Applied Energy 306 (2022) 117926

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

# Energy sector portfolio analysis with uncertainty

James Milford [a], Max Henrion [a], Chad Hunter [b], Emily Newes [b,*], Caroline Hughes [b], Samuel F. Baldwin [c]

[a] Lumina Decision Systems, United States
[b] National Renewable Energy Laboratory, United States
[c] U.S. Department of Energy, United States

## HIGHLIGHTS

- Stochastic Energy Deployment System assesses research and development portfolios.
- Outcomes of federal goals for technology cost and performance are evaluated.
- Interviews obtained estimates of research and development uncertainty.
- Lessons learned on conveying stochastic results to diverse audiences are discussed.

## ARTICLE INFO

*Keywords:*
Portfolio analysis
Energy system
Expert elicitation
Uncertainty
Stochasticity
Stochastic Energy Deployment System

## ABSTRACT

Governments are dealing with the challenge of how to efficiently invest in research and development portfolios related to energy technologies. Research and development investment decisions in the energy space are especially difficult due to numerous risks and uncertainties, and due to the complexity of energy's interactions with the broad economy. Historically, much of the U.S. Department of Energy's in-depth research and development analyses focused on assessing the impact of a research and development activity in isolation from other available opportunities and did not substantially consider risk and uncertainty. Endeavoring to combine integrated energy-economy modeling with uncertainty analysis and technology-specific research and development activities, the U. S. Department of Energy commissioned the development of the Stochastic Energy Deployment System to support and improve public energy research and development decision-making. The Stochastic Energy Deployment System draws from expert-elicited probability distributions for research and development-driven improvements in technology cost and performance, and it uses Monte Carlo simulations to evaluate the likelihood of outcomes within a system dynamics energy-economy model. The framework estimates the uncertain benefits and costs of various research and development portfolios and provides insight into the probability of meeting national technology goals, while accounting for interactions with the larger economy and for interactions among research and development investments spanning many energy sectors.

## 1. Introduction

Too often those designing portfolios of research and development (R&D) projects fail to adequately address the risk and uncertainty inherent in R&D. The uncertainties are not just about the technical probability of success but also market adoption and its associated economic impact. Decision analysis offers a range of tools to evaluate and optimize R&D portfolios, including methods to explicitly represent uncertainties and evaluate their effects on portfolio selection. Quantitative treatment of uncertainty and stochastic analysis of R&D portfolios can provide valuable insights into potential benefits and help R&D managers develop portfolios that are more robust and flexible in the light of a wide range of possible futures. By nature, portfolio assessment under uncertainty indicates the robustness of R&D investments by providing decision makers with most likely outcomes and ranges of outcomes. When paired with good visualization platforms, planners can quickly identify portfolios with high likelihood of success and acceptable levels of downside risk. Many of the existing portfolio analysis efforts focus on a

* Corresponding author.
*E-mail address:* emily.newes@nrel.gov (E. Newes).

https://doi.org/10.1016/j.apenergy.2021.117926
Received 23 April 2021; Received in revised form 14 September 2021; Accepted 20 September 2021
Available online 9 October 2021

single sector, rather than the broader energy economy. Since energy R&D has many downstream effects, modeling the interactions among multiple energy sectors and the impacts on the larger economy provides decision makers with richer information to evaluate R&D investments. In this paper, we describe an energy-economy modeling framework that has the potential to support and improve public energy R&D decisions by explicitly accounting for risk and uncertainty.

The Stochastic Energy Deployment System (SEDS) model[1] is an energy market model, using a system dynamics methodology,[2] that explicitly addresses uncertainties in future energy technologies, markets, and policy. SEDS was designed to provide new uncertainty-informed insights to U.S. Department of Energy (DOE) managers in the Office of Energy Efficiency and Renewable Energy (EERE), and other interested stakeholders, in order to make more informed decisions about DOE's R&D portfolio. SEDS was developed by an interdisciplinary team led by a group at the National Renewable Energy Laboratory (NREL), and SEDS modules were developed by five other national laboratories[3] and Lumina Decision Systems between 2007 and 2011, building on an associated R&D risk analysis effort begun in 2004. The model uses elicitations from panels of technology experts to assess the uncertainty about the cost and performance for 32 energy technologies given alternative R&D budgets. And it uses stochastic simulation to examine the effects of alternative R&D funding levels and technology portfolios on technology success, future market adoption, energy costs and consumption, and greenhouse gas (GHG) emissions for the entire United States for up to 25 years into the future.

This article identifies key lessons learned from the development and use of SEDS. The lessons should be of value to the international energy-modeling and R&D-planning communities by illustrating a useful approach that helps decision makers evaluate and prioritize R&D projects for energy technology innovation. Instead of presenting quantitative findings, which were preliminary and now outdated, we present illustrative results, describe key methods used to develop the model, and discuss the advantages and disadvantages relative to other methods for R&D portfolio management.

Section 2 describes previous and related work, highlighting the lack of other efforts that evaluate R&D portfolios under risk and uncertainty across all sectors of the energy economy. Each of the following sections address both a research question and the corresponding results. Section 3 discusses the expert elicitation process used to estimate the effect of R&D budgets on future performance of energy technologies, resulting in a discussion on the comparison of this approach and others in the literature. Section 4 highlights the research methodology and describes the SEDS modeling architecture; a key takeaway is the trade-offs for usability by stakeholders. Section 5 reviews the methods for communicating the modeling framework, highlighting graphic styles that resulted from this work. Section 6 highlights conclusions, lessons learned, and issues for future work.

## 2. Previous and related work

Should one invest a limited R&D budget in one or just a few technologies in the hope of making rapid advances, or should one spread the investment over a wider range of technologies as a hedge against uncertainty but risk slower progress? Researchers in many fields have studied such general questions of portfolio management under uncertainty over the last few decades. The first such work was in the financial sector [1,2] which was then applied to industry R&D [3,4,5,6,7,8], and more recently to public R&D investment [9,10]. Yet, there is still no consensus on the best or most practical method of evaluating portfolios which depends on the specific needs of an organization [11,12] and the technologies being evaluated [13].

Key criteria used to evaluate approaches to portfolio allocation include their ability to manage multiple objectives, account for uncertainty, communicate insightful recommendations, and update the approach over time. Dutra et al. [12] and Verbano and Nosella [14] classify analytic methods into three types: qualitative, quantitative, and hybrid.

Common qualitative approaches include the Balanced Scorecard [15,16], which can help determine how the criteria evaluated for a project impact an organization's strategic vision, and simple scoring protocols [3,17] that seek to balance project selection through structured question frameworks. These types of approaches have the advantage of being easy to communicate to stakeholders and simple to update over time. However, it is challenging to use them with multiple criteria and to incorporate risk and uncertainty explicitly.

Quantitative methods include financial analysis, data envelope analysis [18,19], and numerous optimization techniques, including linear programming [20,21,22], integer programming [20,21,22,23,24], nonlinear programming [25,26], and dynamic programming [27,22,28,17,29]. In general, these techniques evaluate quantitative trade-offs between decision variables to optimize their criteria or objective function. They can handle uncertainty exogenously using sensitivity analysis, scenario analysis, and Monte Carlo analysis, or endogenously using stochastic dynamic programming with constraints. However, stochastic dynamic programs can be difficult to solve computationally and usually require dramatic simplification to be tractable. Though quantitative methods can provide sounder and more-principled results than purely qualitative methods, they have much greater demands for data and quantified expert judgments, as well as much computational complexity [30,12,31].

Hybrid approaches, such as using bubble charts and direct scoring, combine quantitative methods with qualitative input data. These approaches have sometimes been found to improve the success of a project and the portfolio selection process, as measured by project alignment with strategic direction, portfolio value, project delivery, and balance [30,12,17]. The analytic hierarchy process is another hybrid method that uses a set of criteria and considers both qualitative and quantitative input data to recommend a decision [32]. However, the qualitative elements of hybrid approaches render them more subject to bias or overconfidence, which potentially leads to less reliable and consistent portfolio decision-making.

For any method, a key early task for decision makers is to select the criteria to evaluate portfolios and outcomes. Selection criteria may be categorized as technological, economic, environmental, and social [31], and each of these metrics may be represented as a probabilistic outcome. In the technological category, typical evaluation criteria include performance attributes, such as efficiency [25,33], reliability, and safety [34]. Economic criteria may include total investment cost [35], input costs (e.g., fuels, feedstocks, and electricity) [36], net present value [37,38], and payback period. Environmental metrics may include emissions of criteria pollutants and GHGs [39], water quality, land use, and noise [40]. Criteria in the social category may include job creation and total social benefits [41].

Table 1 lists references to analytic methods organized by the three types (quantitative, qualitative, and hybrid) over the four categories of criteria. We review these approaches below for selected historical applications, first in industry, and then for supporting public-sector decisions on energy R&D, of most relevance to SEDS.

[1] The model can be found at https://www.nrel.gov/analysis/seds/.

[2] In contrast to equilibrium models, system dynamics neither defaults to the assumption that systems or economies are inherently in equilibrium nor assumes market actors have perfect information or are perfectly rational. The goal of system dynamics models is to simulate nonlinear dynamics and feedback loops observed in real-world systems using traceable and interpretable sequences of causal effects and decision criteria that can be of high value to decision makers.

[3] Argonne National Laboratory, Lawrence Berkeley National Laboratory, National Energy Technology Laboratory, Oak Ridge National Laboratory, and Pacific Northwest National Laboratory

**Table 1**
Overview of representative portfolio and project evaluation studies, broken down by subject matter and whether they are quantitative versus qualitative.

| Quantitative | Qualitative | Hybrid |
|---|---|---|
| Economic | | |
| [1,5,7–9,13,20–23,26,27,29,37–39,44,46,54,87–108] | [3,11,24,30,33,34,36,93,103] | [3,9,12,24,32,89,95,106,109–111] |
| Environmental | | |
| [9,13,20,37,39,46,54,56,87,90,99,108,112–115] | [33,34,36] | [9,116,117] |
| Social | | |
| [37,99,108,114,118] | [33,34,36,41] | [17,41] |
| Technology | | |
| [9,20,22,25,27,37,46,64,99] | [3,33,34] | [25,41,111] |

### 2.1. Applications to R&D investment decision-making

Analytical approaches to R&D decisions have been used in many industries, including pharmaceuticals [7,8], biotechnology, and energy. For example, a multi-objective optimization was used to maximize both profit and the probability of being profitable across a portfolio of five therapeutic antibody projects [42]. One multi-objective strategy applied to new product development combined stochastic simulation with genetic algorithms [43]. Real options methods were used to analyze strategic partnerships for biotechnology start-ups, based on entrepreneurs' perceptions of the market and the promise of new technologies [44].

For an example in the energy sector, [28] developed an analytical tool to assess the role of enhanced oil recovery in a carbon capture and storage (CCS) portfolio. Their goal was to allocate research funding strategically to forestall decreased funding for large-scale demonstration projects. They used expert elicitation to assess the future costs of carbon capture under policy scenarios [45,46]. Similarly, Bistline [27] developed a stochastic R&D portfolio management framework and applied it to the electric power sector by using expert elicitation data of technological progress [47,48].

Such industry-supported approaches have typically been limited to narrow sets of projects within a single sector, whereas public R&D decision-making, particularly in the energy sector, typically spans multiple sectors and systems. This broader perspective poses new challenges, including comparing technologies across sectors (e.g., building efficiency, vehicle technology, and electric power) and understanding the economic and environmental effects on society as a whole.

### 2.2. Recent approaches in economy-wide energy R&D portfolios

Several studies in the last decade have addressed the need for improved energy R&D portfolio management and investment modeling in the public sector [49,50,51,52,53]. To develop optimal R&D portfolios, one must estimate the effect of R&D spending on technology performance and hence on resulting market adoption. A major limitation of much R&D portfolio modeling has been the lack of explicit characterization of uncertainty in both research and commercialization outcomes [10]. However, recent research, including the SEDS project described here, has demonstrated modeling approaches that do both. They use expert elicitation, technology-specific techno-economic modeling, and market modeling and/or integrated assessment models (IAMs) within a decision framework [9,54,55,56,57]. See the Supplementary Information for additional explanation of such an approach.

Anadon et al. [9] identify the continued need for innovation and progress in the public energy R&D decision support modeling frameworks. Specifically, there continues to be a need for a full modeling framework that explicitly accounts for uncertainty in future costs based on various public R&D funding levels at a very granular level and for market dynamics such as competition, substitution, and complements between technologies. Additionally, this modeling framework needs to provide this information clearly and transparently [9,57].

Many of the efforts we reviewed in the literature focus on a single sector and/or are limited by their macroeconomic scope [27]. However, for energy R&D, virtually every part of the economy is impacted. In this paper, we describe an energy-economy modeling framework, SEDS, that has the potential to support and improve public energy R&D decision-making. SEDS was designed to draw from expert-elicited probability distributions of the potential improvement in technology cost and performance for different investments in R&D. SEDS then competes these potential improvements for each technology to generate distributions of the potential market penetration of the different technologies for the various levels of R&D investment.

SEDS handles evaluation of multiple objectives (including economic impacts, public health impacts, climate impacts, and returns on R&D investment), which are essential for a diverse stakeholder group. SEDS also incorporates technology interactions over time. Further, SEDS provides insight on the probability of achieving the goals set for technologies, on the value of a portfolio approach to R&D, and on the balance of the R&D portfolio over risk, return, time frames, technologies, and markets. SEDS was designed to have very fast runtimes so that it could provide real-time support for decision makers, but to do this resulted in various model and computational simplifications that raise important issues, as always happens with modeling efforts.

## 3. Expert elicitation process

Any attempt to project the effects of R&D on emerging energy technologies faces large uncertainties. It is difficult to predict whether or when R&D will lead to technical breakthroughs and, if it does, how much it will improve performance and reduce costs. Separate, but also difficult, is predicting how far any such improvements will accelerate market adoption, and hence affect the cost of energy and GHG emissions decades into the future. It is in the nature of innovations that there is little or no past data from which to estimate their future performance.

Thus, as part of the SEDS project and associated Risk effort at DOE, we turned to structured interviews (expert elicitations) from panels of experts to obtain estimates of the uncertain effect of R&D investments in each technology on its future performance. We asked the experts to express their considered judgment, including their uncertainty in the form of points on probability distributions. Each expert provided distributions of the costs, efficiency, and other metrics for each technology at one or two future points in time for different levels of R&D funding. These distributions were then used in Monte Carlo simulations of the techno-economic performance of each technology. We developed tornado diagrams of the effects of each parameter on the performance of each technology to obtain an approximate ranking of where R&D might have the largest benefit (e.g., [58]). These risk analyses were conducted for an initial set of energy efficiency and renewable energy technologies on an experimental basis to see how well this elicitation and analysis process worked and what changes were needed. Many of the results from the Risk/SEDS team were published in technology-specific reports and presentations [59,60,61,62,58,63].

Expert elicitations of the effect of R&D on future improvements in energy technologies were also done in this period by teams at Harvard University [47], the University of Massachusetts [64], and Fondazione Eni Enrico Mattei (FEEM) in Italy [65]. Their expert elicitations examined biofuels, bioelectricity, carbon capture and sequestration, nuclear power, and solar technologies.

### 3.1. Scope of elicitation

The Risk/SEDS project addressed 36 technologies, including three types of photovoltaics; two types of concentrating solar power; seven technologies to produce and store hydrogen; two kinds of geothermal, cellulosic ethanol, onshore and offshore wind; and multiple technologies for energy efficiency in buildings and industrial processes. Each expert typically assessed several related technologies within a single DOE technology program—such as all photovoltaics or all technologies to produce hydrogen. The experts included scientists and engineers with professional experience in each technology, from universities, national laboratories, and industry. The SEDS team interviewed 3–9 experts (average 4.6) for each technology, and a total of 167 experts.

Experts estimated several parameters for each technology—such as conversion efficiency, unit capital cost, and operating and maintenance cost—and an average of 4.5 parameters per technology. Interviews were first done for the Risk studies between 2006 and 2008, and then to also support SEDS in 2009 and 2010. Experts were asked for estimates in two future "goal years," usually 2015 and 2025. Experts were also asked to estimate technology performance contingent on three levels of R&D funding from DOE—zero, the current plan, or double the current plan. In some cases, experts also estimated future learning rates (i.e., percentage decrease in unit cost per doubling of cumulative capacity of the technology manufactured and deployed) after the farthest goal year. In each case, experts provided a minimum and maximum conceivable value for each quantity. A total of 1,304 quantities were assessed (technologies × parameters × funding levels × goal years).

Experts were provided a paper for the in-person elicitations or an online form on which to record estimates for each technology and parameter, for each of two goal years and three R&D funding levels, including:

- A reference value: current best estimate of the technology parameter
- Minimum and maximum: extreme conceivable limits for the quantity generally based on physical limits and material costs
- Probability Of Advance (POA): characterizes how likely it is that the R&D investment generates an appreciable advance in the technology—a value of up to 100%—or that the research fails
- Triangular Distribution: If the R&D is successful, the advance in the technology is characterized by a triangular distribution described by the 10th percentile, mode and 90th percentile, with the 10th/90th percentiles the values such that there is a 10%/90% chance the actual value would be less than, or greater than, these respective percentiles.

The mode and 10th/90th percentiles define a triangular distribution for how much improvement in the technology could be realized by the R&D investment, conditional on the probability of advance that the R&D is successful. Each expert assessed a distribution for each of the two goal years and each of the three R&D investment levels in each technology, defining the likelihood that the R&D investment would be successful (POA), and if so, what the triangular probability distribution would be. Interviewers checked initial results for any possible inconsistencies—such as more R&D leading to worse performance—and gave experts time to carefully review and revise their estimates.

### 3.2. Protocol to minimize biases

Cognitive psychologists have long studied the process of human judgment in expressing uncertain knowledge using probability distributions [66,67]. In experiments looking at distributions for known "almanac" quantities, the cognitive psychologists have found that these judgments are subject to systematic errors and biases. A consistent finding is of overconfidence (i.e., that people tend to underestimate the probability that the true value is far from the value they consider most likely). One cause is confirmation bias, which is the tendency to believe evidence that confirms your expectations and dismiss evidence that does not. Another is the anchoring and adjustment heuristic, which is the tendency to focus on the value a person considers to be most likely and then adjust it insufficiently to reflect "surprise" factors that might lead to a more extreme outcome, either much higher or much lower. Though much of the empirical research used college students as subjects, research shows these effects also apply to experts making judgments in their field of expertise [68].

Practicing decision analysts have developed protocols to conduct expert elicitations employing a variety of strategies to minimize these errors and biases [69,67,70]. For example, to reduce the confirmation bias, the interviewer starts with a careful review and discussion of relevant studies and evidence, asking each expert to carefully consider evidence that runs counter to expectations. To counter the anchoring bias, interviewers use "mental stretching" exercises: they ask each expert to brainstorm and describe conceivable extreme events or factors that could lead the quantity of interest (e.g., the future cost of photovoltaics) to be surprisingly large or small.

The Risk/SEDS team adapted a standard protocol for expert elicitation described in Morgan & Henrion [67] that used these and other strategies to minimize biases. The team provided a two-day workshop to train interviewers for each technology program. These interviewers then conducted the elicitations. Most elicitations were conducted face-to-face, but some were done remotely via telephone or web-meeting. In all cases, experts filled out the forms—paper or online—described above.

### 3.3. Aggregating over experts

Several methods have been proposed to combine assessments from multiple experts [71,72] based on different models of their dependence. Most comparisons of their performance have concluded that the simple method of averaging of probabilities—not quantiles—gives good results, perhaps because doing so tends to counteract overconfidence. Like most expert elicitation projects, we adopted that simple method and weighted each expert equally in the absence of reliable information about their individual expertise [73,69,74,75].

The results from the aggregated distributions were provided as inputs into SEDS, which used them in the Monte Carlo simulation to propagate the uncertainties through the model. SEDS interpolated performance for each year from the base year through to each goal year. In some cases, it used a learning rate (percentage improvement per doubling of cumulative capacity of that technology) to project performance after the final goal year, subject to the extreme limits provided on each parameter.

### 3.4. Reflections on the expert elicitations

A comparison of the three expert elicitation studies of the effects of R&D on energy technologies by groups at Harvard, the University of Massachusetts, and FEEM [64] found considerable differences among expert opinions on many metrics, with little overlap of their distributions. For several quantities, the variance that was due to differences among experts exceeded the variance that was due to the uncertainty expressed by each expert. In a few cases, these could reflect substantial differences of opinion among experts, but the differences suggest most experts were poorly calibrated and expressed overly narrow ranges, which is consistent with many studies of expert elicitation. The aggregation process, which involved calculating a simple weighted average of the probability density over the experts, tends to reduce such overconfidence in the aggregate distributions. The comparison found good agreement among the aggregated distributions from the three studies. The variance within each study dominated the variance between the studies, except for nuclear power, for which there was substantial disagreement among the studies.

These three studies used a range of elicitation protocols. Some emailed experts survey forms with little or no opportunity for personal interviews and with limited opportunity to offer methods to reduce biases. The Risk/SEDS study largely interviewed experts face-to-face, and interviewers were encouraged to follow a protocol to reduce overconfidence. Because the Risk/SEDS expert elicitation was a first experimental test, its results were not publicly released; thus, we could not compare them with the results of the three other studies, even though they addressed similar technologies. Nor could we compare the results with actual progress of these technologies over the decade since the assessments were made. Preliminary comparison of the results from the Harvard, University of Massachusetts, and FEEM studies with actual values in 2018–2019 [76] show that the cost of some technologies, notably photovoltaics, dropped far more rapidly than most of the experts estimated they would less than a decade earlier. After just 10 years, photovoltaics is already competitive with fossil fuels for many applications, including grid-level power in most parts of the world—an outcome that had less than 1% probability by 2030, according to the aggregated distributions from those studies.[4] Far more rapid reductions in costs than experts projected have similarly been seen for wind [77].

One might have expected experts would tend toward overoptimism about technologies on which they were working in R&D. Surprisingly, many have turned out to have been overly pessimistic. Nemet [78] describes the many factors contributing to the dramatic and sustained fall in the prices for photovoltaics—including high early demand from niche applications that were not cost-sensitive, such as satellites; government policies to incentivize the market, such as volume purchasing, credits, and subsidies, notably in the United States and then in Germany, Japan, and China; and persistence by farsighted entrepreneurs and commercial investors. Government R&D was particularly important in early stages, but these other factors also played important roles in long-run learning curves and adoption rates. By describing the many interacting factors, Nemet [78] underscores the challenge in distinguishing the effects of government R&D funding from the many other factors around the world on the cost-performance of energy technologies. Nevertheless, the process of making these judgments explicit, including the uncertainties, comparing estimates from multiple experts (and multiple studies), and exploring their implications via an integrated model has provided valuable insights to guide R&D planning that would be unavailable without quantitative modeling of the uncertainties.

## 4. Research methodology for SEDS

The expert elicitation described above estimates the uncertain degree to which R&D may improve the technical performance and cost of each energy technology, but it does not address commercial adoption. Even a breakthrough in an innovative technology that would reduce the cost of electricity by a factor of four would not be adopted unless it became less costly than competing technologies for important applications. The ultimate impact of R&D on an energy technology thus also depends on the progress of competing technologies. Cross-sector interactions can also be important. For example, widespread adoption of efficient electric heat pumps for space heating might reduce the demand for natural gas, lowering its market price and making it more competitive for electric power generation. That might reduce the leverage of R&D that reduces the costs of renewable electric technologies to move them into the market. The need to model such market dynamics within the energy-economic system and the need to evaluate other impacts, including GHG emissions, were key motivations to develop SEDS.

The design of SEDS reflects its primary goal of forecasting the impacts of technology R&D to help decision makers prioritize R&D funding investments. Therefore, we used a system dynamics framework that enabled rapid computation and use as an interactive tool, necessary qualities for decision makers. We recognized from the start the importance of representing uncertainty. Following practices in the field of decision analysis, SEDS focuses explicitly on decisions, uncertainties (chance variables), and objectives. The primary decisions are the funding levels of EERE R&D programs in energy efficiency and renewable energy. Uncertainties include not only the effect of R&D funding on the cost and performance of emerging technologies but also a broad array of macroeconomic, energy supply and pricing, and policy considerations that affect technology adoption, economic, and environmental impacts. The three primary objectives used were to minimize consumer expenditures, GHG emissions, and energy imports. However, the number and types of objectives can be readily expanded within the modeling framework.

In SEDS, we represented R&D funding decisions at the three funding levels shown in Table 2. Each funding level affects the distribution of cost and performance forecasts for modeled EERE technologies. Though the funding levels' distributions are permitted to overlap, increased funding leads to an equal or higher probability of a technology having lower cost and improved performance than at a lower funding level. For a given SEDS simulation, the modeled R&D funding level can vary by EERE technology, which permits extensive funding scenario analyses and identification of optimal funding strategies or portfolios.

This section provides an overview of the SEDS architecture, including uncertainties, objectives, model scope, the system dynamics framework, technology adoption methodology, and modeling consumer expectations. The SEDS development process was a unique collaboration among nearly 30 experts from 6 national laboratories and three consulting organizations. For more information on the development process, see the supplementary information.

### 4.1. Modeling uncertainty

The final version of SEDS captures uncertainty in the energy economy by sampling from probability distributions specified for the variables in Table 3. These uncertainties were relevant at the time of initial model development, and they were chosen for a variety of reasons. Technology road mapping and sensitivity analysis on the cost of energy generated and, for energy efficiency measures, the cost of energy conserved highlighted the technology-specific uncertainties of highest consequence to consider for expert elicitation and probabilistic representation. The analysis focused on macroeconomic uncertainties most likely to affect aggregate demand for goods and services, and thus energy consumption. Wherever policy implementation was highly uncertain and likely to influence the outcome of R&D investments, the team modeled those policies probabilistically to capture a range of implementation pathways. Lastly, stochastic representation of oil, gas and coal supply and price, along with several consequential market determinants, provided a tractable alternative to endogenously modeling the breadth of global commodity markets.

In most cases, SEDS represents these uncertainties using triangular distributions because of their simplicity in capturing minimum, most likely, and maximum values. For the costs, performance, and learning rates for each technology, the distributions are based on appropriately aggregating the distributions from the expert elicitations. The probability of uncertain discrete events, such as enactment of a carbon tax or emissions cap, is captured through Bernoulli distributions. Early

**Table 2**
R&D funding level decisions.

| R&D Funding Level | Description |
|---|---|
| None | No R&D funding from EERE |
| Target | Planned funding from EERE |
| Over-Target | Double the planned funding from EERE |

[4] An important caveat is these assessments had baseline assumptions on which the experts built their estimations. For example, Verdolini et al. [107] used a certain capacity factor assumption, which may have caused associated equations to be higher than the experts may have intended.

**Table 3**
Uncertain variables in SEDS classified by overarching categories of technology, policy, macroeconomics, and energy supply and price.

| Technology | Policy | Energy supply and price |
|---|---|---|
| • Cost | • Corn and cellulosic ethanol subsidies | • Alaska gas pipeline opening date |
| • Performance | • Carbon policy (tax or cap) | • Alaska and Gulf of Mexico gas hydrates supply |
| • Learning rate | • Renewable fuel standards | • Shale gas supply |
| • Geothermal resource supply | • Electricity renewable portfolio standards | • World oil supply shocks |
| • Hydrogen distribution cost | • Production and investment tax credit expiration years | • OPEC actions |
| • Carbon separation rate from power plant flue gases | • Nuclear waste disposal policy | • U.S. oil supply growth rate |
| **Macroeconomics** | • National building codes impacting energy intensity | • World oil price |
| • Gross domestic product | • National policy impacting building floor space | • Coal price and supply |
| • Manufacturing output | | • Coal-to-liquids supply |
| • Interest rate | | |
| • Population | | |
| • Disposable personal income | | |

implementations of uncertainty in SEDS did not consider correlations among probabilistic distributions, and thus treated all uncertainties as independent distributions. However, SEDS allows for the specification of correlation among uncertainties, and the team viewed this as an important area for future data collection because the representation of correlations can strongly affect simulated outcomes. In addition, the integrated nature of the SEDS modeling architecture results in correlated outcomes. For example, a highly successful wind turbine R&D program that lowers the cost of wind turbines will result in greater deployment of wind turbines at the expense of natural gas or solar power plants. The cause-and-effect relationship between competing technologies and market environments naturally creates correlation between uncertain variables (e.g., natural gas prices) and the realized benefits of R&D programs. See Supplementary Information for further discussion.

Some components rely on scenarios generated by a combination of uncertain assumptions in more specialized deterministic models, such as low, medium, and high macroeconomic scenarios. SEDS converts these to probabilistic values by drawing from a triangular distribution with a minimum value of 1 (the low scenario), a most-likely value of 2 (the medium scenario) and a maximum of value of 3 (the high scenario). Whenever the value is not a whole number, SEDS interpolates between the nearest scenarios using linear weighting. For example, given a random draw of 2.5 for the macroeconomic scenario, SEDS interpolates between the medium and high macroeconomic scenarios' values for gross domestic product, interest rates, and so on. This preserves the inherent dependence among those variables in the deterministic model—with a modest loss of fidelity. SEDS also models dependence between technology costs, performance, and learning rates to ensure these characteristics can only improve or stay constant over time and for increasing R&D funding levels.

SEDS supports extensive methods for sensitivity analysis to estimate and compare the effects of uncertainties in each input quantity. A user can hold one or more uncertain inputs at a single value (or set of values over time) or set a range of discrete values, while other uncertain variables are randomly sampled during a Monte Carlo simulation. A user can also include or exclude a wide variety of policies and explore R&D funding levels for a portfolio of technologies. *Importance analysis* estimates the relative effect of uncertainty in each uncertain input on results of interest using the rank correlation of the random samples for each input and the result. This provides guidance on which uncertain inputs might be priorities for further work that could refine the analysis, like gathering more evidence or expert judgments to refine the analysis.

### 4.2. Objectives

The objectives of the R&D funding focus on three metrics to minimize cost of energy, GHG emissions, and energy imports—though the model can expand to consider any number of objectives and beneficial outcomes from R&D funding (e.g., pollutant reduction, job creation, etc.). SEDS compares decisions on energy-related R&D funding levels and allocation by their effect on the probability distributions for these three metrics, which may be summarized by their expected (mean) benefits and variance or percentile ranges. Some portfolio decisions lead to synergistic improvements in the objectives, where the benefits of the portfolio exceed the sum of the benefits from individual technology funding decisions.

These objectives can be combined into a single weighted composite score, such as equivalent dollar value or utility provided. This enables a Markowitz-style efficient frontier curve to compare the mean scores (expected benefit) of selected portfolios against their standard deviation (risk)—where standard deviation, the square root of the variance, measures how widely the probabilistic outcomes deviate from the mean score. This view helps identify which portfolios provide the greatest benefit at a chosen level of acceptable risk, as illustrated in Fig. 1.

SEDS calculates the cost-effectiveness of energy-related R&D funding for each technology—for example, comparing the change in funding from Target to Over-Target levels with the associated benefit (reductions in expected energy cost, oil imports, and GHG emissions). Cost effectiveness metrics can vary among benefits per dollar (e.g., barrels of imported oil saved per dollar of funding), utility per dollar (e.g., the weighted composite score per dollar of funding), the rate of return (e.g., the annual rate of return in reduced energy expenditures for an R&D investment) or payback times (e.g., how many years before the R&D investment pays for itself). R&D planners can view these metrics as probabilistic distributions or as some statistics (e.g., mean, variance, means or percentiles) for the distribution. This can guide prioritization of R&D funding by technology subject to a finite budget, recognizing that model simplifications may not capture all the benefits of a technology. For example, in the power sector, the focus on levelized cost of energy may not capture a technology's contribution to capacity value or ancillary services.

### 4.3. Model scope

The model runs from 2005 through 2050 using an annual time step. The main structure relies on a single national region for the United States, though the building sector includes detail at the level of U.S. Census regions. The model treats world oil prices as exogenous, with explicit treatment of the large uncertainty. SEDS is composed of 13 modules addressing the major drivers of national energy consumption (Fig. 2). Experts in relevant segments of the energy economy developed each of the key modules, and renewable energy is represented as both entire modules (e.g., Biofuels module) and within modules (e.g., photovoltaics providing energy in the Electricity module).

Several modules use forecast scenarios generated by preexisting deterministic models. For instance, the Macroeconomics, Oil, and Coal modules rely on multiple forecast scenarios from the U.S. Energy Information Administration's National Energy Modeling System [79]. The Natural Gas module employs forecast price and supply scenarios from a Market Allocation Model [80] analysis performed for DOE Government Performance Results Act (GPRA) benefits analysis. The Biomass module is based on forecasts from the University of Tennessee's Policy Analysis System model [81]. Most modules incorporate time-changing and scenario-dependent price and supply curves to ensure robust responses

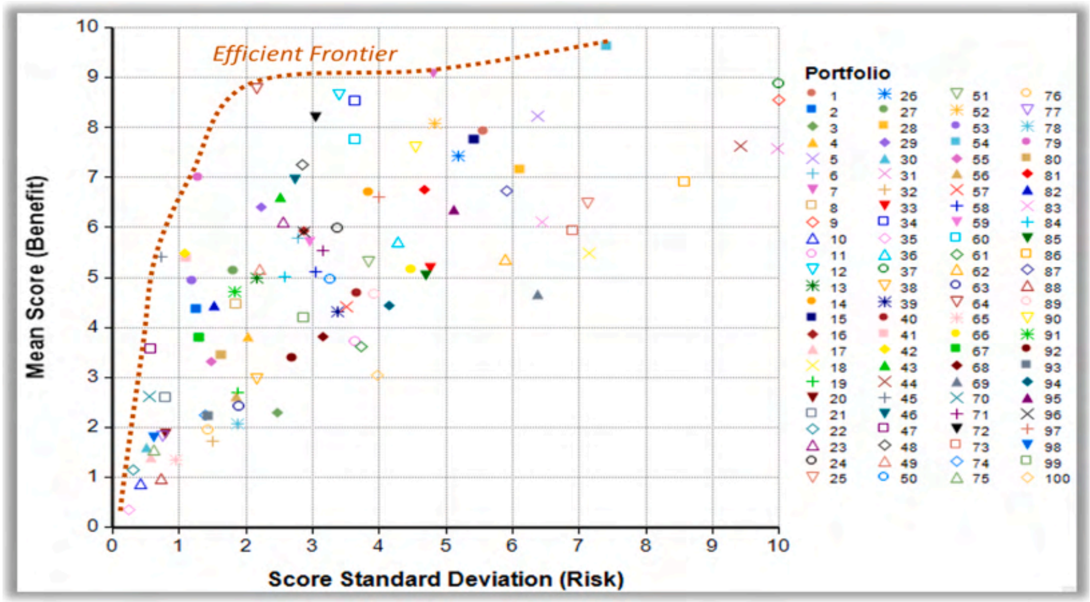


**Fig. 1.** Illustrative efficient frontier of portfolio scores looking at mean score versus score standard deviation.

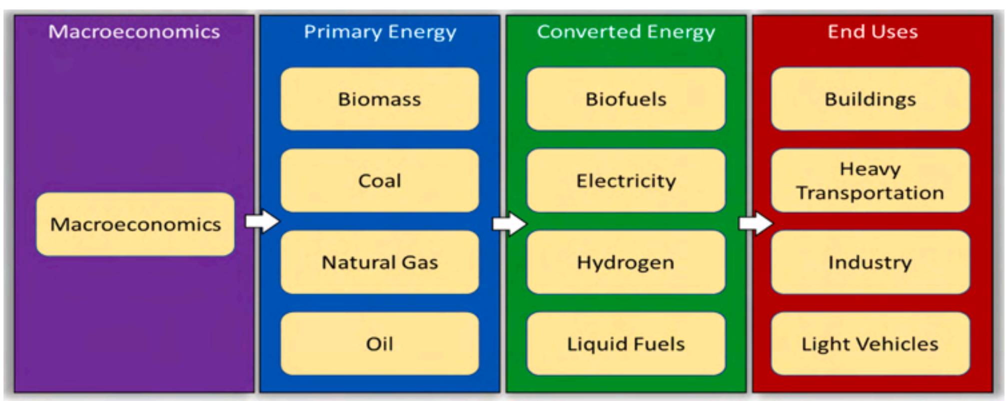


**Fig. 2.** Major SEDS modules categorized by macroeconomics, primary energy, converted energy, and end uses.

to SEDS' endogenous energy demands. The remaining modules use a bottom-up approach to calculate energy price, supply, or demand.

### *4.4. Modeling software platform*

After building a limited spreadsheet prototype, NREL reviewed software platforms for model development. The review resulted in the selection of the Analytica [82] platform as best able to meet SEDS' functional requirements, including integrated Monte Carlo uncertainty analysis, flexible and efficient handling of multidimensional arrays, visual diagrams to document model structure, and system dynamics modeling. (Additional information on Analytica can be found in the Supplementary Information.)

SEDS is organized as a hierarchy of modules, each depicting variables and submodules as an influence diagram. Fig. 3 shows an influence diagram to depict relationships among variables for the electric sector operating costs. These diagrams, along with internal self-documentation for each variable, also shown, give easy access to the underlying algorithms. This transparency was developed to help alleviate the "black box" concerns of stakeholders.

### *4.5. System dynamics framework*

SEDS uses a system dynamics framework with stocks, flows, and feedback loops [83]. For example, the stock of electric power plants of each type changes each time period as a result of the flow of retirements of old plants and building of new generation. The feedback loop from costs to consumer choice models a "virtuous cycle" in which lower costs for photovoltaics, for example, increase demand, which in turn moves the technology more rapidly down the learning curve.

There are several reasons the SEDS team chose a system dynamics framework instead of a linear optimization or a general equilibrium framework, which are often used in other energy-economic models. A key reason was computational simplicity, which is essential for a stochastic model performing hundreds of Monte Carlo simulations and for exploring many scenarios each with a full simulation. In the most recent version of SEDS, a single deterministic run on a conventional desktop computer (2.2 GHz processor) took a few seconds, and a Monte Carlo simulation with 100 random samples took a few minutes. It is, therefore, practical to perform and compare dozens of probabilistic scenarios. A second reason for a system dynamics framework is the traceability of cause and effect within the model logic. The team's goal was to develop a model formulation that represents the market dynamics in a way that is easily interpreted by reviewers and avoids the hidden behaviors and

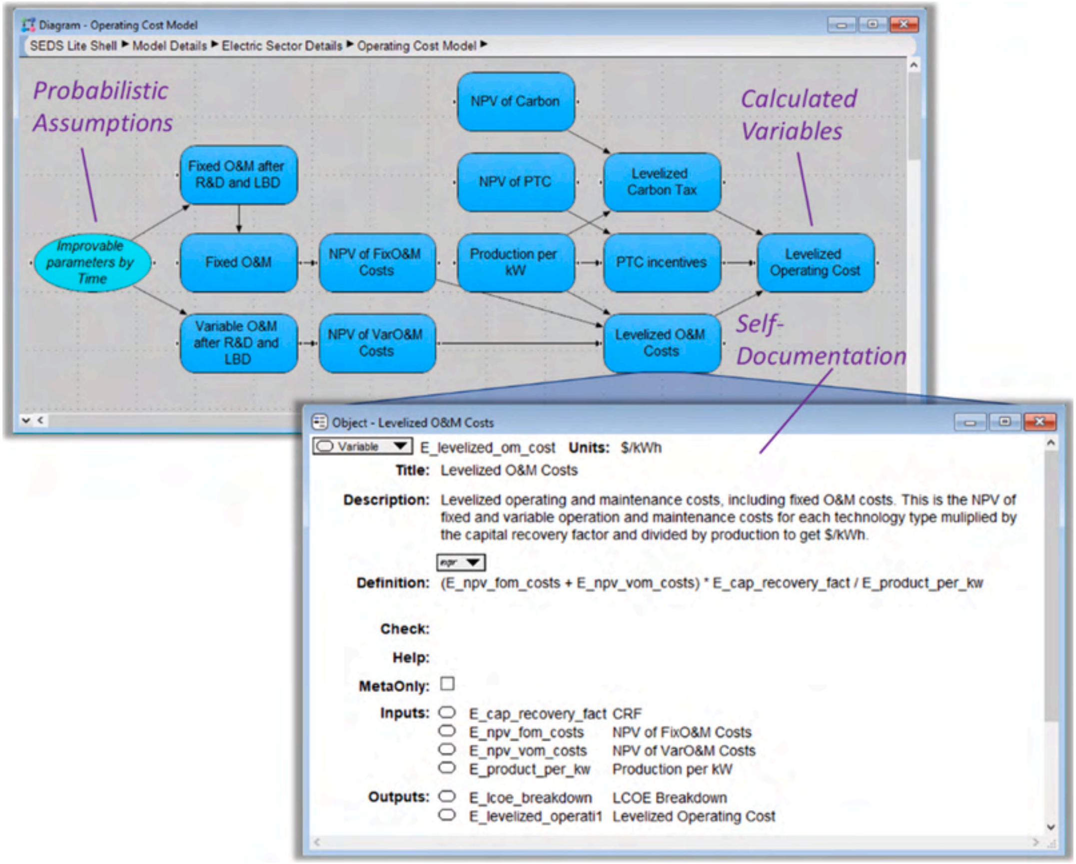


**Fig. 3.** Influence diagram for the electric sector's operating costs.

implicit relations inherent in optimization or equilibrium formulations. Third, the stock-and-flow framework is well-suited for bottom-up modeling of plant, equipment, and vehicle stocks tracked in the Converted Energy and End Use modules. The system dynamics framework efficiently computes and tracks stocks over time, including additions and retirements, while also capturing age-dependent characteristics of the stocks, which is difficult or impossible to do in alternative frameworks.

A system dynamics framework poses some challenges. It is harder to impose strict constraints like a carbon cap or some supply limitations. Therefore, SEDS relies on shadow prices to push the model to meet a carbon cap. The SEDS team found that using proportional-integral control algorithms worked well at goal-seeking and equilibrium-seeking via shadow prices. Using smaller time steps would lead to shadow prices with more accuracy in achieving their desired goals.

### 4.6. Technology market share and adoption

SEDS uses a multinomial logit model to estimate market share among competitive energy technologies. (For a full list of technologies considered in SEDS, see the Supplementary Information.) Technology choice is driven by the perceived utility of each energy technology to the consumer (purchaser) when selecting from competing technologies. A collection of attributes characterizes each technology. Attributes always include cost and usually non-cost attributes. For example, attributes of light-duty vehicles include capital, fuel, and maintenance costs, which determine total cost of ownership. Additional attributes include acceleration, range, luggage space, home refueling, and so on, which affect consumer appeal. The utility of each technology (i.e., its relative desirability or value to the purchaser) is modeled as a weighted sum of its attribute values (Equation (1)).

$$Utility_{tech} = \sum_{attrib}\left(Weight_{attrib} \times AttributeValue_{tech,attrib}\right) + Preference_{tech} \quad (1)$$

Where

$AttributeValue_{tech,attrib}$ = the value of each attribute corresponding to a given technology[5]

$Weight_{attrib}$ = the weight or importance of each attribute to the utility

$Preference_{tech}$ = purchaser preference for each technology based on attributes other than those modeled explicitly, such as familiarity with a technology, environmental friendliness, perceptions of being "cutting-edge", and other preferences unlikely to be captured by cost and performance attributes.

The logit model estimates market share of each technology based on its utility relative to the other technologies (Equation (2)):

$$MarketShare_{tech} = \frac{\mathrm{Exp}(Sensitivity \times Utility_{tech})}{\sum_{tech} Exp(Sensitivity \times Utility_{tech})} \quad (2)$$

Where *Sensitivity* defines how sensitive purchasers' choices are to the modeled utilities.

Attribute values vary considerably for a given technology because of regional differences and market imperfections. Consider photovoltaics: the levelized cost of energy varies considerably because of differences in

[5] In the electric sector's formulation, electrical generating technologies' key attribute is levelized cost of energy, which is a function of capital cost, operating cost, fuel efficiency, utilization factor, and financing structure. An update might include electric generator attributes such as ramping rates, ability to provide various ancillary services, such as contributions to reserve requirements, and other critical aspects of the investment decision; and the model itself should be able to evaluate effective load carrying capabilities and other factors.

regional insolation, technology performance, supplier prices, developer costs, and operation and maintenance. Decision makers also vary in the importance they assign to each attribute (expressed by the *Weights*) and their view of each technology (expressed by the *Preference* parameter). The *Sensitivity* parameter (often designated as *alpha* in the literature) provides a simple and effective way to model this variability by controlling the degree to which market share goes to the apparent "best" (highest utility) technology versus competing technologies. A high *Sensitivity* value means most market share goes to the technology with highest utility. A low value results in market share being more spread out among technologies that are close to the "best." The simple way in which this parameter models variability and spreads the market share is a key advantage of using logit models over other optimization methods, especially linear programming, which suffer from the "knife-edge" problem: they allocate all market share to the single "best" technology and swing suddenly to other technologies due to small changes in relative utility.

We calibrated the logit parameters (*Weights, Preference,* and *Sensitivity*) to fit historical market share among technologies using a combination of regression, sensitivity analysis, and nonlinear optimization to fit historical market shares, technology characteristics, and market conditions with some expert judgment for new technologies. Where appropriate, SEDS employs nested logit models. For instance, competition for light-duty vehicles occurs in two stages. The first stage estimates market share among general technology groups (e.g., internal combustion engine, battery electric, or hydrogen fuel cells). The second stage estimates market share within each group (e.g., gasoline, diesel, hybrid, biofuels within the internal combustion engine group). This nested logit scheme reduces the problem of independence from irrelevant alternatives (the Red-Bus/Blue-Bus Problem) common to single-level logit formulations.

Even logit models can produce rapid changes in technology adoption rates as a new technology becomes less costly. Sudden changes may be unrealistic because of limits in how rapidly the manufacturing, raw material supply, and infrastructure can respond to dramatic growth in demand (e.g., limited feedstock supply for biofuels or manufacturing capacity for photovoltaics or batteries). Temporary shortages may lead to price increases. In such situations, SEDS imposes constraints on rates of capacity growth or uses an iterative process to modify the logit allocation to reach an equilibrium market share.

### 4.7. *Modeling consumer expectations*

Many technologies, such as power plants, have lifetimes of decades. An ideal consumer (purchaser) selects a technology based on total present value or levelized cost of ownership over the lifetime in comparison with competing technologies. Thus, technology choice is based not just on the current situation but expectations about the future, including uncertain future fuel costs, which may be subject to policy changes such as emission permits or carbon prices for fossil fuels. Some economic models use "perfect foresight" to model these expectations and drive technology choice. SEDS models consumer expectations for fuel and other operating costs based on simple extrapolation from the last few years before the date when the choice is made and extrapolating recent fuel and operating costs for the length of each competing technology's investment term. This method, which is often used in systems dynamics models of market choice, could be seen as what is known as myopic expectation. However, there is good evidence that individual consumers—if they look at total cost of ownership at all—focus on current costs of fuel and maintenance and do not consider much future change beyond recent trends. Even large and sophisticated companies usually use straightforward forecasts of future costs using simple extrapolation. It seems likely that these "myopic" models of consumer foresight better represent actual decision-making than models assuming perfect foresight.

## 5. Effectively communicating the value of stochastic portfolio analysis

Providing insight into the probability of meeting DOE technology goals, exploring the uncertain benefits of various energy R&D portfolios, and estimating the risks of funding decisions are key capabilities that the SEDS team aspired to provide decision makers. At the time of SEDS development, probabilistic analysis of DOE R&D portfolios was uncommon, and there was little experience with how best to communicate the results and methodology in an insightful and understandable way. This section highlights helpful communication approaches and addresses expected concerns, such as programs facing additional challenges in an often-complicated funding and operational environment.

Communicating model results to a broad audience of stakeholders is often difficult, especially considering the heterogenous nature of their backgrounds and their uses for the results. This diversity of stakeholders, especially inherent in the myriad energy industries, can lead to misinterpretation of the results or overconfidence in results without fully understanding their nuances. When dealing with stochastic results, the richness of results multiplies these challenges. Ultimately, the goal is to relay the uncertainty of an outcome while balancing stakeholders' needs to interpret the results and to make decisions based on them.

During initial demonstrations of SEDS' results (Fig. 4), the SEDS team provided primers on interpreting statistical charts to facilitate a common understanding of the results to DOE and other stakeholders interested in stochastic modeling. Routine questions from these audiences made it apparent that the necessary statistical background often could not be adequately conveyed using just a short primer. Moreover, the team found that time spent explaining how to interpret advanced statistical plots took time away from the goal of communicating key insights from the model.

The display of SEDS results evolved to more succinct and easily interpreted formats that required less explanation and freed time for presenting key takeaways from results. The SEDS team found box plots or box-and-whisker plots to be intuitive and effective methods for comparing uncertainties among multiple single-point-in-time results [84]. One shortcoming of box plots—and the other plots described below—are their inability to call attention to multimodal distributions. In such situations, one should consider adding a note to highlight such distributions. For demonstrating a small number of time-changing results, the team favored percentile bands and fan charts. However, these approaches also have drawbacks. For example, to avoid providing a detailed description of the meaning of percentiles and to prevent clutter within a graph, it is often necessary to limit the percentile bands to median (50th percentile) and lower and upper uncertainty ranges (e.g., 5th and 95th percentiles). Moreover, there are limits to the number of time-series one can display using percentile bands and fan charts. The requirement that each time-series include at least three percentile bands quickly leads to a tangled and unreadable graph, and fan charts are only comprehensible when their color shading overlaps minimally.

To compare many probabilistic time-series results in a single plot, the SEDS team preferred using frames of box plots, as depicted in Fig. 5. Each frame represents a single point in time, and a collection of frames displays the uncertain results at successive points in time, often separated by a time interval of multiple years. Though this method loses some time granularity, it conveys much time-dependent information in an understandable format. Additionally, this approach was helpful for comparing collections of results among multiple scenarios.

Though it is important that a model's methodology and highly technical details be understood and validated through continuous review processes, that information can easily become a distraction when communicating the insights to decision makers. Given the novelty of the modeling approach, the SEDS team initially felt compelled to provide audiences with a brief overview of the methodological framework and a summary of key insights. In hindsight, it might have been more effective to reserve technical details and jargon to audiences charged with

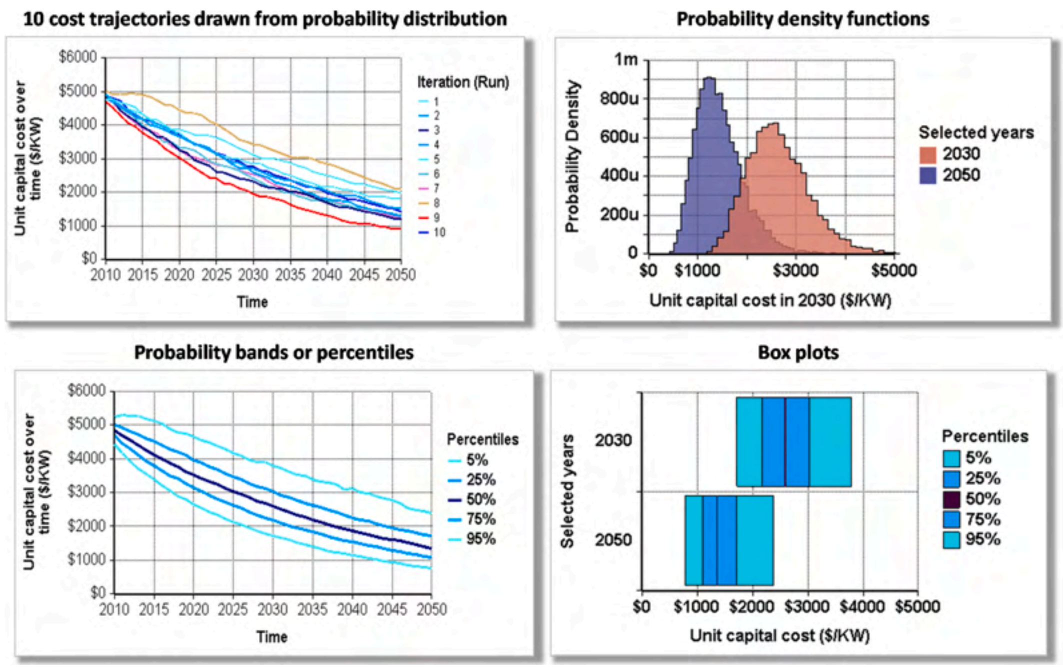


**Fig. 4.** Example of four ways uncertainty was initially visualized using SEDS, including cost trajectories drawn from probability distribution, probability density function, probability bands or percentiles, and box plots.

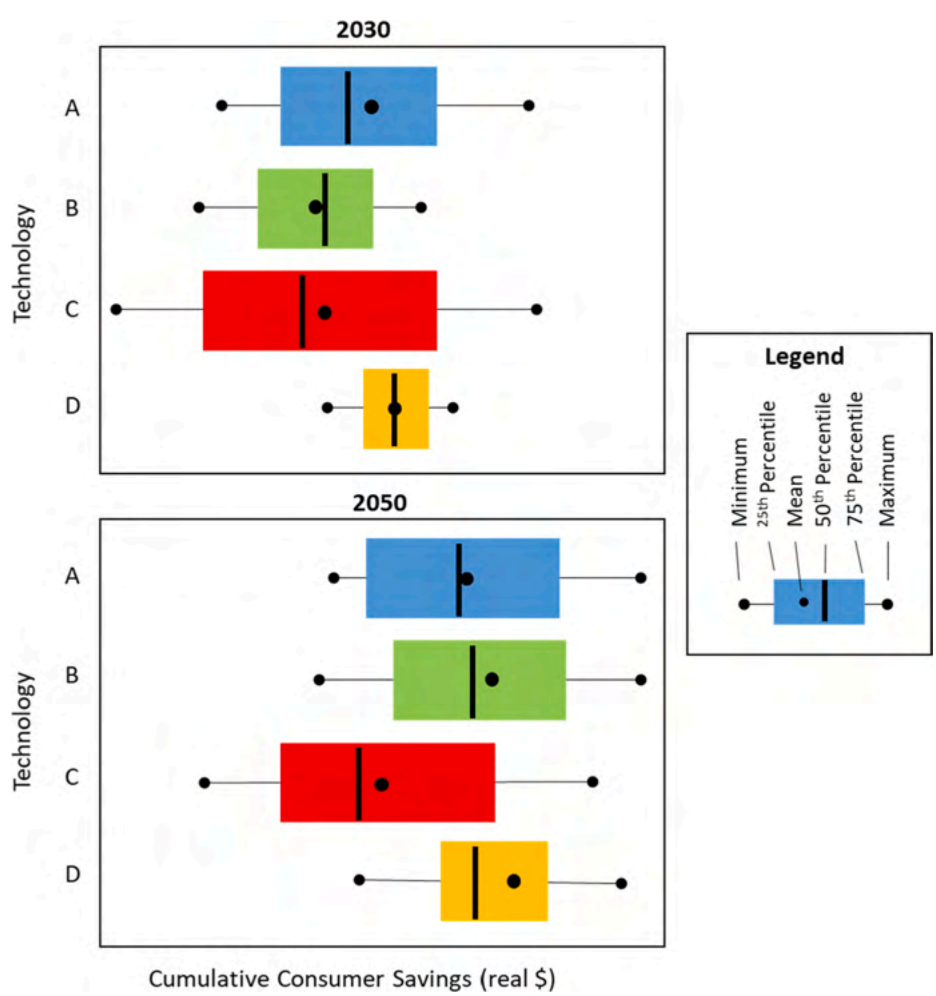


**Fig. 5.** Illustrative year-dependent frames of box plots, detailing the relationship between technology and cumulative consumer savings.

scrutinizing the approach and to instead focus only on key insights from the approach when presenting to other audiences. The most successful strategy for communicating to decision makers likely involves relaying a compelling explanation founded on key model insights, focusing on the results of greatest consequence, and avoiding losing some of the audience in technical details.

## 6. Summary of lessons learned

Development of the Stochastic Energy Deployment System model constituted a large effort within a short period of time, with many lessons learned. The lessons span topics including model architecture, collaboration across institutions, communication of results, and system boundaries, to name a few. As mentioned in Section 4, there were many challenging model architecture decisions and takeaways. First, the Stochastic Energy Deployment System model would benefit from a variable time step allowing shorter near-term time steps and longer time steps for distant future time periods. Applying shorter time steps to near-term forecast periods would reduce challenges addressing fast-changing market dynamics, closer supply-demand equilibrium for supply-constrained energy types, and goal-seeking routines like estimating carbon prices to achieve a given carbon dioxide emissions level. Conversely, longer time steps would be more computationally efficient for highly uncertain forecasts 20 or more years into the future.

Second, the Stochastic Energy Deployment System model would benefit from more global feedback to better represent the international energy system. For simplicity, the model includes few endogenous variables related to global markets. The Stochastic Energy Deployment System team recognized additional global representation as a longer-term goal, particularly as it relates to modeling technology learning rates as a function of cumulative global installations.

Third, in the electric sector's original formulation, electrical generating technologies' key attribute is levelized cost of energy, which is a function of capital cost, operating cost, fuel efficiency, utilization factor, and financing structure. However, there is a need to go beyond levelized cost of energy—for example, to capture the broader range of benefits of technologies contributing to the portfolio and providing synergies across each other in operations (e.g., solar photovoltaics during the day and wind at night, electric vehicle charging linked with renewable power availability, and managed electric vehicle charging to assist grid stability). A current revision of the Stochastic Energy Deployment System model should include electric generator attributes such as the ability to provide reliability services (e.g., operating reserve) and other ancillary services, a generator's effective load carrying capabilities, and other critical aspects of the investment decision.

Using a system dynamics framework enabled rapid computation and use as an interactive tool, but also posed two noteworthy challenges and limitations. First, imposing strict constraints like a carbon cap or definitive supply limitations is difficult. So, the model relies on shadow prices to push the model in the desired direction. The Stochastic Energy Deployment System model team found that using proportional-integral control algorithms worked reasonably well at goal-seeking and equilibrium-seeking via shadow prices. As mentioned previously, using smaller time steps would lead to shadow prices with more accuracy in achieving their desired goals. Second, simultaneously addressing multiple objectives is more difficult in the system dynamics framework. For example, cost-effectively building electric generating capacity to simultaneously meet power and capacity requirements is more challenging than it would be in a linear optimization model, yet the team developed methods to overcome these challenges.

The development process for the Stochastic Energy Deployment System model depended on effective communication among developers. Using the same templates across all modules for similar concepts was very helpful for quality checking the entire model. However, having developers across multiple institutions meant also competing with alternative work priorities at a larger scale, which was sometimes challenging but was mostly met by determined efforts by the various teams.

Designing tools that emphasize the impacts of research and development within an entire energy system—rather than in just a single segment of the system—is inherently more complex because a broader view may imply competition or complementarity within and across sectors. It is important to consider a wide array of services provided by a technology and to avoid limiting the technology's characterization to a subset of attributes. For example, using only generator levelized cost of energy for the electricity sector oversimplifies competition between electric technologies; more complete models would recognize the role of different technologies in providing various ancillary services and other important roles beyond levelized cost of energy. Similarly, a cross-sector perspective may indicate competition or synergies between improving electric end-use technologies (e.g., lighting and pumping) and improving electric generation technology.

Though the Stochastic Energy Deployment System model was still in the development phase, it was generally well-received during reviews by the U.S. Department of Energy program analysts. Presenters of stochastic modeling insights can trial the methods highlighted in Section 5 to more effectively convey the insights from and the dynamics within system models. Communicating nonlinear concepts can be difficult. The typical visual tools in Fig. 5 can be extended to include stochastic tornado diagrams, waterfall charts, and other visualizations that help communicate risk and uncertainty in a technology and in a portfolio analysis.

Going forward, work is underway to advance stochastic multi-objective optimization tools to evaluate the risk and uncertainty of energy R&D investments at the technology level. An open-source on-line tool for expert elicitation is in the final stages of development, building on the NearZero platform [85]. Work is now beginning to extend this technology-level analysis to the portfolio level, building on the lessons learned and experience with SEDS [86].

In this article, we have covered the structure of the Stochastic Energy Deployment System model, literature relevant to portfolio analysis, and lessons learned through the Stochastic Energy Deployment System model development and communication of stochastic results. We hope the article serves as a useful background for those who use and advance the model and as a reference for the community of practitioners who are continuously advancing the science of portfolio analysis with uncertainty.

## CRediT authorship contribution statement

**James Milford:** Conceptualization, Methodology, Validation, Writing – original draft, Visualization. **Max Henrion:** Conceptualization, Methodology, Validation, Writing – original draft. **Chad Hunter:** Conceptualization, Writing – original draft. **Emily Newes:** Conceptualization, Methodology, Writing – original draft. **Caroline Hughes:** Writing – original draft. **Samuel F. Baldwin:** Conceptualization, Writing – review & editing, Supervision.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

*Acknowledgements*

The authors would like to express their deep appreciation for the support of this work by the Office of Strategic Programs under contract number DE-AC36-08GO28308. Early contributors to the SEDS work included Walter Short, as initiator and conceptual lead; Tom Ferguson, as the initial electric market module co-developer and programmer; Max Henrion, as Analytica consultant; and Michael Leifman, as initiator of the SEDS multi-laboratory development team.

In addition, we acknowledge the initial developers of SEDS as part of the multi-laboratory consortium: Donald Hanson, Deena Patel, and Anant Vyas (Argonne National Laboratory); Chris Marnay, Alan Sanstadt, Michael Stadler, Ryoichi Komiyama, Inez Lima Azevedo, Sam Borgeson, Brian Coffey, and Judy Lai (Lawrence Berkeley National Laboratory); Surya Swamy (Lumina Decision Systems); Donald Remson (National Energy Technology Laboratory); Cory Welch, James Milford, and Emily Newes (National Renewable Energy Laboratory); David Greene and W.T. Wilson (Oak Ridge National Laboratory); Frances Wood (OnLocation); Joe Roop and Olga Livingston (Pacific Northwest National Laboratory); and Dave Schmalzer (Schmalzer Consulting). Finally, we would like to thank all those who were involved in the DOE Risk work that helped inform SEDS development: Arlene Anderson, Chad Augustine, Sam Baldwin, Darrell Beschen, Anne-Marie Borbely-Bartis, Jay Braitsch, Stan Calvert, Chris Cameron, Joe Cohen, Jim Daley, Mike Duffy, Ray Fortuna, Scott Hassell, Thomas Jenkin, Fred Joseck, Tom Kimbis, Mark Lausten, Michael Leifman, James McVeigh, Doug Norland; Ed Pollock, Neil Rossmeissl, Mark Ruth, Tom Sheahan, Thomas Schweizer, Kevin Stork, Robert Vallario, Maria Vargas, Martin Vorum, Tex Wilkins, Frances Wood, Katherine Young, and many others.

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U. S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Office of Strategic Programs. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117926.

## References

[1] Frost PA, Savarino JE. An Empirical Bayes Approach to Efficient Portfolio Selection. J Financial Quantitative Anal 1986;21(3):293–305. https://doi.org/10.2307/2331043.

[2] Markowitz H. Portfolio Selection. J Am Finance Association 1952;7(1):77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.

[3] Cooper RG, Edgett SJ, Kleinschmidt EJ. *Portfolio Management for New Products: Second Edition* (2nd edition). Basic Books; 2002.

[4] Dye LD, Pennypacker JS. Project Portfolio Management: Selecting and Prioritizing Projects for Competitive Advantage. Center for Business Practices; 1999.

[5] Gustafsson J, Salo A. Contingent Portfolio Programming for the Management of Risky Projects. Oper Res 2005;53(6):946–56. https://doi.org/10.1287/opre.1050.0225.

[6] Ringuest JL, Graves SB, Case RH. Mean-Gini analysis in R&D portfolio selection. Eur J Oper Res 2004;154(1):157–69. https://doi.org/10.1016/S0377-2217(02)00708-7.

[7] Rogers MJ, Gupta A, Maranas CD. Real Options Based Analysis of Optimal Pharmaceutical Research and Development Portfolios. Ind Eng Chem Res 2002;41(25):6607–20. https://doi.org/10.1021/ie020385p.

[8] Rogers, M. J., Gupta, A., & Maranas, C. D. (2003). Risk Management in Real Options Based Pharmaceutical Portfolio Planning. Proceedings Foundations of Computer-Aided Process Operations. FOCAPO 2003.

[9] Anadón LD, Baker E, Bosetti V. Integrating uncertainty into public energy research and development decisions. Nat Energy 2017;2(5):17071. https://doi.org/10.1038/nenergy.2017.71.

[10] Baker E, Bosetti V, Anadon LD. Special issue on defining robust energy R&D portfolios. Energy Policy 2015;80:215–8. https://doi.org/10.1016/j.enpol.2015.02.001.

[11] Baker E, Bosetti V, Salo A. Robust portfolio decision analysis: An application to the energy research and development portfolio problem. Eur J Oper Res 2020;284(3):1107–20. https://doi.org/10.1016/j.ejor.2020.01.038.

[12] Dutra CC, Ribeiro JLD, de Carvalho MM. An economic–probabilistic model for project selection and prioritization. Int J Project Manage 2014;32(6):1042–55. https://doi.org/10.1016/j.ijproman.2013.12.004.

[13] Way R, Lafond F, Lillo F, Panchenko V, Farmer JD. Wright meets Markowitz: How standard portfolio theory changes when assets are technologies following experience curves. Journal of Economic Dynamics and Control 2019;101:211–38. https://doi.org/10.1016/j.jedc.2018.10.006.

[14] Verbano C, Nosella A. Addressing R&D investment decisions: a cross analysis of R&D project selection methods. European J Innovation Management 2010;13(3):355–79. https://doi.org/10.1108/14601061011060166.

[15] Eilat H, Golany B, Shtub A. R&D project evaluation: An integrated DEA and balanced scorecard approach. Omega 2008;36(5):895–912. https://doi.org/10.1016/j.omega.2006.05.002.

[16] Kaplan RS, Norton DP. Linking the Balanced Scorecard to Strategy. California Management Review 1996;39(1):53–79. https://doi.org/10.2307/41165876.

[17] Henriksen AD, Traynor AJ. A practical R D project-selection scoring tool. IEEE Trans Eng Manage 1999;46(2):158–70. https://doi.org/10.1109/17.759144.

[18] Cooper William W, Seiford Lawrence M, Zhu Joe. In: International Series in Operations Research & Management ScienceHandbook on Data Envelopment Analysis. Boston: Kluwer Academic Publishers; 2004. p. 1–39. https://doi.org/10.1007/1-4020-7798-X_1.

[19] Oral M, Kettani O, Çınar Ü. Project evaluation and selection in a network of collaboration: A consensual disaggregation multi-criterion approach. Eur J Oper Res 2001;130(2):332–46. https://doi.org/10.1016/S0377-2217(00)00040-0.

[20] Cranmer A, Baker E, Liesiö J, Salo A. A portfolio model for siting offshore wind farms with economic and environmental objectives. Eur J Oper Res 2018;267(1):304–14. https://doi.org/10.1016/j.ejor.2017.11.026.

[21] Ding J, Somani A. A Long-Term Investment Planning Model for Mixed Energy Infrastructure Integrated with Renewable Energy. IEEE Green Technologies Conference 2010;2010:1–10. https://doi.org/10.1109/GREEN.2010.5453785.

[22] Eckhause JM, Gabriel SA, Hughes DR. An Integer Programming Approach for Evaluating R&D Funding Decisions with Optimal Budget Allocations. IEEE Trans Eng Manage 2012;59(4):679–91. https://doi.org/10.1109/TEM.2012.2183132.

[23] Solak S, Clarke J-PB, Johnson EL, Barnes ER. Optimization of R&D project portfolios under endogenous uncertainty. Eur J Oper Res 2010;207(1):420–33. https://doi.org/10.1016/j.ejor.2010.04.032.

[24] Wang J, Hwang W-L. A fuzzy set approach for R&D portfolio selection using a real options valuation model. Omega 2007;35(3):247–57. https://doi.org/10.1016/j.omega.2005.06.002.

[25] Teter Michael D, Royset Johannes O, Newman Alexandra M. Modeling uncertainty of expert elicitation for use in risk-based optimization. Ann Oper Res 2019;280(1-2):189–210. https://doi.org/10.1007/s10479-018-3011-z.

[26] Santen, N. R., Webster, M. D., Popp, D., & Pérez-Arriaga, I. (2014). Inter-temporal R&D and Capital Investment Portfolios for the Electricity Industry's Low Carbon Future (Working Paper No. 20783). National Bureau of Economic Research. https://doi.org/10.3386/w20783.

[27] Bistline JE. Energy technology R&D portfolio management: Modeling uncertain returns and market diffusion. Appl Energy 2016;183:1181–96. https://doi.org/10.1016/j.apenergy.2016.09.062.

[28] Eide J, Herzog H, Webster M. Rethinking CCS – Developing Quantitative Tools for Analyzing Investments in CCS. Energy Procedia 2013;37:7647–67. https://doi.org/10.1016/j.egypro.2013.06.711.

[29] Soyer R, Tanyeri K. Bayesian portfolio selection with multi-variate random variance models. Eur J Oper Res 2006;171(3):977–90. https://doi.org/10.1016/j.ejor.2005.01.012.

[30] Cooper Robert, Edgett Scott, Kleinschmidt Elko. Portfolio management for new product development: results of an industry practices study. R&D Management 2001;31(4):361–80. https://doi.org/10.1111/radm.2001.31.issue-410.1111/1467-9310.00225.

[31] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew Sustain Energy Rev 2009;13(9):2263–78. https://doi.org/10.1016/j.rser.2009.06.021.

[32] Saaty Thomas L. In: Mathematical Models for Decision Support. Berlin, Heidelberg: Springer Berlin Heidelberg; 1988. p. 109–21. https://doi.org/10.1007/978-3-642-83555-1_5.

[33] Zachmann, G., Roth, A., Way, R., Lafond, F., Doyne, J., Teng, F., Tu, Cristina Tommasino, M., Virdis, M., Zini, A., Trollip, H., Keen, S., Moyo, A., & Rennkamp, B. (2018). COP21 RIPPLES: Results and Implications for Pathways and Policies for Low Emissions European Societies. https://cordis.europa.eu/project/rcn/206263/factsheet/en.

[34] Nock D, Baker E. Holistic multi-criteria decision analysis evaluation of sustainable electric generation portfolios: New England case study. Appl Energy 2019;242:655–73. https://doi.org/10.1016/j.apenergy.2019.03.019.

[35] Gabriel SA, Ordóñez JF, Faria JA. Contingency Planning in Project Selection Using Multiobjective Optimization and Chance Constraints. J Infrastruct Syst 2006;12(2):112–20. https://doi.org/10.1061/(ASCE)1076-0342(2006)12:2(112).

[36] Sehatpour M-H, Kazemi A. Sustainable fuel portfolio optimization: Integrated fuzzy multi-objective programming and multi-criteria decision making. J Cleaner Prod 2018;176:304–19. https://doi.org/10.1016/j.jclepro.2017.12.092.

[37] Ashrafi M, Davoudpour H, Abbassi M. Developing a decision support system for R&D project portfolio selection with interdependencies. AIP Conf Proc 2012;1499(1):370–8. https://doi.org/10.1063/1.4769016.

[38] Shafiee M, Alghamdi A, Sansom C, Hart P, Encinas-Oropesa A. A Through-Life Cost Analysis Model to Support Investment Decision-Making in Concentrated

Solar Power Projects. Energies 2020;13(7):1553. https://doi.org/10.3390/en13071553.
[39] Svensson E, Berntsson T, Strömberg A-B, Patriksson M. An optimization methodology for identifying robust process integration investments under uncertainty. Energy Policy 2009;37(2):680–5. https://doi.org/10.1016/j.enpol.2008.10.023.
[40] Messina V, Bosetti V. Integrating stochastic programming and decision tree techniques in land conversion problems. Ann Oper Res 2006;142(1):243–58. https://doi.org/10.1007/s10479-006-6170-2.
[41] Alvarez-García B, Fernández-Castro AS. A comprehensive approach for the selection of a portfolio of interdependent projects. An application to subsidized projects in Spain. Comput Ind Eng 2018;118:153–9. https://doi.org/10.1016/j.cie.2018.02.025.
[42] George ED, Farid SS. Stochastic Combinatorial Optimization Approach to Biopharmaceutical Portfolio Management. Ind Eng Chem Res 2008;47(22):8762–74. https://doi.org/10.1021/ie8003144.
[43] Perez-Escobedo JL, Azzaro-Pantel C, Pibouleau L. Multiobjective strategies for New Product Development in the pharmaceutical industry. Comput Chem Eng 2012;37:278–96. https://doi.org/10.1016/j.compchemeng.2011.10.004.
[44] Fujiwara T. Real options analysis on strategic partnerships of biotechnological start-ups. Technology Analysis & Strategic Management 2014;26(6):617–38. https://doi.org/10.1080/09537325.2014.923834.
[45] Baker E, Chon H, Keisler J. Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy. Clim Change 2009;96(3):379–408. https://doi.org/10.1007/s10584-009-9634-y.
[46] Nemet GF, Baker E, Jenni KE. Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios. Energy 2013;56:218–28. https://doi.org/10.1016/j.energy.2013.04.047.
[47] Anadon LD, Bunn M, Narayanamurti V, editors. Transforming US Energy Innovation. (1 edition). Cambridge University Press; 2014.
[48] Bistline JE. Energy technology expert elicitations: An application to natural gas turbine efficiencies. Technol Forecast Soc Chang 2014;86:177–87. https://doi.org/10.1016/j.techfore.2013.11.003.
[49] Columbia SIPA Center on Global Energy Policy. Energizing America. Columbia SPIA. 2020 https://www.energypolicy.columbia.edu/sites/default/files/file-uploads/EnergizingAmerica_FINAL_DIGITAL.pdf.
[50] InterAcademy Council. (2010). Climate change assessments: review of the processes and procedure of the IPCC (p. 123). InterAcademy Council. https://archive.ipcc.ch/pdf/IAC_report/IAC%20Report.pdf.
[51] National Research Council. (2005). Prospective Evaluation of Applied Energy Research and Development at DOE (Phase One): A First Look Forward. https://doi.org/10.17226/11277.
[52] National Research Council. (2007). Prospective Evaluation of Applied Energy Research and Development at DOE (Phase Two). National Research Council.
[53] President's Committee of Advisors on Science and Technology. Report to the President on Federal Energy Research and Development for the Challenges of the Twenty-First Century. Executive Office of the President. 1997 https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/pcast-nov2007.pdf.
[54] Baker E, Bosetti V, Anadon LD, Henrion M, Aleluia Reis L. Future costs of key low-carbon energy technologies: Harmonization and aggregation of energy technology expert elicitation data. Energy Policy 2015;80:219–32. https://doi.org/10.1016/j.enpol.2014.10.008.
[55] Barron R, McJeon H. The differential impact of low-carbon technologies on climate change mitigation cost under a range of socioeconomic and climate policy scenarios. Energy Policy 2015;80:264–74. https://doi.org/10.1016/j.enpol.2015.01.038.
[56] Bosetti Valentina, Marangoni Giacomo, Borgonovo Emanuele, Diaz Anadon Laura, Barron Robert, McJeon Haewon C, et al. Sensitivity to energy technology costs: A multi-model comparison analysis. Energy Policy 2015;80:244–63. https://doi.org/10.1016/j.enpol.2014.12.012.
[57] Chan, G., & Anadon, L.-D. (2016). Improving Decision Making for Public R&D Investment in Energy: Utilizing Expert Elicitation in Parametric Models [Working Paper]. Faculty of Economics. https://doi.org/10.17863/CAM.7842.
[58] McVeigh J, Cohen J, Vorum M, Porro G, Nix G. *Preliminary Technical Risk Analysis for the Geothermal Technologies Program* (NREL/TP-640-41156). National Renewable Energy Laboratory. 2007 https://www.energy.gov/sites/prod/files/2014/02/f7/41156.pdf.
[59] Augustine, C. (2011). Updated U.S. Geothermal Supply Characterization and Representation for Market Penetration Model Input (NREL/TP-6A2-47459). National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy12osti/47459.pdf.
[60] McVeigh, J., Lausten, M., Eugeni, E., & Soni, A. (2010). 2009 Technical Risk and Uncertainty Analysis of the U.S. Department of Energy's Solar Energy Technologies Program Concentrating Solar Power and Photovoltaics R&D (NREL/SR-6A20-48043). National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy11osti/48043.pdf.
[61] Young, K., Augustine, C., & Anderson, A. (2010). Report on the U.S. DOE Geothermal Technologies Program's 2009 Risk Analysis. Stanford Geothermal Workshop, Stanford, CA. https://www.nrel.gov/docs/fy10osti/47388.pdf.
[62] Ruth, M., Duffy, M., & Jalalzadeh, A. (2009). DOE Hydrogen Program Risk Analysis in Support of EERE's Portfolio Analysis (project #ANP2). 2009 DOE Hydrogen Program Review, Arlington, VA. https://www.nrel.gov/docs/fy09osti/45700.pdf.
[63] Wind and Hydropower Technologies Program. (2007). Wind Energy Multiyear Program Plan for 2007-2012 (DOE/GO-102007-2451). U.S. Department of Energy. http://www1.eere.energy.gov/library/asset_handler.aspx?src=https://www1.eere.energy.gov/wind/pdfs/40593.pdf&id=5468.
[64] Baker E, Olaleye O, Aleluia Reis L. Decision frameworks and the investment in R&D. Energy Policy 2015;80:275–85. https://doi.org/10.1016/j.enpol.2015.01.027.
[65] Bosetti V, Catenacci M, Fiorese G, Verdolini E. The future prospect of PV and CSP solar technologies: An expert elicitation survey. Energy Policy 2012;49:308–17. https://doi.org/10.1016/j.enpol.2012.06.024.
[66] Gilovich T, Griffin D, Kahneman D, editors. Heuristics and Biases: The Psychology of Intuitive Judgement. Press: Cambridge Univ; 2002. http://biasandbelief.pbworks.com/w/page/6537194/Heuristics%20and%20Biases%3A%20The%20Psychology%20of%20Intuitive%20Judgement.
[67] Morgan MG, Henrion M. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge Univ. Press; 1990.
[68] Henrion M, Fischhoff B. Assessing uncertainty in physical constants. Am J Phys 1986;54(9):791–8. https://doi.org/10.1119/1.14447.
[69] Colson AR, Cooke RM. Expert Elicitation: Using the Classical Model to Validate Experts' Judgments. Review of Environmental Economics and Policy 2018;12(1):113–32. https://doi.org/10.1093/reep/rex022.
[70] Spetzler C, Stael von Holstein C-A. Probability Coding in Decision Analysis. Manage Sci 1975;22(3):340–58.
[71] Clemen RT, Winkler RL. Combining Probability Distributions From Experts in Risk Analysis. Risk Anal 1999;19(2):187–203. https://doi.org/10.1023/A:1006917509560.
[72] Clemen Robert T, Winkler Robert L, Edwards Ward, Miles Ralph F Jr, von Winterfeldt Detlof. In: Advances in Decision Analysis: From Foundations to Applications. Cambridge: Cambridge University Press; 2007. p. 154–76. https://doi.org/10.1017/CBO9780511611308.010.
[73] Clemen RT. Comment on Cooke's classical method. Reliab Eng Syst Saf 2008;93(5):760–5. https://doi.org/10.1016/j.ress.2008.02.003.
[74] Cooke Roger M. In: Making Essential Choices with Scant Information. London: Palgrave Macmillan UK; 2009. p. 257–76. https://doi.org/10.1057/9780230236837_13.
[75] Cooke RM. Validation in the Classical Model. In *Elicitation*. Cham: Springer; 2018. p. 37–59.
[76] Verdolini E, Anadón LD, Baker E, Bosetti V, Aleluia Reis L. Future Prospects for Energy Technologies: Insights from Expert Elicitations. Review of Environmental Economics and Policy 2018;12(1):133–53. https://doi.org/10.1093/reep/rex028.
[77] Wiser Ryan, Rand Joseph, Seel Joachim, Beiter Philipp, Baker Erin, Lantz Eric, et al. Expert elicitation survey predicts 37% to 49% declines in wind energy costs by 2050. Nat Energy 2021;6(5):555–65. https://doi.org/10.1038/s41560-021-00810-z.
[78] Nemet, G. F. (2019). How Solar Energy Became Cheap: A Model for Low-Carbon Innovation (1st ed.). Routledge. https://www.routledge.com/How-Solar-Energy-Became-Cheap-A-Model-for-Low-Carbon-Innovation-1st-Edition/Nemet/p/book/9780367136598.
[79] Energy Information Administration. (2018). Documentation of the National Energy Modeling System (NEMS) Modules. https://www.eia.gov/outlooks/aeo/nems/documentation/index.php.
[80] Loulou, R., Goldstein, G., & Noble, K. (2004). Documentation for the MARKAL Family of Models. 389.
[81] The University of Tennessee. (2020, January 6). POLYSYS - All Documents. https://ag.tennessee.edu/arec/Documents/Forms/AllItems.aspx?RootFolder=%2farec%2fDocuments%2fPOLYSYS&FolderCTID=0x0120002DC0063B4E83AE4AB74DEBEEBB7CDDDF.
[82] Lumina Decision Systems. (2020). Analytica Visionary Modeling. https://lumina.com/.
[83] Sterman JD. *Business Dynamics: Systems Thinking and Modeling for a Complex World* (HAR/CDR edition). McGraw-Hill Education; 2000.
[84] Wickham, H., & Stryjewski, L. (2012). 40 years of boxplots. https://vita.had.co.nz/papers/boxplots.pdf.
[85] NearZero. (2021). NearZero Elicitation Engine [JavaScript]. NearZero. https://github.com/nearzero/elicitation-engine.
[86] Bush, Brian, et al (2020), Workshop Report on Methods for R&D Portfolio Analysis and Evaluation. National Renewable Energy Laboratory, Technical Report NREL/TP-6A20-75314, September 2020, https://www.energy.gov/eere/analysis/downloads/workshop-report-methods-rd-portfolio-analysis-and-evaluation and https://www.nrel.gov/docs/fy20osti/75314.pdf.
[87] Barron R, Djimadoumbaye N, Baker E. How grid integration costs impact the optimal R&D portfolio into electricity supply technologies in the face of climate change. Sustainable Energy Technol Assess 2014;7:22–9. https://doi.org/10.1016/j.seta.2014.02.007.
[88] Belz A. Real options valuation of a federally funded small Business portfolio. IEEE Technology Engineering Management Conference (TEMSCON) 2017;2017:19–24. https://doi.org/10.1109/TEMSCON.2017.7998348.
[89] Beraldi P, Violi A, Simone FD, Costabile M, Massabò I, Russo E. A multistage stochastic programming approach for capital budgeting problems under uncertainty. IMA J Manage Math 2013;24(1):89–110. https://doi.org/10.1093/imaman/dps018.
[90] Champion BR, Gabriel SA. A multistage stochastic energy model with endogenous probabilities and a rolling horizon. Energy Build 2017;135:338–49. https://doi.org/10.1016/j.enbuild.2016.11.058.
[91] Davis GA, Owens B. Optimizing the level of renewable electric R&D expenditures using real options analysis. Energy Policy 2003;31(15):1589–608. https://doi.org/10.1016/S0301-4215(02)00225-2.

[92] Fabozzi, F. J., Huang, D., & Zhou, G. (2010). Robust portfolios: contributions from operations research and finance. Annals of Operations Research, 176(1), 191–220. https://doi.org/10.1007/s10479-009-0515-6.
[93] Fang Y, Lai KK, Wang S. Fuzzy Portfolio Optimization: Theory and Methods, Vol. 609. Springer Science & Business Media; 2008.
[94] Gutjahr WJ, Pichler A. Stochastic multi-objective optimization: a survey on non-scalarizing methods. Ann Oper Res 2016;236(2):475–99. https://doi.org/10.1007/s10479-013-1369-5.
[95] Hannah, L. (2010). Stochastic search, optimization and regression with energy applications [Doctoral Dissertation, Princeton University]. https://search.proquest.com/openview/8b6e296e4d38c4576aa4b0e89d80aabc/1?pq-origsite=gscholar&cbl=18750&diss=y.
[96] Hannah L, Powell W, Stewart J. One-stage R&D portfolio optimization with an application to solid oxide fuel cells. Energy Syst 2010;1(2):141–63. https://doi.org/10.1007/s12667-009-0008-3.
[97] Hwang W-S, Yeo Y, Oh I, Hong C, Jung S, Yang H, et al. CGE analysis of R&D investment policy considering trade-offs between economic growth and stability. Science and Public Policy 2020;scaa068. https://doi.org/10.1093/scipol/scaa068.
[98] Lee J, Yang J-S. Strategic R&D budget allocation to achieve national energy policy targets: the case of Korea. Policy Studies 2020:1–30. https://doi.org/10.1080/01442872.2020.1772216.
[99] Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T. M., & Popper, S. W. (Eds.). (2019). Decision Making under Deep Uncertainty: From Theory to Practice. Springer International Publishing. https://www.springer.com/gp/book/9783030052515.
[100] Martinek, J., Wagner, M., Zolan, A., Boyd, M., Newman, A., Morton, D., Leyffer, S., Larson, J., & USDOE Office of Energy Efficiency and Renewable Energy (EERE), S. E. T. O. (EE-4S). (2019). Design, Analysis, and Operations Toolkit (DAO-Tk). National Renewable Energy Lab. (NREL), Golden, CO (United States); Argonne National Lab. (ANL), Argonne, IL (United States). https://doi.org/10.11578/dc.20190513.3.
[101] Mockus J. Application of Bayesian approach to numerical methods of global and stochastic optimization. J Global Optim 1994;4(4):347–65. https://doi.org/10.1007/BF01099263.
[102] Pugh G, Clarke L, Marlay R, Kyle P, Wise M, McJeon H, et al. Energy R&D portfolio analysis based on climate change mitigation. Energy Econ 2011;33(4):634–43. https://doi.org/10.1016/j.eneco.2010.11.007.
[103] Shakhsi-Niaei M, Torabi SA, Iranmanesh SH. A comprehensive framework for project selection problem under uncertainty and real-world constraints. Comput Ind Eng 2011;61(1):226–37. https://doi.org/10.1016/j.cie.2011.03.015.
[104] Siddiqui S, Gabriel SA, Azarm S. Solving mixed-integer robust optimization problems with interval uncertainty using Benders decomposition. Journal of the Operational Research Society 2015;66(4):664–73. https://doi.org/10.1057/jors.2014.41.
[105] Tofighian Ali Asghar, Moezzi Hamid, Khakzar Barfuei Morteza, Shafiee Mahmood. Multi-period project portfolio selection under risk considerations and stochastic income. Journal of Industrial Engineering International 2018;14(3):571–84. https://doi.org/10.1007/s40092-017-0242-6.
[106] Vilkkumaa E, Liesiö J, Salo A. Optimal strategies for selecting project portfolios using uncertain value estimates. Eur J Oper Res 2014;233(3):772–83. https://doi.org/10.1016/j.ejor.2013.09.023.
[107] Webster, M., Fisher-Vanden, K., Popp, D., & Santen, N. (2015). Should We Give Up After Solyndra? Optimal Technology R&D Portfolios under Uncertainty (Working Paper No. 21396). National Bureau of Economic Research. https://doi.org/10.3386/w21396.
[108] Ziolkowska JR. Evaluating sustainability of biofuels feedstocks: A multi-objective framework for supporting decision making. Biomass Bioenergy 2013;59:425–40. https://doi.org/10.1016/j.biombioe.2013.09.008.
[109] Abbassi M, Ashrafi M, Sharifi Tashnizi E. Selecting balanced portfolios of R&D projects with interdependencies: A Cross-Entropy based methodology. Technovation 2014;34(1):54–63. https://doi.org/10.1016/j.technovation.2013.09.001.
[110] Kurth M, Keisler JM, Bates ME, Bridges TS, Summers J, Linkov I. A portfolio decision analysis approach to support energy research and development resource allocation. Energy Policy 2017;105:128–35. https://doi.org/10.1016/j.enpol.2017.02.030.
[111] Terrile RJ, Jackson BL, Belz AP. Consideration of risk and reward in balancing technology portfolios. IEEE Aerospace Conference 2014;2014:1–8. https://doi.org/10.1109/AERO.2014.6836475.
[112] Baker E, Solak S. Management of Energy Technology for Sustainability: How to Fund Energy Technology Research and Development. Production and Operations Management 2013;23(3):348–65. https://doi.org/10.1111/poms.12068.
[113] Bauer Nico, Calvin Katherine, Emmerling Johannes, Fricko Oliver, Fujimori Shinichiro, Hilaire Jérôme, et al. Shared Socio-Economic Pathways of the Energy Sector – Quantifying the Narratives. Global Environ Change 2017;42:316–30. https://doi.org/10.1016/j.gloenvcha.2016.07.006.
[114] Isley SC, Lempert RJ, Popper SW, Vardavas R. The effect of near-term policy choices on long-term greenhouse gas transformation pathways. Global Environ Change 2015;34:147–58. https://doi.org/10.1016/j.gloenvcha.2015.06.008.
[115] Shittu E, Baker E. Optimal Energy R&D Portfolio Investments in Response to a Carbon Tax. IEEE Trans Eng Manage 2010;57(4):547–59. https://doi.org/10.1109/TEM.2009.2023107.
[116] Baker E, Solak S. Climate change and optimal energy technology R&D policy. Eur J Oper Res 2011;213(2):442–54. https://doi.org/10.1016/j.ejor.2011.03.046.
[117] Bosetti V, Carraro C, Massetti E, Sgobbi A, Tavoni M. Optimal energy investment and R&D strategies to stabilize atmospheric greenhouse gas concentrations. Resource and Energy Economics 2009;31(2):123–37. https://doi.org/10.1016/j.reseneeco.2009.01.001.
[118] Arratia M., N. M., López I., F., Schaeffer, S. E., & Cruz-Reyes, L. (2016). Static R&D project portfolio selection in public organizations. Decision Support Systems, 84, 53–63. https://doi.org/10.1016/j.dss.2016.01.006.