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An agent-based approach to study the diffusion rate and the effect of policies on joint placement of photovoltaic panels and green roof under climate change uncertainty

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HIGHLIGHTS

- We investigate the diffusion of green technologies under uncertainties.
- Uncertainties from both climate change and human behaviors are considered.
- We develop an integrated framework for stochastic programming and agent-based models.
- We conduct a case study over a mid-sized city in the U.S.
- We evaluate the effects of promotional policies on the diffusion rate.

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ABSTRACT

As two of the highest trending green technologies, photovoltaic panels and green roofs are proven to be effective practices for energy generation and energy saving. The achievable impact from the widespread installation of such technologies is, however, not clearly established. This is mainly because the degree of this impact highly depends on the inherently uncertain environmental and climate factors, as well as the unknown adoption rates of these technologies, which in turn depend on different characteristics of decision makers and interactions among them. To that end, this study aims to investigate the diffusion rate of these green technologies under uncertainties caused by climate change, characteristics of adopters, and their interactions. An integrated framework is developed to capture the interplay between financial and attitudinal aspects, as well as the uncertainties due to both the stochastic nature of system parameters and the interactions among agents involving human beings. Specifically, this framework consists of a integer programming model to optimize the green roof and/or photovoltaic panel installation settings for a given building under climate change uncertainty, and an agent-based model to factor in the role of human behavior and interactions. A case study for the city of Knoxville, TN, is presented to evaluate the effects of different policies on the diffusion rate of the green technologies of interest. The results show that the affordability of green technologies and public awareness are the key drivers of the adoption of these technologies, which highlight the important role of the decision makers in impacting the diffusion rate.

1. Introduction

The utilization of renewable energy (RE) sources and the implementation of energy efficient (EE) practices have been a key factor in developing more sustainable economies and societies, reducing pollution and mitigating the effects of climate change. The adoption of new, cleaner technologies still remains a major challenge to policymakers [1] and is proven to be a time-consuming task, even with the commercially-available technologies [2]. Such issues have led governments over the world to take different measures in order to increase the adoption rate of RE and EE practices, either through regulations or incentives. In the past few years, policymakers have passed several laws and regulations to foster the global rate of implementation of RE and EE practices. For example, the French parliament has made the installation of green roofs (GR) and photovoltaic (PV) panels mandatory for all the new buildings in commercial zones across the country [3]. The city of San Francisco

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legislation requires between 15% and 30% of the rooftops of new buildings in most new construction projects to be covered by PV panels, GRs, or a combination of both [4]. A similar law has been passed by the city of Denver, which requires all the buildings over 25,000 square feet to include GRs, PV panels, or a combination of both [5]. As of 2019, the most recent (and most comprehensive) regulation regarding green technologies has been passed in California, which makes the installation of PV panels mandatory on every new building, effective 2020 [6].

While such regulations help to increase the diffusion and adoption rate of RE and EE practices, they are mostly considered insufficient as many of them only affect new *commercial* buildings and none of them affect currently *existing* commercial and residential buildings. Moreover, some claim that such regulations can negatively impact the competitiveness in society [7]. Hence, studying the diffusion rate of green technologies and the effect of *promotional policies* on their diffusion rate becomes increasingly important. In this section, some basic information on two of the most popular green technologies, i.e., PV panels as a RE source and GRs for EE practices, is presented. Next, the role of climate change on the outcome of the mentioned green technologies is investigated. Lastly, a literature review on currently available diffusion models and policy evaluation studies, as well as the contributions of this study are provided.

1.1. Photovoltaic panels and green roofs

PV panels, considered as the fastest growing renewable energy [8], and GRs, i.e., rooftops covered with a vegetative layer, have gained increasing attention over the past few years as two of the most important green technologies in the development of more sustainable societies [9]. PV panels harness solar irradiation and turn it into electricity, through which affordable electricity can be generated in both utility and residential levels. Over the past few years, the installation rate of PV panels has been steadily increasing due to the decrease in their cost, increase in their output, as well as state and federal incentives [8]. There is an abundant body of literature with a focus on PV panels from different perspectives (e.g., technological aspects such as underlying materials or cell technology [10,11]), best placement options of PV arrays [12], and optimal placement of PV systems [13]). GRs can provide numerous benefits to the environment where they are installed (namely, heat island mitigation [14], energy savings [15], and storm-water runoff reduction [16]). Different studies have assessed achievable benefits through the installation of GRs, indicating that savings of 7 to 10 billion USD can be obtained by the widespread installation of GRs throughout the U.S. [17]. GRs have also been thoroughly studied for their energy saving properties, proving their capability to provide savings of up to 16% of the energy consumed for space conditioning during cooling degree days. However, the reported values for such savings during heating degree days range between −10% to 10% [18–21].

PV panels rely on solar irradiation to generate electricity, which adversely affects their output due to increasing the surface temperature of the panels. The output efficiency of PV systems approximately decreases by 0.5% for every 1 °C increase in the surface temperature of PV panels [22]. This issue can be mitigated through the integration of PV panels and GRs. That is, GRs reduce the temperature of their surrounding environment, thus reducing the surface temperature of PV panels, leading to an increase in the output efficiency of PV systems. Several empirical studies have focused on the integration of PV panels and GRs to evaluate PV panels' output efficiency and GRs' benefits as a direct result of their cooling effect on the surrounding environment [23].

1.2. Climate change

The current increasing trend of the Earth's temperature and climate change is widely believed to be a direct result of human activity [24]. Studies claim that at the current pace, by the end of the century the average global temperature will rise by up to 5.8 °C [25,26]. This fact becomes important to our study as the output of PV panels and GRs are directly affected by the changes in temperature and precipitation. That is, while various studies agree that GRs reduce the level of energy consumption for the buildings underneath them in cooling degree days, some studies claim that GRs lead to a higher level of energy consumption during heating degree days. The electricity output of PV panels directly relies on the level of solar irradiation to which they are exposed. Hence, higher levels of precipitation, which can roughly be considered as more frequent rain and consequently less peak sunlight hours, results in lower levels of electricity output from the panels. In this study, we include the changes in the outputs of PV systems and GRs as a result of climate change by considering ten different climate forecasting models provided by the Oak Ridge National Laboratory's (ORNL) Urban Dynamics Institute (UDI) [27] and Oak Ridge National Laboratory's Climate Change Science Institute (CCSI) [28].

1.3. Agent based modeling and diffusion models

Studies about technology diffusion and the effect of policies, social interactions, and economic factors started from the pioneer papers of Hagerstrand [29] and Rogers [30], and have been carried out for various products and technologies [31–33] to the present [34,35]. In the literature, diffusion models are often studied via agent-based modeling (ABM), defined as a system of agents (autonomous elements) which can be described as identifiable discrete goal oriented autonomous entities holding a certain set of characteristics [36]. Agents are capable of interacting with other agents inside their environment, and making individual decisions based on their current state and interactions considering a set of rules set by the environment in which they exist and interact with one another [9]. ABMs have been studied over a wide range of different problems such as social sciences [37], marketing [38] energy [39], and economics [40]. ABMs are well-designed to study systems made up of individual decision makers to evaluate and forecast the outcomes of problems that rely on the interactions among agents as well as their individual traits [41], namely the diffusion rate of green technologies.

Many studies have investigated the diffusion rate of green technologies through the implementation of ABMs while taking different approaches. For example, Bollinger and Gillingham [42] and Graziano and Gillingham [43] emphasize the role of communication, visibility of technologies, and social media in the adoption rate. Another group of studies, such as Palm [44] and Gillingham and Bollinger [45] have focused on the importance of peer effect on the adoption rate of new technologies. Other green technology diffusion studies have explored different aspects of the problem. For instance, Robinson and Rai [46] have studied this subject through the geographic information system (GIS). Zhao et al. [47] have taken the perspective of a utility company to study the diffusion rate of plug-in hybrid electric vehicles and PV systems, and Mittal et al. [48] evaluated a utility company's expansion plan through the installation of distributed PV systems.

Evaluation of the effects of promoting policies on the adoption rate of green technologies has been the subject of numerous ABM studies. For instance, Zhao et al. [49] have investigated the potential of investment tax credit and feed in tariffs in their study. In another study, Dong et al. [50] have investigated the effect of different policies, such as federal investment tax credit and California net energy metering policy on the residual PV panel installation in California. In the study conducted by Adepetu and Keshav [51], the authors have explored the effects of different policies on the adoption rate of integrated PV panels and battery systems in the city of Ontario, concluding that the best policy to encourage households to develop PV systems is to reduce the implementation cost.

The diffusion models are generally centered around two main aspects, i.e., attitudinal and/or financial. For the attitudinal aspect, studies often rely on available historical data of adoption rates for the green technologies in the region where they have conducted the study. The financial aspect, however, has been taken into account differently in different studies. That is, while studies consider the diffusion rate of these green technologies based on the behavior of the agents in the system, as well as accounting for the financial returns from developing such technologies in a direct form, they approach the integration of financial and behavioral aspects differently. Studies mainly include both behavioral and financial aspects simultaneously [42], mainly in forms of a constraint which is added to the behavioral model. However, a number of studies include two parallel models where one focuses on the behavioral aspect and the other focuses on the financial output of the green technologies [52]. While both approaches account for the financial aspect of the studies, the parallel incorporation of two different models provides more opportunities to study each aspect in a more detailed and comprehensive fashion. For instance, Rai and Robinson [52] presented an empirically driven agent-based model for technology adoption with an application in residential PV systems through the development of two different sub-models, i.e., financial, and attitudinal sub-models. In another study, Dong et al. [48] provided an ABM that evaluates the incorporation of consumer-adoption of distributed PV systems in a utility company's expansion plan by considering three sub-models, i.e., attitude assessment, financial assessment, and decision. Zhao et al. [49] developed a decision support tool to evaluate the effectiveness of different policies (i.e., incentives and regulations) on the growth rate of PV systems using a two-level framework, where the lower-level model calculates the PV systems' payback for each individual household, and the higher-level model considers a broader time-step and studies the household adoption behaviors.

In this study, an agent-based framework that integrates two parallel sub-models, i.e., behavioral and financial sub-models, is developed. Then, the outputs of the model are evaluated using a case study over the city of Knoxville, TN. Note that the behavioral models mainly rely on historical data from the adopters over the region of the study. According to the Google Project Sunroof [53], there are approximately 78 installed PV systems over the city of Knoxville, including the systems installed by the University of Tennessee, Knoxville, for research purposes. Google Project Sunroof [53] also shows that 83% of buildings in the city of Knoxville (from approximately 209,000 buildings [54]) are solar viable (they receive a minimum of 75% of maximum solar irradiation for the county). These numbers indicate that there exists a great potential for PV system utilization throughout the city of Knoxville. However, due to the limited number of installed PV systems and lack of historical data, it is not possible to develop a behavioral model based on historical behavior and diffusion rate of PV systems in the city of Knoxville (a similar study over the city of Knoxville for personal hybrid electrical vehicles resorted to synthetic data generation due to the lack of data availability [55]). Hence, the behavioral sub-model used in this study as an integrated part of the developed framework is adopted from the existing literature.

While the existing studies have incorporated the profit gained by green technologies or their costs in some fashion, none of them accounts for the uncertainty due to the nature of input parameters as a result of climate change and its effects on the performance and output of these technologies, nor do they include multiple green technologies while considering the potential outcomes due to their integration. In order to account for the stochastic output of PV panels and GRs, as well as the role of climate change in the achievable potential profit from such practices, this study evaluates the output of PV panels and GRs over the next 20 years from the day of installation while considering 10 different climate projection models provided by UDI [27] and CCSI [28]. The developed optimization model focuses on the changes in the adoption rate of PV panels and/or GRs as a result of promotional policies while incorporating different climate scenarios (in which climate change has been accounted for) to calculate the potentially achievable income from the installation of green infrastructures throughout their lifespan. A mathematical optimization model is developed to find the best setup through which candidate sites can maximize their income from the installation of the green technologies, i.e., PV, GR, and GR integrated PV. Note that the model aims to maximize the profit from these technologies; therefore, if they are not financially profitable, no green technologies will be installed.

The main contributions of this study are as follows: (*i*) This study accounts for multiple green technologies with inherently different structures and the interactions among them; (*ii*) It provides an ABM framework to capture the interplay between financial and behavioral sub-models, as well as the uncertainties that arise due to climate change and human behaviors; and (*iii*) it evaluates the effects of several stochastic components on the diffusion rate of green technologies in a case study.

The remainder of the paper is organized as follows. Section 2 thoroughly describes the developed model to cover the financial aspect of the diffusion model. Moreover, a description of different behavioral models, as well as the model adopted from the existing literature is provided. Finally, an agent-based framework, entailing the mathematical and diffusion sub-models to study the effect of promotional policies on the adoption rate of the green technologies, is developed. Section 3 provides the model calibration and description over the parameters used in the model. Next, Section 4 presents the results from a case study over the city of Knoxville, TN, as well as sensitivity analysis and policy evaluation. Section 6 provides high level insights, investigates the future opportunities for research, and discusses the study limitations. Lastly, Section 7 provides the conclusions from the study.

2. Methods

In this section, the structure of our ABM framework, as well as its underlying components are presented. Two separate models, i.e., financial and attitudinal, are developed in which both financial and behavioral aspects of the model are accounted for. In the following, Section 2.1 first introduces the mathematical model developed to calculate the potential outcome from the installation of PV panels and GRs. Then, Section 2.2 introduces the attitudinal model that is adopted from the existing literature. Finally, Section 2.3 discusses the structure of the ABM framework.

2.1. Financial model

Section 1 introduces a number of studies in which some models are developed to calculate the payback and financial profitability of different green technologies. However, these studies do not assume any uncertainty in the outcome of the green technologies as a result of the stochastic nature of them. That is, studies often assume that the level of generated electricity by PV panels is given for each agent, thereby not accounting for any sort of uncertainty (e.g., climate change), the availability of different packages for each agent, and multiple green technologies and their interactions (PV panels, GR, and GR integrated PV panels). Moreover, they do not account for the changes in the cost efficiency of the PV systems. In order to tackle these shortcomings, this section presents a mathematical model that accounts for the climate change uncertainty as well as other factors.

The mathematical model developed in this study calculates the direct potential income from the installation of PV panels and/or GRs for a single building, while accounting for climate change and interaction between PV panels and GRs. An integer programming model is developed with the intent to find the optimal settings that maximize the profit gained from the installation of PV panels and/or GRs for an individual building, while considering the solar irradiation and shading of that building. Each building is offered a set of available green technologies consisting of a combination of PV panels and GRs that can be installed over them. The available packages used in this study are

Table 1
Model notations for financial sub-model.

Index	Description	Level
Sets		
t	Day index, where $t \in [0, T]$ and T representing the length of the planning horizon	Environment
p	Green technology package index, where $p \in P$	Environment
ω	Climate scenario index, where $\omega \in \Omega$	Environment
Variables		
x_p	Binary variable, which equals to 1 if package p is installed, 0 otherwise	Household
Parameters		
C_p	Installation and maintenance cost of package p (USD)	Environment
μ	Cost of 1 kWh of electricity from the grid(USD)	Environment
π_p	Potential income achieved through installation of package p (USD)	Household
O_p^ω	Potential level of total electricity output through installation of package p under the climate scenario ω (kWh)	Household
S_p^ω	Potential level of total energy saving through installation of package p under climate scenario ω (kWh)	Household
η^ω	Realization probability of climate scenario ω, where $\sum_\omega \eta_\omega = 1$	Environment
$I^{\omega t}$	Daily solar irradiation available during day t under climate scenario ω (kWh/m^2)	Grid
A_p	Total area of PV arrays for package p (m^2)	Environment
E_p^t	PV output efficiency for package p during day t (%)	Household
α_p	Energy saving percentage from GR installation in cooling degree days for package p (%)	Environment
β_p	Energy saving percentage from GR installation in heating degree days for package p (%)	Environment
$\tau_c^{\omega t}$	Indicator of cooling degree days in climate scenario ω, which equals 1 if t is a cooling degree day, 0 otherwise (days)	Grid
$\tau_h^{\omega t}$	Indicator of heating degree days in climate scenario ω, which equals 1 if t is a heating degree day, 0 otherwise (days)	Grid
U^t	Daily energy consumption for space conditioning for the building in day t (kWh)	Household
H	Total area of the household (m^2)	Household
λ	The performance ratio of the PV system, where $\lambda \in [0, 1]$	Environment

further described in Section 3. Table 1 presents the notations used in the financial sub-model.

The objective function of this model is to maximize the level of potential profit achievable through the installation of packages over a building,

$$\max Z = \sum_{p \in P} (\pi_p - C_p) x_p, \tag{1}$$

subject to

$$\sum_{p \in P} x_p \leqslant 1, \tag{2}$$

$$\pi_p = \sum_{\omega \in \Omega} \eta^\omega [O_p^\omega + S_p^\omega] \mu, \qquad \forall\, p \in P, \tag{3}$$

$$x_p \in \{0, 1\}. \tag{4}$$

Eq. (2) guarantees that at most, only one package is assigned for installation over a building. Eq. (3) calculates the achievable income through energy generation and/or saving via installation of each package over all the probable climate scenarios. Eq. (4) imposes the binary restriction for variable x_p. In order to assess the achievable level of electricity generation for each package, Eq. (5) calculates the potential electricity generation for each package based on the level of solar irradiation available, the size of the package, and its output efficiency under each climate scenario,

$$O_p^\omega = \sum_{t \in T} I^{\omega t} A_P E_p^t \lambda \qquad \forall\, p \in P, \omega \in \Omega. \tag{5}$$

The level of energy saving achieved by installation of each package due to GR energy reduction properties is calculated by Eq. (6),

$$S_p^\omega = \sum_{t \in T} (\alpha_p \tau_h^{\omega t} + \beta_p \tau_c^{\omega t}) U^t, \qquad \forall\, p \in P, \omega \in \Omega. \tag{6}$$

Different levels of energy saving are considered during heating and cooling degree days, which are described thoroughly in Section 3.

2.2. Attitudinal model

Studies have shown that while the economical aspect of a model plays a vital role in maintaining the diffusion rate of green technologies, the behavioral aspect of adopters also has a significant impact on the results. This section introduces the behavioral model for this study which is developed based on the models in the existing literature. In order to incorporate the behavioral aspect of the agents in this study, due to the limitations mentioned in Section 1, the authors opt to adopt the behavioral model from the literature with a focus on the studies that have a similar framework structure, i.e., attitudinal models which seek to define the underlying structure of agents' behaviors toward the adoption of new technologies based on their characteristics such as demographics, profitability of the technology, social status, and interactions with other agents.

The changes in agents' behavior and their magnitude as a result of interactions among the agents in a system is mainly studied through the implementation of a set of rules and regulations, either developed based on the subject of the study or through the adoption of theories developed from different fields of science [36]. Such theories mainly have their roots in psychology and social sciences, such as the Theory of Planned Behavior [56], Diffusion of Innovation [57], Tit for Tat [58], and Relative Agreement [59]. Nevertheless, there exists a number of models that have emerged based on the theories in other fields of science, namely the Ising model which has its roots in the field of physics [60]. In the present study, the main structure of the attitudinal model is based on the Theory of Diffusion of Innovation (TDI) by Rogers [57]. This theory emphasizes the fact that while the diffusion of a technology relies considerably on the technology itself, one must take into account the effect of the communication channels, time, and social system. While studying the adoption of new technologies, TDI divides agents into three major groups, i.e., non-adopters, potential-adopters, and adopters [61]. The main difference between non-adopters and potential-adopters is in the fact that potential-adopters are agents who consider adopting green technologies, and are mainly restrained by the financial outcome of them. Non-adopters, on the other hand, do not consider the adoption of green technologies even if they are financially profitable. In order to assess the overall behavior of each agent toward

Table 2
Common social networks utilized in the literature for ABM [98].

Social network	Description
Fully Connected	Homogeneous network in which each agent is connected to all other agents in the network.
Random	Agents are randomly connected to other agents in the network based on a given probability, independent of other agents in the network.
Regular Lattice	Agents are connected to other agents in the network only based on a distance threshold.
Ring Lattice	Distance based connection of the agents within a given distance threshold, forming a ring.
Small World	A Ring Lattice network which also includes a number of long-distance connections. This includes strongly clustered isolated networks that are also connected with other isolated networks based on a given probability.
Scale Free	The majority of the agents have a small number of connections while some agents have a large number of connections (hubs).

the adoption of green technologies, three different models, developed by Rasoulkhani et al. [62], Lee and Hong [63], and Zhao et al. [49], are evaluated in this study. The model, developed by Rasoulkhani et al. [62], is mainly designed to study the adoption of new water-saving technologies and considers variables, such as garden and pool size, which are not considered as key factors when studying technologies such as PV systems. Lee and Hong [63] developed a behavioral model mainly to evaluate the outputs of PV systems and focus on the level of solar irradiation received by the household which makes the model unfit for studying technologies such as GRs, which do not necessarily benefit from such factors. The current study focuses on the model developed by Zhao et al. [49] in which they use a linear regression model to calculate the probability of a household adopting solar panels, denoted by ρ. The independent variables in the linear regression are the potential income of the technologies which are accounted for in the calculation of the payback period, the characteristics of the household which is considered in the number of residents of each household, as well as the average income of the household. Moreover, the visibility of the green technologies is also considered in the developed regression model through the inclusion of the total number of advertisements received by the residents of the household. This linear regression returns a value between 0 and 1, indicating how likely an agent is to adopt green technologies. This is ideal for the purpose of this study as not only the regression model accounts for different aspects of green technologies, but it generates the resulting value in a scale which is easy to interpret while calculating the values for the parameters related to the ABM framework, namely, opinion and uncertainty. Note that by considering the profitability of the green technologies through calculating the payback period, this model can evaluate green technologies, such as GRs and PV systems, hence making it a suitable fit for the scope of this study. A more thorough description of the regression model and its components is provided in Section 3.

2.3. ABM framework

In this section, the ABM framework developed here to study the adoption rate of the green technologies is presented. Three different agent types are considered, i.e., candidate sites, green technology packages, and zip codes. Each candidate site is assigned to a zip code, based on their coordinates, and a number of characteristics of the candidate site (parameters) are assigned based on their relative zip code. This is mainly to provide an estimate for the parameter values that are not available in the household level. For instance, parameters such as building size or level of solar irradiation received by each building are provided by UDI [27] and CCSI [28] in the household level, whereas, for characteristics such as property value, the average age of the residents, and income level, the median values reported for their relative zip codes are used. The parameters of the model are set by the environment and are updated as the time passes or new regulations are introduced into the model. At the beginning of each time-step, the package with the maximum potential profit over the next 20 years is chosen using the model presented in Section 2.1. Based on the behavioral model in Section 2.2, for each agent to adopt a green technology, two main criteria must be met: 1) the green technology should be profitable (including the incentives and tax-cuts), and 2) the opinion of the agent should surpass a certain global threshold (ϕ_{global}). The attitudinal sub-model also takes the characteristics of the agent into consideration by calculating ρ. The attitude of the agents changes over time, as well as their demographics. While the demographics change over time, the attitude is changed due to agents' interactions inside their network with other agents. While some of the changes in demographics over time are easy to calculate, some cannot be tracked without certain assumptions. For example, the average age of residents in a household cannot be predicted without making the assumption that residents in these households do not change over time. Hence, consistent with the existing literature [62,52,49], we make the assumption that the demographics of the agents remain unchanged over the time of the study, as well as the assumption that when an agent installs a green technology, they do not consider installing green technologies anymore.

Social network structures are mainly used to define the patterns through which agents interact with one another, mainly to calculate the changes in the attitudes of agents over time. In Table 2, we provide a number of common network algorithms currently being utilized in the literature. In order to simulate the interaction among agents, we use the Small World network proposed by Watts and Strogatz [64]. The Small World network configuration contains locally clustered networks where the average path lengths between nodes in the network are reduced using randomly rewired links. Algorithm 1 shows the pseudo-code for the Small World network algorithm. In this study, P_{sw} and K_{sw} denote the probability and number of connections in the Small World network, respectively.

Algorithm 1. Pseudo-code Small World network algorithm used to connect the agents in the ABM framework.

Set the set of agents N
Set the rewiring probability P_{sw}
Set the node degree K_{sw} where $N \gg K_{sw} \gg logN \gg 1$
for all $i \in N$ **do**
  Connect to the nearest K_{sw} nodes
end for
for all $i \in N$ **do**
  for all $j \in (1, K_{sw})$ **do**
    $j_i \leftarrow$ agents connected nodes to j
    $r \leftarrow Unif(0, 1)$
    if $r \leqslant p$
      Select $m \in N \setminus \{j, j_i\}$
      rewire j to node m
    end if
  end for
end for

Using the social network structure, the ABM framework simulates the interactions among agents and calculates attitude and income model for each agent while accounting for over time evolution of the variables in the environment of the simulation. Based on the Small World network, each agent interacts with a number of other agents in the network through their local and global networks. The local network is based on the physical distance of the agents from one another, where the threshold for distance or the number of connections are given as inputs for the environment of the model. Through the interactions with other agents, the opinion of each agent changes. To calculate the level of changes in agents' behavior, this study uses the Relative Agreement (RA) algorithm developed by Deffuant et al. [59]. In RA, an agent randomly interacts with another agent in its network. Then, each agent, based on their opinion and their uncertainty, updates its opinion as a result of the new information they obtain through these interactions. Hence, each agent holds two characteristics: opinion, ϕ_i, and uncertainty ζ_i, where opinion ranges between -1 and 1, and uncertainty ranges between 0 to 2 [65]. The RA between two agents i and j is calculated as

$$\mathrm{RA}_{ij} = \frac{h_{ij}}{\zeta_i} - 1, \tag{7}$$

where h_{ij} denotes the overlap between the two agents' bounds and is calculated as

$$h_{ij} = min(\phi_i + \zeta_i, \phi_j + \zeta_j) - max(\phi_i - \zeta_i, \phi_j - \zeta_j). \tag{8}$$

Then, for positive values of RA between two agents i and j, an agent's opinion and uncertainty is updated, i.e.,

$$\phi_j := \phi_j + \xi \cdot RA_{ij} \cdot (\phi_i - \phi_j), \tag{9}$$

and

$$\zeta_j := \zeta_j + \xi \cdot RA_{ij} \cdot (\zeta_i - \zeta_j), \tag{10}$$

where ξ is a parameter defined by the environment of the ABM that is responsible for controlling the speed of population convergence. Note that in this way, agents with vastly different opinions are unlikely to affect one another. It is important to consider that agents' opinions evolve over time based on the changes in their behaviors due to interactions with other agents, and hence, two agents with vastly different opinions have the possibility to affect one another as time progresses and their opinions evolve. If an agent's opinion surpasses the global threshold, i.e., ϕ_{global}, the agent turns into a potential adopter, and the installation of green technologies takes place only if they are profitable.

In order to calculate the agent's opinion, ϕ, and uncertainty, ζ, this study utilizes the results from the attitudinal model, i.e., ρ,. In this study, it is assumed that those with a value of $\rho = 1$ hold an extremely positive opinion towards green technologies, i.e., $\phi = 1$, while those with a ρ value of 0 hold an extremely negative opinion, i.e., $\phi = -1$, and those with a value of $\rho = 0.5$ are neutral toward the green technologies, i.e., $\phi = 0$. Eq. (11) shows the formulation used to calculate the opinion for each agent, i.e.,

$$\phi = 2(\rho - 0.5). \tag{11}$$

Studies have demonstrated that those who hold a more extreme opinion toward a subject have lower levels of uncertainty [52]. In this study, the uncertainty for each agent is calculated based on their opinion. That is, the agents who have absolute opinion values of 1 are assigned an uncertainty of 0, while those with an opinion of 0 have uncertainties equal to 2, i.e.,

$$\zeta = 2(1 - |\phi|). \tag{12}$$

Fig. 1 represents the structure of the ABM framework used in this study.

3. Model calibration

In this section, the values reported in the literature, along with experts' opinions and publicly available datasets as well as data sets provided by UDI [27] and CCSI [28] are used to calibrate the model formulated in Section 2.1.

Planning horizon, T. This study considers a planning horizon of 20 years since the currently commercially available PV systems generally have a lifespan of 20 to 30 years [66] while GRs last about 30–40 years [67,68].

Green technology packages, P, installation and maintenance cost of package p, C_p, and total area of PV arrays for package p, A_p. The focus of this study is residential and small commercial PV systems with a size ranging between 2 kW and 10 kW [66]. Hence, five different PV system sizes with two different output efficiency levels of 15% and 20% are considered, where each PV system is offered with and without GRs. Note that installing stand-alone GRs is also another available option. This results in 21 different packages, which are offered to each agent, with their relative costs presented in Table 3. The GR installation cost is directly related to its size. That is, GRs cost approximately \$12.5 per m^2, while it costs \$7.5 per m^2 for GRs larger than 929 m^2 [69]. Hence, the cost of GR installation for each agent is calculated based on its rooftop size. SPR [70] report that for PV systems with output efficiency values of 15% and 20%, each 15 Watts and 20 Watts have an area of 0.093 m^2, respectively, based on which the total area of PV arrays for package p, A_p, presented in Table 3, are calculated. Ramshani et al. [71] state that the annual maintenance costs for PV panels range between 15 to 90 cents per m^2, while extensive GR maintenance cost is negligible. Hence, an annual cost of 90 cents per m^2 is assigned to the packages that include PV systems.

Table 4 shows the per Watt price of installed PV systems from 2014 to 2018. In order to account for the changes in this study, a linear regression model is fitted to the cost per Watt of PV systems. Note that no new green technology packages are offered in this study, but the cost of currently existing packages changes in time to capture the existing trend in the overall cost of PV systems. Fig. 2 shows the linear regression model fitted to the data presented in Table 4.

Climate scenarios, Ω, indicator of cooling degree days in climate scenario ω, $\tau_c^{\omega t}$, indicator of heating degree days in climate scenario ω, $\tau_h^{\omega t}$, and realization probability of climate scenario ω. The values of these parameters are calculated using the climate forecasts provided by UDI [27] and CCSI [28]. The climate forecasts are generated using 10 different coupled general circulation models (GCMS) [72], and include daily values for maximum and minimum daily temperatures, as well as precipitation levels for each day starting from January 2011 up to December 2050 for grids of 1 km^2 and 4 km^2 for the city of Knoxville, TN. In this study, the climate projections from the ten different CGCMs listed in Table 5 are used as the climate scenarios and are assigned an equal realization probability, i.e., 10%. Note that this study considers a planning horizon, T, of 20 years, starting from January 2011.

In order to provide a higher level of details on the projection models used in this study, Table 6 presents the maximum, average, and range of standard deviation for daily pairwise comparisons across the ten climate projections. That is, the absolute values of the differences between the projections for each two pairs of climate models over the given planning horizon are calculated. Then, the average of the differences over all of the pairwise comparisons is calculated and shown in the average column of the table. The maximum column shows the maximum value observed over all the pairwise comparisons. Also, the standard deviation range column shows the range of standard deviations calculated for each pairwise comparison for the values reported in the average column. The results shown in the table highlight the existing variations in the projected values. In this study, to classify each day as a cooling/heating degree day, cut-off values are used. First, the average daily temperature is calculated by taking the average of the maximum and minimum daily temperature. Then, the recommended temperatures for human comfort in the literature i.e., 17.5 and 14.2 degrees Celsius for cooling and heating degree days, respectively [73–75], are used as cut-off thresholds to classify each day as a cooling/heating day. Note that the days with an average temperature that falls between the two thresholds are neither a cooling nor a heating degree day.

Cost of 1 kWh electricity from the grid, μ. In this study, it is assumed

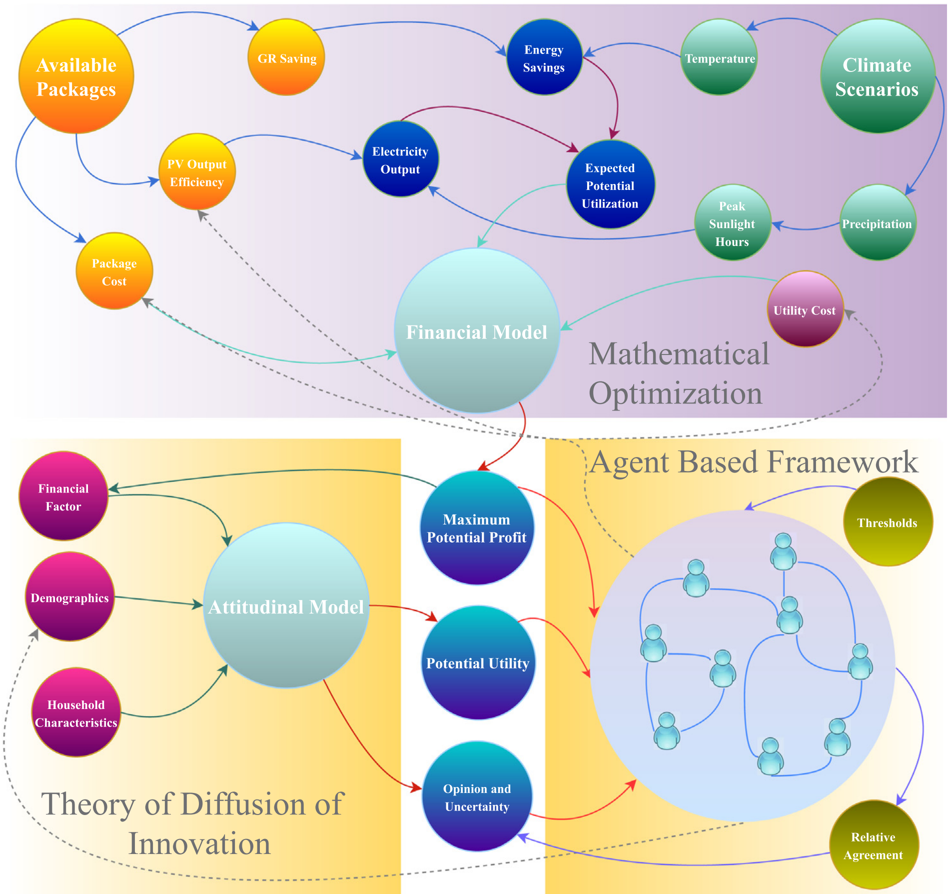


Fig. 1. The structure of the proposed framework, including the Attitudinal and Financial model as well as the ABM. The dashed lines indicate the feedback from interactions and time evolution of model variables which originate from the ABM and is fed to the models.

Table 3
The cost for different PV system sizes in USD for southern U.S. for two different panel output efficiencis of 15% and 20% [66].

PV system size (kW)	15% efficiency		20% efficiency	
	Cost (USD)	Area (m^2)	Cost (USD)	Area (m^2)
2	5,900	12.39	6,800	9.29
3	9,000	18.58	10,200	13.94
4	12,000	24.77	13,500	18.58
5	15,000	30.97	17,000	23.23
10	30,000	61.94	34,000	46.45

Table 4
Price for per Watts installed PV systems from 2014 to 2018 reported by Energy Sage [99].

Year	2014		2015		2016		2017		2018	
	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2
Cost (USD/ Watts)	–	3.86	3.79	3.69	3.57	3.36	3.17	3.13	3.12	3.05

that net metering is available for the agents. Net metering allows agents to send the extra electricity generated to the grid at normal retail value and receive credit for it, which is commonly supported by most utility providers in the U.S. [76]. The agents can later consume the electricity provided by the grid equal to the credit they received without any payments. The cost of electricity is set equal to 10.3 cents per kWh consistent with the price of electricity in the city of Knoxville, TN [77].

PV output efficiency for package p during day t, E_p^t. NREL [78] reports that in the past 40 years, PV cell output efficiency experienced a constant increase and recently developed PV cells have an efficiency ranging between 11.5% and 46%. However, the current commercially available PV cells have an output efficiency ranging between 13.5% and 20% [79]. Hence, in this study, a variety of PV packages are considered with efficiencies ranging between 13.5% and 20%. During each day t, the output efficiency of each package is calculated based on the average temperature during that day using Eq. (13),

$$E_p^t = \begin{cases} E_p(1.091 + 0.0013\mathbb{T}_t) & \text{if package } p \text{ contains GR} \\ E_p & \text{o. w. ,} \end{cases} \tag{13}$$

where $\mathbb{T}_t$ denotes the average daily temperature for the grid in which the building is located, and E_p denotes the output efficiency of the package. In Eq. (13), the output efficiency of the installed PV package increases only if it is integrated with GRs. The level of increase in output efficiency of PV panels, due to integration with GRs, have been subject to empirical investigation, and the reported values range from 3.33% to 8% [80,81]. Note that the reason for this output efficiency increase is the reduction in GRs' temperature of their surrounding region. Hence, the higher the temperature, the greater the cooling effect and the higher the efficiency increase. In order to capture this relationship, a linear regression is fitted to the reported values from the literature and the maximum and minimum temperatures from the climate forecasts, which results in the regression line shown in Eq. (13).

Energy saving percentage from GR installation in cooling and heating degree days for package p, α and β, respectively. The percentage of energy saving in cooling degree days achieved due to the installation of GRs differs across various studies, ranging from 10% to 16.7% [74,17,82–86]. Most of the studies agree that GR installation results in

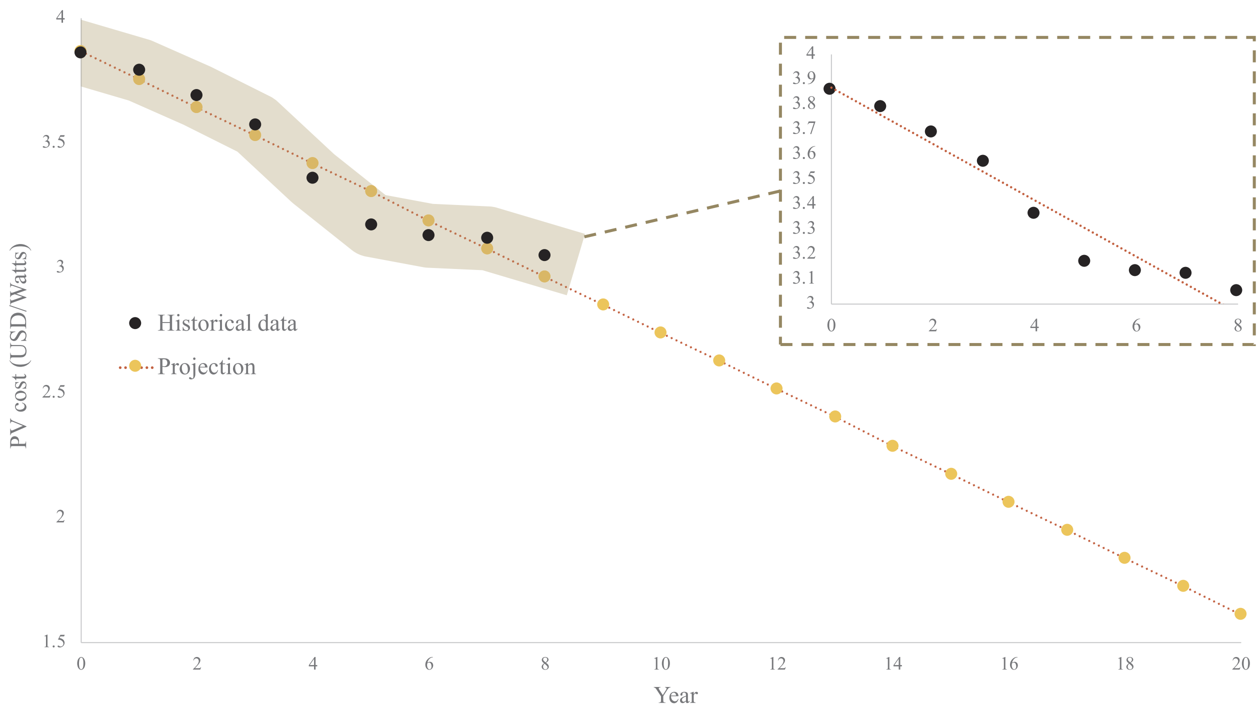


Fig. 2. The regression model fitted to the data presented in Table 4.

savings in cooling degree days, whereas a few empirical studies show that GR installation results in energy loss in heating degree days. Also, other studies report that GRs result in energy savings in cooling degree days. Coma et al. [74] report that GRs result in a 6.2% increase in energy consumption for space conditioning during heating degree days. However, Feng and Hewage [84] report that GRs result in 4% to 6% energy consumption reduction for space conditioning during heating degree days. In this study, the values for α and β are set equal to 10% and 0%, respectively, as all the studies agree on the fact that GRs result in energy savings during cooling degree days, but the reported values for energy savings during heating degree days are contradictory. Note that in this study cooling and heating degree days are considered as days during which the average temperature is greater than 22 °C and less than 17 °C, respectively.

Daily solar irradiation available during day t in climate scenario ω, $I^{\omega t}$. In order to calculate the daily solar irradiation, this study utilizes the daily average value of solar irradiation for each building for the city of Knoxville, TN. Fig. 3 shows the average level of solar irradiation for a number of buildings in Knoxville, TN, provided by UDI [27] and CCSI [28]. These levels reflect the level of solar irradiation during a day in which the average number of peak sunlight hours are available in the city of Knoxville, i.e., 4.5 h [87]. Note that the level of solar irradiation available during each day in this study is calculated based on the number of daily peak sunlight hours available during that day. In order to estimate the available daily peak sunlight hours, this study makes the assumption that there is a direct relationship between the value for this parameter and the level of daily precipitation during a given day. The historical precipitation data and recorded average peak sunlight hours for each month from 1960 to 1990 for the city of Knoxville [87,88] is used to calculate a linear regression for each month. Then, these regression lines are used to forecast the peak sunlight hours value for each day of each month using the level of precipitation from the climate projections. Fig. 4a and b show the monthly average peak sunlight hours and precipitation from 1960 to 1990 for the city of Knoxville, TN. Table 7 shows the slope and intercept for the calculated linear regressions for peak sunlight hours versus precipitation level for each month.

Table 5
The ten coupled general circulation models (CGCMs) provided by CCSI [28] and UDI [27]. The projections are generated through utilization of high-performance computing resources, including Titan, America's fastest supercomputer [28].

Model	Institute of development
Japanese Meteorological Research Institute Coupled Global Climate Model (MRI-CGCM3)	Meteorological Research Institute of the Japan Meteorological Agency [100]
Max-Planck-Institute Earth System Model Mixed Resolution (MPI-ESM-MR)	Max Planck Institute for Meteorology [101]
Geophysical Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2M)	Geophysical Fluid Dynamics Laboratory [102]
The Australian Community Climate and Earth System Simulator (ACCESS)	Commonwealth Scientific and Industrial Research Organization [103]
The NCAR's Community Climate System Model (CCSM4)	Climate and Global Dynamics Laboratory at the National Center for Atmospheric Research [104]
The Institute Pierre Simon Laplace Climate Model (IPSL-CM5A)	Institute Pierre Simon Laplace [105]
The Beijing Climate Center Climate System Model (BCC-CSM)	Beijing Climate Center, China Meteorological Administration [106]
Norwegian Earth System Model (NorESM1-M)	Multi-institutional, Coordinated Climate Research in Norway [107]
The Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate Model (CMCC-CM)	Euro-Mediterranean Center on Climate Change [108]
Flexible Global Ocean Atmosphere Land System (FGOALS)	Institute of Atmospheric Physics, Chinese Academy of Sciences, State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics [109]

Table 6
The results from the daily pairwise comparison for the ten CGCMs shown in Table 5 starting from January 2011, showing the maximum, average, and standard deviation range for pairwise comparison of the climate models. The minimum value for each parameter it is equal to 0, hence omitted from the table.

Parameter	Maximum	Average	Standard deviation range
Daily minimum temperature (°C)	31.41	4.72	[0.79,7.95]
Daily maximum temperature (°C)	41.58	4.79	[0.47,11.22]
Daily precipitation (mm)	105.26	5.45	[0.02,38.88]

Hence, the value of $I^{\omega t}$ for each household under each scenario is calculated based on the precipitation forecasts provided by the ten climate projections.

Daily energy consumption for space conditioning for the building in day t, U^t. Electricity consumption usually increases in building size [89]. The data from a 2009 survey by the EIA [89] is used to estimate the relationship between the average daily energy consumption levels for conditioning and the size of the building. The data show an obvious linear relationship between the size of the building and its energy consumption for space conditioning. Eq. (14) shows the resulting linear regression used to calculate the average daily energy consumption for each household in this study, i.e.,

$$U^t = 0.0941H + 11.472. \tag{14}$$

The performance ratio of the PV system, λ. According to Photovoltaic Software [90], the quality of PV installation can drastically reduce the output of the PV system due to reasons such as inverter, temperature, and DC and AC cable losses, which can result in a decrease in the efficiency of a PV system up to 100% of its actual efficiency. We set the value for this parameter equal to 75% consistent with the experts' opinion [90].

The probability of a household adopting solar panels, ρ. In order to estimate the value for this variable, we use the model developed by Zhao et al. [49]. Table 8 shows the parameters used in this linear regression model, their units, corresponding coefficients, and the data source.

In order to calculate the value for each of the factors in the regression model, this study follows the formulation proposed by Zhao et al. [49]. That is, the payback period is calculated as

$$F_1 = \frac{Max(PP) - PP_i}{Max(PP) - Min(PP)} \tag{15}$$

where PP denotes payback period, PP_i denotes the payback period for agent i, and maximum and minimum PP are set to the lifespan of common PV systems (i.e., 25) plus one, and one, respectively [91]. The household income factor is calculated as

$$F_2 = \frac{(e^{\mathbb{X}-12.4})/n}{1-(e^{\mathbb{X}-12.4})(n)}, \tag{16}$$

where $\mathbb{X}$ denotes the income of the household in 5000 USD, and n is the number of family members, e.g., the size of the household. The Advertisement factor that accounts for the total number of advertisements about green technologies received by a family is calculated by using a piecewise linear function, i.e.,

$$F_3 = \begin{cases} 0.02Adv & \text{if } 0 < Adv \leqslant 5, \\ 0.04Adv - 0.1 & \text{if } 5 < Adv \leqslant 10, \\ 0.06Adv - 0.3 & \text{if } 10 < Adv \leqslant 15, \\ 0.08Adv - 0.6 & \text{if } 15 < Adv \leqslant 20, \\ 1 & \text{if } Adv > 20, \end{cases} \tag{17}$$

where Adv denotes the total number of advertisements received by a family during each time step. In order to calculate the neighborhood factor, F_4 is calculated:

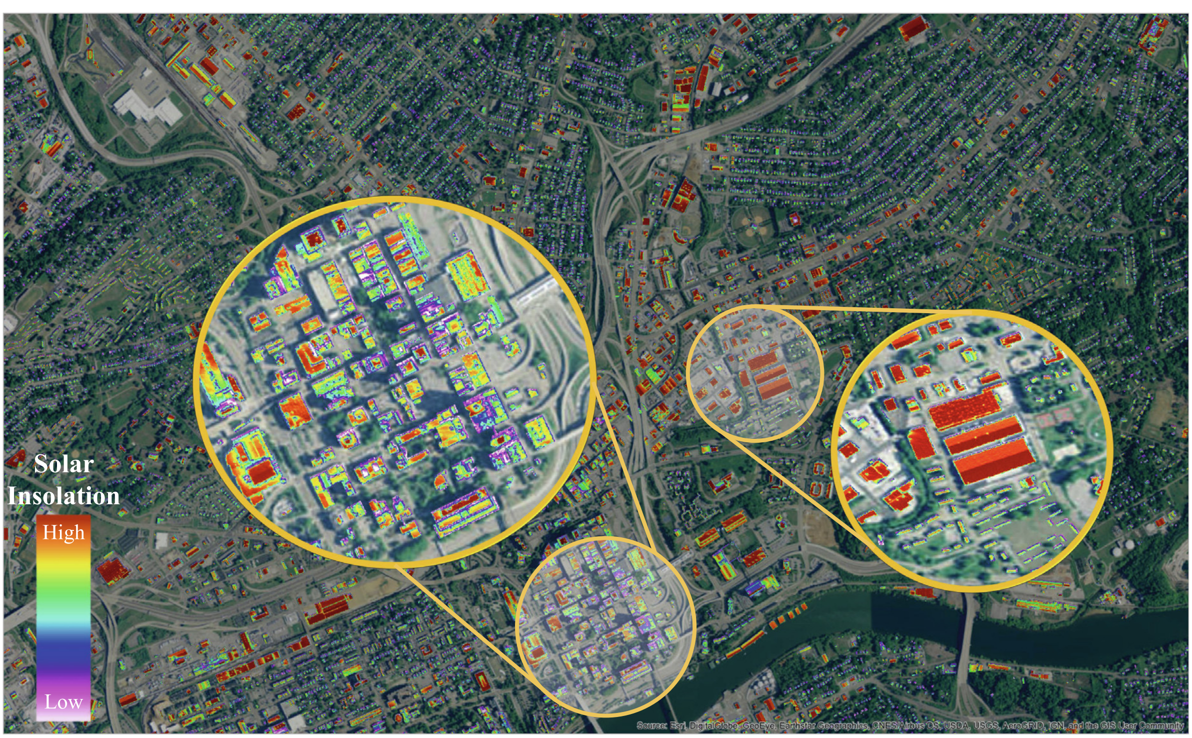
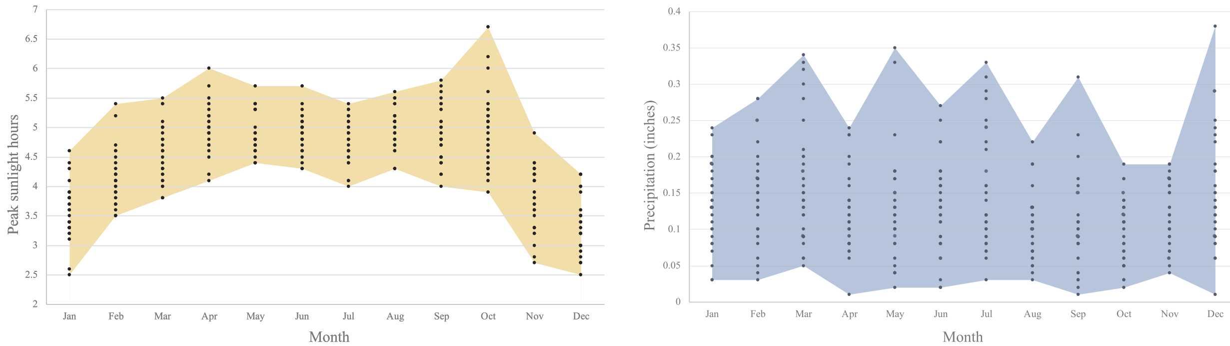


Fig. 3. Visual-SOLAR radiation map for the city of Knoxville, TN [54].



(a) Monthly average peak sunlight hours for city of Knoxville, TN, from 1960 to 1990 provided by NREL (2019b).

(b) Monthly average precipitation level for the city of Knoxville, TN, from 1960 to 1990 provided by NOAA (2019).

Fig. 4. Historical peak sunlight hours and precipitation data for the city of Knoxville over 30 years from 1960 to 1990.

$$F_4 = \frac{e^{\mathbb{N}-4}}{1 - e^{\mathbb{N}-4}} \tag{18}$$

where $\mathbb{N}$ denotes the number of neighbors in the neighborhood who adopted green technologies. U.S Census Bureau [92] defines a neighborhood as the area in a radius of 650 m to 1,060 m around a household. Hence, we set the neighborhood for each agent as the number of agents in a radius of 1,060 m from the agent's geographical location.

4. Computational studies

In this section, the results from a case study on a sample of households in the city of Knoxville, TN, is presented first. Next, the effects of the changes in the social network of the model on the results are investigated through a series of sensitivity analysis. Lastly, the impact from different promotional policies on the results of the model are evaluated.

4.1. Case study

This section provides a case study on a sample of households in the city of Knoxville, TN. This sample is a random subset of the actual households in Knoxville, TN, with a size of 1,045 households, i.e., 0.5% of the actual data. That is, this section provides the results from the diffusion of green technologies throughout a sample society under a case in which the agents are only exposed to the information from the financial model. The hyper-parameters of the Small World network are set to 2, 10%, and 60% for N_{sw}, P_{sw}, and ϕ_{Global}, respectively, with an average of 4 interactions per time step. Fig. 5 shows the results from the model after 20 years of simulation.

The results from the model show that after 20 years of simulation, the majority of installed packages are in the central Knoxville area, i.e., downtown Knoxville, as well as Northshore and Farragut. Note that the number of GR integrated PV systems, as well as stand-alone GRs in these regions, is higher than the number of stand-alone PV systems, with the highest number of installations for the GR integrated PV systems. The buildings in the regions with the most number of installations generally receive a high level of solar irradiation due to the lack of shading and the topological properties of the region, thus making PV systems more economically efficient in these neighborhoods.

Fig. 6 shows the daily maximum and minimum temperature values for the city of Knoxville, TN, for the year 2030 for the ACCESS CGCM. The highlighted areas represent the regions with the most number of installations. One can observe that the values for maximum and minimum daily temperatures for these two regions are higher compared to their surrounding areas, mainly due to the high density of the buildings and/or lack of vegetation (these observations are consistent over other climate projection models). This study assumes that GRs provide a higher level of energy saving during cooling degree days, which means areas with higher average temperaturew benefit more from GRs energy savings properties. Therefore, a higher number of GRs (stand-alone or integrated with PV systems) installed in the marked regions align with the observations from Fig. 6 and assumptions of the model, i.e., warmer regions benefit more from GRs energy saving properties. The neighborhoods with the highest number of adoptions have a median income of approximately 100,000textsuperscript+ USD, which makes them relatively wealthy neighborhoods as the average median income for the city of Knoxville is equal to $52,458 as of 2019 [93]. These observations reflect the structure of the attitudinal model, i.e., a higher level of income increases the willingness of the agent to install green technologies. Hence, the results indicate that, in general, more affluent neighborhoods are a better starting zone to target for promotional policies.

4.2. Sensitivity analysis

This section provides the results from the sensitivity analysis over a number of parameters of the model, studying the effects of changes in the value of the hyper-parameters of the Small World network, the decision threshold, and the number of interactions on the outputs from the model. A Small World network with a high probability value, P_{sw}, resembles a Random network as the high values for P_{sw} translates to a higher probability of randomly connecting to agents which are not neighbors, whereas a Small World network with low probability values resembles a Lattice network [64]. Hence, three different rewiring probabilities, i.e., P_{sw}, of 10%, 50%, and 90% are considered in order to study the outcomes of the model under three different network

Table 7
Intercept and slope for monthly regression models for peaks sunlight hours versus precipitation level in millimeters based on historical data for the city of Knoxville, TN, based on the data provided by NREL [87] and NOAA [88].

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Intercept	4.1973	4.6561	5.0258	5.3702	5.1199	5.2159	5.1398	5.1985	5.2722	5.4577	4.1238	3.6984
Slope	−0.1843	−0.1441	−0.1040	−0.1235	−0.0712	−0.0960	−0.0944	−0.0681	−0.1611	−0.2170	−0.0986	−0.1043

Table 8
The independent variables and their corresponding normalized coefficients developed by Zhao et al. [49].

Factor	Normalized weight	Independent variable	Value/Source
Payback period	0.319	Payback period (years)	Income model
Household income	0.247	Yearly income (divided by 5 thousand USD) Family size (persons)	*Triangular* distribution based on zip code levels provided by [93]
Advertisement	0.281	Number of advertisements received per family (∈ [0–25])	*Triangular*(1, 5, 3.2) per person based on the values used by [49]
Neighborhood	0.153	Number of green technologies installed per neighborhood (# of installed units)	withing a 1,060 m^2 radius as the distance defined by [92] to describe a neighborhood
ϕ_{Global}	—	adoption threshold (%)	[53.3%-54.5%] based on a study conducted by [91]

structures. The number of interactions indicates the average annual number of times that each agent interacts with other agents in its networks. These interactions can result in changes in opinion, ϕ, and uncertainty, U, values. In order to reduce the randomness of the model to get a better understanding of the effects of the changes in the network settings on the results, the number of advertisements received per family is set to a constant value, i.e., 20, during each year.

Table 9 shows the results of 54 different settings for parameters of the Small World network, as well as the decision threshold over 20 years.

The results from the table show that the total number of installations decreases in decision threshold, ϕ_{Golbal}, which is representative of the fact that in a society, there is a small number of people that hold an extreme opinion toward a subject, whereas the majority of the society holds a relatively moderate opinion.

It can be observed that the total number of installations increases in the number of connections N_{sw} and the number of interactions, where the highest number of installations is for $N_{sw} = 4$ and 8 interactions under a P_{sw} of 90%. The results show that a higher number of interactions often results in a higher number of installations, while it generally does not result in an increase in the number of agents with an extreme opinion. This means that agents in a more active network tend to hold less extreme opinions, as for $N_{sw} = 4$, $P_{sw} = 90\%$, and 8 interactions (which roughly translates to a society in which agents have a high number of connections, many of which are spread throughout the society and they actively interact) the total number of agents with an opinion higher than 70% is smaller than the other settings.

The changes in the total number of installed systems show that a more diverse network generally results in an increase in the number of adopters. That is, as the probability of agents connecting to other agents that are not in their geographical neighborhood increases, i.e., higher values of P_{sw}, the interactions result in a more positive opinion toward the adoption of green technologies. Note that this does not positively affect the number of adopters under high levels of decision threshold as

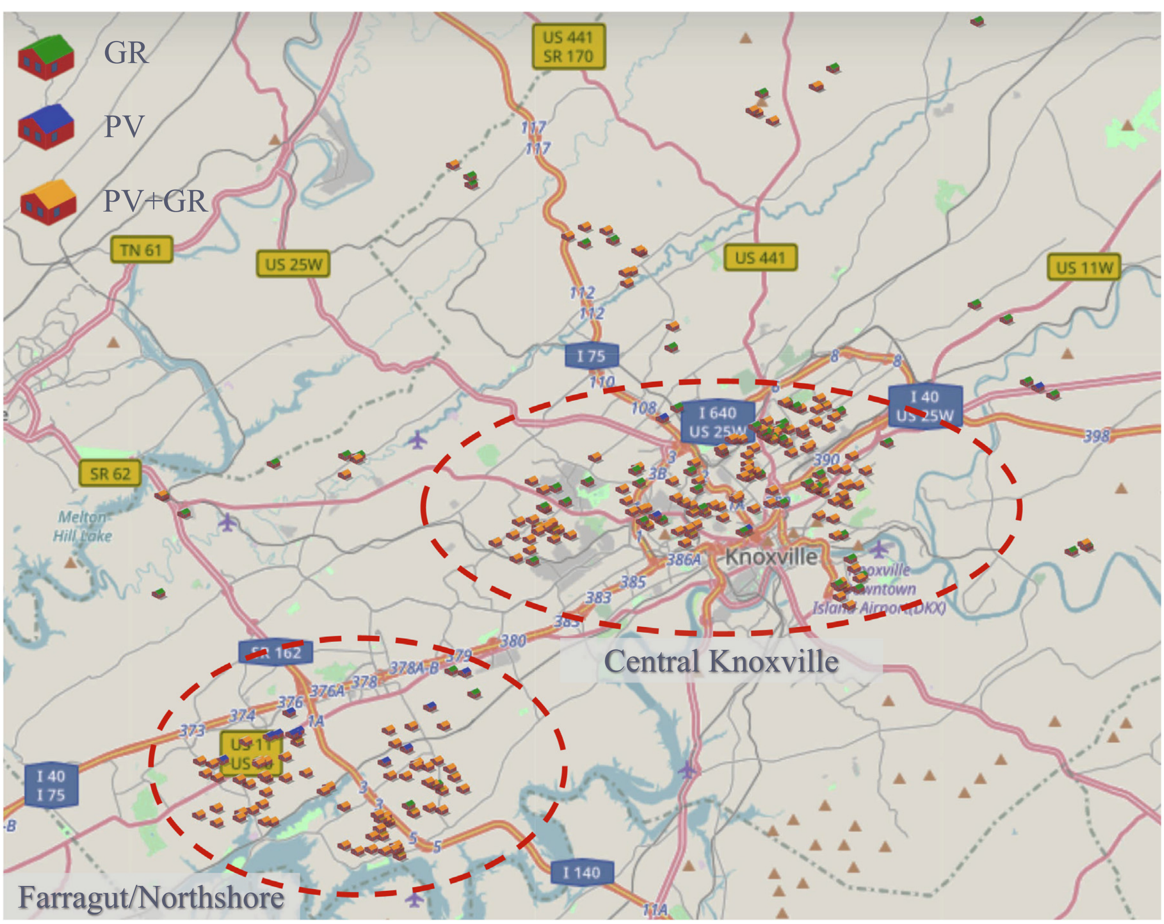


Fig. 5. The total number of installed packages for a sample of 1,045 buildings in the city of Knoxville, TN, over 20 years. The highlighted areas are the neighborhoods with the highest number of installed green technologies. This figure only shows the households with an installed package in order to improve the presentation of the results.

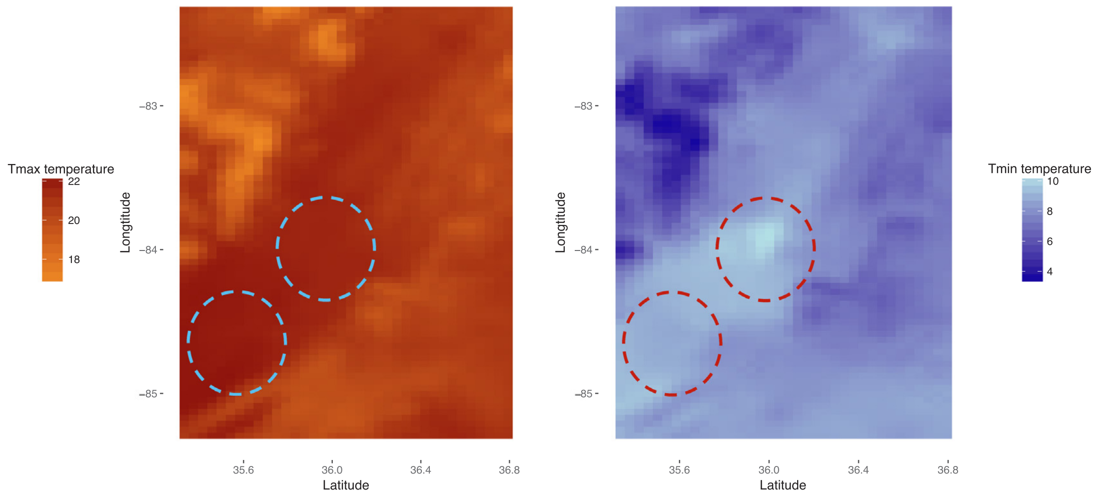


Fig. 6. The average maximum (Tmax) and minimum (Tmin) temperature over the year of 2030 from the ACCESS CGCM model for the city of Knoxville, TN. The marked regions represent the regions with the highest number of installed packages.

Table 9
The total number of installed PV system, GRs, and GR integrated PV systems for different values of network hyper-parameters, decision threshold, and social interactions over twenty years, starting from January 2011.

			Number of interactions = 4				Number of interactions = 8			
Number of connections (N_{sw})	Probability (P_{sw})	Decision threshold (ϕ_{Global})	PV only	GR only	PV and GR	Total # of systems	PV only	GR only	PV and GR	Total # of systems
1	10%	50%	35	110	358	503	39	127	434	600
		60%	11	40	128	179	21	51	182	254
		70%	0	5	6	11	0	5	6	11
	50%	50%	43	112	353	508	48	128	440	616
		60%	13	47	130	190	32	83	267	382
		70%	0	5	6	11	0	5	6	11
	90%	50%	34	115	324	473	48	130	441	619
		60%	13	48	148	209	26	86	303	415
		70%	0	5	6	11	0	5	6	11
2	10%	50%	50	121	430	601	55	142	513	710
		60%	12	46	135	193	42	103	419	564
		70%	0	5	6	11	0	5	6	11
	50%	50%	45	124	445	614	51	143	526	720
		60%	12	43	127	182	38	93	396	527
		70%	0	5	6	11	0	5	6	11
	90%	50%	44	118	432	594	52	161	530	743
		60%	13	59	194	266	42	112	406	560
		70%	0	5	6	11	0	5	6	11
4	10%	50%	50	137	495	682	60	167	557	784
		60%	27	75	247	349	53	129	513	695
		70%	0	5	6	11	0	5	6	11
	50%	50%	51	135	496	682	62	169	582	813
		60%	33	83	291	407	50	137	510	697
		70%	0	5	5	10	0	4	0	4
	90%	50%	49	138	505	692	60	171	603	834
		60%	17	39	132	188	52	148	544	744
		70%	0	5	6	11	0	4	0	4

more diverse interactions result in less extreme opinions.

4.3. Policy evaluation

In order to aid in the expansion of residential solar energy adoption, the Federal Government, state governments, utility companies, and individual organizations provide a variety of programs through which they aim to encourage the installation of green technologies. These programs can be divided into two main categories, i.e., the programs that aim to make green technologies more economically profitable through tax cuts, rebates, and incentives [94], and those that aim to increase the diffusion rate of such technologies by increasing their exposure in a society mainly by means of advertisement, installations, and providing information about the benefits and advantages of such technologies [43]. This section evaluates the impact of incentives and promotional campaigns on the diffusion rate of green technologies in the city of Knoxville, TN. Note that the results from these evaluations are based on the assumptions made in this study, and providing the model with more accurate data or behavioral models that are tailored using the actual data from the city of Knoxville, can result in more accurate results. In order to study the effects of programs that increase the financial viability of green technologies, this study takes the Solar

Investment Tax Credit (ITC) into account. The ITC is provided by the federal government since the Energy Policy Act of 2005 through which a deduction of 30% of the installation cost of a PV system is allocated to the adopters [94]. Moreover, there exists a similar incentive for GRs that provides a tax cut of about 30% of the installation cost for the adopters [95]. Hence, ITC policy accounts for a 30% reduction in the cost of PV systems and GR installation.

The role of the visibility and advertisement which encourages the adoption of green technologies has been proven to be significant in the literature [43,49,52]. Therefore, this study investigates the impact of increasing the exposure and visibility of green technologies by evaluating the effect of an increase in the number of advertisements toward promoting green technologies through promotional campaigns (PC). That is, each household receives the maximum number of advertisements assumed in the model, i.e., 20 per family per year, and the resulting effects on the outcomes of the model are studied. Lastly, the level of effectiveness for a combination of both policies is studied.

In order to evaluate the effect of policies on the adoption rate of the green technologies, the effects of the ITC incentive is studied under two different scenarios, i.e., when ITC exists only for the first five years of the time horizon, and when ITC exists throughout the entire time horizon. That is, a five-year ITC indicates that only the households that install green technologies during the first five years of the time horizon qualify for the ITC, and the households that install green technologies from the sixth year onward do not benefit from this incentive. Next, the effect of the promotions policies through the implementation of PC over the entire time horizon is evaluated, with and without the ITC. Next, the results are compared with the case where no incentives exist and agents are only provided with the information from the model outputs. Lastly, the ideal world is defined as the case under which the only criterion is whether or not the green technologies are profitable and all the agents are potential adopters. The values for K_{sw}, P_{sw}, and ϕ_{Global} are set equal to 2, 10%, and 50%, respectively, with an average of four annual interactions between the agents and their connections.

Fig. 7 shows the total number of installed green technologies under the implementation of different policies. The results show that a 5-year ITC slightly increases the adoption rate during its implementation, but for the remaining time horizon, the total number of installations is not drastically different from the case with no policies. It can be observed that while PC performs better than ITC over the first 10 years, a 20-year ITC eventually outperforms it. This shows the fact that while informing the public about the benefits of green technology helps increase the total number of installations, a financially beneficial policy has the potential of increasing the diffusion rate of the green technologies. This emphasizes the fact that the financial viability of such technologies is the main factor in their penetration rate. The results also show that the combination of both PC and ITC leads to the most number of installed green technologies. That is, while providing information about the advantages of green technologies can help the adoption rate, many adopters do not find the payback period short enough to invest in such technologies. Hence, by reducing the payback period through tax cuts and incentives, governing bodies can achieve a higher diffusion rate. The Lost Opportunity represents the actual potential of the sample society versus the results from the best policies. As the price of PV systems reduces over time and more financially profitable systems are introduced, a combination of ITC and PC can reduce the gap and achieve results near to those of the ideal world. Note that the total number of installed green technologies in the neighborhood of an agent also plays an important role in the adoption rate of green technologies. Hence, by making investments in improving the visibility of such technologies, decision makers can further reduce the level of Lost Opportunity.

5. Results

This section provides an overview on the overall results from the case study, sensitivity analysis, and policy evaluation, and further discusses the insights from those findings.

The results from the case study show that there exists a direct relationship between the total number of installations and the cost of these technologies. That is, the total number of installed packages increases as their cost decreases over time. The results also show that the installed GRs (stand-alone or PV integrated) are mainly centered around the warmer geographical grids (Downtown Knoxville, and Farragut) throughout the city. As shown in Fig. 6, the neighborhoods with the most number of installed GRs are placed in warmer regions of the city, hence benefiting more from GR saving properties. The effect of green technology cost on their adoption rate is also traceable in the neighborhoods with the highest number of installations, i.e., Farragut and Downtown Knoxville. These neighborhoods have a median income of 100,000textsuperscript+ USD, which makes them relatively more affluent neighborhoods, compared to 52,458 USD as the median income over the entire city of Knoxville. This indicates that with the current cost of green technologies, it is best to target more affluent neighborhoods as a starting point for promotional policies, as they have the highest potential to adopt green technologies.

The results from the sensitivity analysis show the important effect of the social structure of the society on the adoption rate of green technologies. A more isolated society is less likely to adopt green technologies, whereas a society in which the individuals are more actively interacting tends to adopt a higher number of green technologies. This

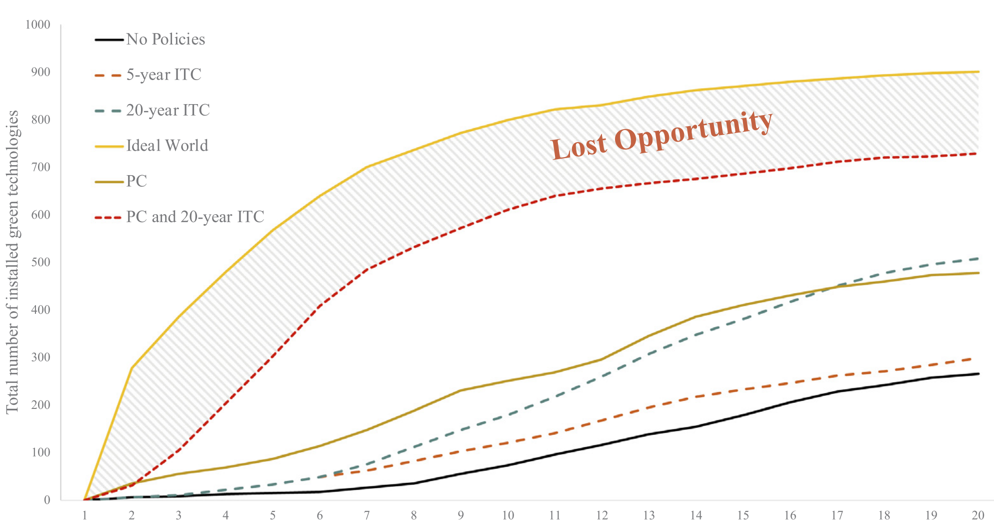


Fig. 7. The total number of installed packages under 6 different cases, i.e., ideal world, no policies, five-year and 20-year ITC, PC, and PC and 20-year ITC, where the dashed lines show the cases with ITC policy. The Lost Opportunity shows the difference between the ideal installation of green technologies and the results form the policy with the most installations.

is captured in the results of the sensitivity analysis, as by reducing the total number of connections, the average annual number of interactions between the agent and its connections, and the rewiring probability, the total number of installed technologies drops. The results from the analysis also show that in a society with a more positive mindset toward green practices, the adoption rate is higher, regardless of how isolated or connected the members of the society are. This observation is based on changes in the global threshold for the adoption of the green technologies. Lower global thresholds represent societies with a more positive mindset about green technologies. That is, if all the other aspects of the society remains unchanged, a lower global threshold eventually leads to a higher total number of installed green practices. This further highlights the important role of public awareness in the adoption rate, showing the key role of policy makers in growing the adoption rate of green technologies through increasing the pubic awareness.

Policy evaluation investigates two common types of promoting policies, i.e., policies that focus on the financial viability of green technologies, and those that emphasize increasing the adoption rate through raising public awareness. The results from policy evaluation show that the policies designed to increase the public awareness have a higher impact over a short period of time, whereas those which focus on increasing the affordability of green technologies yield better results over longer periods of time. Ideally, a combination of both types of policies out performs individual implementation of this policy specifically over the long run.

Overall, the results from the case study, sensitivity analysis, and policy evaluation are aligned with one another, highlighting the significance of the financial viability of green technologies, as well as the important role of public awareness in the adoption rate of green technologies. The results show that while affordability contributes more to the adoption rate of green technologies, a combination of both cost reduction and awareness increasing policies yields the best results.

6. Discussion

The importance of moving away from fossil fuels and adopting renewable sources of energy has become increasingly evident over the past few decades. It is indeed extremely timely to develop more sustainable societies and mitigate the adverse effects of climate change. Although numerous scientific advancements in recent years have contributed to the efficiency and affordability of green technologies, such practices are yet to be utilized to their full potential. Decades of empirical and theoretical research has well established that to achieve the true potential of green technologies, various complementary measures need to be undertaken. Governments not only have to aggressively invest in research and development mainly to make these technologies more economically affordable (through efficiency increase and cost reduction), but also they need to put more emphasis on studying the behavior of their target societies. Initiative has been undertaken by the NREL [96] to make green technologies more affordable, mainly by focusing on soft-cost reductions. Nevertheless, there is a noticeable lack of investment in behavioral modeling and mathematical analysis in the target societies to investigate the adoption rate of the green technologies, specifically in the U.S. Such investments can significantly contribute to raising the awareness of individuals about the potentials and benefits of green technologies, hence resulting in an increase in the adoption rate of these technologies. This study highlights the important role of the governing bodies, mainly through investigation of the results from the policy evaluations, showing that even with common promotional policies and incentives, there exists a noticeable gap between the current results and the achievable potential. Such insights are particularly valuable as they help identify methods through which the adoption rate of green technologies can be improved,.

The framework proposed in this study is designed to capture various important aspects of green technology adoption in order to provide decision makers with helpful insights when setting their renewable energy goals. Many assumptions had to be made throughout this study mainly due to data limitations or inaccessibility. In order to improve the precision of the results from this study and other similar studies that target the adoption rate of green technologies, policy makers need to collect and provide more accurate data, specifically household-level and individual-level data. This would allow models to more accurately capture the decisions made by homeowners, the extent of peer effect on the adoption rate, and the role of climate change and climate uncertainty on the decisions made by the individuals.

The positive effect of the incentives and promotional policies have been well established in the literature, and are believed to have resulted in a 10,000% growth in the solar industry alone since 2006 [42]. While many major cities such as in California have largely benefited from these incentives and promotions, there is a large number of mid-sized and small cities that were not targeted by such campaigns. As a result, the current number of adopters in these cities is considerably lower than their achievable potential. For instance, as of September 2019, the city of Knoxville has fewer than a total of 80 installed PV systems. To improve the utilization of green practices in cities with adoption rates similar to those of city of Knoxville, pilot campaigns should be designed and developed to promote the implementation of green technologies, increase the public awareness, and help with data collection. Such campaigns, which are often held in collaboration with academia, have been tested in other states (such as the project undertaken by Bollinger and Gillingham [42]), and have proven to be exceptionally successful in both increasing the awareness of the public about green technologies and their various benefits, as well as helping the researchers studying the attitude of households toward these technologies. It is worth mentioning Solar ITC program, which is one of the most successful incentive programs and is claimed to be the main contributing factor to the growth of the solar industry in the U.S. (with an annual average of 50% over the past decade), is set to be phased out by 2022 [97]. Such effective incentives should be promoted and tailored to target regions with highly underutilized green technology potentials.

Further validation of the results, beyond what has been presented, is one of the major limitations of this study and remains a future work. One approach to validating the results is through a comparison with a similar study in the same geographical region, i.e., the city of Knoxville. There exist studies in the literature that evaluate the financial viability of green technologies via an ABM framework [9], examine their optimal placement using stochastic programming [71], or focus on the effects of their penetration rate (particularly for plug-in hybrid vehicles effect on the electric distribution network) [55], in the city of Knoxville. However, none of these studies can be used to validate the results of the current study as they do not capture all dynamics considered in the current study. Another approach to such validation is through the implementation of this study over another geographical region where similar studies exist to further validate the results. Although such an approach is viable, it requires additional data collection efforts to gain access to all data used in this study, specifically the climate models used as the future scenarios that currently are not available over other regions.

This study and other similar studies can provide valuable insights for policy makers to establish green technology adoption goals and evaluate different policies and incentives in order to expand the reach of such practices, especially to lower-income households and apartment dwellers. Cities such as the city of Knoxville have a vastly underutilized potential in green technology adoption. Achieving the true potential of green technologies in such cities can significantly contribute to climate change mitigation and development of sustainable cities, and cannot be achieved without the investment and help of the governing bodies.

7. Conclusion

This paper investigates the diffusion rate of green technologies under uncertainties due to climate change, as well as agents' decision making and their interactions in society. An optimization model is developed to account for the uncertain nature of the model parameters and building-specific properties, in order to find the most economically profitable package for each individual building. Furthermore, an agent-based modeling framework is developed to simulate the interactions between the agents over time and the effects they have on the final decision made by the agents. This integrated framework captures the interplay between the integer programming optimization model and behavioral model to account for financial and attitudinal aspects, as well as the uncertainties due to both the stochastic nature of system parameters and the interactions among agents involving human behaviors.

To calculate the parameters for the behavioral sub-model, a regression model from the existing literature is adopted. This model provides the ability to capture the interactions among individuals in society and their effects on the potential outcomes from the mathematical model.

A case study over a sample of 1,046 households in the city of Knoxville, TN, shows that by merely accounting for the over time cost reduction of PV panels, these green technologies will become financially profitable for a significant proportion of the households. In order to study the effects of the changes in the values of the parameters of the attitudinal model, a sensitivity analysis is conducted over 54 different input parameter combinations. The results show that a more interactive society results in fewer agents with an extreme opinion. This results in a higher adoption rate of green technologies in general, except for the case with high decision thresholds, which results in a smaller number of adopters as the overall number of agents with extreme opinions lowers in a highly interactive society.

Lastly, the effect of some of the currently common policies on the outcome of the model and the diffusion rate of the green technologies are examined. The results show that while financial incentives can perform well, they perform significantly better when combined with promotional campaigns. These results also show that the cost efficiency of the green technologies is the most important factor in their adoption rate.

An interesting observation from the results is that the sole act of providing the potential of the green technologies for each household can result in a noticeable increase in the adoption rate of green technologies. This emphasizes the important role of awareness in society, leading to an increase in their adoption rate.

While this study only evaluates the currently commercially available technologies, new emerging green technologies and innovations can be incorporated in the same framework to evaluate their affordability and profitability and compare them with older green technologies. This framework can also provide valuable insights for policy makers to investigate the potential of new emerging technologies to set regulations and incentives to further improve their adoption rate.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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