Portfolio Decision Analysis to Support Energy Research and Development Resource Allocation

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Abstract

The United States aims to transform the energy sector to achieve greater energy independence as well as to abate its contribution to anthropogenic climate change. However, to achieve its goals, substantial research and development (R&D) is needed, and from an administrative stand point, must make resource allocation decisions which are complex and dynamic. This is due to multiple factors including a finite budget, the inherent risk of investing in emerging technologies, the multi-objective goals required to satisfy a heterogeneous marketplace, and the constraints imposed by numerous external drivers. Decision analysis is a well-recognized method for structuring and supporting decisions that are confounded by such complexities. The goal of this study is to develop and test a model to be used by the DOE Office of Fossil Energy's Carbon Capture and Storage R&D program to demonstrate how portfolio decision analysis can support R&D funding allocation to advance energy technology program areas toward their goals. A multiattribute value model is developed to embody the values of decision makers in order to evaluate alternative portfolio options. Mathematical optimization is used to identify the configuration of funding allocations to the technology program areas that maximize the value of the total budget, especially with respect to externally imposed budget changes. The results demonstrate that, as opposed to equal distribution of a budget change among technology program areas, explicitly funding the most value-generating options results in greater expected research and development progress.

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1. Introduction and Problem Motivation

Decision-making in public sector research and development (R&D) resource allocation is complicated by the need to consider multiple factors as well as by uncertainty in outcomes, investment risk, and external drivers such as budget and policy. The US Department of Energy (DOE) faces important R&D decisions which, despite their challenge, are essential, in combination with carefully crafted policy, for driving the nation to meet its aspirational emissions and energy transition goals (Anadon, Chan, & Lee, 2014; Folger, 2010). The United States aims to transform the energy sector to achieve greater energy independence as well as to abate its contribution to anthropogenic climate change. The Presidential Climate Action Plan, released in June 2013, sets the groundwork for plans to cut carbon emissions (Executive Office of the President [EOP], 2013) and a 2013 Presidential Memorandum directs the EPA to take decisive regulatory steps to that end (Office of the Press Secretary [OPS], 2013), which will likely include new emissions rules for power plants. While DOE R&D is responsible for facilitating a new energy future for the nation, their annual budget is volatile, a factor which complicates resource allocation decision-making and merits an approach for reacting to budgetary changes and justifying request.

The DOE and other government agencies can benefit from methods to structure and support complex decisions that are confounded by uncertainty, with R&D being a classic example. The history of R&D budget decision-making at DOE includes some mostly-isolated attempts to employ systematic budget planning, such as by tying funding levels to program assessment-based estimated benefits, but which lacked the consistency and transparency necessary to become common practice (Anadon et al., 2014). Decision analysis, a discipline built on the pillars of systems analysis, decision theory, probability, and cognitive psychology

(Howard, 2007), is often used to explicitly remedy this very problem and further, it affords decision makers a way to leverage diverse sources of information and expert judgment. The fittingness of these methods for developing an effective R&D strategy to meet US energy goals was recently asserted in a 2010 workshop by the DOE Office of Policy and International Affairs that convened at the Joint Global Change Research Institute to recognize and coordinate the role of portfolio analysis, including that of decision-analytics (Baker & Clarke, 2011). A special issue in Energy Policy on defining robust energy R&D portfolios, further articulates this need and which highlights the research response to the workshop (Baker, Bosetti, & Anadon, 2015). The goal of this study is to develop and test a decision support system to be used by the DOE Office of Fossil Energy's Carbon Capture and Storage R&D program to demonstrate how portfolio decision analysis (PDA) can support R&D funding allocation to advance energy technology program areas toward their goals.

2. Background on Carbon Capture and Storage Research and Development

While a shift to cleaner modes of energy generation is recognized as a critical and even primary driving force of the economy and society, energy supplies need to be maintained in a reliable and affordable fashion (EOP, 2013). Carbon Capture and Storage (CCS) systems can be used in conjunction with combustion-based utility infrastructure to avert wasteful carbon emissions which would otherwise be added to the rising concentration of greenhouse gases in the atmosphere. Conventional pulverized coal-fueled plants comprise a significant portion, 40%, of the country's electricity generation and, as a result, account for 35% of US CO_2 emissions (Office of Fossil Energy, n.d.), thus, this is an area where substantial improvements can be made resulting in a tremendous potential impact on the nation's carbon emissions while maintaining energy supply. Additionally, although alternative fuel and energy generation modes continue to comprise a growing portion of the energy profile, pulverized coal will likely remain an important energy source long into the future in this country and elsewhere due to its low cost and wide distribution globally ("The Future of Coal", 2007).

R&D is necessary to provide a suite of second generation technologies that can safely and cost-effectively be implemented along a stepwise process and across a range of electric utility and industrial scenarios. Government R&D can launch technology development forward; drive down costs and overcome other barriers to implementation at scale; and build confidence in the market by adequately demonstrating technologies, all of which are necessary before significant uptake will occur in the currently-voluntary power generation market (Folger, 2014). However, the characteristics of newly-emerging and yet-to-be-discovered technologies that relegate their exploration to the government R&D auspices are the same ones that confound decisions about funding them. For example, government agencies take up the exploration of technologies for which market failures and high risk prevent private sector investment; where payoffs exist primarily in the realm of social-benefit; and there is a need for proving cost-effectiveness in order to build market confidence (Anadon et al., 2014).

An important distinction between the R&D decision presented in this paper and similar contexts which have received decision support is the purview of the decision makers. Numerous studies have focused on improving project selection and prioritization in R&D and acquisitions by evaluating and ranking projects in order to identify a discrete set to comprise a portfolio (Duncan & Merrick, 2011; Heidenberger & Stummer, 1999; as well as numerous examples in Keisler, 2011). The Division of CCS R&D however, is one level removed from project selection and plays the strategic planning role by allocating funds among the programmatic areas that focus on the various technological modes of capturing and storing carbon that are under R&D, called pathways. The decision then is not which efforts to fund but at what level to fund each.

The level of funding that each pathway receives should be driven, in part, by how much it will advance technologies toward maturity, or a state that constitutes readiness for deployment. DOE's R&D implementation arm, the National Energy Technology Laboratory (NETL), evaluates the maturity of each active project and benchmarks the advancement of technologies under R&D from concept to deployment with a Technology Readiness Level (TRL) (United States Department of Energy [DOE], 2012). Initially developed by NASA (n.d.) in the 1970, the TRL scale has become common place in many government agencies and has spread to private industry as an assessment tool to inform decision making (Olechowski, Eppinger, & Joglekar, 2015). DOE provides guidance for using TRL data in critical decisions about capital assets acquisitions (DOE Order 413.3B or companion guidance) but it does not logically extend to R&D applications. Beyond providing information that is amenable to policy makers (DOE, 2012) TRLs in R&D have limited utility in project or program management, as they are essentially snapshots of the state of the program, as opposed to actionable information (Olechowski et al., 2015). Technology R&D investment decisions are likely better supported by forecasting technological change (Garcia & Bray, 1997). Models have emerged that do just that; introducing transition variables that capture the time or cost required to move from one TRL to the next (El-Khoury & Kenley, 2014). Expert elicitation is a common and important method for predicting technological progress and characterizing uncertainty (Bistline, 2014) because there is not a reliable relationship between future progress based on past transition information. The decision model developed for the Division of CCS R&D leverages TRL data as an initial state from which experts can anticipate technological progress as a result of resource allocation to R&D.

The CCS R&D effort, administered by the Department of Energy, Office of Fossil Energy (DOE/FE) is currently exploring a wide range of approaches to CCS to make short-term incremental cost improvement as well as long-term transformational scientific advances (National Energy Technology Laboratory [NETL], 2013). Resource allocation to R&D of CCS technologies represents a complex and dynamic decision problem; due to a finite budget, the inherent risk of investing in emerging technologies, the multi-objective goals required to satisfy a heterogeneous marketplace, and the constraints imposed by numerous external drivers. A decision support system (DSS) that is tailored to the decision-making structure of the DOE CCS R&D management to support resource allocation could benefit the program and thus the nation. The DSS presented here uses portfolio decision analysis and leverages existing data as well as expert judgment to inform strategic level resource allocation to R&D.

3. Theoretical Support for Modeling Approach

The challenge of how to allocate finite resources is well known in business and government, as well as in the operations research and management science communities that seek approaches to improve decisions-making. Support for resource allocation decisions from the research community arises in the form of analytic tools and, while they diverge somewhat by discipline and industry, share foundations in how to structure complexity and leverage mathematical programming techniques. Although many of the fundamentals of the field have long been established (Keeney & Raiffa, 1976), novel and decision-specific formulations continue to be sought. Government sector R&D strategic planning shares qualities with classic model-supported resource allocation cases from which techniques can be adapted to formulate a model that is tailored to the salient problem characteristics and decision maker requirements. In particular, a multi-attribute value function is defined by expert evaluation and forecasting for programmatic areas and is formulated such that resource allocation can be optimized to maximize total value. The following section highlights the relevant theoretical support for the DSS developed in this study and previews their connection to the CCS R&D model application.

As with financially motivated portfolio investment, government R&D allocates a limited budget among a set of items with the expectation that there is reward to taking the risk to invest, without certainty about either the reward or the risk. However, unlike traditional investment decisions, which are often based on predictions about monetary returns expressed by a single metric (e.g., net present value) (Steuer, Qi, & Hirschberger, 2005), public sector R&D funding allocation is motivated by non-financial factors and generates non-monetary value. Portfolio Decision Analysis (PDA), formally introduced by Salo, Keisler, and Morton (2011), augments traditional decision support methods, such as financial portfolio management and capital budgeting tools, with techniques from decision analysis. PDA can enable a more flexible and sophisticated process than traditional portfolio management practices (Duncan & Merrick, 2011) and offers methods to expand the definition of value to include multiple and novel attributes that constitute value, especially non-financial ones, that influence decisions (Fernholz, 2011). A value model is defined by a set of attributes, each representing an objective of the project in question, to enable evaluation of benefits over multiple objectives (Kleinmuntz, 2007). This affords the decision process a structure for diverse types of information and a systematic and repeatable process for evaluating alternatives with respect to goals (Keeney & Raiffa, 1976).

Whereas previous decision models to support energy R&D evaluate investment alternatives in terms of high level, fundamental objectives (e.g., to optimal cost of emissions abatement (Baker & Solak, 2011), economic and social welfare (Blanford, 2009), quantity of emissions reduction (Pugh et al., 2011)), it is more appropriate for the Division of CCS R&D to align funding and define value with respect to strategic goals. The office does not promote one particular CCS technology pathway over another, but seeks to develop a suite of technologies suitable for introduction into the marketplace, and therefore, are concerned with balanced progress in addition to total progress overall. Rouse and Boff (2001) define value of R&D in terms of readiness for transition, productivity, and innovation. A particularly poignant elaboration they make is that “value implies relevance, usability, and usefulness” as assessed by the beneficiaries of the R&D outcomes. For the case of CCS R&D resource administration, it is appropriate to use similar intermediate, or means, objectives (see Keeney (1992) for means versus fundamental objectives); evaluating the technological modes for capturing carbon by the extent to which they are ready to be deployed in the market place, can be integrated into existing utility infrastructure, and have an attractive cost/tonne of carbon captured. Collapsing these multiple dimensions of benefit into a single value function (Phillips & Bana e Costa, 2007) enables the formulation of an optimization model to identify resource allocations that maximize the aggregated dimensions.

The decision hierarchy for CCS R&D warrants the use of portfolio-level metrics to support strategic planning; the Office of CCS R&D administers funds to portfolios of projects, leaving NETL to further distribute them to individual R&D projects. Montibeller, Franco, Lord, and Iglesias (2009) describe a framework for structuring multi-criteria portfolio models that deal with area-grouped options and Montibeller and Franco (2011) discuss the utility of multi-criteria decision analysis in facilitating the process of strategy development. However, the literature has not yet moved from decisions on individual projects to how to manage overall portfolios more effectively (Kester, Griffen, Hultink & Lauche, 2011). Kloeber (2011) notes that portfolio-level metrics can provide information that would otherwise be overlooked especially with respect to strategic goals. Examples from the oil and pharmaceuticals industries provide evidence that aggregated performance of a portfolio is a better measure of success of a firm's R&D strategy (Reinsvold, Johnson, & Menke, 2008; Evans, Hinds, Hammock, 2009). Burk and Parnell (2011) call attention to the challenge of calculating portfolio value and point to the approach used by Parnell et al. (2004) in which sets of projects are scored with respect to value measures, as defined by a value model. Using a similar approach, this study evaluates resource allocation alternatives with portfolio-level attributes that distinguish them each other.

4. Portfolio Decision Analysis Model Development

A PDA model is developed to represent the salient characteristics of the DOE CCS R&D decision problem and is designed to support strategic planning for resource allocation, especially for the purposes of budget justification and allocation readjustment in reaction to external drivers that impact total budget. The underlying assumption and mechanism for the PDA is that each pathway has some inherent value to the DOE which can be expressed as a set of attributes and that the model user has the ability to assess technology pathways with respect to these attributes. Further, it is assumed that decision makers have an equal interest in the attributes and prefer more of each attribute to less.

4.1 Multiattribute Value Function

CCS R&D objectives are defined as a set of attributes and implemented in the model such that pathways are evaluated with regard how they advance the program toward its objectives. The attributes are described in Figure 1. Pathway Aggregated TRL is used as an initial maturity state for a funding cycle. A new TRL, produced by the model (i.e., at t=1), represents progress made from the initial state according to a monotonic increasing function of the funding allocation to R&D activities. Applicability and impact are attributes that are normalized and essentially scale the relative value of investing in the different technology pathways for reducing carbon pollutions. While each attribute is of equal value; i.e., a pathway does not have any value if it is lacking a score for one attribute, the normalized scalar attributes are multiplied by the pathway aggregated TRL so that the model output is on the TRL scale. Total programmatic value, in turn, is the summation of the value of all of the pathways.

Attribute	**Description**
Pathway Aggregated Technology Readiness Level (TRL)	The NETL-assessed TRLs for the projects that comprise each pathway are aggregated (by averaging) into a single value. *Pathway Aggregated TRL* is used as an initial maturity state from which funding will advance readiness according to a user-defined "progress function"
Applicability to Fleet	The user scores technology pathways based on how applicable the fully developed technology is expected to be to existing and/or future electric utility infrastructure, expressed as percent of the fleet to which a technology can be applied
Cost Impact	The user scores technology pathways based on how much impact the fully developed technology is expected to have reducing the cost of capturing a tonne of CO_2, expressed in the reduction of dollars to capture 1 tonne of CO_2 (check this)

Figure 9 Portfolio-Level Attributes

4.2 Building Progress Functions

Technology areas advance through readiness (TRL) milestones via processes that comprise unique production functions and, in the absence of a priori functions that relate R&D progress and resource input, expert elicitation is important for mapping expected change. For each technology pathway, experts build a function that describes the progress that they anticipate can be made as a result of funding. Because a primary purpose of the tool is to support budget readjustment, the process of building the progress functions is framed as a budget increase/decrease scenario. The user defines an "Expected"/ "Historical" allocation for each pathway and the progress functions are built based on percentages of this allocation where the "Expected"/ "Historical" represented the 100% of funding scenario. The user estimates the progress, in terms of TRL, that will be achieved by each level of funding. In this way, they build a piecewise linear function where the slope of each segment represents the expected cost effectiveness of an R&D investment; the greater the slope between two points, the lower the expected cost of advancing the technology from the first TRL to the second. The inclusion of the continuous functions results in a model that resembles a marginal analysis.

4.3 Model formulation

The benefits of investing in R&D are evaluated with a multiattribute value model, comprised of portfolio-level attributes, and is subsequently used as the objective function for mathematical optimization model. The model is formulated as follows:

Maximize

$$V = \sum_{i=1}^{n} w_i f_i(x_i)$$

Subject to

$$\sum_{i=1}^{n} x_i \leq X$$

$$x_i \geq 0$$

Where

$$f_i(x_i) = \sum_{j=1}^{m} c_j x_{i,j}$$

$$w_i = \frac{a_i \cdot b_i}{\sum a_i \cdot b_i}$$

$$x_i = \sum_{j=1}^{m} x_{i,j}$$

The following indices are use:

i = index of technologies pathways 1…n where n is the number of pathways

j = index of segments of piecewise linear progress functions 1…m where m is the number of segments

The decision variable is:

x_i = funding allocation ($) to each technology pathway, changed to maximize the objective function V

The following model parameters are used:

a_i: expected applicability of technology pathway (% of fleet)

b_i: expected impact of technology pathway on reducing the cost of capturing CO_2 ($/tonne)

c_i: slope of progress function segments

Resource constraints:

X = total funding available for allocation to pathways ($)

4.4 Time Step

The DSS time step represents one funding cycle. The initial maturity state of the pathways must be reset for each new funding cycle because, at the pathway level, aggregated TRL does not necessarily increase continuously over its R&D lifespan. This is because funds that are designated for a particular technology pathway are further allocated among a dynamic set of projects that research and develop components of the technology system and that varying in maturity stage. For a particular funding cycle, a pathway R&D program might continue incremental improvements of a relatively mature system component and initiate a set of immature, yet potentially revolutionary bench-scale projects, yielding a lower aggregated TRL score than in a previous funding cycle.

4.5 Optimization Method

The optimization methodology used with the PDA model will be case specific. The piecewise linear formulation is an artifact of how the progress functions are built but a piecewise linear optimization method will not necessarily be best for every case. This is because it can be assumed that the functions are monotonic increasing, but not that they are always convex. The sophistication of an evolutionary algorithm makes it an appropriate method because it will accommodate variable function shapes.

5. Case Study Application: Post-Combustion Carbon Capture

5.1 Scenario Description

The model was applied for the post-combustion carbon capture R&D program which pursues three technology pathways: solvent, sorbent, and membranes. In order to compare model-supported with non-model supported resource allocation, the DSS is populated with stylized inputs and applied for a budget decrement scenario.

Initial TRLs as of October 2012 (2013 Technology Program Plan Appendix B) are averaged to yield an initial readiness state for each pathway (Figure 2).

A progress function which anticipates the relationship between TRL advancement and R&D investment is defined for each pathway is by stylized expert judgement. For the case study, the post-combustion carbon capture R&D budget for the last fiscal year was ninety million dollars which they distributed as follows: solvents, thirty million; sorbents, forty five million; and membranes, fifteen million. The model user enters the expected TRL that would result from investing 70%, 85%, 100%, 115%, and 130% of the historical allocation (Figure 3). Figure 4 displays the progress functions that results from plotting funding allocation and progress in terms of TRL.

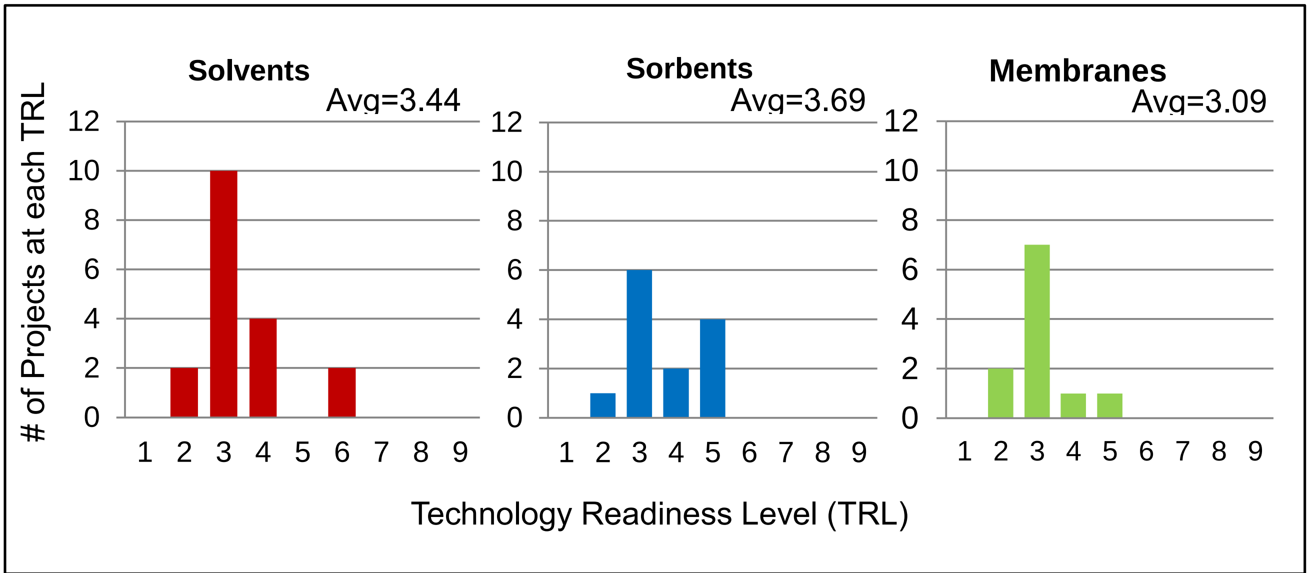

Figure 10 Histograms of Project TRLs in R&D Pathways

		Expected Allocation	Funding Scenarios, Percent of Expected Allocation 70%	85%	100%	115%	130%
Solvents	*Funding ($M)*	30.00	21.00	25.50	30.00	34.50	39.00
	Aggregated TRL	3.44	3.46	3.50	4.00	4.50	4.60
Sorbents	*Funding ($M)*	45.00	31.50	38.25	45.00	51.75	58.50
	Aggregated TRL	3.69	3.80	4.90	5.40	5.80	6.00
Membranes	*Funding ($M)*	15.00	10.50	12.75	15.00	17.25	19.50
	Aggregated TRL	3.09	3.09	3.50	3.80	4.00	4.00
	Total Budget ($M)	90.00	63.00	76.50	90.00	103.50	117.00

Figure 11 Stylized Expert Elicitation for Building Progress Functions. Table cells in light blue are for user inputs

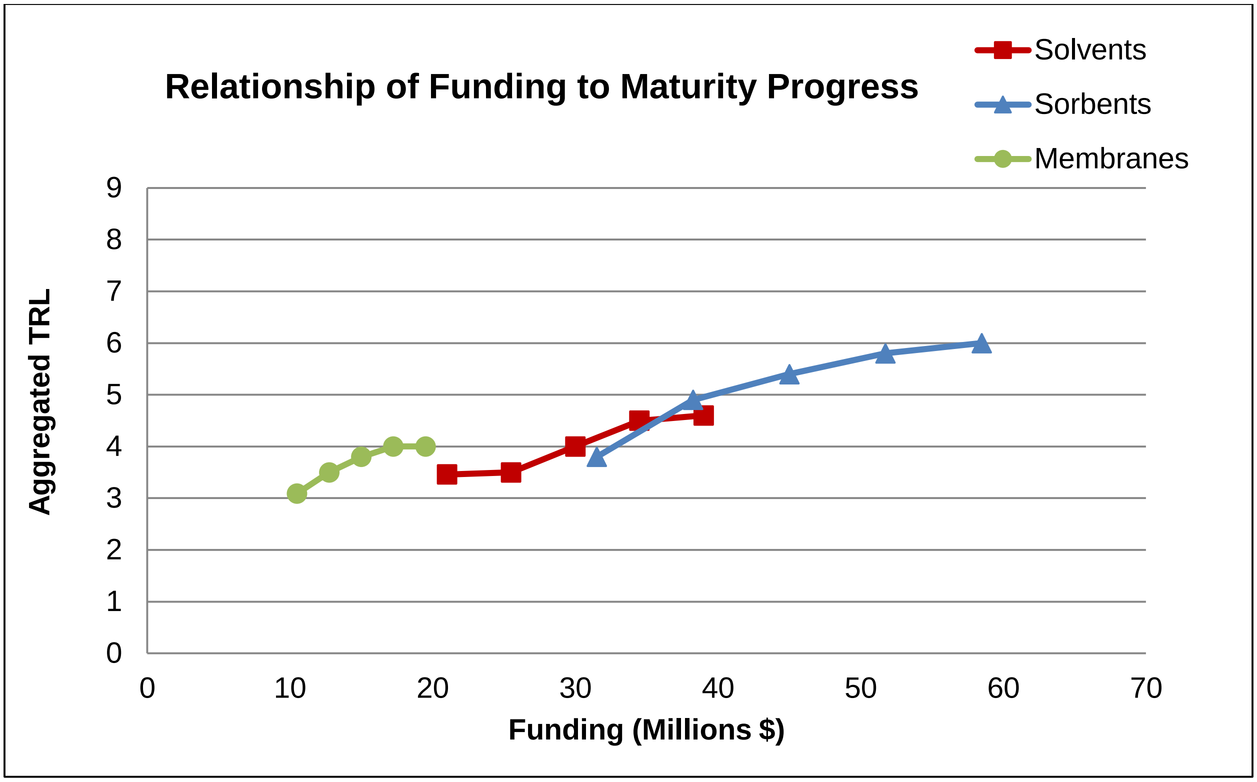

Figure 12 Stylized Progress Functions for CCS R&D Technology Pathways

Pathways are scored based on expert expectations for fully developed systems of technologies. The 2013 Clean Coal Research Program Carbon Capture Technology Program Plan (NETL, 2013) lays out the targets for technology contributions to cost-of-capture goals. For example, meeting the target for post-combustion capture in new plants to $40/tonne of CO_2 by 2025 requires a $17/tonne reduction. Cost impact is assessed in dollars/tonne and applicability in percent of relevant fleet.

	Cost reduction ($/tonne)	Applicability (%)
Solvents	6.00	30%
Sorbents	9.00	10%
Membranes	5.00	70%

Figure 13 Cost Impact and Applicability Scores used in Stylized Case Study Model Application

5.2 Model Implementation

The budget decrement scenario is implemented by running the model for the historical budget ($90M) and a twenty percent budget cut ($72M) to observe how the model reconfigures resource allocation to maximize value, or minimize the value that is lost as a result of the decrement. In addition to illustrating the difference in expected value generated by optimized and non-optimized resource allocation, a Pareto frontier is generated by optimizing allocations for multiple budgets.

The model is implemented in Microsoft Excel with the evolutionary algorithm from the Solver add-in to optimize allocation of resources based on value model inputs. Inputs are easily changed in the tool's user-friendly interface, which facilitates rapid scenario testing, as well as adaptive planning as the state-of-the-art technologies progress through higher generations of the technologies.

5.3 Case Study Results

The expectation for the tool is that, if the overall budget is changed, funding allocation to the technology pathways will be rearranged such that the greatest possible progress, or value, can still be achieved. Explicitly funding the most value-generating options results in expected outcomes that would not necessarily be accomplished by equally distributing the change among pathways.

5.3.1 Value generated in budget decrement year

For the case study, the office is issued a twenty percent decrement for the new fiscal year as opposed to the previous one. The office's options for reallocating funds to technology pathways include equally distributing the eighteen million dollar cut among the three pathways or inform their reallocation with an optimized solution. Figure 6 shows the budget readjustments using the two methods and figure 7 displays the value that the respective levels of funding are expected to be achieved. The magnitudes of the value generated illustrate that PDA with optimization can help identify funding configurations that diminish the overall impact of the budget decrement. Significantly, equally distributing the cut results in 79% of historical allocation value whereas an optimized distribution results in less disturbance, maintaining 94% of historical allocation value.

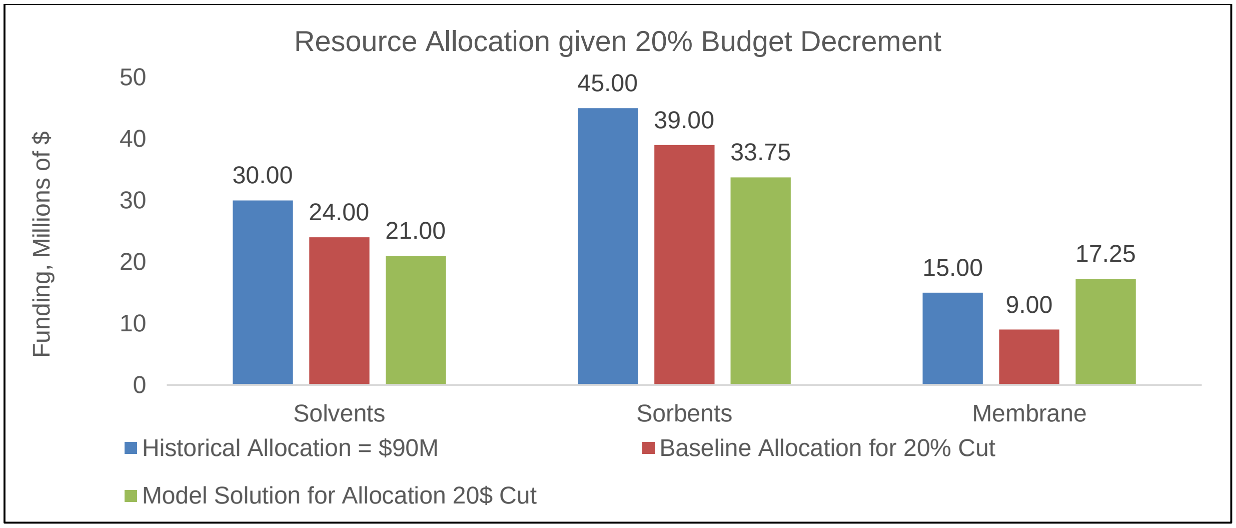

Figure 14 Resource Allocation to Pathways for Historical Budget, Equally Distributed Baseline Cut, and Model Optimized Cut

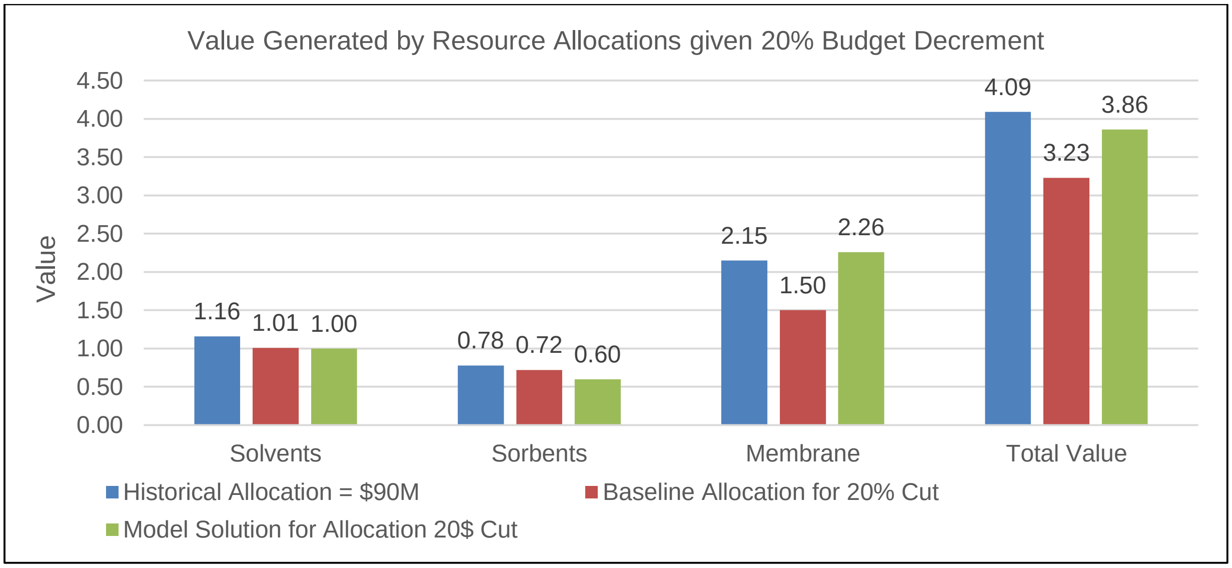

Figure 15 Expected Value Generated as a Result of Resource Allocation Configurations

5.3.2 Pareto frontier of resource allocations

Plotting the expected value generated by the optimized resource allocations for multiple budget scenarios yields a Pareto frontier (Figure 8). Viewing the optimized allocations for multiple budget scenarios is can provide insight into how value generation changes depending on the magnitude of funding and coinciding expected progress. For example, it is more value generating to fund sorbents up until the point where solvent marginal returns begin to exceed that of sorbets. When the total budget can accommodate the amount required to progress the solvent pathway, the model reconfigures allocations to that pathway and away from sorbents.

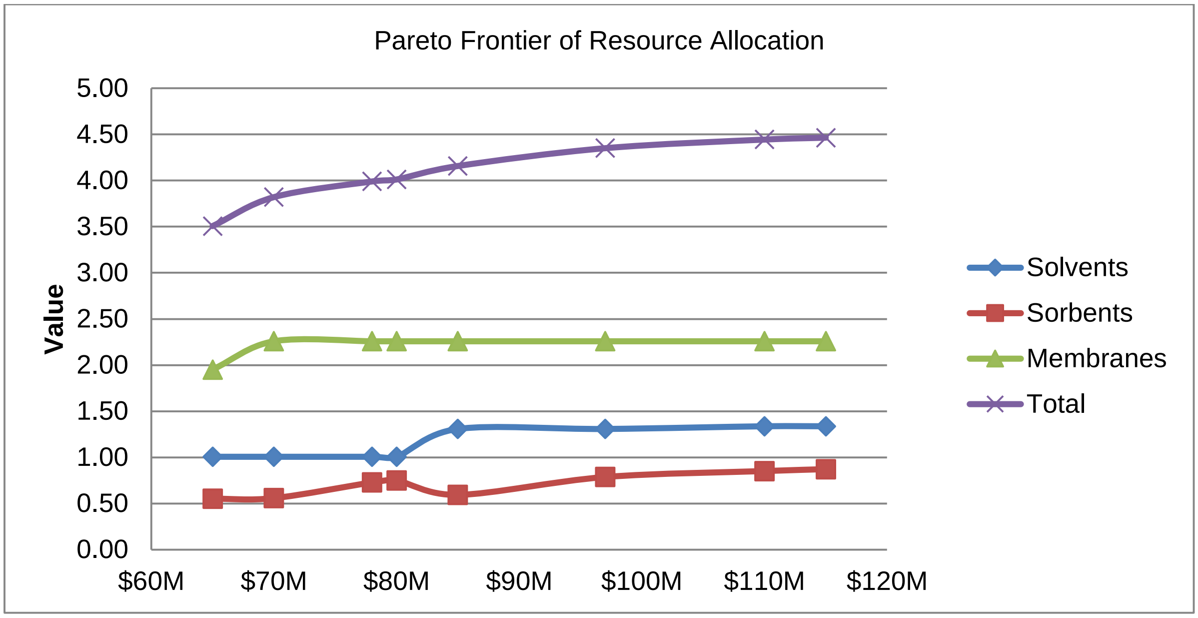

Figure 16 Optimal Allocations for Various Budget Scenarios

6. Discussion and Conclusions

The task faced by the US DOE R&D to lead the country's energy system transformation is challenging, particularly due to technical complexity and uncertainty and ever-changing external factors. The field of decision analysis has well established methods for supporting decision making under uncertainty and can benefit DOE management because it 1) provides a structure for the layers of information that comprise cognitively challenging analytical tasks; 2) is well suited for integrating technical information and expert judgment into a common framework; 3) is transparent and therefore supports accountability checks and decision justification; and 4) enables users to experiment with hypothetical scenarios.

In this study, a decision support system is developed for the DOE Office of Fossil Energy's Carbon Capture and Storage R&D program to support R&D funding allocation to technology pathways. Pathways are essentially portfolios of projects that advance a particular technology system and are evaluated in this study with portfolio-level attributes to suit the strategic planning purview of decision makers.

Progress functions form one attribute in a multiattribute value function and leverage available data on technology transition milestones and expert judgement about the cost of transition. Milestone data, or technology readiness level (TRL), is an increasingly common metric used in government and private industry and can be made actionable in R&D settings by mapping TRL advancement with time or cost predictions. The marginal progress functions are scaled with attributes that represent other critical considerations. The structure of this analysis and flexible design make the model broadly applicable to resource allocation decision making.

The PDA model is applied to a stylized case of post-combustion carbon capture R&D and run for multiple budget scenarios. As the overall budget is changed, funding allocation to the technology pathways is rearranged such that the greatest possible progress, or value, is achieved. The results demonstrate that, as opposed to equal distribution of a budget change among technology program areas, explicitly funding the most value-generating options results in greater expected research and development progress. Visualizing multiple budget scenarios provides insights that will benefit strategic planning and iterative budget passback with the Office of Management and Budget.

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