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Quantifying the Effects of Budget Management on Project Cost and Success

Edouard Kujawski
Engineering Division, Ernest Orlando Lawrence Berkeley National Laboratory, University of California, Berkeley, California 94720
e_kujawski@lbl.gov

Mariana L. Alvaro
Department of Statistics, California State University, Hayward, California 94542
mariana@alvaro.com.ar

Abstract

Today's typical probabilistic cost analysis assumes an "ideal" project in which whenever a cost element comes in low its savings are passed on where they are needed. Unfortunately in the real world “Money Allocated is Money Spent" (MAIMS principle), and cost underruns are rarely available to protect against cost overruns while task overruns are passed on to the total project cost. Realistic cost estimates require a modified probabilistic cost analysis because the project cost at a given confidence level cannot be estimated until the budget management practices including allocation is specified. We present a probabilistic cost analysis that integrates valid mathematical with sound management techniques to obtain realistic cost estimates and effectively achieve project success. The analysis is readily implemented using standard Monte Carlo simulation Excel add-ins. We illustrate the approach and its implications for a representative design and engineering project. The analysis substantiates that today's typical probabilistic cost analysis is likely to severely underestimate project cost for probability of success values of importance to contractors and procuring activities. Budget management practices have a substantial impact on the cost of the project and/or probability of success. Using this information we develop a viable strategy for effectively allocating budgets and managing contingencies.

Introduction

It is standard practice for project management to allocate definite budgets to cost elements and maintain a budget contingency for dealing with unforeseen in-scope events. Nevertheless actual project costs often exceed the initial estimates and are delivered late and/or with a reduced scope. These include the full spectrum of projects such as remodeling one's residence, commercial ventures, construction projects, and R&D projects. Projects that come-in under cost, within schedule, and meet all requirements (including non-functional ones such as quality/reliability) do not necessarily deserve kudos. They may have carried budgets with excessive padding that lead to unnecessarily high costs and misallocation of resources. In today's highly competitive business environment, it is critical to improve the realism of cost estimates and how budgets are managed.

In the 1990's the Lockheed Missiles and Space Co. carried out a study which concluded that the following deficiencies in cost modeling and contingency management have been major contributors to both project high costs and overruns (Gordon 997)

1. Use of invalid mathematics such as arithmetically summing uncertain cost elements instead of using statistical methods.
2. Overlooking that "Money Allocated Is Money Spent" (MAIMS principle).
3. Failure to coordinate cost analysis and cost management.
4. Hidden incentives in management styles.
5. Hidden incentives in procurement.

The MAIMS principle accounts for the fact that projects rarely underrun their allocated budgets. It is the money analog of Parkinson's Law -"Work expands to fill the time allotted"- and Goldratt's observation that negative human behavior is a major cause of the project-scheduling problem. Goldratt (1997) developed the Critical Chain Project Management (CCPM) as a management philosophy and solution that simultaneously reduces project duration and protects against schedule risk. A key CCPM principle is to aggregate task buffers at the project-level for use where and when needed. But the original CCPM method only approximately treats the probabilistic nature of project risks (Schuyler 2000). A number of simple alternatives to estimate and sum buffers have been proposed (Newbold 1998). We think that their use is now no longer justified because of the availability of Monte Carlo simulation tools such as @Risk and Crystal Ball®. The original CCPM also proposed the following guidelines for sizing buffers: (1) Cut task duration estimates in half, and (2) Add approximately 25% of the original estimate to the project buffer. These appear to be rather arbitrary, and many technical managers are uncomfortable with them (Givens Filiatrault and Peterson 2000).

The premise of this paper is that a credible Probabilistic Cost Analysis (PCA) needs to integrate findings on human behavior with mathematically valid models and sound management techniques to obtain realistic cost estimates and achieve project success. Building on these concepts, we develop a practical yet realistic and mathematically valid model that remedies several of the identified shortcomings prevalent in today's PCAs and adversely impact project management.

Proposed Modifications to Today's Typical PCA

Assessing Uncertain Cost Elements. R&D and complex engineering projects rely heavily on engineering/expert judgment for the assessment of uncertain cost elements. Unfortunately the subjective assessments are often performed in a rather ad-hoc manner, and they have been identified as a critical source of uncertainty in probabilistic risk analyses (Keeney and von Winterfeld 1991). The Direct Fractile Assessment (DFA) method has been investigated in numerous psychological experiments and found to provide one of the most reliable and least bias-prone procedures for eliciting uncertain quantities (Alpert and Raiffa 1982). We advocate its use for subjectively estimating uncertain cost elements of R&D and engineering design projects.

The elicitation process influences the assessed values and is of critical importance to the validity of the PCA. We recommend that experienced analysts and domain experts determine the 10th, 50th, and 90th percentiles for uncertain cost elements. While other percentiles may be used, these seem to be most practical (Dillon et al. 2002). For similar reasons, analysts should avoid seeking extreme values, abstract measures such as the mean and the standard deviation, or specific distributions. Analysts may further calibrate each set of percentiles to account for human behavior and project specific considerations such as optimism or pessimism (Clemen and Lichtendahl 2002). As a default calibration to account for overconfidence and as a defense against overly optimistic estimates, cost analysts might opt to shift the assessed 90th percentile to the 80th or 75th percentiles. Key decision points as well as low-probability/high-consequence events should be explicitly modeled using scenarios (Kujawski 2002).

Fitting Cost Elements with Realistic Probability Density Functions (PDF). Uncertain cost elements are more appropriately modeled as continuous than discrete random variables. We favor the use of the three-parameter Weibull distribution because it is an open-ended function that can assume a wide variety of shapes. It is also more flexible than the three-parameter lognormal even though both are characterized by three independent parameters. The use of more complex PDFs seemed unwarranted for fitting three subjectively assessed percentiles. Analysts and assessors should always validate that they feel comfortable with the shape of the fitted distribution.

Incorporating the MAIMS Principle. The MAIMS principle plays a significant role in PCA. Once a cost element is allocated a budget x* it becomes a random variable with minimum value x* rather than the lower range of the original PDF. The cost element is then given by a PDF with a delta-like function at x* that accounts for all random values less than or equal to x* and the original distribution for values greater than x*. The associated Complementary Distribution Function (CDF) has a step-function behavior at x* and is identical to the original CDF above x*. Since the mean increases and the standard deviation decreases with increasing values of x*, the MAIMS principle plays a significant role in PCA and budget management. As a caution we stress that the MAIMS-modified PDFs are not the same as the Crystal Ball® and @Risk truncated PDFs.

Modeling Correlations. Cost elements are correlated because project characteristics such as complexity, criticality, management, staff, and processes, are likely to impact multiple cost elements at the subsystem and system levels. Also, the realization of any one risk is likely to influence other risks and to increase their probabilities and/or consequences

The assessment of correlation coefficients is a difficult problem; but it does warrant PCAs that neglect correlations among cost elements (Book 2000/2001; Chapman and Ward 2000). We use the Two-Level Correlation Model (TLCM) developed by Kujawski et al. (2004). It greatly reduces the number of parameters needed to specify a mathematically valid and physically realistic correlation matrix. In its simplest form it models correlations among cost elements of the same and different subsystems with only two parameters, ρ_{int} and ρ_{ext}. The use of reasonable correlation values in the range 0.3 to 0.6 with $\rho_{int} > \rho_{ext}$ should lead to more realistic cost estimates than the overly optimistic values assuming independent cost elements ($\rho = 0$) or the overly pessimistic values assuming perfectly correlated cost elements ($\rho = 1$).

Application to a Representative Design and Engineering Project

To investigate the concepts and issues discussed in the previous sections we consider the hypothetical project with the Work Breakdown Structure (WBS) in Table 1.

Table 1: Illustrative project WBS and assessed cost elements

WBS Cost Elements	Estimated Percentiles K$		
	X_{10}	X_{50}	X_{90}
1.0 Total project/system			
1.1 Project/system-level			
1.1.1 Project management	382	421	499
1.1.2 Systems engineering	220	232	257
1.1.3 Integration & test	887	1,010	1,256
1.2 Subsystem X, C_2			
1.2.1 Mechanical components	970	1088	1,323
1.2.2 Electrical components	742	846	1,054
1.2.3 Integration & test	596	724	980
1.3 Subsystem Y			
1.3.1 Software development	1,069	1,282	1,708
1.3.2 Firmware	634	743	961
1.3.3 Integration & test	541	656	886

Given a WBS, the first step of a PCA is to develop an appropriate Cost Work Breakdown Structure (CWBS). Assume that the CWBS is given by the WBS level 3 in Table 1. The second step is to systematically assess the cost elements using the DFA method. Assume that the 10th, 50th, and 90th percentiles in Table 1 specify the assessed cost elements. These values may be further calibrated for biases in the assessments. The third step is to fit realistic PDFs to these percentiles. As already indicated, we favor the three-parameter Weibull distribution. At this point, the proposed approach deviates significantly from today's typical PCA. We implement the MCS as follows:

1. A budget is allocated to each cost element.
2. Each cost element PDF is modified in accordance with the MAIMS principle. The minimum cost is the allocated budget.
3. Statistical interrelationships among the cost elements are modeled using the TLCM.

Figure 1 depicts different budget allocation strategies for a given set of PDFs and correlation matrix.

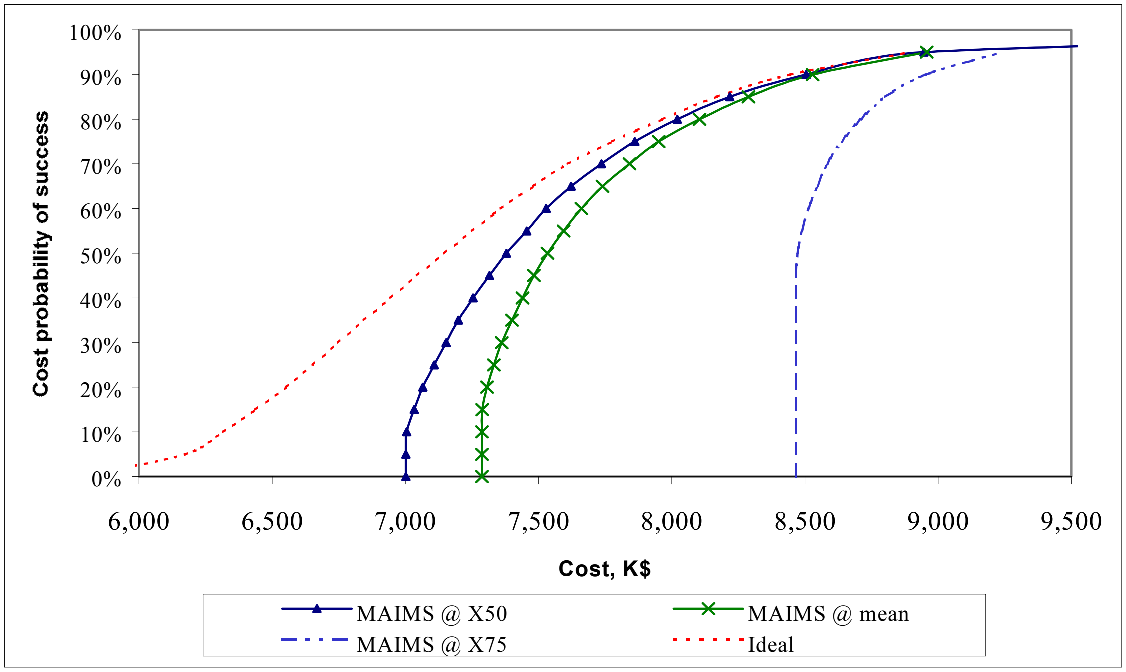

Figure 1. Impact of different budget allocation strategies on the PCA for the project in Table 1. Cost elements with Weibull distributions fitted to the 10th, 50th, and 90th fractiles; TLCM parameter values of 0.6 and 0.4.

All calculations were performed using Crystal Ball® and 10,000 trials. The “ideal curve” corresponds to the model where the project staff rationally spends money only as necessary to satisfy the project requirements. The actual costs may be less than the budgeted costs and the savings are available to support other project elements on an as-needed basis. In the MAIMS_@_X50 and MAIMS_@_X75 curves all cost elements are allocated equal percentiles of 50% and 75%, respectively[1]. The MAIMS_@_mean curve corresponds to the case where each cost element is allocated its mean or expected value. Each cost element is then budgeted at a percentile that depends on the shape of the assessed PDF. While some may not consider this to be equitable, we note in its defense that it has mathematical merit and compensates somewhat for high risks (Kindinger 1999). The MAIMS effects increase with higher allocated budgets and are substantial over a wide range of probability of success values of interest to PCA. We also note that the assessment of the cost elements, the interrelationships among them, the budget allocation and management of contingencies constitute important and confounding factors. The results strongly suggest that realistic cost predictions require PCAs that simultaneously rather than individually account for these effects

Budget Allocation, Contingency, and Project Cost

The project manager or a designee, because of either contractual requirement or management expediency, allocates definite budgets that constitute the Project Baseline Cost (PBC) to the cost managers. Typically, he/she also establishes a Management Cost

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[1] We use Xn to denote the nth percentile of a cost element to differentiate it from the project cost probability of success or percentile.

Contingency[2] (MCC) for management flexibility in executing in-work scope and dealing with unforeseen in-scope events. He/she than allocates available contingency funds on an as-needed basis throughout the life of the project.

Our objective is to integrate the presented concepts into a sound methodology for determining an optimal but realistic Total Estimated Cost (TEC) and budget allocation/management strategy for a given Probability of Success (PoS). The combination of cost uncertainties and the MAIMS principle complicates the situation. As we have shown, the TEC depends not only on the desired PoS but also the budget allocation and the management of contingencies. The project cost cannot be estimated until the cost management strategy including budget allocation is specified. We like to think that this contains a flavor of the Heisenberg Uncertainty Principle.

Much has been written on cost contingency; but there is still much confusion (Baccarini 1999; INCOSE 2003). To shed additional light on the subject, we express the MCC in a form that exhibits its dependence on the PoS and the cost management strategy,

$$\mathrm{MCC}(\mathrm{PoS},\mathrm{PBC}_1,\ldots,\mathrm{PBC}_n)$$
$$\equiv \mathrm{TEC}(\mathrm{PoS}, \mathrm{PBC}_1,\ldots,\mathrm{PBC}_n) - \mathrm{PBC}.$$

PBC_i is the baseline budget for cost element C_i; PBC is the sum over all cost elements. The above relationship contrasts with both (1) the deterministic practice that allocates a percentage of the PBC as MCC, and (2) today's typical PCA that provides a MCC that is independent of the budget allocation strategy.

Consider the illustrative project in Table 1 under the following budget management strategies: (1) all cost elements are baselined at their mean values; (2) all cost elements are baselined at the 50% CL; and (3) all cost elements are baselined at the 75% CL. Figure 2 depicts the resulting TECs and MCCs and the “ideal” project TEC.

The budget management strategy has a significant impact on the TEC for a given PoS. The effects of the MAIMS principle increase with increasing budget allocations and are substantial for all but the very highest PoS values. The MAIMS principle has little impact at the very high confidence levels (CL > 95%) because each contributing cost element must then be near its maximum or 100th percentile value.

The above results have important implications for cost management. For example, sizeable cost reductions are achieved by allocating budgets to the cost elements at the 50% CL rather the 75% CL. The standard PCA that assumes an “ideal” project provides a false sense of confidence and it may be a major source of cost overruns even for projects with high contingencies.

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[2] There is no standard terminology and usage of terms and definitions vary widely with organizations.

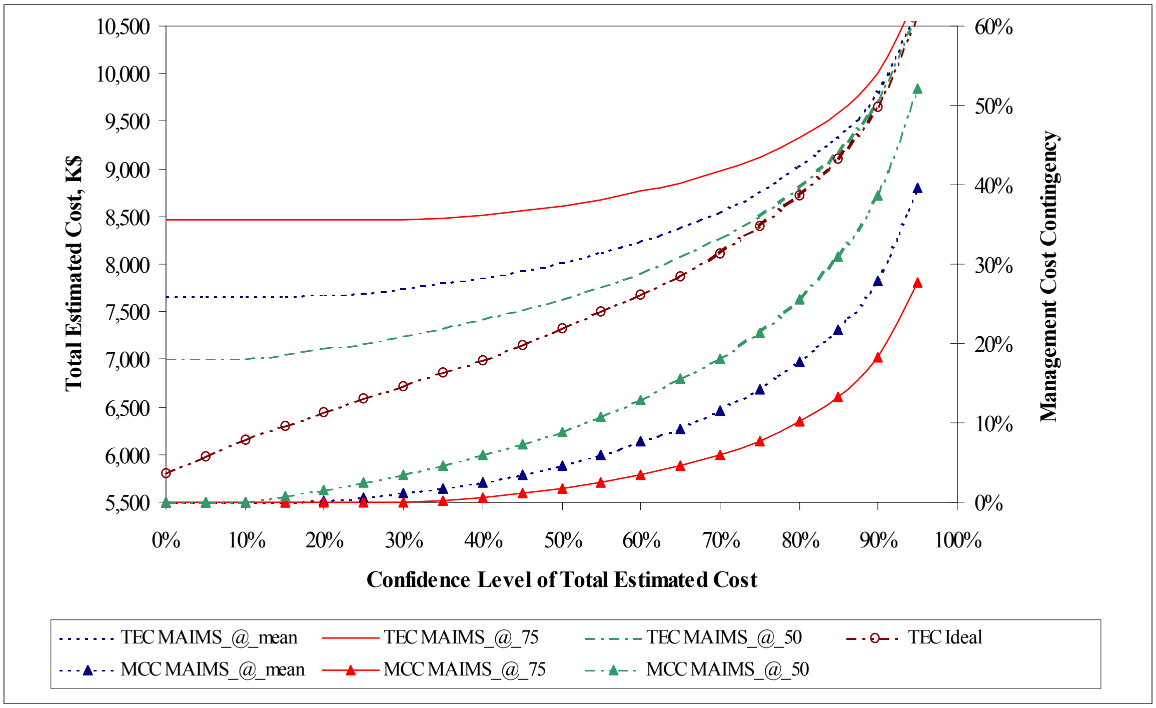

Figure 2. Impact of different cost management strategies on the cost and contingency for the project in Table 1.

Figure 2 contains valuable information for both the procuring activity and the contractor. Consider a hypothetical request for proposal for the project in Table 1. To level the playing field, the procuring activity specifies that all bids should provide the 50% CL cost. Contractor A has a certain level of sophistication. He prepares a PCA with every bid; he systematically assesses the cost elements including uncertainties; he baselines and allocates budgets to the cost elements at their mean values; management establishes and controls a contingency that equals the difference between the bid and the mean TEC. But Contractor A is not cognisant of the MAIMS principle. He performs today's typical PCA and obtains the CDF in Fig. 2 labeled “TEC Ideal” and a P50 TEC of 7,348 K$. This P50 value or median is 317 K$ less than the mean value of 7,655 K$ because the cost elements are given by positively skewed PDFs. Based on his analysis, Contractor A submits a bid of 7,348 K$ and rationalizes that his practices are very conservative given that the P50 value is 30% above the low estimate of 5,633 K$. But because of the MAIMS principle Contractor A's risks are significantly greater than he thinks. Given that the cost elements are budgeted at their mean values, the TEC is really given by the CDF in Fig. 2 labeled “PEC MAIMS_@_mean”, the P50 TEC is 8,071 K$, and the PBC of 7,665 K$ is the lowest achievable cost. Based on our analysis we conclude that there is a negligible likelihood that Contractor A given his practices can deliver the project for the submitted bid of 7,348 K$. The criticality of the situation is further aggravated by the fact that Contractor A has stumbled onto Russo and Schoemaker's (1990) Decision Trap Number 5 "implicitly trusting the most readily available information or anchoring too much on convenient facts." Table 2 summarizes this and several other scenarios.

Table 2. Some summary data of the different cost management strategies depicted in Figure 2

Management	Strategy	MAIMS-Modified PCA				Typical PCA			
Budget Allocation	Desired PoS	TEC $K	MCC $K	MCC %	Real. PoS	TEC $K	MCC $K	MCC %	Real. PoS
Mean	20%	7,673	0	0%	20%	6,445	-1,220	-16%	0%
	50%	8,071	406	5%	50%	7,348	-317	-4%	0%
	80%	8,987	1,322	17%	80%	8,626	961	13%	73%
50% CL	20%	7,111	0	0%	20%	6,445	-557	-8%	0%
	50%	7,692	690	10%	50%	7,348	346	5%	37%
	80%	8,771	1,769	25%	80%	8,626	1,624	23%	77%
75% CL	20%	8,466	0	0%	20%	6,445	-2,021	-24%	0%
	50%	8,613	147	2%	50%	7,348	-1,118	-13%	0%
	80%	9,330	864	10%	80%	8,626	160	2%	52%

Concluding Remarks

We think that the proposed approach provides a framework for obtaining more accurate predictions than those provided by today's typical probabilistic cost analysis. With more accurate predictions and realistic expectations project managers can develop more viable plans and make better decisions. The results are projects that are delivered for a lower cost and higher probability of success. We acknowledge that it takes effort to develop these more realistic models and that all models are only approximations to reality. But given the magnitude of the cost overrun problem, there is no excuse for not pursuing improved cost analysis and management techniques; the benefits are likely to be significant.

We, however, do not claim that the proposed approach is the silver bullet that will slay the cost overrun monster. We have focused only on cost and the macroscopic perspective. Cost is but one element of the performance-cost-schedule triad. By their very nature R&D and complex engineering projects are susceptible to high-consequence risks that are better modeled with decision trees, influence diagrams, and other decision tools. Probabilistic cost analysis should integrate the microscopic and macroscopic approaches to ensure that they properly address all risks and cost uncertainties and that they adequately support risk reduction activities. It is also critical to explicitly deal with behavioral and organizational considerations that Sage (1981) has documented as essential to project success. The work of psychologists on human behavior and judgment under uncertainty is having a profound influence in many fields including decision-making, management, and economics (Rabin 1998). We think that these findings should also be given greater consideration in systems engineering. Other areas that need additional research and development include (1) eliciting and integrating data from multiple experts (Clemen and Winkler 1999); (2) budgeting and managing contingencies for multiple projects (Dillon and Paté-Cornell 2001); and (3) quantifying human and organizational behaviors of R&D and complex engineering projects. Our own experience is that the single greatest challenge to the development and use of improved probabilistic cost analysis is the implementation of systems thinking at the personnel, organizational, and institutional levels.

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Biography

Edouard Kujawski practices systems engineering at the Lawrence Berkeley National Laboratory. He specializes in the design and analysis of high reliability/availability systems, risk analysis, and the implementation of systems engineering practices. He has also held lead positions at General Electric and Lockheed-Martin. He has contributed to the design of particle accelerators, space observatories, commercial communication systems, the Space Station, and nuclear power plants. He has written and published several papers on risk analysis and decision analysis. He was a participant and contributor to the Lockheed Martin LM21 Risk Management Best Practices. He is a member of the San Francisco Bay Area Chapter of INCOSE and has served on the board of directors. He recently taught systems engineering at San Jose State University. He received a Ph.D. in physics from MIT following which he spent several years in research and teaching.

Mariana Alvaro is a graduate student and research assistant in the Statistics Department at California State University Hayward, where she is pursuing studies in biostatistics and bioinformatics. She received a BS degree in Computer Science at CAECE University in Argentina, in 1997. She also holds an International Diploma on Project Management from the University of California Berkeley Extension. She worked on this paper while she was a computer systems engineer at the Lawrence Berkeley National Laboratory. She founded a successful software consulting company where she became a developer partner for Ericsson Mobility World in Argentina. Her areas of expertise include wireless communication systems and databases.