Quantifying the Importance of Solar Soft Costs: A New Method to Apply Sensitivity Analysis to a Value Function

Sita M. Syal
Mechanical Engineering
Stanford University
Stanford, California, USA
syalsm@stanford.edu

Erin F. MacDonald
Mechanical Engineering
Stanford University
Stanford, California, USA
erinmacd@stanford.edu

Notes:
- This paper is intended for the Analysis and Design of Sociotechnical Systems special issue.
- This paper was also submitted and accepted to IDETC 2020, ASME no. DETC2020-19179

ABSTRACT

This paper presents a new approach to building a decision model for government funding agencies, such as the U.S. Department of Energy (DOE) solar office, to evaluate solar research funding strategies. High solar project costs - including technology costs, such as modules, and soft costs, such as permitting - currently hinder many installations; project cost reduction could lead to a lower project levelized cost of energy (LCOE) and in turn, higher installation rates. Government R&D funding is a crucial driver to solar industry growth and potential cost reduction; however, DOE solar funding has not aligned with the priorities for LCOE reduction. Solar technology has received significantly higher research funding from the DOE compared to soft costs. Increased research funding to soft cost programs could spur needed innovation and accelerate cost reduction for the industry. To this end, we build a cost model to calculate the LCOE
of a utility-scale solar development using technology and soft costs and conduct a sensitivity analysis to quantify how the inputs influence the LCOE. Using these results, we develop a multi-attribute value function and evaluate six funding strategies as possible alternatives. We find the strategy based on current DOE allocations results in the lowest calculated value and the strategy that prioritizes soft cost results in the highest calculated value, suggesting alternative ways for government solar agencies to prioritize R&D funding and potentially spur future cost reduction.

1. INTRODUCTION

Solar energy is an important part of the future carbon-free energy portfolio; currently, the global share of total solar power generation is expected to grow by a factor of ten in the next 20 years [1]. In the United States, only 1.8% of total utility-scale electricity generation was attributed to solar energy as of 2019 [2]. Government research and development (R&D) funding is widely accepted as a crucial driver to the growth of the solar industry and will remain important to meet these aggressive solar projections [3] and ultimately, our global climate goals [4]. Within the United States, the Department of Energy (DOE) is the largest funder of energy research [5] and responsible for administering R&D funds that “reduce the cost of solar, increase the competitiveness of American manufacturing and businesses, and improve the reliability of the grid” [6]. Efforts made by the DOE to accelerate solar innovation can not only produce benefits to the country but can also catalyze additional public and private funding efforts to advance the industry as a whole.

While the DOE strives to gain benefits from every funding dollar administered, a review of the Department’s funding practices notes that the DOE does not have a consistent, transparent decision-making process by which they allocate their funding and determine expected benefits to
be realized [5]. To contribute to a focused portion of this need, we present a new approach to building a decision model for the DOE solar office to evaluate solar R&D funding strategies. We use a multi-attribute value function (MAVF) [7], an approach used by past researchers in R&D funding decisions [8], and focus on a benefit prioritized by the DOE to build the decision model: cost reduction. While solar PV costs have decreased in the US, a survey of over 100 solar professionals reported that the largest barriers to implementing solar projects are still “financial in nature” [9]. The DOE has indicated the importance of supporting ongoing solar PV cost reduction in various ways: the SunShot initiative pledges to support projects to make solar energy more affordable for Americans [10]; a dedicated team of researchers at the National Renewable Energy Laboratory (NREL), the DOE-affiliated national lab, present quarterly solar cost updates [11]; the front page of the Solar Energy Technologies Office (SETO) even states the goals of their office center around “sweeping cost reductions” for solar energy [12]. We mirror this economic priority and inform our decision model parameters based on a solar cost model that measures the “levelized cost of energy” (LCOE), as calculated by Eq. 1. Note that pertinent symbols in this equation and subsequent equations throughout the paper are included in the Nomenclature table for reference.

\[
LCOE = \frac{\text{Total project costs}}{\text{Total power generated}}
\]  

LCOE is a convenient measure to compare the cost competitiveness of different energy sources [13]; the DOE solar office uses LCOE to measure how comparable solar energy is to more traditional fossil fuels and similarly, solar industry developers use LCOE to measure the financial viability of their projects. Comparing project costs alone is not a fair comparison. A 100 MW natural gas plant will certainly cost more than a 250 kW rooftop solar system. By “levelizing” the cost of energy calculations - in other words, by dividing the total project costs by the total power...
generated - the resulting LCOE can be compared between energy sources. To decrease the LCOE, research projects typically focus on decreasing the numerator, or lowering total project costs.

The solar development process is a complex, sociotechnical system and total project costs span both technology and human-driven costs, also known in the industry as “soft costs.” NREL defines soft costs as customer acquisition, permitting, interconnection, installation labor, taxes, indirect costs, supply chain, and finance costs [14], while technology costs are related to the hardware, such as panels and inverters. Soft costs are highly variable, can account for 35%-63% of total project costs depending on project size [11], and can even cause projects to completely fail. While the DOE acknowledges soft costs as an important factor to solar development [15], recent DOE budget shows that funding decisions are not being made to support soft costs at the same level as technology costs. The 2020 Congressional Budget showed that DOE received $228M for solar PV R&D and allocated 97.3% of the funding to technology-related projects and 2.6% of funding to soft cost-related projects [16]. When DOE funding allocations are compared with the breakdown of solar project costs, as shown in Fig. 1, we see the proportions between technology costs and soft costs are significantly different.
We build a decision model by considering both technology costs and soft costs to assist and potentially improve DOE solar R&D funding decision-making. In our analysis, we focus on utility-scale solar, as NREL projects the majority of the growth in U.S. solar PV energy is expected to come from the utility-scale sector and will dominate solar economics [17]. We apply two approaches from the JMD community, sensitivity analysis and a MAVF, in a new way and address two themes of the JMD Special Issue for *Analysis and Design of Sociotechnical Systems*: 1) Risk and uncertainty in sociotechnical systems, by integrating a sensitivity analysis to determine the decision model parameters; 2) Modeling the interaction of systems and organizational architecture, by understand the interactions between technology and stakeholders within the solar cost model and resulting decision model. In the discussion section, we again
specifically bring up these themes and how our findings inform them. Fig. 2 presents the workflow of this paper in a flow chart format.

**FIGURE 2**: FLOW CHART REPRESENTATION OF THE METHOD PRESENTED IN THE PAPER

First, we build a cost model to calculate the LCOE of a utility-scale solar development using both soft costs and technology costs as inputs. Using industry data for the inputs, we conduct a sensitivity analysis (SA) to quantify the effect each input has on the output LCOE. Second, we use the results from the SA as weights for a MAVF, which we use to calculate the value of six hypothetical funding strategies the DOE solar office could adopt. For the decision parameters determined in this analysis, the results from our model show the strategy that closely matches the current DOE solar funding allocations results the lowest calculated value and the strategy that prioritizes soft cost funding resulted the highest calculated value. We discuss these results and suggest future work to validate the model. The decision model presented in this paper is a simple approach to demonstrate how both technology and soft costs can be considered in DOE solar R&D funding allocation decisions, and future work should include additional data gathering, model validation, and exploration of advanced decision-making models.

The paper is organized as follows: Section 2 provides a background of previous literature and Section 3 details the methods for building the cost model, conducting the SA, and developing the
decision model. Sections 4 and 5 present the results and discussion, respectively, while the paper ends with conclusions and future work in Section 6.

2. BACKGROUND

2.1 Utility-Scale Solar Development as a Sociotechnical System

In this paper, we define the utility-scale solar development process as a complex, sociotechnical system. The industry does not have one definition of what size solar plant constitutes as “utility-scale,” but for this paper we follow the definition set by Bolinger and Seel [18] as any system greater than 5 MW$_{AC}$ and connected to the utility grid. Development at this scale requires both a complex network of stakeholders as well as a multitude of engineered systems [19]. The basic map of the stakeholders their relationships are mapped in Fig. 3. Contrary to other engineering design systems, stakeholders in large-scale energy systems actively make independent decisions based on their own regulations to optimize their objectives and the systems are not controlled solely by designers [20,21]. The technology subsystem includes solar PV panels, inverters, mounting equipment, electrical equipment, and transmission lines. While the final engineered design is ultimately responsible for delivering the desired power output, success in development cannot be achieved without the decision-making from the complex network of stakeholders.
FIGURE 3: NETWORK OF STAKEHOLDERS IN UTILITY-SCALE SOLAR DEVELOPMENT

The developer manages all aspects of the project and carries out the following steps at a minimum: (1) acquire sufficient land and negotiate land lease(s); (2) secure investment for the project; (3) submit permitting and other required paperwork; (4) submit an interconnection request to the utility and upgrade any potential grid equipment; (5) contract an Engineering, Procurement, and Construction company (EPC) to design, build and procure materials for the project; and (6) engage with the local government and community. Developers use early-stage cost models to predict the financial viability of the project, which ultimately helps them decide whether to go forward with installation or not. Considering both the “social” and “technical” factors of the utility-
scale development system can help better understand how the system works [22] and can lead to a more appropriate solution [23]; however, quantifying the diverse range of factors that affect large engineering systems can be challenging. Welfare economists have considered multiple factors, both soft cost- and technology-related, to quantify how large projects and policies will affect overall societal welfare [24]. Cost-Benefit analysis, one of the most common tools used for evaluating large engineering projects, quantifies all factors of a system using monetary values [25,26]. We draw from this technique and represent the inputs to our sociotechnical system using monetary (or monetary-related) values in a cost model. Our approach presents one way to quantify a diverse set of factors that make up a complex system and gain insight from the integrated perspective.

2.2 Decisions in Government Energy R&D Funding

Government R&D funding has been historically important in advancing technical industries. DeGrasse Tyson lists some of the most important technologies that came from U.S.-funded R&D projects, such as kidney-dialysis machines, global positioning satellites, and corrosion-resistant coatings [27]. In the area of energy, an external committee that evaluated over 20 years of DOE activities concluded that “significant benefits” came from the DOE R&D programs in the areas of fossil fuels and energy efficiency [28]. However as mentioned in the introduction, the DOE does not have a consistent and integrated decision-making process by which they allocate their funding to different areas and compare these expected benefits [5]. Each DOE office currently performs their own independent assessment to decide their funding allocation strategy, which is then collated by the Secretary of Energy and submitted as a proposed budget to Congress. Congress then makes modifications based on factors that are out of the DOE’s control.
and then sets the budget for the year. A systematic decision framework that the DOE could use consistently across all offices to carefully assess different funding strategies would benefit the department greatly and perhaps increase the overall societal benefits from the funding [5]. The goal of such a quantitative decision framework is not to necessarily to provide the DOE with one optimal funding strategy, but rather to “shed light on the impact of decisions, uncertainty, and preferences” to improve funding strategies [29]. While the model presented in this paper is intended to focus only on solar R&D funding decisions allocated by the DOE solar office, future work could adapt this approach for developing consistent decision-making process across the DOE.

Decision frameworks to determine R&D funding allocation strategies have been studied in the management literature, see [8] for a review of quantitative techniques that have been used in previous literature. Within the area of energy, Santen and Anadon create a quantitative model to capture decision-making under uncertainty for allocating R&D funds for the electric power sector, focusing on solar PV technology investment planning [30]. Kurth et al. develop a decision model using a MAVF to evaluate DOE funding strategies for carbon capture and storage R&D [31]. We follow the general MAVF structure from this paper and develop our model to use funding allocations (in $) and weights to calculate the value of each funding strategy in a particular sub office of the DOE, the solar office in our case. We build on this existing work in two ways. First, while the authors calculate the weights of their MAVF using expert elicitation of technology readiness levels, we present a mathematical method, SA, to calculate weights that captures the industry preference of each attribute but does not introduce potential biases from expert elicitation. Second, the work done by Kurth et al., and other decision frameworks for energy R&D funding to our knowledge, take into account technology in their analysis, but do not consider the soft cost-
related projects that could influence their systems and funding. While studies often note the importance of studying the non-technical barriers to energy deployment [29,32] and the need to reduce these barriers [5], funding decision models do not incorporate these non-technical aspects. We expand this approach and incorporate both technical and social costs into our analysis to be more representative of the solar industry during the solar R&D funding decision-making process.

Building a decision framework for the DOE to use for R&D funding allocation strategies inherently assumes that R&D funding will translate into some “benefit” to the DOE and to society; many studies assume this benefit to be in the form of a cost reduction, although it is important to note that determining this relationship is not straightforward. An accepted practice to predict potential cost reduction for energy technologies given R&D funding is expert elicitation; for example, Curtright et al. and Bosetti et al. use this technique for solar technology cost reduction prediction in the US and European Union, respectively [32,33]. However, Anadon et al. note that challenges still exist in the accuracy of the results, including expert availability, time to conduct studies, and cognitive biases from the experts [5]. Researchers have also looked back on past data to draw positive correlations between R&D funding and technology cost reduction in the aerospace industry [34], natural sciences [35], and the energy industry [3,36]. Of course, these results point toward positive correlations, not causations. While these previous studies may suggest that government agencies will reap cost reduction benefits from allocating funding dollars, it is important to note the studies presented do not account for the non-technical barriers - soft costs - that researchers and DOE alike have cited as important to the solar industry.

Since our proposed decision model incorporates both technology and soft costs, we assume that government R&D funding to both technology and soft costs will result in a benefit in the form of cost reduction. As the basis for this assumption, we look toward the documented need for
additional social science-related research funding dollars for climate change mitigation detailed in [37] as well as an initial study conducted by NREL researchers [38]. The authors of the NREL study explore data from a DOE-funded soft cost program, the Rooftop Solar Challenge Program, that streamlined permitting programs for rooftop PV solar projects. They found that cities with more favorable permitting processes set from this program had “lower-than-average” PV residential system prices. The results suggest that funding this soft cost program positively correlates with cost reduction. While this study is a promising start, this paper as well as previous studies that present a correlation between government R&D and cost reduction are limited in scope, data availability, and cannot claim causation. In order to fully validate this assumption, we would need to additional industry data and could perform an expert elicitation, much like what has been done for technology. See Section 5.2.1 for a discussion on model validation for future steps. Overall, we believe this assumption and our approach has merit, as we do not know of any energy governmental funding agency that incorporates both technical costs and soft costs into their decision framework using a mathematically validated approach.

2.3 Multi-Attribute Value Functions

Multi-attribute decision-making (MADM) is an important tool used when considering a decision that has multiple criteria [7]; designers have drawn on this area of decision theory to consider and quantify human inputs into engineering decisions [39–41]. MADM approaches have also been used in past literature for R&D funding allocation strategies, particularly in the energy sectors as detailed in Section 2.2. Under deterministic conditions, we build value functions to calculate a decision-maker’s preference and under uncertain conditions, we build utility functions [39,42]. For this paper, we assume deterministic conditions and represent funding strategy
decisions with a multi-attribute value function (MAVF); while this approach may be simplistic initially, we begin with these assumptions to demonstrate the new method proposed in this paper and discuss next steps to incorporate uncertainty into future decision models.

MAVF is comprised of multiple decision alternatives and each alternative consists of different attributes; the outcome quantifies the preference order in which the decision maker ranks the decision alternatives. Among the different approaches that exist, the “weighted sum” value function that is widely used due to its ease of use [39]:

\[ V_a = \sum_{i=1}^{I} w_i r_{ai} \]  

(2)

\( w_i \) is the weight for attribute \( i \), \( r_{ai} \) is the score for alternative \( a \) and attribute \( i \), and each alternative has a total number of \( I \) attributes. Eq. 2 assumes the attributes are independent [42]. The weights have the following property:

\[ \sum_{i=1}^{I} w_i = 1 \]  

(3)

The decision-maker is not interested in the specific outcomes of each individual value function, \( V_a \), but rather the resulting rank order that comes from comparing the outcomes of each value function.

The challenge often lies in determining the parameters to build the functions to align with decision-maker preferences [43]. In particular, many strategies exist to determine the weights of a weighted sum value function. Belton notes that many common methods require preference elicitation from decision makers to identify which attribute is the most important and then weight the subsequent attributes accordingly [44]. Krishnamurthy notes three methods to determine weights - direct estimation, swing weights, and trade-off weights - all of which include the decision-maker directly assigning values, ranking, or finding an indifference point between attributes to assign weights [45]. While determining weights subjectively captures the preference
of the decision-maker, this approach can lead to varied outcomes of the value function [46], presenting a disadvantage to using a value function that requires weights. Additional approaches exist to determining weights, see [39] and [47] for more details; in this paper, we propose a method for determining the weights of a funding allocation value function that offers a mathematical approach to capturing preference of the solar industry through industry data in a cost model.

3. METHODS

3.1 Building the Utility-Scale Solar Cost Model

While most solar cost models are generally proprietary, we used cost model structures and equations published by NREL and Lawrence Berkeley National Laboratory [48–50] to build our model in Python\(^1\). Fig. 4 presents the overall structure of the model. This section will explain how the different components shown in Fig. 4 are calculated.

\(^1\) The model is available at the public GitHub repository: https://github.com/syalsm/SolarCostModel_Syal.
We assume the project technology is ground-mounted PV panels with single-axis tracking and no battery storage. We choose the generator nameplate capacity, \( G \), of the project to be constant at 100 MW for this analysis. This constant, and other constant values are in the analysis are detailed in the Appendix in Table A-1.

### 3.1.1 Levelized Cost of Energy

The model calculates the LCOE of the given solar PV project. \( LCOE \) (\( \epsilon \)/kWh) is calculated by the following equation used in the NREL System Advisor Model (SAM), originally published in [51]:


![Image of mathematical equations]

Where \( d_r \) and \( d_m \) are the real and nominal discount rates, respectively, \( C_0 \) is the initial project investment ($), \( C_n \) is the annual project costs in year \( n \) ($) in year \( n \), \( Q_n \) is the electricity generated (kWh) in year \( n \), and \( N \) is the project lifetime (years). The following sections further describe each component of the LCOE. A detailed table of the model inputs is included in the Appendix in Table A-2.

### 3.1.2 Discount Rate

The discount rate is a measure of the time value of money and set subjectively by the investor of the project [49]. Investors generally draw on their own past experiences and advice from external consultants to appropriately value the cost of capital of the project and set the real discount rate [52]. Therefore, there is very little data published on the real discount rate values for solar projects.

The nominal discount rate is calculated based on the real discount rate and inflation, assumed to be \( r_l = 2.1\% \) as per the U.S. Bureau of Labor Statistics in the last 12 months [53]. The following equation describes the nominal discount rate calculation from [51]:

\[
d_m = (1 + d_r) \times (1 + r_l) - 1
\]

### 3.1.3 Initial Project Investment

The initial investment of the project is calculated based on the following equation from the NREL Cost of Renewable Energy Spreadsheet Tool (CREST) [48]:

\[
C_0 = C_G + C_B + C_t + C_D + C_F
\]
Where $C_G$ is the generation equipment cost, $C_B$ is the balance of plant cost, $C_I$ is the interconnection cost, $C_D$ is the development cost and fees, and $C_F$ is the financing and reserves cost. The generation equipment cost and balance of plant cost are calculated follows:

$$C_G = G \times (c_p + c_v)$$  \hspace{1cm} (7)$$

$$C_B = G \times (c_M + c_T + c_W)$$  \hspace{1cm} (8)$$

Where $c_p$ is the cost per watt of PV modules, $c_v$ is the cost per watt of the inverter, $c_M$ is the cost per watt of mounting equipment, $c_T$ is the cost per watt of transmission equipment, and $c_W$ is the cost per watt of wiring equipment.

The interconnection cost is input directly into the model and not calculated via sub-inputs. The development cost is calculated in the following steps. The initial development cost, $C_{D1}$ is comprised of permitting cost, $C_p$, landowner acquisition cost per watt, $c_a$, and labor & construction fees per watt, $c_l$:

$$C_{D1} = C_p + G \times (c_a + c_l)$$  \hspace{1cm} (9)$$

The developer hires an EPC to complete the source materials and construct the project. The EPC takes an overhead percentage, $o_{EPC}$, on initial development costs and equipment costs

$$C_{D2} = C_{D1} + o_{EPC} \times (C_{D1} + C_G + C_B)$$  \hspace{1cm} (10)$$

as well as an additional profit percentage, $p_{EPC}$, on all development costs and equipment costs.

$$C_{D3} = C_{D2} + p_{EPC} \times (C_{D2} + C_G + C_B)$$  \hspace{1cm} (11)$$

The developer then adds contingency, $c$, on the all the development costs incurred up to this point, as well as an overhead percentage, $o_{DEV}$, to result in the final development cost and fees:

$$C_D = C_{D3}(1 + c + o_{DEV} + c \times o_{DEV})$$  \hspace{1cm} (12)$$

The financing cost includes lender fees at a rate of $l$ on total borrowed funds at $p_D$ percent debt, interest from construction at rate $i_c$, closing costs, $C_c$, and funding reserves, $C_R$, required by lenders:
The funding reserves required by the lenders depends on the monthly loan principal, $p_l$, and interest, $i_l$, and the average monthly project cost. We assume the lender requires 6 months of reserves, $m_r$:

$$C_r = m_r \times (p_l + i_l + \overline{C_n}/12)$$

3.1.4 Annual Project Costs

The annual project cost, $C_n$, is calculated as per the CREST model [48]:

$$C_n = F_n + V_n + I_n + P_n + L_n + T_n$$

Where in year $n$, $F_n$ is the fixed operations and maintenance cost (O&M), $V_n$ is the variable O&M cost, $I_n$ is the insurance cost, $P_n$ is the project administration cost, $L_n$ is the land lease cost, and $T_n$ is the tax cost. All sub-terms are calculated the same as the CREST model, except one deviation: land lease cost is calculated based on the land footprint required for the project and the annual lease rate:

$$L_n = G \times E \times R$$

Where $E$ is the number of acres per MW required for the project and $R$ is the annual land lease rate per acre paid to the landowner.

3.1.5 Annual Electricity Generated

The electricity generated per year depends on how effective the solar panels are and how sunny the location of the project is. The equation is from the CREST model [48]:

$$Q_n = \begin{cases} G \times NCF \times 8760, & n = 1 \\ Q_{n-1} \times (1 - d), & n > 1 \end{cases}$$
Where $NCF$ is the net capacity factor and $d$ is the project degradation. The constant value of 8760 is equivalent to the number of hours in one year. Recall that $G$, the generator nameplate capacity, is set to 100 MW for this analysis.

To calculate the NCF, we deviate from the CREST model and use a more nuanced linear regression model proposed by Bolinger et al. [50]:

$$NCF = 0.478 \times GHI + 0.0429 \times T + 0.2391 \times \ln(ILR) + 0.2328$$

(18)

Where $GHI$ is global horizontal irradiance to measure how sunny the chosen location is, $T$ is set to 1 or 0 based on if the technology is tracking or not (set to 1 in this analysis), and $ILR$ is inverter loading ratio, based on the size of inverters installed compared to the size of the plant.

### 3.2 Quantifying Input Factors: Sensitivity Analysis

To quantify the influence of each input on the LCOE, we conducted a SA using the “One-At-Time” (OAT) method [54,55]. The SA in our approach is not used as a probabilistic analysis of an engineered quantity, but rather a way to quantify which inputs LCOE is most sensitive to. We will use the results from this analysis in the next section to develop the decision model used to compare funding strategies.

The OAT method consists of assigning a base case to each input and varying each input one at a time based on predetermined value ranges. This method gives insight into the “magnitude and…direction” an input has on the output [54]. Using the notation from Borgonovo and Plischke [54], the upper and lower sensitivities of the output $LCOE = f(x)$ are calculated by Eqs. 19 and 20, respectively, based on an input $x_i$ and the vector $x^0$ of base case values:

$$\Delta^+ LCOE = f(x_i + \Delta^+ x, \ x^0_{-i} ) - f(x^0)$$

(19)

$$\Delta^- LCOE = f(x^0) - f(x_i + \Delta^- x, \ x^0_{-i} )$$

(20)
The terms \((x_i + \Delta_i^+ x)\) and \((x_i + \Delta_i^- x)\) represent the input \(x_i\) whose value is shifted by the respective amounts, \(\Delta_i^+ x\) and \(\Delta_i^- x\), and \(\mathbf{x}_0^i\) represents the vector of base case values for all other inputs \(\neq x_i\). Due to the variable nature of the solar projects, there is no one “base case” to choose for each input; only high and low values were reported in the data. For analysis consistency, we took the base case to be the average value based on the given data range.

To illustrate an example, suppose we wanted to calculate the LCOE sensitivities due to project degradation, \(d\). The base case value is 0.00625, the high value is 0.01 and the low value is 0.0025. All other inputs remain at their base case values. The upper and lower sensitivities would be calculated in Eqs. 21 and 22, respectively.

\[
\Delta_i^+ LCOE = f(0.01, \mathbf{x}_{-d}) - f(0.00625, \mathbf{x}_{-d}) \tag{21}
\]

\[
\Delta_i^- LCOE = f(0.00625, \mathbf{x}_{-d}) - f(0.0025, \mathbf{x}_{-d}) \tag{22}
\]

This process is repeated for every input, resulting in a high and low LCOE value based on the ranges of each input. We analyze ten inputs: 1) Real Discount Rate, 2) Generation Equipment Cost, 3) Balance of Plant Cost, 4) Interconnection Cost, 5) Development Cost and Fees, 6) Debt Parameters, 7) Fixed O&M, 8) Land Lease Cost, 9) Net Capacity Factor, and 10) Project Degradation. These numbered inputs and their sub-inputs are detailed in the Appendix in Table A-2. Additionally, each input is categorized as a soft cost, technology cost, or both, as per [14].

An effective graphical representation of the results from an OAT analysis is a tornado diagram, as introduced by Howard in [56]. Inputs are sorted from largest to smallest differences and shown on a two-way bar graph to illustrate the high and low LCOE values from the SA. A tornado diagram with our results is presented in Section 4.
3.3 Decision Model: Multi-Attribute Value Function

We use the results from the SA as well as inputs from the cost model to build a MAVF as a tool to evaluate DOE solar R&D funding strategies (Eqs. 2 and 3 outlined in Section 2.3). We introduce our implementation by comparison to an example familiar to the design literature: suppose a company is deciding between different airplane alternatives. Each airplane has a set number of attributes, such as max speed, number of passengers, etc. that the company wants to compare, and each attribute is assigned a weight based on the relative preference of each attribute. The scores are assigned based on the value of each attribute for each alternative (i.e. the max speed for airplane 1, max speed for airplane 2, etc.). The scores are often normalized to reduce dimensions when the units of each attribute are different [43]. Finally, Eq. 2 is used to calculate the value for each alternative and the alternative with the maximum value is considered to be the most desirable or preferred design.

We adapt this method for the decision-making of the DOE solar R&D funding agency. A visual version of this adaptation is presented in Fig. 5.

FIGURE 5: MULTI-ATTRIBUTE VALUE FUNCTION STRUCTURE FOR A) AIRPLANE ALTERNATIVE EXAMPLE AND B) ADAPTATION FOR THIS PAPER
Suppose the agency is deciding between different funding strategies - focusing on technology, focusing on soft costs, or some combination of both. We define these funding strategies to be the alternatives of our decision problem. Each funding strategy has $I$ attributes, which we assume to be the 10 inputs analyzed in the SA, and each attribute has a weight that is calculated from the results of the SA. Recall from the previous section, the goal of our SA was to quantify which inputs LCOE is most sensitive to. The results identify which inputs can be used as “levers” to have the greatest change in LCOE and can be prioritized in our decision model.

To calculate the weights, we perform the following calculations. Using the results from Eqs. 21 and 22, we calculate the difference between the upper and lower LCOE sensitivities for each input, $i$.

$$
\Delta_i LCOE = \Delta_i^+ LCOE - \Delta_i^- LCOE
$$

(23)

Next, we calculate the sum of all the differences in LCOE sensitivities.

$$
\sum \Delta LCOE = \sum_{i=1}^{I} (\Delta_i^+ LCOE - \Delta_i^- LCOE)
$$

(24)

Finally, for each input $i$, we divide the result from Eq. 23 by the result from Eq. 24 to calculate the weight for each attribute in the decision model.

$$
w_i = \frac{\Delta_i LCOE}{\sum \Delta LCOE}
$$

(25)

For this demonstration, we define the score $r_{al}$ for alternative $a$ and attribute $i$ to be the budget allocation to each attribute in $\text{\$M}$. We assume solar office can allocate the money to each attribute depending on their funding strategy. Recall that we categorized each input based on previous literature (see Table A-2, column 5); we used these categorizations to allocate budget to each alternative based on the focus of six hypothetical funding strategies. For the more technology-focused strategies, the technology costs were allocated a higher budget. For the soft cost-focused strategies, the soft costs were allocated a higher budget.
For our analysis, we calculated the value of six funding strategies. The first strategy is directly adapted from the actual DOE solar funding allocation as per the congressional budget [16]. The subsequent strategies range from Very Technology-Focused to Very Soft Cost-Focused to test a wide variety of funding focuses. Table 1 shows the alternatives, attributes, and scores used in the analysis:

**TABLE 1: FUNDING STRATEGY ALTERNATIVES AND BUDGET ALLOCATION SCORES FOR EACH ATTRIBUTE. ALL DOLLAR VALUES ARE IN $M.**

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Soft</th>
<th>Tech</th>
<th>Soft</th>
<th>Soft</th>
<th>Tech</th>
<th>Soft</th>
<th>Soft</th>
<th>Both</th>
<th>Both</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification -&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DOE Allocation</td>
<td>1.0</td>
<td>100</td>
<td>50</td>
<td>2.0</td>
<td>2.0</td>
<td>30</td>
<td>1.0</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Very Technology-Focused</td>
<td>1.0</td>
<td>70</td>
<td>40</td>
<td>1.0</td>
<td>1.0</td>
<td>41</td>
<td>1.0</td>
<td>30</td>
<td>42</td>
</tr>
<tr>
<td>Moderately Technology-Focused</td>
<td>10.0</td>
<td>50</td>
<td>20</td>
<td>10.0</td>
<td>10.0</td>
<td>35</td>
<td>10.0</td>
<td>30</td>
<td>33</td>
</tr>
<tr>
<td>Equal-Focused</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
<td>22.8</td>
</tr>
<tr>
<td>Moderately Soft Cost-Focused</td>
<td>21.0</td>
<td>15.0</td>
<td>8.0</td>
<td>50.0</td>
<td>38.0</td>
<td>20.0</td>
<td>8.0</td>
<td>30.0</td>
<td>30.0</td>
</tr>
<tr>
<td>Very Soft Cost-Focused</td>
<td>15.0</td>
<td>1.0</td>
<td>1.0</td>
<td>70.0</td>
<td>55.0</td>
<td>15.0</td>
<td>1.0</td>
<td>38.0</td>
<td>30.0</td>
</tr>
</tbody>
</table>

4. RESULTS

4.1 Sensitivity Analysis Results

The results of the SA are presented in the tornado diagram in Fig. 6. The inputs are ordered from greatest LCOE sensitivity (highest) to least LCOE sensitivity (lowest) based on the OAT
The results show that LCOE is most sensitive to the interconnection cost, a soft cost, with a difference of 3.37 ¢/kWh. Interconnection cost is followed by net capacity factor, both a technology cost and soft cost, with a difference of 3.27 ¢/kWh. There is a significant decrease to the next input, generation equipment cost, which is a technology cost. It is interesting to note that as per our analysis, LCOE is most sensitive to a soft cost; in order of LCOE sensitivities, the highest technology cost is below both a soft cost and a cost categorized as both. Below the top

*T = Technology cost; S = Soft Cost; B = Both

FIGURE 6: TORNADO DIAGRAM OF SOLAR COST MODEL INPUTS
three ordered inputs, two soft costs - land lease and development cost and fees - come next, followed by three technology costs - fixed O&M, project degradation, and balance of plant costs. The costs that LCOE is least sensitive to as per our analysis are two soft costs - debt parameters and real discount rate.

Note from the tornado diagram that net capacity factor and the debt parameters have flipped lower and higher values; this indicates the maximum values for these inputs resulted in lower values for LCOE and vice versa. All other inputs resulted in expected changes in LCOE.

4.2 Decision Model Results

From the results of the SA presented above, we calculated the weights of each attribute. Table 2 shows the weight for each attribute, in order of largest to smallest weight - the same order as presented in the tornado diagram. The cost classification - technology cost, soft cost, or both - are also provided for reference. For additional information about each attribute and the range of values tested in the SA, please refer to Table A-2 in the Appendix.

**TABLE 2: WEIGHTS OF EACH ATTRIBUTE DETERMINED BY SENSITIVITY ANALYSIS, IN ORDER OF LARGEST TO SMALLEST WEIGHT, AND COST CLASSIFICATION**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Classification</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interconnection</td>
<td>Soft</td>
<td>0.274</td>
</tr>
<tr>
<td>Net Capacity Factor</td>
<td>Both</td>
<td>0.266</td>
</tr>
<tr>
<td>Generation Equipment Cost</td>
<td>Technology</td>
<td>0.102</td>
</tr>
<tr>
<td>Land Lease Cost</td>
<td>Soft</td>
<td>0.076</td>
</tr>
<tr>
<td>Development Cost and Fees</td>
<td>Soft</td>
<td>0.071</td>
</tr>
<tr>
<td>Fixed O&amp;M</td>
<td>Technology</td>
<td>0.070</td>
</tr>
<tr>
<td>Project Degradation</td>
<td>Technology</td>
<td>0.056</td>
</tr>
<tr>
<td>Balance of Plant Cost</td>
<td>Technology</td>
<td>0.045</td>
</tr>
<tr>
<td>Debt Parameters</td>
<td>Soft</td>
<td>0.028</td>
</tr>
</tbody>
</table>
Real Discount Rate  Soft  0.013

Table 3 is a revised version of Table 1 presented in Section 3.3 to include 1) the weight for each attribute and 2) the value calculated for each alternative. The new information is highlighted in grey for clarity. Finally, Fig. 7 shows the results of the value calculations for each alternative in a visual format.

**TABLE 3: REVISED VERSION OF TABLE 1, NOW INCLUDING WEIGTHS FOR EACH ATTRIBUTE AND CALCULATED VALUES FOR EACH ALTERNATIVE. ALL DOLLAR VALUES ARE IN $M.**

<table>
<thead>
<tr>
<th>ATTRAIBUTES</th>
<th>Real Discount Rate</th>
<th>Generation Equipment Cost</th>
<th>Balance of Plant Cost</th>
<th>Interconnection Cost</th>
<th>Development Cost and Fees</th>
<th>Debt Parameters</th>
<th>Fixed O&amp;M</th>
<th>Land Lease Cost</th>
<th>Net Capacity Factor</th>
<th>Project Degradation</th>
<th>Total Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Classification -&gt;</strong></td>
<td>Soft</td>
<td>Tech</td>
<td>Soft</td>
<td>Soft</td>
<td>Tech</td>
<td>Soft</td>
<td>Soft</td>
<td>Both</td>
<td>Tech</td>
<td><strong>Weight -&gt;</strong></td>
<td>0.013</td>
</tr>
<tr>
<td><strong>DOE Allocation</strong></td>
<td>$1.0</td>
<td>$100.0</td>
<td>$50.0</td>
<td>$2.0</td>
<td>$2.0</td>
<td>$30.0</td>
<td>$1.0</td>
<td>$20.0</td>
<td>$20.0</td>
<td><strong>Total Value</strong></td>
<td>21.77</td>
</tr>
<tr>
<td>Very Technology-Focused</td>
<td>$1.0</td>
<td>$70.0</td>
<td>$40.0</td>
<td>$1.0</td>
<td>$1.0</td>
<td>$41.0</td>
<td>$1.0</td>
<td>$30.0</td>
<td>$42.0</td>
<td>22.56</td>
<td></td>
</tr>
<tr>
<td>Moderately Technology-Focused</td>
<td>$10.0</td>
<td>$50.0</td>
<td>$20.0</td>
<td>$20.0</td>
<td>$10.0</td>
<td>$35.0</td>
<td>$10.0</td>
<td>$30.0</td>
<td>$33.0</td>
<td>25.61</td>
<td></td>
</tr>
<tr>
<td>Equal-Focused</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>$22.8</td>
<td>22.80</td>
<td></td>
</tr>
<tr>
<td>Moderately Soft Cost-Focused</td>
<td>$21.0</td>
<td>$15.0</td>
<td>$8.0</td>
<td>$50.0</td>
<td>$38.0</td>
<td>$20.0</td>
<td>$8.0</td>
<td>$30.0</td>
<td>$30.0</td>
<td>30.36</td>
<td></td>
</tr>
<tr>
<td>Very Soft Cost-Focused</td>
<td>$15.0</td>
<td>$1.0</td>
<td>$1.0</td>
<td>$70.0</td>
<td>$55.0</td>
<td>$15.0</td>
<td>$1.0</td>
<td>$38.0</td>
<td>$30.0</td>
<td>34.87</td>
<td></td>
</tr>
</tbody>
</table>
FIGURE 7: RESULTING VALUE OF EACH FUNDING STRATEGY TESTED IN THE ANALYSIS. THE FUNDING STRATEGY THAT IS MOST FOCUSED ON SOFT COSTS RESULTS IN THE HIGHEST VALUE OF THE STRATEGIES CONSIDERED.

From the results, we see the Very Soft-Cost Focused strategy yields the highest value. We also find the DOE Allocation strategy, the closest strategy to what is being used today in the DOE, yields the lowest value calculation. The Very Tech-Focused and Equal-Focused strategies yielded approximately equal values, while both moderate strategies resulted in increased value.

5. DISCUSSION

5.1 Sensitivity Analysis Discussion

The results of the SA show the LCOE is most sensitive to interconnection cost and net capacity factor; these results align with the anecdotes shared by developers and utilities. We received these
perspectives through interviews that were conducted via phone and email, with follow-up questions sent by email. Note that the interviewees did not wish to have the conversations documented, as is often the case with proprietary competitive information. Both stakeholders shared the initial strategy for project development often starts by finding the sunniest locations (higher net capacity factor) with the greatest access to existing interconnection infrastructure (lower interconnection costs), as these factors are most important for determining project costs and development. The outcome of the SA mirrors these priorities and offers insight into how and where developers/utilities design solar projects. If a land parcel is available in a sunny region but has minimal grid infrastructure around it, a project may not be financially worth designing there.

The LCOE was least sensitive to the debt parameters and real discount rate. Securing financing is crucial to developers to move forward with project, however the investor-set values available to developers, such as debt term, discount rate, and debt percentage, may not be a large enough range to make a significant impact on the final LCOE. This analysis does not capture the nuances of these inputs and their full effects on solar project developments; contrary to our results, securing financing can make or break a project’s future. However, the analysis does suggest that developers may not have as much option in controlling these costs to lower their project LCOE and may want to focus their efforts to decrease costs in other areas of development.

Particularly focusing on the cost inputs, the analysis showed the inputs with the largest numerical ranges yielded higher LCOE sensitivity. The input ranges used in the OAT analysis were defined by industry literature for past utility-scale solar projects; this result suggests the inputs with the largest cost ranges either 1) are the least well-known and vary based on the circumstances or 2) have additional uncertainty/risk factors to consider. External factors can make an input “more important” to project development but would not be captured by the OAT method.
For example, generation equipment cost can widely vary based on manufacturing, shipment and procurement logistics, and the ever-changing domestic and foreign politics that govern the solar PV market. The analysis shows this input is the third in the order of LCOE sensitivities, which could be explained due to the many external factors listed above. In contrast, development cost and fees, an input comprised of soft costs such as permitting and labor, appears to be low in the order of LCOE differences as per the OAT analysis; this result can be explained due to the smaller input range compared to interconnection cost and generation equipment cost. However, it is well-known in the industry that permitting issues can cause unexpectedly large time delays, cost increases, and even project failures, which can be caused by any number of external factors such as community backlash, lack of engagement, or uninformed local governments. These trends were not observed in the available quantitative data, thus is not captured in our analysis. Exploring the uncertainty and risk within these systems is important and we suggest future work to quantify these unexpected costs and delays using additional data mining and probabilistic modeling.

5.2 Decision Model Discussion

To calculate the value of the six hypothetical funding strategies, we integrated the results of the sensitivity analysis as weights, cost model inputs as attributes, and funding strategies as alternatives. Each alternative serves a strategy that the DOE solar office could adopt. The strategy that allocated funding based on the current DOE funding numbers resulted in the lowest value in our analysis. This result suggests regardless of soft costs and technology costs, the DOE solar office is not prioritizing their funding allocation based on the factors of utility-scale solar development to which the LCOE is most sensitive. According to the parameters in our model,
redistribution of the funding to prioritize factors that have a greater influence on LCOE may result in a higher value for the DOE.

In contrast, the Very Soft Cost-Focused strategy resulted in the highest calculated value. The DOE may gain higher value from allocating funding that prioritizes soft costs. Examples of soft cost R&D programs could be streamlined permitting processes, redesigned community engagement strategies, data-backed initiatives to improve land lease valuations and investor project valuations, and stakeholder relationship improvement. Funding soft cost research could lead to cost reduction, better system design, subsequent technology advancement, and decreased unintended consequences that often plague developments. Modeling the interaction between systems and the organizations in which they exist can help identify these unintended consequences and lead to better results. For instance, funding a project to develop a nationally administered solar permitting process could decrease time for developers, leaving budget open to purchase more efficient technology and deliver higher power to the end users for the same cost. Additionally, funding soft cost research could decrease the number of costs that are incurred during a solar development project. The factors that affect solar developments are truly interconnected and advancement should be considered from all angles by stakeholders and funding agencies alike for the greatest benefit.

In addition to the soft-cost focus, it is important to note that while the “moderate” funding strategies do not offer the maximum value, they do offer increased value compared to the current DOE allocation. These results suggest allocating funding to a more diverse range of solar project development factors, not just hardware costs, may result in more value to the funding agency and in turn, may result in cost reduction for the industry.
5.2.1 Decision Model Validation

An important next step to this work is to validate the decision model and develop credibility such that funding agencies, such as the DOE solar office, would trust this decision model enough to use it when making funding allocations. While the input ranges used in the SA are grounded in published industry data, the funding strategies tested in the decision model are hypothetical and defined to test a range of alternatives. Future work could apply this method to actual solar funding budgets from historical data and understand the range of calculated values. Additionally, quantifying the correlation between soft cost research and soft cost reduction in the industry can help substantiate the benefits of DOE solar R&D funding allocation and validate the funding effectiveness assumptions in our model. Finally, developing model credibility is required for the decision-maker to trust the results and actually use the model [57]. Future actions that could be implemented to build credibility include 1) meetings with funding agency decision makers, 2) full transparency of the code developed as part of this analysis, and 3) an interactive tool for decision makers to be able to test the model in a user-friendly way and customize their results.

5.3 Limitations and Future Work

While the analysis presented in this paper is a simple decision-making model for the DOE solar office to allocate R&D funding, the approach has some limitations we would like to acknowledge. First, the proprietary nature of the solar industry has given us limited information to build a cost model. The model for our analysis is based largely on sources that come from National Laboratories. The models built by these institutions may differ from the way a traditional solar developer might build a cost model, which could potentially affect our results. We also note that limited data for each input exists in the industry; the data we used to define the
input ranges was not comprehensive of all solar projects in the U.S. Additional data may affect the results of the SA and in turn, alter the weights used in the decision model. We did not take into account correlations between inputs, an assumption which may also be updated by additional data or more sophisticated uncertainty quantification techniques. Similarly, we categorized the inputs as soft and technology based on previous literature; however, many inputs may blur the lines between soft and technology and can be interpreted in different ways. Additional categorizations could lead to different decision model results.

Second, we chose to focus this study on utility-scale solar based on the data available and the large growth potential in the U.S.; however, it is well-known in industry that costs for smaller-scale solar developments (residential or commercial) can be different from utility-scale. This analysis did not take into account smaller-scale solar developments and should be included in future work to test the applicability of these methods across the solar industry.

Third, we defined the boundary of our system to be a utility-scale solar development; we acknowledge this system itself has many subsystems for which we did not consider as its own sociotechnical system. For instance, module cost is determined by a multitude of factors that may range from manufacturing costs to material costs and depend on technology, tariffs, and geopolitics. We did not granularize these subsystems in our analysis but predict further analysis in this area would offer interesting insights to the solar industry to expand on the findings in this paper.

Fourth, we did not include private sector funding or funding considerations from other industries in our analysis. Private R&D funding is important to the industry but difficult to find detailed information on and is often catalyzed by public R&D funding. Kavlak et al. found through their analysis of the solar PV cost reductions that public R&D funding for the solar
industry remains important and may offer the “major innovations” needed for the industry where public funding usually focuses on incremental changes [3]. For this initial analysis, we chose to focus on public R&D funding allocation in the solar industry; however, future iterations of this design model should consider the effects of private R&D, especially in the area of soft cost reduction. Public-private partnerships or “cost share” funding opportunities may be effective for future soft cost projects. Additionally, other industries, such as the construction management industry, can also provide valuable lessons to the solar industry for future model iterations.

Finally, the MAVF we used is based on deterministic weights, does not take into account uncertainty [39], and may be limited by the implications of Arrow’s Impossibility Theorem [42]. Future work should explore expected utility theory when analyzing a funding agency’s decision making to produce more realistic results. Additionally, we assume attributes to be independent for this analysis; however, in reality, independence may not hold. We chose to conduct this analysis with as simple additive model for initial results, but suggest additional work using utility theory should be explored in the future.

6. CONCLUSION

In this paper, we presented a decision model for the DOE solar office to use and evaluate solar R&D funding strategies. We built a solar cost model, comprised of both technology and soft cost inputs, to calculate the LCOE of a utility-scale solar development. Using this model, we conducted a sensitivity analysis to quantify the effect of each input on the output LCOE. Using these results as weights, we developed a decision model using a multi-attribute value function and evaluated six hypothetical funding strategies. The results of the model suggest that allocating funding closest to the current DOE solar funding strategy had the lowest calculated value to the
decision-maker, while allocating R&D funding to prioritize soft costs resulted in the highest calculated value. This suggests the DOE solar office could gain more value from shifting funding dollars to cover more diverse areas like soft cost projects. Aligning funding based on how solar project costs are broken down may offer benefits to the DOE and potential cost reduction in the industry.

The decision model presented in this paper requires validation to be used in a real-world context and gain credibility with decision-makers like the DOE solar office. Additionally, we suggest conducting a deeper study of decision-making models under uncertainty for future model iterations. Overall, this approach to quantifying technology and soft costs in a sociotechnical system and incorporating those costs into funding decisions can be generalized to study other areas of design that are influenced by people and technology. For future study, we see value in applying this approach to these other systems to gain insights, drive innovation, and potentially spur cost reduction.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation Research Fellowship. Thanks to our colleagues at Michigan State University for their thoughtful discussions about this paper and to the anonymous reviewers for their helpful comments.
REFERENCES


2018, National Renewable Energy Laboratory, Golden CO.


Cambridge University Press, pp. 112-134.


[40] Chen, W., Hoyle, C., and Wassenaar, H. J., 2013, *Decision Based Design: Integrating Consumer


[52] Freyman, T., and Tran, T., 2019, Renewable Energy Discount Rate Survey Results - 2018, Grant Thornton UK LLP.


# NOMENCLATURE

- **$LCOE$**: Levelized cost of energy
- **$G$**: Generator nameplate capacity
- **$d_r$**: Real discount rate
- **$d_m$**: Nominal discount rate
- **$r_i$**: Inflation rate
- **$C_0$**: Initial project investment ($)
- **$Q_n$**: Annual electricity generated by the plant in year $n$ (kWh)
- **$N$**: Project Lifetime (years)
- **$C_n$**: Annual project costs in year $n$ ($)
- **$C_G$**: Generation equipment cost ($)
- **$C_B$**: Balance of plant cost ($)
- **$C_I$**: Interconnection cost ($)
- **$C_D$**: Development cost and fees ($)
- **$C_F$**: Financing and reserves cost ($)
- **$c_p$**: PV module cost ($/W$)
- **$c_v$**: Inverter cost ($/W$)
- **$c_M$**: Mounting cost ($/W$)
- **$c_T$**: Transmission cost ($/W$)
- **$c_W$**: Wiring equipment cost ($/W$)
- **$C_P$**: Permitting cost ($)
- **$c_a$**: Landowner acquisition cost ($/W$)
- **$c_l$**: Labor and construction fees ($/W$)
- **$\sigma_{EPC}$**: Engineering, procurement, and construction overhead (%)
- **$p_{EPC}$**: Engineering, procurement, and construction profit (%)
- **$c$**: Developer contingency (%)
- **$\sigma_{DEV}$**: Developer overhead (%)
- **$l$**: Lending fee (%)
- **$p_D$**: Debt percent (%) 
- **$T_D$**: Debt term (years)
- **$i_D$**: Debt interest rate (%)
- **$m_r$**: Required reserves (months)
- **$p_l$**: Monthly loan principle ($)
\( i_i \) Monthly loan interest ($)
\( F_n \) Fixed operations and maintenance cost for year \( n \) ($)
\( V_n \) Variable operations and maintenance cost for year \( n \) ($)
\( I_n \) Insurance cost for year \( n \) ($)
\( P_n \) Project administration cost for year \( n \) ($)
\( L_n \) Land lease cost for year \( n \) ($)
\( T_n \) Taxes for year \( n \) ($)
\( E \) Acres required per MW (acres/MW)
\( R \) Annual land lease rate paid to landowners ($)
\( NCF \) Net capacity factor
\( d \) Project degradation
\( GHI \) Global horizontal irradiance (kWh/m\(^2\)/day)
\( T \) Type of tracking technology (1 for tracking, 0 for fixed)
\( ILR \) Inverter loading ratio
\( f(x) \) Function to calculate output value of Levelized Cost of Energy
\( x_i \) Value of input \( i \) used in sensitivity analysis
\( \Delta^+_{LCOE} \) Upper sensitivity value of the output \( LCOE \) for input \( i \)
\( \Delta^-_{LCOE} \) Lower sensitivity value of the output \( LCOE \) for input \( i \)
\( \Delta^+_i x \) Upper shift in input \( i \)'s value, used to calculate sensitivity analysis of output
\( \Delta^-_i x \) Lower shift in input \( i \)'s value, used to calculate sensitivity analysis of output
\( x^0 \) Vector of base case input values
\( x^0_{-i} \) Vector of base case values for all inputs \( \neq x_i \)
\( V_a \) Value of alternative \( a \)
\( w_i \) Weight of attribute \( i \)
\( r_{ai} \) Score for alternative \( a \) and attribute \( b \)
\( I \) Total number of attributes
\( \Delta_i LCOE \) Difference between upper and lower LCOE sensitivity for each input, \( i \)
\( \sum \Delta LCOE \) Sum of differences in LCOE sensitivities for all inputs
APPENDIX: INPUTS FOR THE SOLAR COST MODEL

Note: All dollar values reported are in 2018 U.S. dollars and all power values are reported in Direct Current (DC) units.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Input</th>
<th>Description</th>
<th>Assumed Value</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>--</td>
<td>Type of technology</td>
<td>The type of solar technology analyzed in the cost model</td>
<td>Photovoltaic, Single axis tracking, no storage</td>
<td>Choice of the authors, designed to follow [58]</td>
</tr>
<tr>
<td>G</td>
<td>Generator Nameplate Capacity</td>
<td>Capacity of the solar plant</td>
<td>100 MW</td>
<td>Choice of the authors, designed to follow [58]</td>
</tr>
<tr>
<td>N</td>
<td>Project Lifetime</td>
<td>The number of years a project will last</td>
<td>30 years</td>
<td>[58,59]</td>
</tr>
<tr>
<td>r_i</td>
<td>Inflation Rate</td>
<td>Rate of inflation as per the US Bureau of Labor statistics</td>
<td>2.1%</td>
<td>[53]</td>
</tr>
<tr>
<td>c_w</td>
<td>Wiring and Electrical Cost</td>
<td>Cost of the electrical equipment required for the project</td>
<td>0.17 USD/W</td>
<td>[58]</td>
</tr>
<tr>
<td>c_a</td>
<td>Landowner Acquisition Cost</td>
<td>Cost to acquire the landowners required for the project</td>
<td>0.03 USD/W</td>
<td>[58]</td>
</tr>
<tr>
<td>l</td>
<td>Lender’s Fee</td>
<td>Fee required to the lender when taking on debt</td>
<td>3%</td>
<td>[48]</td>
</tr>
<tr>
<td>N_c</td>
<td>Construction Duration</td>
<td>Number of months required for construction prior to installation</td>
<td>6 months</td>
<td>[58]</td>
</tr>
<tr>
<td></td>
<td>Construction Interest Rate</td>
<td>Annual interest rate set for construction funds</td>
<td>4%</td>
<td>[58]</td>
</tr>
<tr>
<td>c_c</td>
<td>Closing Costs</td>
<td>Other required costs to the developer for due diligence and to lenders</td>
<td>0 USD</td>
<td>[48]</td>
</tr>
<tr>
<td>m_r</td>
<td>Required Reserves</td>
<td>Number of months of reserve funds the lender requires developers to have</td>
<td>6 months</td>
<td>[48]</td>
</tr>
<tr>
<td>P_n</td>
<td>Project Administration</td>
<td>Project management costs required to manage Power Purchase Agreements or other activities related to the project</td>
<td>$0</td>
<td>[48]</td>
</tr>
<tr>
<td>--</td>
<td>Insurance Rate</td>
<td>Rate of insurance required for developers to carry</td>
<td>0.4%</td>
<td>[48]</td>
</tr>
<tr>
<td>--</td>
<td>Owner is a taxable entity?</td>
<td>Determine if the financial owner of the project is a taxable entity</td>
<td>Yes</td>
<td>[58]</td>
</tr>
<tr>
<td>--</td>
<td>Federal Tax Credit for Solar</td>
<td>Tax credit offered by the US federal government for solar technology</td>
<td>30%</td>
<td>[60]</td>
</tr>
<tr>
<td>--</td>
<td>Location of Project</td>
<td>The location in which the project is installed</td>
<td>California, USA</td>
<td>Choice of authors</td>
</tr>
<tr>
<td>--</td>
<td>Depreciation</td>
<td>The schedule on which the assets in the solar plant reduce in value over time</td>
<td>5-year MACRS</td>
<td>[58]</td>
</tr>
<tr>
<td>--</td>
<td>Replacement</td>
<td>Number of years between inverter replacement</td>
<td>12 years</td>
<td>[58]</td>
</tr>
</tbody>
</table>
### TABLE A-2: INPUTS USED IN SENSITIVITY ANALYSIS (NUMBERED AND SHADED), SUB-INPUTS, VALUE RANGES, SOFT COST VS. TECHNOLOGY COST CLASSIFICATIONS, AND DATA SOURCES

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Input Description</th>
<th>Value Range</th>
<th>Classification</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_r$</td>
<td>1) Real Discount Rate</td>
<td>Opportunity cost of capital for the project</td>
<td>6.3% - 6.5%</td>
<td>Soft Cost [52,61]</td>
</tr>
<tr>
<td>$c_p$</td>
<td>PV Module Cost</td>
<td>Cost of the photovoltaic modules required for the project</td>
<td>0.47 - 0.69 USD/W</td>
<td>Technology Cost [11,58]</td>
</tr>
<tr>
<td>$c_v$</td>
<td>Inverter Cost</td>
<td>Cost of the inverters required for the project</td>
<td>0.05 - 0.12 USD/W</td>
<td>Technology Cost [11,58]</td>
</tr>
<tr>
<td>$C_B$</td>
<td>3) Balance of Plant Cost</td>
<td>Mounting Cost, Transmission Cost</td>
<td>Technology Cost</td>
<td>[11,58]</td>
</tr>
<tr>
<td>$c_M$</td>
<td>Mounting Cost</td>
<td>Cost of equipment necessary to mount PV modules and inverters</td>
<td>0.1 - 0.21 USD/W</td>
<td>Technology Cost [11,58]</td>
</tr>
<tr>
<td>$c_T$</td>
<td>Transmission Cost</td>
<td>Cost of transmission equipment required to connect project to the utility grid</td>
<td>0.02 - 0.03 USD/W</td>
<td>Technology Cost [58]</td>
</tr>
<tr>
<td>$C_i$</td>
<td>4) Interconnection Cost</td>
<td>Cost of interconnection study and upgrades to the grid required to connect project to the utility grid</td>
<td>0.02 - 0.99 USD/W</td>
<td>Soft Cost [58,62]</td>
</tr>
<tr>
<td>$C_D$</td>
<td>5) Development Cost and Fees</td>
<td>Permitting Cost, Labor and Construction Cost</td>
<td>Soft Cost</td>
<td>[58]</td>
</tr>
<tr>
<td>$C_P$</td>
<td>Permitting Cost</td>
<td>Cost to acquire necessary permits to build the project</td>
<td>211,889 - 1,059,447 USD</td>
<td>Soft Cost [58]</td>
</tr>
<tr>
<td>$c_l$</td>
<td>Labor and Construction Cost</td>
<td>Cost of the labor and construction equipment required to build the project</td>
<td>0.35 - 0.38 USD/W</td>
<td>Soft Cost [58]</td>
</tr>
<tr>
<td>$o_{EPC}$</td>
<td>EPC Overhead</td>
<td>Overhead required by the EPC to construct the project</td>
<td>8.67% - 13%</td>
<td>Soft Cost [11]</td>
</tr>
<tr>
<td>$P_{EPC}$</td>
<td>EPC Profit</td>
<td>Profit required by the EPC to construct the project</td>
<td>5% - 8%</td>
<td>Soft Cost [11]</td>
</tr>
<tr>
<td>$c_D$</td>
<td>Developer Contingency</td>
<td>Extra funds required by the developer used as an allowance for unexpected events and risks</td>
<td>3% - 4%</td>
<td>Soft Cost [11,58]</td>
</tr>
<tr>
<td>$o_{DEV}$</td>
<td>Developer Overhead</td>
<td>Overhead required by the developer, may include due diligence, legal services, etc.</td>
<td>2% - 12%</td>
<td>Soft Cost [11]</td>
</tr>
<tr>
<td>$p_D$</td>
<td>Project Debt Percentage</td>
<td>Portion of the project expenses that is borrowed</td>
<td>40% - 50%</td>
<td>Soft Cost [61]</td>
</tr>
<tr>
<td>$T_D$</td>
<td>Debt Term</td>
<td>Length of debt repayment period</td>
<td>5-20 years</td>
<td>Soft Cost [61]</td>
</tr>
<tr>
<td>$i_D$</td>
<td>Debt Interest Rate</td>
<td>Interest rate on the loans for the project</td>
<td>3.5% - 5.25%</td>
<td>Soft Cost [61]</td>
</tr>
<tr>
<td>$F_n$</td>
<td>7) Fixed Operations and Maintenance</td>
<td>Fixed cost to maintain and operate the solar plant yearly</td>
<td>10.40 - 30.85 USD/kW·yr</td>
<td>Technology Cost</td>
</tr>
<tr>
<td>------</td>
<td>----------------------------------</td>
<td>-------------------------------------------------</td>
<td>-----------------</td>
<td>----------------</td>
</tr>
<tr>
<td>$L_n$</td>
<td>8) Land Lease Cost</td>
<td>Land required for the project</td>
<td>4.29 - 13.12 acres/MW$_{dc}$</td>
<td>Soft Cost</td>
</tr>
<tr>
<td>$E$</td>
<td>Land Use</td>
<td>Annual payment to each landowner</td>
<td>1,000 - 2,000 USD/acre</td>
<td>Soft Cost</td>
</tr>
<tr>
<td>$R$</td>
<td>Annual Land Lease Rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCF</td>
<td>9) Net Capacity Factor</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$GHI$</td>
<td>Global Horizontal Irradiance</td>
<td>Total irradiance from the sun on a horizontal surface of the earth</td>
<td>4.8 - 6.3 kWh/m$^2$/day</td>
<td>Soft Cost</td>
</tr>
<tr>
<td>$ILR$</td>
<td>Inverter Loading Ratio</td>
<td>Ratio between the DC solar array and the AC inverter</td>
<td>1.22 - 1.34</td>
<td>Technology Cost</td>
</tr>
<tr>
<td>$d$</td>
<td>10) Project Degradation</td>
<td>The degradation of solar panels each year</td>
<td>0.25% - 1.0%</td>
<td>Technology Cost</td>
</tr>
</tbody>
</table>