A Portfolio Decision Analysis Approach to Support Energy Research and Development Resource Allocation

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Abstract

Research sponsored by the US Department of Energy (DOE) aims to facilitate a clean and independent energy future for the nation. Strategic planning for energy research and development (R&D) can be complex and dynamic, in part due to federal budgetary constraints and volatility. Managing R&D funding to advance energy technologies, in spite of these challenges, is a crucial component of the nation's long term energy policy. This study demonstrates a portfolio decision analysis (PDA) approach to support R&D resource allocation decisions for the DOE Office of Fossil Energy's Carbon Capture and Storage R&D program. A multi-attribute value model uses technology readiness levels (TRLs) and other metrics to represent the overall objectives of the R&D program in order to evaluate alternative research portfolios given limited funding. Mathematical optimization identifies efficient funding allocations for each technology program area to maximize the multi-attribute value generated from the total budget. This is especially useful for responding to externally imposed budget

changes. As the case study demonstrates, explicitly funding the most value-generating options leads to greater expected R&D programmatic value than typical strategies of equal or proportional distributions of a budget change among technology program areas.

Keywords: Portfolio Decision Analysis (PDA), Research and Development (R&D), Technology Readiness Level (TRL), Multi-Attribute Value Model

1. *Introduction*

The Presidential Climate Action Plan, released in June 2013, sets the groundwork for plans to abate the country's contribution to anthropogenic climate change and achieve greater energy independence (Executive Office of the President [EOP], 2013). The US Department of Energy (DOE) is responsible for conducting research and development (R&D) that will, in combination with carefully crafted policy, drive the nation to meet its aspirational clean energy goals (Anadon, Chan, & Lee, 2014; Folger, 2013). Government R&D has the ability to catalyze the development of second generation and breakthrough technologies; 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 of new technologies will occur in the current power generation market (Folger, 2014). However, the characteristics of newly emerging and yet-to-be-discovered technologies that make them more suitable for government R&D are some of the same factors that confound decisions about R&D prioritization. Specifically, the DOE and other government agencies sponsor exploration of technologies where market failures and high risk prevent private sector investment, and where

payoffs exist primarily in the realm of shared social benefits (Anadon et al., 2014), factors which obfuscate the links between R&D investment and eventual quantifiable benefit.

DOE offices that administer R&D programs face these challenges in their strategic planning, which involves predicting budgetary needs and engaging in the iterative congressional budget process (Heniff, 2008). Strategic planning for R&D is concerned with allocating finite resources among portfolios of projects and partnerships that will advance a suite of technologies suitable for introduction into the marketplace, balancing progress between technologies with progress across the overall portfolio. A decision support tool can benefit DOE management given the volatility of external influences and necessity to plan for potential programmatic readjustment.

The history of R&D budget decision making at DOE includes periodic attempts to employ systematic budget planning, such as by tying funding levels to estimated benefits, but these attempts have 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 problem and further, it affords decision makers a way to leverage diverse sources of information and expert judgment. Portfolio Decision Analysis (PDA), as summarized by Salo, Keisler & Morton (2011), augments traditional decision support methods such as financial portfolio management and capital budgeting tools with techniques from decision analysis and operations research. The appropriateness of decision-analytic methods for developing an effective R&D strategy to meet US energy goals was 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 (Baker & Clarke,

2011). A special issue in Energy Policy on defining robust energy R&D portfolios, further articulates this need and highlights the research response to the workshop (Baker, Bosetti, and Anadon, 2015).

The present study contributes to the community's effort to develop energy technology portfolio analyses that support current and pressing energy decisions. A PDA model (PDAM) is developed and demonstrated for the carbon capture and storage (CCS) R&D allocation efforts that are administered by the DOE Office of Fossil Energy (DOE/FE). DOE/FE is currently exploring a wide range of approaches to CCS to make short-term incremental cost improvements as well as long-term transformational scientific advances (National Energy Technology Laboratory [NETL], 2013). R&D resource allocation for CCS technologies presents a complex and dynamic decision problem due to a finite budget, inherent risks from 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 streamline progress towards national goals. Our case study illustrates how PDA methods can advance DOE R&D resource allocation decision making and support strategic planning, especially for the purposes of budget justification and allocation readjustment in response to external drivers that impact total budget.

2. Background and Literature Review

The DOE/FE CCS R&D program administers resources among systems of technologies that are needed to successfully reduce carbon emissions from the heterogeneous fleet of fossil fuel fired utility infrastructure. CCS technology has been designated as an important component of the national carbon management agenda for a number of reasons. First, conventional

pulverized coal-fueled plants comprise a substantial portion (40%) of the country's electricity generation and, as a result, account for 35% of US CO₂ emissions (Office of Fossil Energy, n.d.). Thus, there is tremendous potential to impact the nation's contribution to the rising concentration of greenhouse gases in the atmosphere by addressing these emissions. 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 the United States and elsewhere due to its low cost and wide distribution globally ("The Future of Coal", 2007). Lastly, 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 throughout the transition in a reliable and affordable fashion (EOP, 2013).

The challenge of how to allocate finite resources is well known in business and government, as well as widely addressed in the operations research and management science communities that seek to develop improved decision making approaches and decision support systems, e.g., with methods ranging from dominance sets (Augeri et al., 2011) to simulation based optimization (Lee, Chew and Manikam, 2006) and in areas ranging from counterterrorism (Haphuriwat and Bier, 2011) to healthcare (McKenna et al., 2010). 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 making decisions in the face of multiple objectives are long 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. The following paragraphs highlight the relevant theoretical support for the DSS developed in this study and previews its connection to the CCS R&D model application. The elements that are integral to the model are decision analysis, technology forecasting, and portfolio level performance metrics.

Similar to financial portfolio investments, CCS R&D strategic resource planning allocates a limited budget among portfolios of technologies with the expectation of potential reward in exchange for investment risk, 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 decisions are also motivated by non-financial factors and, in turn, also generate non-monetary value. Adapting traditional portfolio management tools with decision analysis methods can enable a more flexible and sophisticated process (Duncan & Merrick, 2011). This is because decision analysis offers methods to expand the definition of value to include multiple domain-specific (and often non-monetary) attributes that influence decisions (Fernholz, 2011).

Growing concern about climate change has increasingly motivated researchers to take up the question of how government funding for energy technology R&D should be allocated. Whereas previous decision models to support energy R&D evaluate investment alternatives in terms of high level, fundamental climate objectives (e.g., to optimal cost of emissions abatement (Baker and 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 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 and Bana e Costa, 2007) enables the formulation of an optimization model to identify resource allocations that maximize the aggregated dimensions.

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. The DOE R&D implementation arm, 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 1970s, 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 alone have limited utility in R&D project or program management, as they are essentially snapshots of the state of the program, without

any concept of progress over time (Olechowski et al., 2015). Investment decisions for technology R&D can be better supported by forecasting the technological change that will be driven funding (Garcia & Bray, 1997). Models have emerged that do just that; introducing transition variables that capture the time or cost required to move technologies 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. For example, Baker, Chon, and Keisler (2009) rely on expert elicitation to understand how different funding scenarios for CCS R&D will impact marginal abatement cost curves. The PDAM developed for the Division of CCS R&D leverages TRL data as an initial state from which experts must anticipate technological progress as a result of resource allocation to R&D.

A further 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 National Energy Technology Laboratory (NETL) further distributes and discriminates funding between individual R&D projects within a pathway. The decision for the Division of CCS R&D is not which efforts to fund but at what level to fund each.

A PDAM with portfolio-level metrics is therefore best suited for CCS R&D strategic planning. 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 multi-attribute value model. Using a similar approach, this study evaluates resource allocation alternatives with portfolio-level attributes that distinguish portfolio alternatives from one another.

While the case of CCS programs is itself of relevance, the challenges in this case meet a gap in the literature. A common PDA approach to R&D defines specific technical hurdles to reaching defined endpoints and obtains expert judgments about the probability that R&D will overcome those hurdles as well as relates these specific technical achievements to societal value for that progress. In the case here, however, the decision maker is necessarily removed from the management details of the particular R&D areas and is unable to apply PDA in that way. The TRL is a potentially useful and established concept for characterizing – at a distance – technology developments, but is used more as a monitoring device rather than as a basis for resource allocation. This naturally raises the engineering research question of how these concepts might be combined, and the empirical question of whether such a combination is practical and productive.

The first question is resolved by the definition and implementation of the model in sections 3 and 4. Our innovation here is in the modeling phase of mapping from the real-world

problem to the formal representation, in this case to incorporate of TRL measures within the PDA framework. This facilitates straightforward application of optimization techniques. The R&D areas, for which funding is to be determined, are characterized in terms of an initial TRL and the potential advancement on the TRL during a funding cycle. In order to realize this combined TRL/PDA approach, the TRLs are structured so as to facilitate (1) judgments by available experts, (2) computation of an overall multi-attribute value function for the program based on decision maker judgments, and consequently (3) solution and analysis with mathematical programming. With these structures defined, actual elicitation of judgments about prospects and values can follow standard decision analytic procedures. A preliminary answer to the empirical question is provided by comparing the type of model produced against reasonable criteria: Does it (1) capture essential features of the problem; (2) require inputs that are amenable to provision by the decision makers; and (3) result in a method that is no more complex to use than necessary to gain guidance about action? The final section of this paper includes such a qualitative evaluation of the model and its product.

3. PDAM Model Development

A PDAM is developed in coordination with US Department of Energy CCS R&D management to serve their decision-making structure and challenges. This joint approach for developing decision support is key to overcoming the gap that often exists between analysts and decision-makers (Baker & Clarke, 2011). Effectively supporting resource allocation necessitates a model that accurately represents the salient characteristics of the decision problem and defines measures in a way that facilitates assessment of benefits of investment by experts (Bresnick, Johnson, & Parnell, 2013). The PDAM that emerged from our coordinated efforts is therefore

integrated with its application but is designed with the intent of expanding the scope beyond that of the case study and can also be adapted to other resource allocation decisions.

A multi-attribute value function that describes the expected benefit of investment drives the PDAM and is formulated so that mathematical optimization can be implemented to identify funding allocations that maximize total value for a given budget. Mostly notably, the value function contains a continuous term for technological progress as a function of funding, which is built by expert technology forecasting, and introduces resemblance of the PDAM to marginal analysis. Further, the tool is designed such that resource allocation alternatives are evaluated with portfolio-level attributes that distinguish the alternatives from one another. The tool provides a structure for diverse types of information that need to be included in resource allocation decisions and a systematic and repeatable process for evaluating alternatives with respect to goals.

3.1 Defining a Multi-Attribute Value Model

The underlying assumption and mechanism for the PDAM is that each pathway has some inherent value to the DOE which can be expressed as a set of attributes and that the 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. For the PDAM, a set of attributes is defined to represent specific CCS R&D objectives such that the technologies can be evaluated on how it performs with respect to each goal (Table 1).

3.1.1 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 can estimate the progress, in terms of TRL, that will be achieved by each level of funding. Leveraging this, the model includes 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 (Table 2 & Figure 1).

3.2 Model Formulation

The benefits of investing in R&D are evaluated with a multi-attribute 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:

$$V = \sum_{i=1}^n w_i \sum_{j=1}^m c_j x_{i,j} \quad (1)$$

Subject to:

$$\sum_{i=1}^n x_i \leq X, x_i \geq 0, \quad (2)$$

where

$$w_i = \frac{a_i \cdot b_i}{\sum a_i \cdot b_i} \quad (3)$$

$$x_i = \sum_{j=1}^m x_{i,j} \quad (4)$$

The following indices are used:

i = index of technologies pathways $1 \dots n$ where n is the number of pathways

j = index of segments of piecewise linear progress functions $1 \dots m$ 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 CO₂ (\$/tonne)

c_j : slope of progress function segments

Resource constraints:

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

3.2.1 Time Step

The model's 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 vary 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.

3.2.2 Optimization Method

The optimization method used with the PDAM is selected on practical considerations. A piecewise linear formulation was used for the monotonically increasing progress functions but since these are not necessarily convex, piecewise linear optimization may not suffice. An evolutionary algorithm, used here, is more able to accommodate variable function shapes.

4. Case Study Application: Post-Combustion Carbon Capture

The PDAM was applied for the post-combustion carbon capture R&D program, which pursues three technology pathways: solvents, sorbents, and membranes. In order to compare model-supported with non-model supported resource allocation, the case is prepared with actual initial readiness levels along with stylized judgment inputs for the progress functions (Table 2 and Figure 1). These readiness levels (TRLs) are periodically established by DOE for each active project, through a systematic assessment process that is based on the scale, degree of system integration, and test environment in which the technology has been successfully demonstrated. TRLs published by NETL in the 2013 Clean Coal Research Program Carbon Capture Technology Program Plan (NETL, 2013) were used for case study application of the PDAM. The initial TRLs for building the progress functions are averages of the projects in each pathway. As of the NETL publication, there were 18 solvent projects (average TRL 3.44), 13 sorbent projects (average TRL 3.69), and 11 membrane projects (average TRL 3.09).

In practice, experts will build similar progress functions by predicting how R&D will proceed and will score pathways based on how they expect fully developed systems of technologies to perform. 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 of \$40/tonne of CO₂ by 2025 requires a \$17/tonne reduction. Cost impact is assessed in dollars/tonne and applicability in percent of relevant fleet (e.g., the percent of total coal fuel power plants where the capture technology can be applied). In this case study, estimation for the parameters, i.e., TRL progress functions, scores for applicability, and cost impact, are hypothetical and intended only for proof-of-concept demonstration.

4.1 Model Implementation

A budget decrement scenario is implemented by running the model for the historical budget (here, \$90M) and a twenty percent budget cut from the historical (down to \$72M) to observe how the model reconfigures resource allocation to maximize value, or minimize the value that is lost as a result of the budget decrement. In addition to illustrating the difference in the 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. Spreadsheets are formatted for easy data entry, facilitating rapid scenario testing, as well as adaptive planning as the state-of-the-art technologies progress through higher generations of the technologies.

5. Results and Discussion

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 overall 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 – or even proportionally – distributing the change among pathways.

For the case study, a twenty percent decrement to the previous year's CCS R&D budget was imposed for the new fiscal year. The Division's options for reallocating funds among the technology pathways include distributing the eighteen million dollar cut in a "fair" manner, i.e., as equal amounts or similar simplistic rules such as equal percentages (not analyzed here) for each pathway, or in a more sophisticated manner, such as with an optimized solution. Figure 2 shows the budget readjustments using the two methods and Figure 3 displays the value that the respective levels of funding are expected to be achieved.

Both the historical allocation and the 20% budget cut are shown to be inefficient in comparison to the optimized model solution that identifies the funding configuration that maintains the greatest possible expected value. As opposed to a "fair" cut across all pathways, the model suggests cuts even greater than 20% for sorbents and solvents in order to increase funding over the baseline for membranes (Figure 2). In the case study, membranes are at a point in the readiness-to-cost curve (progress function) where additional funding can most increase total programmatic value.

Figure 3, when interpreted in conjunction with Figure 2, shows the cost-benefit trade-offs of different budget changes in terms of the total value provided. For example, in the "fair" scenario, solvents receive a six million dollar cut from the historical allocation, resulting in a 0.15 loss of value units. However, the PDAM suggests that cutting the solvent budget by three million dollars more than in the "fair" scenario would only result in 0.01 additional loss of value units, or very little value loss for a substantial amount of money that could be reallocated elsewhere. In the case study, additional money removed from solvents and sorbents is

reallocated to membranes to increase membrane funding by two and a quarter million dollars over the baseline, resulting in an increase in membrane value of 0.11 above that achieved by the historical budget scenario. The magnitudes of the value generated illustrate that PDAM 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 retains 94% of historical allocation value.

5.1 Pareto frontier of resource allocations

Examining the optimized allocations for multiple budget scenarios, or the Pareto frontier (Figure 4), in which each budget scenario is plotted against the portfolio that provides more expected value than any other portfolio of equal or less cost. It 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 sorbents. When the total budget can fulfill the resource requirement to advance the solvent pathway, the model reconfigures allocations to fund that pathway and away from sorbents.

5.2 Variance Term

The model we describe could be extended to include an attribute for risk and TRL balance, additional concepts that are often important for challenging R&D decisions. Including the expected variance of the total value generated would be one means for incorporating decision-maker risk attitudes in portfolio composition that is not otherwise captured. A decision-maker might, for example, prefer to allocate funds in a manner that would accelerate the development of the most mature technology pathway to increase the probability that it will succeed or, alternatively, to fund a technology portfolio that has a full range of maturity levels.

Further, particularly in the presence of deadlines and organization pressures, it is important to consider the implications and tradeoffs of under and over performance. Representing risk in the model with a simple measure of variance performance is similar to the classic Markowitz mean-variance approach, or quadratic loss measure. Risk of investment can be combined with expected benefit of investment to create a risk adjusted score for a given funding allocation plan.

6. Conclusions and Policy Implications

The task faced by US DOE R&D to lead the country's energy system transformation is challenging, particularly due to technical complexity, uncertainty about R&D outcomes, and ever-changing external political and funding factors. The field of decision analysis has well established methods for supporting decision making under uncertainty and can benefit DOE management. It provides a structure for the layers of information that comprise cognitively challenging analytical tasks and is well suited for integrating diverse technical information and expert judgment into a common framework. Additionally, decision analysis as a discipline seeks approaches to facilitate a transparent and repeatable decision-making processes, which support accountability checks and decision justification. This is important, both internally, as agency-governed R&D efforts compete for resources, and externally, due to the nature and source of the funding at stake.

The approach developed here shows promise to be sufficiently insightful, simple and feasible. The modeling structure requires judgments and data that seem practical for program managers to provide. While technical project characteristics and complex internal and external interactions are excluded, the model nonetheless provides practical guidance of direct relevance on the decisions faced by program management.

In this study, a decision support system (DSS) is developed for the DOE Office of Fossil Energy's Carbon Capture and Storage (CCS) 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 CCS decision makers. Progress functions form one attribute in a multi-attribute value function and leverage available data on technology transition milestones, or TRLs, and expert judgment about the cost of transition. The marginal progress functions are scaled with attributes that represent other critical considerations. Although the model and the case study application are integrated, the structure of this analysis and flexible design make the model broadly applicable to resource allocation decision making.

The DSS, which takes the form of a portfolio decision analysis model (PDAM), is applied to a stylized case of post-combustion carbon capture R&D, a system of technologies that is actively being pursued by government funded R&D. The model is run for multiple budget scenarios and, 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 simplistic distribution of a budget change among technology program areas, explicitly funding the most value-generating options results in greater expected research and development progress. Given the history of volatile funding to DOE R&D and the necessity to redistribute funding at various points in the cycle, the result that greater expected benefits are yielded by differentially funding technologies is not trivial and does represent a break from typical budget readjustment processes.

Improved coordination of R&D funding is key to crafting the transition of the nation's energy system. The distinguishing characteristics of the case study are clearly present in but are

not unique to energy R&D; strategic planning is concerned with funding portfolios of projects of all types and must balance progress between systems of technologies with progress across the overall portfolio. Further, milestone data, such as TRLs, have become commonplace metrics in government and private industry for evaluating the state of individual technologies. This information needs to be made actionable in for an R&D setting by mapping TRL advancement with time or cost predictions, so that decision can be based on the trajectory of technologies toward market readiness. The PDAM facilitates expert forecasting of R&D trajectories, as well as expected impact when deployed, so that the model-identified funding levels are driven by how advancement can be made toward maturity.

Acknowledgements

This work was funded by the Office of Fossil Energy, US Department of Energy. Permission was granted by authority of the Chief of Engineers, US Army Corps of Engineers to publish this material. The views and opinions expressed in this paper are those of the individual authors and not those of the US Army, or other sponsor organization.

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Tables and Figures

Table 1. Portfolio-Level Model Attributes.

Attribute	Description
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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. <i>Pathway Aggregated TRL</i> 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

Table 2. Stylized Expert Elicitation for Building Progress Functions

			Funding Scenarios, Percent of Expected Allocation				
		Expected Allocation	70%	85%	100%	115%	130%
Solvents	<i>Funding (\$M)</i>	30.00	21.00	25.50	30.00	34.50	39.00
	<i>Aggregated TRL</i>	3.44	3.46	3.50	4.00	4.50	4.60
Sorbents	<i>Funding (\$M)</i>	45.00	31.50	38.25	45.00	51.75	58.50

<i>Aggregated TRL</i>		3.69	3.80	4.90	5.40	5.80	6.00
Membranes	<i>Funding (\$M)</i>	15.00	10.50	12.75	15.00	17.25	19.50
	<i>Aggregated TRL</i>	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

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” represents the 100% of funding scenario. Table cells in light blue are for user inputs.

Figure 1 Stylized Progress Functions for CCS R&D Technology Pathways.

Table 3 Stylized Cost Impact and Applicability Scores used in Case Study Model.

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

Figure 2 Resource Allocation to Pathways for Historical Budget, Equally Distributed Baseline Cut, and Model Optimized Cut.

Figure 3

Expected Value Generated as a Result of Resource Allocation Configurations.

Figure 4 Optimal Allocations for Various Budget Scenarios.