COST EFFECTIVE ALLOCATION OF RESEARCH FUNDS FOR THE DEVELOPMENT OF EMERGING TECHNOLOGIES

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ABSTRACT: Developers of emerging technologies and the agencies who fund them need an alternative to traditional cost-based risk prediction methods to help them predict how the costs of their technologies may change under future deployment scenarios. Often the only source of data for predicting risk is limited but complex data generated by field testing emerging technologies in the prototype phase of development. This paper presents a conceptual framework for evaluating cost and performance constraints of emerging technologies that can be used to prioritize the allocation of research and development funds for the development of such technologies.

KEYWORDS: cost estimating, cost drivers, constraints, allocation, risk, emerging technology

THE PROBLEM OF COST PREDICTION FOR RESEARCH AND DEVELOPMENT FUNDING OF EMERGING TECHNOLOGIES

Society is becoming increasingly dependent on technological solutions to solve the problems of humanity. Not only do we rely on technology to meet our needs and aspirations, we also increasingly require its assistance in cleaning up our messes and mistakes, such as in environmental remediation. Many new technological solutions are being developed to address the myriad of problems and needs of society, ranging from robots that recover and treat hazardous waste, to automated navigation systems based on global positioning technology, to so-called "hypercars" running on hydrogen fuel cells. Many of these innovations are drastically different in both design and application from existing technologies. These

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emerging technologies pose a challenge to agents responsible for funding their development, since no past experience or historical information is available to help predict how much development may cost, or how much the technology will cost to deploy after it has been developed.

The tradeoff between development costs and deployment costs is difficult to estimate, particularly for emerging technologies dramatically different from past solutions. One party to this tradeoff is the research and development agent for the technology ("technology developer"), whose aim is to obtain funding to develop the technology to its maximum potential. A second party is the funding agent, who pays for research and development (R&D) with the hope that it will result in a cost-effective and well-performing product that can meet deployment objectives. In essence, the transaction between funding agent and technology developer is an exchange of dollars in anticipation of the development and deployment of a product that does not yet exist. In theory, the more funding appropriated to the technology development process, the more likely that the technology will effectively meet the needs of the funding agent supporting its development. However, unlimited funding for R&D can also result in a "black hole" of technology development, where dollars are spent on over-optimizing components of the product that may not significantly improve or contribute to its functional performance or effectiveness.

Problem Statement

Funding agents for R&D of emerging technologies need a framework to examine tradeoffs between dollars spent on research and cost-effectiveness of deployment in funding research programs. Likewise, technology developers should be able to conceptualize their proposed work in terms of how it will affect the final costs of deployment in various situations, so that their work produces effective products to meet the needs for which they were developed. After initial funding has been provided, technology developers need a way to focus and prioritize their research thrusts within limited budgets for technology development. To support this effort to manage the prioritization and allocation of efforts, decision-makers need to know information about cost drivers, i.e., the contribution of each project element to the overall cost of development. This is especially true during prototype demonstration and deployment in the field.

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Field performance data for prototype technologies is typically complex, multivariate, and nondeterministic. Under these conditions, traditional methods for predicting the risk of cost escalation of future development, such as regression-based parametric, cost build-up, or shell-based expert system estimating, become ineffectual or impossible to implement. Developers need an alternative to traditional prediction methods to help them predict how the costs of their technologies may change under future development scenarios, based on limited but complex data generated by field testing technologies in the prototype phase of development.

A complementary problem is how to optimize allocation of funds for research and development to produce cost-effective technologies at the deployment phase. If the limiting factors to cost-effective deployment are known, then funding can be focused or more funding allocated to finding ways to remove the limiting factors, resulting in a more cost-effective deployed product or in more timely deployment. Thus, the ability to identify limiting factors and/or cost drivers for technologies in the prototype stage would allow developers to focus future development on finding solutions to the technological barriers that control the cost of implementation or deployment.

Objectives

Given the need for funding agents and technology developers to prioritize funding for research efforts, this paper is organized around the following objectives:

- To examine trends in the allocation process for funding of research and development
- To establish the role of cost prediction in the funding allocation process
- To review existing costing techniques and tools in the context of the funding allocation process
- To develop a conceptual framework for prioritizing research and development funding
- To identify research needs and opportunities in the area of cost prediction using the framework

The remainder of the paper seeks to meet these objectives. We begin with a review of the process of allocating research and development (R&D) funds for emerging technologies, followed by a comparison of existing cost prediction tools and techniques for emerging technologies. We then present a conceptual framework for R&D funding prioritization, based on cost and performance constraints of emerging technologies. The paper concludes with an overview of research needs and opportunities suggested by the conceptual framework.

THE PROCESS OF ALLOCATING R&D FUNDS FOR EMERGING TECHNOLOGIES

Before proposing ways to improve the cost-effectiveness of funding allocation, it is necessary to first examine how funding is typically allocated in a situation of many competing projects with limited available resources. This process is integrally tied to the technology development process, as described in the following sections.

The R&D Funding Allocation Process

The funding allocation process for research and development of emerging technologies follows a cyclic path that generally centers around the funding cycle of the sponsoring organization. Figure 1 shows a conceptual framework of the process. Beginning in the lower left corner, stakeholder needs and objectives ultimately drive the process, and represent a combination of the objectives of the “funder” or funding agency, the “fundee” or technology developer, and the ultimate “customer” of the technology. The way in which these objectives are incorporated into the allocation process can vary greatly depending on the nature and contextual organizational structures and missions of the various stakeholders involved.

These stakeholder objectives are represented in terms of potential projects for which the fundee seeks funding support from the funding agency or sponsor. Within each funding cycle, this set of potential projects enters a queue and waits to be evaluated, in hopes of receiving funding from the sponsor. The evaluation process or filter in the conceptual framework represents the funding organization’s process for reviewing the set of potential projects, eliminating projects in which it is not interested, and prioritizing the remaining projects according to how well those projects will meet anticipated stakeholder objectives. The outcome of the evaluation process is a prioritized list of projects, which is matched against available resources to result in a selected set of projects or project allocations that meet stakeholder needs and objectives.

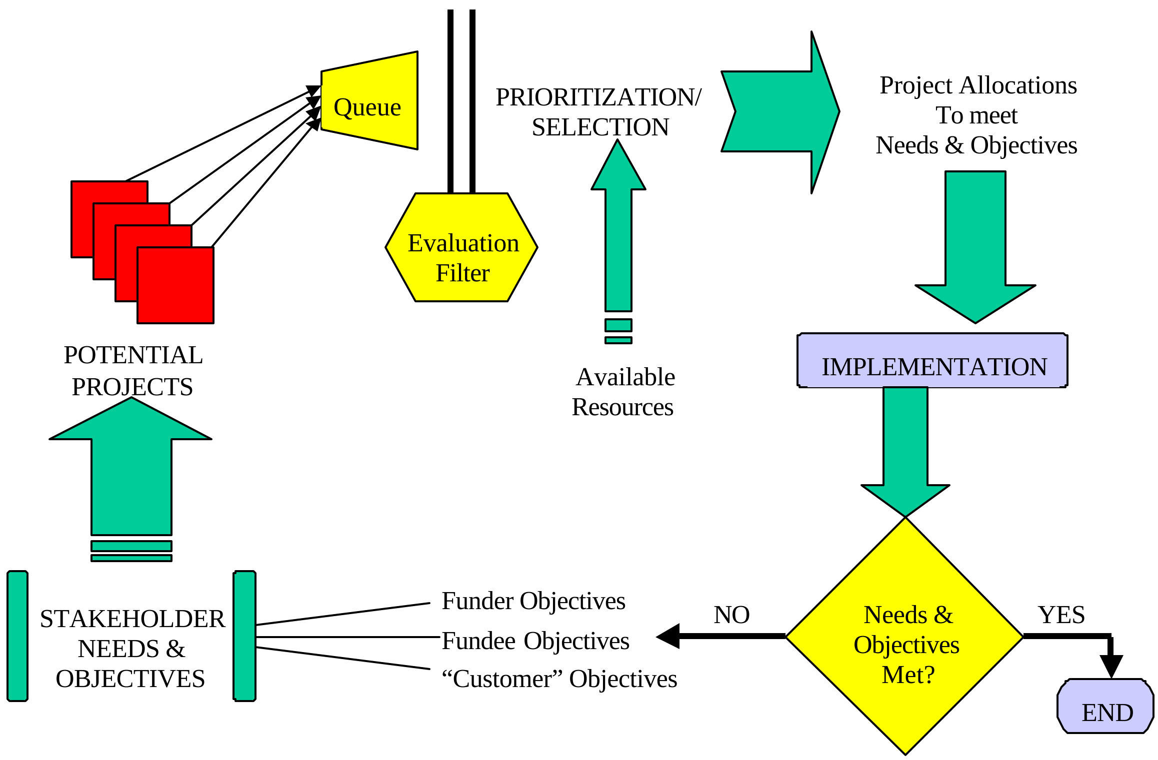

Figure 1: The R&D Funding Allocation Process

At this point, the funder informs the fundee of the allocated amount to complete the project, and each funded project mo ves into an implementation phase during which the proposed work is carried out. At the end of the implementation stage, another evaluation point occurs where the final product is evaluated in terms of how well it meets the original needs and objectives of the involved stakeholders. If the project meets those objectives, then the research and development phase of the technology life cycle is complete, and the project moves into deployment. If needs and objectives have not been met by the project, then it may reenter the cycle for further refinement and development, subject to the same constraints as in the original process.

The Technology Development Process

The process for developing emerging technologies runs in a cyclic fashion in parallel with the allocation process as shown in Figure 1. Figure 2 shows a conceptual framework for the major phases in technology development. The first step in the process is needs assessment, which amounts to assessing the needs and objectives of stakeholders as described in the first part of the R&D funding allocation project. The developers of the emerging technology assess not only the needs of their customers to be served by the technology, but also the needs of their potential sponsors in order to frame their project in contextually-relevant terms for that sponsor.

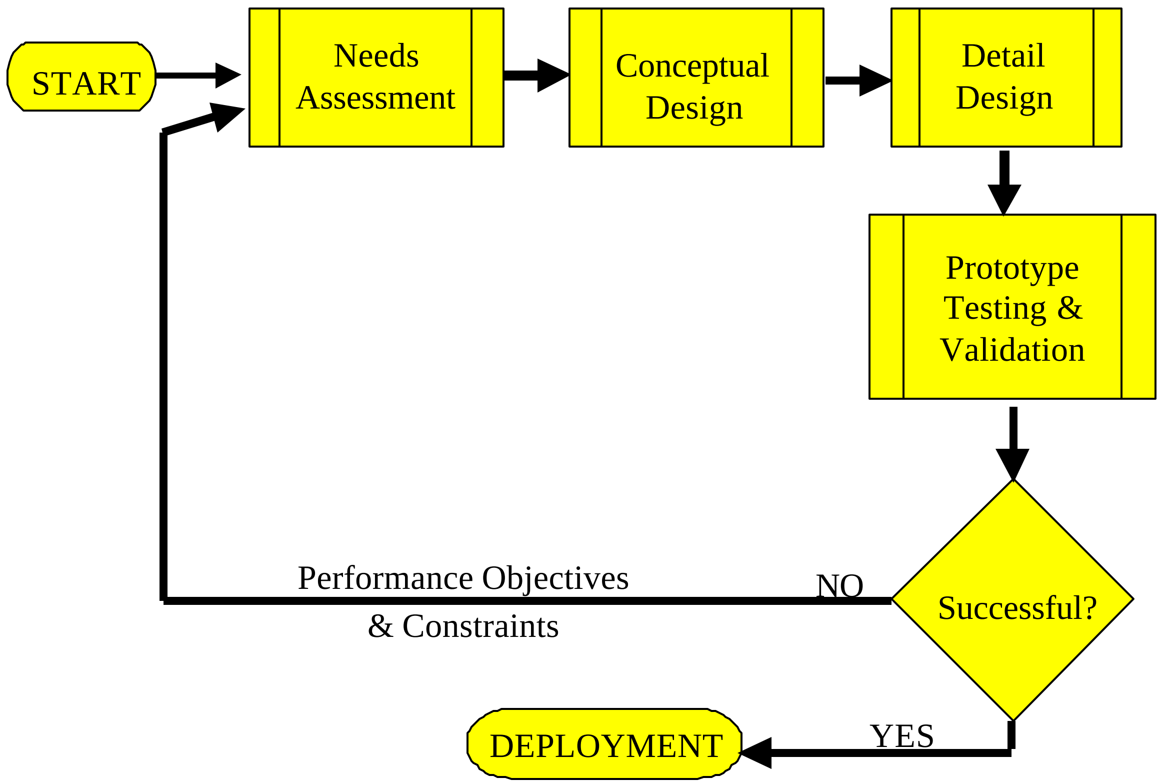

Figure 2: The Technology Development Process

Based on the availability of resources from the allocation process, the project may or may not be able to proceed to subsequent phases. If resources are obtained for developing the technology, its development process will typically progress from conceptual design through increasingly detailed levels of design, resulting in a prototype project ready for testing and validation. The prototype is typically subjected to testing to determine how well it meets the original governing needs it was developed to serve, and validated in terms of the appropriateness of the methods it uses to meet them.

If testing and validation are successful, the technology is ready for deployment in the context of its intended use. If it does not successfully meet the needs for which it was developed, the cycle returns to its beginning or any of the interim steps based on new performance objectives and constraints illuminated by the testing and validation process.

Predicting Costs for Development and Deployment of Emerging Technologies

The role of cost in developing new technologies is an important driver of which technologies can successfully be developed to meet the needs they had been intended to address. Given an accurate prediction of the cost to deployment, funding agents have the ability to objectively assess whether or not the cost of technology development is worthwhile, in terms of the needs and objectives it will meet. However, forecasting the costs of R&D for emerging technologies is a challenging task, for which few alternatives are appropriate to result in a sufficiently accurate prediction. The next section examines the range of existing tools and techniques for cost estimating, in terms of the special needs and requirements of emerging technologies.

COMPARISON OF COST PREDICTION ALTERNATIVES FOR EMERGING TECHNOLOGIES

Extensive literature exists on the general subjects of cost estimating, cost analyses, and range estimating (Gregory 1992). Several professional societies (e.g., American Association of Cost Engineers, International Society of Parametric Analysts, and Society of Cost Estimating and Analysis) set their charters around the advancement, training and regulation of cost control, cost analysis, and/or cost estimating. Almost all references begin with a classification of methods of estimating, the accuracy expected with different classifications, and the applications at differing stages of design or development. For example, Hardie uses two broad titles--approximate estimates and detailed estimates (Hardie 1986)--while Sinclair divides the types into conceptual estimates, preliminary estimates, and final design/bid estimates (Sinclair 1988). Regardless of categorizations and projections of accuracy, traditional techniques for cost estimating can be generally grouped into engineering build-up estimates, parametric estimates, and Artificial Intelligence-based estimates. The following sections provide background on each of these classes of techniques, and discuss their applicability to the problem of cost forecasting and management for emerging technologies. The review concludes with a look at an emerging subset of Artificial Intelligence-based cost estimating: Artificial Neural Networks.

Engineering Build-Up

The traditional estimating technique of engineering-build-up, called quantity-take-off estimating in construction engineering, is the most commonly used when a system has matured enough to provide the details needed for this technique. Quantity-take-off estimating is a process of counting every component of a design to the lowest level of detail. The term literally comes from counting (measuring the quantities of) material, labor, and equipment from detail design (take-off from the drawings). A traditional engineering build-up or quantity takeoff estimate is developed at the latter stages of the design phase (or in research and development at the systems development stage) once the drawings or design is complete. A quantity-take-off estimate is undertaken by developing a work breakdown structure and counting the individual components "taken off" the detailed design plans. This detailed estimate can be performed using several approaches. One approach to consider is using an assemblies format to structure the estimate. This strategy involves breaking the design into assemblies or logical groupings of components, for which quantities and prices are developed. This approach is appropriate for technologies whose components lend themselves to logical groupings, or where separate subcontractors or developers provide different assemblies. It is commonly used in estimating the cost of buildings, where typical assemblies include foundations and exterior enclosure (R.S. Means 1997). Comparatively, a component breakdown could be done where the actual components of the technology are counted individually and entered as line items in a spreadsheet format. Regardless of the approach, once the quantities are available, prices must be estimated for each cost item. Prices can be estimated by contacting material suppliers or consulting subcontractor bids. The advantage of this system is that it is very accurate for systems with advanced design development. (Mosely 1997).

Engineering-build-up or quantity-take-off estimating is only applicable to cost management to estimate for the design of a specific technology where the research and design process is largely completed. It is not suitable for cost analysis to develop range estimates for prospective technologies during early planning or conceptual design.

Parametric Estimating

Traditional parametric estimating uses comparative techniques by applying some form of regression analysis to historical data. The cost estimate is derived by comparing a current project to past projects – thus the term "comparative". Comparative estimates include unit costs, square foot costs, and parametric estimates derived from historical cost curves. A major problem in developing comparative estimates is that there is no standard method of defining the technical or descriptive characteristics of the individual systems or collecting historical costs associated with these characteristics. If the original data are not collected with the system's or scenario's unique characteristics spelled out, no amount of statistical manipulation or regression analyses can account for the differences with any degree of reliability or validity. This problem of data characterization is especially difficult for complex projects such as hazardous waste clean up or unexploded ordnance cleanup because of the large number of interrelated variables inherent in the technology and the context, system, or environment in which it will be deployed. Typical statistical requirements such as independence and conditionality are not achievable for variables and parameters in these scenarios (Gregory 1992).

This technique is also not suitable for analyzing one-of-a-kind or innovative technologies, since collected data for these kinds of projects does not typically flag or identify the special system design characteristics needed to develop parametric comparisons. Plus, if the project is a new or one-of-a-kind system, there is no cost history or data from which a valid cost comparison can be made (Gregory 1992).

Artificial Intelligence-based Cost Estimating

A third approach to cost estimating based on artificial intelligence (AI) has emerged to address the explosion of information inherent most research and development efforts today. The need for AI to manage and synthesize data is expanding at an unprecedented rate. The information explosion and the rapid communication systems of today and tomorrow require near immediate synthesis of data and expert knowledge to solve complex technical problems. New materials; computerized control systems; voluminous legal, regulatory, environmental, and safety requirements; and continuously evolving component technologies are just a few examples of the rapidly expanding information fields that technology developers must synthesize today (Gregory 1992).

Although most references graphically display AI systems in discrete boxes, the set of tools could be more accurately described as a continuum of emerging tools with overlapping applications (Gregory 1992). Harmon and Maus describe AI as "an academic research program" with five most active areas of commercial application: natural language, robotics, improved human interfaces, exploratory programming, and expert systems. The expert systems area, as described by Harmon and Maus, is "a program that manifests some comb ination of concepts, procedures, and techniques to allow people to design and develop computer systems that use knowledge and inference techniques to analyze and solve problems" (Harmon and Maus 1988).

Three key areas from AI research that apply to this research are 1) new ways to represent knowledge, 2) heuristic search, and 3) the separation of knowledge from inference and control (ibid.). In context of expert systems, Harmon defines knowledge as a body of information about a particular topic that is organized to be useful. Knowledge-based programs rely on rules-of-thumb or heuristics rather than algorithms and mathematical certainty; therefore, they allow the analyst to look at problems that are unorganized or have incomplete or not clean data (Gregory 1991). These techniques allow an expert to examine the contents of data without knowing how the content is derived or manipulated (ibid.). A key element of knowledge engineering is that a database and a knowledge base can look similar, but the way in which the information is organized and manipulated is significantly different (ibid.). A knowledge base can incorporate such heuristics as simple as a step functions or the complex ability to make on-course corrections from real time feedback from complex, multiple sensor fusion. AI systems allow knowledge bases to adjust the body of procedures and selected algorithms to create and apply new algorithms. These processes are not and cannot be modeled with mathematical algorithms. That an AI-based system can generate the decisions to which algorithms and calculations are applied is the attribute that makes this technique hold promise for range estimating in innovative or one-of-a-kind situations. To further clarify, AI-based systems can handle innovative cases because operators can infer causal relationships between input and output based on the internal logic and learning capabilities of these systems.

Neural Network Cost Estimating Techniques

Artificial Neural Networks (ANNs), as a new field of AI, offer an alternative to traditional methods of cost prediction based on parametric or quantity takeoff techniques. With their capacity to learn from examples and to generalize that knowledge to novel cases, ANNs provide the capability to undertake rapid modeling of systems in which the interaction between input and output variables is unknown but where representative examples of inputs and outputs exist (Wasserman 1989). ANN modeling of the process of technology cost prediction provides potentially important clues to the relationships between initial planning-phase project variables and final cost. Without relying on historical data, ANNs have the potential to synthesize noisy or incomplete data from field testing of emerging technologies to identify and characterize the bottlenecks and/or cost drivers on which future development should be focused. The framework developed in this research utilizes this fourth approach to cost prediction as a model for data synthesis and identification and prioritization of research focus areas, as described in the next section of the paper for the dormitory case.

A CONCEPTUAL FRAMEWORK FOR R&D FUNDING PRIORITIZATION BASED ON COST/PERFORMANCE CONSTRAINTS

As discussed earlier, funding agents need to be able to accurately and objectively assess tradeoffs between the costs of R&D for emerging technologies and the magnitude of needs those technologies will meet. While additional research can result in products that better meet stakeholder needs and objectives, the cost of additional research may not always be money well-spent in meeting those needs. Technology developers should be able to conceptualize their proposed work in terms of how it will affect the final costs of deployment in various situations and the success it may have in terms of meeting stakeholder objectives, so that funding agents can assess tradeoffs between dollars spent on research and cost-effectiveness of deployment. Likewise, funding agents need a framework for prioritizing potential R&D projects in terms of not only how much they will cost to develop, but also in terms of how funding R&D may lead to a product with lower deployment costs and better ability to meet stakeholder needs. Figure 3 presents a conceptual framework for prioritization of R&D funding to meet this need. The following subsections describe each step of the process in Figure 3.

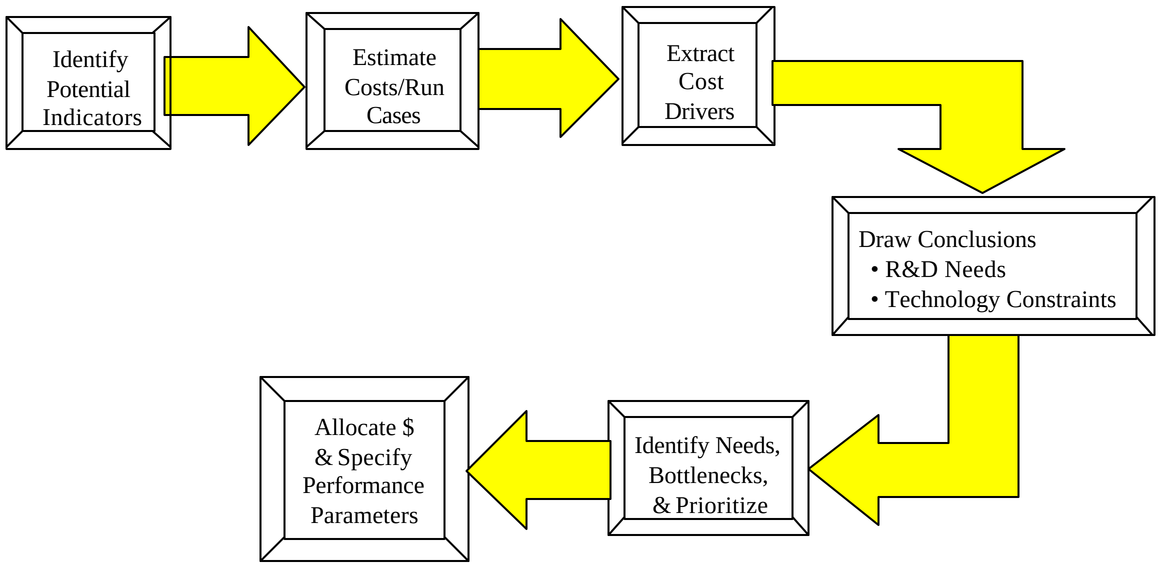

Figure 3: Framework for R&D Funding Prioritization

Identifying Potential Cost/Performance Drivers

The first step in the prioritization process is to identify potentially important factors or variables that "drive" the cost or performance of the technology. One useful breakdown of potential drivers consists of three classes (Figure 4): features of the deployment context, features of the technology itself, and features of the problem or task the technology is designed to address. Identifying drivers within these classes can be based on several factors, including the availability of data or its ability to be collected. In the case of an emerging technology in the prototype phase, cost and performance drivers may be measured or derived from field data during testing of the prototype. Drivers will necessarily be specific to the type of technology being developed, but should fall within the hierarchy of dimensions in Figure 4. Alternative classifications of cost and performance drivers may be appropriate for different types of technologies.

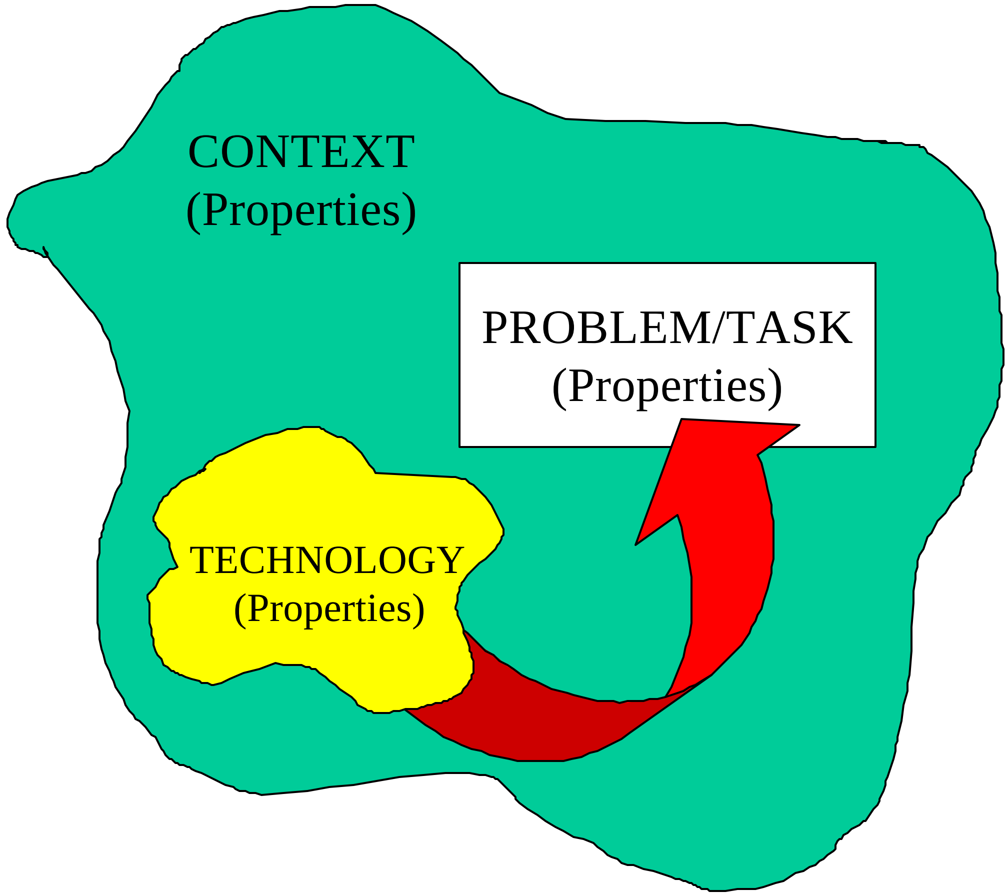

Figure 4: Classification of Cost and Performance Drivers

Evaluating Cost/Performance Indicators

The second step in the framework is to specify and evaluate cost and performance indicators for the technology, based on the initial objectives the technology was developed to meet. Within this framework, cost and performance are indicators of how well the technology meets the needs for which it was developed. As discussed in the first part of the paper, cost is generally a governing factor for the success of an emerging technology, and therefore is a logical choice as an indicator of the success of the technology. For example, if a technology is too expensive to be used in the situation for which it was designed, then it can hardly be called successful. Likewise, if the cost to develop a technology is beyond the budgeting capability of a funding agency, it will probably not be developed in the first place. Thus, development and operational costs are good candidates for indicators of the success of the technology.

In the same way, performance indicators can be used to measure how well the technology does the job it was designed to do. While performance criteria are by definition specific to the technology under consideration, they are always related to the initial need the technology was proposed to fill, and can often be derived from initial project objectives. For example, a material designed to reduce heat loss through a building wall could use "heat loss through wall" as a performance indicator for that technology. If the technology performs well, then heat loss through the wall will be small, whereas poor performance of the technology will be indicated by large heat loss.

The set of cost and performance indicators provide the capability to distinguish between example deployments of the technology, permitting comparisons and analyses of the drivers that influence cost and performance under a variety of conditions. The next step, then, is to estimate the significance of the drivers in controlling desired or undesired performance or cost for deployment of the technology.

Estimating Significance of Cost/Performance Drivers

Based on the complexity of the factors and relationships that drive technology performance, determining the significance of cost and performance drivers may be as simple as performing a statistical regression on examples of data from technology deployment. In some cases, algorithmic relationships between drivers and performance or cost may be already known, and the significance of the variables can be determined from mathematical relationships in the known algorithms.

In more complex cases, new approaches to evaluating the significance of the driver variables may be required. For example, in estimating the significance of variables contributing to the cost of military dormitory construction, Pearce (1997) found that Artificial Neural Networks (ANNs) were able to prioritize the significance of drivers having a complex multivariate relationship with dormitory construction costs. To develop the ANN model, the research team used simulated examples of real dormitory projects, and "trained" the ANN to understand the connections between input variables or drivers and output variables or performance indicators. In this way, the ANN model was able to represent the relationships between drivers and performance indicators, and could be used to infer the relative weighting or significance of cost drivers in achieving desired performance. This analysis was done on lump-sum total project historic costs with no details available that would be required by traditional estimating processes. The technological contribution of ANNs in cost estimating applications is the ability to infer the relationships with ONLY inputs and outputs.

The final outcome of the ANN model analysis was a matrix of weighted cost drivers, showing which factors were most significant in controlling the final cost of a dormitory project. As shown in this example, ANN modeling is an alternative for estimating the significance of cost or performance drivers in situations where algorithms are unknown and variable relationships are too complex to perform multivariate or regression analysis. Whatever the method for estimating significance of drivers, the outcome of this step of the framework should be a significance matrix showing the estimated relationships between driver variables and cost/performance indicators.

Prioritizing Constraining Factors

Given an understanding of the significance of driver variables in controlling the cost or performance of the technology, the next step in the framework is to prioritize drivers in terms of their relative significance. For example, in the military dormitory research, Pearce found that building perimeter was a significant cost driver, strongly influencing the cost of exterior enclosure and interior construction for constructed facilities (ibid.). Based on this finding, the research team inferred that the length of the building perimeter was a constraining factor for achieving a low-cost dormitory building. They subsequently recommended that building perimeter should be minimized as much as possible without reducing the performance of the facility in other respects, in order to keep construction costs low. In this case, building perimeter was seen as a constraining factor for achieving the performance objective of low construction costs. Since building perimeter can be controlled during the design phase of facility development, this constraint can be used to reduce final facility cost by either shrinking the perimeter of facilities, or by developing new types of exterior enclosure or interior construction that are not cost-controlled by this factor.

Allocating Funding to Improve Cost Effectiveness and Performance

After constraining factors have been identified and prioritized in the previous steps, the final function of the framework is to allocate funds or focus research efforts on removing these constraints to effective cost and performance of the technology under consideration. To use the military dormitory example discussed in the previous steps, if building perimeter length emerges as the most critical driver of facility constructed cost, then funds could be allocated to examine ways to remove this constraint to cost-effectiveness. For example, an R&D project could be funded to develop and analyze the cost of new types of exterior enclosure or interior construction methods that are not cost-controlled by building perimeter. Or more importantly, management actions could be employed in lieu of adding funding. In the dormitory example, design instructions could direct perimeter constraints and/or provide design criteria for finishes or glazing ratios. For other cost drivers, parameters could be used for source selection criteria to select qualified designers or constructors. Information on cost drivers or R&D limiting factors provide researchers and developers with the framework to make informed decisions on adding funding or other management alternatives to reach stated goals. If the overall goal of funding for R&D were to create cost-effective technologies in the deployment phase, then focusing on the most critical cost drivers in future research is likely to reduce the cost of deployment for the evolved technology. Thus, funding can be more objectively and effectively allocated if the relationships between driving factors and measurable performance indicators are known. Prioritization can be given to finding alternatives or solutions to the factors or problems that constrain or control cost-effective performance.

RESEARCH NEEDS AND OPPORTUNITIES

Based on the framework described in this paper, there are many opportunities and needs for further research in optimizing the allocation process. First, while identifying potential indicators to evaluate the cost effectiveness of research, there is an important tradeoff between the availability and cost of collecting data to populate the indicators, and the accuracy of the analysis to determine cost drivers. As mentioned in the previous section, Artificial Neural Networks are one promising analysis tool to enable the mining or fuzzy analysis of large quantities of data that are easily available, without necessarily needing fine-tuned quantitative data as required by other costing techniques. ANNs are only beginning to be applied to the task of cost driver analysis in the domain of cost estimating, and hold promise for being an effective tool with future research.

Secondly, algorithmic techniques for drawing conclusions based on a knowledge of cost drivers do not yet exist. While expert knowledge can fill this gap, more research is needed to understand how technology constraints and bottlenecks can be directly linked to their role in driving costs. Existing techniques such as the Delphi method can help by developing consensus among disparate expert opinions, forming the basis for developing better models of expert knowledge.

Finally, while this paper is limited to defining a process for funding allocation at a conceptual level, the conceptual framework developed herein has the potential to impact how projects are funded by many organizations seeking to increase their accountability due to laws like the Government Performance and Results Act (GRPA 1993). GPRA provides a mandate to Federal agencies to account for program results through he integration of strategic planning, budgeting, and performance measurement. The framework in this paper can help funding agents to address such accountability concerns proactively before projects are funded, rather than reactively as a result of overrun budgets with technologies that do not meet the needs for which they were designed. It can also provide technology developers seeking funding with a way to frame their funding requests in terms that are meaningful and relevant to funding agents. Managers can use these tools to choose among various management alternatives to focus research thrusts or speed up development. Together, these impacts can lead to a more effective research and development process for technologies that meet stakeholder needs in a cost-effective way.

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