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

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This paper presents a new approach to build a decision model for government funding agencies, such as the US 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 research funding is a crucial driver to solar industry growth and potential cost reduction; however, DOE solar funding has not historically aligned with the industry 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 the DOE solar office to prioritize research funding and potentially spur future cost reduction. [DOI: 10.1115/1.4048456]

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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 2020 [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 US, 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 this end, 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 cost reduction as the main benefit to the DOE. While solar photovoltaic (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, for example: 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), a DOE-affiliated national lab, investigates and presents quarterly solar cost updates [11]; the Solar Energy Technologies Office (SETO) states the goals of their office prioritize "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 calculates 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 section for reference.

$$LCOE = \frac{\text{Total project costs}}{\text{Total power generated}} \tag{1}$$

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.

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The solar development process is a complex, sociotechnical system, and total project costs span both technology and human-driven costs, also known 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], the recent DOE budget shows that funding decisions are not being made to study soft costs at the same level as technology costs. The 2020 US Congressional Budget shows that the 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.

In this paper, 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. We focus on utility-scale solar in our analysis, as NREL projects the majority of the growth in US solar PV energy is expected to come from the utility-scale sector and will dominate future 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 understanding 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. Figure 2 presents the workflow of this paper in a flowchart format.

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 allocation results the lowest calculated value, thus suggesting the strategy is less desirable to the decision maker. The strategy that prioritizes soft cost funding results in 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 decisions, and future work should include additional data gathering, model validation, and exploration of advanced decision-making models.

The paper is organized as follows: Sec. 2 provides a background of previous literature and Sec. 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 in Sec. 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 and 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 [20,21]. The technology subsystem that stakeholders interact with 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.

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,

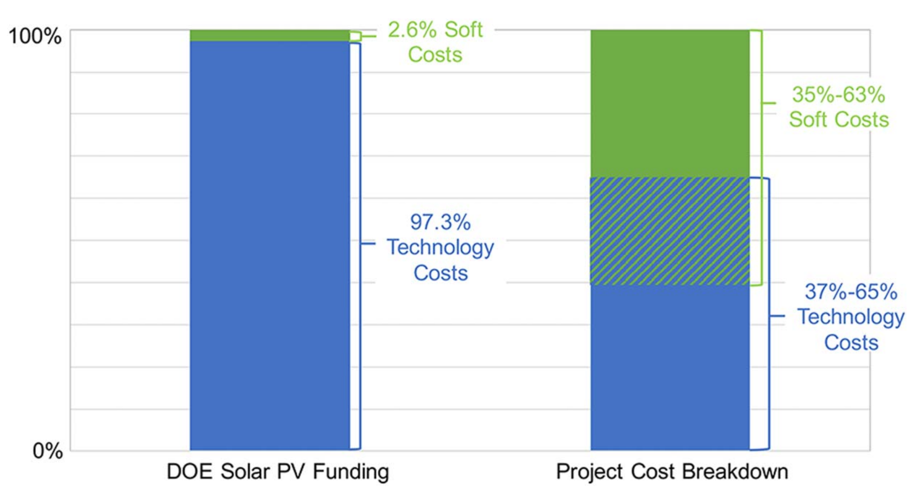

Fig. 1 US DOE 2020 solar R&D funding allocations compared with solar PV project cost breakdown. US DOE data are from Ref. [16] and solar project cost data are Ref. [11].

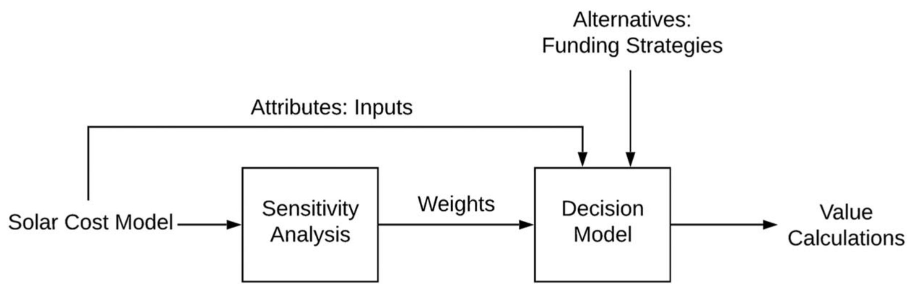

Fig. 2 Flowchart representation of the method presented in the paper

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 US-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 Sec. 1, the DOE does not have a consistent decision-making process across offices by which they allocate their funding to different areas and compare these expected benefits [5]. Each DOE office currently performs its 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 makes modifications based on factors that are out of the DOE's control and sets the budget for the year. A systematic decision framework that the DOE could use consistently across all offices to assess different funding strategies would benefit the department greatly and perhaps increase the overall societal benefits from the funded projects [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 offices.

Decision frameworks to determine R&D funding allocation strategies have been studied in the management literature, see Ref. [8] for a review of quantitative techniques and models that have been used in previous funding allocation literature. Within the area of

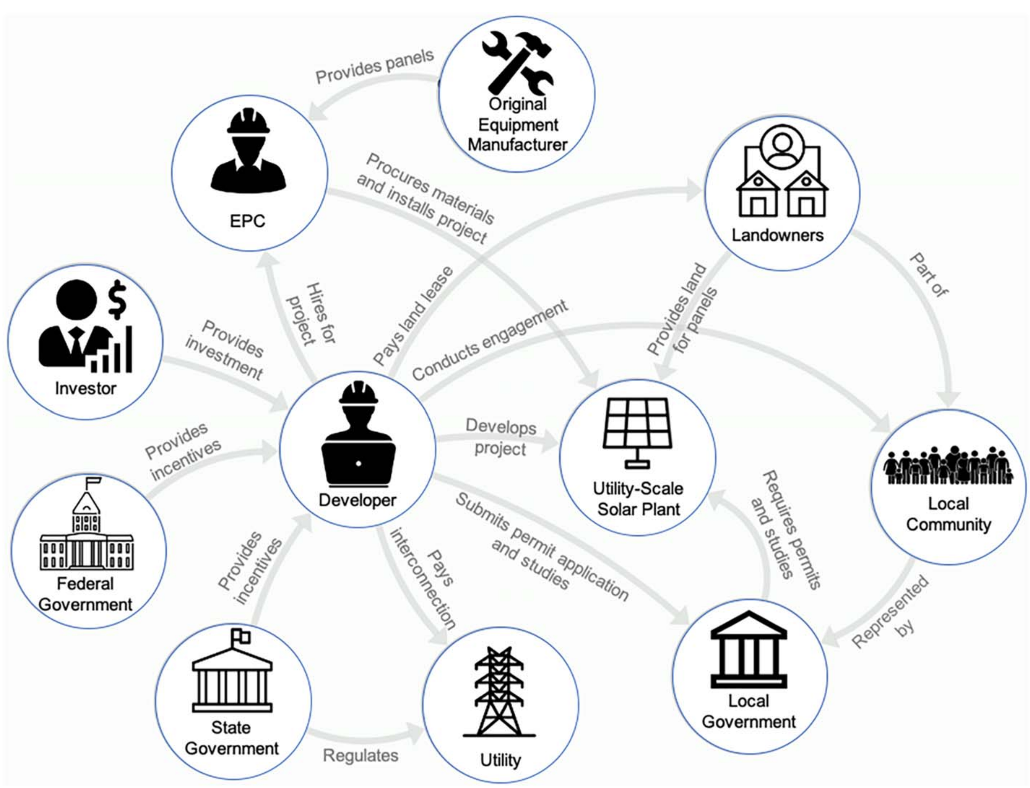

Fig. 3 Network of stakeholders in utility-scale solar development

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 and develop our model to use funding allocations (in USD) and weights to calculate the value of each funding strategy for the DOE solar office. We build on the work from the existing work in Ref. [31] in two ways. First, while the Kurth et al. calculate the weights of their MAVF using expert elicitation of technology readiness levels, we present a mathematical method, SA, to calculate weights that capture the industry preference of each attribute while eliminating 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, include technology in their analysis, but do not consider the soft cost-related projects that could influence their systems and funding. While studies often qualitatively 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 generally do not incorporate these non-technical aspects. We expand this approach and incorporate both technical and soft 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 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 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 R&D funding for both types of projects will result in 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 Ref. [37], as well as an initial study conducted by NREL researchers. Dong and Wiser explore data from a DOE-funded soft cost program, the Rooftop Solar Challenge Program, responsible for streamlining permitting programs for rooftop PV solar projects [38]. They found that cities with more favorable permitting processes set by the program had "lower-than-average" PV system prices. The results suggest that funding this soft cost program positively correlates with soft 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 acquire additional industry data or perform an expert elicitation, much like what has been done for technology. See Sec. 5.2.1 for a discussion on future steps for model validation. Overall, we believe this assumption and our approach has merit, as we do not know of any energy governmental funding agencies that incorporate 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 to evaluate R&D funding strategies, particularly in the energy industry as detailed in Sec. 2.2. Under deterministic conditions, we build *value functions* to calculate a decision-maker's preference; under uncertain conditions, we build *utility functions* [39,42]. For this paper, we assume deterministic conditions and represent funding strategy decisions with a 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.

MAVFs are composed of multiple decision alternatives and each alternative consists of multiple attributes; the outcome quantifies the preference order in which the decision maker ranks the decision alternatives. The "weighted sum" value function, shown in Eq. (2), is a popular MAVF due to its ease of use [39]:

$$V_a = \sum_{i=1}^{I} w_i r_{ai} \tag{2}$$

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. Equation (2) assumes the attributes are independent [42]. The weights have the following property:

$$\sum_{i=1}^{I} w_i = 1 \tag{3}$$

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.

The challenge in using this model often lies in determining the function parameters 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 assign weights to the 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 can capture 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 Refs. [39] and [47] for more details. In this paper, we propose a method for determining the weights of a MAVF that offers a mathematical approach to capturing preferences 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 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] Figure 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

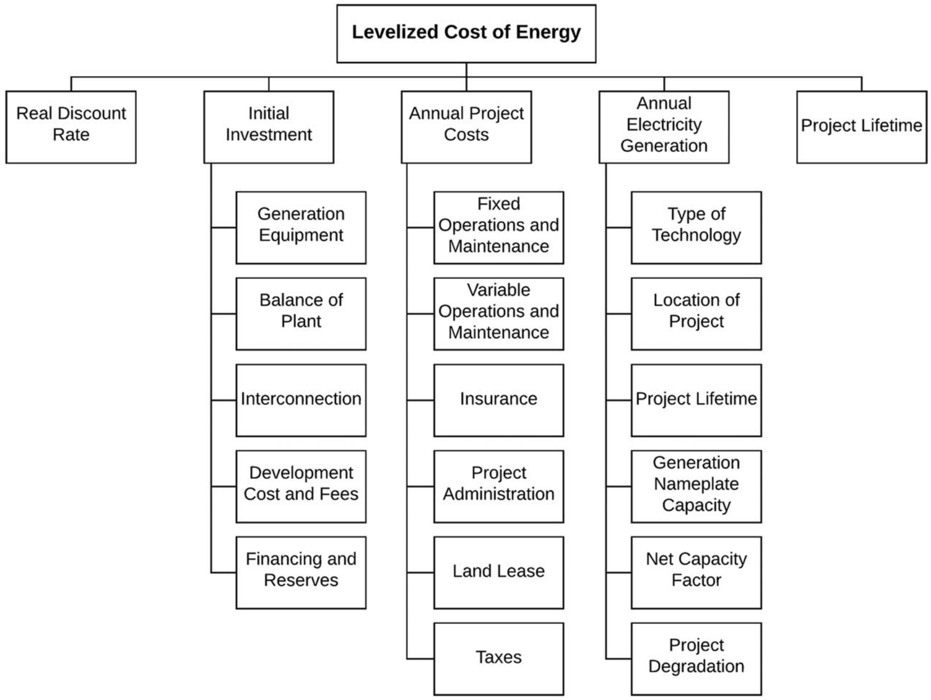

Fig. 4 Overview of cost model structure

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 used in the analysis are detailed in the Appendix in Table 4.

3.1.1 Levelized Cost of Energy. The model calculates the LCOE of the given solar PV project. $LCOE$ (¢/kWh) is calculated by the following equation used in the NREL System Advisor Model (SAM), originally published in Ref. [51]:

$$LCOE = \frac{C_0 + \sum_{n=1}^{N} \frac{C_n}{(1+d_m)^n}}{\sum_{n=1}^{N} \frac{Q_n}{(1+d_r)^n}} \tag{4}$$

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, Q_n is the electricity generated in year n, and N is the project lifetime. The following sections further describe each component of the $LCOE$. A detailed table of the model inputs is included in the Appendix in Table 5.

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 $r_i = 2.1\%$ as per the US Bureau of Labor Statistics [53]. The following equation describes the nominal discount rate calculation from [51]

$$d_m = (1 + d_r) \times (1 + r_i) - 1 \tag{5}$$

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]:

$$C_0 = C_G + C_B + C_I + C_D + C_F \tag{6}$$

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:

$$C_G = G * (c_P + c_V) \tag{7}$$

$$C_B = G * (c_M + c_T + c_W) \tag{8}$$

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. The development cost is calculated in the following steps. The initial development cost, C_{D1} is composed of permitting cost, C_p, landowner acquisition cost per watt, c_a, and labor and construction fees per watt, c_l:

$$C_{D1} = C_P + G * (c_a + c_l) \tag{9}$$

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

$$C_{D2} = C_{D1} + o_{EPC} * (C_{D1} + C_G + C_B) \tag{10}$$

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

$$C_{D3} = C_{D2} + p_{EPC} * (C_{D2} + C_G + C_B) \tag{11}$$

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:

$$C_D = C_{D3}(1 + c + o_{DEV} + c * o_{DEV}) \tag{12}$$

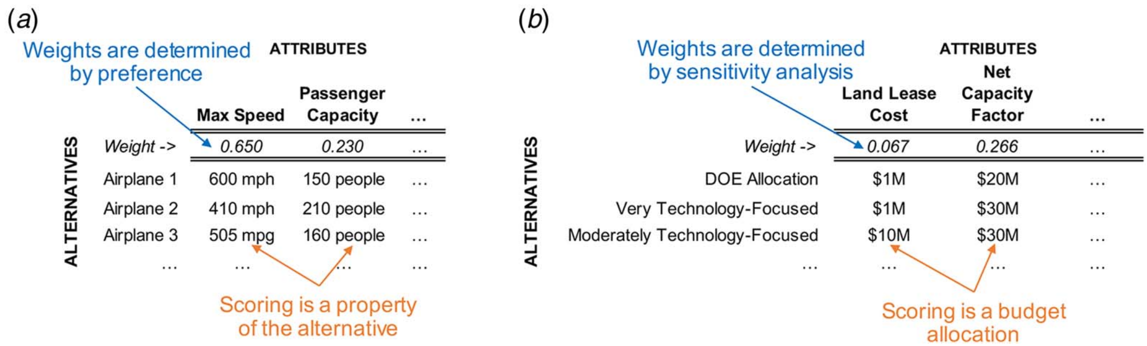

Fig. 5 Multi-attribute value function structure for (*a*) airplane alternative example and (*b*) adaptation for this paper

The financing cost includes lender fees at a rate of l on total borrowed funds at percent debt of p_D, construction interest at rate i_c, closing costs, C_c, and funding reserves, C_R, required by lenders:

$$C_F = (l * p_D * (C_G + C_B + C_I + C_D)) + (i_c * C_0) + C_C + C_R \tag{13}$$

The funding reserves required by the lenders depends on the monthly loan principal, p_l, interest, i_l, and the average monthly project cost. We assume the lender requires 6 months of reserves, m_r:

$$C_r = m_r * \left(p_l + i_l + \frac{\overline{C_n}}{12}\right) \tag{14}$$

3.1.4 Annual Project Costs. The annual project cost, C_n, is calculated as per the CREST model [48]:

$$C_n = F_n + V_n + I_n + P_n + L_n + T_n \tag{15}$$

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:

$$L_n = G * E * R \tag{16}$$

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 following equation is from the CREST model [48]:

$$Q_n = \begin{cases} G * NCF * 8760, & n = 1 \\ Q_{n-1} * (1-d), & n > 1 \end{cases} \tag{17}$$

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 1 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]:

$$NCF = 0.478 * GHI + 0.0429 * T + 0.2391 * \ln(ILR) + 0.2328 \tag{18}$$

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 the 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 value 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 $LCOE = f(\boldsymbol{x})$ are calculated by Eqs. (19) and (20), respectively, based on an input x_i and the vector $\boldsymbol{x}^0$ of base case values:

$$\Delta_i^+ LCOE = f(x_i + \Delta_i^+ x, \boldsymbol{x}_{\sim i}^0) - f(\boldsymbol{x}^0) \tag{19}$$

$$\Delta_i^- LCOE = f(\boldsymbol{x}^0) - f(x_i + \Delta_i^- x, \quad \boldsymbol{x}_{\sim i}^0) \tag{20}$$

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 $\boldsymbol{x}_{\sim i}^0$ represents the vector of base case values for all other inputs $\neq x_i$. Due to the variable nature of 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 calculated from 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.

$$\Delta_d^+ LCOE = f(0.01, \quad \boldsymbol{x}_{\sim d}^0) - f(0.00625, \quad \boldsymbol{x}_{\sim d}^0) \tag{21}$$

$$\Delta_d^- LCOE = f(0.00625, \quad \boldsymbol{x}_{\sim d}^0) - f(0.0025, \quad \boldsymbol{x}_{\sim d}^0) \tag{22}$$

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 Table 5. Additionally, each input is categorized as a soft cost, technology cost, or both, guided by Ref. [14].

An effective graphical representation of the results from an OAT analysis is a tornado diagram, as introduced by Howard in Ref. [56].

Table 1 Funding strategy alternatives and budget allocation scores for each attribute. All dollar values are in $M.

	Real discount rate	Generation equipment cost	Balance of plant cost	Interconnection cost	Development cost	Debt parameters	Fixed O&M	Land lease cost	Net capacity factor	Project degradation
Classification ->	Soft	Tech	Tech	Soft	Soft	Soft	Tech	Soft	Both	Tech
Alternatives										
DOE allocation	$1.0	$100.0	$50.0	$2.0	$2.0	$2.0	$30.0	$1.0	$20.0	$20.0
Very technology-focused	$1.0	$70.0	$40.0	$1.0	$1.0	$1.0	$41.0	$1.0	$30.0	$42.0
Moderately technology-focused	$10.0	$50.0	$20.0	$20.0	$10.0	$10.0	$35.0	$10.0	$30.0	$33.0
Equal-focused	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8
Moderately soft cost-focused	$21.0	$15.0	$8.0	$50.0	$38.0	$20.0	$8.0	$30.0	$30.0	$8.0
Very soft cost-focused	$15.0	$1.0	$1.0	$70.0	$55.0	$15.0	$1.0	$38.0	$30.0	$2.0

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 showing our results is presented in Sec. 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 Sec. 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 office. A visual version of this adaptation is presented in Fig. 5.

Suppose the agency is deciding between different funding strategies—focusing on technology, 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.

$$\Delta_i LCOE = \Delta_i^+ LCOE - \Delta_i^- LCOE \tag{23}$$

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

$$\sum \Delta LCOE = \sum_{i=1}^{I} (\Delta_i^+ LCOE - \Delta_i^- LCOE) \tag{24}$$

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.

$$w_i = \frac{\Delta_i LCOE}{\sum \Delta LCOE} \tag{25}$$

For this demonstration, we define the score r_{ai} for alternative a and attribute i to be the budget allocation to each attribute in $M. We assume the solar office can allocate the money to each attribute depending on their funding strategy. Recall that we categorized each input based on the previous literature (see Table 5, column 5); we used these categorizations to determine 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, the first strategy is directly adapted from the actual DOE solar funding allocation as per the 2020 congressional budget [16]. The subsequent strategies range from Very Technology-Focused to Very Soft Cost-Focused to test a wide

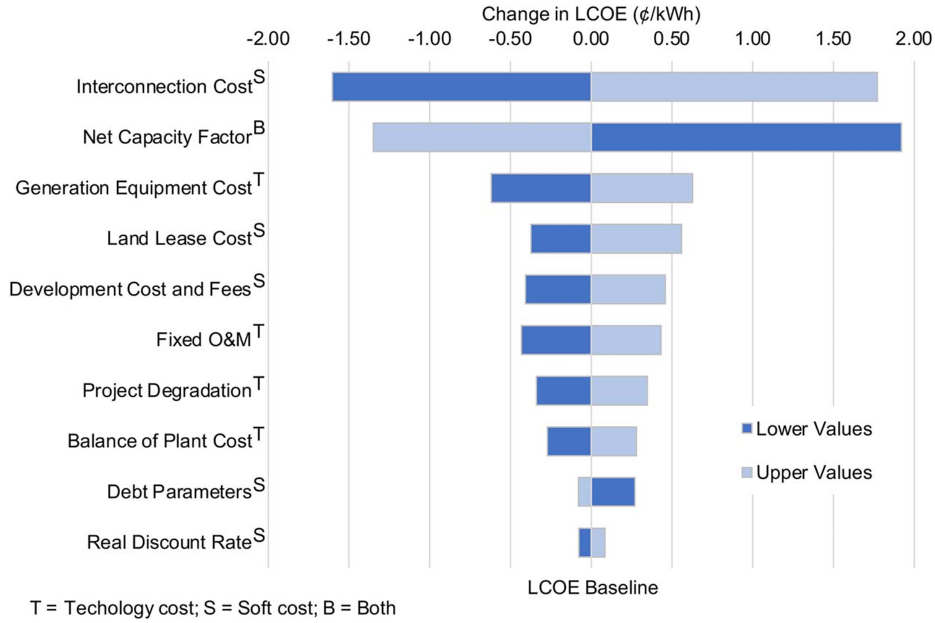

Fig. 6 Tornado diagram of solar cost model inputs

variety of funding focuses. Table 1 shows the alternatives, attributes, and scores used in the analysis:

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 top to bottom from greatest LCOE sensitivity to least LCOE sensitivity based on the OAT analysis.

The results show that LCOE is most sensitive to the interconnection cost with a difference of 3.37 ¢/kWh. Interconnection cost is followed by net capacity factor with a difference of 3.27 ¢/kWh. There is a significant decrease to the next input, generation equipment cost. As per our analysis, LCOE is most sensitive to a soft cost and a cost categorized as both technology and soft, and least sensitive to 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. 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—is also provided for reference. For additional information about each attribute and the range of values tested in the SA, please refer to Table 5.

Table 3 is a revised version of Table 1 presented in Sec. 3.3 to include (1) the weight for each attribute and (2) the value calculated for each alternative. Finally, Fig. 7 shows the results of the value calculations for each alternative in a visual format.

From the results, we see that 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 technology-focused and equal-focused strategies yielded approximately equal values, while both moderate strategies resulted in increased value from the DOE strategy.

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 e-mail, with follow-up questions sent by e-mail. Note that the interviewees did not wish to have the conversations documented, as is often the case with proprietary competitive information. Both stakeholders noted 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 and utilities build 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.

As per the analysis, the LCOE is 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

Table 2 Weights of each attribute determined by sensitivity analysis, in order of largest to smallest weight, and cost classification

Attribute	Classification	Weight
Interconnection	Soft	0.274
Net capacity factor	Both	0.266
Generation equipment cost	Technology	0.102
Land lease cost	Soft	0.076
Development cost and fees	Soft	0.071
Fixed O&M	Technology	0.070
Project degradation	Technology	0.056
Balance of plant cost	Technology	0.045
Debt parameters	Soft	0.028
Real discount rate	Soft	0.013

Table 3 Revised version of Table 1, now including weights for each attribute and calculated values for each alternative. All dollar values are in $M.

	Real discount rate	Generation equipment cost	Balance of plant cost	Interconnection cost	Development cost	Debt parameters	Fixed O&M	Land lease cost	Project degradation	Net capacity factor	Total value
Classification ->	Soft	Tech	Tech	Soft	Soft	Soft	Tech	Soft	Both	Tech	
Weight ->	0.013	0.102	0.045	0.274	0.071	0.028	0.070	0.076	0.266	0.056	
Alternatives											
DOE allocation	$1.0	$100.0	$50.0	$2.0	$2.0	$2.0	$30.0	$1.0	$20.0	$20.0	21.77
Very technology-focused	$1.0	$70.0	$40.0	$1.0	$1.0	$1.0	$41.0	$1.0	$30.0	$42.0	22.56
Moderately technology-focused	$10.0	$50.0	$20.0	$20.0	$10.0	$10.0	$35.0	$10.0	$30.0	$33.0	25.61
Equal-focused	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	$22.8	22.80
Moderately soft cost-focused	$21.0	$15.0	$8.0	$50.0	$38.0	$20.0	$8.0	$30.0	$30.0	$8.0	30.36
Very soft cost-focused	$15.0	$1.0	$1.0	$70.0	$55.0	$15.0	$1.0	$38.0	$30.0	$2.0	34.87

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.

The analysis shows 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 project 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 composed of soft costs such as permitting and labor, appears to be low in the order of LCOE sensitivities as per the OAT analysis; this result can be explained due to the smaller data 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 integrate 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 budget 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 solar office.

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 budget. These results suggest allocating funding to a more diverse range of

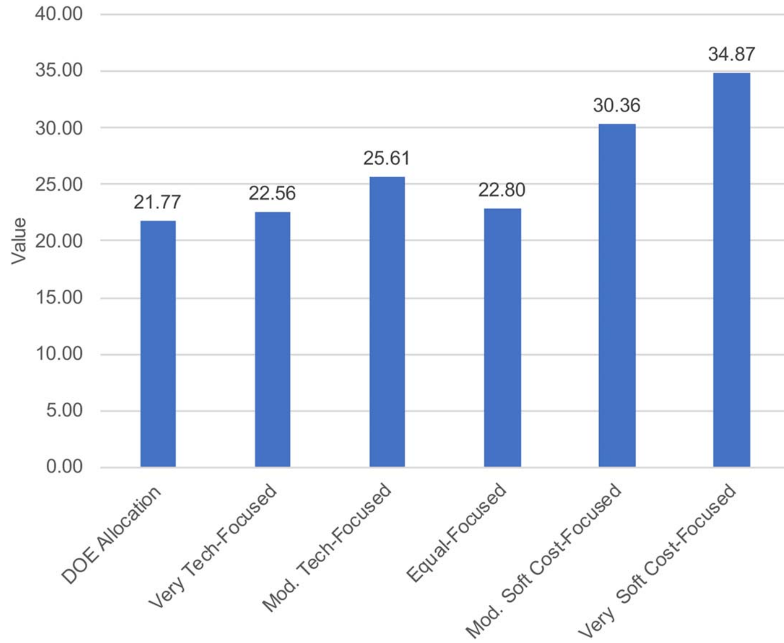

Fig. 7 Resulting value of each hypothetical funding strategy tested in the analysis. The funding strategy that is most focused on soft costs results in the highest value of the strategies considered.

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 agencies, such as the DOE solar office, would trust this decision model enough to use it when evaluating funding strategies. 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 and understand the range of calculated values. Additionally, quantifying the correlation between soft cost research projects and cost reduction in the industry can help substantiate the benefits of soft cost 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 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 in the 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 uses a simple decision-making model to evaluate R&D funding strategies, the approach has 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 influence 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 US. 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 that may also be updated by additional data or more sophisticated uncertainty quantification techniques. Similarly, we categorized the inputs as soft costs and technology costs guided by previous literature; however, many inputs may blur the definition line 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 United States; however, it is 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 construction management, 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 an 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 a weighted sum model for initial results, but suggest additional work using utility theory should be explored in the future.

6 Conclusion

In this paper, we present a new approach to building a decision model that can aid funding agencies, such as the DOE solar office, in evaluating solar R&D funding strategies. We build a solar cost model, composed of both technology and soft cost inputs, to calculate the LCOE of a utility-scale solar development. Using this model, we conduct a sensitivity analysis to quantify the effect of each input on the output LCOE. Using these results as weights, we develop a decision model using a multi-attribute value function and evaluate 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, thus less desirable to the decision-maker, while allocating 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 industry solar project costs may offer benefits to the DOE and potential project cost reduction.

The decision model presented in this paper requires validation to be used in a real-world context and gain credibility with decision-makers, such as 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 costs 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 other systems to gain insights, drive innovation, and potentially spur cost reduction.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request. The data and information that support the findings of this article are freely available.[2]

Nomenclature

c = developer contingency (%)
d = project degradation
l = lending fee (%)
E = acres required per MW (acres/MW)
I = total number of attributes
G = generator nameplate capacity
N = project lifetime (years)
R = annual land lease rate paid to landowners (USD)
T = type of tracking technology (1 for tracking, 0 for fixed)
c_a = landowner acquisition cost (USD/W)
c_l = labor and construction fees (USD/W)
c_M = mounting cost (USD/W)
c_T = transmission cost (USD/W)
c_P = PV module cost (USD/W)
c_V = inverter cost (USD/W)
c_W = wiring equipment cost (USD/W)
d_r = real discount rate
d_m = nominal discount rate
i_C = construction interest rate (%)
i_D = debt interest rate (%)
i_l = monthly loan interest (USD)
m_r = required reserves (months)
o_{DEV} = developer overhead (%)
o_{EPC} = engineering, procurement, and construction overhead (%)
p_{EPC} = engineering, procurement, and construction profit (%)
p_D = debt percent (%)
p_l = monthly loan principle (USD)
r_{ai} = score for alternative a and attribute b
r_i = inflation rate
x_i = value of input i used in sensitivity analysis
w_i = weight of attribute i
C_0 = initial project investment (USD)
C_{B} = balance of plant cost (USD)
C_D = development cost and fees (USD)
C_{F} = financing and reserves cost (USD)
C_{G} = generation equipment cost (USD)
C_I = interconnection cost (USD)
C_n = annual project costs in year n (USD)
C_P = permitting cost (USD)
F_n = fixed operations and maintenance cost for year n (USD)
I_n = insurance cost for year n (USD)
L_n = land least cost for year n (USD)
P_n = project administration cost for year n (USD)
Q_n = annual electricity generated by the plant in year n (kWh)
T_D = debt term (years)
T_n = taxes for year n (USD)
V_a = value of alternative a
V_n = variable operations and maintenance cost for year n (USD)
$\boldsymbol{x}^0$ = vector of base case input values
$\boldsymbol{x}^0_{\sim i}$ = vector of base case values for all inputs $\neq x_i$
$f(\boldsymbol{x})$ = function to calculate output value of levelized cost of energy
GHI = global horizontal irradiance (kWh/m^2/day)
ILR = inverter loading ratio
NCF = net capacity factor
$\Delta_i^+ LCOE$ = upper sensitivity value of the output $LCOE$ for input i
$\Delta_i^- LCOE$ = 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
$\Delta_i LCOE$ = difference between upper and lower LCOE sensitivity for each input, i
$\sum \Delta LCOE$ = sum of differences in LCOE sensitivities for all inputs

[2] See Note 1.

Appendix: Inputs for the Solar Cost Model **In Tables 4 and 5, all dollar values reported are in 2018 US dollars and all power values are reported in direct current (DC) units.**

Table 4 Constant values

Symbol	Input	Description	Assumed value	Sources
–	Type of technology	The type of solar technology analyzed in the cost model	Photovoltaic, single-axis tracking, no storage	Choice of the authors, designed to follow [58]
G	Generator nameplate capacity	Capacity of the solar plant	100 MW	Choice of the authors, designed to follow [58]
N	Project lifetime	The number of years a project will last	30 years	[58,59]
r_i	Inflation rate	Rate of inflation as per the US Bureau of Labor statistics	2.1%	[53]
c_W	Wiring and electrical cost	Cost of the electrical equipment required for the project	0.17 USD/W	[58]
c_a	Landowner acquisition cost	Cost to acquire the landowners required for the project	0.03 USD/W	[58]
l	Lender's fee	Fee required to the lender when taking on debt	3%	[48]
N_C	Construction duration	Number of months required for construction prior to installation	6 months	[58]
i_C	Construction interest rate	Annual interest rate set for construction funds	4%	[58]
C_C	Closing costs	Other required costs to the developer for due diligence and to lenders	0 USD	[48]
m_r	Required reserves	Number of months of reserve funds the lender requires developers to have	6 months	[48]
P_n	Project administration	Project management costs required to manage Power Purchase Agreements or other activities related to the project	$0	[48]
–	Insurance rate	Rate of insurance required for developers to carry	0.4%	[48]
–	Owner is a taxable entity?	Determine if the financial owner of the project is a taxable entity	Yes	[58]
–	Federal tax credit for solar	Tax credit offered by the US federal government for solar technology	30%	[60]
–	Location of project	The location in which the project is installed	California, USA	Choice of authors
–	Depreciation	The schedule on which the assets in the solar plant reduce in value over time	5-year MACRS	[58]
–	Replacement	Number of years between inverter replacement	12 years	[58]

Table 5 Inputs used in sensitivity analysis (numbered), sub-inputs, value ranges, soft cost versus technology cost classifications, and data sources

Symbol	Input	Description	Value range	Classification	Source
d_r	(1) Real discount rate	Opportunity cost of capital for the project	6.3—6.5%	Soft cost	[52,61]
C_G	(2) Generation equipment cost			Technology cost	
c_P	PV module cost	Cost of the photovoltaic modules required for the project	0.47–0.69 USD/W	Technology cost	[11,58]
c_V	Inverter cost	Cost of the inverters required for the project	0.05–0.12 USD/W	Technology cost	[11,58]
C_B	(3) Balance of plant cost			Technology cost	
c_M	Mounting cost	Cost of equipment necessary to mount PV modules and inverters	0.1–0.21 USD/W	Technology cost	[11,58]
c_T	Transmission cost	Cost of transmission equipment required to connect project to the utility grid	0.02–0.03 USD/W	Technology cost	[58]
C_I	(4) Interconnection cost	Cost of interconnection study and upgrades to the grid required to connect project to the utility grid	0.02–0.99 USD/W	Soft cost	[58,62]
C_D	(5) Development cost and fees			Soft cost	
C_P	Permitting cost	Cost to acquire necessary permits to build the project	211,889–1,059,447 USD	Soft cost	[58]
c_l	Labor and construction cost	Cost of the labor and construction equipment required to build the project	0.35–0.38 USD/W	Soft cost	[58]
o_{EPC}	EPC overhead	Overhead required by the EPC to construct the project	8.67–13%	Soft cost	[11]
p_{EPC}	EPC profit	Profit required by the EPC to construct the project	5–8%	Soft cost	[11]
c	Developer contingency	Extra funds required by the developer used as an allowance for unexpected events and risks	3–4%	Soft cost	[11,58]
o_{DEV}	Developer overhead	Overhead required by the developer, may include due diligence, legal services, etc.	2–12%	Soft cost	[11]
–	(6) Debt parameters			Soft cost	
p_D	Project debt percentage	Portion of the project expenses that is borrowed	40–50%	Soft cost	[61]
T_D	Debt term	Length of debt repayment period	5–20 years	Soft cost	[61]
i_D	Debt interest rate	Interest rate on the loans for the project	3.5–5.25%	Soft cost	[61]
F_n	(7) Fixed operations and maintenance	Fixed cost to maintain and operate the solar plant yearly	10.40–30.85 USD/kW-yr	Technology cost	[11,18,63]
L_n	(8) Land lease cost			Soft cost	
E	Land use	Land required for the project	4.29–13.12 acres/MW_{dc}	Soft cost	[64]
R	Annual land lease rate	Annual payment to each landowner	1000–2000 USD/acre	Soft cost	[65]
NCF	(9) Net capacity factor			Both	
GHI	Global Horizontal Irradiance	Total irradiance from the sun on a horizontal surface of the earth	4.8–6.3 kWh/m^2/day	Soft cost	[66]
ILR	Inverter loading ratio	Ratio between the DC solar array and the AC inverter	1.22–1.34	Technology cost	[67]
d	(10) Project degradation	The degradation of solar panels each year	0.25–1.0%	Technology cost	[18,58]

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