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A DATA-DRIVEN FRAMEWORK FOR DEPLOYING SOLAR PV AT PENN STATE UNIVERSITY

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Abstract

The Pennsylvania State University has set greenhouse gas (GHG) emissions reduction goals that must be met with minimal impact on tuition rates. Investment in solar photovoltaic (PV) generation is a key part of this mission, and site selection is a critical component of the decision-making process. The decision framework Penn State developed to investigate the economic impacts of solar PV installation site selection on the University Park campus are detailed as a case study that other institutions, organizations, or corporations, could readily adopt. The case study shows the power of a data-driven, objective decision-making process to compare multiple (competing) criteria using a single framework to explore many possible solutions.

The framework relies on analyzing options through modeling the interaction of both decision-maker controlled and externally controlled factors, visualizing the impacts of potential decision tradeoffs on the outcomes over a range of possible futures, and developing preferences while exploring simulation resultant data. The methods and tools used during the process are described as are the results and insights gained by comparing options. Finally, the next steps in Penn State's transition to decreasing its GHG emissions are discussed.

Keywords: *solar investment, multi-objective decision-making, GHG emissions reduction, tradeoffs*

1. Introduction

The Pennsylvania State University (henceforth referred to as *The University*) has put a priority on decreasing its contribution to climate change, and thus has set specific goals to decrease its Greenhouse Gas (GHG) emissions. Energy usage is the largest contributor to the University's GHG emissions profile due to the electricity and heating/cooling needs of its 24 campuses and is the current focus of GHG reduction efforts. Reaching these reduction goals, while continuing and expanding the University's academic and research mission, involves focusing on energy conservation and energy efficiency wherever possible and investing in GHG reducing technologies (renewable energy generation) when fiscally responsible. The University is currently implementing a $60 million 5 year investment towards energy efficiency *and* conservation initiatives while exploring potential technologies to remediate GHG emissions.

In particular, the University has already achieved some success in energy conservation (achieving

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approximately an 18% reduction in GHG emissions from 2005 levels) albeit this was supplemented with the purchase of renewable energy credits (RECs). Reaching the reduction goal of 35% by 2020 will continue to be anchored with conservation efforts, but will be supplemented with an increased level of combined heat and power (CHP), low-carbon energy production, and hydropower. The strategy for 2020 and beyond will further integrate and increase the use of the suite of renewable technologies continually developing. A complete guide to the sustainability efforts at the University can be found at sustainability.psu.edu/energy-environment.

The research detailed in this paper explores the utilization of decision-making tools, simulation models, and human-in-the-loop processes to help define a robust decision-making strategy for deploying solar PV at the University Park campus. Solar PV is a mature technology with constantly improving finances, and it can be readily acquired, installed, and used to produce energy on all the campuses across the commonwealth, making it part of a strategic initiative. This study details the exploration of the feasibility and decision-making process to ascertain where solar PV would be a good investment for an organization similar to the University, decision-making criteria and strategy to make commitments, and processes and tools to aid in the decision-making process. The decisions made during the process and plans for future efforts are briefly described.

2. Background

The University currently owns facilities that could be generating energy using solar photovoltaics' (PV) on the buildings (e.g. roofs), land (e.g., agricultural), and parking structures. The University has reduced its campus greenhouse gas emissions by 18% since 2005 and has set its sights on the next reduction goal of 35% by 2020 (compared to 1990 levels). As the costs of solar PV installation and energy generation are consistently declining (see Barbose et al, 2016), it has become prudent to invest in the technology.

There are several options for financing the installation of PV panels. Direct Purchase (DP) is when an entity purchases the system and pays for it directly. Power Purchasing Agreements (PPA) is when a company installs their own system on an entity's property, for which the entity then pays the company for electricity at a contracted price. Finally, leases and loans, which are very similar to DP, however standard loan or lease agreements are made with a bank to finance the purchase. The DP and PPA financing options are compared in this study for both economic and sustainability decision criteria.

The future is stochastic in nature and uncertainty exists in the financial outlook. If the University were to invest strategically in solar PV now, what sort of futures may be realized? Is the current cost amenable such that tuition increases can be avoided (or minimized)? What effect would different grid electricity rates have on the overall project? Do any of the specific sites have conditions that would be more or less conducive to a solar installation? These questions led to quantifying those uncertainties wherever possible such that decision-makers can act upon criteria and assessments of robust investments by exploring their individual risk propensity to a multitude of potential outcomes.

A data-driven decision framework is a culmination of models, simulation, and visualizations. Here, we describe the incorporation of a financial model with a sustainability model into an adaptive decision assistance tool. Identification of potential sites was driven by a third-party, Lightbox Energy (www.lightboxenergy.com), who used screening criteria such as the size of the rooftop or solar area, the historic significance, the building function, and the proximity of the site to the power grid to evaluate well over 150 potential sites. These criteria, along with decision-maker solicited preferences, steered the conversation to a subset of top potential sites for detailed evaluation, including on-site assessments and analytics. The financial and environmental models constituted the tool that was used to assess more than 50 candidate sites on the University's main campus; sites were prioritized for solar PV development and a single site was selected for current development. The adaptive tool gives the University the ability to reassess the investment potential of various sites rapidly when market trends or infrastructure planning changes occur or the uncertainties in installation costs, grid energy prices, and site upgrade costs change. The tools can be leveraged to easily analyze trends, discover preferences, explore possibilities, and make and explain the resultant decisions.

The paper is organized by presenting the background on the decision making framework, then the tools used to accomplish the assessment (the models and visualizations) are described, and finally the resulting decisions and next steps are discussed.

3. Decision Framework

Analyzing the potential costs and benefits of installing solar photovoltaic (PV) electricity generation capacity at the University raises many important questions. Practical experience and research shows that much of decision making related to design is actually an iterative process of simultaneously looking for alternatives while refining an individual's value/preference function (Miller et al., 2013; Simpson et al., 2008); Balling (1999) referred to this process as *Design by Shopping*. This naturally imposes an iteration on the design decision making process. Building upon our experience and the current research, the proposed decision framework casts a decision problem in terms of external factors that the decision-maker must take into account in the decision process (X), levers the decision-maker may manipulate that constitute the actual decision (L), the system relationships (R), and the performance metrics on which the optimality of the decision is based (M). This XLRM framework (Lembert et al, 2003) aids decision-makers to ask questions under data-driven/data-supported thought experiments that address uncertainty in potential future actualization, such as

- How robust will the project be to energy rate changes?
- How would alternate installation costs affect the overall cost of the project?
- How robust will the project be to potential solar panel degradation?
- What are the drivers that affect the overall savings due to the project over the desired project lifecycle?
- What if the site conditions need improvement investments for the solar PV to be installed?

In order to answer the above questions, simulation models using uncertainty in process and financial parameters were sampled to identify and quantify the effect of what factors may impact the likelihood that the University would install a solar electricity generation capability on the University Park campus. Potential futures of these identified important factors were surveyed in the literature and from subject matter experts, from which relevant future scenarios were generated. The scenarios were then used to perform an analysis in OpenMORDM (Multi-Objective Robust Decision Making), an ARL/PSU developed tool (Hadka et al., 2015), to determine robust solar PV investments and inform the University of the impact of future uncertainty on their decision to invest. Both OpenMORDM and the ARL Trade Space Visualizer (ATSV, www.atsv.psu.edu) were used to analyze the costs and benefits of installing solar PV panels.

Through exploration of the aforementioned questions with the University decision-makers for a few representative solar PV installation sites, an understanding was reached of the specific preferences and trade-offs that needed to be better understood. Therefore, a higher fidelity and more accessible decision-making tool was developed with the University decisions-makers to answer the question of what sites out of 50 likely sites would make the best investment. This tool was used to assess the trade-offs between specific sites on the University Park campus.

3.1 Identification of Uncertain Model Parameters

Installation costs are the primary expense for solar projects that involve a direct purchase of the system due to the low cost of yearly maintenance on solar PV panels once they are installed. The installation costs of a PV system include both materials (panels, inverters, wiring, etc) and soft costs (labor, design, permitting, inspection, etc), and are generally reported as a cost per Watt. The major factors that affect the installation costs are size of the installation, hardware costs, labor rates, and condition and complexity of the installation site. This cost is directly correlated with the size of a solar PV system where small systems have a higher cost per watt compared to larger systems (Barbose et al, 2016). As system size increases, the labor and material requirements increase, but certain fixed costs may not change significantly and the economy of scale comes into play.

Other drivers of the installation costs are the variability and complexity of the installation site. This is due to the increasing labor necessary to complete complex installations (potentially including labor such as structural analysis), and the additional costs of renting and/or operating equipment for some installations, e.g., installation in a field versus a sloped building roof.

Another source of variability in solar panel installation costs is the cost of permits and inspections. The approval of the state or municipality will be required, and the cost to obtain these permits is typically a function of the size of the system. This factored into the cost per Watt to install the system. Inspection and permit costs will vary depending on local laws, but they are generally more expensive per watt for smaller, residential systems. If the system is obtained via DP, these costs are not usually significant compared to other costs and will not have a large impact on the overall installation cost.

3.2 Model Definition

In the analysis performed here, installation costs were treated as a dollar per Watt value, with a different expected range for each installation site type considered. The range of values used in the analysis spans the range of average installation costs across the country, and is lower than the average Pennsylvania residential solar PV installation cost ($4.50/W from SolarReviews (2018)). This is expected to be the case due to the University likely installing a larger commercial-type system, which should be cheaper to install than residential installations. The parking structures were assumed to cost the most, then buildings, and ground mounted land installations were the lowest with values in the range:

- Buildings (assuming a low-slope roof rack system): $2-2.75
- Parking lot (assuming a carport w/structure): $2.9 - 4.00
- Pasture land (assuming a ground mount w/footings): $1.75 - 2.30

The cost drivers for a PPA are the contract base rate and the inflation rate, which are negotiated by the buyer and PPA provider at the time of purchase. As this cost is negotiated, it varies widely from location to location. In general, to be competitive in a specific region, the base PPA rate needs to be equal to or less than the current cost of electricity. PPAs are currently not common in Pennsylvania due to the low value of Solar Renewable Energy Credits (SRECs) in the state. The average contract rate of PPAs in Pennsylvania is $0.10 – $0.15/kWh (Heeter and O'Shaughnessy, 2016), making them financially feasible for locations such as Philadelphia, PA. For the University, the current utility rate is ~$0.06/kWh. Thus, for a PPA to be financially desirable, the base rate would need to be competitive so a range of values were taken from $0.06/kWh – $0.10/kWh.

PPA agreements generally include an escalation rate, which is the annual rate at which the costs increase over the life of the contract. This rate is a negotiated contract term, thus there is variability associated with that value. The range of values used here was 2%/year – 3.5%/year (Sol Systems, 2016).

While installing solar PV panels is a large investment, the cost of the electricity generated by the panels is essentially free (plus some very small operation and maintenance costs). To calculate the financial impact of installing solar PV panels over the life of the investment, a comparison is needed against the cost of continuing to buy electricity from the grid, which also contains uncertainty. The cost of electricity varies over time and may increase or decrease significantly over the 20–30 year life of solar panels. The US Energy Information Administration (EIA, 2018) forecasts grid energy prices through 2040 for 21 different scenarios. The range of growth in prices among those cases is between 1.6 and 3.3%; the range of values used here as (exploratory) 1.5 – 5%. The larger utility escalation rate was included due to the possibility of increases in the net cost of buying electricity from the grid due to a carbon tax (Zalaznick, 2016) or other increase in the cost of energy due to environmental concerns.

Greenhouse gas emissions due to the electricity used on the University are directly related to the amount of grid energy purchased and the sources of that energy. For this study, carbon dioxide (CO_2) is examined. Currently the electricity generated in Pennsylvania is sourced from predominantly nuclear power, natural gas and coal (EPA, 2018a). The CO_2 emitted by this mix of fuels is approximately 1.38 metric tons per kWh (EPA, 2018b). Although the amount of CO_2 emitted by electricity generated for the utility grid will potentially change over the next 25 years, this uncertainty was outside the scope of this analysis. A constant value of 1.38 metric tons was used as the amount of CO_2 emissions *avoided* per kWh of electricity generated by the solar PV panels.

The amount of electricity generated by solar PV panels can be estimated using modeling tools such as Helioscope (www.helioscope.com) and Skelion (www.skelion.com). These tools use historic weather data to determine how much electricity will be likely to be generated at a specific location. Due to the uncertainty in future weather and any errors that could be inherent in the modeling of a PV system prior to installation, a range of values were used for the solar electricity production of a PV system for this analysis. The average value for Central Pennsylvania of solar electricity production is 1300 kWh/kW (communiqué with subject matter expert). For the OpenMORDM analysis, this was used as the baseline value, with a negative 20% to positive 20% sampling bound. When 50 high potential sites were defined, an output from Helioscope for each site was used without an uncertainty range.

Another potential uncertainty around the electricity generation from solar PV panels is degradation of the electricity generated by the PV panels over time. This is generally seen as the degradation of electricity generation due to normal wear and tear of the panels, and is estimated to be very low by panel manufacturers (0.4 – 0.7% per year). For the analysis here, a larger bound on panel degradation was used, considering 0.4 – 3% per year. The higher degradation rate per year could be due to circumstances such as new shading of a site (planting trees, or new buildings being constructed) or damage to panels (due to extreme weather events or other physical damage).

3.3 Modeling and Simulation

OpenMORDM (Hadka et al, 2015) was used to analyze the robustness of solar PV panel investments in the scenarios discussed in the previous section. A financial model generated by Lightbox Energy was integrated into OpenMORDM, with inputs and outputs as shown in Fig. 1. The inputs in bold were assigned feasible ranges as discussed in the previous section and the outputs in bold are those analyzed here.

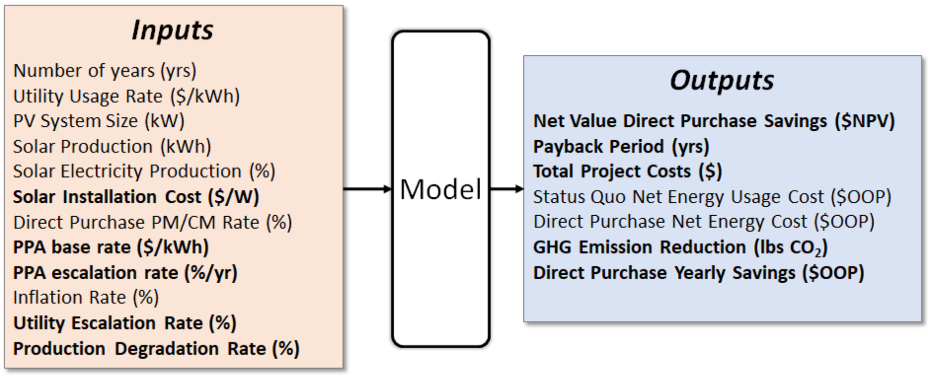

Fig. 1: Model input and output

This framework casts the decision problem using the XLRM framework of Lambert et al (2013) as:

- X = site data (size, type, potential solar generation), avoidable study rate, degradation rate, upgrades budgets, inflation rate, utility rate
- L = site, contract type (PPA, DP), $/kWh price
- R = functional relationships
- M = levelized cost of energy (LCOE), first year budget impact, net savings, lbs of CO_2 avoided, payback period

States-of-the-world (SOW) are random samples from multi-dimensional distributions over the uncertainty across input parameters. For each site analyzed, sampling of the uncertainty distributions 5000 times (assuming independence) generated a rich dataset of SOWs from which trends were determined. Inputs that are not considered to be uncertain in this analysis include:

- the number of years over which to evaluate the investment – 25 years
- the size (in kW) of the system – value specific to each independent site
- the base utility grid rate – $0.06362/kWh
- the reduction in greenhouse gas emissions – 1.38 mt CO_2/kWh

The other assumptions made in the analysis were:

- The University will always use all the electricity generated by solar PV panels on campus
- The CO_2 generated by the grid-produced electricity is constant over time
- Net Savings is equal to the Net Present Value of the yearly savings minus the initial system costs

- The payback period is the number of years required to recuperate the up-front costs of the system (for direct purchase)
- The PPA base cost and inflation rates are constant over the life of the contract

The major trade-offs analyzed in this first step were comparing the financial outcome of a DP to a PPA, the costs of different installation site types, and the cost of GHG emission reduction. After generation of the static dataset, tradeoffs were visualized and explored directly with the decision-makers. Through this process, specific preferences were determined and used to identify priority sites for solar PV installations. The following section shows the comparison between a DP and PPA as an example of trend identification using this type of analysis, and visualizations that led to the identification of the top priority solar PV installation sites.

4. Solar Feasibility Assessment

ARL/PSU analyzed sites across the University Park campus using on-site assessment information from Lightbox Energy. By including uncertainty in grid electricity costs, PPA rates, installation costs, and the University's break even rate, the most robust investments over the lifetime of a solar PV installation's useful life were determined. Visualizing and understanding the uncertainty inherent to SOWs and the tradeoffs between DP and PPA are highlighted in this section.

4.1 Analyse Trends

Figure 2 shows the relationships between each site and the LCOE and the first year budget impact for both DP and PPA. The violin plots show the *distribution* of LCOE per site for the realized SOWs (left side). Large sites have the best economics (lowest LCOE) and there is a wide range of LCOE for the building sites on campus. The lowest LCOE for the sites considered here is a direct purchase (DP) of a ground mounted solar PV installation. However, the first year budget impact (right side of Fig. 2) shows the drawback of a DP is its *much larger* financial impact up-front than a PPA (note the differences in the scale). The first year budget impacts for a DP are directly related to the size of the installation. Noted, by exploration of the SOWs in these visualizations, is that some building sites have the potential for lower first year budget impacts than other sites but other (often) non-quantifiable criteria reduces the prospect of selecting these sites.

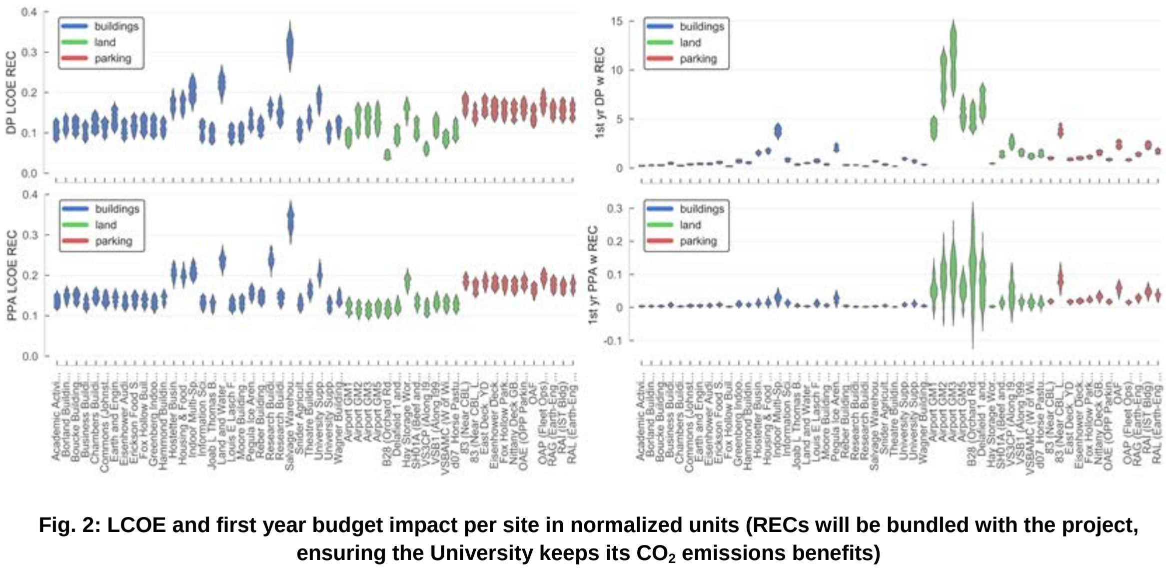

Fig. 2: LCOE and first year budget impact per site in normalized units (RECs will be bundled with the project, ensuring the University keeps its CO_2 emissions benefits)

4.2 Discover Preferences

Decision-makers explored the trends discovered in the data at the University in larger group meetings as well as individually. Decision-maker comments and questions during the meetings served to start the process of eliciting their preference and risk structures. Further specific information was gleaned when the higher fidelity model of the finances were created. For example, risk in the investment of solar PV was assessed by examining visualizations such as Fig. 3 whereby robustness of selecting a site and risk attitude could be entertained.

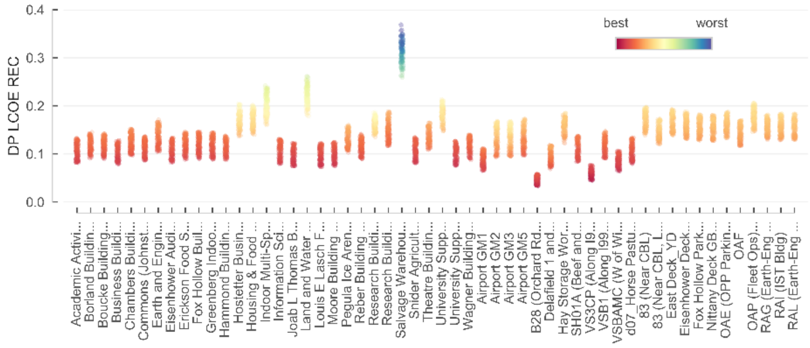

Fig 3. DP LCOE for individual sites, with color indicating preference for minimizing the LCOE and the DP first year budget impact.

In Fig. 3, the colored dots represent the SOWs that result when realizing the uncertainty through the assessment model. The color represents an assumed preference of minimizing LCOE (both DP and PPA) and the DP first year budget impact. Sites whose risk exposure is low have tight groupings of mostly reddish points, whereas higher risk sites contain a wider spread of points with more varied coloring.

Exploration of the data, highlighting trends and real-time impacts of decision criteria weightings/constraints with decision-makers made it clear that the top priority at the current time is to minimize the first year budget impact of a project. This priority resonated such that the GHG emissions avoided are maximized by developing solar on a larger site while still being financially feasible without tuition increases. Although this means that a PPA will be used for any projects currently pursued by the University, this will be reassessed as time passes so in future the financial benefits of a DP could be realized. Thus, the decision-maker preferences elicited were, for a PPA:

- Maximize the GHG emissions reduction
- Minimize the first year budget impact (thus focusing on a PPA)
- Minimize the operating budget impact (LCOE)

4.3 Explore Possibilities and Identify Priority Sites

Elicitation of the preference structure allows for focus on specific regions of the data. For example, here the main two preferences deal with GHG emissions and operating budget, therefore Fig. 4 shows the PPA LCOE against the amount of CO_2 emissions avoided. The left side plot shows all the SOWs for sites with a low LCOE such that the vertical “lines” are groupings of instances of SOWs for specific sites. Collapsing the uncertainty to the mean results in the right-hand plot. Individual sites are identified on the continuum of avoided GHG emissions and PPA LCOE. The circled site is simultaneously the lowest PPA LCOE (determined using external, non-quantifiable metric, e.g., not at the airport), and offsets the maximal CO_2 emissions of all the sites, making it the highest priority site for solar PV development at this time. As the plots also indicate, several additional sites might be of interest for development in the near future.

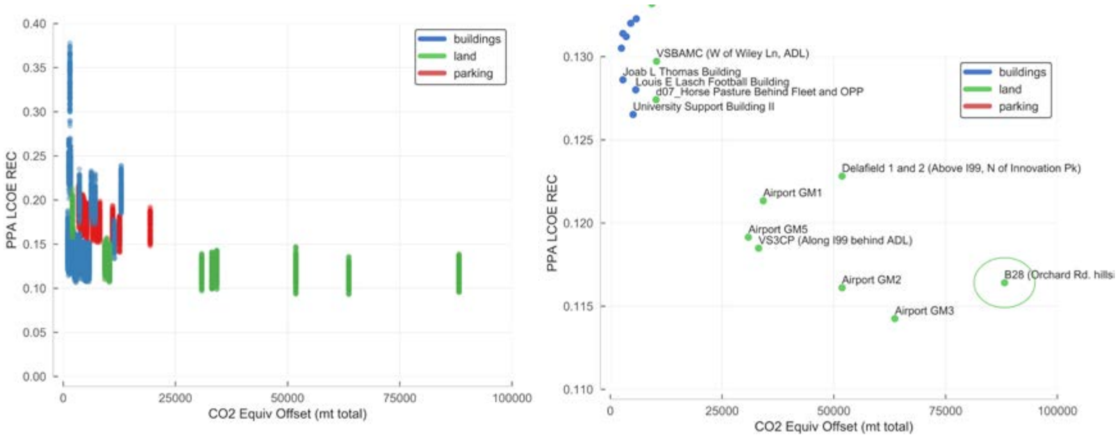

Fig 4. Relationship between PPA LCOE REC and CO_2 offsets for different sites evaluated for many SOWs. (left) SOWs (right) mean values zoomed in.

5. Conclusions

This feasibility analysis showed that if the most important decision-making factor is maximizing the amount of CO_2 avoided, then the direct purchase of solar PV systems for land sites would be the most robust investment at this time. However, when minimizing the first year budget impact of the investment is the highest priority, a power purchase agreement makes more financial sense. PPAs have the potential to be close to equivalent in cost to utility costs, and although historically Pennsylvania has not been a high PPA development area due to regulations and low market value of SRECs in state, that is changing.

By facilitating direct decision-maker interaction with data showing the potential financial outcomes of various investments, decision-maker preferences were determined. Once preferences were known, priority development sites were identified by maximizing the CO_2 emissions avoided and minimizing the first year budget impact. A single site is currently being developed at the University that was identified as the top priority site, and additional potential sites were identified through this process.

Although large scale solar PV investment on the Pennsylvania State University campus is not currently feasible due to financial constraints, the work completed here gives the University decision makers the tools and information they need to focus on the best campus sites, and to reassess the market quickly over the coming years. With continued technology improvements and market improvements for renewable energy generation, it is possible that the viability of all sites will improve in the short term (2-5 years).

6. Future Work/Discussion

Along with reassessing the main University campus, future work includes generating a more automated process for site feasibility analysis on other campuses around the State. There are varied economics and infrastructures at the other University campuses that could provide the University with additional opportunities for solar PV development. The University is engaging faculty and students to develop and deploy this methodology and identify potential sites for solar PV investments across Pennsylvania.

The framework and process presented here is expandable and adaptable to any organization, municipality, or institution interested in analyzing the tradeoffs and economic feasibility of renewable energy deployment. The majority of the tools used here are openly available. This could be reproduced at very low cost, giving anyone the power to analyze their own systems in a way that empowers them to make a data-driven decision.

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