A Scenario-Based Method for Cost Risk Analysis

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ABSTRACT

This article presents an approach for performing an analysis of a program's cost risk. The approach is referred to as the scenario-based method (SBM). This method provides program managers and decision-makers an assessment of the amount of cost reserve needed to protect a program from cost overruns due to risk. The approach can be applied without the use of advanced statistical concepts or Monte Carlo simulations, yet is flexible in that confidence measures for various possible program costs can be derived.

INTRODUCTION

This article* introduces an analytical, non-Monte-Carlo-simulation approach, for quantifying a program's cost risks and deriving recommended levels of cost reserve. The approach is called the Scenario-Based Method (SBM). This method emphasizes the development of written scenarios as the basis for deriving and defending a program's cost and cost reserve recommendations.

The method presented in this article grew from a question posed by a government agency. The question was *Can a valid cost risk analysis (that is traceable and defensible) be conducted with minimal (to no) reliance on Monte Carlo simulation or other statistical methods?* The question was motivated by the agency's unsatisfactory experiences in developing and implementing Monte Carlo simulations to derive "risk-adjusted" costs of future systems. In response to the question posed by the agency, the method reflects an alternative approach whereby a technically valid measure of cost risk can be derived without Monte Carlo simulations or advanced statistical methods. A "statistically-light" analytical augmentation to this method is also presented that enables one to assess probabilities that a program's cost will (or will not) be exceeded.

TERMS AND DEFINITIONS

Throughout this article certain technical terms and distinctions between them are used. This section presents these terms and explains the subtleties between their meanings. First, we'll briefly discuss the concept of a subjective probability. This will be followed by a discussion of risk versus uncertainty and the differences between them. This sets the stage for introducing the SBM.

Subjective Probability Assessments (Garvey 2000): Probability theory is a well-established formalism for quantifying uncertainty. Its application to real-world systems engineering and cost analysis problems often involves the use of subjective probabilities. Subjective probabilities are those assigned to events on the basis of personal judgment. They are measures of a person's degree-of-belief an event will occur.

Subjective probabilities are associated with one-time, non-repeatable, events whose probabilities cannot be objectively determined from a sample space of outcomes developed by repeated trials or experimentation. Subjective probabilities must be consistent with the axioms of probability (Garvey 2000). For instance, if an engineer assigns a probability of 0.70 to the event "*the number of gates for the new processor chip will not*

*This paper was originally written for the United States Air Force Cost Analysis Agency.

exceed 12,000" then it must follow the chip will exceed 12,000 gates with probability 0.30. Subjective probabilities are conditional on the state of the person's knowledge, which may change with time.

To be credible, subjective probabilities should be assigned to events by only subject matter experts, persons with significant experience with events similar to the one under consideration. Instead of assigning a single subjective probability to an event, subject experts often find it easier to describe a mathematical function that depicts a distribution of probabilities. Such a distribution is sometimes called a subjective probability distribution. Subjective probability distributions are governed by the same mathematical properties as probability distributions associated with discrete or continuous random variables.

Subjective probability distributions are most common in cost uncertainty analysis, particularly on the input side of the process. Because of their nature, subjective probability distributions can be thought of as "belief functions." They describe a subject expert's belief in the distribution of probabilities for an event under consideration. Probability theory provides the mathematical formalism with which we operate (add, subtract, multiply, and divide) on these belief functions.

Risk versus Uncertainty (Garvey 2000): There is an important distinction between the terms risk and uncertainty. Risk is the chance of loss or injury. In a situation that includes favorable and unfavorable events, risk is the *probability an unfavorable event occurs*. Uncertainty is the *indefiniteness* about the outcome of a situation. We analyze uncertainty for the purpose of measuring risk.

In systems engineering the analysis might focus on measuring the risk of failing to achieve performance objectives, overrunning the budgeted cost, or delivering the system too late to meet user needs. Conducting the analysis involves varying degrees of subjectivity. This includes defining the events of concern, as well as specifying their subjective probabilities.

Given this, it is fair to ask whether it's meaningful to apply rigorous procedures to such analyses. In a speech before the 1955 Operations Research Society of America meeting, Charles Hitch addressed this question. He stated (Hitch 1965):

> *"Systems analyses provide a framework which permits the judgment of experts in many fields to be combined to yield results that transcend any individual judgment. The systems analyst [cost analyst] may have to be content with better rather than optimal solutions; or with devising and costing sensible methods of hedging; or merely with discovering critical sensitivities. We tend to be worse, in an absolute sense, in applying analysis or scientific method to broad context problems; but unaided intuition in such problems is also much worse in the absolute sense. Let's not deprive ourselves of any useful tools, however short of perfection they may fail."*

Given the above, it is worth a brief review of what we mean by cost uncertainty analysis and cost risk analysis. Cost uncertainty analysis is a process of quantifying the cost impacts of uncertainties associated with a system's technical definition and cost estimation methodologies. Cost risk analysis is a process of quantifying the cost impacts of risks associated with a system's technical definition and cost estimation methodologies. Cost risk is a measure of the chance that, due to unfavorable events, the planned or budgeted cost of a project will be exceeded.

Why conduct the analysis? There are many answers to this question; one answer is to produce a defensible assessment of the cost needed such that this amount has an acceptable probability of not being exceeded.

THE SCENARIO-BASED METHOD (SBM): A NON-STATISTICAL IMPLEMENTATION

Given the "what" and "why" of cost risk analysis, *a minimum acceptable method* is one that operates on specified scenarios that, if they occurred, would result in costs higher than the level planned or budgeted. These scenarios should not represent worst-case extremes; rather, they should reflect a set of possible events of reasonable concern, to a program manager or decision-maker, to warrant sufficient budget to guard against should any or all of them occur. For purposes of this discussion, we'll call this approach the "Scenario-Based Method" (SBM) for cost risk analysis.

The SBM derives from what could be called "sensitivity analysis", but with one difference. Instead of arbitrarily varying one or more variables to measure the sensitivity (or change) in cost, the SBM involves specifying *a well-defined set of technical and programmatic events that collectively affect a number of cost-related variables and associated work breakdown structure* (*WBS*) *elements in a way that increase cost beyond what was planned*. Defining these events, describing *the extent one event affects other events* (and/or other aspects of the program), and integrating this information into a coherent risk "story" about what the program faces is what is meant by the term "*scenario*".

The process of defining scenarios is a best practice. It builds the supportive rationale and provides a traceable and defensible analytical basis behind a "derived" measure of cost risk, which is often lacking in traditional simulation approaches. Visibility, traceability, defensibility, and the cost impacts of specifically identified risk events are principal strengths of the SBM. Figure 1 illustrates the process flow behind the non-statistical SBM.

The first step (in Figure 1) is input to the process. It is the program's point estimate cost (PE). For purposes of this article, the point estimate cost is defined as the cost that does not include an allowance for cost reserve. It is the sum of the cost element costs summed across the program's work breakdown structure *without adjustments for uncertainty*. Often, the point estimate cost is developed from the program's cost analysis requirements description (CARD).

Next, is the effort to define a protect scenario (PS). The key to a "good PS" is one that identifies, not an extreme worst-case, but a scenario that captures the impacts of the <u>major known risks</u> to the program – those events the program manager or decision-maker must monitor and guard the costs of the program against. Thus, the PS is not arbitrary. Nor is it stationary. It should reflect the above, as well as provide a possible program cost that, in the opinion of the engineering and analysis team, has *an acceptable chance of <u>not</u> being exceeded*.

In practice, it is envisioned that management will converge on a PS after a series of discussions, refinements, and iterations from the initially defined scenario. This part of the process aims to ensure all parties reach a consensus understanding of the risks the program faces and how they are best represented by the PS and then subsequently closely monitored.

Once the PS has been defined and agreed to its cost is then determined. The next step (in Figure 1) is computing the amount of cost reserve (CR) dollars needed to protect the program's cost against identified risk. This step of the process defines cost reserve as the difference between the PS cost and the point estimate cost (PE). Shown in Figure 1, there

FIGURE 1. A non-statistical scenario-based method.

may be additional refinements to the cost estimated for the PS based on management reviews and considerations. This too may be an iterative process until the reasonableness of the magnitude of this figure is accepted by the management team. It is important to emphasize the need to monitor, refine, and update the PE and the PS as the program matures in its acquisition or because of change in near-term or strategic needs.

A Valid Cost Risk Analysis

This approach, though simple in appearance, is a valid cost risk analysis; *why*? The process of defining scenarios is a deliberate exercise in identifying the risks the program faces. Without the need to define scenarios, cost risk analyses can be superficial with its basis not well-defined or carefully thought through.

Scenario definition encourages a discourse on program risks that otherwise might not occur, particularly in the early phases. The SBM requires risks to be made fully visible, traceable, and "costable" to program managers and decision-makers. This facilitates instituting formal risk management and monitoring practices across the program's life-cycle. Defining, iterating, and converging on a PS is valuable for understanding the "elasticity" in program costs and identifying those sets of risks (e.g., weight growth, software size increases, schedule slippages, etc.) the program must guard its costs against.

The non-statistical SBM described above has limits. Mentioned earlier, cost risk, by definition, is a measure of the chance that, due to unfavorable events, the planned or budgeted cost of a program will be exceeded. A non-statistical SBM does not produce mathematically derived confidence measures. The chance the cost of the PS, or the cost of any defined scenario, will not be exceeded is not explicitly computed. One might ask whether such a measure is necessary ***if*** the protect scenario has been well-developed and reflects the best understanding of the program's risks, as they can be reasonably anticipated at the given time.

Nonetheless, it is possible to modify the non-statistical SBM to produce confidence measures while maintaining its simplicity and analytical features. The following describes one way this might be done.

THE SCENARIO-BASED METHOD (SBM): A STATISTICAL IMPLEMENTATION

This section presents a statistical, non-Monte Carlo simulation, implementation of the SBM. It is an optional augmentation to the methodology discussed above. It can be implemented with a spreadsheet, a few algebraic equations, and a few technical assumptions and guidance.

There are many reasons to implement a statistical SBM. These include (1) a way to develop confidence measures; specifically, confidence measures on the dollars to plan so the program's cost has an acceptable chance of not being exceeded (2) a means by which management can examine changes in confidence measures, as a function of how much reserve to "buy" to ensure program success from a cost control perspective and (3) a way to assess where costs of scenarios of interest different from the PS fall on the probability distribution of the program's total cost.

Approach & Assumptions

Figure 2 illustrates the basic approach involved in implementing a statistical SBM. Observe that parts of the approach include the same steps required in the non-statistical SBM. So, the statistical SBM is really an augmentation to the non-statistical SBM. The following explains the approach, discusses key technical assumptions, and highlights selected steps with computational examples.

Mentioned above, the statistical SBM follows a set of steps similar to the non-statistical SBM. In Figure 2, the top three activities are essentially the same as described in the non-statistical SBM with the following exception. Two statistical inputs are needed. They

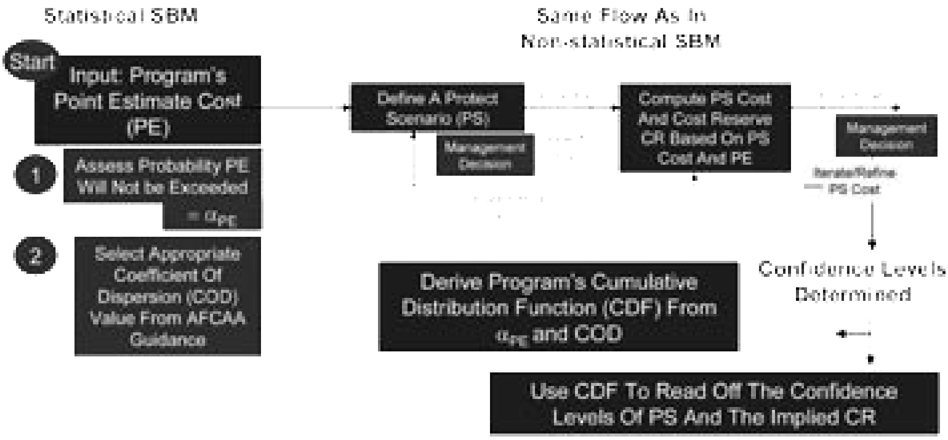

FIGURE 2. A statistical scenario-based method.

are the probability α_{PE} that the point estimate cost (PE) will not be exceeded and the coefficient of dispersion (CoD).

POINT ESTIMATE PROBABILITY

For the statistical SBM, we need the probability

$$P(Cost \le x_{PE}) = \alpha_{PE} \tag{1}$$

where $Cost$ is the true, but unknown, total cost of the program and x_{PE} is the program's PE. Here, the probability α_{PE} is a judgmental or subjective probability. It is assessed by the engineering and analysis team. In practice, α_{PE} often falls in the interval $0.10 \le \alpha_{PE} \le 0.50$.

COEFFICIENT OF DISPERSION (COD)

What is the CoD? It is a statistical measure defined as the ratio of distribution's standard deviation to its mean. It is one way to look at the variability of a distribution at one standard deviation around its mean. The general form of the CoD is given by equation 2.

$$D = \frac{\sigma}{\mu} \tag{2}$$

Figure 3 illustrates this statistical measure.

Here, the CoD statistic is a judgmental value but one guided by Air Force Cost Analysis Agency (AFCAA) and industry experiences with programs in various phases of the ac-

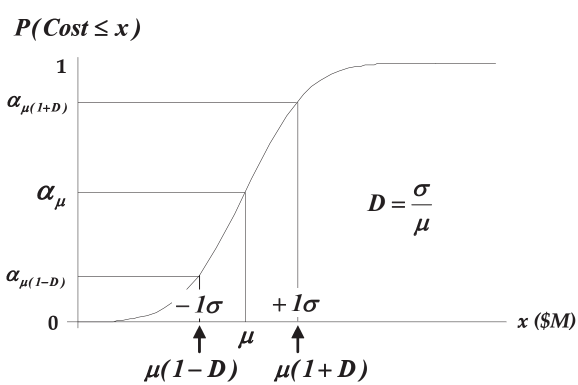

FIGURE 3. The coefficient of dispersion.

quisition process. As will be discussed later in this article, a sensitivity analysis should be conducted on both statistical inputs, namely α_{PE} and CoD, to assess where changes in assumed values affect cost risk and estimated levels of reserve funds.

The next two steps along the top of the process flow in Figure 2 follow the procedures described in the non-statistical SBM. Notice these two steps do not use the statistical measures α_{PE} and CoD. It is not until you reach the last steps of this process that these measures come into play.

As will be shown in the forthcoming examples, the distribution function of the program's total cost can be derived from just the three values identified on the far-left side of the process flow in Figure 2. Specifically, with just the point estimate cost PE, α_{PE}, and CoD the underlying distribution function of the program's total cost can be determined. With this, other possible program costs, such as the PS cost, can be mapped onto the function. From this, the confidence level of the PS and its implied cost reserve (CR) can be seen.

This completes an overview description of the statistical SBM process. The following presents two computational examples that illustrate how the statistical SBM works.

STATISTICAL SBM: ASSUMED UNDERLYING NORMAL

Here, we assume the underlying probability distribution of $Cost$ is normally distributed and the point (x_{PE}, α_{PE}) falls along this normal. If we're given just the point estimate PE, α_{PE}, and CoD then the mean and standard deviation of $Cost$ are given by the following equations.

$$\mu = \frac{x_{PE}}{z_{PE}D + 1} \tag{3}$$

$$\sigma = \frac{Dx_{PE}}{1 + Dz_{PE}} \tag{4}$$

where D is the CoD, x_{PE} is the program's point estimate cost, z_{PE} is the value such that $P(Z \leq z_{PE}) = \alpha_{PE}$ and Z is the standard normal random variable, namely $Z \sim N(0,1)$.

The value of z_{PE} can be calculated in Microsoft Excel by using built-in functions that generate numerical values associated with the standard normal distribution function. In particular, the Excel built-in function NORMSDIST gives the value of α, given z, and the inverse function NORMSINV gives z, given α.

Once μ and σ are computed, the entire distribution function of the normal can be specified, along with the probability that $Cost$ may take any particular outcome, such as the PS cost. The following illustrates how these equations work.

Example 1

Suppose the distribution function for $Cost$ is normal. Suppose the point estimate cost of the program is 100 ($M) and that cost was assessed to fall at the 25th percentile. Suppose the type and phase of the program is such that 30 percent variability (CoD = 0.30) in cost around the mean has been historically seen. Suppose the PS was defined and determined to cost 145 ($M). Given all this,

a) Compute μ and σ.
b) Plot the distribution function of $Cost$.
c) Determine the confidence level of the PS cost and its associated CR.

Solution

a) From the information given and from equation 3 and equation 4 we have, respectively,

$$\mu = \frac{x_{PE}}{z_{PE}D + 1} = \frac{100}{(0.3)z_{PE} + 1}$$

$$\sigma = \frac{Dx_{PE}}{1 + Dz_{PE}} = \frac{(0.3)(100)}{1 + (0.3)z_{PE}}$$

We need to know the numerical value of z_{PE} to complete these computations. From the information given, we know $P(Z \le z_{PE}) = 0.25$. Since Z is assumed to be a standard normal random variable, we can use a built-in Excel function to find z_{PE}. Therefore,

$$z_{PE} = NORMSINV(0.25) = -0.6745,$$

so that

$$\mu = \frac{100}{(0.3)z_{PE} + 1} = \frac{100}{(0.3)(-0.6745) + 1} = 125.37 \text{ (\$M)}$$

$$\sigma = \frac{Dx_{PE}}{1 + Dz_{PE}} = \frac{(0.3)(100)}{1 + (0.3)(-0.6745)} = 37.61 \text{ (\$M)}$$

b) A plot of the distribution function of *Cost* is shown in Figure 4. This is a plot of a normal distribution with mean 125.37 ($M) and standard deviation 37.61 ($M).

c) To determine the confidence level of the PS we need to find α_{PS} such that

$$P(Cost \le x_{PS} = 145) = \alpha_{PS}$$

Finding α_{PS} is equivalent to solving

$$\mu + z_{PS}\sigma = x_{PS}$$

for z_{PS}. From the above, we can write the expression

$$z_{PS} = \frac{x_{PS} - \mu}{\sigma} \qquad (4)$$

Since x_{PS} = 145, μ = 125.37, and σ = 37.61, it follows that

$$z_{PS} = \frac{x_{PS} - \mu}{\sigma} = \frac{145 - 125.37}{37.61} = 0.522$$

We then calculate $\alpha_{PS} = NORMSDIST(0.522) = 0.70$. Therefore, the PS cost of 145 ($M) falls at approximately the 70th percentile of the distribution, thereby suggesting a CR in the amount of 45 ($M). Figure 5 illustrates these results graphically. This concludes example 1.

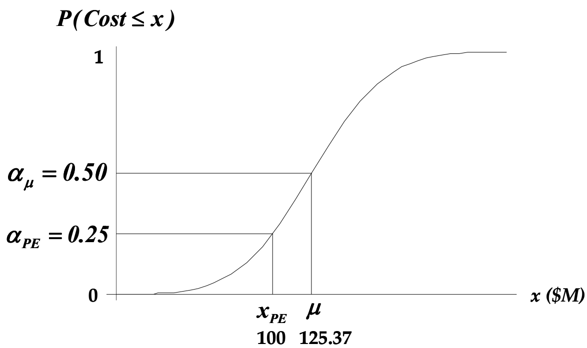

Figure 4. A plot of the normal distribution: Mean 125.37, sigma 37.61.

The following provides formulas for the mean and standard deviation of ***Cost*** if the underlying distribution of possible program costs is represented by a lognormal. The lognormal is related to the normal in that ***ln(Cost)*** is normally distributed instead of ***Cost*** itself being normally distributed. However, the lognormal is different from the normal distribution in the sense that it is skewed towards the positive end of the range instead of being symmetric about the mean. The lognormal distribution is always non-negative.

Numerous studies (reported in Garvey 2000) have empirically shown the normal or lognormal to be excellent approximations to the overall distribution function of a program's total cost, even in the presence of correlations among cost element costs. The decision to use one over the other is a matter of analyst preference and judgment. In practice, it is simple enough to execute an analysis using both distributions to examine if there are significant differences between them. Then, use judgment to select the distribution that best reflects the cost and risk conditions of the program.

STATISTICAL SBM: ASSUMED UNDERLYING LOGNORMAL

Here, we assume the underlying probability distribution of ***Cost*** is lognormally distributed and the point (y_{PE}, α_{PE}) falls along this lognormal. There are two steps involved in computing the mean and standard deviation of ***Cost***. The first is to compute the mean and standard deviation of $ln(Cost)$. The second is to invert or translate these values into the mean and standard deviation of ***Cost***, so the units are in dollars instead of "log-dollars." The following demonstrates these steps.

The lognormal distribution is the exponentiation of a normal distribution; that is, if X is a normal random variable with mean P and standard deviation Q, then $Y = e^X$ is a lognormal random variable with mean μ and standard deviation σ. In particular, if y_{PE} is the point estimate on the lognormal distribution, then $x_{PE} = ln\,(y_{PE})$ is the equivalent of y_{PE} on the corresponding normal distribution. Now, P and Q are related to μ and σ by the following formulas:

$$P = \frac{1}{2}\ell n\left(\frac{\mu^2}{1+D^2}\right) \tag{6}$$

and

$$Q = \sqrt{\ell n(1+D^2)} \tag{7}$$

If z_{PE} is as before, namely the point on the standardized normal distribution corresponding to the cumulative probability α_{PE}, then

$$z_{PE} = \frac{x_{PE} - P}{Q} = \frac{\ell n(y_{PE}) - P}{\sqrt{\ell n(1+D^2)}}$$

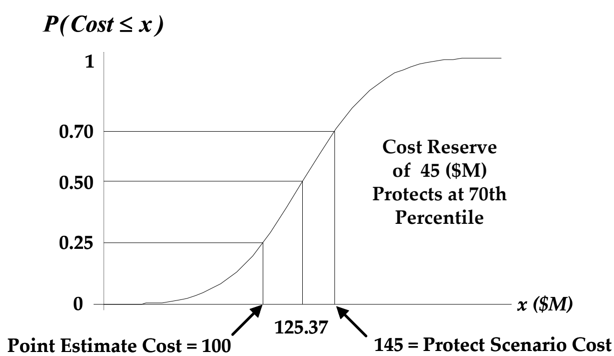

FIGURE 5. Example 1 illustrated: Assumed *normal* distribution.

so that $$P = \ell n(y_{PE}) - z_{PE}\sqrt{\ell n(1+D^2)} \tag{8}$$

Inverting relationships (6) and (7) we get have

$$\mu = e^{P+\frac{1}{2}Q^2} \tag{9}$$

and $$\sigma = e^{P+\frac{1}{2}Q^2}\sqrt{e^{Q^2}-1} \tag{10}$$

Example 2

Suppose the distribution function for ***Cost*** is lognormal. Suppose the point estimate cost of the program is $y_{PE} = 100\ (\$M)$ and this cost was assessed to fall at the 25th percentile. Again, suppose the type and phase of the program is such that 30 percent variability in cost around the mean has been historically seen. Suppose the PS was defined and determined to cost 145 ($M). Given this,

a) Compute μ and σ.
b) Plot the distribution function of ***Cost***.
c) Determine the confidence level of the PS cost and its associated CR.

Solution

a) From equation 8 and equation 7 it follows that

$$P = \ell n(y_{PE}) - z_{PE}\sqrt{ln(1+D^2)} = ln(100) - (-0.6745)\sqrt{ln(1+(0.3)^2)} = 4.80318$$

and

$$Q = \sqrt{ln(1+D^2)} = \sqrt{ln(1+(0.3)^2)} = 0.29356$$

From equation 9 and equation 10, we translate the above mean and standard deviation into dollar units; that is,

$$\mu = e^{P+\frac{1}{2}Q^2} = e^{4.80318+\frac{1}{2}(0.29356)^2} \approx 127.26\quad (\$M)$$

$$\sigma = \mu\sqrt{e^{Q^2}-1} = 127.26\sqrt{(e^{(0.29356)^2}-1)} \approx 38.18\quad (\$M)$$

b) A plot of the distribution function of ***Cost*** is shown in figure 6. This is a plot of a lognormal distribution with mean 127.26 and standard deviation 38.18. Additionally, the confidence level of the mean, using the built-in Excel function, is

$$\alpha_{\mu} = NORMSDIST((ln(127.26) - 4.80318)/0.29356)) = NORMSDIST(0.14666) = 0.558.$$

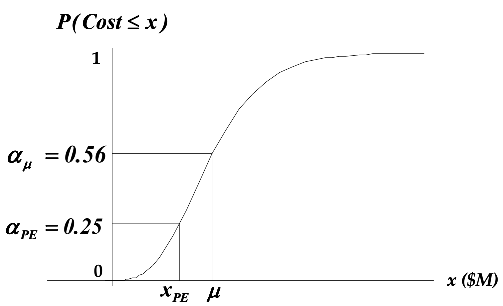

Figure 6. A Plot of the lognormal distribution: Mean 127. 26, Sigma 38. 18.

c) To determine the confidence level of the PS we need to find α_{PS} such that

$$P(Cost \leq x_{PS} = 145) = \alpha_{PS}$$

Finding α_{PS} is equivalent to solving

$$\ell n(y_{PS}) = \mu + z_{PS}\sigma$$

for z_{ps}. From the above, we can write the expression

$$z_{PS} = \frac{\ell n y_{PS} - \mu}{\sigma} = \frac{\ell n 145 - 4.80318}{0.29356} = 0.5912.$$

It follows that $\alpha_{PS} = NORMSDIST(0.5912) = 0.723$, using the built-in Excel function. Therefore, the PS cost of 145 ($M) falls at approximately the 72nd percentile of the distribution, indicating a CR of 45 ($M). Figure 7 shows these results graphically. This concludes example 2.

A Sensitivity Analysis

There are many ways to design and perform a sensitivity analysis on the SBM, particularly the statistical SBM. In this mode, one might vary the statistical inputs, namely α_{PE} and/or the CoD.

From experience, we know α_{PE} will often fall in the interval $0.10 < \alpha_{PE} < 0.50$. For this article, we set $\alpha_{PE} = 0.25$ and the CoD equal to 0.30 to illustrate the statistical aspects of the SBM. In practice, these measures will vary for each program — not only as a function of the program's type (e.g., space, C4ISR) but also as a function of its maturity and phase in the acquisition timeline. The following shows a sensitivity analysis on the statistical SBM with varying levels of the CoD. This is done in the context of example 2.

Figure 8 illustrates how either the confidence level can vary as a function of the CoD or how the dollar level can vary as a function of the CoD. Here, the left-most family of lognormal distributions, in Figure 8, shows, for a PS cost of 145 ($M), that the confidence level can range from 0.545 to 0.885 depending in the magnitude of the CoD. The right-most family of lognormal distributions, in Figure 8, shows for a confidence level of just over 70 percent the dollars can range from 129 ($M) to 182 ($M), depending on the magnitude of the CoD.

The above analysis is intended to demonstrate the sensitivity of the analysis results to wide variations in the CoD. In practice, a program would not experience such wide swings in CoD values. However, it is good practice to vary the CoD by some amount around the "point" value to see what possible variations in confidence levels or dollars results.

This analysis was based on the assumption that a program's cost uncertainty can be represented by a lognormal distribution. It is important to note the lognormal is bounded

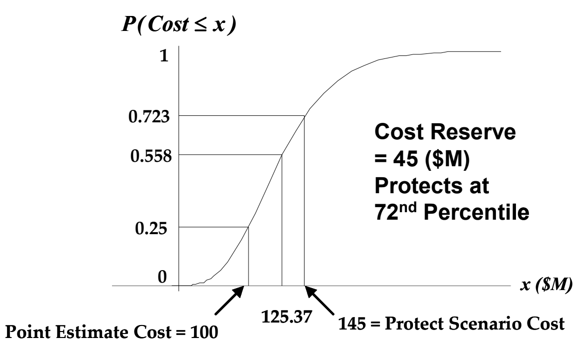

Figure 7. Example 2 illustrated: Assumed *lognormal* distribution.

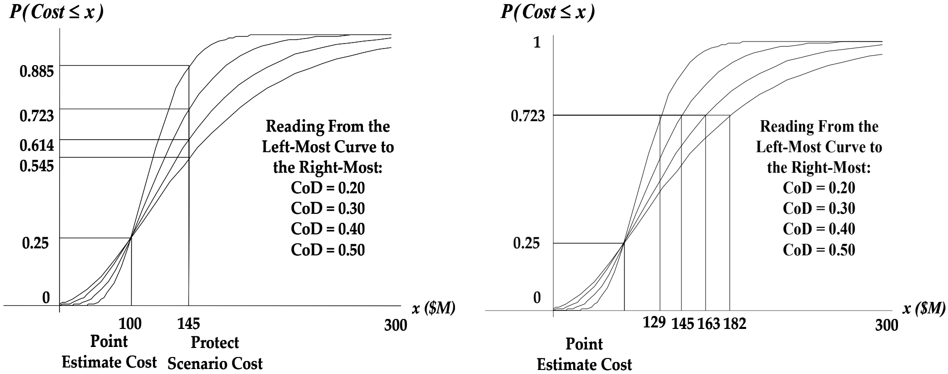

Figure 8. A sensitivity analysis on the coefficient of dispersion: Families of lognormal distributions.

below by zero; hence, the cost associated with that kind of distribution will always be non-negative. If the cost distribution were assumed to be normal, however, in the sensitivity analysis presented here it is possible that the coefficient of dispersion could be so large as to drive program costs into the range of negative values (since the normal distribution extends infinitely in both the positive and negative directions). As the SBM is tested and a record of implementation experiences with the approach is compiled, it may be decided the lognormal distribution assumption is the "better" of the two to use as a model.

As a good practice point a sensitivity analysis should always be conducted, especially when implementing the statistical SBM. The analysis can signal where additional refinements to scenarios and the underling analytical assumptions may be needed. This is what good analysis is all about.

SUMMARY

This article presented an approach called the scenario-based method for performing an analysis of a program's cost risk. The SBM provides program managers and decision-makers a scenario-based and scenario-driven assessment of the amount of cost reserve needed to protect a program from cost overruns due to risk. The approach can be applied without the use of advanced statistical concepts or Monte Carlo simulations, yet is flexible enough that confidence measures for various possible program costs can be derived, should that kind of information be needed.

Features of this approach include the following:

- It provides an analytic argument for deriving the amount of cost reserve needed to guard against well-defined "scenarios";
- It brings the discussion of "scenarios" and their credibility to the decision-makers; this is a more meaningful topic to focus on, instead of statistical abstractions the classical analysis can sometimes introduce;
- The non-statistical version does not require the use of statistical methods to develop a valid measure of cost risk reserve;
- Percentiles (confidence measures) can be designed into the approach with a minimum set of statistical assumptions;
- Percentiles (as well as the mean, median, variance) can be calculated algebraically and executed in near-real time within a simple spreadsheet environment; Monte Carlo simulation is not needed;
- It does not require analysts to develop probability distribution functions for the uncertain variables in a WBS, which can be time-consuming and hard to justify;
- Correlation is indirectly captured in the analysis by the scenario and by magnitude of the CoD applied to the analysis;

- The approach fully supports traceability and focuses attention on key risk events that have the potential to drive costs higher than expected.

It is important to note the SBM process focuses on developing and documenting scenarios that best characterize the risk of an acquisition program. Application experience with SBM is needed to learn: (1) how scenarios can be objectively developed and (2) how bias, with respect to optimism and advocacy, can be minimized or avoided in scenario generation.

The SBM is a deliberately deliberative and collaborative approach to understanding and evaluating a program's cost risk. Scenarios in SBM represent a program's "risk story" as understood at a specific time in its life-cycle. Time is best spent building these case arguments for how a confluence of risk events might drive the program to a particular percentile rather than debating what percentile to select (without really knowing what those dollars are protecting). This is where the debate and the analysis should center. This is how a program manager and decision-maker can rationalize the need for cost reserve levels that may initially exceed expectations. It is also a vehicle for identifying, early-on, where risk mitigation actions should be implemented to reduce cost risk and the chances of program costs growing out of control.

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