20 Resource Allocation Decisions

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ABSTRACT. Organizations typically have more good ideas for projects than they have resources available to pursue those ideas. Decision analysis can provide practical guidance to the organization on how to get the maximum benefit from those limited resources. This chapter reviews methods for prioritizing projects using mathematical optimization or benefit-cost ratios in concert with standard decision-analysis and risk-analysis tools. These tools include multiattribute utility and value models, decision trees, influence diagrams, and Monte Carlo simulation. To illustrate issues that arise in implementing these approaches in organizations, the use of resource allocation models in hospital capital budgeting is described at length. The chapter concludes with a call for more research on the use of decision analysis in organizational settings.

The Challenge of Organizational Resource Allocation

What universal dilemma is confronted by organizations of every size, type, and purpose? Stated simply, they have more good ideas for projects, programs, and investments than they have resources available to pursue those ideas. These ideas include facilities expansion or construction, new equipment, innovative manufacturing or service delivery technologies, and information technology upgrades. In addition, many organizations engage in research and development efforts that require identifying the most promising new products, technologies, or process improvements.

Often, the limiting resource is financial because an organization's capacity to borrow funds or raise equity capital has practical limits. There also may be insufficient facility capacity, or not enough time to pursue every idea. In other instances, specialized skills or expertise are the limiting factor. An important example of limited expertise occurs when executives lack the time to oversee the implementation of too many projects. Whatever the resource limitations, the implication is that projects cannot be considered in isolation. Choosing one project implies that fewer resources will remain for the rest. As a consequence, poor choices lead to high opportunity costs as the organization squanders scarce resources.

Most organizations engage in some type of regular capital budgeting or project portfolio selection process. Plans are evaluated and decisions made about which projects to pursue and which to either reject or postpone. Although these processes are as varied as the organizations that pursue them, there are common elements shared across many settings: First, the lists of plans and proposals are

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dauntingly long, measured in the dozens, hundreds, or even thousands, depending on organization size. Second, no one person can possibly have a complete understanding of each and every project, with relevant information spread across many individuals. Finally, there is the ever-present temptation for organizational stakeholders to scramble to exert influence to secure resources for favorite projects. In part, this reflects the narrow pursuit of self-interest. All too often, however, not even top-level decision makers have a clear picture of which projects are in their organization's best interest, and this confusion leads to uncertainty and conflict.

Given these challenges, there is a clear role for analytical tools and processes to improve organizational resource allocation. The purpose of this chapter is to provide an overview of decision analysis approaches to resource allocation and an extended description of the use of resource allocation methods in a particular setting, capital budgeting in U.S. not-for-profit hospitals. Rather than attempting a comprehensive review of resource allocation applications, I have tried to provide representative examples. Additional applications are reviewed by Corner and Kirkwood (1991) and by Keefer, Kirkwood, and Corner (2002, 2004).

The remainder of the chapter is organized as follows: First, a mathematical optimization framework for resource allocation is introduced. This is followed by a description of two categories of decision analysis models that are used in concert with the optimization framework: Multiattribute utility and value models are used in situations where project benefits are defined over multiple objectives, and decision trees, influence diagrams, and Monte Carlo simulations are used where there are significant uncertainties regarding project benefits and costs. Next, I describe implementation of resource allocation models in hospital capital budgeting and discuss some issues that arise in practice. I conclude with a call for more research on the organizational implementation of decision analysis models and methods.

Capital Allocation Using Mathematical Optimization

Financially oriented capital budgeting approaches are well developed and have been described in many texts and references (see, for example, Bierman and Smidt 1993; Brealey and Myers 1996; Canada, Sullivan, and White 1996; Lang and Merino 1993; Luenberger 1998). The classic financial approach uses discounted cash flows to evaluate projects, based on forecasts of incremental cash flows required to acquire, operate, and then dispose of each plan or project. The cash-flow forecasts are almost always presented as point estimates, although they may be based on extremely detailed deterministic financial models.

Because financial benefits accrue over some period of time, they are almost always measured using a net present value calculation. In most business settings, the discount rate used in this calculation represents the average amount that the organization must pay to obtain funds (i.e., the opportunity cost associated with making the investment). If an organization has no limit on its ability to obtain capital and is concerned only with financial return, then it should accept any project with a positive net present value. However, with limited access to capital, there is a problem of capital rationing: the organization wishes to obtain as much

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benefit as possible while spending no more than the available amount of capital. This is readily modeled with a binary integer programming formulation (for an early discussion, see Weingartner 1963).

The formulation is not complicated: suppose an organization is considering a set of m proposed capital expenditures, and the only decisions to be made are with regards to funding ("yes" or "no") for each project. Let c_i denote the cost to develop the project ($c_i > 0$ for $i = 1$ to m).[1] Let b_i denote the net present value of project benefits ($b_i > 0$ for $i = 1$ to m). Let x_i represent a binary decision variable for each project ($x_i = 0$ or 1 for all i). Finally, let C denote the budgeted amount available to fund project costs. The objective is to maximize aggregate benefits while staying within the budget constraint:

$$\begin{aligned}
&\text{maximize } \sum_{i=1}^{m} b_i x_i \\
&\text{subject to} \\
&\qquad \sum_{i=1}^{m} c_i x_i \leq C \\
&\qquad x_i = (0 \text{ or } 1),\ i = 1, \ldots, m.
\end{aligned}$$

This model assumes that neither benefits nor costs of a project depend on which other projects are selected, with the implication that both benefits and costs are additive. Solution techniques and optimization software for solving these models are readily available, and are described in most operations research textbooks (e.g., Hillier and Lieberman 2005).

An intuitively appealing alternative to optimization is to rank projects using *benefit-cost ratios* (b_i/c_i) or the closely related *profitability index* ($(b_i - c_i)/c_i$). Projects are prioritized by selecting the highest-ratio projects until funds are exhausted. This approach produces the highest value for the amount spent, but may not spend all available funds. If there are less costly projects with nearly the same ratio values as the last projects funded, then substituting these may produce higher aggregate benefit. However, in practical settings, sorting on benefit–cost ratios often produces a reasonable heuristic solution with only a small deviation from the aggregate benefit achievable through optimization.

One advantage to mathematical programming formulations are that they can be readily extended to allow for additional resource limitations or project dependencies that arise with large, complex projects. For instance, the organization might consider projects requiring funds over multiple time periods, with limited funds available for each period. Extending the formulation requires an additional budget constraint for each time period. Similarly, accounting for other limited resources (e.g., human resources or suitable facilities) is accomplished by adding constraints to enforce those limitations.

A form of project dependency that arises in many settings is mutual exclusivity of project choices. For instance, when considering alternative versions of the same

[1] For simplicity of exposition, assume that all project expenditures take place in one year, and that the organization only considers capital allocation one fiscal year at a time.

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project, choice is restricted to at most one version of the project. Suppose the set S represents a subset of projects that are mutually exclusive ($S \subset \{1, \ldots, m\}$). A constraint of the form $\sum_{i \in S} x_i \leq 1$ permits selection of no more than one project from the set of mutually exclusive projects, with the possibility that none would be selected. A constraint of the form $\sum_{i \in S} x_i = 1$ requires selection of exactly one project from the set.

In other instances, projects are contingent, meaning that one project can be chosen only when a second project is also selected. An example is a computer software purchase that is only feasible if necessary computer hardware components are acquired simultaneously. If project i is contingent on project k, then the constraint would be $x_i - x_k \leq 0$. If projects are mutually contingent, then one can be chosen if and only if the other is chosen, requiring a strict equality constraint: $x_i - x_k = 0$.

Sometimes, it is convenient to treat contingent projects as a single project with combined costs and benefits. However, unless there is mutual contingency, this requires introducing mutual exclusivity, to allow for scenarios where one wishes to acquire one project but not the other. For instance, when considering constructing a new office building, one might consider a new parking garage as contingent on the construction of the offices, if the garage would have no useful purpose without the new offices. Alternatively, one could consider "office building" versus "office building plus garage" as mutually exclusive projects if this will make the assessment of benefits and costs more convenient.

Almost any of these extensions to the basic model renders the use of benefit–cost ratios problematic. For instance, with multiple resource constraints, it is not clear which resource to use as the denominator in the benefit–cost ratio because one cannot know in advance which will be the limiting resource. Further, as dependency constraints become more numerous, sorting on ratios is unlikely to produce a solution consistent with all the constraints. Under these circumstances, mathematical optimization is the only practical approach.

One context where mathematical optimization has been used extensively is the analysis of U.S. military procurement decisions, such as the acquisition of military weapons systems. Brown, Dell, and Newman (2004) provide an excellent overview and key references. These decisions routinely involve allocating billions or trillions of dollars over years or decades. According to Brown and colleagues, a number of modeling "embellishments" are essential to capture the realities of the setting: (1) Decision variables involve both whether to acquire a particular weapons system, and, if the system is acquired, the number of units required. (2) Both benefits and costs may be nonlinear in the number of units procured, usually modeled using piecewise linear functions. (3) Certain funds may be restricted as to when they may be spent and what they may be spent on, requiring constraints for different "flavors" of money. (4) Project benefits from multiple systems are greater (or less) than the sum of the parts, requiring multiplicative interaction terms in the benefit functions. (5) Budgets must allow for many years between acquisition, development, and deployment of a system, requiring a series of constraints to reflect these dynamics. (6) Other dynamic consideration include both year-by-year and cumulative resource limitations, overhaul and retirement decisions for older equipment, and mission-related requirements for either sequential or concurrent availability of specific weapon systems. One consequence of these complications is that models may have thousands of decision variables and constraints. Solutions, therefore, require a combination of serious computing power and ingenuity in both model formulation and computational methods.

Measuring Project Benefits Using Multiattribute Value Models

One of the most obvious differences between military procurement and business settings is the way in which project benefits are measured. In for-profit business entities, discounted net present value is generally considered the "gold standard" metric. Because the organization's fundamental objective is generally regarded as maximizing the value of the owners' investment, in the world of corporate finance, this metric has both a clear theoretical rationale and practical relevance. However, in government and not-for-profit entities, the organization's objectives are not exclusively focused on financial value.

Multiattribute utility and value models provide a methodology for evaluating project and program benefits in light of multiple conflicting objectives (Keeney 1992; Keeney and Raiffa 1976). An early application of multiattribute value models to resource allocation is reported by Golabi, Kirkwood, and Sicherman (1981). They propose an optimization framework identical to the one described above, except that project benefits are assessed using multiple evaluation criteria. Golabi and colleagues propose the application of this methodology to government procurement, and describe using it to assist the U.S. Department of Energy in selecting a portfolio of solar energy application experiments.

In particular, they propose using a linear-additive multiattribute value function. Suppose there are *n evaluation attributes* (denoted y_{ij} for project $i = 1$ to m and evaluation attribute $j = 1$ to n). The benefit measure is a *weighted value score* (denoted b_i^* for project i), a weighted average of the benefit assessed on each attribute:

$$b_i^* = \sum_{j=1}^{n} w_j v_j(y_{ij}).$$

Each function $v_j(\cdot)$ is a single-dimensional *measurable value function* (also known as an ordinal utility function) that represents a decision maker's preference for performance differences on a single attribute, scaled to a standard range (e.g., from 0 to 1). The w_j parameters are weights that capture a decision maker's assessment of the relative importance of the evaluation attributes over the range of values observed for the particular set of candidate projects, typically scaled to sum to 1.

Applying this approach to project portfolios requires the usual preference independence assumption for the linear-additive form of the value function (see also Keeney and Raiffa 1976), and additional assumptions to obtain additivity of project values across the portfolio. The latter assumptions permit project benefits to be measured one project at a time, which simplifies the application of the method significantly. Although Golabi and colleagues carefully tested and examined the validity of the independence and additivity assumptions, most applications simply apply linear additive project scoring methods without rigorous testing. These can be ad hoc scoring systems or simplified multiattribute value models familiar to many decision analysts, such as SMARTS, the Simple Multiattribute Rating Technique using Swings (see Edwards and Barron 1994; see also Clemen 1996, chapter 15; or Kirkwood 1997, chapter 4). The project scores are then used to prioritize and select projects, either using integer programming or benefit-cost ratios. The optimization formulation is the one described above, except that weighted value scores (b_i^*) replace financial benefit measures (b_i). Net present value (or some other financial metric) is not neglected, but rather, is often included as an attribute.

This approach has been widely applied to public programs and policy issues (e.g., analyzing alternative technologies for military programs, Burk and Parnell 1997; Parnell, Conley, Jackson, Lehmkuhl and Andrew 1998). However, these methods are not only for public sector applications. A case can be made for applying them in for-profit organizations, where exclusive reliance on financial metrics for enterprise performance can lead to neglect of other relevant strategic considerations (Kaplan and Norton 1996; Keeney 1999; Keeney and McDaniels 1999). In these settings, resource allocation models can help to connect strategic issues with decisions about specific portfolios of projects and plans. Multiattribute value models provide a template for a sound and efficient resource allocation process that considers the full range of organizational objectives, including objectives that are not suitably evaluated using standard financial metrics.

The use of multiattribute approaches is particularly appropriate for resource allocation in private, not-for-profit enterprises, where there are clearly multiple objectives at work. These not-for-profit organizations combine the need for financial discipline typical of for-profit enterprises with the rich set of mission-related objectives found in government and military settings. A multiattribute value model provides a direct means for the organization to consider trade-offs between financial and nonfinancial objectives, often a crucial concern. For instance, Kleinmuntz and Kleinmuntz (1999) describe the use of multiattribute value models to allocate capital resources in not-for-profit hospitals. The method closely follows the multiattribute value modeling approach discussed above, using integer linear programming to identify the best portfolio of projects subject to resource limitations and other constraints. Practical considerations in using these models in hospital settings will be discussed at some length in the next-to-the-last section.

Resource Allocation with Uncertain Benefits and Costs

A significant concern in many settings is that projections of both project benefits and project costs are uncertain. In businesses, organizations often cope with this problem by "risk adjusting" the valuation of projects. They do this by calculating net present values using a discount rate that is higher for riskier projects and lower for less risky projects. Methods for selecting project-specific discount rates are discussed in corporate finance textbooks, but in practice, these risk adjustments usually amount to little more than subjective judgments about each project's perceived risk. This is potentially defensible as a heuristic approach when compared with the use of point estimates with no consideration of uncertainty. However, these perceived risk judgments are problematic from a normative decision perspective because they reflect an unsystematic assessment influenced by both the relevant probability distributions over outcomes as well as the organization's risk tolerance.

Most decision analysts avoid project-specific discount rates by implementing systematic models of project uncertainties using standard approaches (decision trees, influence diagrams, or Monte Carlo simulations) and applying a uniform discount rate for all projects. The remaining challenge, then, is to incorporate the resulting project risk profiles into the portfolio optimization. The most common approach is to assume that the organization is risk neutral over the relevant range of portfolio outcomes. Risk neutrality implies that only expected values of project benefits and costs are relevant, and that the objective is to maximize expected benefits subject to resource and other constraints. Therefore, expected values replace deterministic forecasts when using either benefit-cost ratios or mathematical optimization for prioritization.

A complicating issue arises if project resource expenditures are uncertain because portfolio solutions are no longer guaranteed to be within resource constraints. Solving for optimal portfolios with stochastic constraints is a rapidly developing research area, but the analytical and computational burdens can be considerable (see, for instance, Birge and Louveaux 1997). A widely used pragmatic alternative is to reserve a contingency allocation of the scarce resource sufficient to provide for potential overruns.

One area where decision analysis tools have been frequently applied is selection of research and development (R&D) projects, such as the development of new products, processes, or technologies. R&D project portfolios have been addressed using a wide variety of tools and methods (see review by Henrikson and Traynor 1999). Decision and risk analysis have been particularly successful because the uncertainties associated with an R&D project typically loom quite large. In the initial stages, there is considerable uncertainty regarding both the time and resources required to pursue the project, and technical success is a major risk factor. Conditional on meeting technical objectives at various stages, there are also significant uncertainties regarding the size and duration of realized benefits. Published examples of applications are provided by Bodily and Allen (1999), Matheson and Matheson (1998, 1999), Poland (1999), and Sharpe and Keelin (1998).

Another area where decision analysis has been fruitfully applied is in selection and management of portfolios of petroleum and natural gas producing assets. The uncertainty associated with oil exploration is quite familiar to decision analysts (Raiffa 1968). Walls (2004) reviews portfolio management issues that arise when considering a large number of exploration options. Skaf (1999) describes a comprehensive portfolio system that was implemented at a major oil and gas company to support management of both exploration activities and existing producing assets.

An active area for research and application in recent years has been combining financial options pricing tools with standard decision analysis tools (Perdue, McAllister, King and Berkey, 1999; Smith and McCardle 1998; Smith and Nau 1995). Most risky projects are not simply "go versus no-go" decisions because managers have flexibility to adapt and make subsequent decisions as a project develops over time (e.g., abandon if anticipated benefits do not materialize or expand if prospects improve). Both decision analysis and options pricing methods are capable of accounting for uncertainty and managerial flexibility when valuing projects. However, options pricing methods are based on the no-arbitrage theory of financial markets, whereas standard decision analysis methods do not distinguish between uncertainties associated with market-traded assets versus uncertainties unrelated to financial market prices. Although these methods have sometimes been positioned as competitors (Copeland and Antikarov 2005), the argument that they should be viewed as complements is compelling because projects often have uncertainties both with and without financial market equivalents (Borison 2005a, 2005b). Methods and tools for synthesizing the two approaches are not yet widely disseminated. This may be because they are unfamiliar to decision analysts or may be because they are challenging to implement in a fashion that is both rigorous and accessible (Brandão, Dyer and Hahn 2005a, 2005b; Smith 2005). The convergence of methods from decision analysis and financial engineering is an important and promising area for further research.

Another promising area for research is optimal resource allocation in the presence of risk aversion. Relaxing the assumption of risk neutrality greatly increases the complexity of resource allocation for two reasons: First, as a general rule, nonlinear preference functions imply that project benefits are no longer strictly additive because the incremental benefit of any single project depends on the aggregate benefits achieved by the rest of the portfolio. This requires shifting from linear to nonlinear programming formulations for optimization, which can be conceptually straight-forward but computationally challenging for larger portfolios. An exception applies if an assumption of constant risk aversion is plausible, in which case an exponential utility function can be used to compute certainty equivalents that account for risk tolerance without violating additivity. As a case in point, Walls, Morahan, and Dyer (1995) describe a decision support system that Phillips Petroleum Company implemented to analyze oil and gas exploration projects. The system gave the user the ability to model uncertainties for individual projects and compute certainty equivalents based on an exponential utility function. It was used successfully for both project selection and to evaluate risk-sharing opportunities. Walls and colleagues report that this system gave managers the ability to rank projects and stay within budgets while enforcing a consistent level of risk tolerance across the company.

The second and more serious issue with deviations from risk neutrality is that computing the risk profile of aggregate benefits over an entire portfolio requires assessment of joint distributions over outcomes of multiple projects. Because projects are often probabilistically dependent, this requires assessing the nature and degree of dependence. One method for doing this is to use copula functions, which require marginal probability assessments and pairwise correlations (Clemen and Reilly 1999; Yi and Bier 1998). An alternative approach is based on information theoretic entropy methods that require both marginal and pairwise probability assessments (Abbas 2003, 2006; Jaynes 1968; Lowell 1994; MacKenzie 1994; Smith 1995). One implication of probabilistic dependence is that learning about the outcome of one project may lead to revision of assessed probabilities for another project. This can be particularly important in situations where projects are selected sequentially. Bickel and Smith (2006) have developed an approach that combines entropy methods with dynamic programming to determine an optimal sequence of projects, and have applied the approach to the sequential exploration of oil and gas projects.

Recently, Gustafsson and Salo (2005) have proposed a general modeling framework and methodology called Contingent Portfolio Programming to support the selection of a portfolio of projects or investments where the outcomes of the projects are uncertain and there are dynamic considerations in the evolution of both project uncertainties and project values. Their approach also includes a method for taking into account risk attitudes using a risk-value model or a multiattribute value function. The approach combines various elements of other approaches within a comprehensive modeling approach, and appears to be computational feasible for many R&D portfolio problems. Gustafsson (2005) discusses extensions and proposes some promising applications, particularly for analyzing investments that have both financial market and other uncertainties.

The applications discussed so far in this section all involve only a single financial objective. When multiattribute utility models were a relatively recent discovery, there were a number of reported applications that explicitly analyzed both uncertainty and multiple objectives when selecting project portfolios and allocating scarce resources (Crawford, Huntzinger, and Kirkwood 1978; Keefer 1978; Keefer and Kirkwood 1978; Sarin, Sicherman and Nair 1978). These applications appear to have been successful, but more recent reports of this type are nonexistent. Although it is possible that these methods are being used but have not been published, I believe that it is more likely that the implementation is too burdensome for most organizations. Instead, they focus on either uncertainty or multiple objectives, depending on what is more relevant to their situation. One promising recent development that may help is a robust modeling approach that permits analysis of project portfolios with incomplete information on project performance or decision maker preferences (Liesiö, Mild, and Salo, in press).

As models get more complex, there is a danger that they will be treated as a mysterious "black box" by decision makers, who will be reluctant to rely on them. One analytic strategy that is frequently implemented in practice but rarely discussed in the literature is to approximate complex models with relatively simple linear models. For example, Dyer, Lund, Larsen, Kumar, and Leone (1990) describe a decision support system developed to prioritize oil and gas exploration activities subject to limits on the available teams of geologists and geophysicists. They develop a linear multiattribute value model designed to closely replicate a more complex nonlinear model derived from conventional calculations of value of information. Dyer and colleagues note that the simplicity and transparency of the linear model eased both implementation and acceptance of the model by the decision makers. More research on the performance of all sorts of simplified approaches would help to promote informed decisions about model sophistication when deploying systems for resource allocation.

Hospital Capital Budgeting: Lessons from Practice

This last point suggests that there can be a delicate balance between conceptual and methodological rigor on the one hand and the pragmatic requirements of resource-constrained organizations. In order to illustrate, I will focus at length on the application of these methods to a particular domain, capital budgeting in not-for-profit hospitals and multihospital healthcare systems. This context provides an excellent case study of the realities of model implementation in large, complex organizations.

Capital budgeting is an ongoing challenge for hospitals in the United States. Rapid technology advances, an aging population, and a shifting competitive environment create constant needs to acquire or replace equipment, maintain and expand physical infrastructure, improve quality of care, and offer new service lines. At the same time, financial pressures sharply limit what they can afford but increase certain needs, particularly for investments that generate revenues or improve operational efficiency. As a consequence, hospitals often enter their annual budgeting cycle with requests for funds that exceed capital available by a factor of three or more to one. Because only a small fraction of requests can be approved, the process is difficult, as executives struggle to identify the best projects.

To support this process, Strata Decision Technology (Strata), a company that I cofounded with Catherine Kleinmuntz in 1996, has developed a software system called StrataCap® that includes analytical capabilities based on the multiattribute value modeling and optimization approach discussed earlier. The software is designed to combine financial forecasts and assessment of other evaluation criteria within a consistent, logical framework for capital project evaluation. Although the project evaluation and portfolio optimization capabilities can be duplicated with "off-the-shelf" analytical software (or even with spreadsheets), there is also considerable integrated functionality to support other parts of the capital budgeting process. This includes standardized project proposal forms, an interactive proposal review and approval process, integration with email systems to support collaboration and workflow, and the ability to effectively integrate the system with other information systems internal and external to the organization.

Strata has implemented this software and the associated capital budgeting process hundreds of times in not-for-profit hospitals and multihospital healthcare systems across the United States. These organizations range in size from seventy-five-bed community hospitals to major academic medical centers and multihospital healthcare systems comprising anywhere from two to more than forty hospitals each. Including the affiliates of multihospital systems, the approach

Table 20.1. Implementation process for hospital capital budgeting

1. **Advance preparation and communication: [1 week]**
   - Review existing capital process
   - Define goals and objectives for budget process
   - Establish project timeline, milestone dates, team members, and roles
   - Define standardized capital request form
   - Define structured organizational review process
   - Present finalized recommendations to senior management for approval
2. **Software configuration and training: [1 week]**
   - Configure software to organization's specifications
   - Train hospital budget coordinator on software administrative functions
   - Train hospital managers and program directors on writing high-quality capital requests
   - Train senior managers with proposal review responsibility on how to qualify proposals
   - Familiarize senior management with relevant steps of the capital request and evaluation processes
3. **Capital requests entered into system: [4 weeks]**
   - Create business plans that justify needs and address anticipated questions
   - Analyze incremental financial impact of capital request on existing operations
   - Import external medical technology assessment data to support equipment selection and pricing analyses
4. **Discussion and review of proposals by senior managers and functional experts: [4 weeks]**
   - Examine requests for accuracy and completeness
   - Assess functional feasibility and necessity of request.
   - Provide management sign-off prior to evaluation
   - Reviewers communicate with proposal writers through online discussion forum
5. **Senior leadership team prioritizes capital requests: [1 day]**
   - Team composed of executive-level managers, including clinical/physician leadership
   - Focused discussion of proposals based on identified financial and qualitative criteria
   - Score proposals on qualitative criteria
   - Establish trade-off weights based on strategic considerations
   - Prioritize capital requests using optimization tool and benefit-cost ratios

has been used in more than 750 hospitals and healthcare provider organizations, in some instances for many years.

In tandem with the software implementation, Strata provides consulting services to facilitate the capital budgeting process. A team of two or three consultants guide the organization through a process that starts with a review of existing budgeting practices and culminates in a meeting where the senior leadership team prioritizes requests and arrives at a portfolio recommendation. Over time, Strata consultants have identified best practices for the implementation process (summarized in Table 20.1). In a typical hospital, the entire process will take approximately ten weeks.

The process is designed to emphasize the evaluation criteria that will ultimately guide the decisions. Five evaluation attributes usually cover the major issues of concern to most hospitals (summarized in Table 20.2). These include an attribute related to financial performance (net present value), three related to

Table 20.2. Standard attributes for capital evaluation

Objective	Attribute	Definition
Financial	NPV	Net present value of projected future cash flows (dollars)
Quality	Clinical impact	Improves clinical experience in terms of outcomes, patient safety, waiting times, throughput times, and general comfort (rating from 0 to 100)
	Infrastructure	Improves or maintains quality of hospital and outside facilities and equipment, including expenditures to comply with safety, code, and accreditation standards (rating from 0 to 100)
	Staff/physician relationships	Improves ability of employees and medical staff to work effectively and productively (rating from 0 to 100)
Strategy	Market share	Enhances market share by increasing the number of patients seen and/or increasing ability to attract new patients (rating from 0 to 100)

quality concerns (clinical outcomes, facility quality, and impact on staff and physicians), and one addressing strategic concerns (market share). Although the consultants encourage modifications or additions based on an organization's unique objectives, they also discourage letting the attribute list grow too long because this tends to make the evaluation process more difficult.

The capital evaluation session represents the culmination of the entire process. In a typical hospital, there might be 250 proposals submitted, but only 40 to 50 of the most costly are evaluated by the senior executives, representing 70–80 percent of the requested funds. For the remaining proposals, funding decisions are made by reserving allocation pools for groups of functionally related proposals and letting the relevant functional managers assign those funds as they see fit. Sometimes, these managers also use the software to prioritize the smaller projects. In large multihospital organizations, a similar size-based partition of projects occurs, with the largest projects evaluated by corporate executives and the remaining projects evaluated by local hospital executives.

The senior executive evaluation team usually comprises six to twelve members, including the Chief Operating Officer, Chief Financial Officer, Director of Patient Care, Director of Materials Management, Chief Information Officer, Director of Facilities, and physician representatives. The Chief Executive Officer only sometimes elects to participate. The ideal team represents a cross section of expertise and interests from across the organization.

The evaluation session generally lasts between 4 and 6 hours, with a senior consultant from Strata acting as facilitator. The entire analysis occurs in real time with the evaluation team present. The session is usually held in a location where each evaluator has access to a networked computer. The facilitator starts with a brief review of the evaluation process and guidelines for proposal discussions. Many organizations have managers or directors (the project champions) present each

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proposal and answer questions. Evaluators then immediately score each request on each evaluation criterion using a 0 to 100 judgment scale.[2] Three to five minutes are allocated to discussion and scoring of each proposal. Once presentations are done, evaluators review their ratings and make any necessary adjustments.

Next, the facilitator helps the team determine the relative weights to be assigned to the evaluation criteria and uses the software to calculate aggregate scores and determine the optimal allocation of the available capital dollars. The budget constraint is usually provided by the Chief Financial Officer in advance of the meeting. The facilitator then explains the results and conducts sensitivity analyses based on questions and comments from the evaluation team. The goal of this discussion is to provide the evaluation team with a clear understanding of the modeling process and why the results turn out as they do. The session concludes after the team has converged on a final list of approved capital requests.

Because the system uses optimization, benefit-cost ratios are not an explicit part of the solution process. However, they are still useful because sorting the list of projects using the ratio provides insight into why some projects are or are not included in the optimal portfolio – the projects at the top of the list are clear winners, providing high benefit per dollar expended. Projects at the bottom of the list provide benefits at too high a cost. The discussion naturally focuses on projects in the middle, where slight changes in either benefit or cost estimates could easily alter recommendations.

A particularly useful form of sensitivity analysis is to "force" a proposal into or out of the accepted set and rerun the optimization. In the absence of additional funds, forcing a proposal into the solution set always requires removing one or more of the others. This analysis explicitly identifies the proposals that will be sacrificed to accommodate the new project, emphasizing the zero-sum nature of the budgeting process and making the consequences of funding the lower-rated project salient.

Another issue well suited to sensitivity analysis is the budget constraint. In most organizations, this is a "soft" constraint because the Chief Financial Officer has some degree of discretion to increase or decrease capital spending. Running the optimization with different budget constraints and examining which projects enter or leave the recommended set gives concrete meaning to the consequences of incremental funding shifts.

Because the analysis relies heavily on subjective assessments, it is important to consider systematic judgment biases that may affect the results. One problem often occurs when the evaluated projects differ greatly in size and scope: In early implementations, Strata consultants observed a tendency to neglect scope differences. Consider, for example, an organization comparing a multimillion dollar renovation of a major facility with spending $75 thousand to replace waiting room chairs. A major facility project is generally going to have a huge impact,

[2] An exception is that net present value is usually calculated in advance by hospital finance staff based on deterministic assumptions of incremental effects on patient volumes, revenues, and expenses. The software includes financial modeling templates to support this calculation.

so executives are likely to award it high scores on attributes related to patient comfort or facility quality (e.g., 100 on a 0 to 100 scale). However, they might look at the waiting room furniture, conclude that it is in horrible condition, and assign scores that are nearly as high (e.g., 90). This overemphasizes the impact of a relatively modest improvement and makes it more difficult to justify funding larger projects. Similar insensitivity to scope is well known in studies of the economic valuation of environmental public goods (Kahneman, Ritov, and Schkade 1999).

When this problem was first identified, our initial response was to expand the rating scale to extend from 0 to 1000, and to instruct evaluators to anchor on values of 0, 1, 10, 100, and 1000. The hope was that inducing a log response scale would encourage recognition of project scope. When this was not effective, our response was to return to a 0 to 100 rating scale, but then instruct evaluators to rate each attribute on benefit per dollar expended rather than total benefit realized. Multiplying each rating by the project's proposed cost produced the attribute scores used in the value models. Although I am not aware of any rigorous research that validates this method, evaluators perceive it to be intuitively appealing, and we observe fewer obvious problems with scope neglect.

Another serious problem arose because many of the investments evaluated by hospitals each year are projected to realize little or no financial return, presumably because they are focused on other objectives. The optimization process would sometimes generate a portfolio of projects with a negative aggregate net present value, indicating that the portfolio as a whole was failing to earn more than the cost of the capital invested in that portfolio. When considered in light of a typical hospital's thin profit margin and precarious financial position, most executives would view this negative investment return as unacceptable.

One interpretation is that executives simply were not assigning sufficient weight to financial return. However, healthcare executives were often uncomfortable with increasing this weight enough to make a difference, perhaps because it would constitute an explicit statement that financial return far outweighs the importance of the other objectives. Their concern is that this would effectively undermine their vision of the organization as a mission-focused enterprise primarily concerned with quality and quantity of care delivered rather than financial profit.

In fact, this problem is ultimately related to the additivity and preference independence assumptions required when using linear additive value functions in the optimization objective. Our discussions with healthcare executives suggested that their preferences violated the assumptions. Specifically, when the portfolio's aggregate financial return is negative, improvements in financial return are extremely important to them, but as aggregate financial return increases, their preferences for improvements in financial return become less important relative to improvements in other attributes.

Modeling approaches that account for violations of additivity and preference independence are available, although the required assessments and the associated nonlinear optimizations are more challenging to implement. Our concern was that this added complexity would undermine the practical value of the approach

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because organizations would be less likely to implement the models or accept the results. Instead, our solution was to modify the optimization model by introducing a financial performance constraint. This constraint required that the aggregate net present value meet or exceed a minimum acceptable level. With this constraint in place, portfolios with poor financial performance become infeasible, essentially narrowing the set of possible portfolios to those where it was reasonable to give financial return a relatively low weight. Typically, introducing this constraint forces a few money-losing projects out and replaces them with a few cash-generating projects. This helps the organization achieve an acceptable financial return without ignoring mission-related objectives.

The approach described here makes no attempt to explicitly address uncertainty, except through the use of sensitivity analysis on project benefits and costs. For projects that require significant financial commitments, healthcare organizations can and should use tools like decision trees, influence diagrams, and probabilistic risk analysis (Kleinmuntz, Kleinmuntz, Stephen, and Nordlund 1999). Recently, one of Strata's larger clients, a multistate healthcare system with nearly thirty hospitals, has started to require a quantitative risk analysis for any new project requesting more than $5 million in capital. Their review process places particular emphasis on whether there are adequate risk management plans in place.

However, this organization is the exception rather than the rule. Most hospitals are hard-pressed to develop deterministic financial analyses for their projects. A full-fledged analysis of both uncertainty and multiple objectives is almost certainly beyond their grasp. The approach described here affords a balance between analytical sophistication and implementation effort, while providing a foundation for implementing more advanced models in the future.

Conclusion: Benefits and Costs of Decision Analysis for Resource Allocation

The ultimate test of any decision analysis approach is the impact on the organization and its decision makers. In the hospital setting, executives clearly perceive an improvement relative to the relatively unsystematic and undisciplined process that they previously used. The process is also accessible and relatively easy to implement with the support provided by the software system. Although Strata provides initial support and facilitation, after several years, most hospitals learn to implement the process with minimal involvement from outside consultants.

The open, collaborative nature of the decision process is also a positive. Because the reasoning behind these resource allocation decisions is transparent, there is a sense that everyone is on a level playing field. This promotes consensus around the recommendations that emerge. In the best spirit of decision analysis, it is the sound and logical nature of the process that gives the participants confidence that scarce resources are being put to the best use.

The presumed advantage of any approach for incorporating decision analysis into resource allocation is that decisions are based on reflective, systematic

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analysis. On the other hand, the effort required can be considerable when a portfolio contains dozens or hundreds of candidate projects. Many organizations lack either the resources or the resolve to do rigorous decision analysis on this scale. Where organizations often need the most help is in accurately estimating the true benefits and costs of decision analytic approaches relative to other resource allocation processes.

This is a problem that has received remarkably little research attention. In one of the few investigations of its kind, Kiesler (2004) models the portfolio analysis process and compares different analytical strategies. In particular, he compares systematic prioritization strategies both with and without rigorous project analyses. His conclusion is that systematic prioritization without rigorous project analysis (or using heuristic approaches) merits serious consideration in many organizations because prioritization based on informal project evaluation yields a large fraction of the value realized from prioritization based on rigorous evaluation. Care should be taken in interpreting this result, however, because there is at least some field-based evidence to suggest that the value realized from rigorous analysis far outweighs the resources required to implement it (Clemen and Kwit 2001). One way to shed light on this issue would be to conduct more in-depth evaluations of these models at work in real organizations.

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