turin*.
- Fowlie, M., Greenstone, M., and Wolfram, C. (2015). Are the non-monetary costs of energy efficiency investments large? understanding low take-up of a free energy efficiency program. *American Economic Review*, 105(5):201–04.
- Friege, J., Holtz, G., and Chappin, E. J. (2016). Exploring homeowners insulation activity. *Journal of Artificial Societies and Social Simulation*, 19(1):4.
- Fronczak, A., Fronczak, P., and Holyst, J. A. (2004). Average path length in random networks. *Physical Review E*, 70(5):056110.
- Fuller, M. C. (2010). Driving demand for home energy improvements: Motivating residential customers to invest in comprehensive upgrades that eliminate energy waste, avoid high utility bills, and spur the economy. Technical report, Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, CA (US).
- Gilbert, N. and Troitzsch, K. (2005). *Simulation for the social scientist*. McGraw-Hill Education (UK).
- Godin, G. and Kok, G. (1996). The theory of planned behavior: a review of its applications to health-related behaviors. *American journal of health promotion*, 11(2):87–98.
- Grossman, J. W. and Ion, P. D. (1995). On a portion of the well-known collaboration graph. *Congressus Numerantium*, pages 129–132.
- Hamill, L. and Gilbert, N. (2009). Social circles: A simple structure for agent-based social network models. *Journal of Artificial Societies and Social Simulation*, 12(2):3.
- Harland, P., Staats, H., and Wilke, H. A. (1999). Explaining proenvironmental intention and behavior by personal norms and the theory of planned behavior. *Journal of applied social psychology*, 29(12):2505–2528.

- He, B. J., Zempel, J. M., Snyder, A. Z., and Raichle, M. E. (2010). The temporal structures and functional significance of scale-free brain activity. *Neuron*, 66(3):353–369.
- Hegselmann, R., Krause, U., et al. (2002). Opinion dynamics and bounded confidence models, analysis, and simulation. *Journal of artificial societies and social simulation*, 5(3).
- Hernández, D. and Phillips, D. (2015). Benefit or burden? perceptions of energy efficiency efforts among low-income housing residents in new york city. *Energy research & social science*, 8:52–59.
- Hicks, A. L., Theis, T. L., and Zellner, M. L. (2015). Emergent effects of residential lighting choices: prospects for energy savings. *Journal of Industrial Ecology*, 19(2):285–295.
- Hoffman, I. M. (2017). Gauging the impact of various definitions of low-and moderate-income communities on possible electricity savings from weatherization.
- Houston, J. B., Spialek, M. L., Cox, J., Greenwood, M. M., and First, J. (2015). The centrality of communication and media in fostering community resilience: A framework for assessment and intervention. *American Behavioral Scientist*, 59(2):270–283.
- Huang, W., Krejci, C., Dorneich, M., and Passe, U. (2017). Weatherization adoption in a multilayer social network: An agent-based approach. In *CSSSA's Annual Conference on Computational Social Science*. The Computational Social Science Society of the Americas.
- Hughes, J. E. and Podolefsky, M. (2015). Getting green with solar subsidies: evidence from the california solar initiative. *Journal of the Association of Environmental and Resource Economists*, 2(2):235–275.
- Islam, T. and Meade, N. (2013). The impact of attribute preferences on adoption timing: The case of photo-voltaic (pv) solar cells for household electricity generation. *Energy Policy*, 55:521–530.
- Jagani, C. and Passe, U. (2017). Simulation-based sensitivity analysis of future climate scenario impact on residential weatherization initiatives in the us midwest. In *Simulation for Architecture and Urban Design (SimAUD) conference*. The Society for Modeling and Simulation International.

- Jain, R. K., Gulbinas, R., Taylor, J. E., and Culligan, P. J. (2013). Can social influence drive energy savings? detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback. *Energy and Buildings*, 66:119–127.
- Jeong, H., Mason, S. P., Barabási, A.-L., and Oltvai, Z. N. (2001). Lethality and centrality in protein networks. *Nature*, 411(6833):41.
- Jeong, H., Tombor, B., Albert, R., Oltvai, Z. N., and Barabási, A.-L. (2000). The large-scale organization of metabolic networks. *Nature*, 407(6804):651.
- Johnson, S. L., Faraj, S., and Kudaravalli, S. (2014). Emergence of power laws in online communities: The role of social mechanisms and preferential attachment. *Mis Quarterly*, 38(3):795–808.
- Kang, N. N., Cho, S. H., and Kim, J. T. (2012). The energy-saving effects of apartment residents awareness and behavior. *Energy and Buildings*, 46:112–122.
- Kathleen, G. (2006). Assessing the needs of california’s low-income population. In *Proceedings of the 2006 American Council for an Energy-Efficient Economy Summer Conference*. American Council for an Energy-Efficient Economy.
- Krejci, C. C., Dorneich, M. C., Passe, U., and Peters, N. (2016). A hybrid simulation model for urban weatherization programs. In *Proceedings of the 2016 Winter Simulation Conference*, pages 1630–1641. IEEE Press.
- Kwan, C. L. (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar pv arrays across the united states. *Energy Policy*, 47:332–344.
- Laham, S. and Forgas, J. (2007). Recency effect. *Encyclopedia of social psychology*, 1:729–729.
- Langevin, J., Wen, J., and Gurian, P. L. (2015). Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors. *Building and Environment*, 88:27–45.

- Lebaron, B. (2008). Complex adaptive systems: An introduction to computational models of social life.
- Lee, Y. S. and Malkawi, A. M. (2014). Simulating multiple occupant behaviors in buildings: An agent-based modeling approach. *Energy and Buildings*, 69:407–416.
- Letendre, S., Van Hoesen, J., and Robinson, J. A community-based weatherization initiative in vermont. *Natural Gas*, 8:3.
- Li, M. Y. and Muldowney, J. S. (1995). Global stability for the seir model in epidemiology. *Mathematical biosciences*, 125(2):155–164.
- Macal, C. M. and North, M. J. (2005). Tutorial on agent-based modeling and simulation. In *Simulation conference, 2005 proceedings of the winter*, pages 14–pp. IEEE.
- MacQueen, J. et al. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1, pages 281–297. Oakland, CA, USA.
- Macy, M. W. and Willer, R. (2002). From factors to factors: computational sociology and agent-based modeling. *Annual review of sociology*, 28(1):143–166.
- McEachern, M. and Hanson, S. (2008). Socio-geographic perception in the diffusion of innovation: solar energy technology in sri lanka. *Energy Policy*, 36(7):2578–2590.
- McMichael, M. and Shipworth, D. (2013). The value of social networks in the diffusion of energy-efficiency innovations in uk households. *Energy Policy*, 53:159–168.
- McNeel, R. et al. (2015). Rhinoceros. *NURBS modeling for Windows*: <http://www.rhino3d.com/jewelry.htm>.
- McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27(1):415–444.

- Meadows, M. and Cliff, D. (2012). Reexamining the relative agreement model of opinion dynamics. *Journal of Artificial Societies and Social Simulation*, 15(4):4.
- Merton, R. K. (1968). The matthew effect in science: The reward and communication systems of science are considered. *Science*, 159(3810):56–63.
- Mislove, A., Marcon, M., Gummadi, K. P., Druschel, P., and Bhattacharjee, B. (2007). Measurement and analysis of online social networks. In *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement*, pages 29–42. ACM.
- Mittal, A., Huang, W., and Krejci, C. C. (2017). Consumer-adoption modeling of distributed solar using an agent-based approach. In *The annual Computational Social Science conference*. The Computational Social Science Society of the Americas.
- Mittal, A. and Krejci, C. C. A hybrid simulation modeling framework for regional food hubs. *Journal of Simulation*, pages 1–14.
- Mittal, A. and Krejci, C. C. (2017). Integrating consumer preferences in renewable energy expansion planning using agent-based modeling. In *paper to be presented at the 2017 Winter Simulation Conference, Las Vegas, NV, December 3-6*. IEEE Press.
- Moffitt, R. A. et al. (2001). Policy interventions, low-level equilibria, and social interactions. *Social dynamics*, 4(45-82):6–17.
- Moonen, P., Defraeye, T., Dorer, V., Blocken, B., and Carmeliet, J. (2012). Urban physics: Effect of the micro-climate on comfort, health and energy demand. *Frontiers of Architectural Research*, 1(3):197–228.
- Nicol, J. F. (2001). Characterising occupant behaviour in buildings: towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans. In *Proceedings of the seventh international IBPSA conference, Rio*, volume 2, pages 1073–1078.

- Noonan, D. S., Hsieh, L.-H. C., and Matisoff, D. (2013). Spatial effects in energy-efficient residential hvac technology adoption. *Environment and Behavior*, 45(4):476–503.
- Palmer, J., Sorda, G., and Madlener, R. (2015). Modeling the diffusion of residential photovoltaic systems in italy: An agent-based simulation. *Technological Forecasting and Social Change*, 99:106–131.
- Pathak, S. D., Day, J. M., Nair, A., Sawaya, W. J., and Kristal, M. M. (2007). Complexity and adaptivity in supply networks: Building supply network theory using a complex adaptive systems perspective. *Decision sciences*, 38(4):547–580.
- Patton, S. (2013). Development of a future typical meteorological year with application to building energy use. Master's thesis, Iowa State University, Ames, Iowa.
- Pavlou, P. A. and Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS quarterly*, pages 115–143.
- Petri, Y. and Caldeira, K. (2015). Impacts of global warming on residential heating and cooling degree-days in the united states. *Scientific reports*, 5:12427.
- Rahmandad, H. and Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science*, 54(5):998–1014.
- Rai, V. and Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling & Software*, 70:163–177.
- Reames, T. G. (2016). A community-based approach to low-income residential energy efficiency participation barriers. *Local Environment*, 21(12):1449–1466.

- Reinhart, C., Dogan, T., Jakubiec, J. A., Rakha, T., and Sang, A. (2013). Umi-an urban simulation environment for building energy use, daylighting and walkability. In *13th Conference of International Building Performance Simulation Association, Chambéry, France*.
- Reyna, J. L. and Chester, M. V. (2017). Energy efficiency to reduce residential electricity and natural gas use under climate change. *Nature communications*, 8:14916.
- Rijal, H. B., Tuohy, P., Humphreys, M. A., Nicol, J. F., Samuel, A., Raja, I. A., and Clarke, J. (2008). Development of adaptive algorithms for the operation of windows, fans, and doors to predict thermal comfort and energy use in pakistani buildings. *American Society of Heating Refrigerating and Air Conditioning Engineers (ASHRAE) Transactions*, 114(2):555–573.
- Sawilowsky, S. S. (2009). New effect size rules of thumb.
- Scellato, S., Mascolo, C., Musolesi, M., and Latora, V. (2010). Distance matters: Geo-social metrics for online social networks. In *WOSN*.
- Scott, J. and Carrington, P. J. (2011). *The SAGE handbook of social network analysis*. SAGE publications.
- Smith, J. W., Anderson, D. H., and Moore, R. L. (2012). Social capital, place meanings, and perceived resilience to climate change. *Rural Sociology*, 77(3):380–407.
- Soratana, K. and Marriott, J. (2010). Increasing innovation in home energy efficiency: Monte carlo simulation of potential improvements. *Energy and Buildings*, 42(6):828–833.
- Southwell, B. G. and Murphy, J. (2014). Weatherization behavior and social context: the influences of factual knowledge and social interaction. *Energy Research & Social Science*, 2:59–65.
- Sovacool, B. K. (2014). What are we doing here? analyzing fifteen years of energy scholarship and proposing a social science research agenda. *Energy Research & Social Science*, 1:1–29.
- Sparrow, M. K. (1991). The application of network analysis to criminal intelligence: An assessment of the prospects. *Social networks*, 13(3):251–274.

- Stemers, K. and Yun, G. Y. (2009). Household energy consumption: a study of the role of occupants. *Building Research & Information*, 37(5-6):625–637.
- Stern, P. C., Aronson, E., Darley, J. M., Hill, D. H., Hirst, E., Kempton, W., and Wilbanks, T. J. (1986). The effectiveness of incentives for residential energy conservation. *Evaluation Review*, 10(2):147–176.
- Stonewall, J., Huang, W., , Dorneich, M., Shenk, L., Krejci, C. C., and Passe, U. (2018 (submitted)). Energy use and weatherization practices: Applications for agent-based modeling to support vulnerable populations. In *Proceedings of the 62nd Human Factors and Ergonomics Society Annual Meeting*. Human Factors and Ergonomics Society.
- Ternes, M. P., Schweitzer, M., Tonn, B. E., Schmoyer, R. L., and Eisenberg, J. F. (2007). National evaluation of the weatherization assistance program: Preliminary evaluation plan for program year 2006. Technical report, Oak Ridge National Laboratory (ORNL).
- ACEEE (2018). *Community-Wide Energy Efficiency Goals*. <https://database.aceee.org/city/community-wide-energy-efficiency-goals>.
- City of Ames (2017). *Understanding Your Utility Bill*. <http://www.cityofames.org/home/showdocument?id=431>.
- Energy Star (2017). *Federal Income Tax Credits for Energy Efficiency*. https://www.energystar.gov/about/federal_tax_credits.
- Iowa Department of Human Rights. *Brochure about the Weatherization Assistance Program*. <https://humanrights.iowa.gov/sites/default/files/media/Resources%20-%20Weatherization%20Brochure.pdf>.
- IOWA Department of Human Rights (2017a). *Income Guidelines*. https://humanrights.iowa.gov/sites/default/files/media/LIHEAP_Wx_Income_Guidelines_FY17.pdf.

- IOWA Department of Human Rights (2017b). *Weatherization Assistance Program (WAP)*. <https://humanrights.iowa.gov/dcaa/weatherization>.
- IOWA Department of Human Rights (2017c). *Weatherization FAQs*. <https://humanrights.iowa.gov/dcaa/weatherization/weatherization-faqs>.
- Iowa State University (2018). *Iowa State University Sustainable Cities website*. <http://sustainablecities.cber.iastate.edu>.
- MidAmerican Energy Company (2017). *Iowa Electric Rates*. <https://www.midamericanenergy.com/iowa-rates.aspx>.
- Polk County Assessor website (2015). *Polk County Assessor*. <http://web.assess.co.polk.ia.us/cgi-bin/web/tt/infoqry.cgi?tt=home/index>.
- U.S. Department of Energy (2016). *What is Weatherization?* <http://energy.gov/eere/wipo/what-weatherization>.
- U.S. Department of Energy (2017). *WAP Fact Sheet*. https://energy.gov/sites/prod/files/2017/05/f34/wap_factsheet_FINAL.pdf.
- U.S. Department of Energy (2018). *Home Weatherization*. <https://www.energy.gov/public-services/homes/home-weatherization>.
- U.S. Department of Energys Building Technologies Office (2017). *Home Improvement Catalyst Plan*. https://www.energy.gov/sites/prod/files/2018/01/f47/Nav_EN_HomeImprovementCatalystPlan_1217_REV04.pdf.
- U.S. EERE (2018a). *About the Weatherization Assistance Program*. <https://energy.gov/eere/wipo/about-weatherization-assistance-program-0>.
- U.S. EERE (2018b). *Weatherization Assistance Program: National Evaluations*. https://weatherization.ornl.gov/WAP_NationalEvaluation_WxWorks_v14_blue_8%205%2015.pdf.

- U.S. Energy Information Administration (2017a). *Annual Energy Outlook*. [https://www.eia.gov/outlooks/aeo/pdf/0383\(2017\).pdf](https://www.eia.gov/outlooks/aeo/pdf/0383(2017).pdf).
- U.S. Energy Information Administration (2017b). *Monthly Energy Review*. <https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf>.
- U.S. Energy Information Association (2013). *International Energy Outlook 2013*. <http://www.eia.gov/forecasts/ieo/pdf/0484%282013%29.pdf>.
- Tonn, B., Rose, E., Hawkins, B., and Conlon, B. (2014). Health and household-related benefits attributable to the weatherization assistance program. *ORNL/TM-2014/345, Oak Ridge National Laboratory, Oak Ridge, Tennessee, September*.
- Wang, F.-Y., Carley, K. M., Zeng, D., and Mao, W. (2007). Social computing: From social informatics to social intelligence. *IEEE Intelligent Systems*, 22(2).
- Wang, X. F. and Chen, G. (2003). Complex networks: small-world, scale-free and beyond. *IEEE circuits and systems magazine*, 3(1):6–20.
- Wasserman, S. and Faust, K. (1994). *Social network analysis: Methods and applications*, volume 8. Cambridge university press.
- Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of small-world networks. *nature*, 393(6684):440.
- Wilcox, S. and Marion, W. (2008). Users manual for tmy3 data sets (revised). Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).
- Wilensky, U. (1999). Netlogo. evanston, il: Center for connected learning and computer-based modeling, northwestern university.
- Wilhite, H. and Ling, R. (1995). Measured energy savings from a more informative energy bill. *Energy and buildings*, 22(2):145–155.

- Willinger, W., Alderson, D., and Doyle, J. C. (2009). Mathematics and the internet: A source of enormous confusion and great potential. *Notices of the American Mathematical Society*, 56(5):586–599.
- Wolf, I., Nuss, J., Schröder, T., and de Haan, G. (2012). The adoption of electric vehicles: An empirical agent-based model of attitude formation and change. In *Proceedings of the 8th Conference of the European Association for Social Simulation*, pages 93–98.
- Wolf, J., Adger, W. N., Lorenzoni, I., Abrahamson, V., and Raine, R. (2010). Social capital, individual responses to heat waves and climate change adaptation: An empirical study of two uk cities. *Global Environmental Change*, 20(1):44–52.