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# INTEGRATING CONSUMER PREFERENCES IN RENEWABLE ENERGY EXPANSION PLANNING USING AGENT-BASED MODELING

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## ABSTRACT

As share of renewable sources in the energy sector is increasing, the energy production and distribution network's centralized structure is changing to numerous small-scale distributed networks. Energy consumers in the residential sector are increasingly becoming energy producers by adopting rooftop photo voltaic (PV) systems. However, increasing rooftop PV adoption has contributed to diminishing revenues for utility companies. This paper describes an agent-based model that has been developed to help utility companies better understand the impacts of consumers' preferences and behaviors on adding renewable sources to their energy mix. Experimental results demonstrate that including both consumers and utility companies as stakeholders can help the utilities alleviate revenue losses due to increasing rooftop PV adoption while meeting their renewable energy expansion targets.

## 1 INTRODUCTION

Limited availability and serious environmental consequences of fossil fuels is driving a shift towards renewable energy to meet the ever-growing energy demand. The increasing share of renewable energy sources is expected to change the current structure of the energy sector globally (Klose et al. 2010, Richter 2012). The traditional centralized production and distribution network (i.e., utility-side models) is increasingly confronted with distributed small-scale (i.e., customer-side) renewable energy models, in which energy consumers are the energy producers themselves - also known as "prosumers" (Richter 2012).

Customer-side business models, often referred to as distributed generation models, are receiving increased attention recently from the energy community. They have potential to save energy by reducing transmission and distribution losses, increase the reliability of electricity supply, and decrease the cost of upgrading the existing electrical grid (Akorede, Hizam, and Pouresmaeil 2010). Distributed generation models can be installed and operated rapidly, as they are assembled as independent modules and are not affected by other modules' operation and failure. Distributed generation models can be classified into two types: local level and end-point level (Akorede, Hizam, and Pouresmaeil 2010). Local level power generation plants often include renewable energy technologies that are site specific, such as wind turbines or mid-sized solar systems, and caters the energy needs of few hundreds to couple of thousands of people. At the end-point level, an individual energy consumer can implement many of these same technologies with similar effects. For example, rooftop solar panels installed on consumers' houses is an example of end-point level distributed generation.

Solar is currently the most feasible and popular technology through which the residential customers can generate their own energy. The consumer-sited solar PV systems (typically known as rooftop PV) on the rooftops of owner-occupied residences have grown significantly in the United States over the past several years (Lee, and Moses 2015). The top reasons that best describe why residential consumers are interested in solar PV installation at their homes were to have lower monthly energy costs, help save the environment, want to gain more control and independence from the utility companies and a good home investment option (Shelton Grp, and SEPA 2016). Lower energy costs are attributed to reduced cost to install residential solar over the last few years, federal rebate programs like income tax credit (ITC), and state net metering policies. Net metering allows consumers to offset their energy bills with the excess energy generated by their PV systems. This net metered solar power from rooftop PV's also helps the utility companies meet their required renewable portfolio standard (RPS), under which the utility companies are mandated to provide a fraction of their electricity supply from renewable energy technologies.

Although rooftop solar was growing steadily till 2015 in the U.S., there has been a slowdown in the installation rate in 2016 (GTM Research 2016), due to high upfront cost and lack of easily accessibility of credible information (Noll, Dawes, and Rai 2014). Also, individual consumers do not choose to install a residential system on their home for other reasons like complexity of the government rebate policies, uncertainty in government incentives or homeowners' association regulations (Konkle 2013, Coughlin et al. 2011). Another important reason that contributes to the slow growth is inability of most residential customers to even install rooftop solar. In the U.S., only 22 – 27% of the rooftop area is suitable for installation of photovoltaic panels after adjusting for structural, shading, or ownership issues (Coughlin et al. 2011). Apart from that rooftop solar do not accommodate renters and condominium owners who do not have ownership of the space needed to install solar collectors.

Installation of the rooftop solar benefits the utility companies in meeting their renewable portfolio standards for the energy which is net-metered by their customers, but overall they see installing rooftop solar by their customers as a loss in their revenue. This is because the maintenance and operational costs required for the grid infrastructure are fixed costs and are rolled into electricity rates by the utility companies. If consumers and businesses generate their own electricity and no longer buy as much from utilities, then consumers who don't have the resources to do so will increasingly bear these costs of maintaining the energy infrastructure (Funkhouser et al. 2015). Also, if consumers can obtain all their energy needs from solar, the utility must still be prepared to provide them with energy in case their systems fail or their energy needs increase (Chavez, and Coughlin 2013). Therefore, solar consumers still benefit from the option to use the grid, but may not be paying their "fair" share depending on their energy consumption. In response to these emerging issues, residential solar have seen resistance in recent years from many U.S. utility companies. For example, recently Nevada Public Utilities Commission has reduced the credit by two cents per kilowatt-hour that the homeowners get for the solar-generated electricity sent back to the grid (Garskof 2016).

The utility companies in the U.S. are considering alternative options to satisfy its customer demands for renewable energy. A report by National Renewable Energy Laboratory describes seven different green power procurement mechanisms that allow customers to buy renewable energy in the U.S. (O'Shaughnessy, Liu, and Heeter 2016). These seven mechanisms are utility green pricing programs, utility green tariffs, voluntary unbundled renewable energy certificates (RECs), competitive supplier green power, community choice aggregations (CCAs), voluntary power purchase agreements (PPAs), and community solar. This paper will focus on community solar and green pricing programs.

Community solar, also called "shared solar," is defined by the U.S. Department of Energy's National Renewable Energy Laboratory (NREL) as "a solar-electric system that provides power and/or financial benefit to multiple community members" (Coughlin et al. 2011). Under a community solar program, the actual generation of electricity does not occur at the customer's home or business site. Instead, a customer subscribes to a portion of a community solar project, located elsewhere in the community, and each subscriber receives a benefit that is proportional to their investment (Konkle 2013). In 2010, only five community solar projects existed in the U.S. (Funkhouser et al. 2015). Today there are 101 community solar projects across 26 states, accounting for a combined capacity of about 108 megawatts (Community Solar Hub 2017). Unlike individual rooftop solar, community solar expands the availability of distributed solar to a broader customer base, like lower-income energy consumers, renters, or household owners who do not have sufficient solar resources (McLaren 2014).

Utility companies can also offer their customers green pricing programs. Green pricing programs allow customers to pay a small premium in exchange for electricity generated from renewable ("green") energy sources. The premium covers the increased costs incurred by the utility company when adding renewable energy to its power generation mix. Residential customer participation in green pricing programs increased by about 6.3% from 2014 to 2015, contributing to continued overall growth in green pricing customer participation (O'Shaughnessy, Liu, and Heeter 2016).

Utility companies must make expansion planning decisions that address how they will meet future energy demand. However, the outcomes of a particular expansion policy depend on the consumers' behavioral attributes and social interactions with their peers. For example, peer interactions are important to consider in modeling rooftop PV adoption (Bollinger, and Gillingham 2012). Agent-based modeling (ABM) is a powerful tool to study the outcomes of policies resulting from complex human behaviors and their social interactions (Mittal, and Krejci 2015, Mittal 2016). ABM has previously been used to capture the complexities of electricity markets by modeling heterogeneous actors (e.g., consumers, utility companies, ISOs, and RTOs) and serving as a tool to support utility companies' expansion planning decisions (Botterud et al. 2007).

In particular, to energy consumer behavior modeling, an ABM has been used to understand the discrepancy between consumers' opinions measured by market surveys and their actual participation in the dynamic electricity tariffs programs (Kowalska-Pyzalska et al. 2014). ABM has also been used to represent the effects of energy consumers' heterogeneous behaviors, boundedly rational decision processes, and social interactions on the adoption of various energy technologies over space and time (Rai, and Henry 2016). For example, an ABM has been developed to represent residential rooftop PV adoption in Austin, Texas, and the model has been used to test the effects of various rebate programs on the energy consumers' adoption rate (Rai, and Robinson 2015). Another empirically based ABM has been developed to investigate the adoption of green electricity tariffs by households in Germany (Krebs 2017). In this paper, we have developed an ABM to demonstrate the value of incorporating consumer behaviors into utility companies' renewable energy capacity decisions, with an aim to alleviate the losses incurred from increasing rooftop PV adoption among residential energy consumers.

## 2 AGENT-BASED MODEL

The ABM was developed using NetLogo 6.1.0 and will be described using the ODD (Overview, Design concepts and Details) protocol (Grimm et al. 2010).

First, an overview of the ABM is provided:

*Purpose* – The purpose of this model is to assess the impact of increase in consumer rooftop PV adoption on a utility company's revenue. The model is also used to evaluate different strategies that the utility company could adopt in an effort to mitigate revenue losses.

*Agents* – The ABM contains two types of agents: a utility company agent and residential consumer agents. The utility company agent makes decisions about renewable energy capacity additions in response to the consumer agents' behaviors. The 302 consumer agents comprise a single community in the service territory of the utility company. These consumer agents have the potential to become energy generators through solar PV adoption or participation in a community solar project.

*Overview* – In each time-step (where one time-step represents one quarter of a year), the utility company agent assesses its revenue and decides whether it should introduce either a community solar program or a green pricing program to alleviate losses due to rooftop PV adoption by the consumer agents. Thus, the utility company agent's strategy is driven by the consumer agents' decisions. Each consumer agent assesses in each time-step whether it wants to participate in one of three different renewable energy models to meet its energy needs - install rooftop PV, participate in a community solar project, or enroll in a green pricing program. The availability of the community solar or green pricing program options depends on the utility company's chosen strategy, which is influenced by its lost revenue due to rooftop PV adoption.

It is assumed that a consumer agent's decision to adopt rooftop PV or community solar is driven by financial and attitudinal factors, whereas participation in a green pricing program is solely driven by attitudinal factors. For rooftop PV and community solar, the financial factors are based on the investment payback period and the breakeven period, respectively. The payback period in this model is defined as the amount of time required for the consumer's initial investment in installing rooftop PV to be recovered from future energy bill savings. The breakeven period is defined as the amount of time that a consumer must wait after enrolling in a community solar project before making a profit.

A national survey of energy consumers provides insight on various attitudinal factors that influence consumer decisions to adopt solar PV (Shelton Grp, and SEPA 2016). These factors include a desire to become independent from the utility company, concern for the environment and the future generations, and the influence of recommendations from the people in their social and spatial networks. In the model, the attitudinal factors are broadly characterized as energy ownership ($EO_i$) and overall concern ($OC_i$). Both factors are defined on a scale of 0-1 for each consumer agent, where higher values represent a greater probability that the consumer agent will adopt a renewable energy model.

Next, the model design concepts are described:

*Basic principles* – The financial and attitudinal factors that drive consumer agent decisions are based on data collected from surveys on consumer energy choices, which indicate that these factors are the two broad components in consumers' decisions to adopt solar energy (Shelton Grp, and SEPA 2016, Rai, and Robinson 2015).

*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. Consumer behavior then motivates the utility company agent to take corrective actions, which in turn affects the consumer agents' decisions in future time-steps. This feedback loop between the consumer agents and the utility agent's behavior yields an emergent system-wide adoption of a renewable energy model.

*Objectives* – Each consumer agent's objective is to meet its energy needs by buying directly from the utility company through conventional sources, generating their own energy, supporting the overall cause associated with the renewable energy, or both, by adopting a renewable energy model. These objectives are constrained by the agent's financial position (i.e., its ability to invest). The objective of the utility company agent is to maximize its revenue.

*Interactions* – The 302 consumer agents are grouped into 30 agentsets, which represent their social networks. Of the 30 agentsets, 29 contain 10 consumer agents each, and the remaining group contains 12 consumer agents. It is assumed that in each time-step a consumer agent will interact with each agent in its social network with a probability of 0.3. These interactions impact the attitudinal component of the consumer agent. If a rooftop PV adopter interacts with a non-adopter, both the energy ownership ($EO_i$) and the overall concern ($OC_i$) variables of the non-adopter will increase by 0.05. When a community solar adopter interacts with a non-adopter, the $EO_i$ of the non-adopter increases by 0.025 and the $OC_i$ increases by 0.05. If a green pricing program adopter interacts with a non-adopter, the $OC_i$ variable of the non-adopter increases by 0.05. If two non-adopters interact, it is assumed that there is no effect.

*Observations* – The number of consumer agent adopters of community solar, green pricing program, and rooftop PV are captured in each simulation run. The utility agent's net revenue, its losses due to rooftop PV uptake, the time-step in which the utility company agent introduces community solar or a green pricing program, and the total green power addition by the consumers and the utility company in each time-step are also recorded.

Finally, model details are provided:

*Initialization* – Each consumer agent is initialized to be a non-adopter at the beginning of the simulation run. The utility company agent is initialized to offer only conventional energy to the consumer agents, which it buys from the wholesale electricity market.

*Input data* - Data used to inform the decisions and behavior of the consumer and utility company agents was gathered from publically available sources. All 302 consumer agents were assigned an annual income level based on data from a small city in central Iowa. The resulting income distribution of the consumer agents is shown in Figure 1. Approximately 48% of the residents of this city are renters and 52% are homeowners; this ratio has been applied to the consumer agents. It is assumed that only agents that are homeowners can install rooftop PV, while both homeowners and renters can adopt community solar or participate in the green pricing program.

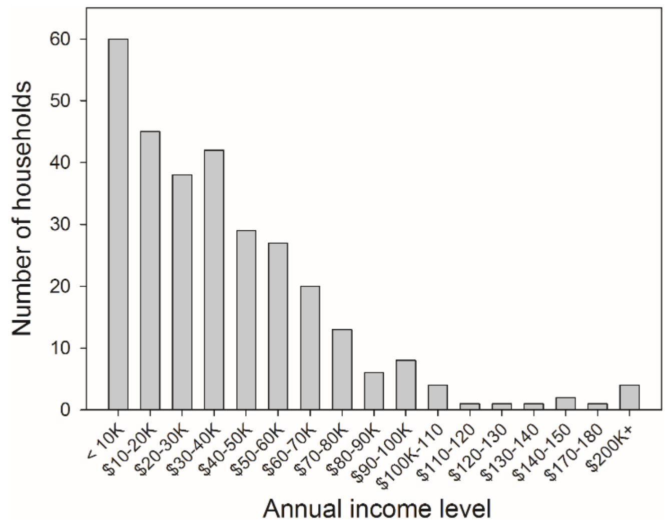


Figure 1: Income distribution of the 302 household consumer agents.

The mean monthly residential electricity consumption in Iowa (873 kWh) 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 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 $q$ percent every quarter. The initial values of the consumer agents' attitude variables ($EO_i$ and $OC_i$) were drawn from a normal distribution with a mean of 0.50 and standard deviation of 0.15 (only non-negative samples were used).

*Sub-models* – The ABM contains four sub-models: Consumer Agent Financial Assessment, Consumer Agent Attitude Assessment, Consumer Agent Decision, and Utility Agent Decision. All four sub-models are executed in each time-step.

*Sub-model 1 – Consumer Agent Financial Assessment*: Each homeowner consumer agent calculate its payback period for installing solar PV, which depends on the size of the system, as well as two time-varying parameters: energy rates and installation cost. Based on the solar PV radiation in this Iowa city, it is assumed that approximately 100 kWh of energy is generated each month for each kW of solar panel installed. Further, it is assumed that if a consumer agent decides to adopt rooftop PV, it will choose a PV module of size $S_i$ (in W) that will be capable of meeting 100% of its monthly energy needs. The total installation cost of rooftop PV ($I_i$) for a consumer agent at a time $t$ is given by (1), where $W_t$ is the installation cost ($/W), and *ITC* is the percentage of federal income tax credit at time $t$. $W_t$ is assumed to be $3.36/W at the beginning of the simulation run, and it decreases by 0.5% in each time-step. This decrease in the installation cost is attributed to the declining prices of rooftop installations. *ITC* is assumed to be constant at 30% for the entire simulation run. It is assumed that the utility company allows its customers to offset 100% of the energy generated by their rooftop PV for net metering.

$$I_i = S_i W_t \left( 1 - ITC \right) \tag{1}$$

The rooftop PV payback period for a consumer agent $i$ ($PBR_i$, in quarters) is given by (2), where $q$ is the percent increase in the price of electricity each quarter, $E_i$ is the quarterly electricity consumption of the consumer agent (assumed to be constant throughout the simulation run), and $C_i$ is the value of electricity at the time when the consumer agent decides to install rooftop PV. This payback period represents the total time required for the consumer agent to recover its upfront investment through monthly energy savings.

$$PBR_i = \frac{\ln\left(1 + \frac{qI_i}{E_i C_i}\right)}{\ln\left(1 + q\right)} \tag{2}$$

A consumer agent's breakeven period is a key financial metric in its decision to adopt community solar. The breakeven period ($n_i$) is the duration (in quarters) from its adoption date to the point in time at which it is neither in a state of profitability nor loss. This occurs when the total cost of the community solar program over $n_i$ quarters ($P_{CS}$) equals the total cost that the agent would have incurred over those $n_i$ quarters if it had not adopted community solar ($P_r$). To calculate $P_{CS}$ and $P_r$ for a consumer agent, it was assumed that the agent pays a fixed premium ($C_p$) per unit of energy in addition to the electricity rate at the time of adoption ($C_j$), and that the total unit price that the agent pays ($C_p$+ $C_j$) is kept constant for the life of the community solar project. In this way, the consumer agent pays more in the initial years of the project, but as electricity rates increase over time (at a rate of $q$ per quarter), it eventually ends up saving money. Based on this assumption, the agent's total cost of adopting community solar over the breakeven period ($P_{CS}$) and the total cost that it would have incurred without adoption ($P_r$) are calculated using (3) and (4), respectively. The value of $n_i$ for which these two costs are equal is the agent's breakeven period.

$$P_{CS} = n_i E_i \left( C_j + C_p \right) \tag{3}$$

$$P_r = \frac{C_j E_i ((1+q)^{n_i} - 1)}{q} \tag{4}$$

*Sub-model 2 - Consumer Agent Attitude Assessment:* The consumer agent's attitude component also affects its decision to adopt a renewable energy model. The energy ownership and overall concern parameters ($EO_i$ and $OC_i$) can take on values of low, medium, or high, where low is between 0 and 0.33, medium is between 0.33 and 0.67, and high is between 0.67 and 1. If $EO_i$ is low and $OC_i$ is high, the consumer agent will prefer a community solar or a green pricing program over rooftop PV. If $EO_i$ is medium and $OC_i$ is high, the consumer agent will prefer to adopt a community solar or a green pricing program (if available) with equal probabilities over the rooftop PV. If $EO_i$ is high and $OC_i$ is high, and the community solar option is available, the consumer agent will prefer either of the rooftop PV or community solar with equal probabilities. In any of the above three cases (i.e. when $OC_i$ is high) and none of the community solar or green pricing program is available, the agent attitudinal component will favor rooftop PV adoption. The three different levels, along with the preference for a renewable energy model, are described in Table 1 (where "?" – indicates that the consumer agent will prefer community solar or green pricing program over rooftop PV).

Table 1: Attitude variables for the consumer agents.

| **Energy ownership ($EO_i$)** | **Overall concern ($OC_i$)** | **Rooftop PV** | **Community solar** | **Green pricing program** |
|---|---|---|---|---|
| low | low | × | × | × |
| low | medium | × | × | × |
| low | high | ? | ✓ | ✓ |
| medium | low | × | × | × |
| medium | medium | × | × | × |
| medium | high | ✓ | ✓ | ✓ |
| high | low | × | × | × |
| high | medium | × | × | × |
| high | high | ✓ | ✓ | × |

*Sub-model 3 – Consumer Agent Decision:* For a consumer agent to adopt rooftop PV or the community solar project, the attitude component should be favorable, and the financial components must be greater than certain thresholds. Each consumer agent has been assigned a payback period threshold ($PBR_{Ti}$) for rooftop PV adoption and a breakeven period threshold for ($n_{Ti}$) community solar adoption. For a consumer agent to adopt rooftop PV, the payback period should be less than $PBR_{Ti}$. Similarly, the breakeven period should be less than $n_{Ti}$ for the agent to adopt community solar. $PBR_{Ti}$ and $n_{Ti}$ have been assigned to the consumer agents based on their annual incomes, where greater income values correspond to greater threshold values. The value is assumed to be equal to 2 for the agents with annual incomes less than 10K, and it increases by 1 as the income level increases between the 17 different levels shown in Figure 1. It is assumed that only the attitude component influences the consumer agent's decision to adopt the green pricing program. If a consumer agent adopts a renewable energy model, it is assumed that it cannot reverse its decision.

*Sub-model 4 - Utility Agent Decision*: The utility company in each time step calculates its net revenue (Equations 5-8) in the quarter based on the consumer decision to adopt to a renewable energy model. $R_m$, given by (5), is the maximum revenue the utility company can acquire from $n$ consumers if none of them adopts any of the renewable energy models. This is evaluated by calculating the total energy costs of all consumer agents ($n$), based on their quarterly electricity consumption and the rate of electricity in that quarter ($C_t$). $R_p$, given by (6), is the total revenue due to premium prices paid by the consumers that enroll in a community solar ($C_p$) or green pricing program ($C_{GP}$). $R_p$ is the sum of energy expenditures of all consumers that have adopted community solar ($n_{CS}$) plus the sum of the premium price paid by consumers that enroll in the green pricing program ($n_{GP}$). $RL_u$, given by (7), is the total loss in revenue of the utility company and is calculated as the sum of the increased price the utility company has to incur for generating power through community solar or buying renewable energy for a green pricing program ($e_{cs}$ and $e_{GP}$ is the percentage increase in cost to generate electricity from community solar or buy it from renewable sources, assumed to be 10 and 5 percent respectively in all experiments; $E_{CS}$ and $E_{GP}$ are planned capacity of community solar and green pricing program by the utility company) and the loss in revenue that the utility company incurs if the rooftop PV adopters ($n_r$) and the community solar adopters ($n_{CS}$) would have bought electricity directly from the utility through conventional sources. The net revenue ($R_n$) is given by (8). If the loss in revenue of the utility company exceeds a certain percentage, the utility company will introduce either a green pricing program or a community solar project in the next time-step to alleviate the revenue losses.

$$R_m = \sum_{n} E_i C_t \tag{5}$$

$$R_p = \sum_{n_{CS}} E_i(C_j + C_p) + \sum_{n_{GP}} E_i C_{GP} \tag{6}$$

$$RL_u = C_t(e_{CS}E_{CS} + e_{GP}E_{GP}) + \sum_{n_r, n_{cs}} E_i C_t \tag{7}$$

$$R_n = R_m + R_p - RL_u \tag{8}$$

## 3 EXPERIMENTATION AND RESULTS

The ABM was used to test the effects of financial and attitudinal factors on consumers' rooftop PV adoption rates, as well as the utility company's revenue over time in the presence of other alternative renewable energy models. For each experiment, 50 replications of 130 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 in the final time-step, averaged over 50 replications, were analyzed.

Table 2 summarizes seven experimental scenarios that test the impacts of the availability of different combinations of rooftop PV (R), community solar (CS), and a green pricing program (GP). The check mark (✓) against a renewable energy model in Table 2 indicates the available options for the consumers to adopt in an experimental scenario. The values in parenthesis following "CS" and "GP" indicate the project capacity (in MW, i.e. $E_{CS}$ for community solar and $E_{GP}$ for green pricing program) and the associated price premium (in ¢, i.e. $C_p$ for community solar and $C_{GP}$ for green pricing program). In all the experimental scenarios electricity rate is assumed to be growing ($q$) at 0.75 percent every quarter. In Scenarios 2-7, it is assumed that the utility company agent will introduce either community solar or a green pricing program when its revenue falls below 2.5% of its maximum possible revenue (i.e., its revenue when there are no rooftop PV adopters).

Table 2: Experimental scenarios.

| Experimental scenario | | R | CS | GP |
|---|---|---|---|---|
| Scenario 1 - | R | ✓ | × | × |
| Scenario 2 - | R, CS (0.44, 1.5) | ✓ | ✓ | × |
| Scenario 3 - | R, CS (0.87, 1.5) | ✓ | ✓ | × |
| Scenario 4 - | R, CS (0.44, 2) | ✓ | ✓ | × |
| Scenario 5 - | R, CS (0.87, 2) | ✓ | ✓ | × |
| Scenario 6 - | R, GP (0.44, 0.5) | ✓ | × | ✓ |
| Scenario 7 - | R, GP (0.87, 0.5) | ✓ | × | ✓ |

In Scenario 1, the utility company agent is inactive. The total number of rooftop PV adopters and the utility company's revenue are captured in each time-step for two different cases, in which consumer agent interactions are 1) allowed and 2) not allowed. Figure 2a shows the number of rooftop PV adopters in each time-step for both cases. When consumer interactions were not allowed, there were 11 rooftop PV adopters in the final time-step for all 50 replications. This is because without interactions, there are no stochastic elements in the model. By contrast, when the agents were allowed to interact, the average number of rooftop PV adopters in the final time-step was 57 (SD=0.7). Figure 2b compares the utility company's revenues over time for three different cases: no rooftop PV adopters (i.e., the upper bound for revenue), rooftop PV adoption allowed but no consumer agent interactions, and rooftop PV adoption and consumer agent interactions allowed. The increased adoption of rooftop PV in the presence of interactions yields a substantial drop (18.9%) in the utility company's revenue at the end of final time-step.

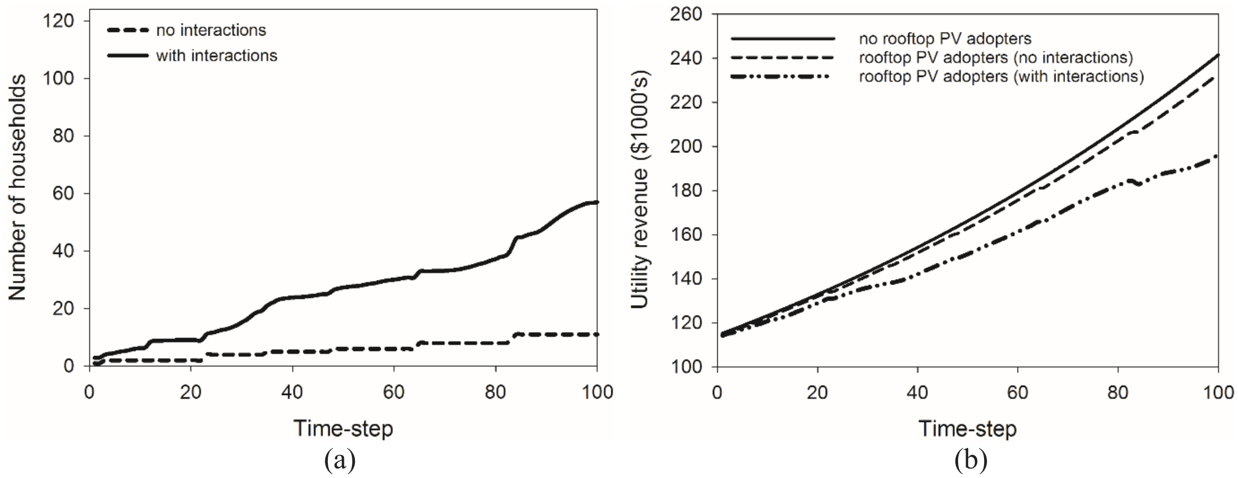


Figure 2: a) Number of consumers adopting rooftop PV in Scenario 1 with and without agent interactions, b) Utility company revenue with no rooftop PV adopters and with and without agent interactions.

Scenarios 2-7 tested the impact of various versions of community solar and green pricing programs on rooftop PV adoption rates and the utility company's revenues. In these six scenarios, consumer agent interactions were allowed. Figure 3 compares the number of consumer agents who are homeowners (i.e., not renters) and adopt either rooftop PV, community solar, or a green pricing program in the final time-step for Scenarios 1-7. The average number of homeowners adopting rooftop PV decreased when the utility company provided a community solar option (Scenarios 2-5) as compared to the number of adoptions in Scenario 1. This is because many potential homeowners who can adopt rooftop PV prefer the community solar option. When $C_p$ is 1.5¢/kWh, and the community solar capacity is increased from 0.44 MW to 0.87 MW (Scenarios 2 and 3), average number of homeowners adopting community solar increased from 19.9 (SD = 1.3) to 42.6 (SD = 1.5), as they chose community solar over rooftop PV. However, when $C_p$ was 2¢/kWh and the community solar capacity was increased (Scenarios 4 and 5), fewer homeowners exhibited a preference for community solar over rooftop PV, because of the increase in the breakeven period threshold for community solar.

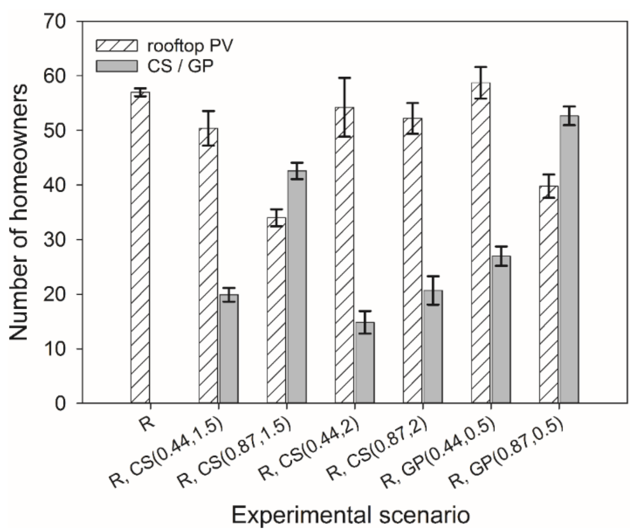


Figure 3: Comparison of number of consumer agents that are homeowners adopting rooftop PV, community solar, or green pricing program in Scenarios 1-7.

Interestingly, when the utility company introduced a 0.44 MW green pricing program (Scenario 6), the average number of homeowners adopting rooftop PV increased (mean = 58.7, SD = 2.9) as compared to Scenario 1. This is a result of the interactions that occurred among the green pricing program adopters and the homeowners that were non-adopters. The interactions encouraged the homeowners that otherwise would not have adopted a renewable energy source to adopt rooftop PV. Further, when the green pricing program capacity was increased from 0.44 MW to 0.87 MW (Scenarios 7), the average number of homeowners adopting the green pricing program increased from 27 (SD = 1.8) to 52.7 (SD = 1.7), and there was a significant drop in homeowners adopting rooftop PV, from 58.7 (SD = 2.9) to 39.8 (SD = 2.1). Therefore, many homeowners preferred the green pricing program over rooftop PV. Also, homeowners that had a very low payback period threshold for rooftop PV but overall concern index ($OC_i$) of the attitudinal component greater than 0.67 also adopted the green pricing program.

Figure 4a compares the utility company agent's revenue at the end of final time-step for all seven experimental scenarios. The green pricing program with capacity of 0.87 MW (Scenario 7) generated the highest revenue - consumer agents enrolled up to 100 percent capacity of the green pricing program by the end of final time-step, and hence, the utility company was able to recover the extra price per unit of electricity ($e_{GP}$) from the green pricing program adopters that it pays to buy the renewable energy.

Though there were fewer rooftop adopters in Scenario 3 than in Scenario 1, the revenue of the utility company at the end of the final-time step in Scenario 3 is less than Scenario 1. This is because of the higher cost of electricity per kWh that the utility company incurs ($e_{CS}$) from the community solar project, as well as loss in revenue from the community solar adopters after they are past breakeven period ($n_i$). Also, though the number of rooftop adopters in Scenario 3 was substantially less than in Scenario 2, the utility company's revenue is still lower in Scenario 3 than in Scenario 2. This is attributed to the increased capacity of community solar in Scenario 3, which led to a drop in utility revenue due to the increased cost of electricity per kWh ($e_{CS}$). Also, the average number of total community solar adopters increased from Scenario 2 (49.9, SD = 0.3) to Scenario 3 (99.86, SD = 0.4) due to increased project capacity. Therefore, the number of consumers buying electricity at a cheaper rate from the community solar in Scenario 3 increased.

Figure 4b shows the total green energy (MWh) incorporated by the entire system at the end of 100 time-steps. The average was greatest in Scenario 5 (398.9, SD = 7.2) - greater than that of Scenario 3 (350.6, SD = 4.1), which has the same community solar capacity, due to the greater number of rooftop adopters in Scenario 5. Although Scenario 7 yields the highest revenue for the utility company and helps it to alleviate the revenue losses due to rooftop PV adoption, fewer rooftop PV adopters than Scenario 5 yields an overall reduced amount of green energy addition at the end of 100 time-steps.

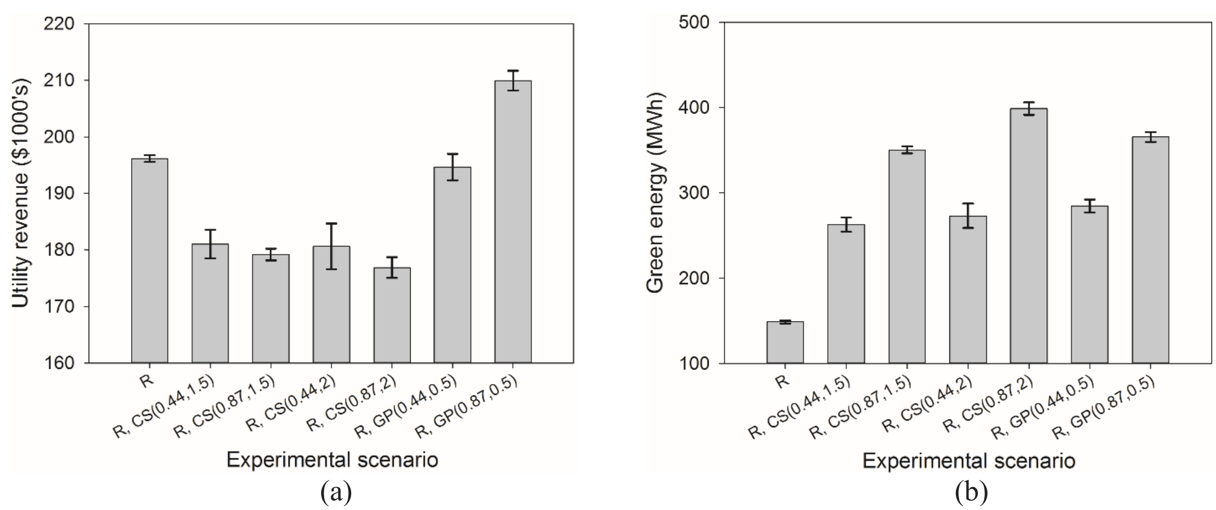


Figure 4: a) Utility company agent revenue at the end of final time-step in Scenarios 1-7, b) Total green energy addition by the utility company and consumer agents at the end of final time-step in Scenario 1-7.

## 4 CONCLUSION AND FUTURE WORK

This paper describes an ABM that was developed to demonstrate the importance of incorporating consumers' energy-related decisions and behaviors into a utility company's renewable energy expansion planning decisions, such that it can determine the right mix of alternative renewable energy models to alleviate revenue losses due to rooftop PV adoption. This modeling framework also has the potential to help utility companies identify tradeoffs and meet specific goals. For example, the results generated by experimentation with this conceptual model suggest that introducing a green pricing program with a capacity of 0.87 MW could help a utility company maximize its revenue, whereas introducing a community solar project of the same capacity could help it meet its renewable energy targets. Additionally, the modeling framework could help utility companies avoid potentially catastrophic consequences of introducing an inappropriate business model. In experimental Scenario 6, for example, introducing a green pricing program proved to be counterproductive for the utility company, as it actually increased rooftop PV adoption, compared with the baseline Scenario 1.

The conceptual model described in this paper will serve as a starting point for the development of an empirically validated model that uses data from central Iowa energy stakeholders as inputs. The model will be extended to incorporate multiple energy technologies, multiple variants of different renewable energy models, and a scaled-up population of consumer agents that represents a service territory of a utility company. Ongoing and future work will also incorporate the effects of heterogeneous consumer attributes (e.g., age, gender, education level) on their social interactions and decision making. Because utility company expansion planning depends on federal and state policies and regulations by regional transmission operators (RTO) and independent system operators (ISO), a future version of this model will also include multiple utilities, RTOs, and ISOs as agents. This will enable the model to more accurately represent real-life wholesale electricity markets and assist utility companies with their expansion planning decisions.

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