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AN OPTIMIZATION VIA AGENT-BASED SIMULATION FRAMEWORK TO INTEGRATE STOCHASTIC PROGRAMMING WITH HUMAN INTRODUCED UNCERTAINTY

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ABSTRACT

Uncertainty is ubiquitous in almost every real world optimization problem. Stochastic programming has been widely utilized to capture the uncertain nature of real world optimization problems in many different aspects. These models, however, often fall short in adequately capturing the stochasticity introduced by the interactions within a system or a society involving human beings or sub-systems. Agent-based modeling, on the other hand, can efficiently handle such randomness resulting from the interactions among different members or elements of a systems. In this study, we develop a framework for stochastic programming optimization by embedding an agent-based model to allow uncertainties due to both stochastic nature of system parameters as well as the interactions among the agents. A case study is presented to show the effectiveness of the proposed framework.

1 INTRODUCTION

Real world problems often include parameters for which the exact values are not known when decisions are being made. Such uncertainties have been the key element of many optimization problems when only an estimation of the true values of parameters are available. Stochastic programming is one of the most well-established modeling approaches that aims to deal with uncertainty. It provides the ability to capture the stochastic nature of parameters by considering the probability of the events (Birge and Louveaux 2011) and has been widely utilized in a variety of different areas of study such as transportation and logistics (Barbarosoğlu and Arda 2004), resource allocation problems (Li et al. 2009), supply chain management and network design (Santoso et al. 2005), unit commitment problem (Takriti et al. 1996), and renewable energies (Ramshani et al. 2018). Stochastic programming models consider the probabilistic nature of the parameters while searching for a feasible solution, and have been implemented in a wide array of studies such as portfolio selection (Abdelaziz et al. 2007), distributed energy systems (Zhou et al. 2013), transportation planning (Barbarosoğlu and Arda 2004), disaster management (Noyan 2012), and scheduling (Parisio and Jones 2015). However, they cannot capture the changes in the state of the input parameters due to inter-system interactions between different parts of the system over time. Such interactions can affect the output of the model by changing the input parameters of the model as well as the final outcomes of the system. This research gap motivated us to search for a methodology that enables modelers to augment stochastic programming models with inputs from interactions between different sub-systems, especially from people. Agent-based modeling (ABM) seems to meet this need.

ABM is defined as a system containing autonomous elements (agents). Agents can be defined as autonomous identifiable goal-oriented entities with a certain set of characteristics that are capable of

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interacting with other agents inside their environment (Axelrod 1997a). In an ABM, agents make individual decisions based on their current state and the interactions with other agents in the system under a set of rules imposed by the existing simulation environment (Li et al. 2017). Such qualities makes ABM a great framework for studying systems and their environments in order to forecast and evaluate future scenarios (Axelrod 1997a). ABMs have been widely applied to a variety of different fields including but not limited to energy (Chen et al. 2012), economics (Bookstaber 2012), social sciences (Smith and Conrey 2007), and marketing (Negahban and Yilmaz 2014). ABMs can be combined with different optimization techniques in order to solve scientific and real world problems (Weiss 1999), and are unique in the sense that they are able to contain the uncertainties introduced by the interactions between decision makers in the system over time. This makes them especially well suited for optimization problems in which not only the input parameters, but also the individual traits of decision makers and their interactions are stochastic in nature and bring uncertainty into the model.

The application of ABM for systems optimization has been studied in the literature in a variety of subjects. For instance, one stream of research focused on the application of ABMs in the context of supply chain and logistic. Davidsson et al. (2005) study the application of ABMs and optimization in logistics and freight transportation and their achievable potential, while pointing out the advantages and shortcomings of ABMs in this area of optimization. Nikolopoulou and Ierapetritou (2012) exploit the advantages of the ABM's capability in dividing large-scale optimization problems into smaller ones in a supply chain management context in order to solve large-scale integer programming problems. Fikar et al. (2018) investigate the effects of transportation disruptions in a disaster relief distribution chain via ABM focusing on two different objectives. Another major group of studies in which a combination of ABMs and optimization have been utilized focuses on resource allocation problems. Ghazali et al. (2018) study the water management problem in the agricultural sector in order to optimize the allocation of scarce water resources through ABM and optimization under different regulations and incentives. Yang et al. (2011) utilize ABM to optimize basin water allocation by considering human and natural water demands and evaluating the socio-economic and environmental consequences of their decisions. While the mentioned studies combine traditional optimization methods and ABM, a group of studies aim to tackle the optimization problems via a combination of ABMs and heuristic and meta-heuristic methods. Shen et al. (2011) combine heuristic methods with ABMs to tackle traffic signal timing problems with a focus on breaking down the optimization problem into small scale problems and handling them using graphics processing units. Zhang et al. (2010) develop an ABM to optimize spatial allocation of land for different purposes utilizing genetic algorithms in order to develop sustainable land use strategies. Zhao et al. (2005) use a particle swarm algorithm to optimize reactive power dispatch in power systems via ABMs in order to decrease the solution time.

The aforementioned studies have combined different optimization methods and algorithms in order to find the optimal solution for their problems of interest. Although different studies have attempted to tackle stochastic problems via implementation of them through ABMs (Feng et al. 2012; Li et al. 2017), to the best of our knowledge, none of the studies have proposed a framework to optimize the decision making process of agents in an ABM while simultaneously taking the stochastic nature of the parameters of the simulation environment, the interactions of the agents, and the changes in the parameters of the stochastic programming due to such interactions into account. We aim to develop a framework to integrate stochastic programming and ABMs to contain two different levels of stochasticity, i.e., the uncertainty due to the nature of the parameters of the environment, and the uncertainty as a result of the interactions between the agents throughout a system.

The remainder of the paper is structured as follows. First we introduce the integrated stochastic programming and ABM framework for optimization problems with uncertainty in Section 2. Then, we provide a case study in the context of green technologies in Section 3. Lastly, we discuss our results in Section 4.

2 FRAMEWORK

In this section, we introduce an integrated ABM optimization framework which aims to address two different levels of uncertainty, i.e., uncertainties due to the stochastic nature of the input parameters and those due to the interactions among agents in a system and the behavioral changes as a result of such interactions.

In ABM, agents evaluate their options through implementation of stochastic optimization methods considering the parameters of the environment and their personal traits, and make a decision based on the results. That is, by using stochastic programming (e.g., two-stage stochastic programming) and the knowledge of the probability of the future scenarios, agents can evaluate the result of their decisions under different scenarios and choose the option which optimizes their outcomes based on the current values of the parameters in the environment and their current personal traits. Next, the agents interact with the other agents in the system which results in changes in their personal beliefs. The interaction of agents with the other agents is often defined based on a social network structure which are used to describe the agents' interaction pattern. Different network structures are used in the literature such as Random network where agents are randomly connected to one another, Fully Connected where all the agents are connected to all the agents in the environment, Lattice networks (regular or ring) that are established upon the idea of having agents connected based on their distance, and Small World in which agents are both connected to one another based on distance and randomly at the same time (Kremers 2013).

As a model progresses over time, some certain parameters evolve (e.g., agent demographics such as age, and cost of their options) due to their time-dependant nature. Therefore, after each time-step, agents will re-evaluate their options and calculate the outcomes of them based on their demographics and cost associated with the option on that certain time-step. During each transition between time-steps, the agents interact with other agents inside the system, resulting in changes in their behavior and beliefs as a result of difference in the state of mind and opinion about the subject of interactions between the agents. The extent to which the behavior of agents are affected by the other agents with whom they interact can be contained through implementation of a set of rules. Generally, studies either use a set of regulations and norms generated based on the concept of their study or utilize and adopt common methods that describe social influences through theories in different fields of study, mainly in social science or psychology (Axelrod 1997a) such as Tit for Tat (Axelrod 1997b), the Theory of Planned Behavior (Ajzen 1991), Diffusion of Innovation (Rogers 2010), and Relative Agreement (Deffuant et al. 2000). However, some theories root in other fields of science such as the Ising model, originating from physics (Cipra 1987). Such theories define the extent to which each agent affects other agents based on their personal characteristics. The changes in the agents' characteristics are then applied to the model, resulting in different outcomes over each time step. Hence, the framework can be divided into three main components, i.e., mathematical component, behavioral component, and the agent based model. Figure 1 shows the overall structure of the proposed framework in this study.

The mathematical component contains mathematical optimization of the model through stochastic programming. The purpose of this component is to capture the stochasticity of the input parameters, the probability of the future scenarios, and the potential outcomes of each available option. This results in the maximum achievable potential outcome from all the available options.

The behavioral component aims to factor in the beliefs and the characteristics of each agent, and the results that it can have on the outcomes. That is, agents have negative/positive views regarding the available options based on their opinion and how certain they are about their opinion, resulting in a decreased/increased level of potential outcomes from the available options, denoted by potential utility.

The ABM takes the outcomes of mathematical and behavioral components of the framework, evaluates them based on the norms and regulations introduced by the environment, and progresses through the time horizon. After each step in time, the interactions among agents via social networks results in changes in agents' opinion and the strength of their opinion. On the other hand, the behavioral and mathematical components change continuously over time. That is, over the course of time, the demographics of the agents as well as the cost and efficiency of the available options change. Hence, the new potential outcome for each

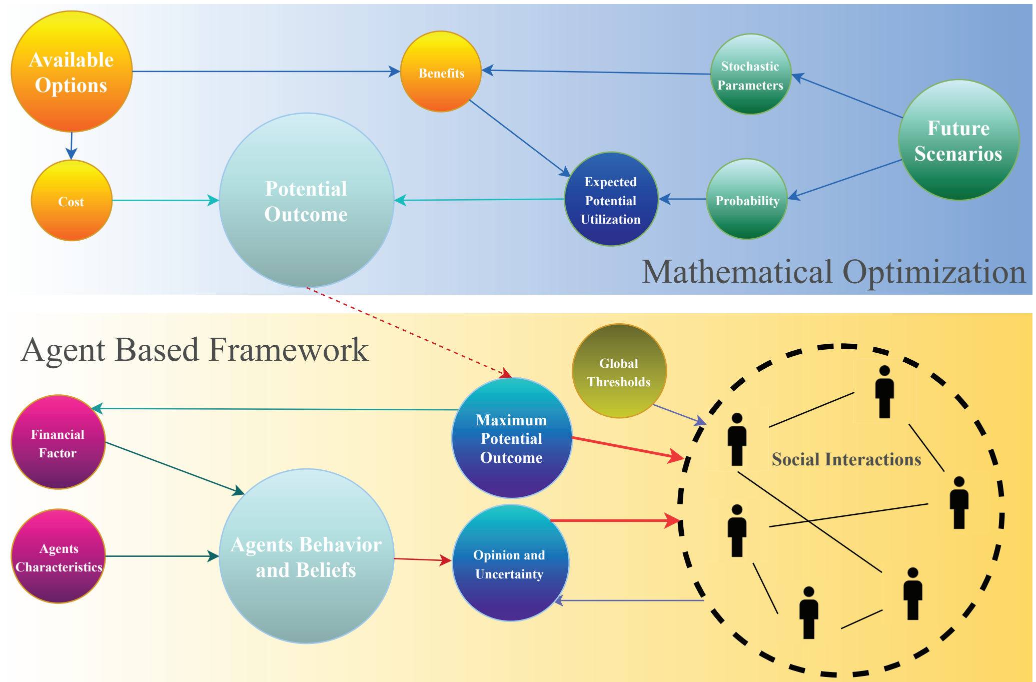

Figure 1: The structure of the proposed framework. The two major components of the proposed framework are the mathematical optimization and the ABM framework. The results from the stochastic optimization are used in the ABM framework as an input while investing the diffusion rate of the green technologies.

available option is recalculated based on the new values for efficiency and cost of options. Simultaneously, the behavioral model evaluates the potential utility, opinion, and the agents' uncertainty using the updated values for demographics. The results are evaluated over time as the model progresses through its planning horizon, leading into a framework that can capture both the stochastic nature of the outcome of the options as well as the uncertainty introduced as a result of agents' beliefs, behaviors and interactions.

3 CASE STUDY

In this section, we provide a case study to showcase the application of the proposed framework and discuss the outputs. We choose to study the implementation of renewable energy sources and energy saving practices as these technologies are reliant on environmental elements such as climate, environment temperature and solar radiation; manipulating these factors can meaningfully change the outputs of their implementation. We study the diffusion models developed in the literature to evaluate the effects of uncertainty on the outputs from the model. We choose two different but closely related green practices, i.e., photovoltaic (PV) systems and green roofs, as they are becoming increasingly popular due to their potential for generating and saving energy, respectively (Amato et al. 2005; Belzer 2009; Chemisana and Lamnatou 2014). In addition, the combination of PV panels and green roofs provides beneficial interactions resulting in higher levels of output efficiency for the installed panels (Witmer 2010). To optimally place green roofs and PV systems, we use the model adopted by Ramshani et al. (2018) which incorporates future climate forecasts that contain climate change as their stochastic input, directly affecting the output of PV systems as well as green roofs. This model returns the optimal technology type and size for each candidate location. In order to capture the role of agents' decision making on the installation of PV systems and green roofs, we use two different behavioral models developed by Lee and Hong (2019), and Zhao et al. (2011), and compare their results. Table 1 shows the independent variables used in each behavioral model.

Table 1: Two behavioral models extracted from the literature for the case study. The independent variables and their units used in each model are shown separately.

Attitudinal models			
Model #1 (Lee and Hong 2019)		Model #2 (Zhao et al. 2011)	
Variables	Units	Variables	Units
Building type	Binary (Residential vs Non-residential)	Payback period	Years
Floor area	m^2	Household income	Five thousand USD
Household density	Households per km^2	Family size	Person per household
Building age	Years	Advertisement	Annual total # of advertisements per person
Land price	USD	Neighboring adopters	Total # of adopters in neighborhood
Rooftop solar PV potential	$kWh/m^2/year$		
Expected payback period	Years		
Neighboring adopters	Total # of adopters in 100 meters radios		

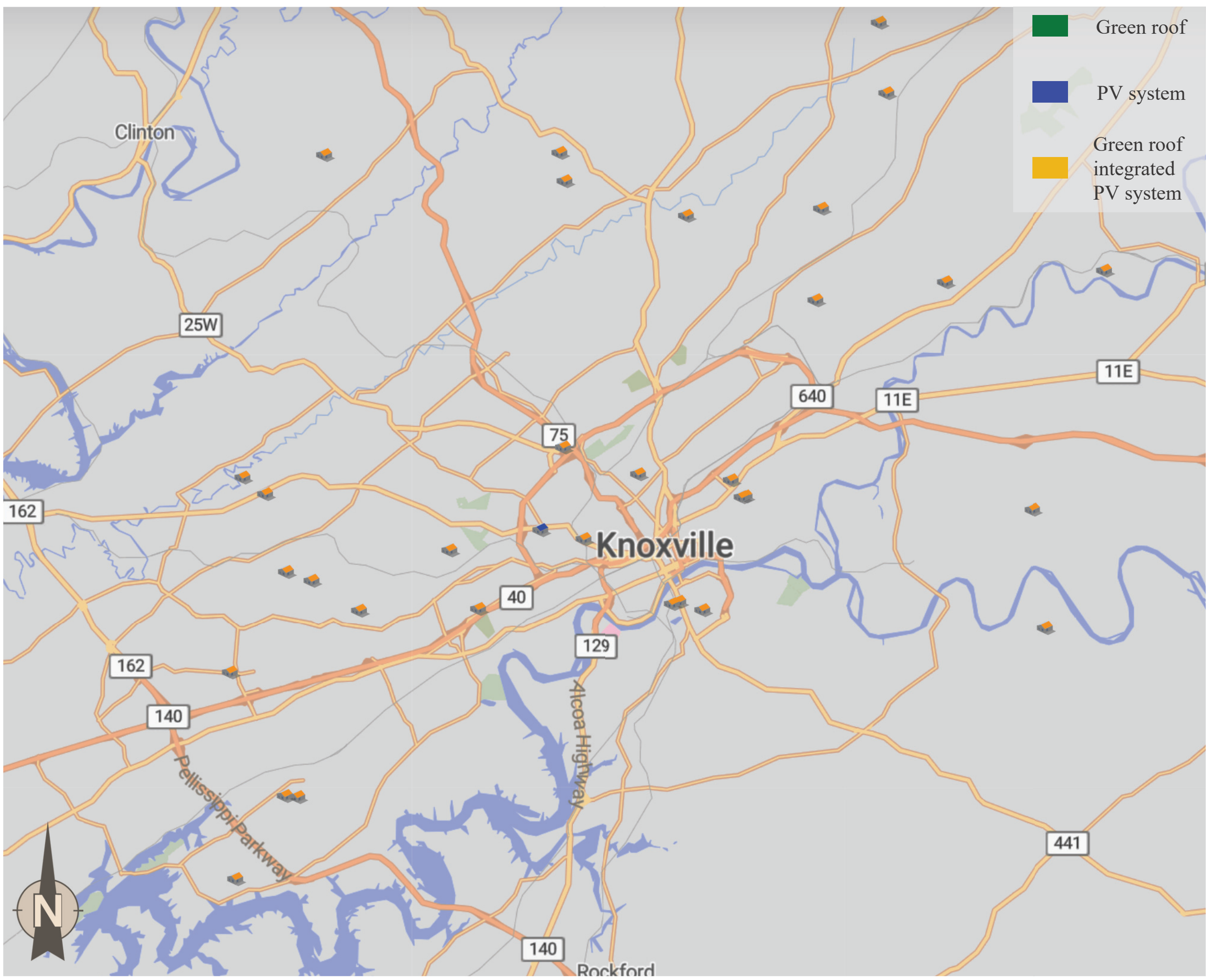

Figure 2: The outputs from implementation of attitudinal Model #1 using the proposed framework. Note that only the households who adopted Green roofs, PV systems, or both of them are presented.

We implement the framework over a time-span of 10 years, and calculate the optimal installation settings for each individual household, the agent selected for this ABM, as well as the output of the attitudinal models. In order to capture the social effect in the framework and account for the social interactions between agents in the model, we implement the Relative Agreement model (RA) which is widely applied in the literature for such purposes (Meadows and Cliff 2012; Rai and Robinson 2015) through the use of of a Small World network (Watts and Strogatz 1998). We use attitudinal models to calculate the values for the opinion and uncertainty of each agent and set a global threshold for the opinion levels. Hence, agents who can potentially benefit from the installation of PV systems and/or green roofs will only install them if the value of their opinion surpasses the global threshold. Through the interactions, each agent randomly selects an agent in their network, evaluates their opinion, and checks whether they hold an opinion much different from their own. If the difference is not on extreme levels based on the RA, these agents interact with one another and adjust their opinion based on the hyper-parameter settings and results from the RA evaluation.

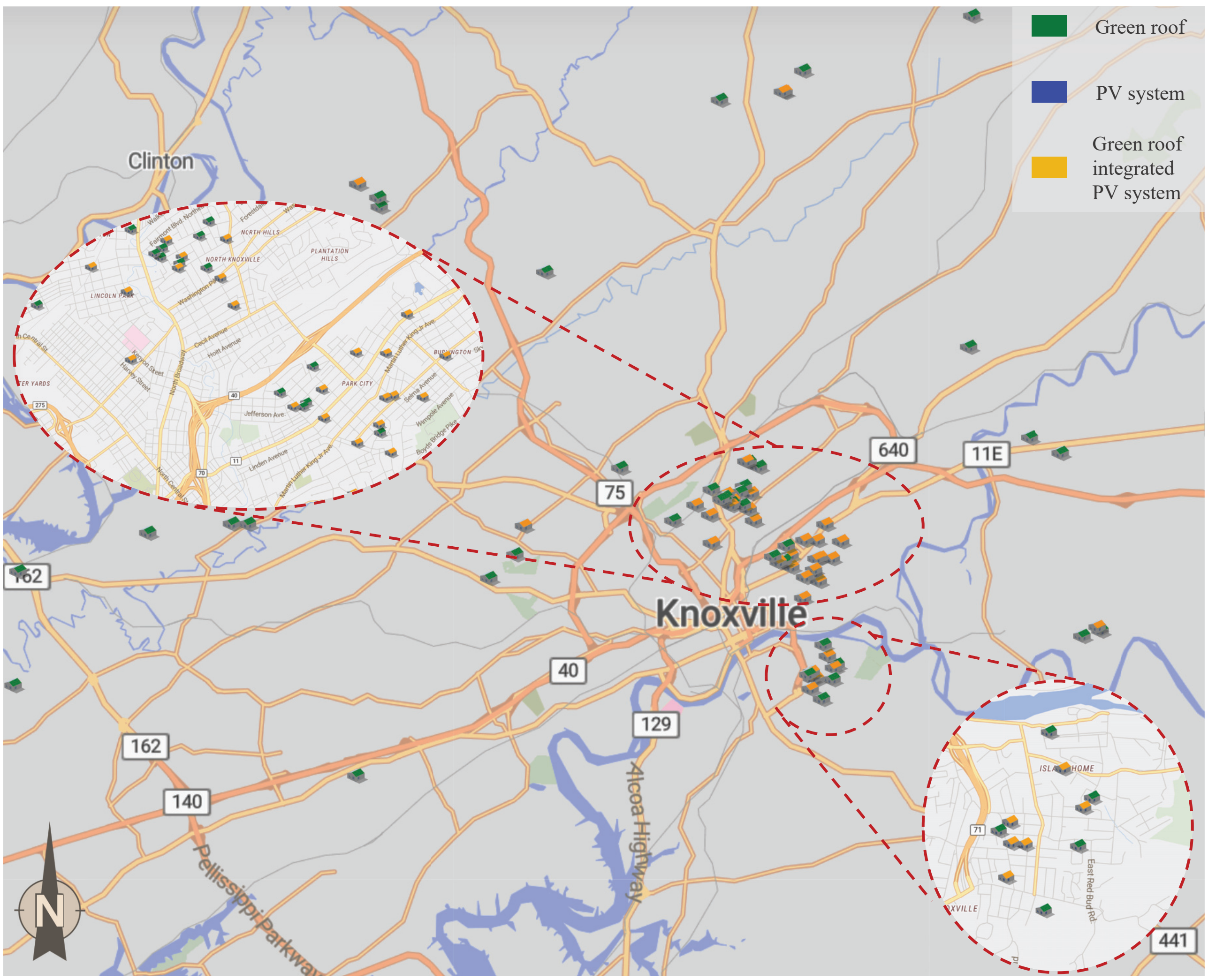

Figure 3: The outputs from implementation of attitudinal Model #2 using the proposed framework. Note that only the households who adopted Green roofs, PV systems, or both of them are presented.

We implement the framework using the mentioned models over a 10 year time horizon while accounting for a 3% reduction in the cost of PV systems to capture the current decreasing trend of the market (EnergySage

2019). We conduct a case study over 900 households in the city of Knoxville, TN. Figures 2 and 3 show the outputs generated from the framework using Model #1 and Model #2, respectively. As Table 1 shows, two different attitudinal models are used for the case study. Each model values different characteristics of the agents while accounting for the diffusion of the green technologies. Hence, for each model, agents include different characteristics. That is, agents in Model #1 are defined as autonomous entities which contain the variables shown under Variables column in Table 1 for the respective model. Hence, the agents contain characteristics such as building type and age while including PV potential and expected payback period. The agents are then connected through a Small World social network through which they interact with one another. The environment of the ABM model contains the available green technology packages and their price, as well as different climate scenarios which are used as future scenarios for the stochastic programming model.

Two main observations are made from the results shown in Figures 2 and 3. We see that there are no stand-alone green roofs installed in the results of Model #1 while the results from Model #2 show a considerable number of stand-alone green roof installations. Moreover, the installations in Model #1 are considerably more scattered compared to those of Model #2. This can be attributed to the difference in variables used and weighted by Models #1 and #2 as shown in Table 1. Model #1 accounts for the total number of adopters in a radius of 100 meters while Model #2 takes the total number of adopters in a neighborhood into account, hence putting more focus on the adopters in the surrounding environment of the agent. This describes the more clustered installations in the results of Model #2 compared to Model #1. Note that while both models account for the payback period, Model #1 also accounts for the rooftop solar PV potential for each building, which translates to higher values for the buildings that receive a higher level of solar irradiation. This increases the adoption chance for the households that have a higher potential for PV systems compared to those which are more suitable for green roof installation. Therefore, the agents with a tendency towards installation of the green roofs which generally receive a low level of solar irradiation are not able to surpass the global threshold for the opinion to install them, while Model #2 makes it possible by giving a higher weight to payback period and excluding the rooftop solar PV potential from the model. The total number of installed PV systems and/or green roofs at each time step for each attitudinal model are shown in Figure 4.

As the results from the figure show, under the implementation of Model #2 there is a greater number total installed systems at end of the time horizon as compared to Model #1. We observe that while the results from Model #1 show a higher number of installed PV systems (with and without green roofs), as the time progresses and the price of PV systems reduces further, the number of PV systems installed under the assumptions of Model #2 increases. As a result, the difference in the installed PV systems under the assumptions of two models decreases over time. Note that Model #2 invests more in standalone green roof installations, while Model #1 mainly utilizes green roofs to benefit from the output efficiency increase they provide to PV systems. This is due to the fact that Model #2 evaluates all three types of installations the same way, i.e., by calculating their payback period. However, Model #1 values PV systems more as it incorporates an independent variable that solely focuses on the households that receive a higher level of solar irradiation.

In order to emphasize the importance of accounting for the interactions between agents, we study the results of Model #2 under different assumptions. That is, we change behavioral settings of the model and compare the results with those of the main settings. Note that under the previous settings, after 10 years, Model #2 results in a total of 58 green technologies installed. We run the model where there are no interactions and agents only decide to adopt based on their own characteristics and beliefs. After 10 years, a total of 77 green technology packages are installed. This shows that without any incentives and promotions, the overall interactions of the agents with the current characteristics result in a decrease in the total number of installations. The importance of incorporation of agents' interactions and behavior is emphasized when we remove the threshold for agents' behavior while looking into the diffusion of green technologies. That is, we only consider the profitability of the technologies, and assume that agents install

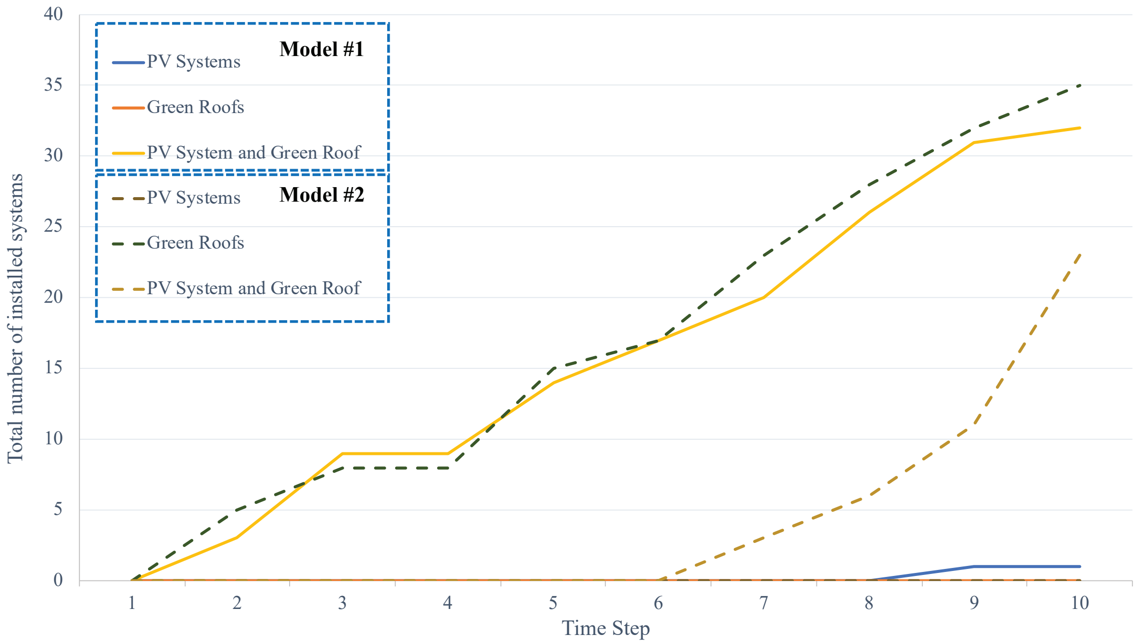

Figure 4: The outputs from implementation of attitudinal Model #2 using the proposed framework. Note that only the households who adopted Green roofs, PV systems, or both of them are presented.

the technologies if they are economically profitable. With this assumption, the results from the model show that after 10 years, a total of 799 systems are installed. This shows a huge difference between the estimations achieved by only considering the mathematical optimization model and incorporating the behavioral model. Hence, focusing on the effect that characteristics of agents have on the results shows the significance of the behavioral aspect of the agent while studying diffusion of green technologies.

4 CONCLUSION

In this paper, we develop a framework of stochastic programming and ABM in order to achieve the optimal results through the consideration of different layers of uncertainty, i.e., those related to the stochastic nature of the input parameters and those that are due to the interactions between the agents inside a system and provide a description on the structure of the model. Further, we evaluate the ability of the framework in working with different models by evaluating the outputs from the implementation of two different models introduced in the literature. One of the models puts more emphasis on the PV potential of the households, whereas the other model mostly focuses on the role of potential income and the visibility of the installed systems. We observe that while both models incorporate the financial evaluation of PV systems and green roofs using the same stochastic model, they show different results due to the different structure of the behavioral models.

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