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Consumer-adoption Modeling of Distributed Solar Using an Agent-based Approach

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ABSTRACT

The electricity market in the U.S. is changing rapidly from a utility-scale centralized generation-distribution model to a more distributed and customer-sited energy model. Increasingly, residential consumers are showing interest in solar-based electricity, which has resulted in increased adoption of distributed solar on the rooftops of owner-occupied residences. However, limited accessibility of rooftop photovoltaic (PV) has led to equity concerns among policymakers. Also, utility companies face a decline in revenues as more residents adopt rooftop PV. In response to these issues, utility companies must consider providing alternative renewable energy options to their customers and incorporate consumer adoption modeling in their expansion planning approach. Agent-based modeling enables energy consumers' socially-motivated adoption decisions to be realistically captured. This paper describes an agent-based model that demonstrates the value of incorporating consumer-adoption modeling in a utility company's expansion planning approach.

KEYWORDS

Agent-based modeling, distributed solar, rooftop PV, community solar, social network, energy consumer modeling

1 INTRODUCTION

The electricity market in the U.S. is changing rapidly. In particular, the share of renewable sources of energy has increased in response to serious environmental consequences associated with fossil fuels. As a result, there has been a structural shift in the electricity market, from a utility-scale centralized generation-distribution model to a more distributed and customer-sited energy model. Figure 1 shows a structural comparison between a utility-scale and consumer-sited energy model. The focus of this paper is on distributed generation in the residential sector. The residential sector is of interest, as it accounts for about one-third of total electricity consumption in the U.S. [1].

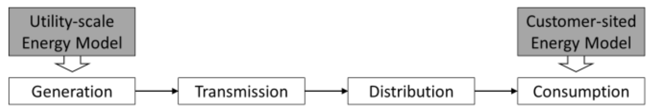

Figure 1: Structural difference between utility-scale and consumer-sited energy model.

Over the last decade solar energy has emerged as a viable option for electricity supply through distributed generation [2]. Residential energy consumers have shown increased interest in solar-based electricity – in a 2015 survey of U.S. residential utility customers, 59% claimed to be interested in using solar electricity at home, and 34% claimed to be "seriously considering" their solar options [3]. This has resulted in a large increase in the adoption of distributed solar panels on the rooftops of owner-occupied residences (typically known as rooftop PV) in the U.S. over the past several years [4]. Adopters are typically motivated by energy cost savings, a desire to own the energy infrastructure, concern for the environment, peer influence, and the ability to gain independence from the utility company. Interactions among peers are of particular interest – research has shown that consumers' energy technology adoption decisions are often socially motivated [5,6,7].

However, the rate of rooftop PV adoption has decreased in recent years, mainly because there are few remaining early technology adopters. There are several other reasons for this decrease in growth. First, the high up-front cost of purchasing and installing rooftop PV has limited access to higher-income households. Although incentives (e.g., income tax credit) and leasing options have attempted to address this issue, the majority of U.S. homeowners are still unable to install rooftop PV. In fact, a National Renewable Energy Laboratory (NREL) study found that only 22–27% of all rooftop area in the U.S. is suitable for installation of PV panels, after adjusting for structural, shading, or ownership issues [8]. Apart from that, rooftop PV does not accommodate renters and apartment owners who do not own the space needed to install solar collectors. This has raised equity concerns among policymakers, since publically-funded rebates are only being distributed to a small number of U.S. households [6].

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Another challenge associated with rooftop PV involves the utility companies. As the number of consumers who generate their own energy using rooftop PV increases, utility companies' revenues decline. Because rooftop PV consumers do not pay their fair share of the cost of maintaining and upgrading the existing electricity infrastructure, utility companies are forced to increase electricity tariffs. This creates an unfair financial burden on consumers who do not have the resources to install rooftop PV. In response to this, many utility companies in the U.S. are changing their policies on rooftop PV adoption. For example, the Iowa Utilities Board has recently approved a policy change on net metering from Alliant Energy (a public utility company) [9]. Net metering allows consumers to offset their energy bills with the excess energy generated by their PV systems. Per the new policy, new customers must significantly reduce the size of their rooftop PV installations. The projected result is a reduction in solar installations in Alliant Energy's territory by at least 70%.

Alternative renewable energy models that involve both consumers and utility companies as stakeholders could help to address these issues. For example, community solar, also called "shared solar," is defined by NREL as "a solar-electric system that provides power and/or financial benefit to multiple community members" [8]. Under a community solar program, the actual generation of renewable energy does not occur at the customer's home. Instead, the customer subscribes to a portion of a shared renewable energy facility (much like a resident may invest in a community garden) located elsewhere in the community, and each subscriber benefits in proportion to their investment [10]. These shared renewable energy facilities can be owned by a third-party entity, a utility company or by a group of consumers themselves. Utilities, mandated by federal and state policies to increase renewable sources in their energy mix, should consider adopting alternative models to increase consumer participation as investors in creating new energy infrastructure. However, utilities must be strategic about structure (e.g., capacity, ownership) of the alternative renewable energy models that they decide to offer. It is important for them to understand how heterogeneous individual customers would respond and what the impacts of these individual decisions would be on the long-term success of the overall system. In particular, while consumer energy choices are driven by perceived benefits such as financial savings and increased convenience, they are also often socially motivated.

Conventional methods for expansion planning (i.e., mathematical modeling) assume aggregate consumer behavior based on extrapolations of historical data and do not account for consumers' social behaviors, such as diffusion of innovation and social learning within spatial and social networks. By contrast, consumer-adoption modeling explicitly uses historical distributed PV deployment data, location-specific generation potential, economic considerations for adopting distributed PV, and end-users' behaviors as predictive factors in expansion forecasting for utility companies [11]. Therefore, in the current energy market with increasing number of consumers interested in becoming stakeholders in the energy infrastructure, it is apparent that the utility companies should incorporate consumer-adoption modeling in their expansion planning approach.

Agent-based modeling (ABM) is a technique that is well-suited to studying the effects of energy consumers' heterogeneous behaviors, boundedly rational decision processes, and social interactions on the adoption of energy technology over space and time [12,13,14]. The nonlinear interactions arising from consumers' decisions could result in an overall system-wide behavior that emerges over time [15,16,17]. ABM has been previously used as a tool to study the consumer adoption of various energy technologies. For example, several ABMs have been developed to study the effects of different policies on rooftop PV adoption among residential energy consumers [6,18,19]. However, the existing work does not aim to help utilities make decisions about how to effectively structure alternative renewable energy models to address the issues associated with increased rooftop PV adoption.

This paper describes an ABM that has been developed to demonstrate the value of incorporating consumer-adoption modeling in a utility company's expansion planning approach. This model captures the decision processes and interactions of heterogeneous individual residential electricity consumers who are given the options of adopting rooftop PV or participating in a community solar project. Model outputs (i.e., system-wide consumer adoption behavior) can be used to help utility companies understand the effects of offering different renewable energy alternatives to their customers.

2 CONCEPTUAL MODEL

The ABM was developed using NetLogo 5.3.1 and will be described using the ODD (Overview, Design concepts and Details) protocol [20]. First, an overview of the ABM is provided:

Purpose – The purpose of this model is to demonstrate the usefulness of incorporating consumer-adoption modeling in a utility company's expansion planning approach. The model can be used to assist utility companies in identifying specific attributes of alternative renewable energy models (e.g., the capacity of a community solar project) that minimize their revenue losses and maximize consumer participation and total green power in their energy portfolios.

Agents – The ABM contains 300 residential consumer agents. The 300 consumer agents are each assigned to one of seven different communities. Communities 1 through 7 consist of 70, 30, 20, 70, 40, 30, and 40 agents, respectively. A community identification number (C_i) has been assigned to each consumer agent, such that agents of the same community have the same value of C_i. Each consumer agent has also been assigned a level for each of four demographic factors (age, income, education level, and race) based on empirical data from a small city in Iowa. Nine levels (0-8) of age (A_i), 16 levels (0-15) of income (I_i) and 6 levels (0-5) of education (E_i) have been defined, where higher levels correspond to larger values of age, income, and educational experience, respectively. Eight levels (0-7) of race (R_i) were also defined, with each level corresponding to a unique race. The income level, education level, and race of an agent are assumed to remain constant throughout the simulation run. However, the age level of each consumer agent increases as simulated time progresses.

The consumer agents can either buy electricity from the utility company through conventional sources, or they have the potential to become energy generators through rooftop PV adoption or participation in a community solar project. Each agent is categorized as being either a house-owner, a renter, or an apartment owner. It is assumed that only house-owner agents can install rooftop PV (either through buying or leasing option), while house-owner, renter, and apartment owner agents can all adopt community solar. The consumer agents are capable of interacting with other agents, both within and outside their own communities. The variables associated with the consumer agents and data sources are explained in Table A1 of Appendix A.

Overview – In each time-step (where one time-step represents one month), each consumer agent assesses whether it wants to participate in one of three different renewable energy models: buy rooftop PV, lease rooftop PV from a solar installer, or enroll in a community solar project offered by the utility company. This decision is driven by the agent's financial position (i.e., its ability to invest), its attitude toward buying solar electricity, its demographic attributes, and influence from other agents in its social and spatial networks. Next, the model design concepts are described:

Basic principles – The various financial, attitudinal, and demographic factors that drive the consumer agents' decisions to adopt a renewable energy model were shortlisted through a review of numerous existing empirical studies that have identified consumers' motivations for adopting solar electricity. In particular, the literature indicates that consumer decisions to adopt energy technology are socially motivated [7], with social and spatial interactions serving as influential factors in residential solar electricity adoption [5,6].

Emergence – The collective behavior of the agents yields emergent properties. Consumer agents' decisions to adopt a renewable energy model will influence other consumer agents' decisions due to the interactions that occur between them. The heterogeneous interactions between the consumer agents yield emergent system-wide adoption of different renewable energy models.

Objectives – Each consumer agent's objective is to meet its energy needs in each time-step. The agent can achieve this objective by sourcing conventionally-produced energy directly from the utility company, or by sourcing renewable energy through adoption of rooftop PV or by participating in a community solar project.

Interactions – Two types of interactions between the consumer agents have been considered in this model. The first type is a visual interaction (i.e., seeing PV panels on a neighbor's roof): if a house-owner agent adopts rooftop PV in a given time-step, in the next time-step every other consumer agent within the same community becomes aware of it. Past research on consumer adoption of rooftop PV has shown that having more rooftop PVs in a zip code increases the likelihood of another household adopting [5].

The second type of interaction involves peer interactions between the consumer agents within their social networks. This type of interaction involves the exchange of information (e.g., availability of a community solar project) and can occur between the agents of the same as well as different communities. Influence due to peer interactions plays an important role in a consumer's decision to adopt solar electricity [5,6]. To create the agents' social network, a small-world network was generated using Watts-Strogatz algorithm, with a rewiring probability of 0.5 [21]. Figure 2 shows a snapshot of the NetLogo user interface after the small-world social network generation, where each node in a circle represents a consumer agent, and the line connecting the node refers to its connection. The seven circles represent the seven different agent communities in the model.

After generating the social network, each of the links between the consumer agents is assigned a similarity index. Consumer similarity (i.e., homophily) is a predictor of the strength of interactions within the generated social network [22]. It is assumed that higher similarity index values yield more influential interactions between the consumer agents. The four demographic characteristics of the consumer agents (age, income, education, and race) are used to determine the similarity index of each link. The similarity of two agents is assumed to be indirectly proportional to the differences in their age (A_i), income (I_i), education (E_i), and race (R_i) levels, with equal weights on each factor. A similarity index is calculated as the sum of the normalized similarity values from each demographic factor. Because the maximum and minimum possible values of similarity from each demographic factor are equal to 0.25 and 0, respectively, the maximum and minimum values of the overall similarity index are 1 and 0, respectively. Similarity index ($Simi_{jk}$) between agents' j and k is evaluated using (1), where R_{jk} is 0 if the race levels of agents' j and k are the same; otherwise it is assigned a value of 1.

$$Simi_{jk} = \left(0.25 - \frac{|A_j - A_k|}{32}\right) + \left(0.25 - \frac{|I_j - I_k|}{60}\right) + \left(0.25 - \frac{|E_j - E_k|}{20}\right) + \left(0.25 - \frac{R_{jk}}{4}\right) \quad (1)$$

Observations – The total number of consumer agents buying rooftop PV, leasing rooftop PV, or adopting community solar are captured in each simulation run. The net revenue and losses of the utility company serving the consumer agents due to rooftop PV uptake is also recorded, as well as the total green power addition in the network. Finally, model details are provided:

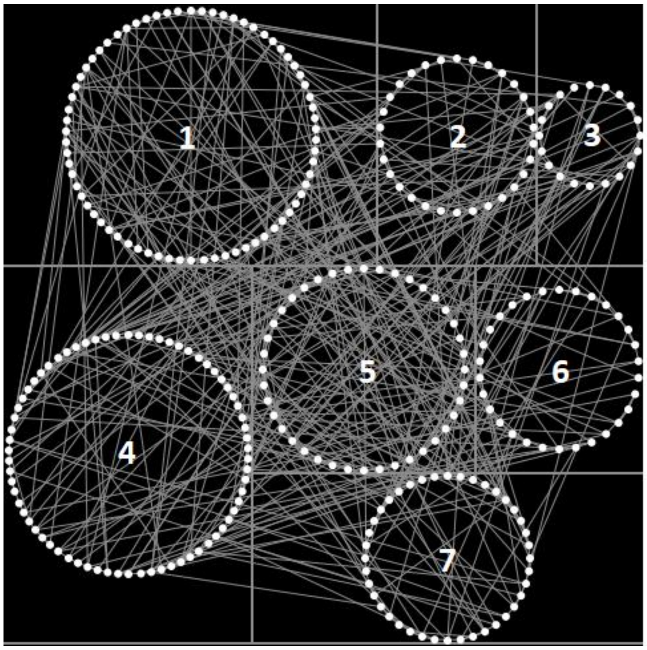

Figure 2: Snapshot of the NetLogo model showing 300 consumer agents living in 7 different communities and socially connected via a small-world network.

Initialization – At the beginning of the simulation run, each consumer agent is initialized to be a non-adopter that buys electricity from the utility company through conventional sources.

Input data – Publically-available data from a city in Iowa was used to inform the decisions and behavior of the consumer agents. Approximately 59% of the residents of this city are house-owners and 41% are either renters or apartment owners. This ratio has been applied to the 300 consumer agents randomly. However, in reality not all house-owners can adopt rooftop solar. In the U.S. only 22-27% of rooftops are suitable for installation of PV panels after adjusting for structural, shading, or ownership issues [8]. Therefore, it is assumed that only 25% of the house-owner consumer agents are capable of adopting rooftop PV, although they can all adopt community solar.

The mean monthly residential electricity consumption of the Iowa city (873 kWh/month) was used to define the probability distribution of the consumer agents' monthly electricity consumption. A normal distribution using this value as the mean and a standard deviation of 50 (i.e., N (873, 50) kWh/month) was assumed, from which monthly consumption values (Q_i) are drawn for each consumer agent. The consumer agents' unit electricity cost was set to the current average residential electricity rate of the city, i.e. 11.63 ¢/kWh. This cost was assumed to increase by four percent annually.

Sub-models – The ABM contains three sub-models: Consumer Agent Attitude Assessment, Consumer Agent Financial Assessment, and Consumer Agent Decision. All the three sub-models are executed in each monthly time-step for each consumer agent.

Sub-model 1 – Consumer Agent Attitude Assessment - Several attitudinal factors are known to influence consumers' decisions to buy solar electricity [3]. These factors include a desire to become independent from the utility company and own the energy infrastructure, concern for protecting the environment for future generations, the complexity involved in buying rooftop PV, the expected duration of staying in the current house, and the influence of recommendations from people in their social and spatial networks.

Each consumer agent is initially assigned an initial awareness index (AW_i) on a scale of 0-1, which is the normalized product of its education level (E_i) and a random number generated between 0 and 1. A higher value of AW_i corresponds to a greater probability that a consumer agent will adopt a renewable energy model. The value of AW_i for a non-adopter may increase over time as a result of visual and peer interactions.

In each time-step, it is assumed that AW_i for a non-adopter increases by 0.1 if a house-owner agent within its community adopts rooftop PV in the previous time-step. This is because it is assumed that every agent can see the panels on the rooftop of a house-owner agent in its community. The value of AW_i for a non-adopter consumer agent also increases when it interacts with an adopter (either rooftop PV or community solar) agent in its social network. This value of this increase is determined by (2), where $AW_{j(before)}$ and $AW_{j(after)}$ are the non-adopter j awareness index values before and after the interaction, AW_k is the adopter k awareness index, and $Simi_{jk}$ is the similarity index value of the link between agent j and k (calculated using Equation 1). It is assumed that the awareness index of an adopter will no longer increase after adoption. It is also assumed that in each time-step a consumer agent will interact with every agent in its social network.

$$AW_{j(after)} = AW_{j(before)} + 0.01 AW_k Simi_{jk} \quad (2)$$

The awareness index of an agent also increases if it interacts with solar installers at renewable energy fairs and/or with utility companies at seminars on the renewable energy programs that they offer for their customers [23]. It is assumed that only house-owner agents who can adopt rooftop PV can attend a renewable energy fair, at which they gain knowledge on rooftop PV buying/leasing options. However, any type of agent can attend a utility company seminar. In each time-step the likelihood that a consumer agent will attend a renewable energy fair and/or a seminar conducted by the utility company depends on the agent's current value of AW_i, where a higher value yields a higher probability of attending a fair or seminar. An agent will attend a solar installers' fair and/or a utility company seminar a maximum of one time during a simulation run. If an agent attends a fair or seminar, its awareness index increases by a value of 0.1. During the interactions in the seminar, the utility company also shares information about the availability of a community solar project. Those consumer agents that attend the seminar will become aware of the community solar option. Additionally, if a consumer agent that is aware of the community solar option interacts with another agent in its social network, the other agent also becomes aware of the community solar option, irrespective of attending the utility company seminar. It is assumed that a consumer agent does not know about community solar if it does not either attend a utility company seminar or interact with another agent in its social network that is aware of the community solar program offered by the utility in its area.

Consumers tend to consider the purchase of rooftop PV to be a complex issue, because of the effort required to learn about installation procedures, federal and state incentive policies, utility companies' net metering policies, house-owners' association regulations, and the required paperwork [8,10,24,25]. However, when a consumer leases solar panels or adopts community solar, project developer handles all of the local permitting and approvals, as well as evaluating incentives to maximize the financial return for their customers. To capture this factor in the agents' decision process, each house-owner consumer agent is assigned a perceived complexity index (PC_i) value on a scale of 0-1. The initial value of this index is assigned randomly to each house-owner consumer agent. Lower values of PC_i correspond to greater probabilities that the house-owner agent will buy rooftop PV. The value of PC_i decreases by 0.25 if a non-adopter house-owner agent interacts with the solar installers at a renewable energy fair. Its value also decreases if the non-adopter house-owner agent interacts with a rooftop PV buyer within its social network. This decrease in the perceived complexity index of a non-adopter house-owner agent j is given by (3), where $PC_{j(before)}$ and $PC_{j(after)}$ are the non-adopter's j perceived complexity index values before and after the interaction, PC_k is the perceived complexity index of rooftop PV buyer k, and $Simi_{jk}$ is the value of the similarity index between agents' j and k.

$$PC_{j(after)} = PC_{j(before)} - 0.01 PC_K Simi_{jk} \tag{3}$$

Each house-owner consumer agent is also assigned an ownership index (O_i) on a scale of 0-1, where higher values of O_i correspond to higher probabilities that the agent would prefer installing rooftop PV over participating in a community solar project. This value is assigned randomly to each house-owner agent. Lastly, a house-owner agent's current age level (A_i) also affects its decision to adopt rooftop PV. Older people are more likely to adopt rooftop PV, as they tend to plan to stay in their existing home and are closer to retirement [23]. Therefore, each house-owner agent has been assigned an age risk index (AR_i) on a scale of 0-1, based on its current age level (A_i). The age risk index of an agent is evaluated by normalizing to 1 the product of its current age level (A_i) and a random number generated between 0 and 1. Higher values of age risk index (AR_i) correspond to greater probabilities that the house-owner agent will buy or lease rooftop PV from a solar installer.

Sub-model 2 – Consumer Agent Financial Assessment - Reducing electric bills is one of the most important factor in a consumer's decision to use solar electricity at home [26]. It is assumed that a consumer agent calculates the Net Present Value (NPV) of a renewable energy model to evaluate its financial viability. The NPV evaluation for each agent is based on a 25-year investment decision, which is the average life of solar panels. Also, based on the solar PV radiation in the Iowa city, it is assumed that 100 kWh (AC) of energy is generated each month for each kW (DC) of solar panel installed through either rooftop PV or a community solar project. Further, it is assumed that if a consumer agent decides to buy or lease rooftop PV or subscribe to a community solar project, it will choose a PV module of size S_i (in kW (DC)) that will be capable of meeting 100% of its monthly energy needs (Q_i).

Each agent is randomly assigned one of five agent types (T_i) based on its optimism towards solar electricity [27]. These agent types are classified as Very Conservative (T_i= 0), Conservative (T_i= 1), Baseline (T_i= 2), Optimistic (T_i= 3), and Very Optimistic (T_i= 4), with higher values of T_i corresponding to greater optimism toward solar power's financial prospects. An agent's type determines its perceived annual growth rate of electricity cost from conventional sources in the future (PG_i), perceived annual discount rate (PD_i), and perceived annual rooftop PV maintenance costs (PM_i) associated with buying rooftop PV, as a percentage of up-front investment. The values of PG_i and PD_i increase, whereas the value of PM_i decreases, from Very Conservative to Very Optimistic agent types. The more optimistic an agent is towards solar electricity, the greater it will perceive the return on investment in solar due to a higher perceived future growth rate of electricity cost from conventional sources. The values for PG_i, PD_i, and PM_i considered in this model are described for each agent type (T_i) in Table 1.

Table 1: Financial parameters assigned to each agent type in the ABM.

Variable	T_i= 0	T_i= 1	T_i= 2	T_i= 3	T_i= 4
PG_i	0.00%	2.60%	2.60%	3.30%	5.00%
PD_i	1.00%	3.00%	5.00%	7.00%	9.00%
PM_i	0.50%	0.25%	0.25%	0.15%	0.00%

Another financial attribute that affects a house-owner agent's decision to adopt rooftop PV is the up-front cost of buying solar panels. High up-front costs deter consumers with lower income levels from installing solar [25,28]. To incorporate this factor, an affordability factor (AF_i) on a scale of 0-1 for each house-owner consumer agent has been defined based on its income-level (I_i). The affordability factor (AF_i) of the agent is evaluated by normalizing to 1 the product of its income level (I_i) and a random number generated between 0 and 1. A higher affordability factor (AF_i) signifies a higher probability that the house-owner consumer agent can afford to pay the high up-front cost of purchasing solar panels.

Each consumer agent evaluates the financial viability of a renewable energy model by calculating its NPV in each time-step. If a house-owner consumer agent has the ability to adopt rooftop PV (i.e., it can afford to purchase rooftop PV and does not face any structural constraints), then it calculates the NPVs for buying and leasing rooftop PV. The house-owner agent will also calculate the NPV of participating in a community solar project in each time-step if it has previously been made aware of its availability. If a house-owner agent cannot adopt rooftop PV due to structural constraints, then it only calculates the NPV of the community solar project in each time-step (if it is aware of it). Every other agent (i.e., agents that are not house-owners) will calculate the NPV for the community solar project, provided that the agent is aware of it.

NPV (buying rooftop PV) - The present value of the installation cost of rooftop PV ($P_{b(install)}$) for a house-owner agent at time t is given by (4), where W_t is the installation cost ($/kW (DC)) and ITC_t is the percentage of federal income tax credit at time t. The federal income tax credit has played a key role in reducing the up-front cost of buying rooftop PV. W_t is assumed to be $3360/kW at the beginning of the simulation run, and it decreases by 4% annually. This decrease in the installation cost is attributed to the declining prices of rooftop PV modules. It is assumed that the utility company allows its customers to offset 100% of the energy generated by their rooftop PV for net metering.

The present value of the future monthly bill savings ($P_{b(mbs)}$) from buying rooftop PV and of the future maintenance cost ($P_{b(maint)}$) associated with rooftop PV are given by (5) and (6), respectively. These costs are evaluated for a 25-year (300 months) time period for each consumer agent, by converting annual discount and electricity growth rates to equivalent monthly values. Finally, the NPV of net perceived savings from adopting rooftop PV ($NPV_{b(saving)}$) at time t is given by (7), which is the present value of the total savings in the future monthly energy bills ($P_{b(mbs)}$) minus the present value of the total up-front investment involved in buying rooftop PV ($P_{b(install)}$) and the present value of the total future maintenance cost ($P_{b(maint)}$).

$$P_{b(install)} = S_i W_t \,(1 - ITC_t) \tag{4}$$

$$P_{b(mbs)} = 100 S_i C_t \sum_{n=1}^{300} \left(\frac{1 + PG_i}{1 + PD_i}\right)^{n-1} \tag{5}$$

$$P_{b(maint)} = 25 PM_i P_{b(install)} \tag{6}$$

$$NPV_{b(saving)} = P_{b(mbs)} - P_{b(install)} - P_{b(maint)} \tag{7}$$

NPV (leasing rooftop PV) – The monthly leasing cost that a house-owner agent must pay if it leases solar panels at time t is decided by the solar installer. This monthly leasing cost depends on the size of the solar panel array (S_i) required by the house-owner agent, the income tax credit rate (ITC_t) at time t, the installation cost of solar panels (W_t), the perceived discount rate by the solar installer (PD_s), and the leasing period (assumed to be 25 years). The total investment made by the utility company to buy solar panels for an agent i is given by (8). This total installation cost (I_i) which the solar installer has invested will be recovered from the consumer agent via part of the fixed monthly leasing cost (M_i) over 25 years.

Apart from the initial investment (I_i), the solar installer will also evaluate the present value of the total maintenance cost ($P_{l(maint)}$) over next 25 years, given by (9). It is assumed that maintenance cost is 4 percent annually (or 0.33 percent monthly) of the total investment cost (I_i), including the solar installer’s expected return. This total maintenance cost will also be recovered by the solar installer as a part of the monthly leasing cost (M_i).

The fixed monthly leasing cost (M_i) is evaluated by the solar installer using (10), which equates the sum of total investment (I_i) made by the solar installer at time t and the present value of total maintenance cost to the present value of the total future leasing cost that the consumer will pay over next 25 years. The NPV of the total savings that the consumer agent will perceive in leasing ($NPV_{l(saving)}$) from the solar installer is the difference between the present value of the total savings it perceives in monthly energy bills over the next 25 years ($P_{b(mbs)}$) and the present value of all the monthly leasing cost that the consumer will pay in leasing rooftop in those years. $NPV_{l(saving)}$ is given by (11).

$$I_i = S_i W_t \,(1 - ITC_t) \tag{8}$$

$$P_{l(maint)} = 0.33 I_i \sum_{n=1}^{300} \left(\frac{1}{1 + PD_S}\right)^{n-1} \tag{9}$$

$$I_i + P_{l(maint)} = M_i \sum_{n=1}^{300} \left(\frac{1}{1 + PD_S}\right)^{n-1} \tag{10}$$

$$NPV_{l(saving)} = P_{b(mbs)} - M_i \sum_{n=1}^{300} \left(\frac{1}{1 + PD_i}\right)^{n-1} \tag{11}$$

NPV (community solar) - It is assumed that if a consumer agent enrolls in a community solar project, it pays a fixed premium (C_p) per unit of energy in addition to the conventional electricity rate at the time of adoption (C_t), and that the total unit price that the agent pays (C_p+ C_t) is kept constant for the life of the community solar project. The present value of the total monthly bills the consumer agent will pay if it chooses to participate in the community solar project (P_{CS}) at time t is given by (12). However, if the consumer agent continues to buy electricity from the utility company through conventional sources, then the present value of its future monthly bills (P_0) is given by (13). The NPV of total savings at time t for enrolling in a community solar project ($NPV_{CS(saving)}$) is the difference between the present value of maintaining the status quo and the present value of enrolling in the community solar, given by (14).

$$P_{CS} = Q_i(C_t + C_p)\sum_{n=1}^{300}\left(\frac{1}{1+PD_i}\right)^{n-1} \tag{12}$$

$$P_o = Q_i C_t \sum_{n=1}^{300}\left(\frac{1+PG_i}{1+PD_i}\right)^{n-1} \tag{13}$$

$$NPV_{CS(saving)} = P_0 - P_{CS} \tag{14}$$

Sub-model 3 – Consumer Agent Decision – For a consumer agent to adopt a renewable energy model, the agent's awareness index must be greater than 0.8, and the NPV of the renewable energy model must be greater than 0. Renters and apartment owner agents will adopt community solar if their NPV of community solar is greater than 0 and their awareness index (AW_i) is greater than 0.8. However, if the awareness index (AW_i) of a house-owner agent is greater than 0.8 and the NPV is greater than 0 for multiple renewable energy models, its final decision to adopt a particular renewable energy model will depend on its current level of perceived complexity (PC_i) in buying rooftop PV, its ownership index (O_i), and its current age risk level (AR_i).

For each house-owner agent in each time-step, a random number is generated between 0 and 1, and if the number is less than the agent's O_i value, then the agent will prefer the rooftop PV option (either buy or lease) over the community solar project. If this number is greater than O_i, the agent's preferences for rooftop PV and community solar will be equal. In any of the above cases, if a house-owner agent favors rooftop PV over community solar, its decision to adopt rooftop PV will depend on its current age risk level (AR_i), and its current perceived complexity (PC_i). A random number is again generated between 0 and 1. If the number is less than the current age risk level (AR_i) of the agent, it will adopt rooftop PV (either buy or lease), otherwise it will not adopt rooftop PV. The agent's final decision between buying or leasing rooftop PV depends on the agent's current perceived complexity (PC_i) in buying rooftop PV. If a random number generated between 0 and 1 is greater than the agent current perceived complexity (PC_i), it will favor buying rooftop PV; otherwise, it will lease rooftop PV.

3 EXPERIMENTATION AND RESULTS

The ABM was used to test the effects of varying several financial, attitudinal, and demographic factors on the consumer agents' adoption of renewable energy models and the utility company's revenue. For each experiment, 50 replications of 270 monthly time-steps each were run. The initial 30 time-steps were used as a warm-up period to allow the system to stabilize, and the output metric values for the remaining 240 time-steps (i.e., 20 years), averaged over 50 replications, were analyzed.

Table 2 summarizes the five experimental scenarios that were tested. Two factors were varied: visual interactions between the consumer agents (enabled or not enabled) and the status of a community solar project (not available or available at different premium prices (C_p)). In all of these experimental scenarios, it was assumed that if an agent does not adopt rooftop PV or participate in a community solar project, it will buy electricity through conventional sources from the utility company. The income tax credit was initialized to be 30% and was reduced to 26% after 90 time-steps, to 22% after 102 time-steps, and to 10% after 114 time-steps. This reduction in income tax credit reflects the current federal rebate policies for rooftop PV consumers. The discount rate of the solar installer (PD_S) is assumed to be 10% annually for all scenarios. The outputs of interest are the total number of rooftop PV adopters, the utility company's revenue, the total green power added in the system, and the degree of participation in the community solar project by renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints.

Figures 3 and 4 show snapshots of the NetLogo interface for a typical replication of Scenario 2, in which only rooftop PV is available for the consumers to adopt, and for Scenario 4, in which both rooftop PV and community solar options are available, respectively. The consumer agents highlighted in green are the rooftop PV adopters that leased their systems, those in red are rooftop PV buyers, and agents in blue are community solar participants at the end of 270 time-steps. These output metrics from the interactive interface were used in the verification of the model. For example, the snapshot from Scenario 2 (Figure 3) shows that none of the agents in community 5 adopted rooftop PV for this particular replication. However, the Scenario 4 snapshot (Figure 4) shows that there were four rooftop PV adopters in community 5. The visual interface allowed for the verification of this result: the awareness index values (AW_i) of these four agents were low in Scenario 2, due to insufficient social interactions.

Figure 5 shows the number of rooftop PV adopters (buy or lease) in each time-step over 20 years for each of the five experimental scenarios. There is a noticeable difference in the number of rooftop PV adopters with and without visual interactions enabled (Scenario 1 vs 2). Interestingly, the final number of rooftop PV adopters in the experimental scenarios with both rooftop PV and community solar options available (Scenarios 3, 4, and 5) was greater than the final number of rooftop PV adopters in Scenario 2. This is because more consumer agents that are capable of adopting rooftop PV (i.e., house-owner agents without any structural constraints) exceeded the threshold awareness index (AW_i), due to the greater number of total solar adopters overall (including both rooftop PV and community solar).

Table 2 – Experimental scenarios.

	Visual Interactions	C_p (¢/ kWh)
Scenario 1	×	NA
Scenario 2	✓	NA
Scenario 3	✓	8
Scenario 4	✓	10
Scenario 5	✓	12

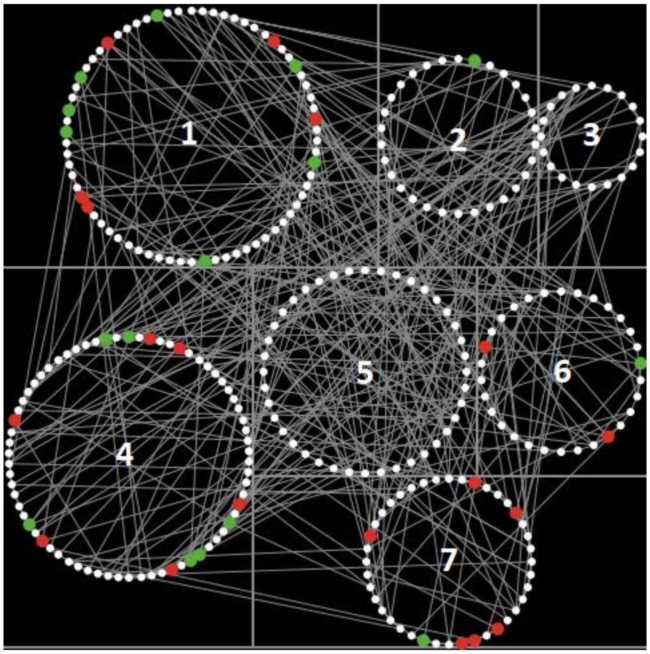

Figure 3: Snapshot of the NetLogo model in Scenario 2 - when consumers can adopt only rooftop PV (either buy or lease).

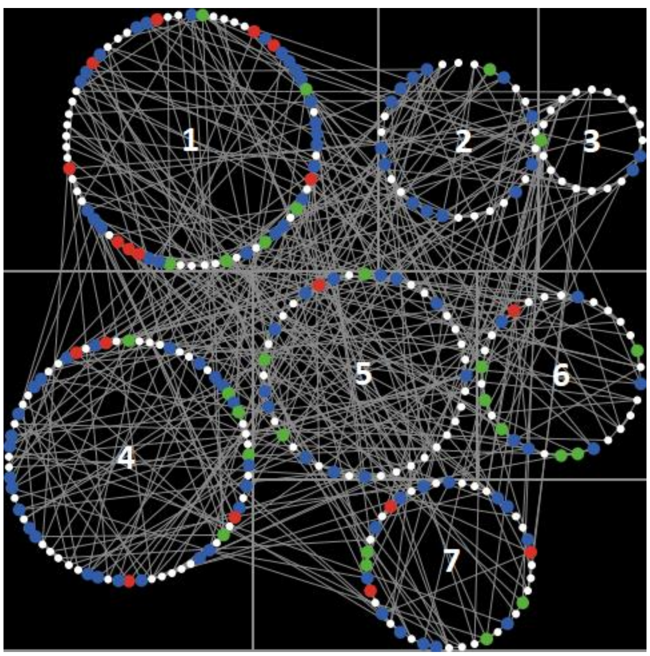

Figure 4: Snapshot of the NetLogo model in Scenario 4 – when consumers can adopt rooftop PV (buy or lease) as well as participate in a community solar project.

Figure 6 shows a comparison of the utility company's total revenue (in $ million) at the end of the final time-step for each experimental scenario, and Figure 7 shows the total capacity of community solar (in kW) that the utility company needed to add for scenario 3-5. These types of outputs could potentially help a utility company to decide on the capacity of community solar it will need to satisfy customer demand for renewable energy, while also meeting their revenue targets.

The utility's revenue in Scenario 1 is greater than its revenue in Scenario 2 because there are fewer rooftop PV adopters in Scenario 1. However, in the scenarios with both rooftop PV and community solar options available (Scenarios 3, 4, and 5), the utility's revenue is the greatest for Scenario 3, despite having the greatest number of rooftop PV adopters. This was a consequence of greater consumer participation in the community solar program in Scenario 3, which increased overall greater revenues due to community solar price premiums (C_p).

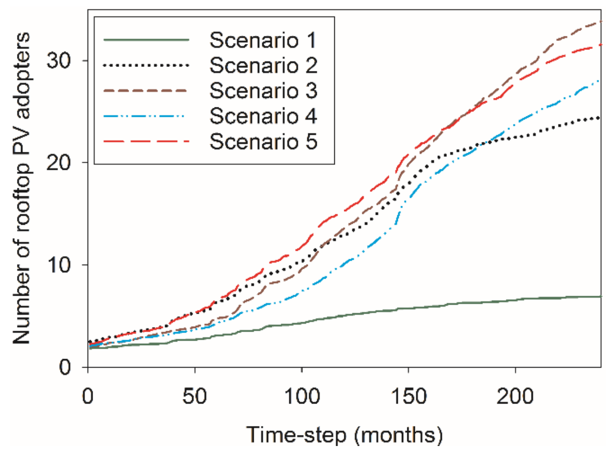

Figure 5: Number of consumer agents adopting rooftop PV in Scenario 1-5.

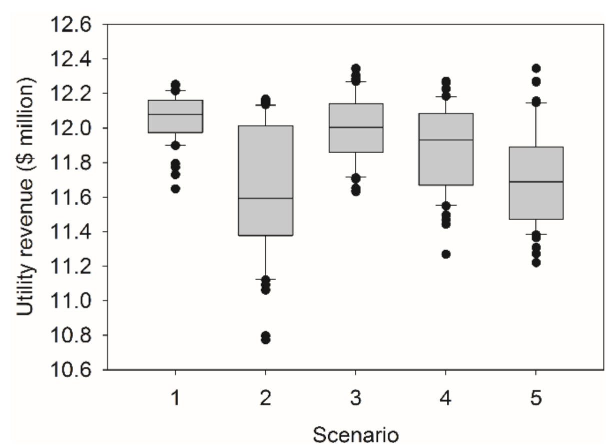

Figure 6: The utility's revenue in the final time-step for Scenarios 1-5.

Scenario 3 also yielded the maximum participation of apartment owners/renters unable adopt rooftop PV (Figure 8). This result would be of interest to the utility, in support of its efforts to address policymakers' equity concerns. The total green power added (in kW) by the rooftop PV adopters and the utility company through the community solar project at the end of 20 years is shown in Figure 9 for each experimental scenario.

Scenario 3, with the greatest number of rooftop PV and community solar adopters, added the most units of green power.

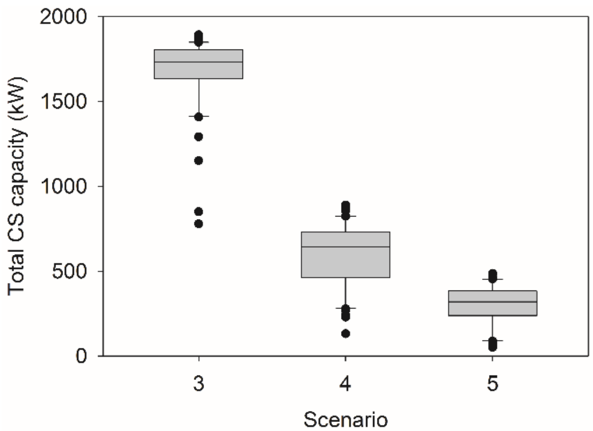

Figure 7: Total required community solar capacity for Scenarios 3-5.

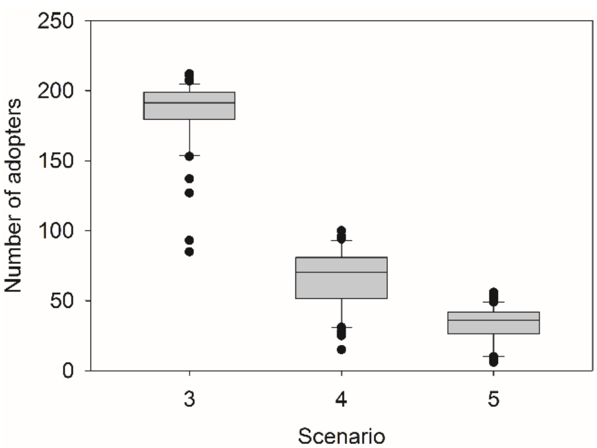

Figure 8: Participation of renters/apartment owners in the community solar project in Scenarios 3-5.

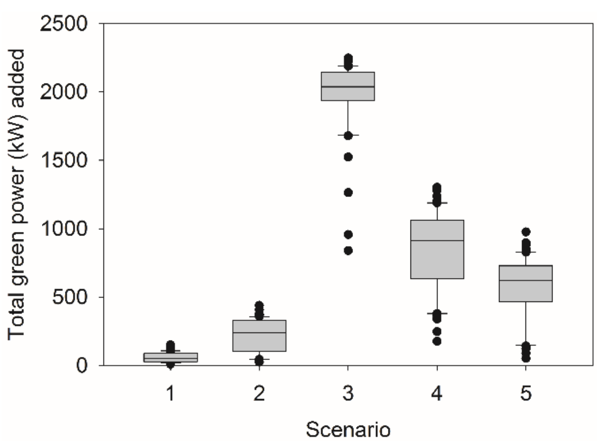

Figure 9: Total green power added to the system through rooftop PV or community solar project in Scenarios 1-5.

These results suggest that, for these specific model parameter values and experimental conditions, Scenario 3 (i.e., providing the community solar option for consumers with C_p equal to 8 ¢/kWh) would not only help to alleviate utility revenue losses due to rooftop PV adoption, but it would also address equity concerns and satisfy the utility's renewable energy portfolio requirement.

4 CONCLUSIONS

This paper describes an ABM that was developed to demonstrate the importance of incorporating consumer-adoption modeling into a utility company's expansion planning approach. Consumer-adoption modeling can help utility companies determine the right mix of alternative renewable energy models for its customers in the long term. This modeling framework also has the potential to help utility companies identify tradeoffs and meet specific goals, such as alleviating revenue losses due to rooftop PV adoption, increasing participation in distributed generation by consumers who cannot adopt rooftop PV, or both. The conceptual model described in this paper will serve as a starting point for future research. In particular, there are several behavioral theories (e.g., theory of planned behavior, value-based norm theory, diffusion of innovation) and social network structures (e.g., community structure, small-world) that map to factors that are known to affect consumers' solar adoption decisions. These will be used to develop agent architectures for different consumer and utility personas, which will provide a foundation for an ABM that can be validated using empirical data from a region that has introduced an alternative renewable energy model.

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Appendix A

Table A1: Consumer agent state variables.

State variables	Description	Possible values	Static/ Dynamic	Source
i	Unique number assigned to each agent	0 - 299	Static	N/A
C_i	Community identification number	0 - 6	Static	N/A
A_i	Age level	0 - 8	Dynamic	Derived from Data USA (https://datausa.io/)
I_i	Income level	0 - 15	Static	Derived from Data USA (https://datausa.io/)
E_i	Education level	0 - 5	Static	Derived from Data USA (https://datausa.io/)
R_i	Race level	0 - 7	Static	Derived from Data USA (https://datausa.io/)
Q_i	Monthly residential electricity consumption	N (873,50)	Static	Derived from Electricity Local (https://www.electricitylocal.com/)
AW_i	Awareness index	0 - 1	Dynamic	Assumption
PC_i	Perceived complexity index	0 - 1	Dynamic	Assumption
O_i	Energy infrastructure ownership index	0 - 1	Static	Assumption
AR_i	Age risk index	0 - 1	Dynamic	Assumption
S_i	Size of the solar panel array agent for rooftop PV or community solar project	Q_i /100	Static	Assumption
T_i	Agent type	0 - 4	Static	Literature [27]
PG_i	Perceived annual growth rate of electricity	0 - 5%	Static	Assumption
PD_i	Perceived annual discount rate	1 - 9%	Static	Assumption
PM_i	Perceived annual maintenance cost involved in rooftop PV as a percentage of total installation cost	0 - 0.5%	Static	Assumption
AF_i	Affordability factor associated with buying rooftop PV system	0 - 1	Static	Assumption