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OPTIMAL EFFICIENCY AND OPERATIONAL COST SAVINGS: A FRAMEWORK FOR AUTOMATED ROOFTOP PV PLACEMENT

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ABSTRACT

Residential energy consumers are charged based on a utility rate structure, such as net metering or feed-in tariff. To lower consumers' electricity bills, expensive batteries are deployed to reduce the electricity fed from the grid during peak hours. However, strategic photovoltaic (PV) panel placement enables the reduction of operational energy cost while considering the spatial feasibility and efficiency for hosting rooftop PV.

In this paper, we present a framework to automatically identify the optimal location of rooftop PV panels on residential buildings. Our framework integrates multiple workflows, including energy and environmental simulation, parametric modeling, and optimization to identify the ideal location of PV panels to balance the demand and supply of residential buildings.

These workflows are linked using the Grasshopper plug-in for Rhinoceros CAD software. The framework includes two different workflows, each satisfying a target for optimal PV placement: (a) maximizing PV panel efficiency, where users aim to maximize energy generation, and (b) minimizing operational energy cost, where "best" panels are selected considering utility rates for operational energy cost. Our framework is demonstrated in a residential community in Fort Collins, Colorado, to generate the optimal PV placement for each of the two aforementioned targets. Results from the two workflows are compared to illustrate the effect of PV location and orientation on solar energy production efficiency and operational energy cost.

The developed workflows are introduced as tools within the Grasshopper plug-in to investigate the solar potential of rooftop PV panels while taking into account factors such as contextual shading, utility rate structures, and buildings' energy demand profiles.

INTRODUCTION

Buildings have the highest share of energy demand—approximately 40% of energy end use (Pérez-Lombard, Ortiz, and Pout 2008). With solar being one of the most popular clean energy technologies (Peng, Huang, and Wu 2011), targets have been set to increase the share of solar energy to satisfy building energy demands.

Consequently, photovoltaics (PV) are becoming more desired, due to their ability to produce on-site electricity without energy supply concerns or environmental harm (Jelle and Breivik 2012). Because of this, rooftop PV deployment is spreading rapidly as the cost of PV decreases. Rooftop-deployed PV has a great advantage over ground-mounted PV, because it can avoid the cost of land use and be integrated within the building's roof structure, reducing additional material and labor costs (Baljit, Chan, and Sopian 2016).

Climate and energy targets (along with the aforementioned benefits) have led to a growing deployment of rooftop solar PV in buildings. Indeed, extensive recent literature has shown that the integration of PV systems in residential neighborhoods is currently the most feasible and practical option (Rodríguez et al. 2016; Scognamiglio, Garde, and Røstvik 2014; Burns and Kang 2012). Therefore, analyzing the solar potential of individual buildings and neighborhoods is critical to informing future adaptive energy policies and utility planning (Wiginton, Nguyen, and Pearce 2010).

When analyzing PV generation and solar potential in residential communities, the implementation goals can be divided into two analysis objectives:

(1) Maximizing PV panel solar radiation through solar access analysis: This analysis focuses on the science of sustainable urban context to quantify the amount of solar access (Amado and Poggi 2012), because mutual shading in residential neighborhoods has a great influence on solar radiation. For example, solar radiation for building rooftops in Osaka, Japan, is reduced by 13.7% when shadows from surrounding buildings are considered, and an additional 7.7% reduction occurs when obstacles on the rooftop are taken into account (Takebayashi et al. 2015; Bergamasco and Asinari 2011). Based on estimates from Navigant Consulting, only 8% of residential rooftops in the United States are flat (Paidipati et al. 2008). For this reason, self-shading from roof structures is expected to have a high impact when calculating the solar radiation absorbed by available roof surfaces. Therefore, it is crucial to consider the shading effect from rooftop obstruction and surrounding context when simulating the solar

radiation in U.S. residential communities.

(2) Matching building energy demand with PV generation: This mismatch leads to unwanted power flow between the household and the grid. This is abundant in residential neighborhoods, even in buildings with equal annual generation and consumption. The daily PV generation and electricity consumption profiles are different, which means buildings need to export a portion of the generated energy back to the grid (Moura et al. 2013). This situation has introduced a lot of management difficulties for the electric grid. It also contributes to a significant financial loss to the end user when the price paid for the consumed energy is higher than the price of energy sold back to the grid. Therefore, it is important to maximize self-consumption of the generated energy (Lang, Ammann, and Girod 2016). In addition, residential energy consumers are charged based on different utility rate structures. To reduce consumers' electricity bills in net zero energy homes and communities, expensive batteries are deployed to reduce the electricity fed from the grid during peak hours (Kousksou et al. 2014). Although this seems to be an attractive solution, optimizing placement of PV panels can minimize operational energy cost while avoiding the financial burden of expensive and large-sized batteries.

Despite abundant literature evaluating the solar potential of individual buildings and urban areas, studying the spatial deployment of PV panels to satisfy the aforementioned objectives has not yet been addressed. Brownsword et al. estimated the PV resources for rooftops in Leicester city, considering only south-west to south-east oriented roofs and taking 75% of total roof area as an efficient area to install PV panels (Brownsword et al. 2005). Lund analyzed the potential deployment of PV panels on roofs by simulating the generation of only 50% of the available roof area and neglecting shading effects (Lund 2012). Energy demand was calculated using load distribution function based on location. Wegertseder et al. combined solar mapping of roofs surfaces with energy consumption patterns of the building stock in Concepcion, Chile, to calculate net power flows in the urban electric grid (Wegertseder et al. 2016). In a more recent attempt, Brito et al. carried out a techno-economic analysis of the feasibility of building-integrated PV in different areas in Portugal by coupling LiDAR and Typical Meteorological Year (TMY) weather data. The demand side of this is estimated using a top-down approach, where the average per capita electricity demand is multiplied by the estimated number of inhabitants (Brito et al. 2017).

All these approaches attempted to calculate the net energy profile. However, these studies relied on simplified assumptions to define areas for efficient rooftop PV application. They also relied on top-down approaches that cannot address different scenarios in terms of energy demand that would require a bottom-up approach (Reinhart and Davila 2016). To fill in the literature gap, this paper introduces workflows that use a bottom-up approach to inform engineers, urban designers, residential project managers, and residential homeowners on the optimal placement of rooftop PV panels, taking into account economic and efficiency targets.

Our approach presents an automated framework to identify the optimal location of rooftop PV panels. The framework is implemented by combining multiple workflows, including energy and environmental simulation, parametric modeling, and optimization to identify the optimal number and location of PV panels on individual buildings for balancing the energy demand and supply of residential buildings. These workflows are linked in the visual scripting interface Grasshopper in Rhinoceros CAD software. The algorithms include two user-identified targets for optimal PV placement: (a) maximizing PV panel efficiency, where users aim to maximize the total energy generation, and (b) minimizing operational energy cost, where best panels are selected considering different utility rates for operational energy cost.

The workflows were demonstrated on a residential community in Fort Collins, Colorado. The developed workflows were implemented to find the optimal rooftop PV placement for each of the two targets. Results from the workflows are discussed in this paper, illustrating the effect of PV location and orientation on solar energy production efficiency and operational energy cost.

The paper is organized as follows: Section 2.1 describes the model generation and simulation of the demand energy profile. Section 2.2 presents a workflow for optimal PV sizing based on panel efficiency. Section 2.3 presents an optimization workflow for selecting panels to minimize operational energy cost. Section 3 illustrates and compares the results of the implemented workflows.

METHODOLOGY

Matching annual PV production to annual community energy demand is subject to the feasibility and efficiency constraints of deploying PV panels on roof surfaces. In this process, we simulated the total demand profile. Then, we developed two different workflows to find optimal PV placement, each with a specific objective.

2.1 Energy Demand Profile Generation

The modeling of the community in Fort Collins was developed using Rhino3D CAD software. Detailed architectural drawings were provided by the project manager and used to model the exact roof and envelope geometry for each building type in the community. This digital massing model provided geometric and spatial information of the built urban environment and is processed using the

Grasshopper tool (a visual scripting plug-in for Rhino3d CAD software) for our analysis.

The energy consumption profiles for each building type were simulated using BEopt™software (Christensen et al. 2005), taking into account the different orientations and occupancy levels. Then the community total building loads were generated by aggregating the building loads from all the residential building types in the community. A 2017 EnergyPlus weather file of Fort Collins was used to run the simulation, and an hourly community aggregate load was generated.

2.2 Workflow 1: Optimal PV Placement Based on Panel Efficiency

This workflow aims to find the most efficient placement of the PV panels to be laid on the building roofs in the community, based on surface efficiency and feasibility. This process is divided in two steps: (1) selection of most efficient panels and (2) PV energy simulation.

2.2.1 *Step 1: Selecting PV Panels to Maximize Solar Radiation Gains*

The first step is divided into three main parts, illustrated in Figure 1 and detailed in the following paragraphs.

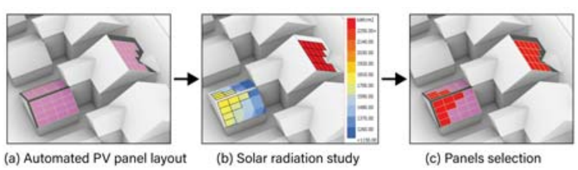

Figure 1: Optimal rooftop PV panel placement steps

(a) First, an automated PV panel layout algorithm is developed to geometrically lay out specific PV panels on complex roof geometry. The PV panel size is defined to be 1686 mm x 1016 mm, based on the PV module selected by the home builders. Based on the PV panel size, the geometric algorithm fits the maximum number of panels on any complex roof geometry. To reduce the computational time of the workflow, the algorithm disregards north surfaces because they are inefficient for PV implementation. Surfaces smaller than 15 m^2 are also disregarded to ensure the spatial feasibility of placing a PV panel. The functionality and output of this algorithm are illustrated in Figure 2.

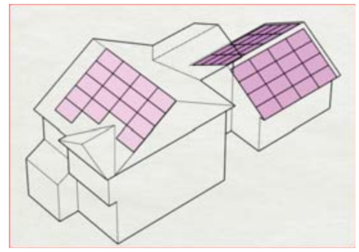

Figure 2: Automated PV panel layout

(b) After populating the roof surfaces with the maximum number of panels, a solar radiation analysis for direct and indirect radiation is performed on all the panels. The Fort Collins EPW weather file with historical data for 2017 was used for this study. This weather file was used to model a cumulative sky matrix by using Radiance's gendaymtx function to calculate the sky's radiation for each hour of the year. Figure 3 shows a visualization of the sky matrix generated from the weather file. Three sky domes are illustrated; the first dome shows the total radiations, the second dome shows diffused radiations, and the third dome shows only direct radiations.

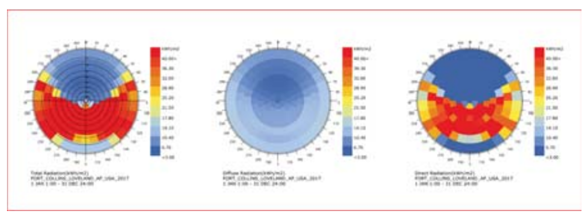

Figure 3: Cumulative sky matrix based on Radiance gendaymtx function

Using the generated sky matrix, the amount of absorbed radiations (kWh/m^2) per year is calculated for all laid panels. In this process, several test points are assigned on each panel, and an average radiation result is returned for each panel. Figure 4 shows a radiation study for panels laid on the roof of a single-family detached building. To reduce the computational time of the workflow, the algorithm disregards north-facing surfaces because they are inefficient for PV implementation. Surfaces smaller than 15 m^2 also are disregarded to ensure the spatial feasibility of placing a PV panel. The solar radiation analysis allows the user to quantify the amount of energy collected by each panel, as well as the number of direct sunlight hours received.

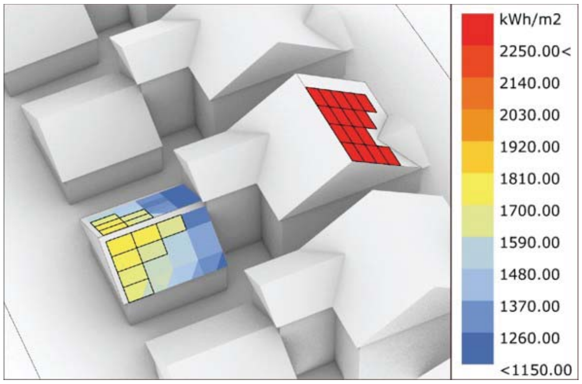

Figure 4: Solar radiation analysis for direct and diffused radiations

(c) Based on the retrieved radiation data for each panel, the best panels are automatically identified by assigning a threshold for a solar radiation value. All panels that have an average radiation below the assigned threshold are considered inefficient and are disregarded. The user can now study different scenarios by assigning different efficiency thresholds. The output of this process is illustrated in Figure 5: based on a defined threshold, the red colored panels were selected as the most efficient panels.

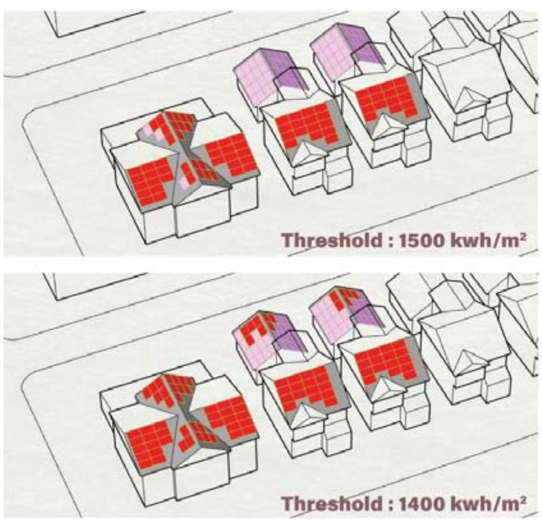

Figure 5: Best panel selection based on a solar radiation threshold

2.2.2 *Step 2: PV Energy Simulation*

In the second step, the electrical energy produced by the selected PV panels is calculated using NREL's PVWatts calculator for crystalline silicon (c-Si) and thin-film photovoltaics (Dobos 2014). The inputs and assumptions for this model are summarized in the following tables:

Table 1: PV Module Settings

PV Module Settings	Inputs
Module material	Crystalline silicon (c-Si)
Mount type	Flush roof mount
Module efficiency	18.7%
Temperature coefficient	$-0.5\%/°C$
Module active area	90%

Table 2: PV System Losses

System Losses Category	Values (%)
Soiling	2
Mismatch	2
Wiring	2
Nameplate rating	1
Light-induced degradation	1.5
Availability	3

The annual shading for each PV panel is calculated to evaluate the losses due to shading. Figure 6 visualizes the annual AC energy percentage of a single panel for each hour of the year. These results are used to account for the shading losses of each panel.

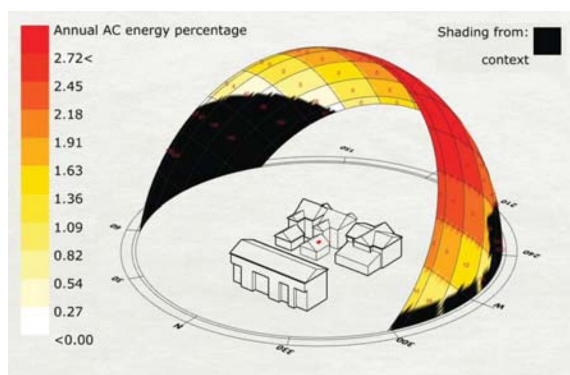

Figure 6: Annual AC energy percentage accounting for losses from shading

Following this simulation process, users can run and compare different scenarios by selecting a threshold for efficiency.

2.3 Workflow 2: Optimal PV Placement Based on Operational Energy Cost

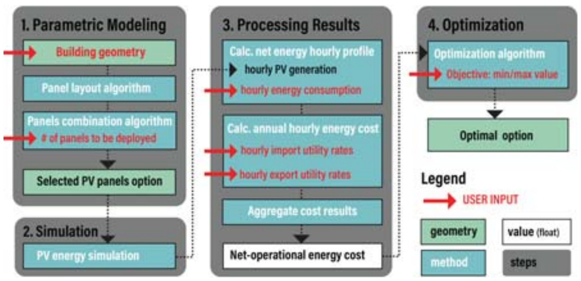

Figure 7: Optimal PV panels selection to minimize operational energy cost

This workflow utilizes a genetic optimization algorithm to find the optimal placement of PV panels with the objective of minimizing operational energy cost. The overall process is illustrated in Figure 7 and consists of four steps: parametric modeling, simulation, processing results, and optimization.

In the parametric modeling step, the panel layout algorithm, described in Section 2.2.1 (Figure 2) is implemented. Then a method is developed and used to select all the possible combinations of a targeted number of panels. The number of panels is specified by users, because this decision depends on the amount of rooftop PV panels the homeowner or community managers decide to invest in. The panel combinations are the genomes input to be investigated by the optimization algorithm.

After, the selected PV panel surfaces are simulated in step 2 using the PV simulation model described in Section 2.2.2 to generate an hourly annual energy generation profile.

During step 3 (processing results), the PV generation profile is subtracted from the energy consumption profile to calculate a net energy hourly profile. Then a utility cost with a time-of-use rate structure is used to calculate the hourly annual energy cost and total operational energy cost for the whole year. Users should specify 8760 hourly values representing utility rates for both the export and import of electricity. This allows users to test and compare different utility rate structure scenarios such as: (1) net-metering scenario, where the assigned rate for purchasing electricity is equal to the sell-back (export) rate; (2) no-sell-back incentive, where residents do not get any financial incentive from giving back excess electricity generated from PV; and (3) specific feed-in tariff, where the users-specified utility rate for the import of electricity is different from the rate of electricity export.

Finally, using a genetic optimization algorithm, each combination of PV panels (genome) is evaluated based on the total operational energy cost value (fitness value) for the corresponding genome. The algorithm searches for the optimal option that minimizes the operational energy cost value.

Figure 8 shows the output of this workflow when applied to a single building. In this example, two panels were specified as inputs to the panel combination algorithm. Also, a utility rate structure with no sell back incentive is used as an input in the processing step. The optimal panels option with the least operational energy cost is then selected for deployment. While the "best" option is automatically selected, users can search and select other options of interest. The best option is illustrated in the panel configuration in Figure 8: one panel was selected to be deployed on the south-facing roof, while the other was selected to be deployed on the west.

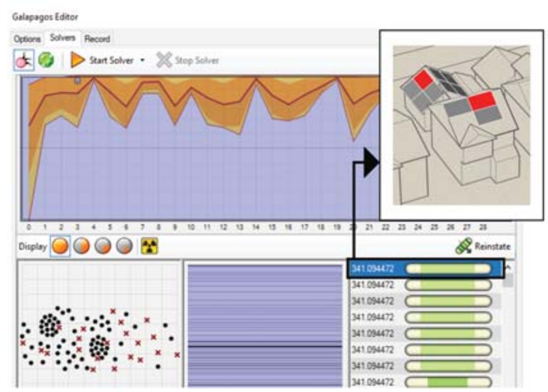

Figure 8: Genetic optimization top 10% options that minimize operational energy cost

RESULTS

Using the developed workflow, users can now perform analyses for optimal PV placement. A sample of the results from both proposed methods is analyzed in this Section.

The developed workflows were tested using Fort Collins, Colorado, as a case study. Figure 9 illustrates three options for selecting optimal PV panel placement for a single-family house in this community. All of these options fall in the top 10% fit genomes when workflow 2 was implemented with an objective to reduce operational energy cost. From these three options, option 2 was selected to be the optimal option when workflow 1 was implemented, where the most efficient placement was identified to maximize PV generation.

The demand profile for the illustrated single-family house is simulated using BEopt. A default schedule for residential occupancy and behavioral schedules (SIA 2006) was used for this simulation.

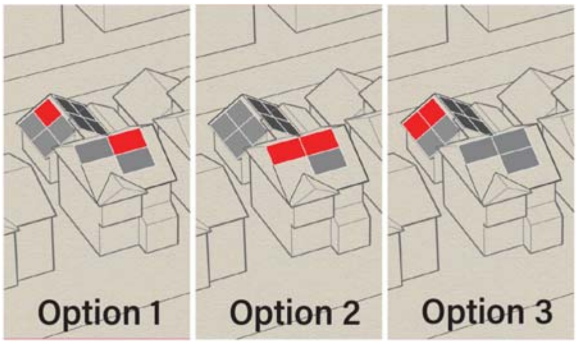

Figure 9: Comparison between different optimal PV panel selection options

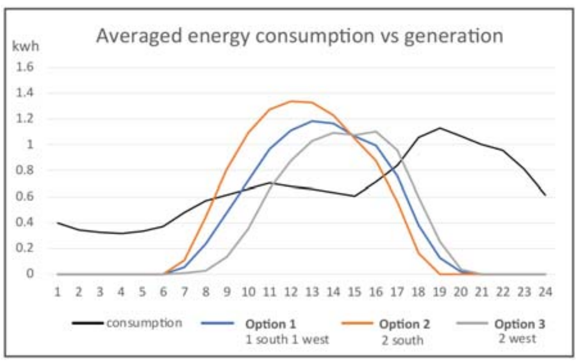

Figure 10: Energy demand profile vs. PV generation profiles for each selected option

Figure 10 shows the demand profile plotted against the PV generation profiles for each of the three options. Based on Figure 10, option 1 provides energy generation covering the largest timeframe (6 a.m. until 8 p.m.). Option 2 provides the highest amount of total energy generation; however, electricity generation drops dramatically starting at 3 p.m. and stops at 6 p.m. when the sun completely shifts to the west. Deploying both panels on the west (option 3) generates a smaller amount of total electricity compared to option 2, but this option provides the highest amount of electricity produced during afternoon hours (4 p.m. to 8 p.m.).

When investigating the solar potential of PV panels, both the demand and generation profiles should be taken into account along with the utility rate structure. For example, when considering a time-of-use billing plan, west-facing solar panels could help avoid paying the higher peak rates by providing more energy when the electricity cost is higher. However, with a net metering or other utility rate structure that provides financial incentive when exporting electricity back to the grid, south-facing panels might provide the most net financial benefit. Moreover, the geographic location and mutual shading of buildings are also important factors to be considered in this investigation, because they define the shape of the generation profile. The developed workflows can be used as tools to investigate the solar potential of rooftop PV panels while taking into account all of the aforementioned factors.

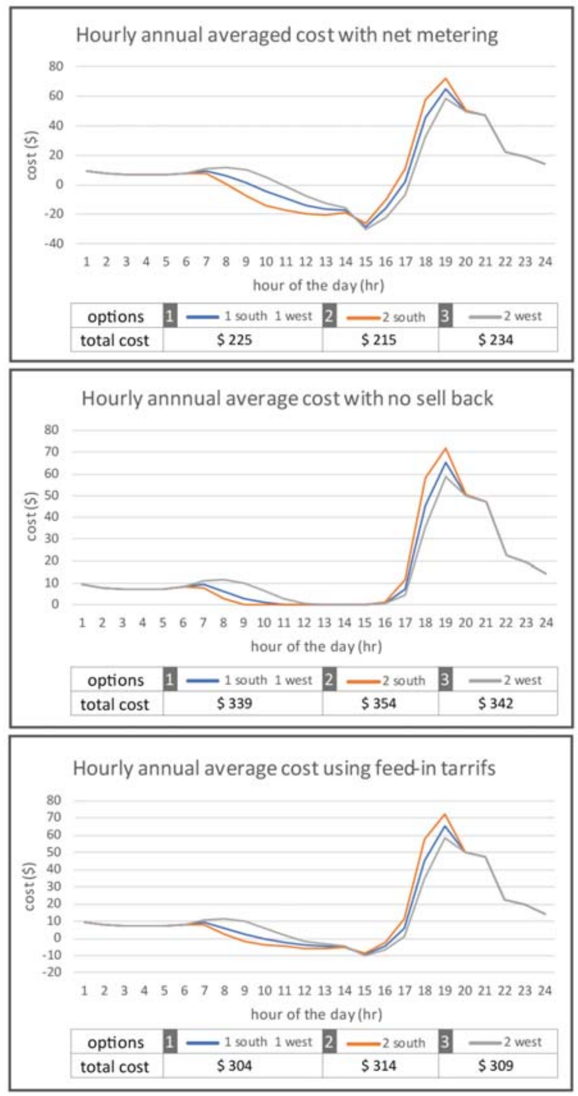

Figure 11: Comparison of operational energy cost profiles for each utility structure scenario

One example of such investigation is illustrated in Figure 11. For each defined option, three different utility rate structure scenarios are tested by comparing the resulting net operational energy cost. The figures illustrate profiles representing hourly annual averaged operational energy cost and document the net annual cost values for each option in a scenario. The three tested scenarios are:

1. Net-metering scenario, where electricity import and export utility rates are equal.
2. Feed-in tariff scenario, where utility rates for electricity export are half the utility rates of electricity import.
3. Scenario representing no economic incentive for electricity sell back, where users do not receive any economic benefit for giving back excess energy to the grid.

Referring to Figure 11, results show that option 2 has the lowest net cost when net metering is applied. The user in this case is selling back excess electricity generation at an equal rate of consumed energy; therefore, maximizing the total PV generation is the best strategy to decrease the net annual cost. As a result, the optimal option is when both panels are deployed at the south-facing roof.

On the contrary, option 1 is the optimal option when no sell back incentive is applied. In this case, setting one panel on the south and another on the west tends to work best because the south-facing panel is reducing the grid energy consumption during midday hours, while the west-facing panel reduces the high cost of peak energy demand.

A similar conclusion is observed in the third graph of Figure 11. In this scenario, the sell-back rate was set to be half the import rate. Overall, options 1 and 3 have similar results, with lower operational energy cost compared to option 2.

CONCLUSION

This paper introduces a novel framework for optimal PV placements in residential communities. Workflows are introduced as tools within the Grasshopper plug-in for Rhinoceros CAD software. The capabilities of the presented workflows are demonstrated by a case study in Fort Collins, Colorado. Utilizing these workflows, users can investigate the solar potential of buildings rooftops.

This analysis reveals the effectiveness of the proposed workflows in informing engineers, urban designers, and homeowners on the optimal placement of rooftop PV panels, considering both economic and efficiency goals. These bottom-up workflows aim to scale renewable energy analysis and are crucial to improving solar penetration into the U.S. building stock.

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