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An Examination of the Decision Analysis Approach to R&D Portfolios

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AN EXAMINATION OF THE DECISION ANLALYSIS APPROACH TO R&D PORTFOLIOS

A Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University.

by

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Abstract

AN EXAMINATION OF THE DECISION ANLALYSIS APPROACH TO R&D

PORTFOLIOS

By Kelly J. Duncan

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University.

Virginia Commonwealth University, 2009

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A portfolio can be defined as “a purposeful combination of items” (Chien and Sainfort 1998). As the topic relates to research and development (R&D) the items in question are technologies, projects or products under consideration for inclusion in a given portfolio. As described by surveys from Cooper *et al* (1998), companies have widely varying practices for portfolio selection. This thesis examines existing literature to determine the key characteristics of good portfolio and portfolio method. The approach needs to handle multiple objectives, account for project interactions, and address the social aspect of decision making. The resulting portfolio should be aligned with business strategy, balanced, and of maximum value. It introduces general concepts that have been used to select single projects and reviews five specific applications and assesses them against the key characteristics from the literature. After identifying gaps in the current approaches, a comprehensive approach is proposed. This approach would (1) apply multi-attribute decision analysis at the portfolio level, (2) apply constraints for common inputs to cost such as resources, and (3) apply probabilistic methods to account for project interaction. This approach incorporates successful elements from existing approaches and addresses the two areas that are not adequately addressed with current approaches.

CHAPTER 1 Introduction

A portfolio can be defined as "a purposeful combination of items" (Chien and Sainfort 1998). As the topic of portfolios relates to research and development (R&D) the items in question are technologies, projects or products under consideration for inclusion in a given portfolio. As described by surveys from Cooper *et al.* (1998), companies have widely varying practices for portfolio selection. This thesis examines existing literature to determine the key characteristics of good portfolio and portfolio method. It first introduces general concepts that have been used to select single projects. It then reviews five specific applications and assesses them against the key characteristics from the literature. After identifying gaps in the current approaches, a comprehensive approach is proposed. This approach incorporates successful elements from existing approaches and addresses the two areas that are not adequately addressed with current approaches.

1.1 Current and Best Practices

A survey of 205 businesses shows that techniques for portfolio management are inconsistent even within industries or groups of successful companies (Cooper *et al.* 1998). The survey asked company executives to identify all methods they used as part of their portfolio management strategy. The executives then identified the dominant strategy among the ones they used. Financial methods ranked as the most popular primary technique. These methods frequently include net present value (NPV) analysis for selecting projects. Project selection based on business strategy was also popular. This method allocates a percentage of the available budget to different strategies or divisions. Projects are then added into the pipeline in these areas until all funding is allocated. Scoring models were next in popularity and establish weights and metrics for various attributes of a project. Scoring methods align expenditures with business strategy but are more cumbersome and less use friendly than the graphical methods of bubble diagrams and portfolio mapping. The graphical methods are next in popularity. These methods typically plot potential projects on a graph of risk versus reward, although other measures can be used on the axes. The graphical methods are easy to read and tend to produce portfolios that are well-balanced but not necessarily strategically aligned with business objectives. The bubble chart is a popular graphical method (Cooper *et al.*1998). Bubble charts allow executives and decision makers to visualize the entire portfolio from a number of perspectives. The visual representation could look at projects based on the decision maker's preference. Two examples of representations are distribution of projects based either on risk or on launch horizon (near or long-term). The sample bubble chart in Figure 1.1 provides a view of a portfolio based on expected NPV and probability of success. In this example, the size of the bubble increases with the uncertainty on the expected NPV. Bubble charts can also present expected benefit versus resources required. A simple checklist was the least popular and least effective method identified. In this technique, projects that satisfied a given number of questions made the cut into the portfolio.

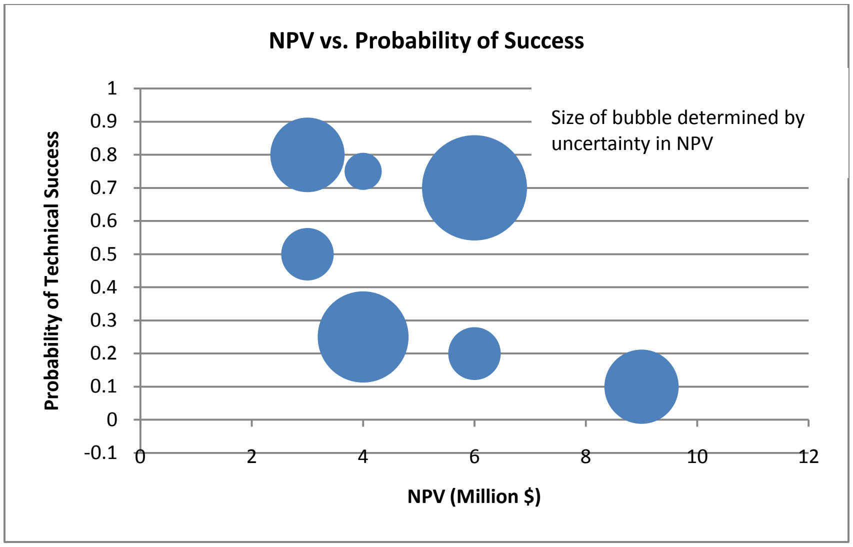

Figure 1.1 Sample bubble chart showing NPV compared to probability of success.

When evaluating the characteristics of companies that ranked near the top in R&D, Cooper *et al.* (1998) find that the most successful companies relied least on financial methods. The top companies use methods that were understood by senior management, perceived to be effective, and used in making Go/Kill decisions. The top firms in *Smart Organizations* use metrics to ensure that projects aligned with corporate strategy (Matheson and Matheson 1998). They also are able to show what creates value for the company and encourage development of projects that increase the value. Human judgment tops the list of the many techniques for portfolio management reported in a survey of pharmaceutical companies (Phillps and Bana e Costa 2007). In the survey, 60% of companies report satisfaction with their current portfolio management strategy. Many of these companies transparency of information for decision-making as contributing to their satisfaction. Companies that were dissatisfied based their views on inability to gain consensus and focus on individual projects instead of overall portfolio (Phillips and Bana e Costa 2007).

1.2 Defining the Problem and Challenges

The problem of R&D portfolio selection is a member of a more general class of problems of resource allocation. In most organizations the availability of good ideas exceeds the resources to execute them (Kleinmuntz 2007). Limiting resources are often financial in nature, but facilities, time, or available skill sets can also pose restrictions. When any type of resource is constrained, project selection cannot be viewed in isolation. Once a project is selected, fewer resources are available for other initiatives. Klienmuntz (2007) asserts that decision analysis can provide a practical framework for an organization that would allow them to make optimal use of the available resources.

The problem of portfolio selection poses a set of unique challenges. Undertaking new projects or products requires accepting some level of risk and addressing the uncertainty of both the technical and market success of the project. Decision makers frequently face the task of balancing benefits against costs and risk of realizing the benefits. Phillips and Bana e Costa (2007) identify five challenges specific to the R&D portfolio problem:

1. Benefits are typically characterized by multiple and possibly conflicting objectives,
2. When a large number of alternatives are presented, the decision maker cannot know the details of each well enough to make an informed decision.
3. If resources are allocated to several organizational units based on individual needs, the result is rarely an optimal allocation for the overall organization. This problem is a situation that illustrates the 'Common's Dilemma'.

4. Many people are generally involved. People providing advice or expert opinions can end up competing against each other. Other times it is difficult to identify all the people with the power to interfere with or influence the decision.
5. Implementation by people that do not agree with the resource allocation can lead to small groups of people working on unapproved projects.

Chien and Sainfort (1998) describe two specific additional complications associated with portfolio selection. First, decision makers face the challenge of measuring preference for the portfolio as a whole against the preference for specific items in a portfolio. The objectives of a portfolio could include measures such as achieving optimal balance among project, whereas objectives for an individual project could include different types of measures such as maximizing technical merit. Second, items in the portfolio often have interrelations. According to Phillips and Bane e Costa (2007), these problems demonstrate the need for an approach that balances the costs, benefits, and risks and takes into account differing perspectives of the people involved. This objective cannot be accomplished solely with a technical solution. A social process to engage the involved parties is also required. Top performing companies maintain portfolios that are aligned with their strategies and objectives, of high value, and balanced.

1.3 Approach

This thesis reviews various decision analysis based approaches to addressing some of the areas key to successful portfolio strategy. The basis for the methodology comes from single project selection. Applications and techniques for handling single technologies will be addressed in Chapter 2. This chapter focuses on the technical approach to solving the problem.

Chapter 3 looks at current approaches to handling portfolios evaluating them from a technical perspective. The various approaches are compared and contrasted in their approach to tackling some of the areas above that are considered critical to successful portfolio management.

Chapter 4 analyzes the success of current applications of decision analysis to portfolio management. The current applications are evaluated against the criteria of:

- alignment with strategy
- balance within the portfolio
- interrelationship between items in a portfolio
- maximizing value of the portfolio
- social acceptance (including transparency and gaining consensus), and
- handling of multiple and conflicting objectives.

This chapter reviews two more theoretical approaches to portfolios which cover some of the gaps identified in current literature (Gustaffson and Salo 2005, Chien and Sainfort 1998). Finally, the chapter proposes a comprehensive approach that incorporates all key elements to a good portfolio approach.

CHAPTER 2 Ranking and Selecting Single Projects

Many decision analysis methods have been applied to the problem of selecting or evaluating R&D projects or technologies. Since selecting a portfolio of projects builds on the single project selection problem, these techniques can be extended to or combined to address the portfolio problem. Applications and extensions to the portfolio problem are addressed in Chapter 3. This chapter includes reviews of many techniques referenced in the literature for use in project selection. Several categorizations for project analysis techniques have been proposed. Poh *et al.* (1999) divide the techniques into the categories of: (1) weighting and ranking and (2) benefit contribution. Cooper *et al.* (2001) separate methods in the groupings of strategic methods, financial methods, scoring model, and bubble diagram. No well-defined grouping of methods has been agreed upon in the literature. This chapter reviews the following techniques that have a basis in decision analysis: financial methods, multi-objective decision analysis, scoring models, (comparative methods including analytic hierarchy process (AHP)), decision trees, and options pricing approach.

2.1 Financial Methods

Financial methods are the single most common method for evaluating projects according to a survey by Cooper *et al*. (2001, Chapter 2). Companies in the survey utilize various financial metrics including net present value (NPV), discounted cash flow (DCF), and return on investment (ROI). The evaluations could either be used to rank projects relative to each other or to compare to a minimum hurdle rate requirement. In a case of unlimited resources, a company would fund all projects with a positive NPV. Since nearly all real world applications have constrained resources, decision makers need a method to select among projects with a positive NPV. In many cases, firms simply fund projects with the highest NPV first. Unfortunately this is not the most efficient use of resources because projects with a lower NPV that use very few resources are often overlooked. A more efficient selection process is to use a cost-benefit analysis. Cooper *et al.* (2001, Chapter 3) call the cost benefit analysis "bang for the buck," where the index is the ratio of NPV to total resources remaining to be spent. Phillips and Bana e Costa (2007) also recommend making selection based on the ratio of NPV to investment costs. In this case all costs and benefits must be assigned monetary values. In the financial analysis, risk can be taken into account by the assignment of higher discount rates to riskier projects. To differentiate discount rates based on risk, judgment of risk is required for each project. In a basic financial method, as described by Poh (2001) and Cooper *et al.* (2001, Chapter 2), risk is not accounted for.

Financial methods for making investment decision in R&D projects or technologies mirrors techniques used in making decisions on purchase of capital equipment. Expected costs associated with the project are laid out along with anticipated revenue. The cash flow over time is then rolled back to a single NPV of the project. With a piece of capital equipment, the costs are often easy to identify: equipment, installation, on-going maintenance, and operational requirements. In the case of funding development of a new product, the costs and revenues can be considerably more difficult to identify. Costs include not only development, implementation, and testing but also marketing and distribution costs. Revenues can also be difficult to predict particularly when evaluating innovative products with no existing market. In many cases, companies compare the NPV or IRR to a pre-defined standard and fund projects that meet this bar until funds are exhausted.

Financial methods are attractive to corporations for their simplicity. Decisions on R&D projects can mirror other procurement decisions, such as purchase of capital equipment, within a company. These methods also force decision makers to fully explore the financial implications of a project while it is in its early stages. The downside of these methods is failure to acknowledge the multiple objectives of R&D within a company. Financial methods address each project individually and do not account for strategic alignment or diversification of projects. Any number of objectives could be considered important within a given organization. For example, Bayer's mission statement indicates that the corporate focus will be on the areas of health care, nutrition, and high-tech materials (http://www.bayer.com/en/Bayer-Mission-Statement.pdfx). One of their aims is to produce products that contribute to people living healthy fulfilling lives. If a decision maker looks only at a financial metric such as NPV when filling a portfolio of projects, it is unlikely that the resulting portfolio would meet fully cover areas defined by the corporate mission. It is also likely that the portfolio would contain projects outside of a company's core competencies.

2.2 Multi-criteria Decision Analysis

One of the challenges associated with R&D project selection is that these types of models are typically characterized by multiple and often competing or conflicting objectives. Thus, one must identify a technical solution that addresses these competing objectives. The area of decision analysis that provides the right tools can generically be referred to as multi-criteria decision analysis (MCDA). The set of techniques under the MCDA umbrella recognize the need to define and address the many attributes or objectives associated with a decision on project selection. A more specific tool in the MCDA category is multiple objective decision analysis which relies on either multiattribute value theory (MAVT), which models preferences, or multiattribute utility theory (MAUT), which also models risk attitudes.

Regardless of the preferred naming convention, nearly all applications of R&D project selection rely on some form of MCDA. The primary exception is reliance strictly on a financial method such as NPV discussed in the previous section. MCDA can act alone as the primary method for project selection or can be used as an input into a decision tree or mathematical program. Integration of multiple techniques will be addressed in reviewing the applications in Chapter 3. In order for decision makers to find success in using MCDA, they must understand the distinction between objectives, values, and attributes; be able to define them as they relate to the decision at hand, and incorporate them into the decision process.

An objective is a specific “thing” that a decision maker wishes to achieve and serves as the basis for determining which alternative is the best solution to a problem

(Clemen and Reilly, p.22). "Values define what is important to that person making a decision" (Clemen and Reilly 2001, p.22). The literature describes a number of methods to elicit objectives in reference to portfolio or technology selection. The first part of any multiobjective decision analysis is defining and clarifying the objectives. A single decision maker would first create a list of all objectives. Techniques for expanding this list include making a wish list; identifying alternatives; considering issues and opportunities; predicting consequences of previous decisions; identifying goals, constraints, and guidelines; considering outside perspectives; looking for strategic objectives; and thinking about high-level generic objectives (Keeney 1994). After developing an exhaustive list, the decision maker should start sorting the objectives into appropriate categories and should also remove any objectives that are outside of the context of this decision. The decision maker then needs to designate each of the remaining set of objectives as either fundamental or means objectives. Means objectives are those which help to attain the fundamental objective. One key tool for distinguishing means objectives from fundamental ones is the question "Why is this important?" For fundamental objectives the answer is often "Because it is important." This question also reveals connections between the objectives (Clemen and Reilly 2001, Chapter 3).

A single person rarely decides the structure of an organizations R&D portfolio. In top companies senior management understands the portfolio management strategy and perceives it as effective (Cooper *et al.* 1998). Engaging the senior management and other impacted individuals in the development of objectives builds understanding and buy-in. Several techniques have been described for developing objectives within organizations through the use of value focused thinking. Several standards have been described for creating alternatives. The Gold Standard approach described by Burk and Parnell (1997) is one such method. This method uses a "Gold Standard" document as the basis for creating a model. This document could be a policy or strategy document universally accepted by key decision makers. If possible, objectives should be pulled directly from one document.

In many cases, there is no Gold Standard document capturing all objectives relevant to the decision context. Parnell *et al.* (1998) describe a Silver Standard technique as a valid alternative for use in the absence of a Gold Standard document. With the Silver Standard, interviews are used to set objectives. Subsequent refinement of this method suggests conducting the interviews in a group setting (Parnell *et al.* 2002). The group setting creates consistent framing of the decision context. Following the group interviews, the objectives are sorted and refined using affinity diagrams (Parnell *et al.* 2001, Parnell *et al.* 2002).

It may be difficult or impractical to bring all the key stakeholders or senior management together at the same time to develop objectives. A Platinum Standard for developing objectives is appropriate in these cases. The stakeholders are interviewed individually to provide many lists of objectives. Once all the objectives are laid out, affinity diagrams are again used to sort objectives. Objectives from existing documentation are added to the diagrams and fundamental and means objective established. The proposed objectives are taken back to the stakeholders and reviewed in an iterative process (Parnell *et al.* 2002).

Attribute scales provide a way to measure fulfillment of the fundamental objectives. Attributes then refer to the quantity measured on the attribute scale. In a case where the objective is minimizing cost, the attribute scale could be defined in terms of dollars, and the attribute could be the dollar cost (Clemen and Reilly 2001, Chapter 3).

The problem can be approached from the perspective of a multiple attribute value problem, which is one of value tradeoffs. The decision maker must trade off fulfillment of one objective against another objective. Determining the implications of the tradeoffs often becomes a question of values and requires subjective judgments from the decision maker. In order to assess these tradeoffs and to combine attributes with different units of measure, it is necessary to convert the magnitudes of the attributes into a value. These values can be combined into a function frequently referred to as a value function or a utility function. If conditions of independence are met the utilities are additive (Keeney and Raffia 1993, Chapter 3). In a case where no uncertainty exists, the attributes must have mutual preferential independence for additivity to apply. An attribute is said to be preferentially independent of another attribute if preferences for specific outcomes of the first attribute do not depend on the level of the second. For example, let the attributes under consideration be time and cost for completion of a project. If one prefers a project time of 5 days to a time of 10 days assuming first the cost for both projects is 100 and also in the case where the cost is 50, then time is preferentially independent of cost. For mutual preferential independence, cost must also be preferentially independent of time. For choices made under cases of certainty, mutual preferential independence is sufficient for an additive utility function to be appropriate. Cases of uncertainty call for a stronger condition of independence, utility independence for an additive utility function to be appropriate (Clemen and Reilly 2001, Chapter 16). For the scenario described previously, the example is repeated below in a condition of uncertainty. When uncertainty exists, it is necessary to define a certainty equivalent, the amount of money that is equivalent to a given situation that involves uncertainty (Clemen and Reilly 2001, Chapter 13). If the certainty equivalent amount for the cost lottery is the same no matter what time, then cost is utility independent of time. If time is also utility independent of cost, the two are mutually utility independent (Clemen and Reilly 2001, Chapter 16). Keeney and Raffia (1993) describe a dialog to ascertain independence. In most cases, the assumption of preferential and utility independence is reasonable but its validity must be verified for all scenarios**.**

Once a user establishes mutual preferential or utility independence for the criteria he can describe an overall utility or value equation. The overall value of option i is described by the equation below

$$V_i = \sum_i w_i v_{ij}$$

where v_{ij} represents the value associated with consequence i on criterion j and w_i represents the weight assigned to criterion i (Phillips and Bana e Costa 2007).

A common error in multi-criteria decision modeling is to attempt to assign weights that reflect the importance of the criteria without consideration of ranges on the value scales and the importance of the range to the decision maker (Phillips and Bana e Costa 2007).

Parnell *et al.* (2001) use multiobjective decision analysis to score, or quantitatively evaluate, the value of various theater missile defense architectures under consideration by the Ballistic Missile Defense Organization. This example is just one of many related to military ranking of projects (Parnell *et al.* 1998, Buede and Bresnick 1992).

2.3 Scoring

The use of a scoring method is mentioned throughout portfolio literature. Throughout these references, no single definition for a scoring model is apparent. Poh *et al.* (2001) state that a scoring model, as its name implies, is a model that evaluates projects by scoring them against pre-defined objectives using a mathematical equation. Once objectives and weights are established projects can be scored and then ranked on the basis of their scores. Krawiec (1984) finds the scoring method an appropriate tool when the complexity of more sophisticated approaches is not needed. Jackson (1983) identified the primary weakness of scoring methods as ill-defined structuring making it hard to justify their use. This shortcoming is a flaw of the implementation not the process. Coldrick *et al.* (2003) propose a method for approaching a selection model that incorporates multi-attribute utility theory. They propose a flow chart to assist decision makers in integrating projects in different stages of development into a scoring model. Sample scoring spreadsheets, such as the one shown in Figure 2.1, are also provided.

FILTER	Criteria		Category		Project
	Score 1-5	Weight	Score 1-5	Weight	Score 1-5
1. Technical					
Technical risk to project completion	?	?	$S_{criterion}$ x $W_{criterion}$		
Technical resource availability	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
2. Corporate and Strategic					
Fit with company business plan	?	?	$S_{criterion}$ x $W_{criterion}$		
Product range growth potential	?	?	$S_{criterion}$ x $W_{criterion}$		
Synergy with other products/proces	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
3. Regulatory					
Risk in obtaining regulatory clearanc	?	?	$S_{criterion}$ x $W_{criterion}$		
Ability to meet likely future regulatio	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
4. Market					
Effect on existing market share	?	?	$S_{criterion}$ x $W_{criterion}$		
Effect on existing market outlook	?	?	$S_{criterion}$ x $W_{criterion}$		
New market potential	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
5. Financial					
Commercial risk of application	?	?	$S_{criterion}$ x $W_{criterion}$		
Potential return on investment	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
6. Application					
Ability to implement production/pro	?	?	$S_{criterion}$ x $W_{criterion}$		
Patentability/design protection	?	?	$S_{criterion}$ x $W_{criterion}$		
		$\Sigma W_{criterion}$	$\Sigma/\Sigma W_{criterion}$	?	$S_{category}$
NB: Use only Categories 1-3 for projects classified as Basic Research				$\Sigma W_{category}$	$S_{project}$

Figure 2.1 Sample scoring table (Coldrick *et al.* 2003).

Cooper *et al*. (2001, Chapter 3) describe the use of scoring models in a wide range of corporate settings. They provide a generic framework for a scoring model based off models used by companies such as Kodak, Bayer, and Exxon. They also discuss a more complex application used by Celanese appropriate for advanced-technology products and platform development.

In some cases the term scoring is used to describe a method covered by MAUT or MAVT. In other cases, the decision maker scores various attributes to produce a final score for a proposed project that does not necessarily follow MAUT or MAVT. One such example is show above in Figure 2.1. Several categories of attributes are defined along with specific requirements within the categories. Weights are assigned to the individual element and the category. Coldrick *et al.* (2003) do not elaborate on how the weights are defined. They could be defined using MAUT or arbitrarily assigned. It is difficult to provide a procedure or definition for scoring methods since there is little consistency in the use of the term. In spite of this difficulty, scoring methods are included in this thesis as a stand-alone category due to the prevalence of reference to them within a range of literature.

2.4 Comparative Methods and Analytic Hierarchy Process

In the comparative method, the project under consideration is compared to another project or set of projects instead of being scored or compared to an absolute standard (Cooper *et al.* 2001, Chapter 3). Mathematical models can be used to compute the overall merit of each project under consideration and allow for determination of the best project (Poh *et al.* 2001). According to Poh *et al.* the method is easy to understand and implement but relies heavily on subjective input. Due to the subjectivity, evaluations vary greatly with the decision maker performing the assessment. Ormala (1986) notes another drawback of the comparative method is that it leaves aggregation of multiple objectives up to the decision maker and does not explicitly address them.

The AHP, developed by Saaty (1980), describes a framework for structuring a decision problem, breaking down the elements and relating them to goals, and evaluating alternatives. Poh *et al.* describe AHP as an intuitive and relatively easy analysis method, which structures a complex problem into a hierarchy with the criteria and relevant factors decomposed according to the situation. The levels typically consist of the goal at the top level, followed by criteria and sub-criteria at mid-levels, and alternatives at the lowest level. A series of pairwise comparisons are used to produce a ranking of the alternatives. This method has been applied to a wide range of decision problems including R&D project selection (Liberatore 1987).

While this method is popular for many decision processes, including several applications for R&D (Brenner 1994, Kocaoglu and Iyigun 1994, Lockett *et al.* 1986), there are a number of drawbacks associated with AHP. As Howard notes (2007) the AHP does not obey the process for multiattribute value theory. A major flaw in the method is that the addition or removal of an alternative can reverse the preference for two other alternatives in a phenomenon known as 'rank reversal' (Poh *et al.* 1999). Howard (2007) speculates that the method remains popular despite of these shortcomings due to its simplicity. Users find the method easier to understand than other methods that can provide greater certainty of picking the best alternative.

2.5 Decision Trees

Decision trees are tools for use in modeling a decision. They can model multiple decision alternatives with uncertain outcomes. A series of decision nodes and chance events represent the decision at hand in a tree and branch format. Probabilities of each branch or outcome occurring at each activity or decision point are assigned. Values, which can be determined based on multiattribute value theory, are assigned to each outcome. The probabilities and values are used to produce an overall expected value from the scenario (Cooper *et al.* 2001, Chapter 4). The conundrum with a decision tree is how much detail should be included in the tree. Von Winterfeldt and Edwards (2007) acknowledge that for some scenarios complicated decision trees with an exhaustive listing of all objectives are warranted. This stance backtracks somewhat from an earlier position that all decision trees should fit on a single page to act as a communication tool to management. They do, however, recommend that if a complex decision tree is used in analysis a high-level version with less complexity be used as a communications tool. Jackson *et al.* (1999) use decision trees in their selection of a portfolio of landfill remediation technologies that will be more fully described in Chapter 3. Parnell *et al.* (2001) follow up a multiobjective decision analysis with the use of a decision tree to determine the best strategies for a theater missile defense.

Despite the use in the aforementioned applications, Phillips (2007) discounts the usefulness of decision trees in the decision making process of managers selecting R&D projects. He repeats a sentiment by Beach (1990) observing that:

> …probabilities mean little to decision makers and have surprisingly little impact on their decisions. Probability is of little concern because decision makers assume that their efforts to implement their decisions will be aimed, in large part, at *making* things happen. Controlling the future.

Shortcomings in the standard use of decision trees from are discussed in Section 2.6.

2.6 Options Pricing Methodology

A common belief among R&D management is that DCF or ROI methods commonly used to evaluate projects are not appropriate tools for evaluating research activities that have a wide range of future applicability or are highly innovative (Perdue *et al.* 1999). When evaluating a potential technology R&D management has the choice to implement a technology, abandon the research, or delay (wait and see). The flexibility to avoid losses without completely ruling out future gains by waiting is not fully captured by standard or naïve NVP. These factors lead a growing group to look at R&D projects as a part of an investment class that has future opportunities to invest ("real" options) and should be valued by a different method (Myers 1984, Kester 1984, Mitchell and Hamilton 1988, Dixit and Pindyck 1995, Faulkner 1996, Perdue *et al.* 1999, Smith and Nau 1999). Dixit and Pindyck show that naïve application of NPV can undervalue research proposals. In standard investment valuing, a project with greater uncertainty has a higher discount rate applied and thus a lower NPV (Perdue *et al.* 1999). The naïve NPV model creates a negative correlation between uncertainty and value. Perdue *et al.* note that:

> Just as the fact that downside risk is eliminated for a call option on a share of stocks sets up a positive relationship between the volatility of the stock price and the current value of the call option, the fact that expected values after the research phase will incorporate only those paths emanating from successful research implies a positive correlation between uncertainty as to the range of research technical and commercial outcomes and the current value of the opportunity to perform that research.

Some tout the advantages associated with viewing research as a real option as proof of superiority over decision analysis techniques. Both Perdue *et al.* (1999) and Smith and Nau (1999) argue that this assertion is not true and that more sophisticated applications of decision trees can provide the same results as an investment options approach. Smith and Nau (1999) conclude that the problems that have been attributed to decision analysis can be attributed to using risk-adjusted discount rates to capture both time and risk preferences and market opportunities to borrow and trade. They show that by using a utility function and explicitly modeling market opportunities decision analysis can produce the same results as options analysis. They also conclude that an even better result can be achieved by integrating the two methods. By integrating the methods, options pricing can be extended to incomplete markets and simplify the analysis of projects that can be partially hedged by trading securities. To simplify the process in practice, they suggest that analysts should use risk-neutral probabilities when risks can be hedged by trading securities; compute NPVs at a risk-free rate; use exponential utility functions to capture risk preferences; and assign risk premiums only to private risk.

Perdue *et al.* (1999) pilot the model on a set of projects from Westinghouse. The model, which is represented by the decision tree shown below in Figure 2.2, requires the following inputs for each project: probability of achieving each technical milestone, the probability of strategic fit, R&D cost in each research phase, the required investment for commercialization, time to complete, and probabilistic estimates for incremental revenue. In Figure 2.2, the model shows four stages of funding decisions. By allowing the decision maker, several opportunities to elect not to fund a project, the NPV is not unfairly burdened with costs associated by the final three stages if a project fails to achieve early technical milestones.

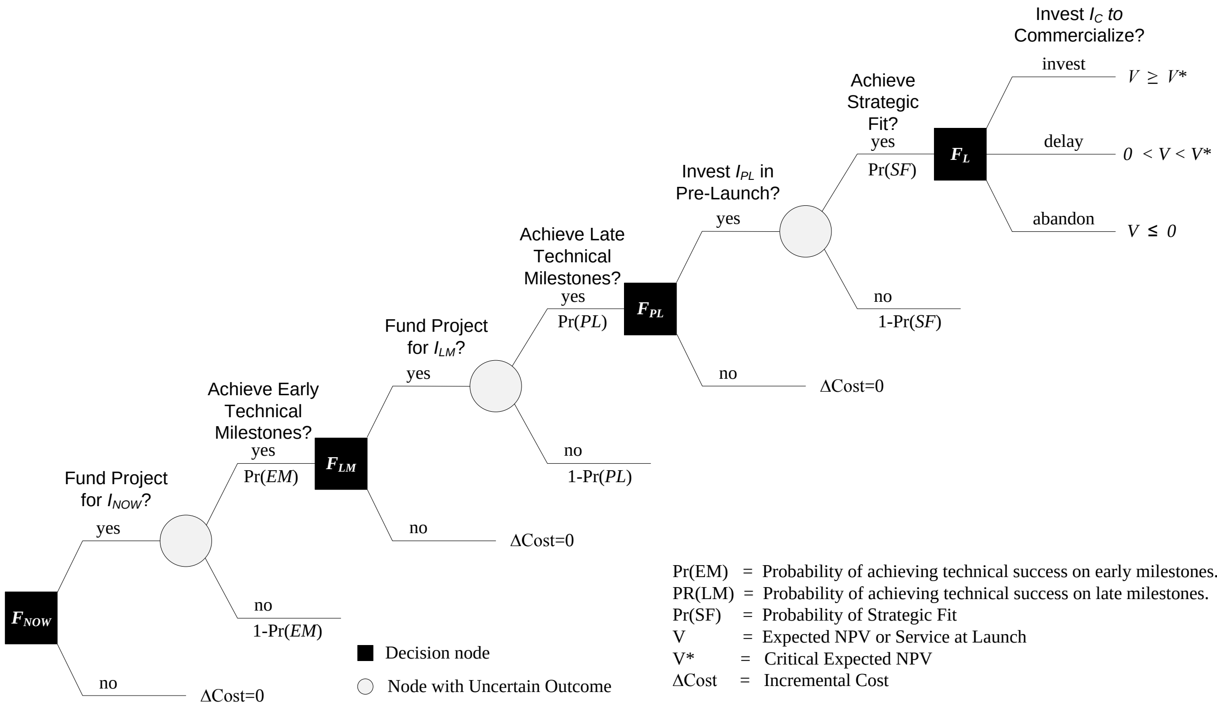

Figure 2.2 Decision tree to integrate options pricing methodology (Perdue *et al.* 1999).

All projects considered in the pilot were in early stages with an average of eight-years expected to complete. Probabilities of technical success were elicited from managers who had enough expertise to be knowledgeable but not directly linked to the project in question to reduce bias. Results from the pilot showed that two projects had been misclassified and were not in the right stage. Several projects increase in value if technical hurdles were cleared. At a nominal investment level standard NPV analysis would have rejected two projects whereas the options model did not reject any. The difference grew when the investment level was increased. NPV rejected six projects whereas the options model rejected no projects. Higher investment levels are more likely to result in bad decisions when using naïve NPV alone. Following the test study in 1996, the authors completed a complete analysis of the Westinghouse portfolio. The results were used to determine how to divide the assets during an acquisition. With new ownership it was unclear the future of this method at Westinghouse.

Each of these tools has been selected for use in varying applications based on their specific strengths and weaknesses as well as traditions within the industry in question. Chapter 3 will review a number of applications that use one or more of these methods.

CHAPTER 3 Applications and Techniques for Portfolio Selection

The techniques described in Chapter 2 can be applied to the problem filling a portfolio with individual projects or technologies. As described in Chapter 1, additional complications emerge when a full portfolio is being examined and not just a single project. Undertaking new projects or products requires accepting some level of risk and addressing the uncertainty of both the technical and market success of the project. In addition, many decision makers can be involved in the process leading to difficulty settling on a decision. It is also hard to capture potential interactions, such as market cannibalization, among interrelated projects. This chapter reviews several approaches to portfolio selection in both government and private sector applications. The use of the project selection techniques described in Chapter 2 is analyzed for each application. The results of each approach are compared to an ideal portfolio which maximizes value, aligns with strategic plans, and achieves balance. The transparency and management acceptance of the described approach is also addressed. The research described within this chapter attempts to tackle these tough issues. This chapter will describe and contrast a range of approaches to addressing the problem of portfolios.

3.1 Selecting a portfolio of remediation techniques using decision trees

In describing an approach for selecting a portfolio of technologies for landfill remediation, Jackson *et al.* look at remediation of nuclear waste storage sites as a complex set of sequential decisions involving interdependent technologies and uncertainties in cost and time. Over a 75 year period, the Department of Energy (DOE) plans to spend a large sum of money to remediate landfills throughout the US and Puerto Rico. There are seven technology process steps associated with stabilizing a landfill: (1) Characterization and Assessment, (2) Stabilization, (3) Retrieval, (4) Treatment, (5) Containment, (6) Disposal, and (7) Monitoring. Several technology options exist to address each of these processes. Technologies under consideration range from proven technologies to prototypes still under laboratory investigation. Risk factors come from the maturity of a given technology, the ability to characterize and assess a waste site with accuracy, and applying the correct technologies to a given site. To incorporate risk into the tool described, one must clearly define the risk. Jackson *et al.* (1999) describe the development of a formal decision analysis tool to support the decision maker when selecting remediation technologies. Known life cycle cost (LCC) simulation models within the DOE can provide inputs to this tool. Decision analysis techniques can combine output from LCC tools with information about technology risk and uncertainty in cost and times to aid the decision maker in selecting the best portfolio of technologies.

A senior DOE official defined the appropriate criteria for this model using value-focused thinking. As a result, decisions focus on risks for cost, time, and safety; cost; and developing better technologies. The decided on multiattribute utility analysis as the approach for modeling this problem. Utility theory provides mathematical functions that incorporate the decision maker's attitude towards risk and develops a straightforward way to evaluate alternatives. The uncertainty and tradeoffs between cost and time make utility functions a good fit for this application. The decision analysis tool proposed by the authors uses sequential remediation decisions to determine the total time required for a project. A distribution of the present value of the portfolio cost is produced. Constraints are added to ensure compatibility of projects and adherence to timelines and budgetary requirements. An additive utility function describes the decision maker's preference and utility for time and cost.

Jackson *et al*. created an influence diagram for each process where a technology selection is required. A sample influence diagram is shown in Figure 3.1. The uncertain events in this model are R&D costs, operations and maintenance (O&M) costs, R&D time, and O&M time. Parameters for the probability distributions in the uncertainty nodes come from estimation of distribution parameters from the LCC model. A selected technology has a chance of failure which would lead to additional time and costs. The probability of failure of a project contributes additional penalty time and cost to the expected values for a technology. The decision makers use the diagrams to visualize and validate the process. A complete model of the decision combines the seven processes described by the influence diagrams into a decision tree. A partial decision tree is shown in Figure 3.2. The decision tree shows the sequential nature of the remediation process. In addition to choosing whether to stabilize and whether to treat or contain, the decision maker selects from several available technologies for each process step.

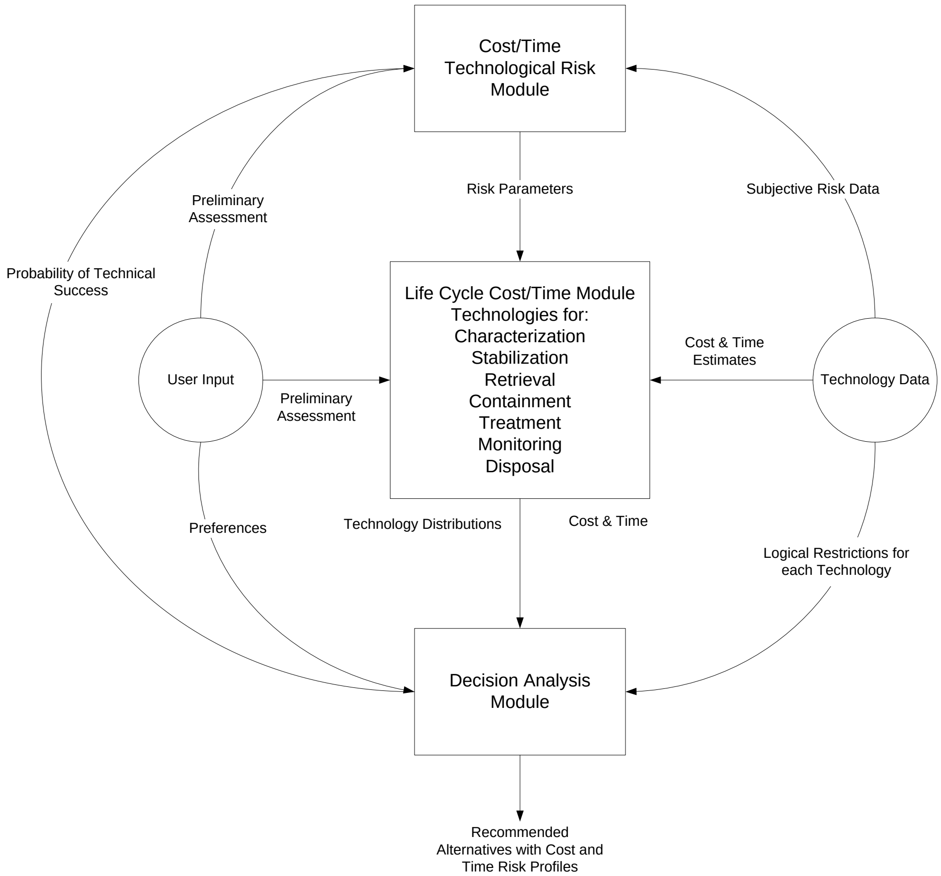

Figure 3.1 Influence diagram for technology selection (Jackson *et al.* 1999).

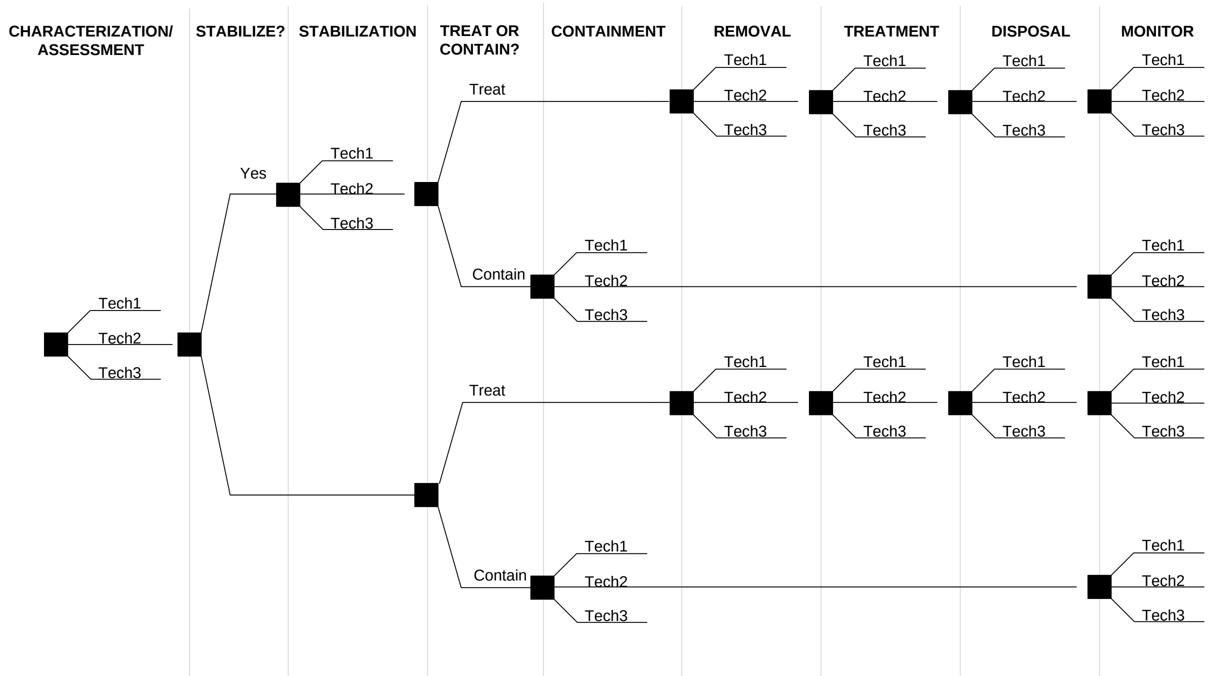

Figure 3.2 Partial decision tree (Jackson *et al.* 1999).

The model accounts for the attributes of cost and time and the category of each technology. Categories ensure technologies in a portfolio are compatible. These constraints can model several types of technology relationships based on Boolean logic and are similar to the approach employed in multi-criteria programming approaches. The total cost and time values constrain the model. A user can use a constraint to penalize any portfolio that exceeds allowed timing or budget by assigning it a penalized objective function. Assessing a high penalty could completely exclude an undesirable portfolio from consideration. Since time and cost uncertainties exist within a portfolio, a portfolio could have a nonzero probability of exceeding either time or budget constraints. The user can penalize a portfolio more as the probability of the portfolio exceeding the limits increases.   For example, in a portfolio with a 0.10 chance of exceeding the limits, the user could assign a utility of -0.5 to the leaves of the decision tree that exceed a constraint. The expected utility function would then account for the possibility of exceeding the limits. The decision tree model produces time and expected NPV for cost for each leaf on the decision tree. A utility function for these attributes takes into account the decision maker's preferences as a basis for selecting technologies. Jackson *et al.* developed a general utility function based on information from the DOE. The DOE has a high utility for costs and times that are below the target plus a 10% error and a very low utility for costs and times that exceed the target values. Using lotteries, decision makers determined the midpoint utilities. From the known points, two exponential utility curves were created. One curve for cost and times less than 10% above target and the other for cost and another for cost and times that exceed target by more than 10%. The user can incorporate the known utility function into the model and choose a portfolio based on highest utility. In this example, the decision makers examined best and worst case values from the portfolio options and a target option. These values determined the starting point for a utility function. The decision maker then adjusted the shape of the function until content with the shape as shown in Figure 3.3.

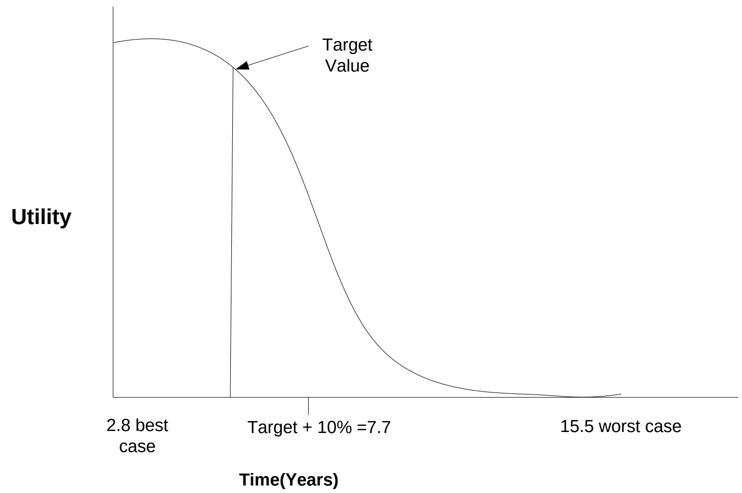

Figure 3.3 Sample utility curve (Jackson *et al.* 1999).

Jackson *et al.* used lotteries to establish utility independence for cost and time attributes. To confirm the stronger additive independence condition, the authors presented each of the decision makers a choice between lottery X, which compares low cost, long time with high cost, short time, and lottery Y, which compares low cost, short time with high cost, long time. All decision makers were indifferent as long as the cost and time were within the established limits. Cost and time satisfy the additive independence constraints if their values are less than the maximum allowed by constraints. If the additive independence conditions are true for both attributes, an additive utility function can represent the decision maker's objective function.

The additive utility function is relatively straightforward and relies on a weighting parameter to represent the decision maker's preference between the attributes. Jackson *et al.* are able to calculate multiattribute utility for a portfolio once all weights are assigned and select the appropriate technology for each stage of the process.

Having drawn from multiple methods from the toolbox of project selection techniques, Jackson *et al.* successfully address the issues of uncertainty particularly as they relate to timing and cost concerns using decision trees and MAUT. They also lay out a transparent method for project selection. In this case transparency needs come from requirements from government funding. The approach could still translate into areas where transparency is required to gain decision maker and stakeholder acceptance. They address issues of compatibility and balance within this portfolio by requiring the selection of one technology per stage. The approach works well for the specific application but would fail to address independence among projects or balance in a portfolio in an application where these specific constraints did not exist.

3.2 Selecting a portfolio of solar energy projects

Golabi *et al.* (1981) take a portfolio view of selecting solar energy projects and expand on popular techniques for use in government procurement. They attempt to address several areas where they identify shortcomings in earlier R&D project selection procedures including: treatment of multiple criteria, handling of project interactions, approach toward nonmonetary aspects of the problem, and the perception of difficulty understanding models. The project they tackle focuses on the selection of solar energy projects for funding. Since the projects focus on increasing the knowledge in this area of study, minimal risk or uncertainty exists. All projects funded will increase the knowledge base.

Golabi *et al.* determine that in order to address the issues identified above, the best approach would be to utilize multiattribute utility theory. For this application, they determine that there is limited interaction potential between proposed projects. Redundancy in project selection was not required, but diversity in technologies was needed. In order to assess these projects using multiattribute utility theory, the selection of a project must be utility independent of its complement. Golabi *et al.* express a concern preference for a project of medium quality or one with equal chances of being high quality or low quality could depend on the overall quality of projects already included in the portfolio. Since the condition of utility independence is not met in this scenario, Golabi *et al.* decide to decouple the evaluation of technical merit from the portfolio problem to avoid the complexity of addressing dependence. The technical evaluators determined that budget and diversity concerns were the primary consideration for the portfolio. Upon reviewing a list of cost and diversity issues, the technical evaluators determined that a portfolio would need to achieve a minimum level of diversity related to each issue. Below the minimum level, the portfolio would be unacceptable but no additional value was gained by increasing diversity beyond this point. Thus, a tradeoff could not be made between budget and diversity. Constraints were added to assure that the desired level of diversity was achieved. One example was determining the allocation of funding to small, medium, and large sized projects. In many cases it was difficult for the technical evaluators to identify the level of diversity. The portfolio problem was first run with only a budgetary constraint. The technical evaluators then reviewed the portfolio of maximum technical utility. If they did not think the identified portfolio demonstrated sufficient diversity, they added diversity constraints and ran the model again.

To assess the technical utility of the entire portfolio, the technical evaluators identified 22 attributes of interest, the utility function associated with the attribute, and the weights given to each attribute. Projects that did not meet a minimum threshold for technical quality were eliminated from consideration. Computer support was used to calculate the utilities once the technical evaluators had input values for each attribute. Once all attributes had been evaluated the model was turned over to a panel to experiment with different levels of funding and diversity and make final project selections. Golabi *et al.* report that this procedure allowed 77 projects to be evaluated over a period of two weeks and the selection of 17 projects to be completed in three days. They report a successful implementation of their procedure to this application. While successful in this application, the procedure does not provide a method for addressing interactions between projects that would occur in an industrial R&D setting. It also fails to address risk and uncertainty as the issue was not deemed relevant to the specific decision process described. Golabi *et al.* do described a more rigorous check for independence than some of the procedures later described.

3.3 Decision conferencing approach to portfolios using MCDA

Phillips and Bana e Costa (2007) describe a MCDA approach to portfolios that they have utilized in numerous consulting applications over various industries. They repeat the use of multiattribute utility theory but place a greater emphasis on the social aspects of the decision. Much of their discussion focuses on transparency and consensus building. The primary metric that Phillips and Bana e Costa use in their evaluation of projects is value for money determined by the ratio of risk-adjusted benefit to cost. The value for money triangle is depicted below in Figure 3.4. They note that much literature recommends this approach but in practice most companies without formal decision analysis support for the process rely on expected benefit not the ratio. The graph in Figure 3.5 shows that this is not the most efficient use of the budget. The benefit only curve is always under the cost adjusted benefit curve.

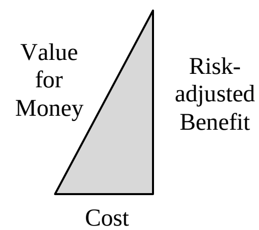

Figure 3.4 Value for money triangle (Phillips and Bana e Costa 2007).

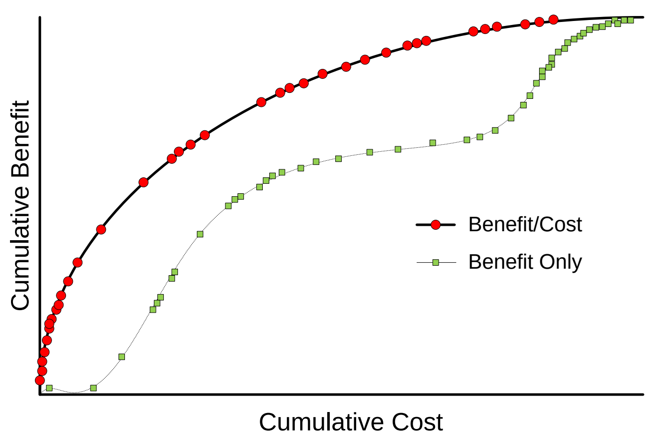

Figure 3.5 Benefit when looking at Benefit/Cost or Benefit Only (Phillips and Bana e Costa 2007).

Similar to the approach previously described by Golabi *et al.*, Phillips and Bana e Costa describe the goal of the MCDA model is to collapse multiple dimensions of benefit into a single risk-adjusted benefit. The benefit criteria must be setup such that they are mutually preference independent in order to justify use of an additive aggregation model. The overall value of option i is described by the equation below

$$V_i = \sum_j w_j v_{ij}$$

where v_{ij} represent the value associated with consequence i on criterion j and w_{ij} represents the weight assigned to criterion j .

Several software programs exist for portfolio analysis. Phillips and Bana e Costa describe the approach taken in the software package EQUITY. The basic structure mimics an organization of K areas whose options are appraised against J benefit and risk criteria, producing K x J scales. The options for each area are appraised against each criterion separately, resulting in a value score v_{ij} for each option i on criterion$j$, such that for each scale 100 represents the most preferred option and 0 the least. Then each of the scales for criterion j will be assigned a within-criterion weight, w_{ij}, using swing weighting. The scale associated with the largest difference in value between two reference points is assigned a weight of 100, and others are given a weight relative to 100. The scales assigned within-criterion weights of 100 for each criterion are compared for their swings, producing a set of across-criteria weights w_j.Value scores, within-criterion weights, and across criterion weights are required inputs for EQUITY to calculate the overall value. EQUITY then calculates the benefit-to-cost ratios by dividing each option's overall value by its total cost.

This process results in a single value-for-money triangle associated with each option. The triangles are stacked in declining order of value-for-money priority to create an efficient frontier of projects as seen in Figure 3.6. The portfolio of projects up to and including F is examined by the group, and projects that fall outside of the portfolio are examined to make sure exclusion is realistic. The shaded area under the efficient frontier includes all possible portfolios.

At this stage in the decision process constraints are introduced. The decision maker could determine that an excluded project is too far along to stop or that new projects are infeasible due to other current conditions. The decision maker can propose a portfolio of current projects only. This proposed portfolio, P, is below the efficient frontier. Observation shows that an improvement could be made by moving to portfolio C (same benefit lower at a lower cost) or portfolio B (same cost increased benefit). In 20 applications of Equity added value from moving from P to B was 30%.

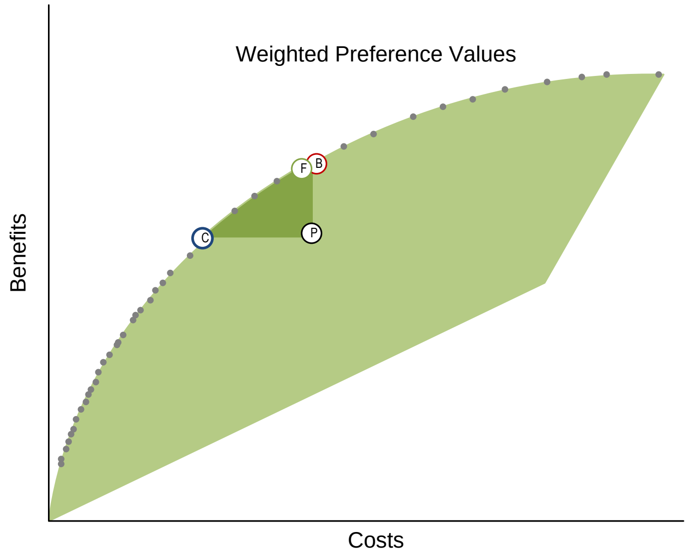

Figure 3.6 Illustration of Efficient Frontier (Phillips and Bana e Costa, 2007).

This approach helps decision makers make difficult decisions to close down projects that do not look promising. Participants gain an understanding that what is best for an individual area is not always best for the whole organization.

The EQUITY structure solves a serious technical issue encountered by the traditional decision analytic approach. Decision trees increase exponentially with increases in the number of areas or options within the areas. In the MCDA approach, the model increases additively.

Constraints are imposed visually. Dependent projects are assumed to be both included. If the proposed portfolio includes or excludes both projects, no further action is required. Otherwise, the omitted project must be forced in and the resulting portfolio analyzed. If two projects are truly dependent on each other, it may be more effective to model them as a single option. They believe that in practice it is efficient to focus only on the few dependencies that matter.

Phillips and Bana e Costa note that a major challenge facing consultants is managing the tradeoff between sophisticated modeling and social acceptance of the process. In opting for an approach that favors social acceptance, Phillips and Bana e Costa neglect to address the complex issue of project interaction. They allow for addressing of alignment to objectives in the benefit assessment. The model does not account for a balance in selected projects but the issue is addressed by visually imposing additional constraints as requested to explore different areas. Phillips and Bana e Costa place the most emphasis on transparency and acceptance. This focus likely comes from the applications in industry that are not tied to the strict requirements of government procurement and rigid procedures and doctrines.

3.4 A consultant's approach to portfolios using strategic themes

Like Phillips and Bana e Costa, Poland (1999) and Skaf (1999) describe the evaluation of portfolios for a variety of industries including pharmaceutical, plastic and packaging, oil and gas, and entertainment. Both authors draw on their experience in consulting with Strategic Decisions Group, now known as Navigant Consulting. Poland focuses on addressing the uncertainty inherent in portfolio problems. He also proposes a unique approach for grouping a portfolio that aligns with the business strategy. The approach Poland describes for setting of portfolio themes is also utilized in Skaf's application in an upstream oil and gas organization.

The assessment of uncertainty by calculating probability distributions on key value measures such as NPV is computationally complex. Poland proposes a simplified method for assessment of the portfolio distribution. It attempts to balance the communication challenge of presenting a large number of probability distributions for multiple businesses in a meaningful way. A presentation with too little detail could mask important insights. A presentation with too much detail could lead to undue focus on certain details and detract from the high-level approach to the analysis (Poland 1999).

The computational requirements for this type of work are high. For example, describing portfolios for a plastics and packaging company with 20 businesses would produce a probability tree with approximately 3.5 billion branches. Poland limits the expansion by focusing on uncertainties with the most impact on the outcome as determined by a tornado chart and fixing the value at the mean for all low-impact items. In many long-term business models roughly the top five uncertainties could account for nearly 90 percent of the total variance, but in portfolio evaluations many more uncertainties could be required.

Poland (1999) uses decision trees to calculate the distributions for various strategies for each business, analytically combined the moments of the distributions for a given portfolio, and fit a distribution for overall risk and return. Initially the consultants evaluate the distributions of business value for various business strategies. Then the senior management sets an overall portfolio strategy theme that would guide the strategy for each business. The theme allows management to account for constraints not explicitly modeled and to some extend could address interactions between items within the portfolio. For example, an overall ‘Aggressive’ strategy could lead to an ‘Expansion’ strategy for Business 1 and an ‘Acquisition’ strategy for Business 2.

Figure 3.7 shows how selection of the portfolio strategy drives the business-level strategy and thus portfolio value. It also shows how both global uncertainties and business-level uncertainties impact the portfolio value.

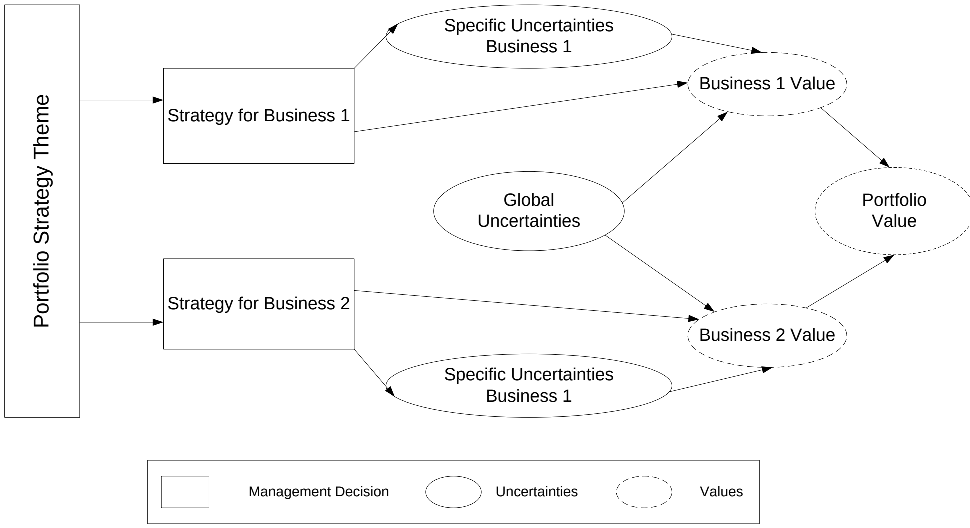

Figure 3.7 Map of a simple probabilistic approach (Poland 1999).

The consultants needed to determine how to approximate distributions of portfolio value quickly given the distribution of value for each value measure, strategy, business, and global scenario. The solution has four steps: summarize business value distribution with the first three cumulants (mean, variance, and skewness); sum cummulants across businesses to get portfolio values (based on the assumption that the values from each business are independent for a global scenario); convert the portfolio cummulants for each global scenario to raw moments and find the overall raw moments for the portfolio; and, fit a smooth distribution to the moments

In a workshop setting, the consultants used a spreadsheet implementation allowed for quick and interactive use and summarized the results in a user friendly-flying bar chart. During the workshop many strategy themes were explored to account for constraints such as resources not accounted for with this value model. The consultants have used these techniques in the areas of drug development, oil and gas fields, telecommunications, agricultural products, and potential TV pilot shows. If some subsets are highly correlated (such as two drugs that could cannibalize each other's markets) they should be pre-evaluated as a single combined asset. Other scenarios could also lead to evaluation of subset groupings. Another area of challenge occurs when the probability distribution is not accurately represented by the first three cummulants (Poland 1999).

While the strategy method does take into account alignment, a key item in successful portfolios, it neglects to address how one would evaluate what makes up an individual business level strategy. For example, there is no explanation for how to choose which 'Expansion' plan to apply to Business 1 in the 'Aggressive' portfolio strategy. Poland's strategy also mentions the issue of interaction in the form of cannibalization but glosses over a plan for evaluating interrelated products as a single asset.

3.5 A hierarchical approach to funding supplemental environmental programs

Peerenboom *et al.* (1989) contribute the decision analysis approaches for portfolios by taking a hierarchical approach to allocating funding to a supplemental environmental program (SEP) related to synthetic fuels. The funding was tied to a multibillion dollar loan agreement between the DOE and the Great Plains coal gasification facility. Two facts contributed to the decision to use decision analysis procedures to produce a well documented and traceable record of the decision process. First, the funding requirements for the proposed projects exceeded the available funds by more than a factor of two. Second, national attention was focused on the Great Plains facility (Peerenboom *et al.* 1989).

The DOE established a steering committee made up of five technical subcommittees to develop the SEP. Each subprogram proposed a number of detailed studies for health or environmental concerns. The subcommittee members did not have explicit budget constraints, but due to the overall limit of $12 million studies requiring tens of millions of dollars were not practical. The complexity of the decision on allocation of the SEP budget came from the following factors: the organizational structure of five independent subcommittees; the uncertainties around research needs, data availability, and costs; value tradeoffs at both the committee and subcommittee levels; and, the numerous strategies of more than 100 projects to evaluate.

This decision analysis procedure builds on previous applications of decision analysis techniques to rank projects and evaluate portfolios. It uses a hierarchical structure to integrate lower level and portfolio level decision analysis. The procedure was tailored to the structure of the committee and subcommittees. Each subcommittee was responsible for ranking its proposed studies. The subcommittee then quantified the degree to which a portfolio met a set of portfolio objectives as a function of funding level. The subcommittees used this information to produce a standardized set of performance curves (Peerenboom *et al.* 1989).

The four steps to the procedure and described below are depicted in Figure 3.8. Step 1 was to define the portfolio objectives and attributes. Committee members developed a hierarchy of objectives in which specific objectives were used to build up to broader, more general objectives. They then developed scales and attributes for each objective to indicate how well each portfolio objective was met by subprogram plans. Step 2 was to rank the subprogram studies and develop performance curves. Each subcommittee developed objectives that were more specific than the overall portfolio objectives. This step required quantifying a multiattribute utility function that represented the subcommittee chairperson's preferences over the subprogram objectives. The process involved determining: 1) the tradeoffs the chairperson was willing to make between competing subprogram objectives, and 2) the chairperson's attitude toward risk. The subcommittee evaluated each proposed study in terms of the utility function developed previously, used probability distributions to represent uncertainty, ranked studies on the basis of expected utility, and performed sensitivity analysis. This step links lower and higher levels in the hierarchy. Each subcommittee quantified how well its proposed studies met the portfolio objectives for given levels of funding. As funding levels were reduced, lower ranked studies were cut first in most cases. Subcommittees reviewed the proposed plan to assure that the selections made sense together. Step 3 was to quantify preferences for portfolio objectives defined in Step 1. In this step the committee quantified a multiattribute utility function to represent the committee chairperson's preferences over portfolio objectives. In addition to determining chairperson's value tradeoffs and attitude towards risk, the committee addressed utility tradeoffs between the five subprogram plans. This evaluation produced a set of subprogram scaling constants. Step 4 was to evaluate and compare feasible funding strategies to finalize SEP portfolio. A model using a backward dynamic programming algorithm to maximize utility from the funding of studies in the subprogram areas was used to identify and evaluate the large number of feasible funding strategies.

The hierarchical approach came in at Step 2 when the subcommittee sets priorities for its set of subprogram studies. This feature is a major contribution of this procedure but represents only one input into the portfolio level decision making.

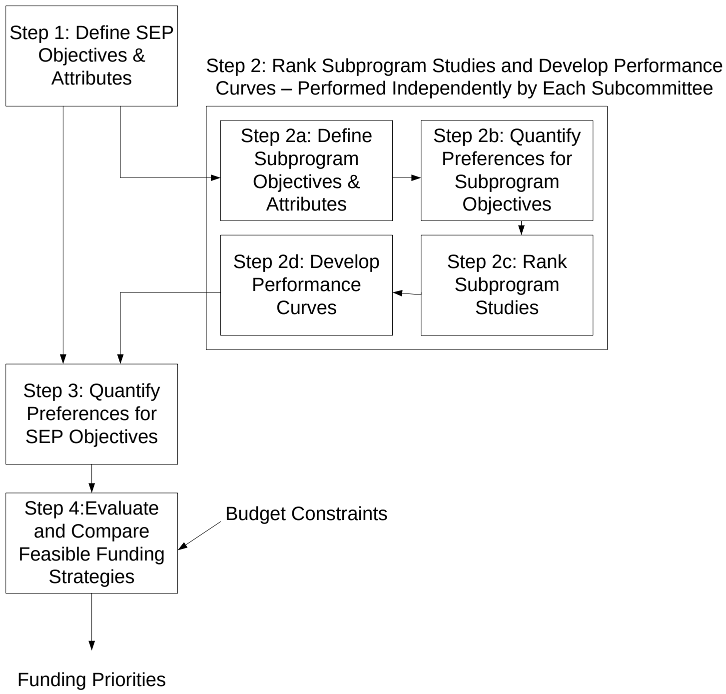

Figure 3.8 Diagram of Hierarchical Process (Parenboom and Buehring 1989).

A model using a backward dynamic programming algorithm to maximize utility from the funding of studies in the subprogram areas was used to identify and evaluate the large number of feasible funding strategies. At the portfolio level the chairperson identified comprehensiveness, relevance, and cost effectiveness as the broad areas of concern. The committee established objectives, attributes, and scoring criteria for each area of broad concern. Performance curves were created for each attribute to show how well the subprogram portfolio would do based on a given percentage of requested funding. Example performance curves from the Toxicology subgroup are shown in

Figure 3.9. The performance curves show that for the attribute of coverage, the value is 100 percent at full funding of the toxicology subprogram. If funding drops by 20%, the coverage of the toxicology subprogram decreases by nearly 50%. The performance curves allow the portfolio to be assessed as a whole unit.

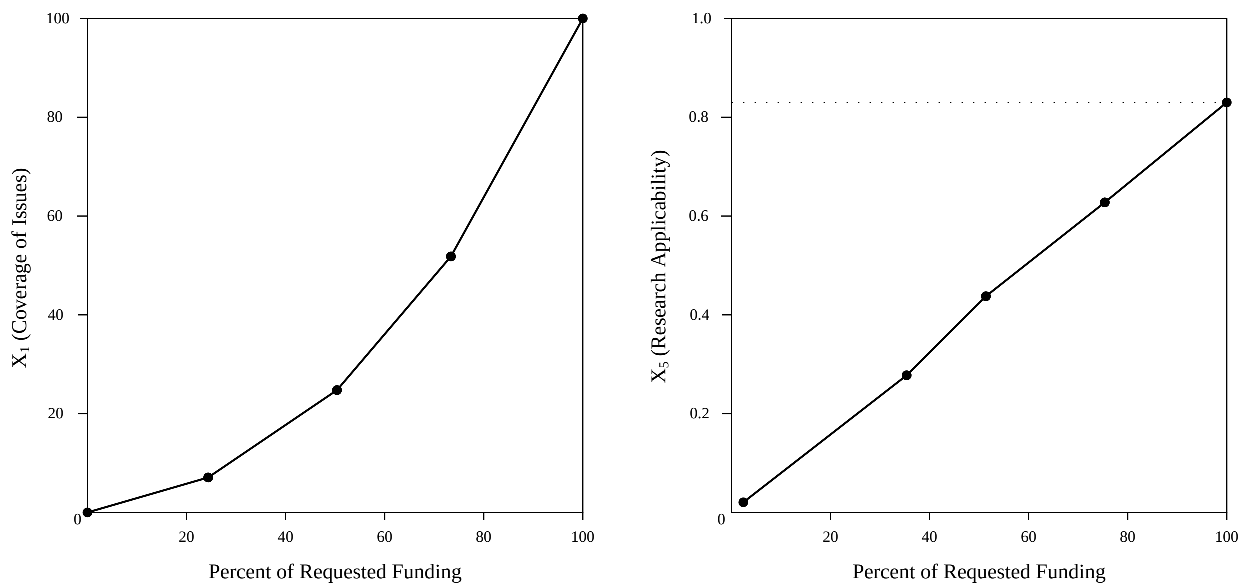

Figure 3.9 Select performance curves for toxicology subprogram (Parenboom and Buehring 1989).

The steering committee allocated a reduced amount of funding of $9 million across the five subprograms. Prior to final allocation sensitivity analysis was completed on changes in levels of 1) subprogram scaling constants, 2) portfolio level utility function scaling constants, and 3) subprogram performance curves. The chairperson adjusted the funding priorities from the model following extensive reviews and discussions with stakeholders. This adjustment impacted only 3 of the 88 proposed studies (Peerenboom *et al.* 1989).

The method described by Perrenboom *et al.* addresses alignment with strategy and handling of multiple criteria. It also creates a transparent process for the decision and allows for adjustment to build consensus among committee members. Some of the attributes, such as coverage, defined at the portfolio level address the balance in the portfolio. The primary area that did not receive full coverage was possible dependence between funded projects.

While the applications described above do address the handling of a portfolio in a given situation, none present a generic framework that integrates all key elements of a good portfolio and method. Chapter 4 will look at what lies ahead for the use of decision analysis techniques for tackling R&D portfolio problems. The practice of R&D portfolio management will be compared to the ideal of portfolio management described in the financial literature. The chapter will also investigate the gaps between the theoretical ideal portfolio and the practical methods provided to date. Several proposed methods that attempt to integrate previous work or fill in the gap related to project interactions will be reviewed. Areas of future study will be identified.

CHAPTER 4 The Future of Portfolio Techniques

The literature presented in the previous chapters presents a variety of techniques for addressing the problem of R&D portfolio selection and a number of applications that integrate both technical and social techniques. This chapter will review the gaps between the ideal portfolio and selection process and those that have been proposed to date. The chapter will also review several theoretical approaches to portfolios that have been proposed to address previously identified shortcomings. Future areas of research will be covered along with a discussion of the value in pursuing better modeling techniques.

4.1 Identifying the gaps

As described earlier, the problem of R&D portfolios is a difficult one. It poses challenges from a technical perspective with requirements to address multiple objectives, uncertainty, and dependence. It also poses the social challenge of trying to incorporate competing objectives and gain consensus among what can be a wide spectrum of decision makers with differing priorities and perspectives. Without fail, literature containing applications or discussions on the topic of R&D portfolios begins with a litany of shortcomings from other approaches. Some methods address interactions but not uncertainty, others the reverse.

Most of the applications in portfolios address two of the three key areas that Cooper *et al.* (2001), maximizing value and aligning with strategy. All methods described focus on improving the value of a portfolio and improving the quality of the decision making process.

Most of the applications reviewed made an effort to align the chosen portfolio with corporate strategy. Of the applications described herein, the landfill remediation technology selection problem pays the least attention to strategic alignment (Jackson *et al.* 1999). The lack of attention in this area was reasonable given the limited scope of the specific problem but would not be appropriate in a corporate setting where project or technology selection was wide open. Poland (1999) addresses the issue of strategic alignment more directly. In the method he describes, strategy themes are established at a corporate level which drives the selection of themes at the business unit level. In Poland's description, the high-level approach could be an aggressive strategy driving other actions such as acquisition or expansion in the business units. While this approach works for Poland in a number of applications, it does not allow for a more complex strategy that is typically described by corporate mission statements and values. The variety of approaches that incorporate MCDA, can successfully tackle the alignment issue if objectives and attributes are well defined.

Attacking the concept of a balanced portfolio proved slightly more complicated. The definition of what makes a balanced portfolio is rather subjective. Peerenboom *et al.* (1999) address the issue of alignment by establishing an attribute at the portfolio level to review coverage of key areas. Phillips and Bana e Costa (2007) address balance by evaluating an optimal portfolio and then adding constraints to shift project selection as needed. Jackson *et al*. (1999) enforced balance by selecting one technology for each stage of the process. In the R&D portfolio literature balance seems to refer to allocation of resources in at an acceptable level across specific category designations. A decision maker could be looking for balance across business units, technology areas of interest, or timing of projects.

The ability to address uncertainty in projects is not addressed in some methods. Phillips (2007) believes that addressing uncertainty is unnecessary and not of interest to decision makers whereas the options pricing literature such as Smith and Nau (1995) focus on acknowledging and accounting for uncertainty as well as the decision maker's risk attitude. Any of the methods or applications that incorporate use of decision trees would be appropriate for decision makers considering highly innovative projects with uncertain outcomes. If the decision maker expresses little concern for consideration of uncertainty, inclusion of decision trees in the process could be an unneeded complication.

Dependence is one area of the decision process that has not been adequately addressed. Many of the applications mention dependence but do not detail the handling. In some cases dependence comes from the sequential nature of projects. Project A could be an extension of Project B but not viable as a standalone project. Phillips and Bana e Costa (2007) suggest ignoring the dependence unless Project A is selected in the optimal portfolio without Project B. If the projects were inappropriately split, an additional constraint could be added to either include B or exclude A. The resulting portfolios can be compared and discussed by the decision makers. Poland (1999) recommends that if there are two projects under consideration that could result in cannibalism of the other's market, the two projects should be combined and evaluated as a single unit. The specific methodology for combing the two is not addressed.

The table below in Figure 4.1 summarizes the findings on the current state of techniques for R&D portfolios. The applications provide full, partial or no coverage of the criteria. For an application to achieve full coverage the literature must clearly explain how the criteria were achieved. Partial coverage refers to a case where a full explanation of a topic is not provided or the implementation is specific to the application. A topic is considered to have no coverage if it is not mentioned or no explanation is provided. All of the applications studied utilize MCDA in some part of the analysis successfully accounting for the multiple objectives present in R&D decisions. They also are geared toward achieving agreement among stakeholders at least touching on the social aspect of the process. The focus on the social aspect varies depending on the industry in question and the practitioner performing the work. Consultants tend to focus heavily on the social aspect. Alignment with the strategy can easily be covered by the multiple objectives defined, but was not relevant to all applications. The two main areas of weakness are balance and interaction.

Application	Alignment	Balance	Maximizes Value	Multiple Objectives	Interaction	Social Process
Landfill Remediation	◐	◐	●	●	○	●
Solar Energy Projects	○	◐	●	●	○	●
Decision Conferencing	●	○	◐	●	○	●
Consultant Approach	◐	◐	◐	●	◐	●
Environmental Programs	●	●	●	●	○	●
Overall	●	◐	●	●	○	●

● Full coverage of topic ◐ Partial coverage of topic ○ Minimal or no coverage of topic

Figure 4.1 Scorecard for meeting key criteria important to a good portfolio method

Sections 4.2 and 4.3 cover two theoretical approaches, which attempts to address pitfalls of previous application. The contingent portfolio programming approach by Gustafsson and Salo (2005) incorporates multi-attribute utility theory with the options pricing approach. The scenario for selecting meals for a nursing home by Chien and Sainfort (1998) tackles the area of interrelation among projects not fully addressed by previous work.

4.2 A Contingent Portfolio Programming Approach

In spite of the interest by academics and practitioners and variety of methods described, Gustafsson and Salo (2005) point out limited acceptance in industrial settings. They indicate that slow industrial uptake is due in part to the inability of existing methods to address all areas relevant to the problem. They build on the existing work from decision analysis, R&D management, and financial portfolios to develop the CPP method. In addition to drawing on the multiattribute aspect of scoring methods, Gustafsson and Salo identify optimization models and dynamic programming models as the most relevant to

CPP. In their view, optimization models are extensions of capital budgeting and capture project interaction and resource constraints while failing to address uncertainty. They group decision trees and real options analysis in the category of dynamic programming. According to Gustafsson and Salo, this group of projects captures the sequential nature of decision making, but fails to address project interaction or resource constraints. They point to the options literature which addresses risk preferences but fails mimics a continuous range of options not a discrete set such as in project selection. They do not address the methods described by Smith and Nau (1995) and Perdue *et al.* (1999) which integrate decision trees and real options.

CPP provides a methodology for a decision maker to select risky projects over multiple time periods. The CPP approach incorporates decision trees to mimic flexibility of the decision maker to make ongoing go/kill decisions based on available information. CPP offers flexibility to accommodate a range of risk attitudes. The CPP model is defined by resource types, a state tree, and decision trees by project. The method accommodates many types of resources both tangible (e.g. capital or equipment) and intangible (e.g. skill sets). In the model resources are designated by r and the set of resources R. Future states of nature are represented by a state tree. The tree starts with a base state s_0 and branches out based on the occurrence of uncertain events. A sample state tree for an example with two projects that will later be described to illustrate the CPP approach is shown below in Figure 4.2 .

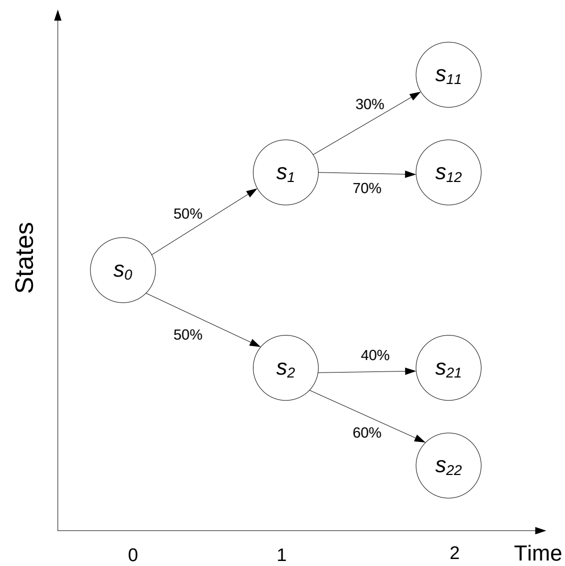

Figure 4.2 Sample state tree (Gustafsson and Salo 2005).

A decision maker has choices at a number of decision points for each project. At each decision point the decision maker choices the action taken. A variable X_a is defined for each action. In many instances the variable will be defined as a binary variable with a value of 1 if the action is made and 0 otherwise. Sample decision trees are defined for two projects A and B and shown in Figure 4.3.

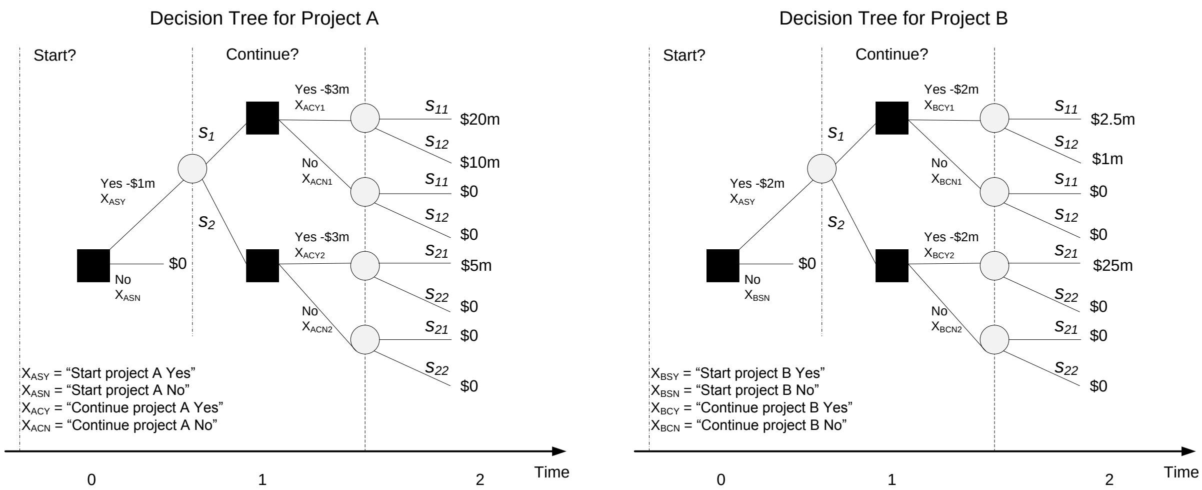

Figure 4.3 Decision trees for Projects A and B (Gustafsson and Salo 2005).

Resource flows are defined at each state. Resources can either be gained or consumed at each point depending on actions chosen by the decision maker. Figure 4.4 shows the cash flow diagram for the example with two projects.

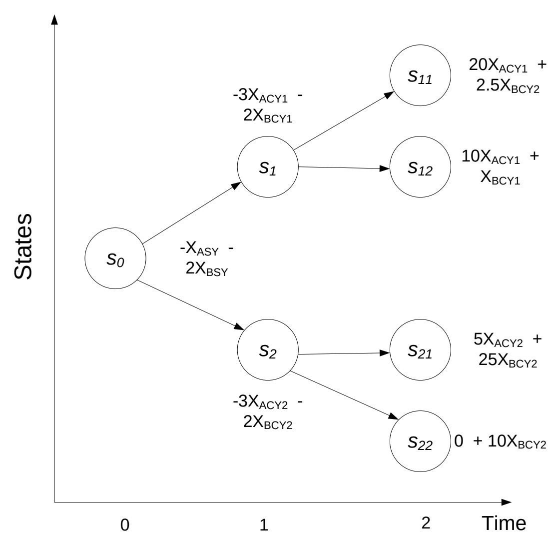

Figure 4.4 Cash flow for a two project portfolio (Gustafsson and Salo 2005).

In evaluating this decision, the decision maker's objective is to maximize utility of the initial position. Gustafsson and Salo focus on a special case that has a reasonable model of risk aversion and is appropriate for linear programming. In addition the objective function, they define several classes of constraints including decision consistency constraints, resource constraints, and a number of optional constraints. The simple two project example demonstrates the benefits to considering the projects together instead of each individually. Project A and B succeed inversely. Project A fares better if state s_1 occurs in period two and Project B fares better if state s_2 occurs. Either project selected individually would have a negative NPV. If the decision maker invests in both projects in the first stage and then makes a decision about which project to fund for the second phase depending on the current state of nature, the expected NPV is positive. The diversification of the portfolio mitigates some of the risk.

As the number of projects, resources, and constraints increase the problem becomes more complex computationally. Gustafsson and Salo test a number of scenarios using C++ and an LP solver. They find that LP models could be solved in a reasonable time frame, but the time to solve MIP formulation increased exponentially with the number of integer variables.

Gustafsson and Salo recommend theoretical extension of the model to include more complex resource dynamics. They identify situations where decision trees can be defined for each project and they projects are correlated. The more complex theoretical approach that Gustaffson and Sarlo embrace stands in stark contrast to the beliefs of Phillips (2007) that lean to a more simplified model and rely on social process to guide decision making.

4.3 Proposal for addressing interrelationships between items in a portfolio

Chien and Sainfort (1998) address the problem of applying multiattribute analysis to selecting a portfolio of interdependent items. Existing techniques to assist decision makers in selecting portfolios have limitations, which come in part from a lack of modeling frame work to tie interrelationships between items to item and portfolio measures.

This study lays out a method for addressing these limitations by looking at preferences for meals in a nursing home. In this case, the meal is a portfolio made up of a selection of food items. The individual foods in the meal interact in a way that impacts the desirability of that meal. Previous linear programming approaches to defining an optimal meal schedule focused on minimizing the cost and meeting certain constraints such as nutritional requirements. They did not account for items such as variety and flavor desirability.

The study aimed to develop a multiattribute index to quantify overall meal desirability to assist the nursing home nutritionist in designing meals. The study considered foods selected for lunch and dinner meals. For this study, a meal is defined as a portfolio of six food items, one from each of the following groups: meat, potato/rice/pasta, vegetables, garnish, bread, and dessert. The term food references a single item in any of the groups. The term meal references the portfolio of food items comprised of one food from each group.

Many models for portfolio evaluation use a “bottom-up” approach. This type of approach typically assumes that (1) a set of evaluation attributes exists to assess the desirability of any element of the portfolio relative to evaluation considerations, (2) these attributes can be combined using a value function, and (3) the value function for each element can be combined to form the total portfolio value. This study uses a “top-down” approach, which assumes that (1) a set of overall evaluation attributes exist to assess the desirability of a portfolio with respect to the evaluation considerations, and (2) the attributes can be combined to using a value function to determine the overall desirability of the portfolio (Chien and Sainfort 1998).

The study followed a general methodology for creating multiattribute utility model described by Keeney and Raffia (1993, Chapter 3) to create a final set of attributes. Five attributes were defined to measure overall meal desirability. The first four attributes: variety of colors; variety of textures; diversification of presentation forms; and distribution of preparation methods can be evaluated in a relatively straight forward approach. The fifth attribute, flavor desirability, requires development of a new method.

The overall flavor of a meal is the most important attribute. It is also the most complex attribute to assess. The approach to assessing meals was to (1) disregard the garnish that many times goes uneaten, (2) focus on the interaction of the other five groups starting with the meat element, and (3) evaluate the desirability of the meal by looking at the compatibility of the other side items with the chosen meat. Since the study evaluates the meal by comparing the remaining four elements to the meat, the probability that a meal is good can be split into four probabilities. Since these probabilities are subjective, the study applies a subjective Bayesian modeling strategy proposed in general form by Gustafson *et al.* (1993) to evaluate the interrelation. The study constructs to hypotheses.

The first, H1, is a meal with a good flavor combination. The second, H2, is a meal with a poor flavor combination. The study then tackles quantifying the odds ratio

$$\frac{P(H_1|S_1,S_2,S_3,S_4,S_5)}{P(H_2|S_1,S_2,S_3,S_4,S_5)}$$

for a meal consisting of the five food items $(S_1,S_2,S_3,S_4,\ S_5)$ where S_1 is a meat, S_2 a potato/rice/pasta, S_3 a vegetable, S_4 a bread, and S_5 a dessert. Since the meat item S_1 is the primary factor in flavor desirability the equation can be decomposed as:

$$\frac{P(H_1|S_1,S_2,S_3,S_4,S_5)}{P(H_2|S_1,S_2,S_3,S_4,S_5)} = \frac{P(S_2,S_3,S_4,S_5|S_1,H_1)}{P(S_2,S_3,S_4,S_5|S_1,H_2)} \times \frac{P(H_1|S_1)}{P(H_2|S_1)}$$

Since the expert only considers the pairing of the meat item with the other four items the equation can be reduced to

$$\frac{P(H_1|S_1,S_2,S_3,S_4,S_5)}{P(H_2|S_1,S_2,S_3,S_4,S_5)} = \prod_{i=2}^{5}\frac{P(S_i|S_1,H_1)}{P(S_i|S_1,H_2)} \times \frac{P(H_1|S_1)}{P(H_2|S_1)}$$

In this study, the desirability of each of the meat items is considered equal. Thus, the prior probabilities can be set to l.

To elicit information necessary to estimate the probabilities the expert answered questions such as. *Considering flavor desirability, assume that 100 meals with 'Roast Beef' as the meat item* <u>have good overall flavor</u>. *Of these 100 meals, how many would you say were served with mashed potatoes __, fried potatoes __, yams__, rice__, and pasta__?*

Since there were five food groups 40 questions were asked to produce 200 probabilities and 100 likelihood ratios. After establishing the likelihood ratios, the study calculates the probability that a meal is good $P(H_1|S_1,S_2,S_3,S_4,S_5)$ using

$$P(H_1|S_1, S_2, S_3, S_4, S_5) + P(H_2|S_1, S_2, S_3, S_4, S_5) = 1$$

To validate the modeling, the study compared the expert's direct holistic judgments of the meals to the overall model. The study combined the five attributes using a simple multiattribute value model (MAV). Even with the simplified MAV, the Pearson's correlation coefficient between the results produced by the model and the expert's assessments was relatively high 0.6279 ($p<0.001$).

The paper shows that a fairly simple Bayesian decomposition can model complex interactions between food items in a meal. Since the simplified MAV model performs relatively well, a more elaborate MAV could lead to an even better overall model. The authors suggest that a linear programming approach to looking at cost and nutritional requirements could be combined with their proposed approach.

One success of this top-down approach was to demonstrate the ability to construct portfolio-level attributes as a function of item-level attributes. The authors believe that the procedure could be generalized to extend to other portfolio scenarios. Additional applications would be needed to confirm use for broader contexts.

Several factors distinguish this application from other portfolio selection problems such as project funding. This application differs from many portfolio scenarios in that the number of items in the portfolio was fixed at six for all portfolios. The specific application does have several common characteristics with general portfolio problems. First, Chien and Sainfort evaluated the preference for the portfolio has a whole not for the individual items. Second, the items in the pool are not preferentially independent. Picking the top item in each of the groups might not result in the best overall portfolio.

Chien and Stainford describe a method for evaluating a portfolio that more fully and directly addresses interactions between items than other methods and applications described above. Since this was a simplified case as a test scenario, they do not address other key issues such as developing consensus among decision makers. Also they do not fully address the computational complexity and resource requirements to implement the described method in a corporate setting. Expanding the approach to a project selection problem would require some refinement of the procedure. As previously noted by Phillips and Bane e Costa and Peerenboom and Buehring, tradeoffs exist between complexity of a model and acceptance by the decision makers.

4.4 A Comprehensive Approach for the Future

Given the gaps in existing implementations and techniques, a comprehensive approach is needed. The approach needs to handle multiple objectives, account for project interactions, and address the social aspect of decision making. The resulting portfolio should be aligned with business strategy, balanced, and of maximum value. The approach proposed below accomplishes all of these goals.

Many of the applications mentioned previously evaluate projects against a set of criteria and then select the projects with highest value that can be implemented given resource restrictions. In order to assure that the entire portfolio is aligned with the business strategy and balanced, multi-attribute analysis should be applied to the overall portfolio level to determine its value, similar to the hierarchical approach taken by

Peerenboom *et al* (1999). Use of the multi-attribute approach assures that the multiple objectives of an R&D portfolio problem are taken into consideration when evaluating the portfolio.

Conducting the evaluation at the portfolio level covers several important factors. First, it assures that the entire portfolio is aligned with the business strategy. It also allows for a check for balance in the critical areas defined by the decision makers. Balance can be achieved either by assigning a utility to achieving a desired level of balance and penalizing alternatives that do not meet the minimum threshold or by applying constraints. In the above mentioned scenario the balance could be across a geographic area, business unit allocation, or other specifically defined category.

In order to successfully address project or product interactions, it is first necessary to consider the different opportunities for and types of interactions or interrelationships. Interactions could occur on the input side. Projects or business units could face common global uncertainties. While these uncertainties could impact the overall value of the portfolio, they are particularly critical when assessing risky projects. A second category of balance comes from the need to balance the risk in a portfolio. If projects are negatively correlated based on future states of the market, maintaining both projects in a portfolio through early stages of development balances the risk and increases the odds of having a successful project included. If the two projects were evaluated separately, both would likely be excluded from the portfolio because future states of the market were unknown. Projects of high-risk and uncertain outcome should be handled through a probabilistic approach such as the one describe by Gustafsson and Salo (2005) which allows for go/kill decisions throughout the course of development. Since this type of analysis is more cumbersome, it should only be applied to a small subset of risky projects. A starting point would be to address the top five risky projects, similar to the approach taken by Poland (1999) when determining which uncertainties to address.

Additional interactions at the input level occur due to potential overlap in resources, assets or skill sets. These interactions should be addressed by applying resource constraints to the overall portfolio. These are interactions that impact the cost of the project.

The most difficult type of interaction to address is the interaction on the benefit side. The easiest of the benefit interactions to describe is market share, which drives expected revenue. If two products are launched into the market there are three scenarios that can occur. First, the products could have no impact on each other in which case the total market share would be the sum of the market share for each project launched alone. An example of this scenario could be launching a new laptop at the same time as a new PDA. Neither product is likely to be impacted by the timing. Second, the products could have a positive impact on each other and the total market share for launching both exceeds the combined market share for launching independently. An example is the launch by Apple, Inc. of the iTunes service at the same time as the launch of the iPod player. The two complementary products enhanced each other’s sales. Third, the projects could negatively impact each other if they have competing consumer bases. In this scenario, the total market share for launching both products would be less than the combined share for launching the two individually. An example could be two drugs which overlap to some extent in application. Depending on the level of overlap, the company might decide to proceed with both as long as potential cannibalization of the marketplace is built into the analysis. Within a group of projects under consideration, most will fall into the first category and not impact each other's potential market. In the few cases where interaction likely to occur, probabilistic analysis of the outcomes should be conducted. If the project interactions are high, the top five should be analyzed.

By proposing a well-defined process of multi-attribute analysis on the portfolios, decision makers should have transparency to the data in making a decision. Some of the more complicated probabilistic analysis could be conducted offline to avoid burdening the decision makers with the additional detail. This compromise allows for a socially acceptable process but provides enough detail to maximize the value of the portfolio.

In summary, a comprehensive approach would (1) apply multi-attribute decision analysis at the portfolio level, (2) apply constraints for common inputs to cost such as resources, and (3) apply probabilistic methods to account for project interaction. This approach would meet the previously defined criteria for a good portfolio approach. This proposal provides a more thorough and rigorous approach than those previously defined.

CHAPTER 5 Conclusion

The topic of R&D portfolios is a complicated one that demands development of adequate tools to address all relevant concerns. While companies use widely varying approaches none of the efforts described to date cover all of the six criteria for a good portfolio. The areas of balance and interaction need additional focus. The proposal for a comprehensive approach addresses these two remaining concerns.

One remaining area for consideration the level of detail needed in a model or technical solution. The industry in question and the corporate environment impact the most appropriate tool for a specific application. There are several schools of thought that shy away from complex models. The extensions suggested above could fill a void in the technical evaluation but might not produce a method that could gain wide acceptance within industry. Keeney and von Winterfeld (2007) discuss "practical" value models, noting that it is not always necessary or desirable to construct a complex value model even though it might be theoretically justifiable. They also acknowledge that in some cases theoretically valid assessment procedures are not required. The appropriate level of complexity is driven by the decision scenario, resources available to gather data or implement a model, and time allowed for making the decision. Phillips (2007) discusses a similar concept of requisite modeling. In a decision conferencing scenario, a requisite model is one that is sufficient to resolve the issues under consideration. He believes that the iterative process between consultants and decision makers to define the model increases the understanding of the situation and resolves decision makers' concerns on validity of output from a model. Phillips considers a model requisite when no additional insight is evolving. The model does not necessarily provide a solution. At best it is prescriptive for the specific problem under current environmental conditions. The model does however capture the decision making context and helps develop a shared set of objectives. Decision makers come to understand that decisions that are best for the whole group do not always align with a decision that is best for their unit.

The specific application for portfolios and the industry in question drives the method selection and implementation plan. In some cases, where specific constraints exist or assumptions such as no interaction between projects are valid, existing techniques as previously described could be a good fit. Also, in industries or companies that do not have a well-defined approach for managing portfolios, techniques which focus heavily on the social process or provide only a requisite model might be the most appropriate selection. Implementing a more rigorous technical solution would likely meet resistance internally. In areas where a well-established program exists, a next step to improve on the process could be implementing the comprehensive approach that would (1) apply multi-attribute decision analysis at the portfolio level, (2) apply constraints for common inputs to cost such as resources, and (3) apply probabilistic methods to account for project interaction.

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VITA

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