RSK06: Enhanced Scenario-Based Method for Cost Risk Analysis: Theory, Application, and Implementation

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Abstract: There is a growing realization within the cost-analysis community that estimates of cumulative probability distributions of cost, or S-curves, too often understate true, underlying risk and uncertainty. Several organizations cite cases where return program acquisition costs, or actuals, fall at the 99th+ percentile on S-curves estimated years previously. This degree of deviation from the mean is a legitimate possibility for any one acquisition program. After all, there's no such thing as an "average" program. Variation is expected. However, the frequency of occurrence of outliers, coupled with an apparent disconnect between estimated and historically-based coefficients of variations (CVs) reflected in S-curves, suggests a systemic rather than an isolated problem. To address this problem, this paper presents recent enhancements to the Scenario-Based Method (SBM), the application of which should result in more realistic S-curves for program cost.

Among the pantheon of procedures for performing cost risk and uncertainty analysis, such as Monte Carlo simulation and sensitivity analysis, the enhanced Scenario-Based Method, or eSBM, offers a unique top-level, historically-based, issue-oriented perspective. Sets of risk events, or scenarios, are defined which represent plausible alternatives to the baseline. Using CVs based on historical results of DoD acquisition programs, S-curves are generated and risks assessed. eSBM can be used as a stand-alone technique to support major milestone decisions, or, as a best practice, in conjunction with other methods.

In 2006, the Scenario-Based Method (SBM) was introduced as an alternative to advanced statistical methods for generating measures of cost risk. Since then, enhancements to SBM have been made. These include integrating historical data into SBM's algorithms and providing a context for applying SBM from a WSARA perspective. Together, these improvements define the enhanced SBM - an historical, data-driven application of SBM.

This paper presents

- eSBM theory;
- Historically-based CVs to employ in generating S-curves, or in checking their accuracy;
- A case study that employs eSBM;
- An illustration of the consequences of using inaccurate S-curves; and
- An easy-to-use tool for generating and comparing S-curves.

In summary, eSBM and the S-curve tool, with benchmark CVs as their foundation, provide invaluable assistance in (1) estimating the risks and uncertainties of major acquisition programs and (2) gauging the accuracy of cost risk assessments, generated by whatever means.

ENHANCED SCENARIO-BASED METHOD FOR COST RISK ANALYSIS: THEORY, APPLICATION, AND IMPLEMENTATION

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In memory of Dr. Steve Book, nulli secundus, for his kindness and devotion, and for his invaluable comments and insights on an earlier draft.

ABSTRACT

In 2006, the Scenario-Based Method (SBM) was introduced as an alternative to advanced statistical methods for generating measures of cost risk. Since then, enhancements to SBM have been made. These include integrating historical cost performance data into SBM's algorithms and providing a context for applying SBM from the perspective of the 2009 Weapon Systems Acquisition Reform Act (WSARA). Together, these improvements define the enhanced SBM (eSBM) – an historical data-driven application of SBM. This paper presents eSBM and illustrates how it promotes realism in estimating future program costs, while offering decision-makers a traceable and defensible basis behind data-derived measures of risk and cost estimate confidence.

KEY WORDS: Scenario-Based Method (SBM), Enhanced Scenario-Based Method (eSBM), Weapon Systems Acquisition Reform Act (WSARA), Cost Estimate, Cost Risk, Historical Cost Data

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1.0 Background

This paper presents eSBM, an enhancement to the Scenario-Based Method (SBM), which was originally developed as a "non-statistical" alternative to advanced statistical methods for generating measures of cost risk. Both SBM and eSBM emphasize the development of written risk scenarios as the foundation for deriving a range of possible program costs and assessing cost estimate confidence.

SBM was developed in 2006 in response to the following question posed by a government agency: *Can a valid cost risk analysis, one that is traceable and defensible, be conducted with minimal (to no) reliance on Monte Carlo simulation or other advanced statistical methods?* The question was motivated by the agency's unsatisfactory experiences in developing, implementing, and defending simulation-derived risk-adjusted program costs of their future systems.

Once developed, SBM has appeared in a number of publications, including the RAND monograph *Impossible Certainty* [Arena, 2006], the United States Air Force *Cost Risk and Uncertainty Analysis Handbook* (2007), and NASA's *Cost Estimating Handbook* (2008). SBM is also referenced in GAO's *Cost Estimating and Assessment Guide* (2009). It was formally published in the *Journal of Cost Analysis and Parametrics* [Garvey, 2008]. Since 2006, interest in SBM has continued to grow, and the method has been enhanced in two ways. First, historical cost data are now integrated into SBM's algorithms. Second, a framework for applying SBM from a WSARA perspective has been built into SBM. The acronym eSBM denotes SBM together with these two enhancements.

In short, eSBM is an historical data-driven application of SBM operating within WSARA. In support of WSARA, eSBM produces a range of possible costs and measures of cost estimate confidence that are driven by past program performance. With its simplified analytics, eSBM eases the mathematical burden on analysts, focusing instead on defining and analyzing risk scenarios as the basis for deliberations on the amount of cost reserve needed to protect a program from unwanted or unexpected cost increases. With eSBM, the cost community is further enabled to achieve cost realism – while offering decision-makers a traceable and defensible basis behind derived measures of risk and cost estimate confidence.

1.1 Requirement

Life-cycle cost estimates of defense programs are inherently uncertain. Estimates are sometimes required when little if any of a program's total definition is known. Years of system development and production and decades of operating and support costs, need to be estimated. Estimates, in turn, are based on historical samples of data that are almost always messy, of limited size, and difficult and costly to obtain. Herculean efforts are commonly required to squeeze usable information from a limited, inconsistent set of data. And no matter what estimating tool or method is used, historical observations never perfectly fit a smooth line or surface, but instead fall above and below an estimated value. To complicate matters, the weapon system or automated information system under study is often of sketchy design. Only limited programmatic information may be available on such key parameters as schedule, quantity, performance, requirements, acquisition strategy, and future evolutionary increments. Further, the historical record has shown that key characteristics of the system actually change as the system proceeds through development and even production. Increases in system weight, complexity, and lines of code are commonplace.

For all of these reasons, a life-cycle cost estimate, when expressed as a single number, is merely one outcome or observation in a probability distribution of costs. That is, the estimate is stochastic rather than deterministic, with uncertainty and risk determining the shape and variance of the distribution.

The terms "risk" and "uncertainty" are often used interchangeably, but they're not the same.

- **Uncertainty** is the indefiniteness or variability of an event. It captures the phenomenon of observations, favorable or unfavorable, high or low, falling to the left or right of a mean or median.
- **Risk** is exposure to loss. In a defense acquisition context, it is "a measure of future uncertainties in achieving program performance goals within defined cost and schedule constraints. It has three components: a future root cause, a likelihood assessed at the present time of that future root cause occurring, and the consequence of that future occurrence." [5]

Risk and uncertainty are related. Uncertainty is probability while risk is probability and consequence.

1.2 Techniques

Defense cost analysis, in its highest form, is an amalgam of scientific rigor and sound judgment. On the one hand, it requires knowledge, insight, and application of statistically-sound principles, and, on the other, critical interpretation of a wide variety of information that is often known with only limited precision. Indeed, Keynes' observation on "the extreme precariousness of the basis of knowledge on which our estimates … have to be made" [6] often applies in defense cost analysis, especially for pre-Milestone (MS) B activities in the acquisition process and even more so for capability-based assessments in the requirements process. Since uncertainty and risk are always present in major defense acquisition programs and capability-based analyses, it's essential to convey to senior leadership, in one fashion or another, the stochastic nature of the cost estimate. To do otherwise could lead to a false sense of security and a misallocation of resources.

Perhaps the ultimate expression of the randomness of a cost estimate is the S-curve, or cumulative probability distribution, employed frequently in both industry and government, often as a standard. Estimating these curves, *accurately and consistently* in a wide domain of applications, remains the Holy Grail in defense cost analysis. According to one school of thought, such distributions are "… rarely, if ever, known [within reasonable bounds of precision] ... for … investment projects."[7] This contention remains an open issue within the international defense cost analysis community. Some practitioners concur, others don't, and still others are unsure.

[5] "Risk Management Guide for DoD Acquisition, Sixth Edition, August 2006; USD(AT&L), Systems and Software Engineering, Enterprise Development, page 33.
[6] The General Theory of Employment, Interest, and Money; Keynes, John Maynard; Harcourt Brace Jovanovich; 1964, page 149.
[7] Economic Theory and Operations Analysis, Baumol, William; Prentice-Hall; 1977, page 621.

Amidst this spectrum of opinion, best-available techniques for conducting risk and uncertainty analysis of life-cycle cost estimates of defense acquisition programs include sensitivity analysis, Monte Carlo simulation, and eSBM.[8] Each technique, *if used properly*, can yield scientifically-sound results.

A best practice is to employ more than one technique and then compare findings. For example, detailed Monte Carlo simulation and eSBM both yield S-curves. Yet, the two techniques are fundamentally different in approach, the former bottoms-up and the latter top-down. Divergence in results between the two procedures is a clarion call for explanation while consistency will inspire confidence in the validity of the estimates. Results of sensitivity analysis should be consistent with those from the other techniques in terms of impact on cost.

1.3 Cost Estimate Confidence: A WSARA Perspective

In May 2009, the US Congress passed the WSARA. This law aims to *improve the organization and procedures of the Department of Defense for the acquisition of weapon systems* [Public Law, 111-23]. WSARA addresses three areas: the organizational structure of the DOD, its acquisition policies, and its congressional reporting requirements. The following discussion offers a perspective on WSARA as it relates to reporting requirements for cost estimate confidence.

Public Law 111-23, Section 101 states the following:

The Director shall … issue guidance relating to the proper selection of confidence levels in cost estimates generally, and specifically, for the proper selection of confidence levels in cost estimates for major defense acquisition programs and major automated information system programs.

The Director of Cost Assessment and Program Evaluation, and the Secretary of the military department concerned or the head of the Defense Agency concerned (as applicable), shall each … disclose the confidence level used in establishing a cost estimate for a major defense acquisition program or major automated information system program, the rationale for selecting such confidence level, and, if such confidence level is less than 80 percent, justification for selecting a confidence level less than 80 percent.

What does cost estimate confidence mean? In general, it is a statement of the surety in an estimate along with a supporting rationale. The intent of WSARA's language suggests this statement is statistically derived; that is, expressing confidence as "*there is an 80 percent chance the program's cost will not exceed $250M*". How is cost estimate confidence measured?

Probability theory is the ideal formalism for deriving measures of confidence. With it, a program's cost can be treated as an uncertain quantity – one sensitive to many conditions and assumptions that change across its acquisition life cycle. Figure 1 illustrates the conceptual process for using probability theory to analyze cost uncertainty and producing confidence measures.

[8] Interestingly, use of Monte Carlo simulation is more popular in the U.S. DoD than in the ministries of defense in other NATO countries where use of sensitivity analysis predominates.

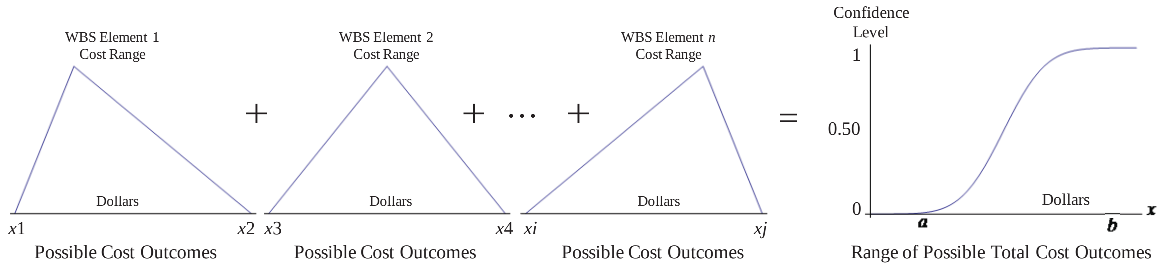

Figure 1. Cost Estimate Confidence: A Summation of Cost Element Cost Ranges

In Figure 1, the uncertainty in the cost of each work breakdown structure (WBS) element is expressed by a probability distribution. These distributions characterize each cost element's range of possible cost outcomes. All distributions are then combined by probability calculus to generate an overall distribution of program total cost. This distribution characterizes the range of total cost outcomes possible for the program. How does the output from this process enable confidence levels to be determined? Consider Figure 2.

Figure 2 illustrates the probability distribution of a program's total cost in cumulative form. It is another way to illustrate the output from a probability analysis of cost uncertainty, as described in Figure 1, specifically one that allows cost estimate confidence to be read from the distribution. For example, there is a 25% chance the program will cost less than or equal to $100M, a 50% chance the program will cost less than or equal to $151M, and an 80% chance the program will cost less than or equal to $214M. These are confidence levels. The right side of Figure 2 shows the WSARA confidence level, as stated in Public Law 111-23, Section 101.

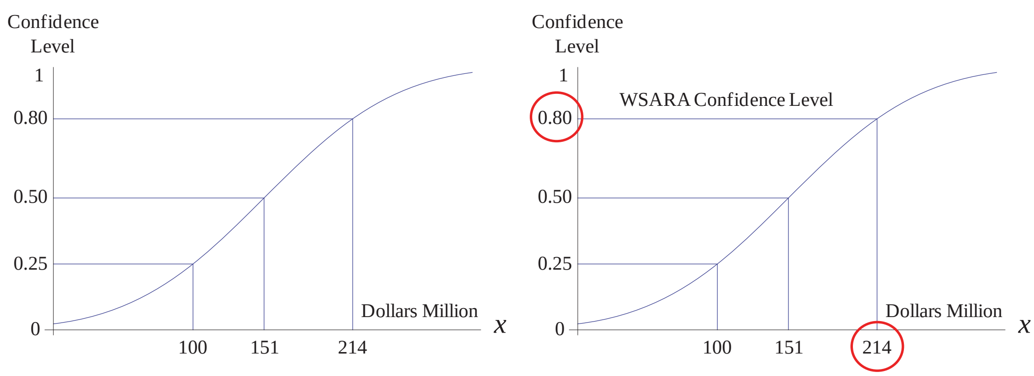

Figure 2. WSARA and Confidence Levels

A statistical technique known as Monte Carlo simulation is the most common approach for determining cost estimate confidence. This technique involves simulating the program cost impacts of all possible outcomes that might occur within a sample space of analyst-defined events. The output of a Monte Carlo simulation is a probability distribution of possible program costs. With this, analysts can present decision-makers a range of costs and a statistically derived measure of confidence the true or final program cost will remain in this range.

However, the soundness a Monte Carlo simulation is highly dependent on the mathematical skills and statistical training of the cost analysts conducting the analysis, traits that vary in the community. There are many subtleties in the underlying formalisms of Monte Carlo simulation, and these must be understood if errors in simulation design and in interpreting its outputs are to be avoided. For example, analysts must understand topics such as correlation and which of its many varieties is appropriate in cost uncertainty analysis. Analysts must understand that the sum of each cost element's most probable cost is not generally the most probable total program cost. In addition to understanding such subtleties, analysis must be skilled in explaining them to others.

SBM/eSBM, whose straightforward algebraic equations ease the mathematical burden on analysts, is an alternative to Monte Carlo simulation. . SBM/eSBM focuses on defining and analyzing risk scenarios as the basis for deliberations on the amount of cost reserve needed to protect a program from unwanted or unexpected cost increases. Such deliberations are a meaningful focus in cost reviews and in advancing cost realism. Defining, iterating, and converging on one or more risk scenarios is valuable for understanding elasticity in program costs, assessing cost estimate confidence, and identifying potential events a program must guard its costs against, if they occur. Scenarios build the necessary rationale for a traceable and defensible measure of cost risk. This discipline is often lacking in traditional Monte Carlo simulation approaches, where focus is often on its mathematical design instead of whether the design coherently models one or more scenarios of events that, if realized, drive costs higher than planned.

Regardless of the approach used, expressing cost estimate confidence by a range of possible cost outcomes has high information value to decision-makers. The breadth of the range itself is a measure of cost uncertainty, which varies across a program's life cycle. Identifying critical elements that drive a program's cost range offers opportunities for targeting risk mitigation actions early in its acquisition phases. Benefits of this analysis include the following three processes:

Establishing a Cost and Schedule Risk Baseline – Baseline probability distributions of program cost and schedule can be developed for a given system configuration, acquisition strategy, and cost-schedule estimation approach. The baseline provides decision-makers visibility into potentially high-payoff areas for risk reduction initiatives. Baseline distributions assist in determining a program's cost and schedule that simultaneously have a specified probability of not being exceeded. They can also provide decision-makers an assessment of the chance of achieving a budgeted (or proposed) cost and schedule, or cost for a given feasible schedule.

Determining Cost Reserve – Cost uncertainty analysis provides a basis for determining cost reserve as a function of the uncertainties specific to a program. The analysis provides the direct link between the amount of cost reserve to recommend and cost confidence levels. An analysis should be conducted to verify the recommended cost reserve covers fortuitous events (e.g., unplanned code growth, unplanned schedule delays) deemed possible by the engineering team.

Conducting Risk Reduction Tradeoff Analyses – Cost uncertainty analyses can be conducted to study the payoff of implementing risk reduction initiatives on lessening a program's cost and schedule risks. Furthermore, families of probability distribution functions can be generated to compare the cost and cost risk impacts of alternative requirements, schedule uncertainties, and competing system configurations or acquisition strategies.

The strength of any cost uncertainty analysis relies on the engineering and cost team's experience, judgment, and knowledge of the program's uncertainties. Documenting the team's insights into these uncertainties is *a critical part of the process*. Without it, credibility of the analysis is easily questioned and difficult to defend. Details about the analysis methodology, including assumptions, are components of the documentation. The methodology *must be technically sound* and offer value-added problem structure and insights otherwise not visible. Decisions that successfully reduce or eliminate uncertainty ultimately rest on human judgment. This at best is aided, not directed, by the methods discussed herein.

2.0 Scenario-Based Method (SBM)

The scenario-based method was developed along two implementation strategies, the non-statistical SBM and the statistical SBM, the latter of which is the form needed for WSARA. The following discussion describes each implementation and their mutual relationship.

2.1 Non-Statistical SBM

The scenario-based method is centered on articulating and costing a program's risk scenarios. Risk scenarios are coherent stories about potential events that, if they occur, increase program cost beyond what was planned.

The process of defining risk scenarios is a good practice. It builds the rationale and case-arguments to justify the reserve needed to protect program cost from the realization of unwanted events. This is lacking in Monte Carlo simulation if designed as arbitrary randomizations of possible program costs, a practice which can lead to reserve recommendations absent clear program context for what these funds are to protect.

Figure 3 illustrates the process flow of the non-statistical implementation of SBM.

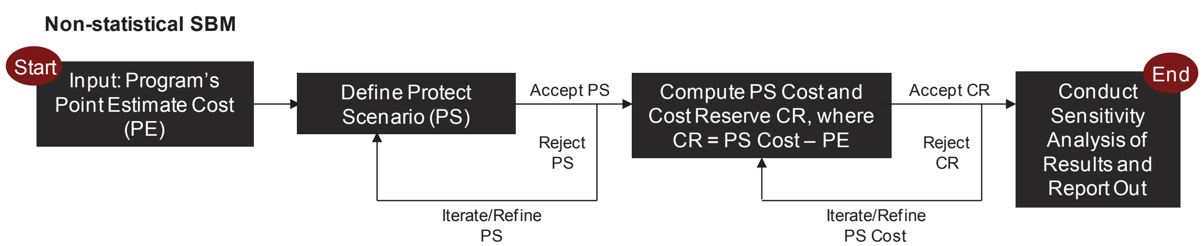

Figure 3. The Non-statistical SBM Process

The first step (Start) is input to the process. It is the program's point estimate (PE) cost. For purposes of this paper, the point estimate cost is the cost that does not include allowances for reserve. The PE cost is the sum of the cost-element costs across the program's work breakdown structure *without adjustments for uncertainty*. The PE cost is often developed from the program's cost analysis requirements description (CARD).

The next step in Figure 3 is defining a protect scenario (PS). A PS captures the cost impacts of major known risks to the program – those events the program must monitor and guard against occurring. The PS is not arbitrary, nor should it reflect extreme worst-case events. It should reflect a possible program cost that, in the judgment of the program, has *an acceptable chance of <u>not</u> being exceeded*. In practice, it is envisioned that management will converge on an “official” protect scenario after deliberations on the one initially defined. This part of the process ensures that all parties reach a consensus understanding of the program’s risks and how they are best described by the protect scenario.

Once the protect scenario is established its cost is then estimated. The amount of cost reserve dollars (CR) needed to protect program cost can be computed as the difference between the PS cost and the PE cost. Shown in Figure 3, there may be additional refinements to the cost estimated for the protect scenario, based on management reviews and other considerations. The process may be iterated until the reasonableness of the magnitude of the cost reserve dollars is accepted by management.

The final step in Figure 3 is a sensitivity analysis to identify critical drivers associated with the protect scenario and the program’s point estimate cost. It is recommended that the sensitivity of the amount of reserve dollars, computed in the preceding step, be assessed with respect to variations in the parameters associated with these drivers.

The non-statistical SBM, though simple in appearance, is a form of cost-risk analysis. The process of defining risk scenarios is a valuable exercise in identifying technical and cost estimation challenges inherent to the program. Without the need to define risk scenarios, cost risk analyses can be superficial, its case-basis not defined or carefully thought through. Scenario definition encourages a discourse on risks that otherwise might not be held, thereby allowing risks to become fully visible, traceable, and estimative to program managers and decision-makers.

The non-statistical SBM, in accordance with its non-statistical nature, does not produce confidence measures. The chance that the protect scenario cost, or of any other defined risk scenario’s cost, will not be exceeded is not explicitly determined. The question is *Can this SBM implementation be modified to produce confidence measures while maintaining its simplicity and analytical features*? The answer is yes, and a way to approach this excursion is discussed next.

2.2 Statistical SBM

This section presents a statistical implementation of SBM. Instead of a Monte Carlo simulation, the statistical SBM is a closed-form analytic approach. It requires only a look-up table and a few algebraic equations.

Among the many reasons to implement a statistical track in SBM are the following: (1) it enables WSARA confidence measures to be determined, (2) it offers a way for management to examine changes in confidence measures as a function of how much reserve to buy to increase the chance of program success, and (3) it provides an ability to measure where the protect scenario cost falls on the probability distribution of the program’s total cost.

Figure 4 illustrates the process flow of the statistical SBM. The upper part replicates the process steps of the non-statistical SBM, and the lower part appends the statistical SBM process steps. Thus, the statistical SBM is an augmentation of the non-statistical SBM.

To work the statistical SBM process, three inputs, as shown on the left in Figure 4, are required. These are the PE, the probability that the PE will not be exceeded, and the coefficient of variation, which will be explained below. The PE cost is the same as previously defined in the non-statistical SBM. The probability that PE cost x_{PE} will not be exceeded is the value α_{PE}, such that

$$P(Cost_{Pgm} \leq x_{PE}) = \alpha_{PE} \tag{1}$$

=