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An agent-based approach to designing residential renewable energy systems

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ABSTRACT

Residential consumers in the U.S. have demonstrated a growing interest in rooftop photovoltaic (PV) systems, resulting in increased adoption over the last decade. However, this has diminished utility revenues, and policymakers have expressed concerns about inequitable consumer access to publicly-funded rooftop PV adoption incentives. In response to these concerns, policymakers and utility companies are changing their policies to discourage rooftop PV adoption. Alternative renewable energy models, such as utility-provided community solar programs, offer a potential solution. However, when designing such programs, it is important to consider the potential impacts on different system stakeholders, including utilities, policymakers, and solar installers. This paper describes an agent-based model that predicts the performance of different residential distributed solar models with respect to these stakeholders' objectives. In this model, consumer agents residing in an urban utility territory decide in each time-step whether they will adopt a particular renewable energy model, and the impacts of their adoption decisions on stakeholder performance metrics are captured over time. Simulation results suggest that if community solar program premium prices are set appropriately, all stakeholders can benefit: the utility can recover part of its revenue losses even as rooftop PV adoption increases, solar installers' businesses can thrive, and increased renewable energy adoption can be achieved equitably. The proposed modeling methodology can help to inform design decisions of distributed solar energy models that avoid benefiting some stakeholders at the unnecessary expense of others.

1. Introduction

Over the last decade, there has been tremendous growth in distributed generation in the U.S. residential energy sector. Recent advances in renewable energy technology, coupled with increased consumer awareness and interest, are yielding a shift in the electricity market from a centralized generation system to a distributed and consumer-driven model [1]. Specifically, solar photovoltaic (PV) technology has become increasingly popular among U.S. residential energy consumers as PV panels have become more reliable and less expensive [2]. PV systems on owner-occupied houses (known as *rooftop PV*) allow consumers to generate their own electricity, thereby enabling them to lower their energy bills, gain ownership and control of the energy infrastructure, and reduce their environmental impact.

However, as more consumers are generating their own energy using rooftop PV systems, utility companies' revenues have declined [3]. Furthermore, not all residential buildings are suitable for rooftop PV installation, many U.S. households are renters, and high installation cost limits access to higher-income households [4–6]. This has caused concern among policymakers about inequitable access to rooftop PV and its associated benefits, which include publicly-funded incentives [7]. In response to these concerns, many policymakers and utility companies are changing their policies to discourage rooftop PV adoption [8]. With fewer government rebates available and waning utility support for grid interconnection, fewer consumers are adopting rooftop PV. As a result, despite several years of positive growth, the installed capacity of residential solar in the U.S. fell by 14% in 2017 [9].

Alternative renewable energy models, such as utility-provided community solar programs, offer a potential solution. Under a community solar program, the generation of solar energy does not occur at the consumer's home. Instead, the consumer subscribes to a portion of a shared PV facility located elsewhere in the community. Such programs allow renters and homeowners who cannot install PV systems due to structural or shading issues to access renewable energy, while allowing utilities to retain their customers and revenues. However, community solar could fail to address policymaker concerns about equitable access if the program is priced inappropriately, and it could also have a negative impact on solar installers' revenues if consumers substitute community solar for rooftop PV.

This paper proposes an agent-based approach to modeling consumer

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adoption behavior in the presence of competing renewable energy models (i.e., rooftop PV and community solar), such that the impacts on multiple stakeholder objectives can be understood. Agent-based modeling is a powerful computational tool that can be used to examine sociotechnical system performance over time, wherein system behavior is subject to complex and dynamic individual human behaviors and social interactions. The conceptual agent-based model (ABM) described in this paper is a novel approach to designing urban residential renewable energy systems that equitably satisfy consumer demand while maintaining solar installers and utility revenues. Fulfilling the conflicting and competing objectives of these key stakeholders will support the overarching goal of greater renewable energy deployment in the energy sector.

The paper is structured as follows: Section 2 provides a review of the relevant literature, Section 3 describes the ABM, Section 4 describes the experiments performed using the model, Section 5 summarizes the experimental results, Section 6 discusses the results and their practical implications, and limitations of this work, and Section 7 concludes the paper.

2. Background and literature review

In a net metering program, consumers' meters are allowed to run backwards if the electricity generated by their PV systems is more than they consume. Even many of the currently installed residential rooftop PV systems in the U.S. with storage (approximately 60%) are also grid-connected [10], which allows consumers to net meter their energy bills. The net metered solar power from rooftop PV systems helps utility companies to meet their required renewable portfolio standard (RPS), under which they are mandated to provide a percentage of their electricity supply from renewable energy technologies [11]. Overall, however, utility companies view their customers' rooftop PV installations as a source of lost revenue [12]. Rooftop PV adoption also increases utilities' operational costs. Because the electricity grids were not originally designed for the dual-flow of electricity, increased rooftop PV adoption has required utilities to make significant upgrades to the transmission and distribution infrastructure to ensure safe PV systems operation and maintain grid reliability [13]. Additionally, utilities retain responsibility for providing solar-powered consumers with energy if their systems fail or if their energy needs increase.

In response, utilities have increased electricity tariffs. These increased tariffs create an unfair financial burden on consumers who do not have the ability to install rooftop PV, and they can result in a feedback loop in which PV adoption accelerates, yielding further tariff increases [14]. Utilities are also discouraging rooftop PV adoption by changing their net metering policies, which has had a negative impact on utility-customer relationships [8]. For example, the Indiana Regulatory Public Commission is considering replacing its current net metering policy with a “buy-all, sell-all” option, in which consumers are charged for their consumption as per the utility's current electricity rate structure and are paid for the electricity generated by their PV systems at the much lower wholesale electricity rates [15].

Increased rooftop PV adoption has also led to equity concerns among policymakers. Publicly-funded incentives have been created that encourage residential rooftop PV adoption, including federal and state income tax credits and property and sales tax exemptions. However, the high up-front cost of purchasing and installing rooftop PV has limited access to higher income households: the median income of U.S. rooftop PV adopters is $32,000 higher than the average U.S. household income [4]. Although leasing and solar power purchase agreement (PPA) options attempt to address this issue by eliminating the need for high up-front investment, most U.S. house-owners are still unable to install rooftop PV systems because of structural, shading, or roof ownership issues. In the U.S., only 57% of all residential buildings are suitable for rooftop PV installation [6], and 36% of the U.S. households are renters [5] who do not own the roof space needed to install PV panels.

Community solar programs have the potential to address both utility and policymaker concerns. In a utility-sponsored community solar model, the utility owns and/or operates a project that is open to voluntary ratepayers [16]. The geographic proximity of community solar subscribers to the solar installation varies by program; for example, the utility can require subscribers to be in the same utility territory, county, or neighborhood as the solar installation [17]. Offering customers the opportunity to invest in a community solar program can help utility companies to stabilize their revenues, increase the renewable sources in their energy portfolios, increase customer satisfaction and engagement, address customer demand for renewable energy, make a transition toward clean energy, and enhance overall grid power quality via a small number of large-sized distributed generating units, as opposed to numerous small rooftop PV systems [18,19]. In addition, as consumers become investors in the creation of new energy infrastructure and utilities maintain control over it, utility-customer relationships can improve [20].

Community solar also expands the availability of distributed solar power to a broader range of consumers. For example, lower-income energy consumers who may not be able to afford rooftop PV can invest in a shared PV system according to their financial ability [21]. Renters and homeowners who are unable to install rooftop PV because they do not own the roof, or because the roof is ill-suited for panels, can also access solar electricity through community solar programs, with the flexibility of selling their subscription when they move or having their solar credits follow them [21]. Community solar is also a viable alternative for consumers who are interested in supporting renewable energy but do not wish to install rooftop PV on their houses because of the perceived complexity of installation procedures and required paperwork, the possibility of moving residences in the future, risk of roof damage, and high investment uncertainty associated with installation [22,23].

However, the success of a community solar program depends on the degree to which its design meets consumer needs and requirements. It is important for the provider (e.g., the utility company) to be able to predict its customers' response to program design parameters, including capacity and duration, household participation limits, payment terms and conditions, site selection, and subscription transfers [20]. Predicting consumer participation requires consideration of consumers' heterogeneous preferences and objectives, which include reducing energy costs, protecting the environment, gaining independence from utility companies, and investing in their homes [24]. Consumer demographics are also known to influence renewable energy adoption decisions. For example, many consumers install rooftop PV just before retirement, coinciding with decisions about whether to stay in their homes [25]. Adoption decisions are also often socially motivated, influenced through peer interactions, online media, and seeing solar panels on neighbors' rooftops [26,27]. Social networks play a crucial role in providing consumers with relevant information to inform their decisions, including the available options, which supplier to choose, and financial incentives [28]. Therefore, consumers’ preferences may also evolve over time as they learn more about different renewable energy models from their friends, family and neighbors.

Agent-based modeling is a method that is well-suited to studying the system-wide effects of individual energy consumers’ heterogeneous behaviors, boundedly rational decision processes, and social interactions on energy technology adoption over space and time [29]. ABMs consist of individual software entities, generally referred to as “agents”, that are situated in a virtual environment [30]. An agent may represent an individual entity (i.e., single consumer) or an aggregate of individuals (e.g., household). Agents may be assigned heterogeneous attributes, preferences, objectives, and behavioral rules in the form of mathematical and/or logical statements, which inform their decisions about the most appropriate action to take in a given situation. Agents can also be programmed to interact with each other and their environment, which can in turn influence future decisions and behaviors through a process of dynamic adaptation. The interactions of decisions, actions, and adaptations among many agents within the same system are non-linear and can result in an overall system-wide behavior that emerges over time [31]. Such emergent system behavior can be difficult to predict without the use of ABM.

ABM has been used to study the effect of consumer behavior on sustainable energy technology adoption [32]. For example, an ABM was developed to understanding the discrepancy between consumers' opinions and their actual participation in dynamic electricity tariffs programs [33]. Rai and Robinson [34] developed an ABM to predict the effects of different rebate programs on residential rooftop PV adoption rates in Austin, Texas, wherein household agent adoption decisions depend on their demographic, attitudinal, and economic characteristics. ABM was also used to study the impact of factors such as geographic location and lifestyle on households' green tariff adoption decisions [35].

While existing models account for heterogeneous consumer behavior, they do not examine the effects of consumer adoption on the conflicting and competing objectives of other key energy system stakeholders, nor do they consider multiple competing renewable energy models, such as rooftop PV and community solar [36,37]. Also, these existing models are specific to a particular geographic location, such that it is difficult to generalize the findings [38]. Thus there is a need to develop conceptual models to demonstrate the capacity of ABM for energy transition studies [38]. A conceptual model is a structured representation of a system that has the purpose of understanding the system's behavior through a consecutive description of all relevant entities [39]. A conceptual ABM can serve as the basis for the future development of more sophisticated and geographic-centric models via interdisciplinary collaboration (e.g., between social scientists, engineers, and policymakers) for the purpose of studying the implications of introducing new policy, planning, and/or technology. This paper describes a conceptual agent-based model for designing a residential renewable energy system, allowing for consumer adoption of multiple models and taking into account the objectives of utilities, solar installers, and policymakers to enable conflict-free energy system decentralization. The City of Des Moines, Iowa, is used as an example to develop the model.

3. Agent-based model

The ABM was developed using NetLogo 6.0.4 and is described using the Overview, Design concepts and Details (ODD) protocol [40].

3.1. Purpose

The purpose of this model is to predict consumer adoption of different renewable energy models and to determine the resulting impacts on energy system performance, in terms of key stakeholders' metrics. Examples of stakeholder metrics include present value of utility and solar installer revenues, total green power added to the grid, and total consumer participation in renewable energy models in each simulated time-step. A complete list of stakeholder metrics captured from the ABM is provided in Section 4.2. Model outputs can be used to inform energy system design decisions in support of individual stakeholder objectives and the overarching objective of increasing renewable energy deployment.

3.2. Entities, state variables, and scales

This conceptual model contains 300 residential consumer agents that reside in the territory of a single hypothetical utility company. The description of state variables associated with the consumer agents, their possible values and data sources are summarized in Table A1 of Appendix A. Each agent has a unique identification number (i), as well as a community identification number (C_i) that corresponds to the community in which the agent resides. Communities 1 through 7 consist of 70, 30, 20, 70, 40, 30, and 40 agents, respectively. These values were chosen as a proof of concept in using the model to design a renewable energy system at an urban scale.

Each consumer agent is characterized by four demographic factors: age (A_i), income (I_i), education (E_i), and race (R_i), with values assigned using probabilities derived from publicly available demographic data for the City of Des Moines, Iowa [41]. The values of I_i, E_i, and R_i remain constant throughout each simulation run, while A_i increases as simulated time progresses. Each agent is also categorized as being either a house-owner, a renter, or an apartment-owner, and this assignment remains constant throughout each simulation run. Of the 300 consumer agents, 174 (58%) are house-owners and 126 (42%) are either renters or apartment-owners, based on the City of Des Moines demographic data. It is assumed that only house-owner agents buy/lease rooftop PV panels, while house-owner, renter, and apartment-owner agents can all adopt community solar. However, only 57% of the house-owner agents' homes are modeled to be structurally capable of accommodating rooftop PV, based on data from Ref. [6].

The distribution of home sizes (in terms of number of bedrooms) for the City of Des Moines was used to assign agent home size values [42]. The average monthly residential electricity consumption in Iowa of 831 kWh [43], was then used to assign each agent a monthly electricity consumption value (Q_i), which is proportional to its home size. The model does not take into account the adoption of energy efficiency measures; therefore, each consumer agent's electricity consumption is assumed to be constant throughout each simulation run.

3.3. Model overview

In each monthly time-step, each consumer agent decides between two courses of action: buy electricity from the utility or adopt one of four different renewable energy models (buy rooftop PV through upfront cash payment, buy rooftop PV through solar loan option, lease rooftop PV from a solar installer, or enroll in a utility-sponsored community solar program). This decision is driven by the agent's financial position, its attitude toward solar electricity, its demographic attributes, influence from other agents in its social network and geographic vicinity, and information received from the utility company and solar installers.

3.4. 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 existing empirical studies that have identified consumers' motivations for adopting renewable energy [23,25,44,45]. These are described in detail in the sub-models' descriptions below.

3.5. Emergence

Consumer agents' decisions to adopt a particular renewable energy model influence other agents' decision via their interactions, yielding emergent system performance [26,34], in terms of stakeholder metrics (e.g., utility/solar installers revenue and equitable consumer access to renewable energy).

3.6. Adaptation

As the attributes of a consumer agent and its environment change over time, its position on adopting a renewable energy model adapts accordingly. For example, changes in electricity prices, PV installation cost, and available tax credits all influence an agent's adoption likelihood. Further, as agents interact and learn from one another about renewable energy options (e.g., community solar), environmental benefits of solar, and PV installation procedures, their adoption decisions may change. In addition, as agents near retirement, they become increasingly likely to adopt rooftop PV.

Utility companies and policymakers are not represented as agents in this model. Therefore, it is assumed that their respective pricing/tax credit policy parameters do not adapt over the course of a simulation run.

3.7. Objectives

Each consumer agent's fundamental objectives are to lower its energy bills and to contribute to a social cause by adopting renewable energy. The achievement of these objectives is informed by the agent's financial position and attitudinal and demographic factors.

3.8. Interactions

Agents interact via visual interactions and information exchange. Research on consumer rooftop PV adoption shows that regions with more rooftop PVs have a greater likelihood of adoption [26]. To capture this, visual interactions (i.e., seeing PV panels on a neighbor's roof) between agents can occur as follows: if a house-owner agent adopts rooftop PV, in the next time-step every other agent within its community becomes aware, and their likelihood of participating in a renewable energy model (rooftop PV or community solar program) in future time-steps increases.

The second type of interaction involves the exchange of information (e.g., about the availability of a community solar program) between agents within their social networks, which can occur between agents of the same as well as different communities. To create the agents' social network, a small-world network was generated using the Watts-Strogatz algorithm [46]. A small-world network structure is considered appropriate for representing consumer social behavior with respect to renewable energy adoption [34,47]. A small-world network is characterized by the number of nodes in the network (n), the number of neighbors a node has (K), and rewiring probability (p), with which the right end of an arc connected to a node is rewired uniformly randomly to any of the other nodes [48]. In this model, the number of nodes is equal to the number of consumer agents ($n = 300$), each node is assumed to be connected to its immediate neighbors ($K = 2$), and the rewiring probability (p) is varied experimentally. Each of the links connecting two consumer agents j and k is assigned a similarity index ($Simi_{jk}$) using (1). Because consumer similarity (i.e., homophily) is a predictor of the strength of interactions within a social network [49], it is assumed that higher $Simi_{jk}$ values will yield more influential interactions. It is assumed that $Simi_{jk}$ is indirectly proportional to the differences in the agents' age (A_i), income (I_i), education (E_i), and race (R_i). The maximum possible value of similarity contributed by each demographic factor is 0.25, which occurs when two agents are at the same level for that factor. The minimum possible value of similarity contributed by each demographic factor is 0, which occurs when the two agents are at opposite ends of the factor's range (e.g., age levels 0 and 6). One exception is the race factor: R_{jk} is 0 if the race of agents j and k are the same; otherwise, it is assigned a value of 1.

$$Simi_{jk} = \left(0.25 - \frac{|A_j - A_k|}{24}\right) + \left(0.25 - \frac{|I_j - I_k|}{60}\right) + \left(0.25 - \frac{|E_j - E_k|}{20}\right) + \left(0.25 - \frac{R_{jk}}{4}\right) \tag{1}$$

3.9. Observations

Consumer agents' decisions to adopt rooftop PV and community solar are captured in each monthly time-step. The present value of utility company and solar installers revenues are also recorded, as well as system-wide green power addition (kW).

3.10. 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. The electricity cost is set to the current average electricity rate for Iowa, i.e. 13.23 ¢/kWh [50]. This cost is assumed to increase by 1.67% annually [51]. The income tax credit (ITC_t) associated with buying rooftop PV (total of federal and State of Iowa) is initialized to 45% and reduces to 39% after 12 time-steps, to 33% after 24 time-steps, and to 0% after 36 time-steps, which reflects current federal and State of Iowa rebate policies [52].

3.11. Sub-models

The ABM contains three sub-models and all three are executed in each monthly time-step for each consumer agent.

3.11.1. Sub-model 1 – consumer agent attitude assessment

Each consumer agent is assigned an initial awareness index (AW_i) on a 0–1 scale, which represents the agent's overall awareness of renewable energy and its environmental benefits. Because individuals with more education are more likely to adopt renewable energy [44], the initial value of AW_i is assigned as the normalized product of an agent's education level (E_i) and a random number (p) between 0 and 1, such that $AW_i = \frac{p(E_i + 1)}{6}$. Larger values of AW_i correspond to a greater probability that an agent will adopt a renewable energy model. If a house-owner agent adopts rooftop PV, the value of AW_i for each non-adopter in its community increases by one percent of its maximum value (a consequence of visual interactions). The value of AW_i for a non-adopter also increases if it interacts with an adopter in its social network. The amount of increase is determined by (2), where $AW_{j(before)}$ and $AW_{j(after)}$ are non-adopter agent j's awareness index values before and after the interaction, AW_k is the adopter agent k's awareness index, and $Simi_{jk}$ is the similarity index value of the link between agents j and k.

$$AW_{j(after)} = AW_{j(before)} + \frac{AW_k Simi_{jk}}{100} \tag{2}$$

The awareness index of an agent also increases if it attends a solar installer's renewable energy fair (focused on rooftop PV) and/or a utility-sponsored renewable energy seminar (focused on community solar) [25]. Only house-owner agents that can adopt rooftop PV can attend a renewable energy fair, but any agent can attend a seminar. In each time-step the likelihood that an agent will attend a fair/seminar depends on AW_i, where a higher value corresponds to a greater probability of attending. If an agent attends a fair/seminar, AW_i increases by 0.1. An agent that attends a seminar becomes aware of community solar, such that its value of CS_i, updates from 0 (unaware) to 1 (aware). If agent j is aware of community solar and interacts with agent k via its social network, agent k also becomes aware of community solar, irrespective of attending a seminar. An agent can attend a fair/seminar only once during a simulation run.

Consumers tend to consider rooftop PV purchase to be a complex issue, because of the effort required to learn about installation procedures, incentive policies, net metering policies, house-owners' association regulations, and the required paperwork [23]. However, when a consumer leases solar panels or adopts community solar, a project developer assumes these responsibilities. Each house-owner agent is initially assigned a random perceived complexity index (PC_i) value on a 0–1 scale. Lower values of PC_i correspond to greater probabilities that an agent will buy rooftop PV. If a non-adopter attends renewable energy fair, PC_i decreases by 0.1. This value also decreases if non-adopter j interacts with a rooftop PV buyer k via its social network, based on (3). $PC_{j(before)}$ and $PC_{j(after)}$ are agent j's perceived complexity index values before and after the interaction, PC_k is the perceived complexity index of agent k, and $Simi_{jk}$ is the agents' similarity index.

$$PC_{j(after)} = PC_{j(before)} - \frac{Simi_{jk}(1 - PC_k)}{100} \quad (3)$$

Each house-owner agent is also randomly assigned an ownership index (O_i) on a 0–1 scale, where higher values of O_i correspond to stronger agent preference for rooftop PV over community solar. This value remains constant throughout the simulation run. Lastly, each house-owner agent is assigned an age-based index (AB_i) on a 0–1 scale, based on its current age level (A_i). AB_i is evaluated by normalizing to 1 the product of A_i and a random number q, such that $AB_i = \frac{q(A_i+1)}{7}$. Higher values of AB_i correspond to greater probabilities that the agent will buy/lease rooftop PV, because consumers tend to adopt rooftop PV as they approach retirement [25].

3.11.2. Sub-model 2 – consumer agent financial assessment

Agents are classified into four agent types (T_x) based on their optimism towards solar electricity [45], where larger values of the index x correspond to greater optimism toward solar power's financial prospects. T_x represents an agent's expectation of future electricity cost growth (PG_i) and annual rooftop PV maintenance costs (PM_i), as a percentage of up-front investment. Table 1 provides values for PG_i, and PM_i for each agent type, adapted from Ref. [45]. An affordability factor (AF_i) on a 0–1 scale is also assigned to each house-owner consumer agent by normalizing to 1 the product of its income level (I_i) and a random number r, such that $AF_i = \frac{r(I_i+1)}{16}$. A higher AF_i corresponds to a greater probability that the agent can afford to pay the high up-front cost of purchasing solar panels.

Table 1
Financial parameters assigned to each agent type.

Parameter	Description	T_1	T_2	T_3	T_4
PG_i	Expectation of future annual growth rate of electricity cost (%)	0.00	2.60	3.30	5.00
PM_i	Expectation of annual rooftop PV maintenance cost as a percentage of up-front system cost (%)	0.50	0.25	0.15	0.00

Each consumer agent evaluates the financial viability of a renewable energy model by calculating its net present value (NPV) in each time-step. An agent will only evaluate NPV of models that are feasible for it to adopt (as summarized in Table 2), and it is assumed that a consumer agent will evaluate the NPV of participating in a community solar program only if it is aware of it ($CS_i = 1$). Based on hourly solar PV insolation and temperature data for the City of Des Moines from 1999 to 2010, it is assumed that 109 kWh of energy is generated each month by each kW (DC) of solar panel installed through either rooftop PV or a community solar program [53]. Further, it is assumed that if an agent decides to buy/lease rooftop PV or subscribe to community solar, it will choose a PV module of size S_i that meets 100% of its monthly energy requirements (Q_i).

NPV (buying rooftop PV through up-front cash payment) – The present value of rooftop PV installation cost ($P_{b(install),i}$) for a house-owner agent i at time t is given by (4), where S_i is the size of the solar panel array (in kW, DC) required by the agent to meet 100% of its energy needs (Q_i (AC)), W_t is the installation cost ($/kW (DC)), and ITC_t is the income tax credit percentage (federal and state) at time t. It is assumed that an agent's minimum tax liability in the year of purchasing rooftop PV is greater than or equal to the corresponding tax rebates it gets from purchasing rooftop PV. Therefore, the income tax credit is not discounted to evaluate the present value of the installation cost. W_t is initialized to be $3430/kW [54], and this value decreases by 6% annually, based on the average decline in residential sector installation prices in the U.S. between 2000 and 2016. It is assumed that the utility allows customers to offset 100% of the energy generated by their rooftop PV systems, as per the current net metering policy in Iowa.

An agent's present value of future monthly bill savings ($P_{b(mbs),i}$) from buying rooftop PV, evaluated over 25 years (the average life of solar panels), is given by (5). $P_{b(mbs),i}$ is calculated by discounting (by annual discount rate d, assumed to be 5%) the annual electricity costs for 25 years that the agent would have paid to the utility if it had not installed rooftop PV. An agent's annual electricity cost is evaluated by multiplying the number of months in a year by its monthly consumption (Q_i) and the current electricity rate (C_t), where C_t increases annually based on the agent's expected growth rate (PG_i). The present value of an agent's future rooftop PV maintenance costs ($P_{b(maint),i}$) is given by (6), in which the present value of installation cost ($P_{b(install),i}$) is multiplied by the agent's expected annual maintenance cost (PM_i) and the expected life of the solar panel array (i.e., 25 years). The NPV of buying rooftop PV ($NPV_{b,i}$) for agent i is given by (7), which is the difference in the present value of total cash inflow and total cash outflow.

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

$$P_{b(mbs),i} = \sum_{t=1}^{25} 12 Q_i C_t \left(\frac{1 + PG_i}{1 + d}\right)^{t-1} \quad (5)$$

$$P_{b(maint),i} = 25 PM_i P_{b(install),i} \quad (6)$$

$$NPV_{b,i} = P_{b(mbs),i} - (P_{b(install),i} + P_{b(maint),i}) \quad (7)$$

NPV (buying rooftop PV through solar loan) – It is assumed that an agent will borrow an amount equal to the cost of the PV system after deducting income tax credits. Thus, calculating the present value of the principal for agent i at time t ($P_{s,i}$) is equivalent to calculating the installation cost of paying cash ($P_{b(install),i}$), given in (4). Similarly, calculating the present value of future total monthly bill savings ($P_{s(mbs),i}$) and maintenance costs ($P_{s(maint),i}$) associated with solar loans is the same as cash payment, given in (5) and (6), respectively. The agent borrows the principal ($P_{s,i}$) through a simple interest loan at a monthly interest rate of r% (assumed to be 0.5%). Each equal monthly installment ($M_{emi,i}$) is given by (8), where N is the total number of installments the agent must pay toward the loan. A 10-year loan is assumed, such that N equals 120. The present value of the monthly installments ($P_{s(emi),i}$) is given by (9), where the total value of installments each year is discounted by an annual discount rate of d% (assumed to be 5%). The NPV of the rooftop PV loan option ($NPV_{s,i}$) is given by (10).

$$M_{emi,i} = P_{s,i}\left(\frac{r(i + r)^N}{(1 + r)^N - 1}\right) \quad (8)$$

$$P_{s(emi),i} = \sum_{t=1}^{10} \frac{12 M_{emi,i}}{(1 + d)^{t-1}} \quad (9)$$

$$NPV_{s,i} = P_{s(mbs),i} - (P_{s(emi),i} + P_{s(maint),i}) \quad (10)$$

NPV (leasing rooftop PV) – If an agent decides to lease solar panels at time t, its monthly leasing cost is determined by the solar installer and depends on the size of the solar panel array (S_i), the income tax credit rate (ITC_t) at time t, the installation cost (I_i), the solar installer's expected rate of return (PD_s, assumed to be 5%), and the leasing period (assumed to be 25 years). The solar installer's total cost (I_i) to install solar panels for agent i is equivalent to the installation cost of paying cash ($P_{b(install),i}$), given by (4), but the solar installer reaps the benefit of income tax credits on behalf of the customer. I_i is recovered from the consumer agent via the fixed monthly leasing cost (M_i) over 25 years. The present value of the total maintenance cost ($P_{l(maint),i}$) for an agent i over the next 25 years is given by (11). $P_{l(maint),i}$ is evaluated by discounting by PD_s (the solar installer's expected return) the annual maintenance cost (m_s, assumed to be 3%) as a percentage of I_i over the 25-year leasing period. This total maintenance cost is also recovered by the solar installer as a part of the monthly leasing cost (M_i).

M_i is evaluated using (12), which equates the sum of I_i and $P_{l(maint),i}$

Table 2
Logic determining consumer agent evaluation of renewable energy models NPV (Y: yes, N: no, NA: not applicable).

Agent Description	Buy Rooftop PV (up-front cash payment)	Buy Rooftop PV (solar loan)	Lease Rooftop PV	Community Solar
House-owner agents who are structurally capable of accommodating rooftop PV and can afford to pay the up-front-cost to install PV systems	Y	Y	Y	Y ($CS_i = 1$) N ($CS_i = 0$)
House-owner agents who are structurally capable of accommodating rooftop PV but cannot afford to pay the up-front-cost to install PV systems	N	Y	Y	Y ($CS_i = 1$) N ($CS_i = 0$)
House-owner agents who are not structurally capable of accommodating rooftop PV	NA	NA	NA	Y ($CS_i = 1$) N ($CS_i = 0$)
Renters and apartment-owner agents	NA	NA	NA	Y ($CS_i = 1$) N ($CS_i = 0$)

to the then present value of the total future leasing cost that the consumer agent will pay over the next 25 years. The NPV of the leasing option ($NPV_{l,i}$) for agent i is the difference between the present value of the total savings in monthly energy bills over the next 25 years (evaluated using (5)) and the present value of the total monthly leasing cost that the consumer pays over 25 years, as shown in (13).

$$P_{l(maint),i} = m_S I_i \sum_{t=1}^{25} \left(\frac{1}{1 + PD_S}\right)^{t-1} \tag{11}$$

$$I_i + P_{l(maint),i} = \sum_{t=1}^{25} \left(\frac{12M_i}{(1 + PD_S)^{t-1}}\right) \tag{12}$$

$$NPV_{l,i} = \sum_{t=1}^{25} 12Q_i C_t \left(\frac{1 + PG_i}{1 + d}\right)^{t-1} - \sum_{t=1}^{25} \left(\frac{12M_i}{(1 + d)^{t-1}}\right) \tag{13}$$

NPV (community solar) – In a typical community solar engagement, a customer pays a fixed premium (C_p) per unit of energy in addition to the conventional electricity rate at the time of adoption (C_{t^*}), such that the total unit price that the customer pays ($C_p + C_{t^*}$) remains constant for the life of the community solar program [55]. A similar pricing structure is assumed in the model. The present value of an agent's total monthly energy bills if it chooses to participate in a community solar program ($P_{cs,i}$) at time t is given by (14), in which the discounted energy bills are summed over 25 years. An agent's NPV of investing in community solar ($NPV_{cs,i}$) is the difference between the present value of its future monthly bills if it continues buying electricity from the utility company ($P_{b(mbs),i}$ – evaluated using (5)) and $P_{cs,i}$, given by (15).

$$P_{cs,i} = \sum_{t=1}^{25} \left(\frac{12Q_i(C_{t^*} + C_p)}{(1 + d)^{t-1}}\right) \tag{14}$$

$$NPV_{cs,i} = P_{b(mbs),i} - P_{cs,i} \tag{15}$$

3.11.3. Sub-model 3 – consumer agent decision

For consumer agent i to adopt a particular renewable energy model, its awareness index (AW_i) must be greater than the threshold (AW_h) value, and the NPV of the renewable energy model must be greater than 0. Thus renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints will adopt community solar if $NPV_{cs,i}$ is greater than 0 and AW_i is greater than the AW_h. However, if a house-owner agent that can adopt rooftop PV has AW_i greater than the AW_h and its NPV is greater than 0 for multiple renewable energy models, its final selection depends on the values of its perceived complexity (PC_i), ownership index (O_i), and age-based index (AB_i). A random number is generated, and if the number is less than O_i, the agent will prefer rooftop PV (either buy, loan, or lease) over community solar. Otherwise, the agent will prefer the option with the highest expected NPV. This randomness is introduced to represent heterogeneity in consumer behaviors that is not explicitly represented by the state variables in the model. If a house-owner agent favors rooftop PV over community solar, a random number is again generated. If the number is less than AB_i, the agent will adopt rooftop PV; otherwise, it will participate in a community solar program. The choice of paying cash, taking a solar loan, or leasing rooftop PV depends on PC_i: a random number is generated, and if it is greater than PC_i, the agent will favor the option with the highest expected financial returns (NPV value); otherwise, it will lease rooftop PV. Fig. 1 summarizes the consumer agent decision process in each time-step.

4. Experiments

The ABM was used to examine the impact of residential consumers' renewable energy adoption decisions on critical performance metrics for utility companies, policymakers, and solar installers, given different combinations of renewable energy models for the consumers to choose from. For each experiment, the output metric values were analyzed over 120 monthly time-steps (i.e., 10 years), averaged over 50 replications. A simulation run length of 10 years was chosen such that potential future disruptions (e.g., the introduction of a new renewable energy technology) could be reasonably ignored.

4.1. Experimental factors and levels

Model parameter settings were varied in six experiments, which are summarized in Table 3. In each experiment, different renewable energy models are available. For example, in experiment BLC(4), consumer agents have three options: buy rooftop PV through up-front cash payment or solar loans, lease rooftop PV from solar installers, or participate in a utility-sponsored community solar program at a premium (C_p) of 4 ¢/kWh.

For all experiments, the rewiring probability (p) of the small-world network is assumed to be 0.5, and the probability of interaction between two connected agents is assumed to be 0.5. All agents' awareness threshold values (AW_h) are initialized to 0.6. The sensitivity of model outputs to varying the values of these parameters was tested. The results (summarized in Appendix B) indicate that the model's behavior is robust, i.e., it is not predicated on a specific set of input parameter values.

4.2. Model outputs

The outputs of interest include performance metrics that are aligned with the objectives of key system stakeholders. These metrics are summarized in Table 4 and are described in detail below:

4.2.1. Utility company

One key performance metric of interest to the utility company is the present value of its revenues. In particular, utility companies are interested in determining which renewable energy model(s) are best able to help them recover the revenue losses resulting from increased consumer rooftop PV adoption. Revenue is considered as a performance metric for the utility company, rather than profit or gross margin, as it is assumed that the utility buys electricity at the same cost either

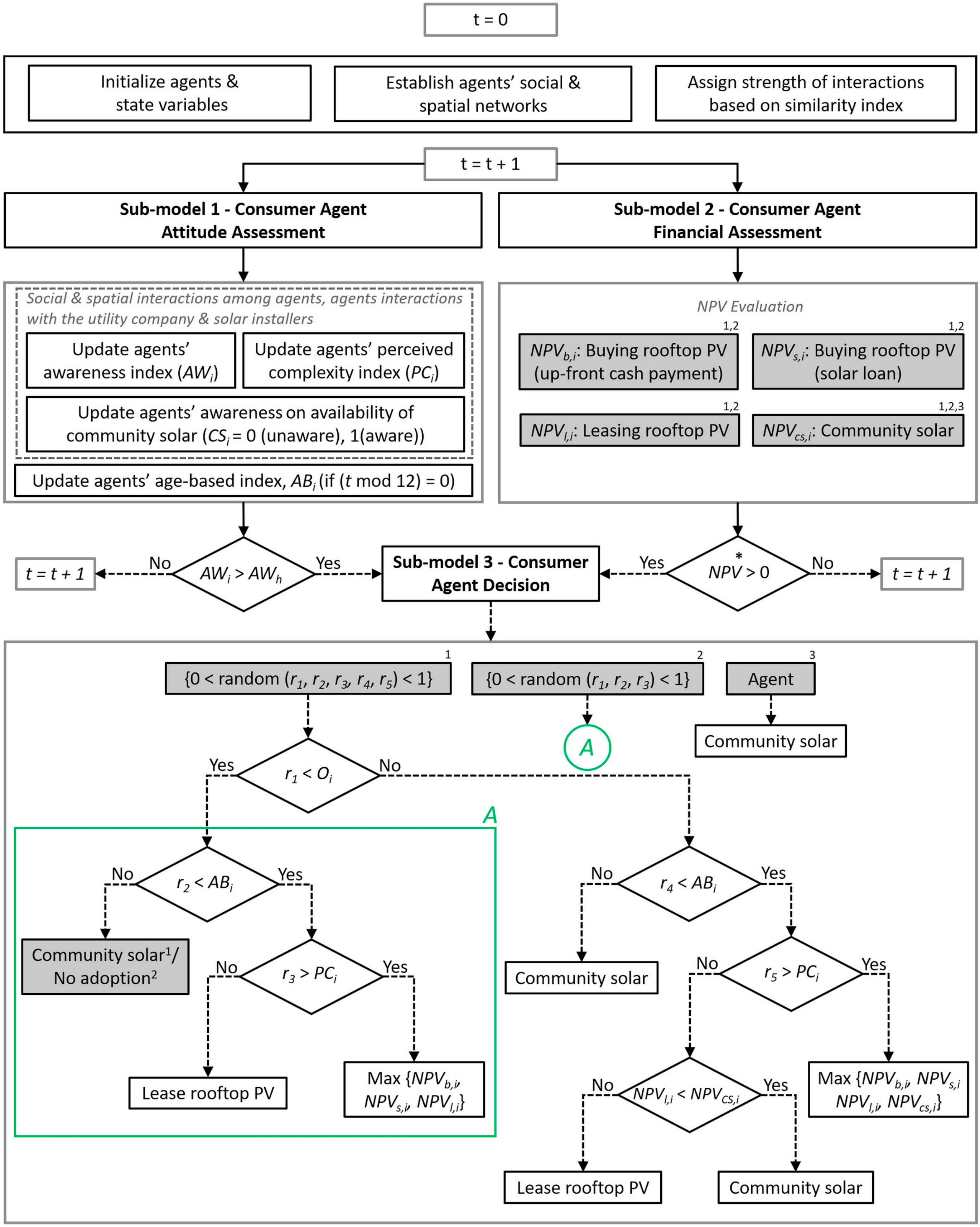

Fig. 1. Flowchart of the consumer agent decision process in each time-step ("*"consumer agent's NPV should be greater than zero for at least one of the renewable energy models). As indicated by the superscripts, the gray decision blocks are specific to the following agents: 1) house-owner agents that can adopt rooftop PV and are aware of the community solar option, 2) house-owner agents that can adopt rooftop PV but are unaware of the community solar option, and 3) renters, apartment owners, or house-owner agents that cannot adopt rooftop PV due to structural constraints, but are aware of the community solar option.

Table 3
Six experiments with different combinations of renewable energy models (Y: available, N: not available).

Experiment	Buy rooftop PV (up-front cash payment)	Buy rooftop PV (solar loan)	Lease rooftop PV	Community solar (C_p, ¢/kWh)
B	Y	Y	N	N
BL	Y	Y	Y	N
BLC(2)	Y	Y	Y	Y (C_p = 2 ¢/kWh)
BLC(3)	Y	Y	Y	Y (C_p = 3 ¢/kWh)
BLC(4)	Y	Y	Y	Y (C_p = 4 ¢/kWh)
BLC(5)	Y	Y	Y	Y (C_p = 5 ¢/kWh)

through wholesale electricity market or via a PPA signed through a community solar program [56]. The utility earns revenues from non-adopters who buy their electricity from the utility at the market rate (C_t) and from community solar adopters who pay the utility a fixed electricity price ($C_p + C_{t^*}$), where C_{t^*} is the price of electricity at the time of adoption, and C_p is the community solar premium. Present value of the utility revenue is evaluated by summing the discounted total revenue each year from non-adopters and community solar adopters assuming an annual discount rate of 5%. Other key performance metrics for the utility are total green power added to the grid through consumer adoption of community solar and rooftop PV and the incremental community solar capacity increases that are needed to satisfy the growing consumer demand for renewable energy. This metric is important for the utility to understand the relative effectiveness of different renewable energy models in meeting the RPS.

4.2.2. Policymakers

Key performance metrics of interest to policymakers are the total number of renewable energy adopters as well as percentage of ‘restricted’ population (renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints) participating in renewable energy. These metrics allow policymakers to determine the degree to which rebate programs for different renewable energy models (e.g., rooftop PV and community solar) lead to their increased adoptions equitably.

4.2.3. Solar installers

The key performance metric for solar installers is the present value of their revenues. This metric will help solar installers understand the financial impact of offering consumers a rooftop PV leasing option, as well as the impact of a utility-sponsored community solar program on their own business. Because the model does not consider solar installers as individual agents, the present value of revenue represents the total revenue for all installers offering similar pricing for PV buying and leasing. The present value of revenue for the solar installers is evaluated as the sum of present value of revenues from consumers buying and leasing rooftop PV. Present value from the PV buying option is evaluated by summing the discounted (annual rate of 5%) up-front cost of each purchased rooftop PV system over 120 time-steps (10 years). The present value of revenue from the PV leasing option is evaluated by summing the discounted value of the annual leasing costs for each adopter over 25 years from the year of adoption.

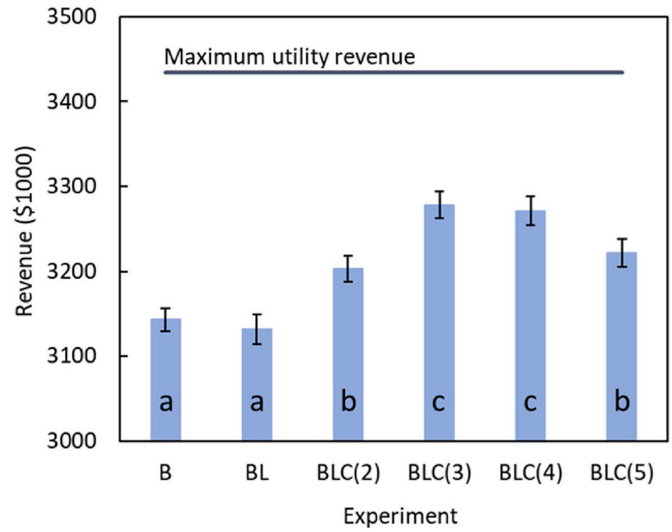

Fig. 2. Present value of utility company's revenue over 10 simulated years (lower-case letters are used to indicate significant pairwise differences between present value of utility company revenue across the six experiments; means that do not share a letter are significantly different).

4.3. Data analysis

As not all of the output data was normally distributed, the Steel-Dwass test (nonparametric version of the Tukey's HSD) was conducted on each pairwise combination of experiments. Error bars in the figures below represent 95% confidence intervals. The results are reported as significant for a significance level alpha < 0.05. When two conditions do not share a letter in the figures, they are significantly different from one another.

5. Results

Fig. 2 compares the present value of the utility company's revenue (in $1000s) over 10 years for each experiment. Present value of utility company's revenue is evaluated using the method described in Section 4.2.1. Utility revenues are the greatest when community solar is available and C_p is 3 and 4 ¢/kWh, with no significant difference in revenues between BLC(3) (M = 3278.3, SD = 55.0) and BLC(4) (M = 3271.1, SD = 59.9), (p = .99). However, the utility's revenue in all six cases is less than the maximum revenue (represented by a horizontal line in Fig. 2) it would have earned if no renewable energy options were available and all agents were forced to purchase wholesale market electricity.

The simulation results were further analyzed to determine the total amount of green power (kW, DC) added to the grid by the rooftop PV and community solar adopters combined. Fig. 3 shows that offering a community solar program at premiums (C_p) of 2, 3 or 4 ¢/kWh yielded the maximum total green power addition, with no significant difference

Table 4
Outputs metrics of interest.

Stakeholder	Metric (unit)	Time of capture
Utility company	Present value of revenue ($1000)	End of each monthly time-step
	Total green power added to the grid (kW)	End of 120 time-steps
	Incremental community solar capacity increase (kW)	End of each monthly time-step
Policymakers	Total adopters (rooftop PV and community solar)	End of each monthly time-step
	Percentage of restricted population participating in renewable energy (%)	End of 120 time-steps
Solar installers	Present value of revenue ($1000)	End of each monthly time-step

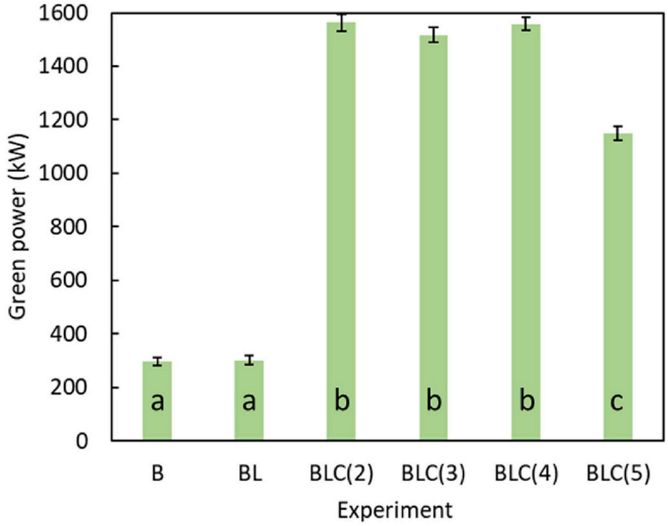

Fig. 3. Total green power (kW) added to the grid in each experiment (lower-case letters are used to indicate significant pairwise differences between total green power added across the six experiments; means that do not share a letter are significantly different).

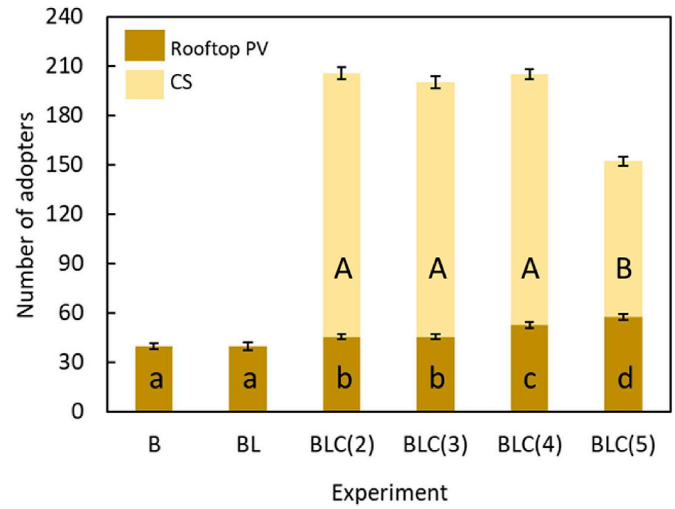

Fig. 5. Total number of rooftop PV and community solar (CS) adopters at the end of 10 simulated years (lower-case and upper-case letters are used to indicate significant pairwise differences between number of rooftop PV and community solar adopters across the six experiments, respectively; means that do not share a letter are significantly different).

in the addition of green power between BLC(2), BLC(3), and BLC(4).

Fig. 4 shows the incremental community solar capacity increases needed each year (kW, DC) to satisfy consumer demand for renewable energy. The capacity increase is high in the first year for the BLC(2) and BLC(3) scenarios but then drops and remains relatively low for the remaining 9 years. In the BLC(4) scenario, this initial spike in required capacity is more evenly distributed between years 1 and 2 but then also drops off from the third year onward.

Fig. 5 shows the number of adopters of rooftop PV and community solar at the end of 120 monthly time-steps for all six experiments. Introducing a community solar program, in addition to offering rooftop PV buying and leasing options (i.e., the four BLC experiments), increased the total number of adopters, compared with offering rooftop PV buying (B) or buying/leasing (BL) only. Fig. 5 also shows that offering community solar increased the number of rooftop PV adopters. This somewhat counterintuitive result is a consequence of an overall increase in the agents' awareness values (AW_i) with the inclusion of an additional renewable energy option. Furthermore, although there were fewer total adopters in BLC(5) than BLC(4), the number of rooftop PV adopters significantly increased (BLC (4): M = 52.5, SD = 6.2, BLC(5): M = 57.5, SD = 6.9), (p < .01), as some consumers preferred rooftop PV over a community solar program with a high premium (C_p).

The cumulative number of adopters (rooftop PV and community solar) each year for all six experiments is shown in Fig. 6. The rate of solar adoption was much higher in BLC(2), BLC(3), BLC(4), and BLC(5) than in the B and BL experiments. The rate of adoption remains fairly constant until the eighth year, after which it begins to decrease in BLC(2), BLC(3), BLC(4) and BLC(5) (also observable in Fig. 4). For example, in the BLC(3) experiment, the percentage of consumer agents adopting solar (rooftop PV and community solar) was 78.3% and 81.6% at the end of 15 and 20 years, respectively.

Fig. 7 shows the percentage of the restricted population (renters, apartment owners, and house-owners that cannot adopt rooftop PV due to structural constraints) participating in renewable energy for all four experiments in which consumers have the option to participate in a

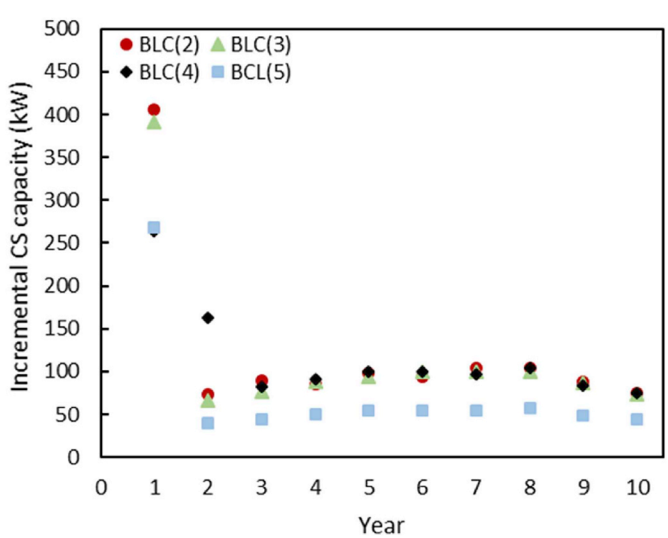

Fig. 4. Incremental community solar (CS) capacity (kW) required to be added by the utility company to meet consumer demand in each experiment.

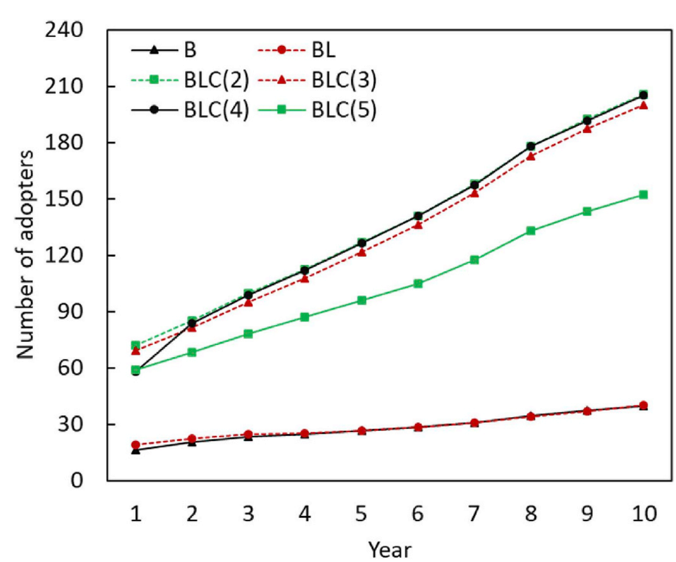

Fig. 6. Cumulative number of rooftop PV and community solar (CS) adopters over 10 simulated years for each experiment.

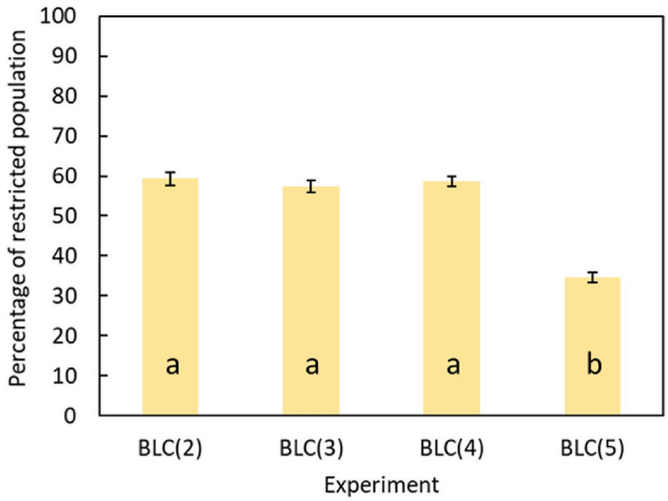

Fig. 7. Percentage of restricted population participating in community solar for the four BLC experiments (lower-case letters are used to represent significant differences in percentage of restricted population participating in community solar across the four experiments; means that do not share a letter are significantly different).

community solar program. Offering community solar at premiums (C_p) of 2, 3 or 4 ¢/kWh results in maximum participation by the restricted population, with no significant difference in the output between BLC(2), BLC(3), and BLC(4).

Finally, the present value of solar installers revenue (in $1000s) over 120 time-steps was captured for all six experiments (Fig. 8). Present value of solar installer revenue is evaluated using the method described in Section 4.2.3. Offering consumers, a rooftop PV leasing option in addition to the buying option (BL) did not significantly increase solar installers revenue (B: $M = 783.4$, $SD = 129.4$, BL: $M = 789.6$ $SD = 160.5$), ($p = .99$). Furthermore, if the utility company offers a community solar program at C_p values of 2 and 3 ¢/kWh (BLC(2) and BLC(3), solar installers revenues do not change significantly. However, when community solar is available at C_p values of 4 and 5 ¢/kWh (BLC(4) and BLC(5)), solar installers revenue increases significantly, as more agents adopt rooftop PV.

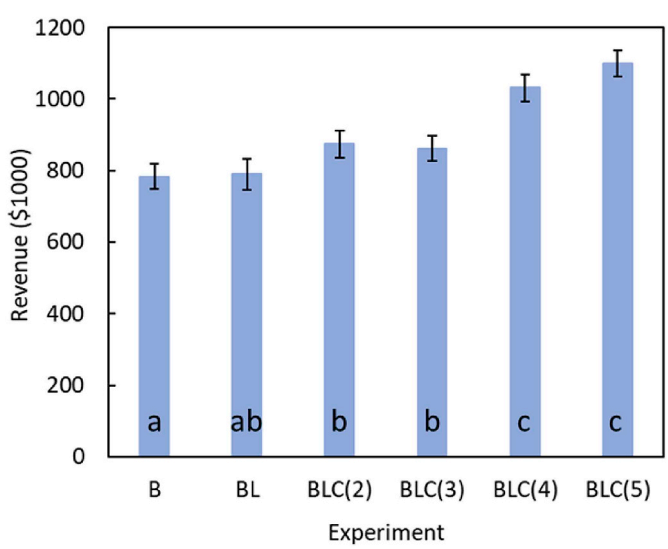

Fig. 8. Present value of solar installers revenue (lower-case letters are used to indicate significant pairwise differences between present value of solar installers revenue across the six experiments; means that do not share a letter are significantly different).

6. Discussion

6.1. Discussion of simulation results

The output from the six experiments provides insight into the degree to which different renewable energy models support the objectives of multiple energy system stakeholders (utility companies, policymakers, and solar installers), while also meeting consumers' demand for renewable energy. The BLC(4) experiment yields the highest utility revenue of all six experiments, which was earned through premiums paid by community solar adopters among the restricted population who otherwise would have been forced to purchase electricity from the utility company at market rates. This enabled the utility company to recover 46% of the revenue losses it experienced due to consumer rooftop PV adoption in the B and BL scenario. The BLC(4) experiment also results in one of the highest amounts of green power added to the grid, which supports the utility's efforts to meet its renewable energy portfolio requirements. Furthermore, the results of the BLC(4) experiment address policymakers' equity concerns, yielding the largest number of residential solar power adopters as well as greatest participation from the restricted population. Remarkably, high rates of community solar adoption in the BLC(4) experiment did not translate into revenue losses for solar installers; in fact, both BLC(4) and BLC(5) experiments yielded the highest present value of solar installers revenue among the six experiments. This result is a consequence of the increased number of social interactions that occurred between potential rooftop PV adopters and the large number of early-adopting community solar participants, such that the awareness of many potential adopters increased in the early time-steps of the simulation.

Alternatively, the utility company could introduce a community solar program at a premium of 3 ¢/kWh (experiment BLC(3)) and achieve the same revenues and green power addition as BLC(4). Experiments BLC(3) and BLC(4) have the same impact on overall solar power adoption and are therefore equivalent in terms of addressing policymakers' equity concerns and satisfying consumer demand for renewable energy. However, over a 10 year period, introducing community solar at 3 ¢/kWh instead of 4 ¢/kWh did not provide any added benefits to the utility company with respect to their objectives but restricted the potential of higher revenues for the solar installers (solar installers revenues were significantly higher in BLC(4) over BLC(3) experiment).

These results demonstrate that, through experimentation, the model enables an exploration of the degree to which different renewable energy offerings could yield mutually beneficial outcomes for all stakeholders. This is a particularly important consideration when certain actions by one stakeholder can negatively impact the others. For example, policymakers predict that increased availability of community solar for residential consumers could rival the rooftop PV market within a decade [57]. Therefore, an important contribution of the system-based modeling approach proposed in this paper is its ability to inform renewable energy model design decisions that avoid benefitting some stakeholders at the unnecessary expense of others.

6.2. Practical significance of the model outputs

Simulation results indicate a consumer agent adoption rate as high as 65%–70% for community solar and rooftop PV after 10 years in scenarios BLC(2), BLC(3), and BLC(4). For these scenarios, the presence of a community solar program provided increased access to solar for the restricted population and for consumer agents that chose not to adopt rooftop PV because of perceived installation complexity and/or risk of moving. Such high adoption rates have been observed in utility territories that have introduced community solar programs for their consumers. For example, within one year of introducing a community solar program, the Cedar Falls Utility in Iowa gained 1200 (around 10% of households) consumer adopters [58,59]. Likewise, a community solar project introduced in Fremont, Nebraska, had 200 adopters (demanding a total capacity of 1.55 MW) within 7 weeks [60]. As utilities transition from centralized generation to more consumer-centric distributed models [61], their ability to achieve high adoption rates can be enhanced by having consumers participate as stakeholders in the energy infrastructure. This is particularly important for cities like Chicago, which has committed to 100% renewable energy by 2035 [62].

The results of experimentation with the conceptual ABM presented in this paper help demonstrate the phenomenon of interdependencies in consumer adoption trends in the presence of different renewable energy models. For example, model outputs indicated that rooftop PV adoption rates may actually increase in the presence of a utility-sponsored community solar option. This phenomenon was observed in the utility territory of Cedar Falls Utilities (CFU), a municipally-owned public utility in northeast Iowa. In an effort to meet consumer demand for solar energy, in 2016 CFU introduced a 1.5 MW community solar program called 'Simple Solar'. CFU initially introduced a 0.5 MW project with each share (i.e., each 170 W panel) priced at $399. However, as a result of strong customer demand, CFU increased the capacity of the project to 1.5 MW, which reduced the cost per share to $270, due to economies of scale. This rate is competitive with that of an equivalent rooftop PV system. As a consequence, the number of new residential rooftop PV installations in CFU's territory initially reduced from five in 2015 to only one in 2016 (the year when the community solar program was introduced). However, the number of customer enquiries on interconnecting rooftop PV with the CFU grid were higher in 2017 than in previous years, with four new residential installations that year [58], likely due to increased awareness among the CFU territory residents about renewable energy.

A mutually beneficial arrangement between energy stakeholders has been observed in practice, as well. Xcel Energy, an investment-owned utility based in Minneapolis, has introduced 169 community solar programs throughout Minnesota to enable consumers become stakeholders in the new energy infrastructure and add capacity to the grid [63]. All of these community solar programs are owned and operated by solar developers or investment companies and are connected to Xcel Energy's system, which provides bill credits to subscribers. Another example of a mutually beneficial partnership between utilities and solar companies is located in New York, which has an aggressive target of meeting 50% of its energy needs from renewable sources by 2030 [64]. The state government has encouraged utilities and solar companies to jointly develop a proposal that would establish distributed energy resources on the grid [65]. The partnership aims to reduce solar installers' risk through increased solar adoption while at the same time ensuring that utilities have sufficient financial resources to manage the grid. Several utilities, including Consolidated Edison Company of New York, New York State Electric & Gas Corporation, and Rochester Gas and Electric have partnered with solar developers like SolarCity and SunEdison to become alternative energy stakeholders [65]. Framing renewable energy policies such that key energy system stakeholders' objectives are aligned can lead to partnerships that increase solar development and consumer participation, as well as improving the electric distribution system.

6.3. Limitations and future research

This conceptual model has several limitations. The model does not consider the potential for future disruptions in the energy sector, such as the introduction of a new renewable energy technology or a sudden drop/rise in electricity prices due to changing fuel prices, which can significantly affect renewable energy adoption trends. The model also has not yet been validated with empirical human behavior data. Finally, as the model was intended as proof-of-concept, some of the assumptions with respect to the agents' decision-making process were implemented rather simplistically. For example, an agent's visual interactions were modeled within a single community, which will be extended in the future version of the model based on the actual locations of the consumer agents.

Future model developments will focus on empirical validation. To develop an empirically informed and validated ABM, an urban area in southern California will serve as a case study in which consumers have multiple renewable energy options. Geospatial and household-level demographic data will be used to inform the model, as well as survey data on consumer adoption behavior and preferences [66]. Model outputs, such as the number of consumer agents adopting distributed solar in a census block group (the smallest entity for which the U.S. Census Bureau publishes the demographic data of its residents) will be compared with historical adoption data for both spatial and numerical validation. Agent-level validation will include a comparison of the demographic characteristics of consumer agents from the ABM and the demographics of actual adopters.

Upon validation, the ABM can be applied to other geographic regions to study consumer adoption of different renewable energy models, given consumer household-level characteristics (e.g., demographics), the serving utility's tariff structure, and available financial incentives. It is important to account for differences in demographics and other factors influencing consumer decision-making across different geographies. For example, community solar projects in different regions of Wisconsin have different subscription rates, despite having similar pricing and payment structures, due to differences in local demographics [67]. The validated model can also be further extended to incorporate other variations specific to certain geographic regions, such as the effect of competition among utilities on their tariff structures in a deregulated electricity market (e.g. the State of Texas in the U.S.).

7. Conclusion

This paper describes an ABM that was developed to predict consumers' renewable energy adoption decisions in the presence of multiple competing models, as well as the effects of these decisions on multiple energy system stakeholders' objectives. Experimental results suggest that, for a renewable energy system to be successful and sustainable in the long term, design decisions should be made with consideration given to the objectives of all key system stakeholders, including utilities, solar installers, and policymakers, as well as the heterogeneous preferences and objectives of consumers. The results also demonstrate how mutually beneficial partnerships between stakeholders (e.g., utility companies and solar installers) and alternative renewable energy models (e.g., community solar program) can help to sustain equitable renewable energy systems.

The conceptual agent-based model described in this paper serves as a starting point for the development of an empirically validated model. Once validated, the model can be used by different stakeholders to help them determine appropriate values for their respective business model parameters. In particular, it could serve as a decision support tool for utility companies and enable them to assess the ability of different alternative renewable energy model structures to satisfy customer demand for solar-based electricity and maintain their renewable energy portfolios and revenues. Similarly, the model can be used to test the effect of varying policy incentives, such as tax benefits, on adoption patterns. The validated model can be used as a tool by solar installers to find their next customer, given behavioral and decision-making attributes. Finally, the model can help policymakers to gauge the likely effects of different policies on improving equitable adoption of renewable energy among consumers.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2019.06.034.

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