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A HYBRID SIMULATION MODEL FOR URBAN WEATHERIZATION PROGRAMS

Caroline C. Krejci
Michael C. Dorneich

Department of Industrial and Manufacturing
Systems Engineering
Iowa State University
3004 Black Engineering Building
Ames, IA 50011, USA

Ulrike Passe
Nathan Peters

Department of Architecture

Iowa State University
158 College of Design
Ames, IA 50011, USA

ABSTRACT

In the face of climate change, cities are becoming interested in developing policies and programs that will increase sustainability and resilience in their neighborhoods. In particular, government officials, planning agencies, and residents of the City of Des Moines, Iowa, would like to find ways to improve the energy efficiency of their urban built environment. Weatherization of residential buildings is one way of reducing energy consumption, particularly in winter months. While financial incentives might increase residents' adoption of weatherization measures, research has shown that social interactions more strongly influence this decision. To enable stakeholders to explore different scenarios for encouraging weatherization, a hybrid simulation model that integrates an urban energy model with an agent-based model has been developed to connect the physical processes of built environment systems with the goals, constraints, and interactions that drive resident behavior. This paper describes an application of the model to a specific residential city block.

1 INTRODUCTION AND BACKGROUND

Buildings in the United States consume approximately 40% and 72% of all energy and electricity use, respectively (US EIA 2013). Existing residential buildings are responsible for much of this consumption. While there has been considerable focus on how to reduce energy use in newly-constructed commercial buildings, many existing residential buildings in urban neighborhoods have poor energy performance conditions and are in need of upgrades. As urban communities attempt to reduce energy use in the face of limited energy resources and changing climate, attention has begun to turn to existing buildings, which have significant potential for energy savings through the implementation of a variety of retrofit strategies, including weatherization. This paper focuses specifically on the impact that individual residents' weatherization decisions have on overall urban energy consumption.

Weatherization includes a wide variety of energy efficiency measures that encompass the building envelope, its heating and cooling systems, its electrical system, and electricity consuming appliances. Weatherization benefits residents by reducing their energy bills over a long period of time. According to the United States Department of Energy (DOE), the average value of weatherization improvements is 2.2 times greater than the cost, with some measures, such as increasing the efficiency of heating/cooling equipment, providing savings for 10-15 years, and other measures, such as insulating walls or roofs, providing savings for the lifetime of a house, i.e., 30 years or more (U.S. DOE 2016a). However, weatherization involves up-front investment and potentially long-term financial payback, which may be unappealing or infeasible, particularly for low-income residents.

To address this issue, federally-funded weatherization programs have been created to increase adoption among low-income residents by subsidizing home improvements. For example, the DOE Weatherization Assistance Program (WAP) provides grants to states, territories, and some Indian tribes to improve the energy efficiency of the homes of low-income families. These governments, in turn, contract with local governments and nonprofit agencies to provide qualified residents with state-of-the-art and cost-effective energy efficiency upgrades that improve their building's thermal performance. Since the program began in 1976, the DOE has helped improve the lives of than 7 million families by reducing their energy bills (U.S. DOE 2016b). Furthermore, these upgrades not only increase energy performance, but also address health concerns associated with poor indoor air quality.

Despite these benefits, government programs that subsidize weatherization are often inefficient and underutilized (Fowlie, Greenstone, and Wolfram 2015). Reasons for this vary. Many low-income residents are unaware that they are qualified to receive weatherization assistance, and even if they are aware, the application and approval process is often slow and inconvenient (Higgins and Lutzenhiser 1995). However, awareness alone is not enough to encourage widespread adoption. In a recent study Ternes et al. (2007) concluded that the success of a weatherization program depends on whether the program is framed as a social policy-oriented program or an energy-related program. This suggests that energy-related benefits are not well understood nor well communicated.

Innate human biases also confound residents' decision to weatherize and contribute to a lack of enthusiasm for weatherization programs. According to Stern (2014, p. 44), the determinants of residents' energy-consuming behaviors are "many, complex, and context-dependent". These behaviors result from complex and sometimes apparently paradoxical interactions among the nature of the decision, the characteristics of the decision-maker, and the natural, designed, and social characteristics of the environment (Guerin, Yust, and Coopet 2000; Madlener and Harmsen-van Hout 2011; Wilson and Dowlatabadi 2007). One ethnographic study found that few households took serious interest in easy weatherization measures, even those that had been willing to invest in expensive retrofits (Wilk and Wilhite 1985). This was due to the relative "invisibility" and lack of "glamour" of weatherization; unlike major home improvements, it does not affect the value of the house, nor does it send a visible sign of identity-related values to neighbors or friends.

Another study revealed that identical weatherization programs offered by different utility companies had rates of uptake almost an order of magnitude apart (Stern et al. 1985). The study concluded that there was no systematic relationship between the adoption of weatherization measures and the size of a subsidy (p. 170). However, "marketing" the incentive through a community group was one of the best ways to improve participation rates, especially for low-income households. A nationally-representative survey confirmed the importance of social variables, finding that having interactions with others about energy issues was the single largest determinant of weatherization (Southwell and Murphy 2014). In fact, residents that participated in such social interactions were more than twice as likely to have weatherized their homes. This is likely because the interactions served to convey locally relevant knowledge about weatherization, as well as social norms, both descriptive ("people like us weatherize") and injunctive ("it's good to weatherize"). By contrast, general knowledge about energy – the ordinary content of most campaigns – had little impact. Based on these findings, it is critical that urban policymakers consider the implications of social interactions for the success of weatherization programs. Understanding how interactions and information sharing in a community influence its residents' decisions could greatly help governments and planners leverage this social tendency for improved energy efficiency outcomes.

Agent-based modeling (ABM) has proven to be a popular method of analyzing the impacts of individual occupants' decisions with respect to energy use and conservation. Most models described in the literature focus on the energy-related behaviors of heterogeneous commercial building occupants (e.g., opening windows, turning on fans, or removing layers of clothing), with an objective of finding ways to reduce energy usage while maintaining adequate occupant thermal comfort (e.g., Langevin, Wen, and Gurian 2015). Many of these models link the ABM to a building energy simulation model, which is typically EnergyPlus (Cao, Wang, and Song 2015; Lee and Malkawi 2014; Azar and Menassa 2012). The literature describing ABMs of residential energy applications is sparser. Hicks, Theis, and Zellner (2015) developed an ABM that captures the adoption of energy-efficient lighting technologies (e.g., LEDs) among individual residents, using survey data to inform agent behavior. Chen, Taylor, and Wei (2012) used individual resident electricity consumption data to inform the development of an ABM to analyze the effects of social network structure on energy conservation behaviors. They found that strong associations among network members had a greater influence on energy conservation behavior than network size. Friege, Holtz, and Chappin (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.

To help the City of Des Moines, Iowa, assess the implications of various policies in support of weatherization, a hybrid simulation model of a residential block in the Capitol East Neighborhood has been developed. An urban energy model, which calculates the monthly energy consumption of the buildings, provides the inputs to an agent-based model, which captures the decision making and interactions of the residents with respect to weatherization. This paper describes the model and provides an example of how the model can be used to assess weatherization adoption rates and overall energy consumption over time for an urban neighborhood under varying experimental conditions.

2 HYBRID SIMULATION MODEL OF URBAN WEATHERIZATION

This section provides relevant background information on the Capitol East Neighborhood, which was selected as a test case for the hybrid simulation modeling methodology. The two constituent simulation models that comprise the hybrid model are then described in detail.

2.1 Case Study: Capitol East Neighborhood

The Capitol East Neighborhood was chosen as a test case for a pilot study, primarily because of its social and economic composition. In the 1990s Capitol East was one of the first neighborhoods in Des Moines to take part in the neighborhood revitalization program "to help enhance, stabilize and revitalize neighborhoods" throughout Des Moines (Capitol East Neighborhood Charter Plan Update 2014). This is an indication for a strong neighborhood association and buy-in by the local residents, which will be important for future development and implementation of modeling and decision support tools.

Capitol East is situated just east of the Iowa state capitol building, near downtown Des Moines. It is a young and diverse neighborhood, but it faces some economic challenges: its median income is less than half the Des Moines average, and there are more renter-occupied properties than other neighborhoods in Des Moines. Capitol East has been targeted by Habitat for Humanity's "Rock the Block" program, which includes building ramps and door modifications, repairing roofs, porches, siding, windows, driveways and sidewalks, insulating, weatherstripping, painting, landscaping and other maintenance projects. The hybrid simulation model described in this paper has been developed as a decision support tool that will help city officials, planners, and residents to develop policies and programs that will enhance these efforts and increase weatherization adoption among Capitol East residents.

2.2 Urban Energy Model

To generate the comparative building energy consumption data that informs the weatherization decisions of the agents in the agent-based model (described below), 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 that was chosen for this analysis 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. Rhinoceros 3D and the Urban Modelling Interface (UMI) plugin from MIT's Sustainable Design Lab (Reinhart et al. 2013) were used to create a digital model of the block and then simulate the energy performance of each house within the selected area, based on generalized building characteristics templates. UMI 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. Datasets that represent pre- and post-weatherization conditions and energy consumption can then be compiled.

The first step in developing the energy use model was to model the physical geometry of the neighborhood with Rhinoceros 3D. Spatial information used to model building footprints, streets, sidewalks and lot boundaries was extracted from GIS maps that are maintained by the City of Des Moines. 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 2015) to extract the building-related data needed to build the UMI simulation 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. Once the 3D model of the neighborhood block was constructed, it was ready be used to simulate each building's energy performance, yielding energy consumption data that would serve as inputs to the agent-based model.

2.3 Agent-Based Model

In this section, the agent-based model (ABM) of the Capitol East Neighborhood block is described. The model was built using NetLogo (v. 5.0.2). First, the agents are described, and then an overview of the ABM submodels is provided.

2.3.1 Agents

A single agent type inhabits the ABM – the household agent. There are 29 household agents in the model, each of which represents the occupants of a household in the selected block of the Capitol East Neighborhood. Each agent represents a household of people, rather than an individual occupant, since the decision to weatherize is assumed to be made at the household level. It is assumed that every agent is qualified to receive weatherization assistance. Weatherization assistance is assumed to include full financial support (i.e., the applicant pays nothing out of pocket) and implementation assistance (i.e., experienced installers perform the weatherization implementation tasks). Each household agent is characterized by four key parameters, which have values that are held constant over the entire 24-month simulation run:

- *House number*: Each household agent is assigned a unique house number, which links the agents to their respective buildings in the Rhino-UMI model.
- *Household monthly energy use*: The energy use generated by each agent's building (provided by the Rhino-UMI simulation output), both before and after weatherization, is assigned to each household agent.
- *Satisfaction threshold*: This defines the satisfaction (i.e., utility) value below which an agent is dissatisfied. The satisfaction threshold has the same value for all agents and is set to 0.25.
- *Social network*: Each agent is assigned to a group of agents that comprises its social network. The size of the agents' networks is varied experimentally. It is assumed that the agent's social network contains only members of the 29-household block of Capitol East that is considered in this study.

Each agent is also characterized by eight state variables that may be updated in each monthly time-step:

- *Current weatherization level*: This variable can either take on a value of zero (i.e., the agent has not weatherized its home) or one (i.e., the agent has weatherized). Once an agent has weatherized, it is assumed that it cannot return to the non-weatherized state.

- *Current utility:* The agent's utility in a given month is assumed to be a linear function of its current energy costs *c*, where the minimum possible value (i.e., a utility of zero) occurs for the agent's maximum possible energy expenditure (c_{max}), and the maximum (i.e., a utility of one) occurs for the agent's minimum possible energy usage (c_{min}). These minimum and maximum values are provided by the Rhino-UMI energy use model. While a nonlinear utility function (e.g., an exponential function) could have been used to capture the effect of diminishing returns, a linear proportional scale was chosen for simplicity, primarily because of a lack of sufficient data to estimate the agents' risk tolerance parameters (Chelst and Canbolat 2012, pp. 137-139). The utility function is defined as follows:

$$U(c) = \frac{c - c_{max}}{c_{min} - c_{max}} \tag{1}$$

- *Utility history*: Each agent stores its "memory" of its energy costs from previous months in a list of length *m*. At the end of each month, the agent appends its current energy costs to the list and removes the oldest value (i.e., it "forgets" this value).
- *Cost history*: As with the utility history, each agent stores *m* energy cost values in this list, which represents the agent's "memory" of previous energy expenditures.
- *Satisfaction level*: Each agent's decision about weatherizing its home and applying for assistance is motivated by a weighted average of its utility history. The agent's current satisfaction level is based on a weighted average of the previous *m* months, where *m* is the experimentally-varied value of the agent's memory. The energy costs of more recent months are weighted more heavily to account for recency effects. For example, if $m = 3$ and u_t is the agent's utility in time-step *t*, in the tenth month the agent's weighted utility is:

$$U = 3u_{10} + 2u_9 + u_8 \tag{2}$$

  If the weighted utility value is less than the agent's threshold value, its satisfaction level is set to one (i.e., satisfied); otherwise, it is set to zero (i.e., dissatisfied).
- *Self-weatherization probability*: This value represents the likelihood in a given month that an agent will decide to pay out of pocket (i.e., without waiting to receive assistance) to weatherize its home. This value depends on the agent's estimate of the length of the payback period for weatherizing, which is calculated 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 the same for each agent. It is also assumed that each agent is able to accurately assess this cost. The probability that an agent decides to pay for weatherization increases/decreases with decreasing/increasing payback period values.
- *Assistance status*: The value of this variable depends upon the stage that the agent is currently in with respect to applying for weatherization assistance. An agent's status can take on one of five discrete values:
  - Level 0: The agent has not yet applied for assistance.
  - Level 1: The agent has applied for assistance and is waiting for a response.
  - Level 2: The agent has been approved to receive assistance.
  - Level 3: The agent has made an appointment to receive weatherization assistance.
  - Level 4: The agent's home has been weatherized by the agency providing the assistance.

  If the agent has made an appointment to receive assistance, it may decide to cancel its appointment (i.e., its status may revert from Level 3 to Level 2). Otherwise, an agent's assistance status cannot return to a previous value.
- *Information level*: This value represents the degree to which an agent is informed about the weatherization assistance program (e.g., how to apply, whether they are eligible, what the potential benefits are). It falls between zero (i.e., completely uninformed) and one (i.e., fully

informed). It is assumed that each agent's level of information will remain the same or will increase in each time-step; the agent never becomes less-informed.

2.3.2 ABM Overview

The ABM consists of five main submodels, which are described below. The initialization submodel is only run once, at the beginning of each simulation run. The remaining four submodels are run in sequence in each monthly time-step.

Initialization: The agents' houses are all assigned a unique number, which corresponds to their location in the neighborhood and the UMI model, and they are all initialized at a weatherization level of zero (i.e., no weatherization). The agents are initialized to an assistance status of zero (i.e., not applied), a satisfaction level of one (i.e., perfectly satisfied), an information level of zero (i.e., no information about assistance), and all entries in the utility history list set to one (i.e., perfect utility). Each agent's social network is also initialized with randomly-selected constituents – it is assumed that membership in a social group does not depend on the proximity of the agents' homes. The size of each agent's network is experimentally varied, and it is assumed that each agent is a member of only one social network (i.e., there are no overlapping groups). Finally, each agent is assigned 24 energy consumption values (in kilowatt hours) that are specific to its own house that were generated by the Rhino-UMI energy use model. The first 12 values correspond to the monthly energy consumption for the agent's house without any weatherization. The remaining 12 values represent the monthly energy consumption with weatherization applied to the agent's home.

Update application and weatherization status: If the agent's assistance status is at level 1 (i.e., it has applied for assistance and is waiting for a response) or level 3 (i.e., it has made an appointment and is waiting for service), and the waiting period for that agent has ended in the current time-step, the agent's status is updated to level 2 (i.e., it has been approved for assistance) or level 4 (i.e., it has received weatherization assistance), respectively. If the agent is now at level 4, its current weatherization status is updated from zero (i.e., not weatherized) to one (i.e., weatherized), and its utility and cost histories will be reinitialized.

Update memory, assess satisfaction, and assess self-weatherization probability: Based on its current weatherization level and the current month, each household agent determines its total monthly energy consumption (in kilowatt hours) and multiplies this value by the current cost per kilowatt hour to obtain the total energy cost for its home. This value is appended to the agent's cost history list, and the oldest value in this list is removed. The agent then calculates the weighted average of this updated list and uses it to update its self-weatherization probability. The agent uses its current energy cost value to calculate its current utility value, which it appends to its utility history list, and the oldest value in the list is removed. The agent accesses this list to calculate its weighted average utility value, which it compares to its threshold utility value. Based on this comparison, the agent's status is updated to "satisfied" or "dissatisfied".

Gather information: This submodel represents the agent's acquisition of information with respect to the weatherization assistance program. If the agent is already fully informed about the program (i.e., its information level is equal to one), then it does not execute this submodel. The increase in an agent's level of information is random and depends upon its interactions with other agents in the neighborhood, 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 zero and 0.05 (if the agent is satisfied) or zero and 0.10 (if the agent is dissatisfied), with an upper bound of 1.0 on the information level. This logic is based on the assumption that a dissatisfied agent will be more motivated to seek out information and will therefore be more likely to increase its knowledge of the assistance program in a given time-step.

If an agent is allowed to interact with other agents, its increase in information will depend upon the number of agents in its social network and the current state of the other agents in the model. In each time-step, it is assumed that an agent is guaranteed to interact and share information with every agent in its social group. It is also possible that an agent will interact with agents outside its social network; however, these interactions are not guaranteed – the probability of interacting with each non-member in a given time-step is 0.10. When Agent A interacts with another Agent B, if Agent B previously received assistance to have its home weatherized and is currently satisfied, then Agent A's information level will increase. The size of the increase is random and depends upon Agent A's current satisfaction level: if Agent A is satisfied, then its information level will be incremented by a random amount between 0 and 0.10; if Agent A is dissatisfied, the increment will be a random value between 0 and 0.25. By contrast, if Agent B's home has been weatherized and it is satisfied, but it did not receive assistance (i.e., it paid for the weatherization out of pocket), then its interaction with Agent A will increase Agent A's self-weatherization probability by a random amount between 0 and 0.10 (if Agent A is currently satisfied) or 0 and 0.25 (if Agent A is currently dissatisfied).

Deliberate: This submodel includes each agent's decision process with respect to weatherization, both with and without support from the weatherization assistance program. If an agent is currently satisfied, the only potential change to its state variables is an update of its assistance status from level 3 to level 2 (i.e., it cancels its appointment). The probability that a satisfied agent cancels its appointment increases for increasing overall utility values, based on the assumption that a highly satisfied agent might not want to bother with the inconvenience of the weatherization appointment. The amount of time remaining is also a factor – if the agent has already waited a long time for the appointment, it is more likely to go ahead with the appointment than if it has just scheduled (i.e., the agent has a sunk cost bias with respect to waiting time). The probability of canceling is:

$$P_{cancel} = U * (t_{appointment} - t_{current}) \tag{3}$$

If an agent is dissatisfied, and its assistance status is at level 0 (i.e., it has not applied for assistance), it must first decide whether it will apply for assistance. This decision depends on the agent's weighted average utility and its information level. The lower the utility value and the higher the information level, the greater the likelihood is that an agent will apply. The probability that an agent with information level i will apply is:

$$P_{apply} = (0.1 - 0.1 * U + 0.1 * i) \tag{4}$$

If the agent decides to apply, its assistance status is updated to level 1. It is also assigned a randomly-selected application waiting period, where the maximum possible wait time is six months. If the agent decides not to apply, it will subsequently consider whether or not it will pay for weatherization out of pocket, with a likelihood that is 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 – its current weatherization status is updated from zero to one in the current time-step.

If an agent is dissatisfied, and its assistance status is at level 1 (i.e., it has applied for assistance and is waiting for a response), 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 larger self-weatherization probability values and 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 (i.e., it has been approved for assistance), 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, where 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., its assistance status is at level 3), it is assumed that the agent will continue waiting for its appointment.

3 EXPERIMENTATION AND RESULTS

Creating a comparative energy consumption dataset required that the energy use model represent pre- and post-weatherization conditions. UMI was used to assign 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 have 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 m^2•K/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 m^2•K/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 (TMY3/EPW) for the City of Des Moines (https://energyplus.net/weather), the model was then used to simulate the monthly energy performance of each household, split into subcategories such as 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. A color-coded visualization of the pre-weatherized energy consumption for the 29 houses is shown in Figure 1.

To verify the ABM and to demonstrate its ability to incorporate the effects of various factors (including social interactions) on household agents' weatherization decisions, a set of experimental scenarios was developed and tested over 24-month replications. In the first set of scenarios, the agents were not allowed to interact or share information about their weatherization experiences. In the second set of experiments, all 29 agents were allowed to share information in each time-step (i.e., there was a single 29-member social network). In the third set of experiments, the agents were broken into six mutually exclusive social networks (i.e., five groups of five agents and one group of four agents), and the agents were allowed to share information within groups. Within all three information-sharing scenarios, the lengths of the agents' utility and cost histories were varied such that they all had either "short" memories (i.e., they could hold two months of data) or "long" memories (i.e., they could hold five months of data), for a total of six unique experimental configurations. The experimental design is summarized in Table 1. For each scenario, thirty 24-month replications were run. In each replication, two measures of system performance were captured: the number of weatherized buildings in each monthly time-step, and the average monthly energy consumption for the entire 29-building block (in kilowatt hours).

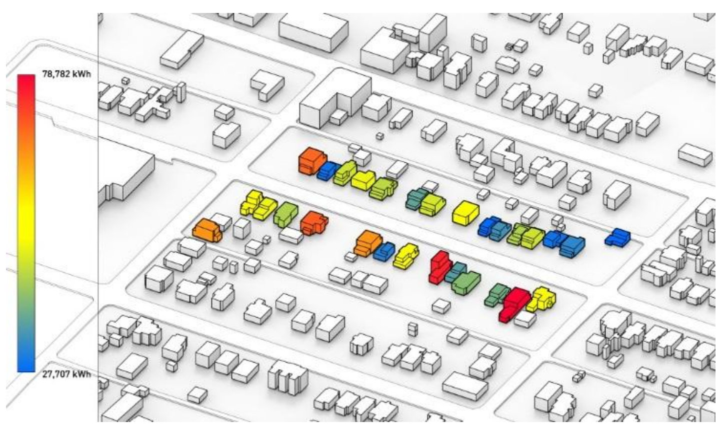
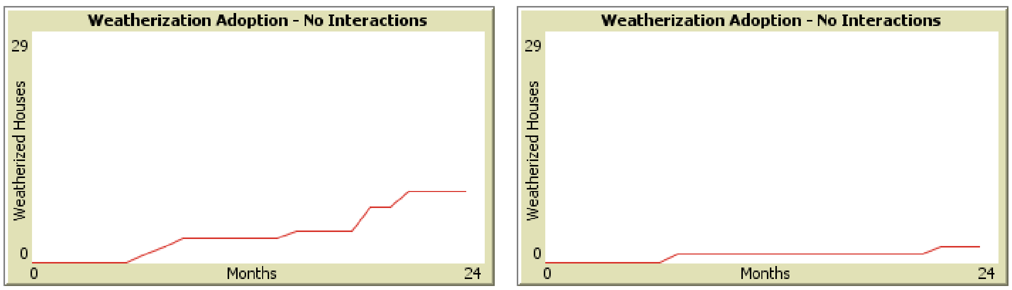


Figure 1: Energy visualization showing the current energy consumption of all residential parcels on a single block in Capitol East for the pre-weatherized condition.

Table 1: Summary of ABM experimental conditions.

Input Parameter	Experimental Values
agent interactions	allowed / not allowed
# agent social groups	one / six
agent memory length	short (2 months) / long (5 months)

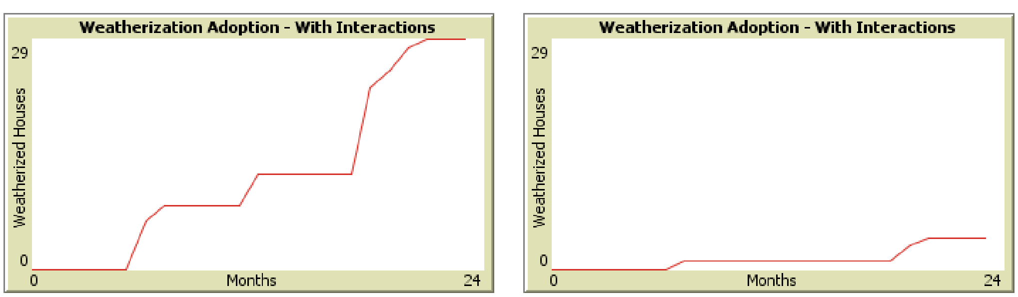
The plots in Figure 2 show how many of the 29 household agents decided to weatherize their homes over the course of a single representative 24-month replication when they were not allowed to interact or share weatherization information with one another. The plot in Figure 2a was generated for the scenario in which the agents had short memories, whereas the plot in Figure 2b shows results for agents with long memories. As the figures indicate, more agents tended to weatherize when they had short memories – they were apparently more sensitive to the high energy costs that occurred in the winter months. However, without any information sharing among agents, overall adoption rates were relatively low.



(a) (b)

Figure 2: Number of weatherized buildings over 24 months for a single replication, without interactions among agents with a) short and b) long memories.

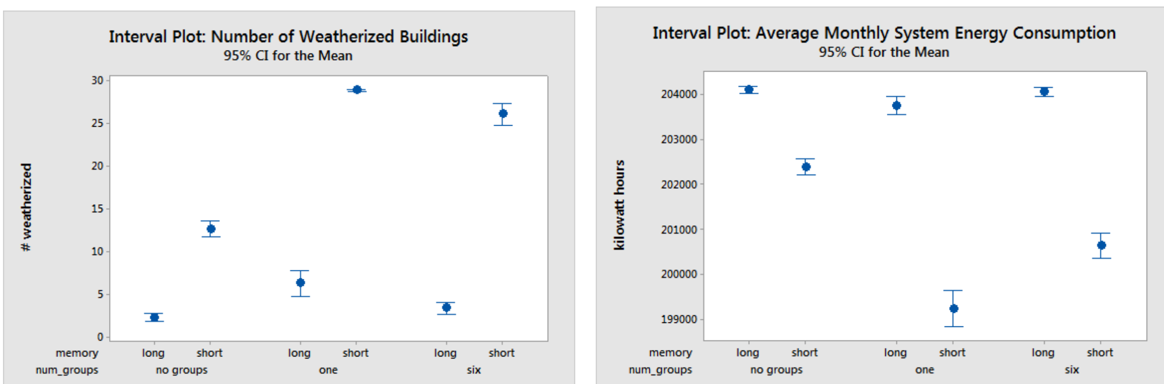
By contrast, when the agents were allowed to interact and share information, the number of agents that decided to weatherize was typically higher, although the length of the agents' memories affected the outcome significantly. The plots in Figure 3 show the number of agents that decided to weatherize over the course of a single representative 24-month replication in which there were six social networks for agent interactions. In the scenario that yielded Figure 3a, the agents' memory lengths were short (i.e., two months). By the end of the simulation run, all 29 agents had decided to weatherize. For the scenario represented by Figure 3b, the agents had long (i.e. 5-month) memories, and only three agents adopted weatherization measures. For the long-memory scenario, it seems that the influence of social interactions was tempered by the reductions in energy costs that occur in the warmer months.



(a) (b)

Figure 3: Number of weatherized buildings over 24 months for a single replication, with interactions occurring within six social networks of agents with a) short and b) long memories.

Figures 4a and 4b show the mean values and associated 95% confidence intervals for the number of weatherized households and overall neighborhood energy consumption, respectively, at the end of each of thirty 24-month simulated replications, for each of the six experimental scenarios. When the household agents are allowed to interact and share information about the positive impacts of weatherization, if they have short memories (i.e., they are more sensitive to energy cost increases that occur in a given month), more agents decide to weatherize, and neighborhood energy consumption reduces accordingly. However, if the agents have long memories, weatherization and energy consumption outcomes do not benefit much from social interactions and information sharing. While longer agent memories were expected to have a tempering effect on weatherization adoption rates, the strength of this effect was somewhat surprising. The results of these experiments suggest that weatherization could be encouraged through periodic reminders to homeowners about high winter heating costs. For example, in the summer, the utility company could send residents a twelve-month graphical energy use summary that clearly indicates the winter peaks. Additionally, the City of Des Moines might consider organizing and/or attending periodic social events (e.g., neighborhood picnics, church events) to encourage discussion about weatherization.



(a) (b)

Figure 4: The effects of different combinations of agent memory length and social network structure on a) the mean number of weatherized buildings and b) the mean monthly system energy consumption.

4 CONCLUSION

This paper has demonstrated the usefulness of combining a Rhino-UMI building energy use simulation model with an agent-based model in modeling weatherization decisions in a community. This conceptual hybrid model is the first step in a larger data collection and modeling effort to assist planners and government officials in the City of Des Moines in making decisions about the most effective policies to encourage residents to weatherize and conserve energy. Although the initial focus of this project is on the Capitol East Neighborhood, other neighborhoods in Des Moines are also of interest. Different neighborhoods are likely to have different types of building construction, and residents will likely differ in their attitudes about weatherization and energy conservation, their financial constraints, and their social network structures. The hybrid Rhino-UMI/ABM modeling methodology 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.

While the energy use model is based on publicly available data for residential buildings in the Capitol East Neighborhood of Des Moines, the other parameter values and the relationships among variables in the ABM, including the agents' logic and behaviors, are theoretical. That is, they are currently based on assumptions that are supported by the literature and expert opinion, rather than empirical data from Capitol East. As such, the version of the model presented in this paper has not been validated. However, ongoing research involves the development of methods to engage the community and gather empirical data about the residents' beliefs, objectives, and social networks. Once this empirical data is available, it will be incorporated into the ABM, and at that time an effort will be made to at least partly validate the model.

In the meantime, there are many potential avenues for future experimentation with and development of the existing theoretical model. For example, in the current version of the ABM, it is assumed that home ownership does not affect the occupants' decisions. However, this assumption could be modified to account for a mix of occupants in the neighborhood – those who own their homes and those who are renters, since this factor will very likely influence the decision to weatherize. Currently, the agents are assumed to have perfect information about the costs and benefits of weatherization – this assumption could be relaxed for greater realism, such that agents have imperfect estimates of these values. Also, in the current model, it was assumed that only two levels of weatherization were possible. However, the Rhino-UMI model has the ability to generate energy consumption values for a variety of different levels of weatherization, and the ABM could be adapted to allow residents to select from multiple weatherization options. With these modifications and the inclusion of empirical data, the hybrid Rhino-UMI/ABM modeling methodology described in this paper has significant potential for supporting urban policy and planning decisions that will yield a more sustainable and resilient City of Des Moines.

REFERENCES

Azar, E. and Menassa, C. 2012. "Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings." *Journal of Computing in Civil Engineering* 26(4):506-518.

Cao, Y., Wang, T., and Song, X. 2015. "An Energy-Aware, Agent-Based Maintenance-Scheduling Framework to Improve Occupant Satisfaction". *Automation in Construction* 60: 49-57.

Capitol East Neighborhood Charter Plan Update. 2014. Retrieved from: https://www.dmgov.org/Departments/CommunityDevelopment/PDF/Capitol%20East%20Neighborhood%20Plan%20Update.pdf (accessed 12/13/2015).

Chelst, K. and Canbolat, Y. B. 2012. *Value-Added Decision Making for Managers*. Boca Raton, FL: Taylor and Francis Group.

Chen, J., Taylor, J.E., and Wei, H. 2012. "Modeling Building Occupant Network Energy Consumption Decision-Making: The Interplay between Network Structure and Conservation". *Energy and Buildings* 47:515-524.

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." *The American Economic Review* 105(5):201-204.

Friege, J., Holtz, G., and Chappin, E. J. L. 2016. "Exploring Homeowners' Insulation Activity". *Journal of Artificial Societies and Social Simulation* 19(1)4. Retrieved from: http://jasss.soc.surrey.ac.uk/19/1/4.html (accessed 7/1/16).

Guerin, D. A., Yust, B. L., and Coopet, J. G. 2000. "Occupant Predictors of Household Energy Behavior and Consumption Change as Found in Energy Studies since 1975." *Family and Consumer Sciences Research Journal* 29(1):48–80.

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.

Higgins, L. and Lutzenhiser, L. 1995. "Ceremonial Equity: Low-Income Energy Assistance and the Failure of Socio-Environmental Policy." *Social Problems* 42(4):468-492.

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.

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.

Madlener, R., and Harmsen-van Hout, M. J. W. 2011. "Consumer Behavior and the Use of Sustainable Energy." In *Handbook of Sustainable Energy*, edited by I. Galarraga, M. González-Eguino, and A. Markandya (181–210). Northampton, MA: Edward Elgar Publishing.

Polk County Assessor website. 2015. Retrieved from: http://web.assess.co.polk.ia.us/cgi-bin/web/tt/infoqry.cgi?tt=home/index (accessed 4/6/16).

Reinhart, C. F., Dogan, T., Jakubiec, J. A., Rakha, T., and Sang, A. 2013. "UMI – An Urban Simulation Environment for Building Energy Use, Daylighting and Walkability." In *Proceedings of the 13th Conference of International Building Performance Simulation Association*. Chambéry, France, August 26-28.

Southwell, B. G., and Murphy, J. 2014. "Weatherization Behavior and Social Context: The Influences of Factual Knowledge and Social Interaction." *Energy Research and Social Science* 2:59–65.

Stern, P. C., Aronson, E., Darley, J. M., and Hill, D. H. 1986. "The Effectiveness of Incentives for Residential Energy Conservation." *Evaluation Review* 10(2):147–176.

Stern, P. C. 2014. "Individual and Household Interactions with Energy Systems: Toward Integrated Understanding". *Energy Research and Social Science* 1:41-48.

Ternes, M. P., Schweitzer, M., Tonn, B., Schmoyer, R., and Eisenberg, J. F. 2007. "National Evaluation of the Weatherization Assistance Program: Preliminary Evaluation Plan for 2006." Retrieved from: http://weatherization.ornl.gov/Retrospectivepdfs/ORNL_CON-498.pdf (accessed 4/6/16).

United States Department of Energy. 2016a. "What is Weatherization?" Retrieved from: http://energy.gov/eere/wipo/what-weatherization (accessed 4/6/16).

United States Department of Energy. 2016b. "Weatherization Assistance Program." Retrieved from: http://energy.gov/eere/wipo/weatherization-assistance-program (accessed 4/6/16).

United States Energy Information Association. 2013. "International Energy Outlook 2013." Retrieved from: http://www.eia.gov/forecasts/ieo/pdf/0484%282013%29.pdf (accessed 4/6/16).

Wilk, R. R., and Wilhite, H. L. 1985. "Why Don't People Weatherize Their Homes? An Ethnographic Solution." *Energy* 10(5):621–629.

Wilson, C., and Dowlatabadi, H. 2007. "Models of Decision Making and Residential Energy Use." *Annual Review of Environment and Resources* 32(1):169–203.

AUTHOR BIOGRAPHIES

CAROLINE C. KREJCI is an Assistant Professor of Industrial and Manufacturing Systems Engineering at Iowa State University. She holds a Ph.D. in Industrial Engineering from the University of Washington. Her research is focused on the development of quantitative methodologies for the analysis and sustainable management of sociotechnical systems, including supply networks and production systems. Her email address is ckrejci@iastate.edu.

ULRIKE PASSE received her Diplom - Ingenieur in Architecture from the Technical University in Berlin, Germany in 1990. She is a licensed architect and founding partner of Passe-Kaelber Architekten, Berlin, with 15 years of architectural practice, specializing in energy-efficient buildings. At Iowa State University she teaches architectural design and environmental technologies. Her multidisciplinary research projects span from "CFD for natural ventilation" to "sustainable cities decision making". Her email address is upasse@iastate.edu.

MICHAEL C. DORNEICH is an Associate Professor of Industrial and Manufacturing Systems Engineering at Iowa State University. He earned his Ph.D. in Industrial Engineering from the University of Illinois at Urbana-Champaign. Specific research and application areas include collaboration and human factors, human-computer interaction, adaptive automation, distributed systems, interactive learning environments, and decision-support systems. His email address is dorneich@iastate.edu.

NATHAN PETERS is currently an undergraduate architecture student at Iowa State University and will soon be starting graduate school at the Harvard University Graduate School of Design to pursue a Masters in Design Studies with a focus in Digital Fabrication and Robotics. His email address is npeters@iastate.edu.