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AN AGENT BASED MODEL FOR JOINT PLACEMENT OF PV PANELS AND GREEN ROOFS

Xueping Li
Mohammad Ramshani
Anahita Khojandi

Department of Industrial and Systems Engineering
University of Tennessee - Knoxville
525 John D. Tickle Building
851 Neyland Drive
Knoxville, TN 37996-2315, USA

Olufemi Omitaomu

Urban Dynamics Institute
Computational Science and Engineering Department
Oak Ridge National Laboratory, Oak Ridge
Tennessee 37831, USA

Jon Michael Hathaway

Department of Civil and Environmental Engineering
University of Tennessee - Knoxville
325 John D. Tickle Building
851 Neyland Drive
Knoxville, TN 37996-2313, USA

ABSTRACT

Photovoltaic panels generate electricity directly from sunlight, making them a favored renewable technology. Green roofs are rooftops covered with vegetation, which provide a variety of benefits, namely, reducing stormwater runoff, improving air quality, and biodiversity. Green roofs are capable of improving the efficiency of Photovoltaic panels, as shown by the recent studies. Optimal placement of Photovoltaic panels and green roofs is a challenging problem due to the complications imposed by uncertainties associated with future climate conditions, specifically due to climate change. An agent based model to optimally place Photovoltaic panels and green roofs is developed in this study. We propose a tabu search metaheuristic algorithm to solve the developed model. Then, a real-world case for a mid-sized city in the U.S. is solved as a case study for the model. We further conduct numerical analysis and provide insights.

1 INTRODUCTION

Numerous studies confirm that global warming is mainly a result of the significant increase in the greenhouse gases level in the atmosphere. The main reason behind this increase is the excessive consumption of fossil fuels (Bose 2010). Residential and commercial sectors are two major consumers in the energy market, and a significant proportion of the energy consumed by these two sectors is used for space heating and/or cooling. To be more specific, space conditioning accounts for 47.7% of residential sector and 34% of commercial sector energy consumption (Administration 2015). It is estimated that by the year 2040, there will be 150 million residential households and 110 billion square feet of commercial space within the U.S. considering the average growth rate in the residential and commercial sector, 0.4%-1.2% and 0.9%-1.1%, respectively (Administration 2015). Hence, a reduction in the proportion of energy consumed due to space conditioning can lead to significant nation-wide savings. Green roofs (GRs) are widely studied for the insulation they provide for the buildings they cover. Studies show that GRs can reduce the surface temperature of the roofs by 30% (Dunec 2012) due to their ability to reduce the amount of solar radiation absorbed by the building. The relationship between GRs energy consumption reduction and their thermal performance has been the subject of many long term studies over the past few decades (Coma et al. 2016, Niachou et al. 2001). Studies show that widespread utilization of GRs over the U.S. can result in savings of $\$7-\$10$ billion (Dunec 2012).

Renewable energy sources, such as solar, wind, and geothermal have been studied to reduce reliance on the fossil fuels. Solar energy is proven as a reliable and clean source of energy which can be harnessed through installation of Photovoltaic (PV) panels. According to Energy Informative Administration (EIA) (Administration 2015), PV panels are the fastest growing renewable source of energy and are becoming an economically viable option to replace fossil fuels due to the declining price of PV panels as well as the incentives provided by State and Federal governments. In fact, over the years 2007 and 2008, PV installations in the U.S. increased by 63% (Scherba et al. 2011), and is anticipated to increase annually by 30% on average (Administration 2015). PV panels have been studied in the literature in a variety of aspects, i.e., their structural properties (Tyagi et al. 2013), the electricity generated and storage capacity optimization (Mulder et al. 2010), etc.

PV panels efficiency drop by almost 0.5% per one degree Celsius increase in their surface temperature (Witmer and Brownson 2011). GRs not only reduce the energy needed for space conditioning in the buildings beneath them but also decrease the temperature of their surrounding environment. Thus, integrating GRs with PV panels can increase the output efficiency of PV panels. A number of empirical studies report different values for efficiency increase in the output of PV panels due to integration with GRs. The reported values range between 0.08% and 8.3% (Chemisana and Lamnatou 2014, Köhler et al. 2007, Hui and Chan 2011).

Large scale implementation of PV panels has been the subject of a number of studies. In (Park et al. 2016), the authors aim to find the optimal strategy to implement PV panels to achieve national carbon emission reduction targets. In another study (Arnette 2013), the income from rooftop PV panels, and the income made by the wind and solar farms are compared while considering greenhouse gas emissions. Nevertheless, these large scale studies do not incorporate the uncertainties caused by future climate conditions and their effects on the outcome of the model. They also do not take into account the savings gained from the GRs, and their integration efficiency increase effect on the output of the PV panels.

PV panels and GRs are considered as long-term investments since their installation costs are considerable. The life-span of available PV panels and GRs range between 20 and 25 years (Energy Informative 2017) and 40 to 50 years (Hui and Chan 2011), respectively. Thus, to accurately evaluate the income from installation of PV panels and GRs, we need to consider the future climate conditions, and take into account the effects of climate change. We utilize ten different climate projections which include the daily precipitation, maximum and minimum temperatures from January 2011 to December 2050. These projections are provided by the Oak Ridge National Laboratory's (ORNL) Urban Dynamics Institute (UDI) (UDI 2017) and Climate Change Science Institute (CCSI) (CCSI 2017). Figure 1 depicts the average over maximum and minimum daily temperatures for May 2021 (Nugent et al. 2017). As shown in the figure, the projected values from the climate projections are considerably different and range by up to 12 degrees Celsius over a given day. For more information on the climate projections used in this paper, please refer to (Ramshani et al. 2017).

To the best of our knowledge, this group is the first to evaluate the income from large scale implementation of PV panels, GRs, and their interactions, under uncertain future climate conditions.The authors (Ramshani et al. 2017) have previously considered the problem of interest using a stochastic programing approach. Specifically, (Ramshani et al. 2017) develop a two-stage stochastic programming model to maximize the energy generated and saved under a series of future climate projections given an initial budget. In (Ramshani et al. 2017), the authors use climate projections as scenarios, calibrate the model using the literature, industry reports, and a few datasets, and conduct a case study and sensitivity analysis to provide insights. In this study, the authors build upon the modeling and calibration efforts presented in (Ramshani et al. 2017) to develop an agent-based model with relaxed assumptions. Specifically, here we

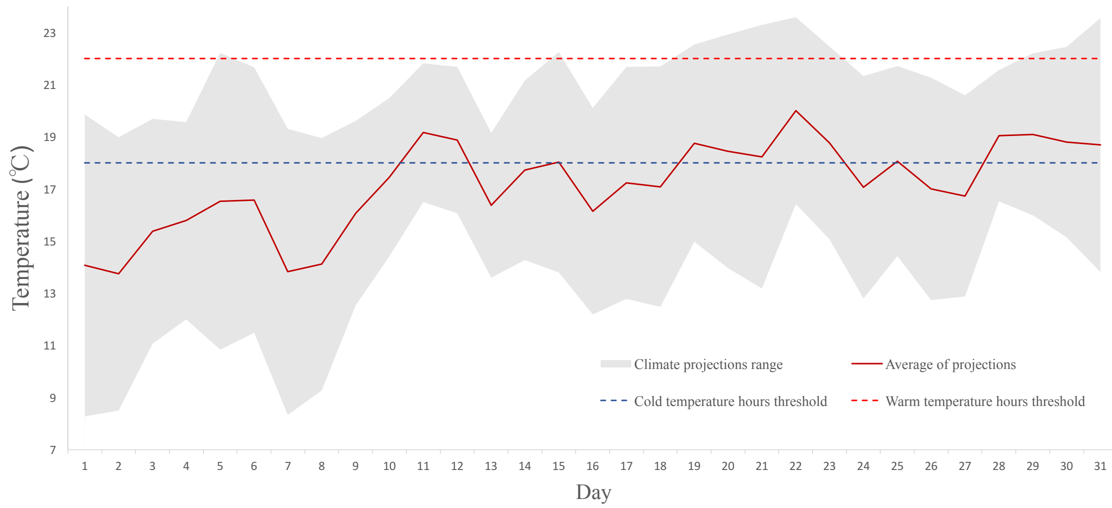


Figure 1: The range of the average over daily minimum and maximum temperatures for May 2021 for City of Knoxville, Tennessee. The two dashed lines represent the thresholds for warm and cold temperature hours.

develop an agent based model (ABM) to simulate the placement of PV panels and GRs over the rooftops under projected daily temperature and precipitation using the probability distributions derived from the data.

ABMs have been widely used over the past few decades in a variety of fields, including energy (Chen et al. 2012), economics (Bookstaber 2012), social sciences (Smith and Conrey 2007), marketing (Negahban and Yilmaz 2014), and so on. Through ABM, a system is formed by a number of autonomous elements, i.e., agents, which can evaluate their current situation, interact with one another, and make decisions individually, considering a number of rules (Bonabeau 2002). ABMs can be used to study an environment, forecast and explore it for future scenarios by considering different values for decision variables (Axelrod 1997). Combined with other techniques, ABMs have also been employed to tackle optimization problems (Weiss 1999).

The remainder of the paper is organized as follows. In Section 2, we present the mathematical formulation for the optimization model of the ABM. In Section 3, we present the values for a number of parameters used in the ABM and the methods applied to obtain them. This section also contains the detailed solution approach used to solve the ABM. In Section 4 we present a case study for City of Knoxville, Tennesse, as well as numerical analysis. We conclude the study in Section 5.

2 MODEL FORMULATION

In this section, we present the mathematical formulation of the optimization model for the ABM. This model, as an expansion of the model proposed in our previous study (Ramshani et al. 2017), aims to find the best locations to install PV panels and GRs in order to maximize the profit through energy generated and/or saved using PV panels and GRs, respectively. Different from (Ramshani et al. 2017), here we randomly allocate the initial budget to a host of agents and allow each individual agent to maximize their own income. Each candidate site is considered as an agent which makes individual decisions by using the model constraints in order to maximize its profit. The attributes for each agent are the available rooftop size, A_i^κ, average hourly energy need for air conditioning, H_i^κ, GR cost per square meter, P_i^κ, energy saving of GRs in warm and cold temperature hours, α and β, respectively, and its region, $\kappa \in K$. Note that we assume the size of each agent to be equal to the size of its available rooftop size. The distribution of the total number of peak sunlight hours, L^κ, warm temperature hours, λ^κ, cold temperature hours, τ^κ, as well as PV panel unit cost, V^κ, for each region are the attributes of the environment. Table 1 reperesents the notations used in the ABM.

$$c_i^\kappa = F x_i^\kappa + k_i^\kappa V^\kappa \qquad \forall i, \kappa. \tag{1}$$

Table 1: Model notation.

Notation	Description
Index	
K	Set of climate regions, where $\kappa \in K$
I^{κ}	Set of agents in region $\kappa \in K$, where $i \in I^{\kappa}$
Variables	
x_i^{κ}	Binary variable, equals to 1 if PV panels are installed at agent i in region κ; 0 otherwise
y_i^{κ}	Binary variable, equals to 1 if GR is installed at agent i in region κ; 0 otherwise
c_i^{κ}	PV panels total installation cost at agent i in region κ
g_i^{κ}	GR total installation cost at agent i in region κ
k_i^{κ}	PV panel size at agent i in region κ
e_i^{κ}	Generated energy by panels at agent i in region κ
s_i^{κ}	Energy saved by GRs at agent i in region κ
Parameters	
F	PV panels overhead cost
V^{κ}	PV panel unit cost in region κ
P_i^{κ}	GR cost per square meter at agent i in region κ
A_i^{κ}	Available rooftop size at agent i in region κ
α	Energy saving of GRs in warm temperature hours
β	Energy saving of GRs in cold temperature hours
B	Initial available budget
Q	PV panel output efficiency
H_i^{κ}	Agent average hourly energy need for air conditioning
θ	Efficiency increase due to GR and PV panels integration
μ	Selling price for one kWh electricity to the grid
ι_i^{κ}	Radiation percentage received for agent i in region κ
L^{κ}	Total number of peak sunlight hours over the decision horizon in region κ
λ^{κ}	Total number of warm temperature hours over the decision horizon in region κ
τ^{κ}	Total number of cold temperature hours over the decision horizon in region κ

$$g_i^{\kappa} = A_i^{\kappa} P_i^{\kappa} y_i^{\kappa} \qquad \forall i, \kappa. \tag{2}$$

$$k_i^{\kappa} \leq A_i^{\kappa} x_i^{\kappa} \qquad \forall i, \kappa. \tag{3}$$

$$e_i^{\kappa} = Q L^{\kappa} k_i^{\kappa} \iota_i^{\kappa} (1 + y_i^{\kappa} \theta) \qquad \forall i, \kappa. \tag{4}$$

$$s_i^{\kappa} = H_i^{\kappa} y_i^{\kappa} (\alpha \lambda^{\kappa} + \beta \tau^{\kappa}) \qquad \forall i, \kappa. \tag{5}$$

$$\sum_i \sum_{\kappa} (c_i^{\kappa} + g_i^{\kappa}) \leq B. \tag{6}$$

$$x_i^{\kappa},\ y_i^{\kappa} \in \{0,1\} \qquad \forall i, \kappa. \tag{7}$$

$$c_i^{\kappa},\ g_i^{\kappa},\ k_i^{\kappa},\ e_i^{\kappa},\ s_i^{\kappa} \geq 0 \qquad \forall i, \kappa. \tag{8}$$

Equations (1)–(5) are used by each agent to calculate the PV panels and GR installation cost, and the income from them. Each agent evaluates its installation cost for stand-alone PV panels, stand-alone GR, and integrated PV panels and GRs by using Equations (1) and (2). As Equation (1) shows, the PV panels cost include fixed panel cost (i.e., labor overhead, DC-AC inverter, and wiring costs), and variable panel cost (i.e., modules, mounting device, and workforce related costs). As shown in Equation (2), we assume that the size of GR installed by each agent should be large enough to cover its rooftop.

Equations (4) and (5) are used by the agents to calculate the income from each type of rooftop installation. Recall from Section 1 that the output efficiency of the panels significantly relies on the PV panel surface temperature, and decreases in the surface temperature. Also, recall that integrating PV panels and GRs increases the panels output efficiency since GRs reduce their surrounding environment temperature.

Therefore, the electricity generated by PV panels for each agent is calculated as represented in Equation (4). This equation calculates the total output of the installed PV panels by each agent considering the PV panel output efficiency, Q, the radiation percentage received for each agent, ι_i^κ, the total number of peak sunlight hours over the decision horizon, L^κ, and the efficiency increase due to GR and PV panels integration, θ. Equation (3) establishes the fact that the surface covered with PV panels by each agent cannot exceed its available rooftop size, A_i^κ. Equation (5) calculates the energy saved by GRs for each agent if GR is installed over them. This constraint includes the total number of warm and cold temperature hours over the decision horizon, λ^κ and τ^κ, respectively, and their respective percentages of energy saving, α and β. The reason that we consider different values for the saving from GRs in cold and warm temperature hours is that different studies claim different amounts of savings is achieved by installing GRs over rooftops in cold and warm hours (Coma et al. 2016, Dunec, JoAnne L 2012). Equation (6) restricts the agents to consider a total initial given budget for their investments. Lastly, Equations (7) and (8) introduce binary variables and impose non-negativity constraint on a number of model variables, respectively.

Equation (9) calculates the overall profit from PV panels and GRs installed by the agents, i.e.,

$$Z = \max \sum_i \sum_\kappa (e_i^\kappa + s_i^\kappa)\mu - (Fx_i^\kappa + k_i^\kappa V^\kappa x_i^\kappa + A_i^\kappa P^\kappa y_i^\kappa). \tag{9}$$

The first part of the equation includes the eletricity generated and saved by PV panels and GRs installed for all the agents, respectively. The second part of the equation contains the total installation cost of GRs and PV panel. Equation (9) plays the role of objective function of the model which we aim to maximize.

3 COMPUTATIONAL STUDY

In this section, first we present values and distributions estimated for the parameters in Section 3.1. Then, in Section 3.2 we present the metaheuristic method used to solve the ABM developed in Section 2.

3.1 Model Calibration

In this section, the values, ranges, and the estimateions used to approximate the value of the parameters of the ABM are presented. We use the data from the literature and industry as well as the climate projections.

Table 2 represents the range and estimation of the rest of the parameters of the ABM. For more detailed description on the values and estimation of the parameters used in this study, please refer to (Ramshani et al. 2017).

3.2 Solution Approach

In this section, we introduce the solution approach used for the developed ABM. We aim to solve the optimization problem through embedding tabu search in the ABM to find near optimal solutions.

Tabu search is a metaheuristic method proposed by Glover (Glover 1989), and can be employed to solve and find near optimal solutions for a variety of optimization problems, e.g., resource management, healthcare systems, and placement problems (Glover and Laguna 2013). The difference between tabu search and local search techniques is that by using short and long term memories, tabu search allows solutions with worse objective function values to be picked in order to escape the local optima (Glover and Laguna 2013). These memories are updated on every iteration until they reach their maximum allowed length. Then, the oldest entry in the memory is removed from the list and is replaced by the newest entry.

The outline of the tabu search for the proposed problem is as follows. First, an initial population of the agents is randomly picked. Each agent is allocated a proportion of the budget equal to the cost of completely covering it with stand-alone PV panels. If the cost to completely cover the agent with PV panels exceeds the remaining budget, the agent is allocated with the remaining budget. The agents in the initial population are added to the long-term memory (tabu list). The number of agents in the initial population and the area of stand-alone PV panels installed over each of them depends on the available budget. That is, the agents are picked and assigned with a proportion of the budget until the initial available budget is met.

Table 2: Parameters, ranges, and their estimated distributions.

Parameter	Ranges	Estimation	Sources
Total number of warm temperature hours, λ^{κ}	–	$TN(960067, 1045, 94506, 98541)$	(Nugent et al. 2017)
Total number of cold temperature hours, τ^{κ}	–	$logistic(477, 52645)$	(Nugent et al. 2017)
Total number of available peak sunlight hours, L^{κ}	–	$TN(18528, 606, 17414, 19610)$	(Nugent et al. 2017)
Energy saving of GRs in warm temperature hours, α	$[10\%, 16.7\%]$	$triangular(10\%, 20\%, \%10)$	(Coma et al. 2016, Dunec, JoAnne L 2012)
Energy saving of GRs in cold temperature hours, β	$[-6.1\%, 10\%]$	$triangular(-10\%, 10\%, 0\%)$	(Coma et al. 2016, Dunec, JoAnne L 2012)
Efficiency increase due to GR and PV panels integration, θ	$[3.33\%, 8\%]$	$triangular(2.5\%, 10\%, 5\%)$	(Chemisana and Lamnatou 2014, Hui and Chan 2011)
Average hourly energy need for air conditioning by each agent, H_i^{κ}	–	$H_i^{\kappa} = 4,450 + 33.71 A_i^{\kappa}$	(Ramshani et al. 2017)
PV panel output efficiency, Q	[13.5%,20%]	–	(Chung et al. 2015)
PV panel unit cost, V^{κ}	[$310,$560]	–	(Ramshani et al. 2017)
PV panel overhead cost, F	$7,000	–	(Ramshani et al. 2017)
GR cost per square meter, P_i^{κ}	–	$P_i^{\kappa} = -5.603e^{-5} A_i^{\kappa} + 12.45$	(U.S. General Service Administration)
Selling price for one kWh electricity to the grid, μ	–	$0.103	(EIA 2017)
Available rooftop size, A_i^{κ}	[15,152534]	–	(Kodysh et al. 2013)
Radiation percentage received by each agent, ι_i^{κ}	[0,1]	–	(Ramshani et al. 2017)

Second, each individual agent calculates the profit gained from different types of rooftops it can install using the budget allocated to it. The profit is calculated as the difference between the income from the type of rooftop chosen and its cost. Each agent conducts the following process to calculate the profit from stand-alone GRs. Firstly, the agent completely covers its rooftop with GR. Then, if the agent's allocated budget is more than its GR cost, the agent installs GRs on other available agents by using the remnant of its allocated budget. That is, the agents which are not in long-term nor in short-term memory list are randomly chosen and the profit of GR installation over them is calculated. This process stops when the agent's allocated budget is met. In the end, the profit from all the GRs that are installed using agent's budget is calculated. The agents that are randomly picked in this stage are added to short-term memory. After evaluating the profit from different types of rooftops, the agent installs the type of rooftop with the highest profit, and if all the rooftop types cost more than the income they make, i.e., negative profit values, the agent chooses to install nothing.

Last, tabu search calculates the total profit made by all the agents using Equation (9), and then repeats the process. The short-term memory is cleaned after each iteration. The long-term memory, however, keeps the agents added to it until the number of the agents in long-term memory is more than its predefined number, 1,000 agents in this study, and then the oldest entry is replaced with the newest one. In this way, as the history of searches is recorded, the direction of the following searches can be controlled. This process is repeated until the termination criterion is met, and then the best answer obtained is reported.

4 NUMERICAL STUDY

In this section, we present a case study for City of Knoxville, Tennessee, for 209,183 agents. In Section 4.1, we present and solve two scenarios. Numerical analysis in Section 4.2 is performed to further analyze the results of the ABM and to capture the effect of different parameter values on it.

4.1 Case Study

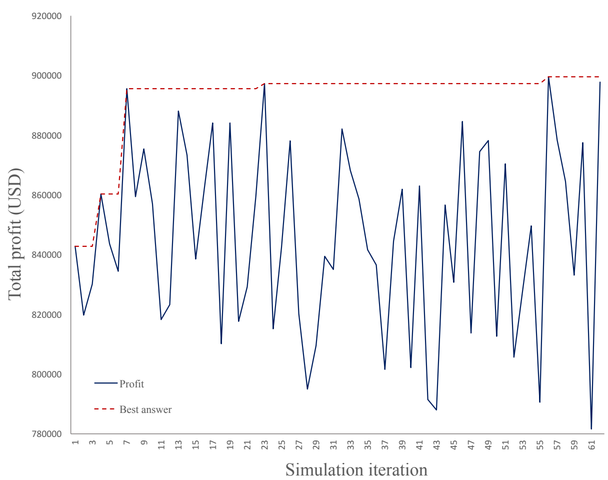
We solve the model for two scenarios. Scenario 1 is designed to represent the price and output of the currently available commercial PV panels. Scenario 2, however, contains more efficient PV panels with a lower variable cost. Scenario 2 aims to capture the current trend in PV panels development, as each year more efficient PV panels are produced with a lower cost (Feldman et al. 2014). The PV panel variable cost, V^{κ}, for each square meter of the panels is considered to be equal to $450 and $200 for each scenario, respectively. The PV panel output efficiency, Q, is considered to be equal to 150 and 200 Watts for each scenario, respectively. Each scenario has an initial available budget of \$20 million.

To calculate the number of simulation iterations required, we run the model for a limited number of iterations, i.e., 20 iterations, calculate the mean and standard deviation of the results, and then using

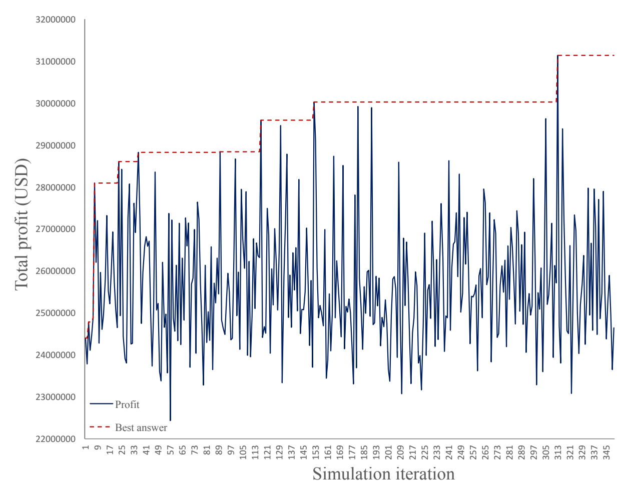
$$N \geq \left(\frac{Z_{1-\alpha/2}SD}{\varepsilon\bar{x}}\right)^2, \tag{10}$$

we obtain the number of iterations required for each scenario, where N denotes the required number of iterations, $Z_{1-\alpha/2}$ denotes the quantile value for standard normal distribution, SD denotes the standard deviation of the results, and $\bar{x}$ denotes mean value of the results from the 20 iterations. In this study, we set ε and α equal to 0.05. The requisite number of iterations in order to fall in the 95% confidence interval for Scenarios 1 and 2 as calculated by Equation (10) are equal to 62 and 367 iterations, respectively.

Figures 2a and 2b depict the total profit of the model for each iteration, and the best profit obtained by the model for Scenarios 1 and 2, respectively. As the figures show, tabu search allows worse decisions by the agents to escape the local optima. Table 3 represents the best profit value obtained for each scenario, and the total budget spent by the agents, as well as the total area of stand-alone PV panels, stand-alone GRs, and integrated PV panels and GRs installed by the agents for the best profit solution.



(a) Total profit of the model for the Scenario 1.



(b) Total profit of the model for the Scenario 2.

Figure 2: Simulation results for Scenarios 1 and 2. The dashed line reperesents the profit value of best answer obtained until each iteration.

The output of the model significantly relies on the PV panel unit cost, V^{κ}, and PV panel output efficiency, Q. That is, when PV panel unit cost is low and PV panel output efficiency is high, Scenario 2, most of the agents opt to install PV panels (stand-alone or integrated with GRs) in order to maximize their individual profit. However, for high values of V^{κ} and low values of Q, Scenario 1, no agents choose to install PV panels. In fact, agents only opt to install GRs as the income from the PV panels is not large enough to at least cover their installation cost. Moreover, the total budget spent on the best obtained solution for Scenarios 1 and 2 are equal to \$454,289 and \$19,557,126, respectively. This shows that a higher available budget does not necessarily lead to a higher number agents installing PV panels and/or GRs, and hence, a higher profit. In fact, only 2.3% of the initial available budget is spent by the agents in order to install GRs in the best obtained solution for Scenario 1.

The agents that chose to install PV panels in the best obtained solution for Scenario 2 have generally large available rooftop sizes, A_i^{κ}, which results to less budget spent on PV panels overhead cost, F. Moreover,

Table 3: Simulation results for the best solution obtained by tabu search for Scenarios 1 and 2.

	Area of stand-alone PV (m^2)	Area of stand-alone GR (m^2)	Area of integrated PV panels and GRs (m^2)	Total profit	Budget spent
Scenario 1	0	33,651	0	899,570	454,289
Scenario 2	78,610	498	15,192	31,136,702	19,557,126

larger rooftops tend to have a higher radiation percentage received, ι_i^κ, compared to smaller rooftops, as they are less likely to be shaded by their surrounding objects. Hence, agents with larger rooftops can achieve a higher profit compared to agents with smaller rooftops. Figure 3 depicts the total area of installed PV panels (stand-alone and integrated with GRs) by the agents for Scenario 2 over each iteration, and compares them with the total area of installed PV panels for the best obtained solution until each iteration. As the results demonstrate, a higher area of PV panels installed by the agents does not necessarily translate to a higher profit. For instance, in the highlighted iteration in Figure 3, while a larger area of PV panels are installed compared to the best obtained solution, the agents which installed the PV panels generally have lower values of ι_i^κ, and hence generate lower amounts of electricity.

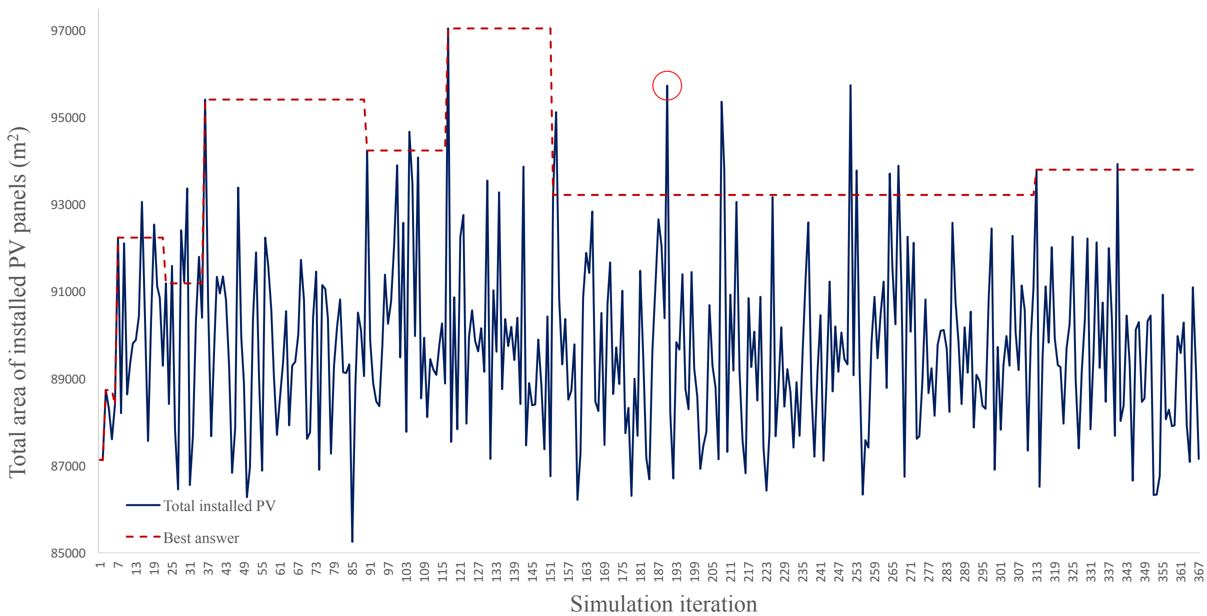


Figure 3: Total area of installed PV panels (stand-alone and integrated with GRs) by the agents for each iteration. The dashed line reperesents the total area of PV panels installed for the best obtained solution.

4.2 Numerical Analysis

Results presented in Table 3 show the effect of PV panel unit cost, V^κ, and PV panel output efficiency, Q, on the results of the model. The other input parameters of the model are considered to be randomly assigned from the distributions presented in Table 2. In this section, we aim to confirm the robustness of the ABM by evaluating the effects of other input parameters on the results through conducting analysis. That is, we assign exact values to the remaining parameters to further investigate their effects on the results.

Table 4 represents the results from the analysis over three different parameters of the ABM, i.e., energy savings values for GRs in hot temperature hours, α, energy saving values for GRs in cold temperature hours, β, and efficiency increase due to GR and PV panels integration, θ. The ABM is solved for a type of PV panels as the one considered in Scenario 2. That is, we consider PV panel unit cost, V^κ, to be equal to

\$200 per square meter, and PV panel output efficiency, Q, to be equal to 200 Watts. We solve the ABM for 100 iterations for each set of parameters for an initial available budget of \$20 million, and report the best answer obtained. The environment parameters are considered to have the distributions presented in Table 2.

As the results from Table 4 show, the total installed area of integrated PV panels and GRs by agents significantly relies on the values of efficiency increase due to GR and PV panels integration, θ. That is, when there is no efficiency increase due to GR and PV panels integration, i.e., θ equal to 0, the agents generally opt to install no integrated PV panels and GRs.

Table 4: Analysis of the results from the model over three different parameters of the ABM.

GR energy saving in hot temperature hours, α	GR energy saving in cold temperature hours, β	Efficiency increase due to GR and PV integration, θ	Area of stand-alone PV panel (m^2)	Area of stand-alone GR (m^2)	Area of integrated PV panels and GRs (m^2)
10%	-10%	0%	97,793	0	0
		10%	0	0	90,588
	10%	0%	94,439	2,192	12
		10%	0	1,010	91,350
20%	**-10%**	**0%**	**95,581**	**1,932**	**81**
		10%	0	44	93,737
	10%	0%	95,696	18190	121
		10%	53,878	3,241	39,838

As shown in the highlighted row of Table 4, in some cases agents decide to install integrated PV panels and GRs regardless of the values of θ. Recall from Section 3.1 that we approximate the average hourly energy need for conditioning for each agent as $H_i^\kappa = 4,450 + 33.71\ A_i^\kappa$, which has a relatively small slope, and does not drastically increase in agent's size. That means agents with smaller rooftops benefit the most from the energy savings provided by GRs. The small area of integrated PV panels and GRs in highlighted row of Table 4 shows that the agents which chose to install this type of rooftop have a small available rooftop size, A_i^κ, and mainly install integrated PV panels and GRs to benefit from the energy savings GRs provide, while generating electricity by installing PV panels. Moreover, the highlighted row shows the fact that tabu search leads to near optimal solutions since the best obtained solution contains agents with small rooftops installing PV panels, while the agents with larger rooftops are the most appropriate for this matter in order to minimize the budget spent on PV panels overhead cost, F, and benefit the most from larger rooftops' higher values of radiation percentage received, ι_i^κ. Overall, the results from Table 4 show the ability of the ABM to correctly capture the effects of the input parameters and choose the solution which is well suited to maximize the income for different parameter settings.

5 CONCLUSIONS & DISCUSSIONS

In this paper, we developed an agent-based simulation model, embedded with a tabu search metaheuristic, to assist with the long-term decision of PV panels and GRs placement in order to maximize the profit. Whether to install PV panels or GRs to generate electricity and/or reduce energy consumption, significantly depends on future climate as the electricity generated by PV panels relies on solar radiation received by them, and the energy savings from GRs rely on the temperature. Since the initial cost of PV panels and GRs are considerable and they have a life-span of 20-25 and 40-50 years, respectively, we must consider the conditions which affect the outcome of this decision and are probable to take place during the time in which we aim to utilize installed PV panels and GRs. Thus, we employed ten different climate projections to more accurately represent the future climate conditions. Moreover, the savings from GRs and the efficiency increase in the output of PV panels due to integration of them with GRs are reported with different values in the literature. Hence, we explicitly incorporate the uncertainties from future climate changes, and other input parameters by estimating the probability distribution of them using the climate projections and data available in the literature.

We developed a tabu search algorithm to solve the proposed ABM for a case study with more than 200,000 candidate sites (agents). The solution obtained from the model provides a PV panel and GRs placement suggestion that results in maximizing the profit gained from PV panels and GRs installation. The results from the simulation indicate that current commercially available PV panels are not an economically viable option to utilize for the mid-sized city of Knoxville, Tennessee, and only a number of candidate sites should be covered with GRs. However, the results show that with more cost efficient PV panels, installing PV panels can lead to high levels of profit. This study does not consider the incentives provided by the governments for PV panels and GRs installation, as they are not the same across different regions. Hence, these incentives for each region should be considered by the decision makers while calculating the cost of PV panels and GRs before executing the model. Also, the proposed model only considers the energy consumption reduction aspect of GRs, and does not take into account other beneficial aspects of them, e.g., reducing CO_2 levels, increasing the rooftop life-span, water runoff reduction, etc. We plan to incorporate the other aspects mentioned in our future studies to better capture the effects of GRs.

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AUTHOR BIOGRAPHIES

Xueping Li is an Associate Professor of Industrial and Systems Engineering and the Director of the Ideation Laboratory (iLab) and co-Director of the Health Innovation Technology and Simulation (HITS) Lab at the

University of Tennessee - Knoxville. His research areas include complex system modeling, simulation, scheduling and optimization, data analytics, and health systems engineering. He is a member of IIE, IEEE, ASEE and INFORMS. His email address is xueping.li@utk.edu.

Mohammad Ramshani is a Ph.D. student in the Department of Industrial and Systems Engineering at the University of Tennessee, Knoxville. He received his M.S. in Socio-economic Systems Engineering from Economic Science University. His email address is m.ramshani@gmail.com.

Anahita Khojandi is an Assistant Professor of Industrial and Systems Engineering at the University of Tennessee, Knoxville. Her research interests include decision making under uncertainty, data mining and machine learning with applications in healthcare and civil infrastructure planning. She is a member of INFORMS, IIE and the Society for Medical Decision Making (SMDM). Her email address is khojandi@utk.edu.

Olufemi Omitaomu is a Senior Research Scientist in the Computational Sciences and Engineering Division at Oak Ridge National Laboratory. He is also a joint ORNL-UT Associate Professor in the Department of Industrial and Systems Engineering. He received a Ph.D. In Industrial Engineering from University of Tennessee; and M.S. and B.S. in Mechanical Engineering. His expertise includes applied artificial intelligence, machine learning, and data mining with applications in infrastructure systems, energy systems, and emergency response. His email address is omitaomuoa@ornl.gov.

Jon Michael Hathaway received his Ph.D. from North Carolina State University in 2010, where he studied the fate, transport, and removal of indicator bacteria in urban stormwater runoff. After a brief research fellowship at Monash University in Melbourne, Australia, and nearly two and half years at one of the nation's leading ecological design and consulting firms, he joined the Department of Civil and Environmental Engineering at the University of Tennessee. He is a 2016 recipient of the National Science Foundation CAREER award. His email address is hathaway@utk.edu.