Proceedings of the 2017 Winter Simulation Conference W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, eds.

AGENT-BASED MODELING FRAMEWORK FOR SIMULATION OF COMPLEX ADAPTIVE MECHANISMS UNDERLYING HOUSEHOLD WATER CONSERVATION TECHNOLOGY ADOPTION

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ABSTRACT

Using new technologies to maintain, construct, and reuse naturally created products like asphalt, soils, and water can reserve the environment (Baqersad et. al 2017, 2016). The objective of this study was to specify and model the behavior of households regarding the installation of water conservation technology and evaluate strategies that could potentially increase water conservation technology adoption at the household level. In particular, this study created an agent-based modeling framework in order to understand various factors and dynamic behaviors affecting the adoption of water conservation technology by households. The model captures various demographic characteristics, household attributes, social network influence, and pricing policies; and then evaluates their influence simultaneously on household decisions in adoption of water conservation technology. The application of the proposed simulation model was demonstrated in a case study of the City of Miami Beach. The simulation results identified the intersectional effects of various factors in household water conservation technology adoption and also investigated the scenario landscape of the adoptions that can inform policy formulation and planning.

1 INTRODUCTION

To mitigate water scarcity, understanding why, and to what extent households adopt water conservation technology is crucial. Most of the recent literature on demand-side conservation management and technology adoption considered some of the following features: public opinion/acceptance, cost, education/awareness, demographics, conservation technology, and peer effect/social network influence. The current studies on water management include some factors that encompass water conservation technology adoption behaviors, but none of them considered to combine effects of multiple phenomena simultaneously. To address this limitation, this study proposes an agent-based modeling (ABM) simulation approach to abstract and model various factors and phenomena affecting households' behaviors regarding water conservation technology adoption. Researchers have shown ABM to be a useful tool to explore behaviors and interactions of individuals in built environment and infrastructure systems (Azar and Menassa 2011; Mostafavi et al. 2015; Mostafavi et al. 2012). In ABM, decision makers are characterized as agents, each with a set of social capabilities and goals, values, and preferences. Agents exist in an environment defined by specific rules/micro-behaviors and can inform or evolve their goals or priorities over time (Gilbert 2008). ABM can account for: (1) various rational and behavioral decision making rules for different agents; and (2) an agent's reactions to other agents' decisions.

ABM has been incredibly successful in studying complex behaviors and policy analysis in infrastructure systems (Mostafavi et al. 2012; Mostafavi et al. 2015). Since ABM allows to look at the micro-behaviors within the system of water conservation and project future actions, it is the best tool for this study. In a real community, as people are connected through different ways such as family, work, neighborhoods and so forth, it is impossible to identify all the possible connection profiles based on the empirical data (Bandiera and Rasul 2006). With surveys and interviews, for example, the data received would not be on actual actions taken in water conservation technology adoption. The results would be more hypothetical with "what if" scenarios rather than a direct action taken. For other objective approaches, this forward-reaching simulation would not be possible. Additionally, surveys and other research tools can only reflect one particular population at a time, while ABM can replicate many different types of populations. ABM has the capabilities to project diverse, tangible scenarios throughout future years (Mostafavi et al. 2013).

ABM as a tool to analyze water management systems has been utilized and shown to be successful in the past (Kanta & Zechman 2014). One such study was conducted by Athanasiadis et al. (2005). In this study, the researchers explored the consumer effect on water-pricing policies using agent-based modeling. The research measured the impact of five different water price policies, and assessed its durability and influence with specific econometric and environmental data. They accounted for peer effect and the water suppliers on consumer-level agents. The results concluded which of the five pricing policies measured garnered the most and least residential water demand. This research showed the potential of agent-based modeling for water management. As sustaining water resources is so prevalent, being able to analyze water policy has growing importance (Athanasiadis et al. 2005). While this study was crucial in understanding the connection between econometric and water policy, it differs from the current research project in that it does not account for many sociodemographic components. Additionally, the focus of Athanasiadis et al.'s (2005) study was on water management policies developed by water agencies and political regulators, whereas the focus of this current research is on household conservation practices.

Another study that used agent-based modeling to simulate water use patterns focused on recreational home gardening (Syme et al, 2004). The researchers combined interview and external data to create a model that identifies the conservation possibilities of household gardens. Individual household gardeners were the agents, and they incorporated variables reflecting lifestyle, garden recreation and interest, conservation attitude, social desirability, and choice demographic factors including lawn size, income, and education. As a result of their research, it was found that the demographic characteristics had the most influence on external water use. The attitudinal parameters also related to external water use; however, the interaction between the parameters had minimal impact (Syme et al., 2004). This study was important because it tied together how water is used in social situations. While water is commonly perceived as a simple utility, it is also important to realize how water is used leisurely. Kanta and Zechman (2014) developed a model framework for assessing the consumer water demand behavior against different degrees of water supply and water supply systems. Their model incorporated both consumers and policy-makers as agents as they adapted their behaviors to different water supply systems and rainfall patterns. Studies such as these have set a precedent that agent-based modeling is a viable research tool for water use and management issues. Therefore, it will be the most effective approach for establishing which factors affect a household's willingness to convert to water-saving technologies.

There have been many studies that analyze the influence of certain demographic, household, social, and external factors on water conservation technology adoption in isolation; however, theoretically, all of these attributes have the potential to influence an agent's adoption utility simultaneously. In this study, the proposed ABM framework captures various demographic characteristics, household attributes, social network influence, and external policies; and then evaluates their influence simultaneously on household adoption of water conservation technology. The presented model assessed the probability of adoption of water conservation technology for each agent (household) based on a set of theoretical elements (e.g., innovation diffusion, peer effect, and affordability) and also empirical data from previous studies. In the ABM framework proposed in this study, the first step requires the abstraction of agents and their attributes. An agent is the main target of influence, and the model shows how the agents' attributes and behaviors change over a designated period of time (20 years). Since this study focuses on information regarding water conservation technology adoption at the household level, each household equals one agent. Most of the characteristics and factors can change and are fluid over time, thus changing its influence on a household. The following sections explain the theoretical framework underlying the proposed ABM and show the computational implementation of the framework in a case study of the City of Miami Beach.

2 SIMULATION MODEL

For the purposes of this study, the research question is: why and to what extent households adopt water conservation technologies based on various influencing factors? To overlay this question, the theory is that a household's willingness to adopt water conservation technology is influenced by other factors. These mechanisms including demographic and building characteristics, external factors and social interactions, all play a role in whether or not a household adopts water conservation technology. More specifically, this means that income level, education, house ownership status, house age, water pricing regimes, rebate availability, technology cost, and social networks for example, all influence a household concurrently. For this research project, the agent is rooted at the household level. While it may have been expected to utilize individuals as the agents, using people as agents requires a lot of granular data that is either not available or difficult to decipher in this type of model. Households will provide the needed information more efficiently and concretely.

Based on the theory of *Innovation Diffusion*, in adopting new technologies, a population can be divided into three groups: *non-adopters*, *potential adopters*, and *adopters* (Lee et al., 2011). Non-adopters are individuals who do not consider adopting a new technology. In contrast, potential adopters are individuals who do consider adopting new technologies. Different demographic and household attributes can influence whether an individual is a non-adopter or potential adopter. A potential adopter may become an adopter if the adoption of a technology is economically affordable for it. Based on the similar premise, in this study, households were divided into three categories (i.e., non-adopter, potential adopter, and adopter) in terms of their position for water conservation technology adoption. The transitions of households between these categories depend on their demographic characteristics and household attributes (combined as utility), peer influence, as well as water and technology price factors (which are underlying the affordability). The theoretical framework of these transitions can be seen below in Figure 1.

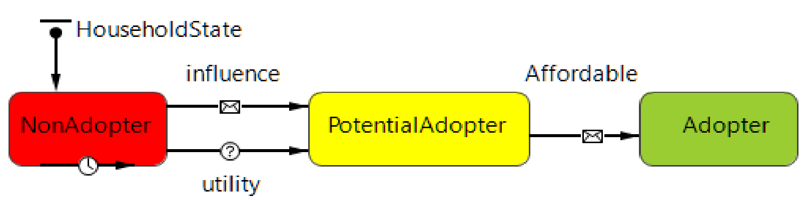

Figure 1: Theoretical framework for simulation approach

A household agent, based on its attributes, can transition from one state to another—from non-adopter to potential adopter and from potential adopter to adopter. These transition functions ultimately influence an agent toward or against a particular output. The demographic and building attributes were combined into one parameter, known as the *Potential Utility* (Equation 1). Equation 1 represents the combined utility value of all the coefficients.

$$\text{Potential Utility} = \sum \text{Coefficient}_{\text{variable}} * \text{Value}_{\text{variable}} \tag{1}$$

The coefficients in Equation 1 were abstracted from prior literature, namely Boyer et al. (2015), Brook and Smith (2001), Cahill (2011), and Chu et al. (2009). The coefficients for each attribute that makes up the potential utility are shown in Table 1.

Table 1: Coefficients and values for the function of *Potential Utility*

Variable	**Value**	**Coefficient**	**Distribution Type**
Education: · High school or less · Some college · College graduate · Advanced Degree	 If Yes=1, if No=0 If Yes=1, if No=0 If Yes=1, if No=0 If Yes=1, if No=0	 1.92 2.58 2.91 4.39	Real Data
Income · Less than $40,000 · $40,000-$75000 · Above $75,000	 If Yes=1, if No=0 If Yes=1, if No=0 If Yes=1, if No=0	 0 1.07 1.58	Triangular
Home Ownership	Owner=1, Renter=0	1.84	Triangular
Head Gender	Female=1, Male=0	1.21	Random
Resident (Head) Age	Years	1.01	Histogram
House Size	Square feet	1	Uniform (70; 56,000)
Garden Size	Square feet	1	Uniform (0; 8,000)
House Age	Years	0.99	Random (1,100)
Household Size	Numbers	0.98	Triangular

For example, a male high school graduate's potential utility, with no other demographics considered, would look like this: $1.92_{\text{education}} * 1_{\text{yes}} + 1.21_{\text{gender}} * 0_{\text{male}}$. If the potential utility value of an agent is greater than or equal to a user-defined utility threshold, it then triggers the transition from non-adopter to potential adopter. The threshold indicates a measure of sensitivity. As the user increases the utility threshold, they thus increase the importance placed on the demographic and household characteristics. The higher the threshold, the greater the demographic and household characteristics have to be in order to adopt (for example, a greater threshold would make it so, in terms of education, only those with an advanced degree would be willing to adopt). Conversely, the lower the threshold, the lower importance is granted to those factors. For this particular model, the lowest possible threshold is 3,000, while the maximum threshold is 60,000. The utility threshold is important because it allows the model to simulate a variety of community profiles. Because the utility value and threshold are based on the demographic and building characteristics and importance of those characteristics, respectively, it is possible to explore communities that are based in the real world. Communities typically have demographic trends, whether it be regarding income, education, or even house size. Because of this, the threshold can pinpoint those trends to simulate these different community profiles.

The function rule that triggers the transition from potential adopter to adopter is based on the *Affordability Theory*. Affordability is defined as the ability of households to pay for their water expenditures (Raftelis 2005). In this model, household affordability is measured by household annual water expenditures as a percentage of annual income (Brook and Smith 2001) (Equation 2). A household's annual water expenditures include the annual water bill plus cost of new water conservation technologies adopted until that year.

$$Affordability\ Index = \frac{AnnualWaterBill + \sum((Tech\ Cost - Tech\ Rebate) * Number\ of\ Tech)}{Annual\ Income} * 100 \tag{2}$$

After a household is in the potential adopter state, it triggers a yearly event where it calculates the affordability of each adoption action (technology adoption). For each adoption action, the model calculates the *Affordability Index* considering the technologies adopted before. If the index is less than the user-defined affordability threshold, the household makes the decision to adopt that technology. If it exceeds the affordability threshold, that means the adoption of technology is not affordable and thus the agent will remain as a potential adopter. The algorithm for this process is described in Figure 2. Different organizations such as California Department of Public Health, US Environmental Protection Agency, and United Nations Development Programs have reported various measures of affordability threshold that range between 1%-3%.

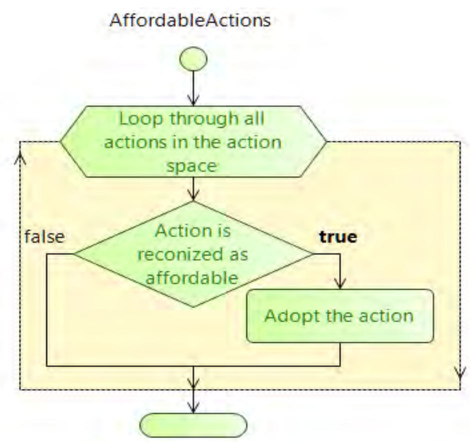

Figure 2: Action chart for transition between potential adopter and adopter

In the affordability measurement process, water price regime is incorporated into the model as an input parameter. Three different water pricing structures were assessed: *flat price*, *fixed charge*, and *block tariffs*. Table 2 outlines how the three strategies were implemented into the ABM framework.

Table 2: Input parameters for water price strategies (Cahill 2011)

Strategy	Attribute	Input Price
Flat Price	Volume Use Charge	$0.0044 per gallon
Fixed Charge	Regardless of Volume Use	$25.24 per month
Block Tariffs (Volumetric Pricing)	First Block: Demand: 0-172 gall/household/day	$0.0036 per gallon
	Second Block: Demand: 172-393 gall/household/day	$0.0043 per gallon
	Third Block: Demand: >393 gall/household/day	$0.0052 per gallon

Equations 1 and 2 make up the *Potential Utility* and *Affordability Index*, which define the adoption state of each household agent (i.e. non-adopter, potential adopter, and adopter). There is another phenomenon that can lead a household agent to transition from the non-adopter state to the potential adopter state and that is social network influence from other agents. Household agents can have a connection to each other; based on the theory of *Peer Effect*, through this connection between non-adopter and adopter households, non-adopter agents may communicate with adopter agents and thus get influenced by them into making decisions regarding the adoption of new technology (Friedkin, 2001). The model considers and implements five structures of social networks: *random, distance-based, ring lattice, small-world* and *scale-free* networks. Table 3 specifies more about how each structure of social network works.

Table 3: Structures, attributes and parameters for the implemented social networks

Network Type	Description	Parameter	Parameter Value
Random	Assigns each agent a random number of connections within the given average.	Average number of connections per agent (N)	N= 0-10
Distance-based	If the distance between two agents is less than the given maximum connection range (the maximum distance in meters between agents for there to be a connection), then both agents are connected.	Maximum connection ranges (R)	R= 0-500
Ring Lattice	Agents are connected according to their closeness to each other while also forming a ring.	Average number of connections per agent (N)	N= 0-10
Small-World	Connections between agents are similar to the ring lattice, while also including some long-distance relationships. The neighbor link probability is the chance that two agents connected to the same neighbor, may also connect to each other (Porter 2012).	Average number of connections per agent (N); and Neighbor link probability (P)	N= 0-10; P= 0-1
Scale-Free	Some agents are very social (or hubs) and may have lots of connections, while others prefer to be loners or have very few connections.	Number of hubs (M)	M= 1-10

Once the model has established a network according to the given parameters, it proceeds to simulate the social influence between connected agents. Every simulated year, the model checks all the non-adopter agents who have connections with adopter agents. Given a user-defined *likelihood of influence*, if the non-adopter agent is connected to an adopter agent, there is a chance that the non-adopter will transition into the potential adopter state. For every connection that the non-adopter agent has with an adopter agent the function randomTrue(p) is used, given the likelihood of influence "p", can return either True or False. If there is at least one instance when the transition is True, the agent transitions to the potential adopter state. The way randomTrue( ) works is that it first creates a random number uniformly distributed in the interval [0, 1). If the value created is less than the given likelihood number "p", then the result is true, else the result is false. For example, if the non-adopter agent is connected to three adopter agents, and the likelihood of influence (p) is 10%, the model calculates randomTrue(0.1) for three times. If in at least one of those calculations is less than 0.1, the result was true, then the agent transitions to potential adopter.

In this model, an agent was able to adopt six main types of water conservation technology shown in Table 4. This table shows the cost information and the potential rebate that the Miami-Dade Utility offers for each of these technologies, which will be incorporated as an input parameter into the model.

Table 4: Cost and potential rebate of tested water conservation technologies

Technology	**Cost**	**Rebate**	**Category**	***Technology***	**Cost**	**Rebate**	**Category**
Bathroom faucet	\$15	\$15	Inexpensive	*Toilet*	\$420	\$50	Expensive
Kitchen faucet	\$15	\$15	Inexpensive	*Washing machine*	\$670	\$150	Expensive
Shower head	\$100	\$25	Inexpensive	*Dishwasher*	\$500	\$50	Expensive

The user of the model can define whether or not the rebates will apply. The rebates can be important to the technology cost as well, since Affordability Index of household agents can be affected by rebates in the model. Income growth and household size growth were the last attribute input parameters for the model. All of these inputs will generate a number of outputs, which demonstrate the basis of the type and timing of technology adoption by household agents. The model outputs include the percentage distribution of all of the adopter states, the overall water demand reduction, and the different types of technology adopted over the twenty-year predetermined time period.

3 MODEL IMPLEMENTATION

Anylogic 7.0 was utilized to create the computational agent-based model. This model incorporates only one class of agent, which is the household. Data from the City of Miami Beach was used in the implementation of this ABM. The City of Miami Beach has more than ten thousand residential water consumers. To reduce the computational complexity of the model and improve its efficiency, a sample of 280 households that statistically represents the demographic distribution of the population (with 95% confidence interval) was selected and modeled. All 280 agents will start out as non-adopters; and, depending on different influences, will transition to potential adopter or adopter. The population of household agents taken from the City of Miami Beach are separated into three zip codes. The model then runs using Census data from these three zip codes, as well as individual household water use data provided by the Miami-Dade Utility. The census data includes information regarding median household income, education, average home ownership and average household size (Figure 3).

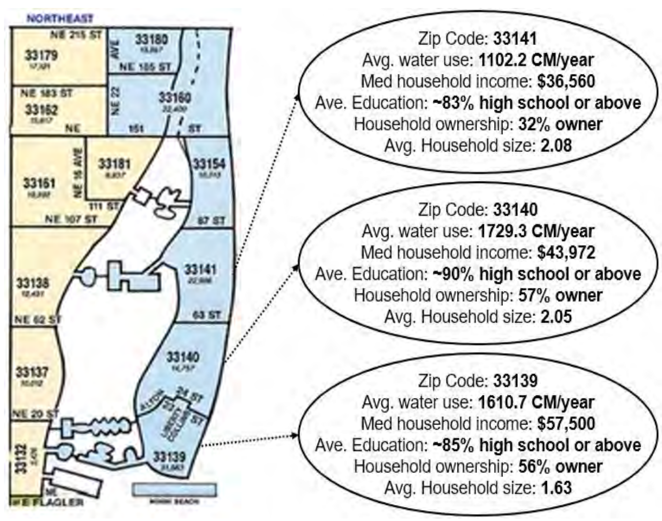

Figure 3: Demographic trends and average water consumption of the zip codes used in the model

Since some of the data provided by the census are only average values, a triangular average distribution was used to assign each household a random value. A uniform distribution was also used to assign the head resident age, garden size, and house size in square feet. Values such as head gender and home age are randomly assigned following no distribution. Moreover, data related to a household's source of water such as the number of showerheads, toilets and faucets come from a custom distribution.

The model input parameters include: water price, rebate status, income growth, household size growth, adoption utility threshold, affordability threshold, type of social network, and likelihood of influence. After twenty years, the model stops and provides the distribution of non-adopter, potential adopter, and adopter, as well as the number of actions adopted by the households. Figure 4 depicts the class diagram of the computational ABM and summarizes the information regarding the attributes and functions implemented.

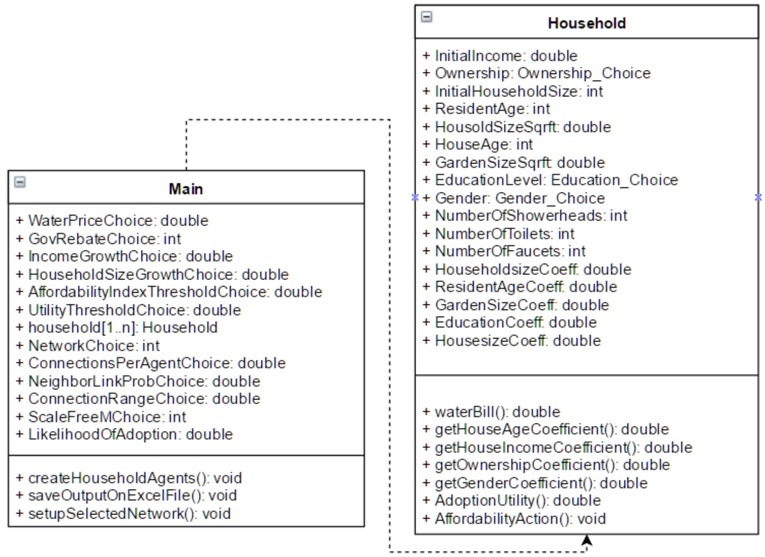

Figure 4: Unified modeling language (UML) class diagram of agents within the model

4 VERIFICATION OF COMPUTATIONAL REPRESENTATION

In this study, verification was conducted through a gradual, systemic, and iterative process. The theoretical and computational model were built rich in causal factors that can be examined to see what leads to particular outcomes. Internal and external validation techniques were implemented focusing on verifying the data, rules, logics, and computational algorithms. The internal validity of the model was ensured through the use of the best available theories for modeling decision and behavioral processes of households. For each component of the model, a component validity assessment was conducted to verify the completeness, coherence, consistency and correctness of each component. There are past studies that, despite using a variety of different methods, found similar findings to the model (Table 5). This, in turn, serves as a point of external validation to the model.

Table 5: External validation of the model

Findings of This Study	**External Validation**
Income growth most influenced the model agents to adopt water conservation technology.	"We have previously found financial variables to be important supplements to attitude measures in technology adoption modelling" (Lynne et al. 1995).
Fixed charge strategy of water pricing, which provides cheaper water for the households, led to greater number of adoptions in the model.	The higher the price of water, the less technology one would adopt; conversely, the lower the price of water, the more technology one would install (Olmstead & Stavins 2009).

5 EXPERIMENTS AND RESULTS

The simulation model was used for scenario analysis in order to specify the effects of different factors on the water conservation technology adoption of households. Each of the three water price strategies were analyzed for different combinations of rebate status, income growth, social network structure, household size growth, utility threshold, and affordability threshold. Evaluating and recording the results led to different outcomes of percent adopter and number of technology adoption. Two different forms of analysis were used to formulate results. The first was scenario analysis, where different animation components from the model are directly compared. Secondly, a trend analysis was conducted. Trend analysis allows for juxtaposing multiple scenarios. For each scenario, one hundred runs of Monte-Carlo experiments were implemented to determine the mean value of each output parameter. The trend analysis was used for visualizing how many households began adopting, as well as which technology they adopted. In order to accurately compare scenarios equally across the analyses, a base case (Table 6) was created to act as a reference point that every other scenario is compared to.

Table 6. Base case scenario parameters

Parameter	***Value***	**Parameter**	***Value***
Water Price Strategy	*Flat Price*	Income Growth	*+1 %*
Rebate Status	*With Rebate*	Household Size Growth	*+1 %*
Likelihood of Adoption	*10 %*	Utility Threshold	*30,000*
Social Network Type	*Small-World (N=1, P=0.1)*	Affordability Threshold	*1.5 %*

The model animation component of the base case over a 20-year analysis horizon is shown in Figure 5. This animation visually and graphically displays the outputs from the base case inputs. It shows the households' state distribution, which reflects the adoption state of all of the agents; the households' adopted actions display how many of each technology was adopted; the map, which geographically shows where the 280 households are located in Miami Beach as well as how they are socially connected to each other (based on a small-world network structure); total adopters, which displays the number of people who adopted; and the overall demand reduction, which shows how much water will be saved (per day) at the end of the analysis horizon.

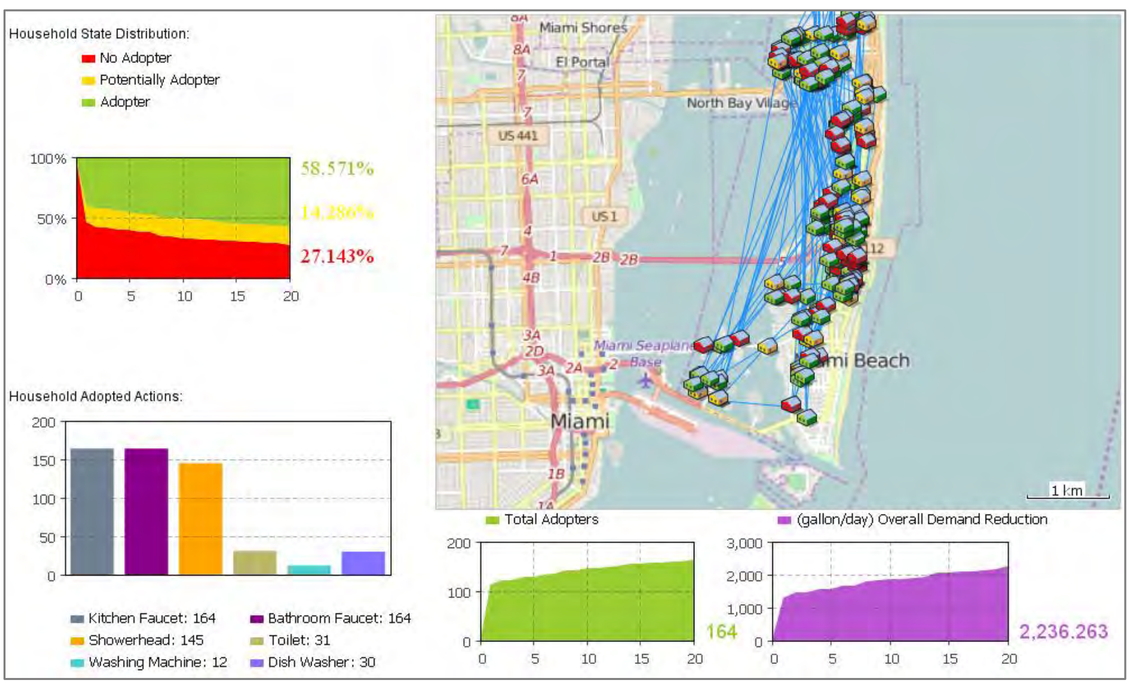

Figure 5: Base case animation from the model

In this base case scenario, 27.1% of households after 20 years remain non-adopters, and 58.6% become adopters that are mostly located in the south of the city where the communities are affluent. Among those who did adopt, kitchen, and bathroom faucets were the most common technologies adopted, while the expensive technologies—toilet, washing machine, and dishwasher—were adopted less frequently. A total of 164 household adopted one or more water conservation technologies, and through adoption of these technologies, the overall water demand is reduced by 2,236 gallons per day, which means around 2% reduction in the average overall daily water demand of the case study.

Various scenarios composed of different combinations of input parameters were simulated, reflecting changes in water price strategy, rebate status, income growth, social network structure, and affordability threshold. Figure 6 shows the number of each technology adopted under different scenarios of water pricing and rebate strategy (while other parameters remained unchanged compared to the base case scenario). It can be observed that inexpensive technologies (i.e., kitchen and bathroom faucets and showerhead) were mostly adopted when the fixed charge strategy was implemented for water pricing. However, for the expensive technology adoption, the impact of water pricing strategy is insignificant. Also, the rebate allocation was more effective along with the volumetric pricing strategies rather than the fixed charge strategy especially in the adoption of expensive technologies.

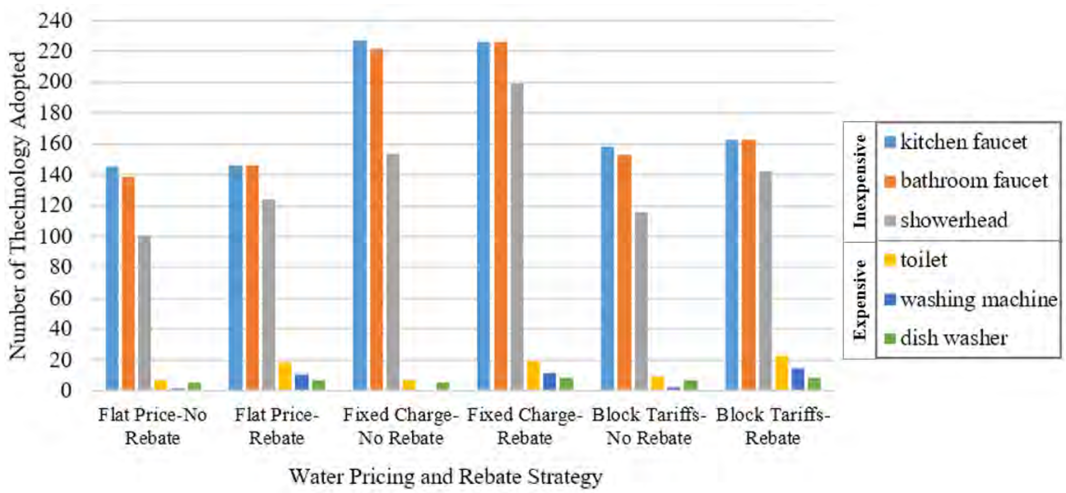

Figure 6: Impact of water pricing and rebate strategy

Figure 7 demonstrates the sensitivity of technology adoption to affordability threshold of households. For all water price strategies and rebate status, as affordability threshold increase, there was a logarithmic and exponential increase in adoption of inexpensive and expensive technologies, respectively. This finding means that adoption of expensive technologies is more sensitive than inexpensive ones to the affordability threshold.

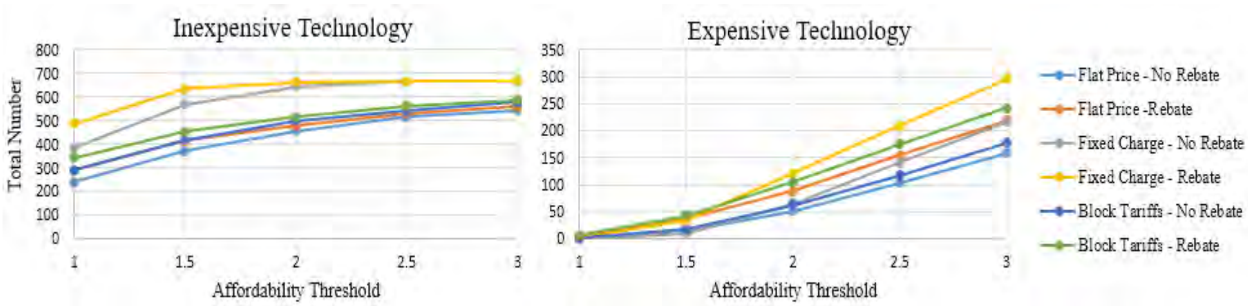

Figure 7: Modeling trends on number of technology adopted and affordability threshold

Finally, the five implemented social network structures were tested under the base case scenario and the results are documented in Figure 8. The results show that, among different social network structures, scale-free structure can lead to a less number of non-adopters in the community. For instance, it leads 10% more adoptions compared to the random social network structure, which is statistically significant.

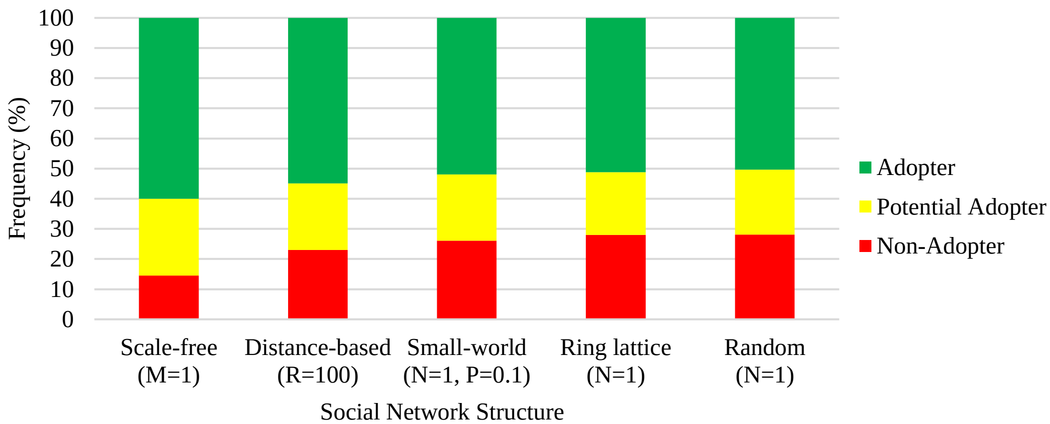

Figure 8: Influence of social network structure on adoption state distribution

6 CONCLUDING REMARKS

This study presented a theoretical agent-based simulation framework to capture the complex adaptive mechanisms influencing the household decisions in adoption of water conservation technology. The results of the study showed that to what extent many demographic characteristics, household attributes, social network interactions, and external water policies affect a household's willingness to adopt water conservation technology simultaneously. Hence, the findings of this study will help municipalities and water agencies to better understand the mechanisms affecting residential water conservation technology adoption and effectively implement strategies to increase the household adoption of water conservation technology—as a demand-side strategy— in order to build resilience against water scarcity. From a theoretical perspective, this study contributes to the growing field of urban science in the context of water management and sustainable planning.

ACKNOWLEDGEMENT

This material is based in part upon work supported by the National Science Foundation under Grant Number 1444758, and the City of Miami Beach Utility. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF or the City of Miami Beach Utility.

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