NPS-AM-09-035

EXCERPT FROM THE PROCEEDINGS

OF THE

SIXTH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

IMPROVED METHODOLOGY FOR DEVELOPING COST UNCERTAINTY MODELS FOR NAVAL VESSELS

Published: 22 April 2009

by

LCDR Cinda Brown

6th Annual Acquisition Research Symposium of the Naval Postgraduate School:

Volume II: Defense Acquisition in Transition

May 13-14, 2009

Approved for public release, distribution is unlimited.

Prepared for: Naval Postgraduate School, Monterey, California 93943

ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF BUSINESS & PUBLIC POLICY
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Improved Methodology for Developing Cost Uncertainty Models for Naval Vessels

Presenter: LCDR Cinda Brown is a native of Phoenix, AZ. She graduated from the United States Naval Academy in May 1998 with a Bachelor of Science in Chemistry and from the Naval Postgraduate School in 2008 with a Master's of Science in Systems Engineering. Brown's sea duty assignments include USS MILIUS (DDG 69) as the Anti-Submarine Warfare Officer and USS COMSTOCK (LSD 45) as the Training Officer and Main Propulsion Assistant. Following her sea duty, she completed a lateral transfer to the Engineering Duty Officer community. Her shore duty assignments include Southwest Regional Maintenance Center and the LSD/LPD-17 Class Squadron.

Cinda L. Brown
Lieutenant Commander, United States Navy
BS, United States Naval Academy, 1998
MS, Naval Postgraduate School, 2008
3985 Cummings Road, Suite 3
San Diego, CA 92116
619-556-6064 (work)
619-980-0697 (cell)
619-556-0506 (fax)
Cinda.brown@navy.mil

Abstract

The purpose of this paper is to analyze the probabilistic cost model currently in use by NAVSEA 05C to predict cost uncertainty in naval vessel construction and to develop a better method of predicting the ultimate cost risk. The data used to develop the improved approach is collected from analysis of the CG(X) class ship by NAVSEA 05C. The NAVSEA 05C cost risk factors are reviewed and analyzed to determine if different factors are better cost predictors. The impact of data elicitation, the Money Allocated Is Money Spent (MAIMS) principle, and correlation effects are incorporated into the research and analysis of this paper. Data quality is directly affected by data elicitation methods and influences the choice of probability distribution used to give the best predictor of cost risk. MAIMS and correlation effects are shown to make a significant impact to the overall cost model. Program managers and analysts can readily implement the enhanced models using commercial Excel® add-ins, such as Crystal Ball® or @Risk and integrate them into their current cost risk analysis and management practices to better mitigate risk and control project cost.

Executive Summary

In order to generate the funds to implement the 30-year plan of future ships and capabilities, the Navy must explore different options for cost savings. Fundamental to the success of complex projects, such as naval vessel construction, is the ability to control, manage, and communicate the status of the risk reduction effort throughout the development and production cycles (Kujawski & Angelis, 2007). It is recognized that the Navy and the shipbuilding industry need to change their technical and business shipbuilding strategies in order to achieve the goal of a future fleet that balances both capability and affordability. Cost risk assessment and analysis is one tool that can be utilized to help recapitalize costs used in the ship acquisition and building process.

This paper analyzes the probabilistic cost model currently in use by Naval Sea Systems Command Cost Engineering and Industrial Analysis Division (NAVSEA 05C) to predict cost uncertainty in naval vessel construction and to develop a method that better predicts the ultimate cost risk. The NAVSEA 05C's cost analysis model for the proposed new cruiser, CG(X), encompasses all aspects of cost for the entire fleet, including inflation and profit. The data used in the NAVSEA model were acquired from subject matter expert (SME) inquiry using three-point estimates of high, most-likely, and low values. The Navy is placing great emphasis on producing the best product for each dollar spent. In order to ensure the continued acquisition of CG(X), it is important that realistic cost risk analysis be performed so that program managers can make informed decisions.

The cost model elements investigated in this paper include data elicitation methods, probability distribution function (PDF) choice, correlation effects, and Money Allocated is Money Spent (MAIMS) principle effects. The most significant impact is seen with MAIMS and data elicitation effects. PDF choice and correlation effects have lesser impact upon the cost model.

Methods of data elicitation are explored and the use of a direct fractile assessment (DFA) is recommended for future use (Kujawski, Alvaro & Edwards, 2004), although the research in this paper does not involve data acquisition. To simulate the use of a DFA methodology, three-parameter Weibull distributions are employed to account for uncertainty associated with SME estimation of data. A Weibull (10%, 50%, 90%) distribution is used to simulate a more optimistic view of the uncertainty of data, while a Weibull (20%, 50%, 80%) distribution models a more pessimistic view.

The methodology in choosing different probability distribution functions and their applicability to the model is evaluated. Specifically, triangular, lognormal, and two variations of the three-parameter Weibull distribution are considered. Once enhanced models are established, program managers can implement them into their current cost risk analysis practice to mitigate risk and control project cost.

Two types of correlation effects are considered and modeled in this paper. The first is the correlation between the components of the radar suite, and the second is the correlation between all the components of the electronics suite. The radar suite is one of the systems that make up the electronics suite. The results suggest that the correlation effects are important for probability values midway between the mean and the extremes, but there is little difference for correlation coefficients beyond 0.5. Further investigations are recommended to quantify correlation effects.

MAIMS modified probability distributions are used to show the significance of budget allocation levels (Kujawski, Alvaro & Edwards, 2004). These distributions reflect an empirically observed effect, namely, that once a budget is allocated, the project cost will most likely be at least equal to the amount allocated. As the MAIMS modification value increases, the overall distribution cost rises with increasing probability.

Credibility and realism are two key cost risk assessment criteria. The use of improved methods, such as those investigated in this paper, are especially significant for today's Navy during a time of budget hardship. If the Navy's plans for a 313-ship fleet are to become a reality, the incorporation of cost risk analysis into acquisition and shipbuilding management is imperative. Reliable cost assessments can help deliver projects on time, at a lower cost, with a higher probability of success. Effective training of personnel involved in cost assessment and continued efforts to improve existing cost models will help improve the Navy's current cost estimating process.

I. Introduction

Admiral Gary Roughead stated in the Chief of Naval Operation's (CNO) Guidance for 2007-2008 that:

> **We manage risk.** We will identify, analyze, mitigate and then accept risk, appreciating that we must always consider the risks in aggregate across the entire force. Zero risk is not achievable nor affordable. We must manage risk and move forward to accomplish the mission while safeguarding our people and infrastructure. (Roughhead, 2007)

Vice Admiral K. M. McCoy took this a step further in 2008, in a statement made on assuming the position of Commander, Naval Sea Systems Command:

> Our Common mission is to develop, deliver and maintain ships and systems on time and on cost for the Navy. To build an affordable future fleet, we will focus on reducing acquisition costs, including applying more risk-based decisions to specifications and requirements. (McCoy, 2008)

The United States Navy is living and functioning in an era of ever-expanding technology, more stringent requirements, and a growing need for more ships and resources, all while working with a limited budget. These factors all lead to inherent cost growth in the projects that are developed to provide the fleet with the capabilities it needs. In order for the United States Navy to acquire and provide a full,
state-of-the-art, 313-ship Navy by 2020, as stated in the fiscal year (FY) 2007 plan (Department of the Navy, 2006) it is imperative that methods allowing full capitalization of each dollar spent by the Navy are developed and implemented.

In February 2006, the United States Navy presented its FY2007 plan, which outlines the objective of increasing the current 285-ship fleet to 313 ships by 2020 (Department of the Navy, 2006). By 2008, the Navy increased the estimate of its annual cost for the 30-year plan by about 44% in real terms, but it is still approximately 7% less than independent cost estimates conducted by the Congressional Budget Office (O'Rourke, 2008). This increase in estimated cost poses a problem for the overall funding of the shipbuilding strategy proposed by the Secretary of the Navy. The credibility of the Navy's estimates and the ability to fund its shipbuilding plans have been questioned by Congress and industry (Cavas, 2008).

In order to adequately generate the funds to implement the 30-year plan of future ships and capabilities, the Navy must explore different options for cost savings. Fundamental to the success of complex projects, such as naval vessel construction, is the ability to control, manage, and communicate the status of the risk reduction effort throughout the development and production cycles (Kujawski & Angelis, 2007). It is recognized that the Navy and shipbuilding industry need to change their technical and business shipbuilding strategies in order to achieve the goal of a future fleet that balances both capability and affordability. Cost risk assessment and analysis is one tool that can be utilized to help recapitalize costs used in the ship acquisition and building process.

A. Background

Risk analysis is an important component of the cost analysis of new vessels because actual costs will always have a probability of differing from the estimate. Several reasons account for the difference between the estimate and actual cost, which can include lack of knowledge about the future, errors associated with assumptions and cost-estimating equations, historical data inconsistencies, and factors considered in making the estimate. The overall purpose of risk analysis is to quantify the potential for error (GAO, 2007). In the case of a cost estimate, it is the probability that the actual cost will exceed the cost estimate or the budget. This cost estimate allows for the assessment of risk of a given program.

Cost overruns and growth are an enduring problem that is not new to the Navy. A 1939 inquiry from Secretary of the Navy Ray Spear asks the question, "Why do naval vessels cost so much?" Answers to this inquiry include increased progress in marine engineering and naval construction, increased horsepower in shipbuilding, improved quality of building materials, inflation, and the practice of paying full price for the best you can buy naturally increases costs. Spear (1939) states that, "care must be taken in approving estimates to make sure that they are reasonable and held to in the cost of production. When contracts are negotiated, the question of costs should be investigated and a detailed knowledge of approximate costs obtained." Just as cost estimation was recognized by the Secretary of the Navy in 1939, it is recognized by today's Navy leadership as an integral part of the ship acquisition process.

Risk analysis and management can be used to help program managers more effectively make acquisition decisions and allocate their resources by allowing for a better understanding of program risks. Risk management is a continuous process in the acquisition and development of naval vessels.

The Naval Sea Systems Command, Cost Engineering and Industrial Analysis (NAVSEA 05C) introduced Cost Risk Analysis (CRA) into the Navy's PR09 Planning, Programming, Budgeting, and Execution System (PPBES) to help assess vessel costs in terms of quantifiable risk. Cost Risk Assessment is defined as the process of quantifying the uncertainties associated with major acquisition programs. It therefore allows for informed decisions with an estimated level of confidence (McCarthy, 2008).

One of the key objectives of CRA is to enable better risk management, which will simultaneously reduce program costs and increase the probability of success. Cost estimating is recognized by NAVSEA 05C as an essential element of effective program management, required for realistic program planning and decision-making. Risk analysis is important because the previous methodology of using point estimates is "precisely wrong" (Deegan, 2007). Risk cannot be assessed with a point estimate, as it represents a single value that serves as a best guess for the parameter to be defined. Decision-makers may not be able to completely understand the influence of different variables on cost with the use of a point estimate. Conversely, the use of risk analysis allows the decision-maker to utilize his or her acquisition experience, while quantifying the qualitative aspects of acquisition scenarios.

Point estimates are not an accurate method for predicting costs in shipbuilding because they do not properly account for problems that may be encountered in the acquisition process, as described above. They may be either overly optimistic or overly pessimistic. Optimistic point estimates ignore the potential risk and uncertainty in a project, which is necessary for management to make informed decisions. Immature technology, uncertain product design, schedule problems, and unforeseen events all have risk associated with their end product. Risk analysis is necessary in order to incorporate the effect of risk into the overall cost. Pessimistic point estimates assume worst scenarios and unlikely high costs. Quantitative risk analysis allows the cost estimator to assign a realistic range of costs around a point estimate, which provides decision-makers with a level of confidence in achieving a credible cost.

The NAVSEA Cost-estimating Process is comprised of three parts, which are further divided into 12 tasks. The three parts consist of Develop Approach, Perform Estimate, and Brief Results. Figure 1 shows the breakdown of the 12 tasks within the three parts. This paper focuses on the Develop Approach and Perform Estimate parts of the cost-estimating process.

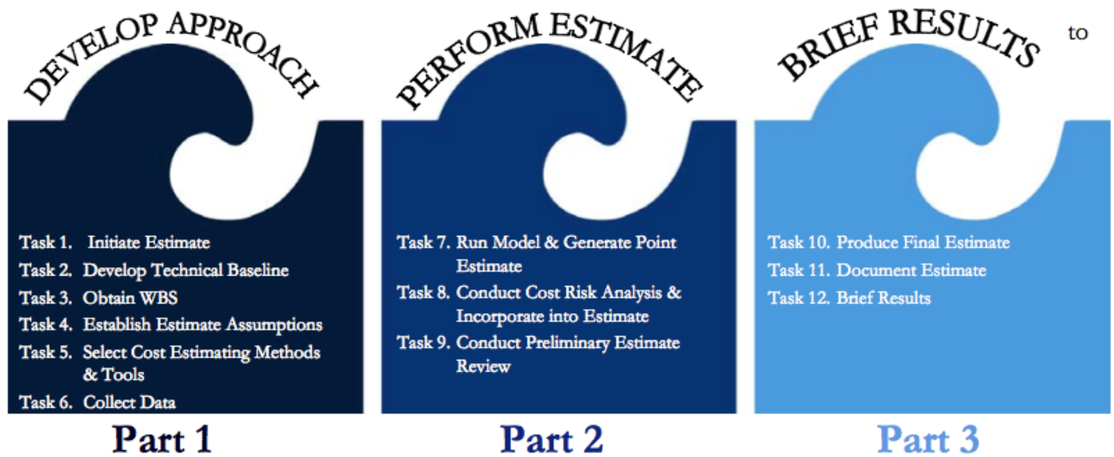


Figure 1. NAVSEA 12-Step Cost-estimating Process
(NAVSEA, 2005)

Data collection is a task within the Develop Approach part of cost estimation and can be regarded as the most important part of risk analysis. Bad data will produce bad results, regardless of the subsequent analysis. Data elicitation is often done ad hoc; however, several reliable methods and sources are available for data collection. Data quality is critical to the success of the analysis and plays a significant part in the results generated for cost estimation. This paper will discuss improved methods for data collection in order to obtain more reliable and standardized data from subject matter experts (SMEs).

Risk analysts use probability distributions rather than point estimates to represent the possible outcomes of an event. There is a significant difference between a point estimate and a distribution, in that the distribution provides the full range of values with their associated probabilities, while the point estimate presents a single value. This allows program management to make budget decisions, based on desired confidence levels. Quality may differ, based on the method of collection. Two methods commonly used for data collection include database queries and interviews of SMEs or stakeholders (Deegan & Fields, 2007). This paper analyzes the current NAVSEA 05C Cruiser (CG(X)) probabilistic cost model including data elicitation.

The direct fractile assessment (DFA) method provides one of the most reliable and least bias-prone procedures for eliciting uncertain quantities from SMEs (Kujawski, Alvaro & Edwards, 2004). Data elicitation from SMEs is innately uncertain; three findings from psychological experiments conducted by Alpert and Raiffia (1982) are:

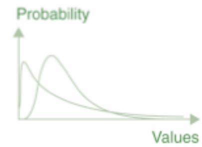
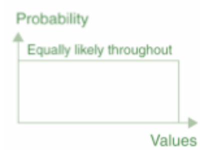
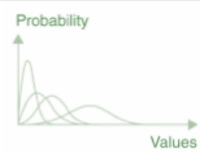
- A systematic bias toward overconfidence is common.
- Extreme value judgment is poor.
- Maximum and minimum values are vague terms. What do these terms really mean?

Based on the findings of Alpert and Raiffia (1982), Kujawski et al. (2004) propose the following guidelines for data elicitation:

- Ask SMEs to provide 10th, 50th, and 90th percentiles values for cost elements. Avoid extreme values, abstract measures such as the mean or standard deviation, or specific distribution functions. Allow for discussion and education of the SME in terms of bias when giving data figures.
- Calibrate each set of percentiles to reflect individual and project specific considerations, both pessimistic and optimistic. For estimates that might be overly optimistic, a cost analyst might choose to shift a 90th percentile value to perhaps 80th or 75th percentiles.

Tasks involved in the Performing Estimate depicted in Figure 1 are running the model and generating a point estimate or probability distribution, conducting a cost risk analysis, and conducting a preliminary estimate review.

Traditionally, triangular distributions have been used in cost estimation models because of the simplicity in entering the required data. The triangular distribution requires minimum or low, most-likely, and high or maximum values. Other commonly used distributions include normal, lognormal, and uniform. Table 1 lists eight of the most common probability distributions used for cost estimation and uncertainty analysis. This paper investigates different methods for data elicitation and selecting appropriate distributions. The effects of using different distributions on cost risk are evaluated and identified.

Distribution	Description	Shape	Typical application
Lognormal	A continuous distribution positively skewed with a limitless upper bound and known lower bound; skewed to the right to reflect the tendency toward higher cost.		To characterize uncertainty in nonlinear cost estimating relationships.
Normal	Used for outcomes likely to occur on either side of the average value; symmetric and continuous, allowing for negative costs and durations. In a normal distribution, about 68% of the values fall within one standard deviation of the mean.		To assess uncertainty with cost estimating methods; the standard deviation or standard error of the estimate is used to determine dispersion.
Beta	Similar to normal distribution but does not allow for negative cost or duration, this continuous distribution can be symmetric or skewed.		To capture outcomes biased toward the tail ends of a range; often used with engineering data or analogy estimates.
Triangular	Characterized by three points—most likely, pessimistic, and optimistic values—can be skewed or symmetric and is easy to understand because it is intuitive. One drawback is the absoluteness of the end points.		To express technical uncertainty, because it works for any system architecture or design; also used to determine schedule uncertainty.
Uniform	Has no peaks because all values, including highest and lowest possible values, are equally likely.		With engineering data or analogy estimates.
Weibull	Versatile, able to take on the characteristics of other distributions, based on the value of the shape parameter "b"—e.g., Rayleigh and exponential distributions can be derived from it.[a]		In life data and reliability analysis because it can mimic other distributions and its objective relationship to reliability modeling.

Source: DOD, NASA, SCEA, and Industry.

[a]The Rayleigh and exponential distributions are a class of continuous probability distribution.

Table 1. Common Probability Distributions Used in Cost-estimating Uncertainty Analysis
(GAO, 2007)

The Money Allocated is Money Spent (MAIMS) principle is based on Parkinson's Law, where "Work expands to fill the time allotted" and "padding schedule estimates directly contribute to cost overruns" (Augustine, 1997). In other words, it suggests that there will be no cost underruns, and that the project will come in at or above the cost to which it is funded. Implementing the MAIMS principle in Monte Carlo simulations modifies the basic probability distribution functions (PDF) by setting any value less than the money allocation point equal to that money allocation value. There will be no costs associated with a value less than this money allocation point. Utilizing the MAIMS principle, the PDFs are modified to include a spike or delta function at an arbitrary point, which is assumed to be the "money allocation point," corresponding to the dollar amount allocated to the program manager for the project and/or project cost elements.

Correlation effects between elements are analyzed. Correlation accounts for interrelationships between cost elements. Data elements can either be negatively, neutrally, or positively correlated and can either exist among cost elements within a subsystem or between elements in different subsystems. For example, take into consideration the elements of a ship. Positive correlation arises when increases in weight, size, and number of weapons systems onboard result in an increase in acquisition and shipbuilding costs. An increase in the complexity of a weapon system further forces an increase in cost of other systems such as power, cooling, control. Analysis would be greatly simplified if analysts could assume that all elements are independent or that all elements are dependent. Since neither statement is true, correct correlation between elements is necessary to provide the most accurate representation of cost.

Many software programs are available for cost risk analysis. This paper uses Crystal Ball® as an add-in to Microsoft Excel®, because of its ease of use and because it is the current program used by NAVSEA 05C. Crystal Ball® generates the Monte Carlo simulations that become the backbone of the cost risk analysis. A Monte Carlo simulation calculates multiple scenarios of a model by repetitively sampling values from the input variable distributions for each uncertain variable and then calculates the result. The resulting cost distributions from Crystal Ball® provide the decision-maker with powerful cost risk information.

A program built on a solid foundation of accurate cost estimating that effectively considers risks, combined with strong systems engineering and program management, gives the program a greater chance of success.

B. Purpose

The purpose of this paper is to analyze the probabilistic cost analysis approach that NAVSEA's Cost Engineering and Industrial Analysis division (SEA 05C) currently uses to predict new naval vessel construction costs and to develop a method that better predicts the ultimate cost risk. This paper uses data collected from analysis of the CG(X) class ship cost model. The model used to determine cost is reviewed and analyzed to determine what factors should be considered to produce more realistic cost estimates.

II. Revised Cost Risk Analysis

A. Introduction

The NAVSEA 05C's cost analysis model of CG(X) encompasses all aspects of cost for the entire fleet including inflation and profit in a 63 worksheet Excel® workbook. The data used in the NAVSEA model were acquired from SME inquiry using three-point estimates of high, most-likely, and low values. In order to ensure the continued acquisition of CG(X), it is important that realistic cost risk analysis be performed so that program managers can make informed decisions.

This chapter presents an approach to improve on the model that NAVSEA 05C has provided for CG(X). The focus is strictly on the methodology used in the cost analysis of the electronics suite of CG(X) cost model and cost uncertainties associated with engineering and manufacturing of the lead vessel. Nine systems make up the electronics suite:

- Radar suite, which consists of the following subsystems: X-band, S-band, Cooling, and Power
- ExComm—External Communications

- TSCE—Total Ship Computing Environment
- IUSW—Integrated Undersea Warfare
- EW-IW—Electronic Warfare-Information Warfare
- EO-IR—Electro Optical-Infrared
- IFF—Identification, Friend or Foe
- MS EI&T (SS Only)—Mission Systems Engineering, Integration, and Testing (Ship Systems Only)
- MS EI&T (CS Only)—Mission Systems Engineering, Integration, and Testing (Combat Systems Only)

The electronics suite cost is determined with the following two equations that treat each of the cost elements as a random variable (RV). The costs in bold represent composite of the costs in regular font, which Crystal Ball® refers to as forecasts and assumptions:

COST(Electronics Suite) = **COST(Radar Suite)** + COST(ExComm) + COST(TSCE) + COST(IUSW) + COST(EW-IW) + COST(EO-IR) + COST(IFF) + COST(MS EI&T (SS Only)) + COST(MS EI&T (CS Only)),

Cost(Radar Suite) = Cost(X-band) + Cost(S-band) + Cost(Cooling) + Cost(Power).

The steps of analysis for the CG(X) model are as follows:

1. Analyze the cost factors used by NAVSEA 05C to develop the electronics suite cost.
2. Analyze the PDFs used for the electronics cost elements.
3. Identify what data elicitation methods were employed.
4. Determine if correlation factors were used in the cost analysis.
5. Develop cost factors to be modeled for cost realism.
6. Decide which PDFs to use for greater fidelity.
7. Develop an improved cost risk model that includes realistic correlation factors; credible PDFs, including MAIMS influences; and SME biases.

B. Review Development of Cost Factors

1. Data Elicitation Methods

The data elicitation methods used by NAVSEA 05C cost analysts are not well documented. It is clear that the engineering and expert judgment of SMEs is heavily relied on for the assessment of uncertain cost elements associated with new designs. This is an area where the use of improved methods can dramatically improve the quality of data that is used in the computation of the cost risk model. Subjective assessments to obtain data have been identified as a critical source of uncertainty in probabilistic risk analyses (Keeney & von Winterfeld, 1991). Kujawski et al. (2004) discuss the use of the DFA method for data elicitation and how this ties in with distribution choice, to provide the most realistic cost assessment.

DFA has been found to provide one of the most consistent and least bias-prone methods for eliciting uncertain quantities (Alpert & Raiffa, 1982). In their research, people were asked to consider uncertain quantities by providing values in terms of percentiles or fractiles. The findings indicated:

- There is a systematic bias toward overconfidence in estimates. The subjective probability distributions were too narrow. Usually, 33% instead of 50% of the actual values fell within the 0.25 to 0.75 fractiles.
- Extreme value judgment is even worse: 20%, rather than 2%, of the actual values fell outside the 0.01 and 0.99 fractiles.
- What is the meaning of minimum and maximum values? Defining these terms, so that they are universal, is difficult.

Kujawski et al. (2004) further suggest using experts to provide the 10th, 50th, and 90th percentile values, as these may be easier to assess than extreme values of maximum and minimum. They recommend avoiding asking for extreme values, abstract values such as the mean or standard deviation, or other specific distribution functions. If the analyst does not fully understand the background of the questions being asked, or if he or she does not fully understand the behavior of the system and associated data, obtaining discrete values will be near impossible.

Education also plays an important role in the quality of the data provided by the SMEs for analysis. The understanding of bias and its role in affecting data elicitation is important. In a presentation to the Navy Cost Analysis Symposium, Fields and Popp (2007) stress the importance of several lessons learned on risk. One of the most interesting of these lessons learned is the importance of training. They indicate that although NAVSEA and its technical community have a broad cross section of educational backgrounds and experience, not everyone has experience in simulation and statistics. The SME for a particular electronics suite component is probably not an expert in probability and statistics, and because of this, tends to give biased answers to the cost analysis. The distributions formed from the biased data have been found to be particularly narrow and centered on a given point estimate, while the extreme values are very rarely taken into account, for reasons described above.

Education of the SMEs while conducting data elicitation is important, so that the experts have a better understanding of what data is required and how it is going to be utilized. This training needs to be continually refreshed due to the high turnover rate of personnel, whether they be military or civilian, and also because of improving methods for cost analysis. An adequate training plan for both the cost analysts and the SMEs providing data will ultimately result in better data acquisition for cost analysis.

In this paper, the use of DFA is simulated though the use of Weibull probability distributions because no new data elicitation was conducted. The differences between the distributions using identical values for 10th, 50th, and 90th percentiles versus the 20th, 50th, and 80th percentiles illustrates data elicitation that is optimistic versus pessimistic. The resulting cost associated with each of the two distributions shows how dramatic the effects of slightly different parameters can have on the estimated cost.

2. Choice and Development of Probability Distribution Functions

Kujawski et al. (2004) emphasize the importance of realistically modeling cost uncertainties through the appropriate choice of probability distribution by meeting the following criteria:

- Capable of fitting three arbitrary percentiles.
- A finite lower range.
- An infinite upper range with reasonable behavior.
- Physically meaningful and easy to estimate parameters.

Three types of PDFs are developed and modeled for this paper, with the goal of finding a realistic and flexible probability distribution. Uncertainty for each cost element in the cost model is represented using the same type of PDF with different parameters (based on NAVSEA data). First, a triangular PDF that uses low, most-likely, and high values for its parameters is developed. A lognormal PDF that uses the mean and standard deviation from the triangular PDF as its parameters is the second distribution. The third PDF is a three-parameter Weibull distribution based on the low, most-likely, and high values of the triangular PDF provided by NAVSEA 05C. The low and high values are calculated by multiplying the low and high percentages obtained with the most-likely value. Two Weibull distributions are created. One of the Weibull distributions uses the data as input for the 10th, 50th, and 90th, percentiles, while the other is more pessimistic and uses these values for the 20th, 50th, and 80th percentiles. For consistency, the triangular distribution is used to determine the 50th percentile. The low, 50th percentile, and high values are substituted for the 20th, 50th, and 80th percentiles and for the 10th, 50th, and 90th, for each three-parameter Weibull distribution, respectively.

a. Triangular Probability Distribution Function

The parameters used to develop the triangular PDF are the low, most-likely, and high values from the Mission Systems Risk Assessment worksheet of the CG(X) model. The determination of the high and low percentages for cost values in the Mission Systems Risk Assessment worksheet were figures given to NAVSEA 05C cost analysts by SMEs from the NSWC Dahlgren. These percentages are based on historical database values and inquiry of the SME for an opinion about what the low and high values would be, based on the most-likely values obtained from the historical databases. In this case, data elicitation plays a big part in the reliability of the data used in the model, which is to be described in more depth in Section IV.B.1.

The triangular distribution is not a good predictor of high and low costs because it uses the low and high values as extreme values for the end points. There is no allowance for costs above or below the input values. It has been argued that a triangular distribution can lead to either underestimates or overestimates. Graves (2001) states that underestimates are likely due to the finite upper limit of the distribution. Moran (1999) believes that overestimates happen because of the distribution’s inability to portray the expert’s confidence level of achieving the most-likely value and/or knowledge of the shape of the distribution. The triangular distribution is assigned a very low score for criteria (i) and (iii) (Kujawski et al., 2004) and is not the chosen distribution to represent cost in the model for this paper.

b. Lognormal Probability Distribution Function

The lognormal PDF is created with the mean and standard deviation parameters taken from the triangular distribution. Characteristics of a lognormal distribution include being positively skewed with a limitless upper bound and known lower bound. This distribution is assigned an acceptable score for criteria (iii), but a low score for (i), due to the always positively skewed nature of the distribution. The lognormal distribution results in a cost profile that closely follows with the triangular distribution and is one of the narrowest profiles modeled. A lognormal PDF has been associated with providing unreasonably high probabilities at high values, due to the relatively slow falloff to the right. For this reason, it gets an acceptable score for the criteria (iii) but scores low on the criteria (i) because of its always positively skewed characteristic (Kujawski et al., 2004).

c. Weibull Probability Distribution Function (10%, 50%, 90%)

The three-parameter Weibull distribution is characterized by being flexible and able to assume a wide variety of shapes, while also being open-ended. Because of its flexible profile and ability to mimic other distributions, it scores high on all criteria. This paper models one of the three-parameter Weibull distributions with the 10th, 50th, and 90th percentile values for cost. The parameters of 10th, 50th, and 90th percentiles are chosen to simulate a cost environment that allows for some cost flexibility on the upper and lower limits rather than making them extreme as in the triangular distribution. Although this 10% change on either side of the distribution seems large, it actually represents a fairly optimistic assessment of cost. This model is best for a situation in which the data obtained for the model is very reliable.

d. Weibull Probability Distribution Function (20%, 50%, 80%)

The three-parameter Weibull distribution using the 20th, 50th, and 80th percentiles for distribution parameters is intended to correct or account for the overly optimistic biases discussed in Section 2 above. Systems that are new and untested have a certain amount of uncertainty inherent in their acquisition, and most cost assessments made on their components are based on past history if components are being reproduced, or a best estimate for new systems and their components. SMEs are naturally optimistic about their systems and have been shown to give cost estimates that are overconfident, resulting in probability distributions that do not accurately reflect the possible range of costs (Kujawski et al., 2004).

Much of the data for the CG(X) electronics suite is the result of SME inquiry, which explains why the Weibull distribution using 20%, 50%, and 80% parameters is chosen to model costs for the electronics suite components in this paper.

e. Cost Comparisons with the Different Probability Distributions

Figure 2 is the Excel® overlay created with Crystal Ball® that shows of a 10,000-run Monte Carlo simulation for the triangular, lognormal, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%) distributions, representing the electronics suite cost of the CG(X). Figure 10 is the cumulative probability distribution derived from the PDF shown in Figure 9. The triangular and lognormal distributions are very similar in both the probability distribution and cumulative frequency functions, which is expected. Since the lognormal distribution uses the mean and standard deviation from the triangular distribution as its parameters, the end result should be very similar. Both the triangular and lognormal functions show a distinct peak and sharp falloff at both the lower and upper bounds. This behavior does not realistically model the electronics suite cost because of the sharp peak with sharp falloff.

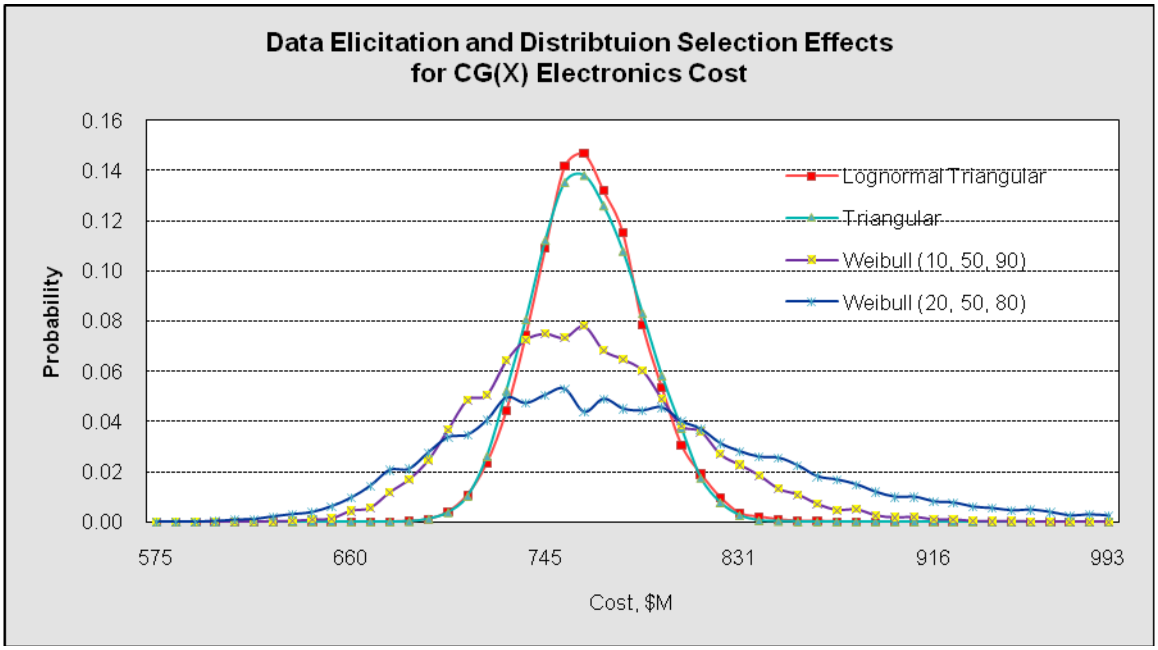


Figure 2. CG(X) Crystal Ball® Analysis, 10,000 Runs Showing the Effects of Distribution Choices on the Cost Probability Distributions

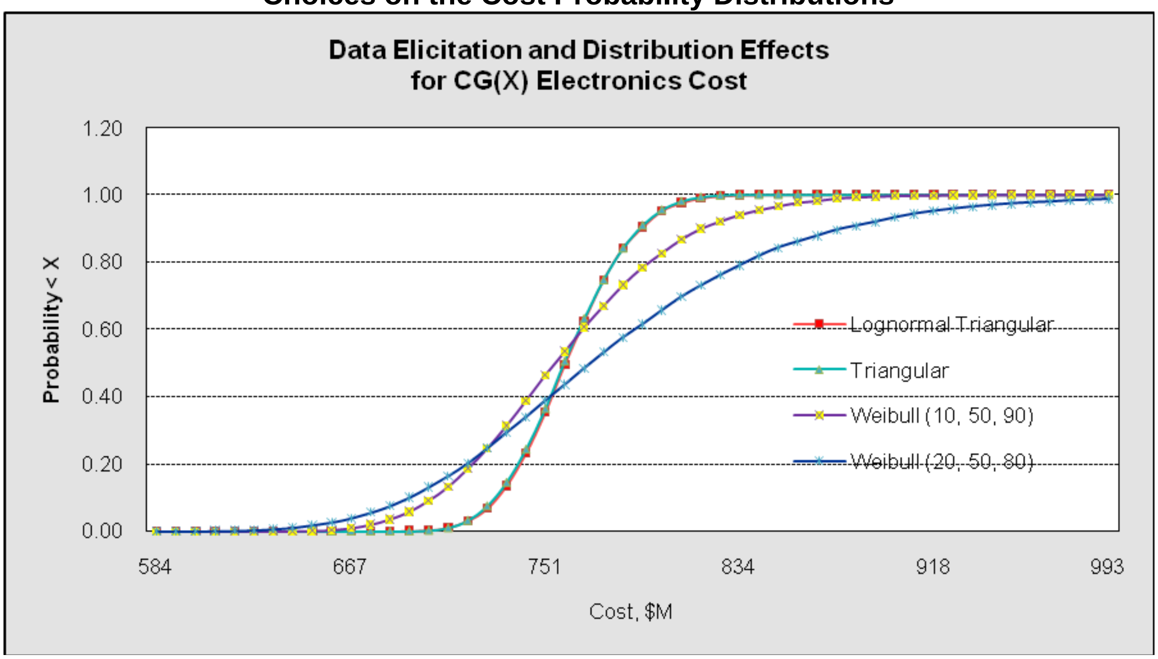


Figure 3. CG(X) Crystal Ball® Analysis, 10,000 Runs Showing the Effects of Distribution Choices on the Cost Cumulative Distribution Functions

The Weibull (10%, 50%, 90%) distribution shows a broader cost range for the given probability brackets. The tapering lower and upper bounds in comparison to the triangular and lognormal distribution represent a more likely cost outcome. The Weibull (20%, 50%, 80%) shows an even larger cost range, which makes sense because this distribution is supposed to model a more pessimistic view of cost. Both of these distributions are associated with higher costs as the probability of the cost increases. It is important to note the difference between the optimistic and pessimistic Weibull distributions in Figure 3. For each, the cost increases with an increase in probability, but it is clear that the model's results indicate that the cost risk is significantly higher using the pessimistic Weibull distribution.

3. Correlation Effects

Correlation effects are potentially important in modeling appropriate cost relationships between different elements of systems and are not conducted enough in current cost analysis models (Book, 2001). Trends with correlation tend to lean toward perfect correlation because of simplicity. Perfect correlation helps to widen the range of outputs in the distribution functions, but this may not be an accurate or reliable representation. Reasonable correlation coefficients may provide more realistic and credible estimates of project costs, rather than assuming perfect or zero correlation. Assessing correlation coefficients is a difficult problem. A need exists for the investigation and development of a realistic and practical model to account for interrelationships between cost elements.

Two types of correlations are modeled in this paper:

- Correlations among cost elements within the radar suite. The radar suite includes elements of X-band, S-band, Cooling, and Power. Dependencies among these components are mainly from subsystem characteristics such as complexity.
- Correlations among cost elements in the entire electronics suite. Dependencies among these cost elements occur from the programmatic and organizational considerations common to all cost elements that are a part of the same project (Kujawski et al., 2004).

There are two types of correlations: Pearson and Spearman. Pearson correlation coefficient determines the degree of linearity between two random variables, while Spearman rank order correlation coefficients measure monotonicity. Correlation among cost elements in the electronics suite is modeled with the use of the Correlation Matrix function in Crystal Ball®. Crystal Ball® uses rank correlations to correlate assumptions. This means that the values are not changed, but they are rearranged to produce the desired correlation. Rank correlation eliminates the need to explicitly model the dependence between the cost elements. Garvey (2000) advocates the use of Pearson's correlation. However, given the limited information, rank correlations offer the advantage of accounting for correlations independent of explicit distribution and dependency models. The use of Monte Carlo simulations generates the full PDF rather than simply expected value and variance.

This paper uses three sets of two correlation coefficients to model the correlation between the radar suite elements and the rest of the electronics suite components. The first set models the distributions with correlation coefficients of 0.5 for the radar suite elements and 0.5 for the entire electronics suite elements. The second set of correlation coefficients is 0.5 and 0.2. The third set uses correlation coefficients of 0.8 and 0.5.

Figure 4 is an overlay of the different probability distributions for the electronics suite cost, produced by using the following three different combinations of correlation coefficients for the radar suite and electronics suite:

- Correlation coefficients of 0.5 among the radar suite components and 0.2 between the different electronic suite components.

- Correlation coefficients of 0.5 among the radar suite components and 0.5 between the different electronic suite components.
- Correlation coefficients of 0.8 among the radar suite components and 0.5 between the different electronic suite components.

As discussed above, positive correlations give rise to broader distributions, which reflect higher uncertainty. The no correlation PDF in Figure 4 is the same as the no correlation shown in Figure 9. They do not appear to be the same due to the difference in scale because they are from separate Monte Carlo simulations. Although the Monte Carlo simulations will give similar results for each run, they will not be identical.

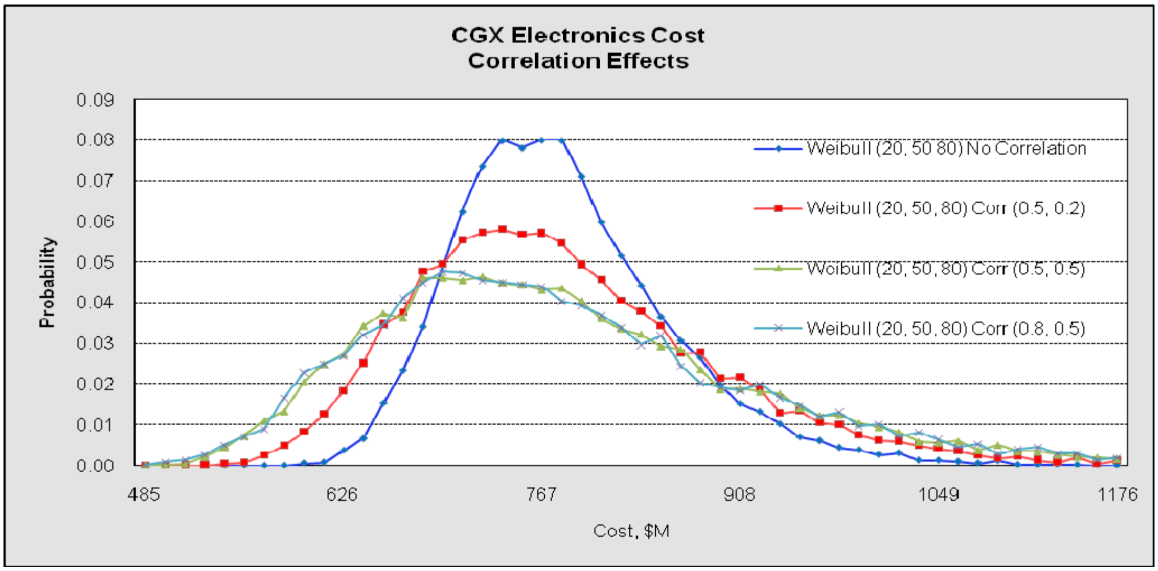


Figure 4. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Based on Different Correlation Effects in Cumulative Probability Form

4. MAIMS Principle Effects

The MAIMS principle is modeled in this paper by using the three-parameter Weibull (20%, 50%, 80%) distribution function and predetermined percentile points for the MAIMS set points. By implementing MAIMS into the distribution function, any value less than the money allocation point is equal to the money allocation value. The percentage parameters used for MAIMS are the 50th percentile or median, the mean, and the 80^{th} percentile funding levels. A spike, or delta function, is observed in the MAIMS modified distributions at the money allocation points. These money allocation points correspond to the budget allocated to the WBS cost elements by the project manager.

The MAIMS modified functions are modeled by using the following equation:

If Distribution *Value < X, then X, else Distribution Value.*

By using this equation, the value of the MAIMS modified distribution will never be less than the value X.

D. Results

1. Effects of Distribution Choice on Cost Forecast

The first distributions modeled were the single electronics suite elements with different distributions. For the purpose of this paper, the element ExComm is chosen for this explanation. Figure 5 shows the cumulative frequency distribution of the different modeled distributions for the ExComm element. The triangular and lognormal distributions show similar characteristics, which is expected since the lognormal distribution uses parameters taken from the triangular distribution (mean and standard deviations). Both Weibull distributions show expected characteristics. The Weibull (20%, 50%, 80%) definitely indicates a more pessimistic cost forecast because as the cumulative probability increases, the cost increases more significantly than for the Weibull (10%, 50%, 90%) distribution. This overlay indicates that the choice of distribution used in modeling plays a significant part in results obtained for cost. The three-parameter Weibull distributions represent a more realistic cost outcome for high-risk components. Weibull distributions allow for modeling of highly complex distributions using DFA, while triangular distributions have a more restrictive shape, making it difficult to fit three arbitrary percentiles for the low, most-likely, and high values (Kujawski et al., 2004).

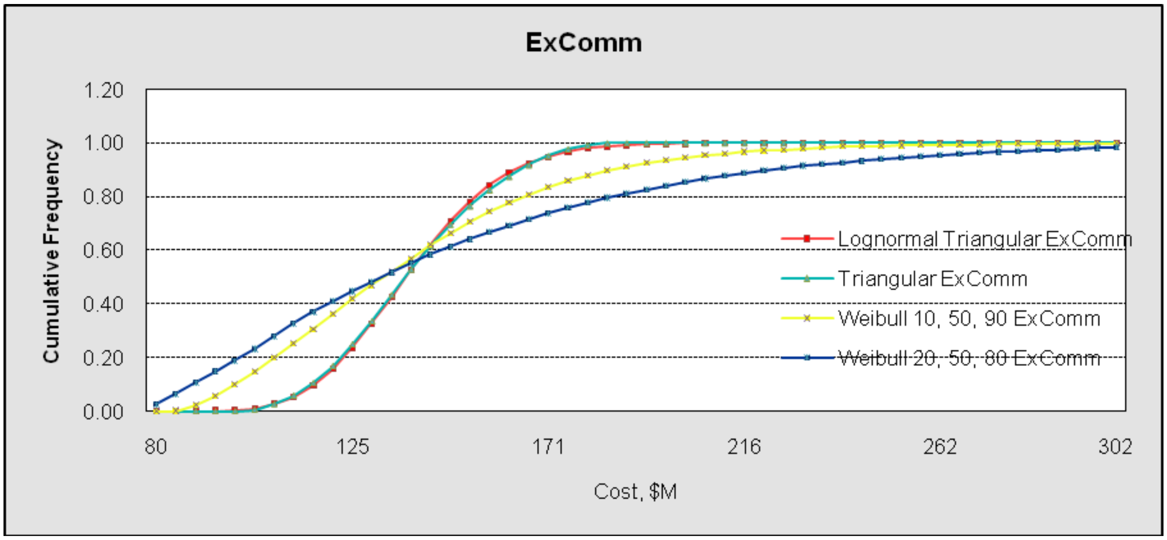


Figure 5. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Element ExComm Cumulative Frequency Distributions for Different Probability Distributions

The probability distribution functions shown in the overlay in Figure 6 illustrate expected behaviors for the ExComm PDFs. Both the triangular and lognormal distributions are narrow because the triangular distribution upper and lower bounds do not allow for infinite upper cost ranges. The sum of the Weibull (20%, 50%, 80%) distributions shows a more pessimistic behavior in comparison to the sum of the Weibull (10%, 50%, 90%) distributions.

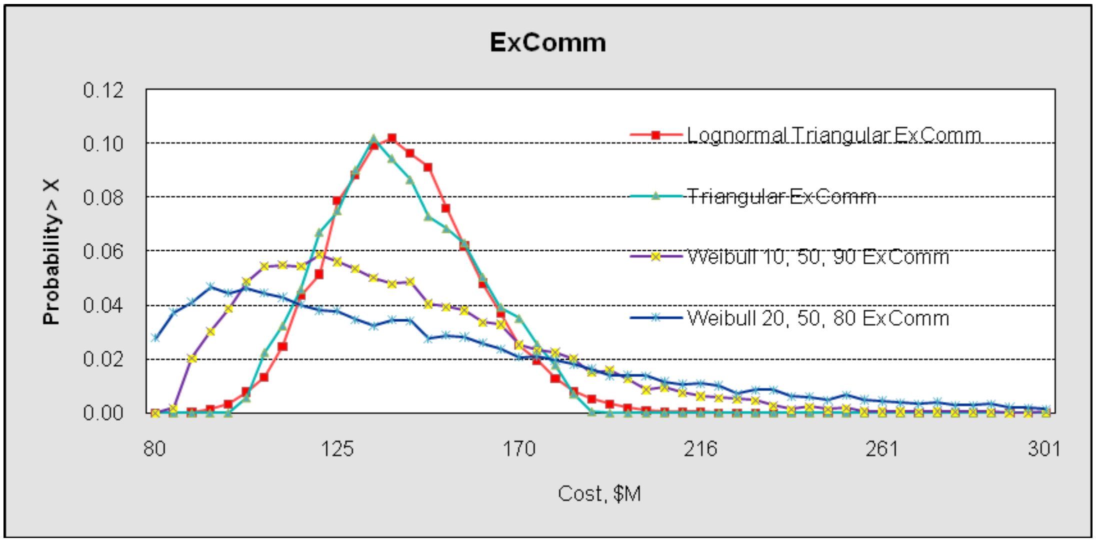


Figure 6. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Element ExComm with Different PDFs

Once all the individual electronics suite elements are modeled, they are summed up probabilistically in the main worksheet in Excel® to obtain the entire electronics suite cost. The simulation selects a random value from each of the element distributions then adds them to create one data point for the total cost. This is repeated 10,000 times to create the total cost distribution. When all the distribution functions (assumption cells in the model) of the electronics suite elements are probabilistically summed, the resulting cost is illustrated in the overlay shown in Figure 7. All four distributions have the appearance of a normal distribution consistent with the Central Limit Theorem (Garvey, 2000).

The lognormal and triangular distribution functions give rise to relatively narrow total cost distributions, consistent with the finite ranges of the contributing triangular distributions and the modeling of the lognormal distributions using the corresponding mean and standard deviation values. The Weibull (10%, 50%, 90%)-based cost distribution shows more narrow behavior for cost range than the Weibull (20%, 50%, 80%)-based distribution. The Weibull (20%, 50%, 80%)-based distribution allows for more uncertainty in data elicitation from SMEs. Weibull distributions not only show higher probabilities of cost overruns but also higher probabilities of cost underruns. These underruns reflect the assumption of 10% and 20% as the low value parameter for the distribution, rather than using it as the minimum value. Figure 8 shows the same data as Figure 7, except that it is in the cumulative probability form.

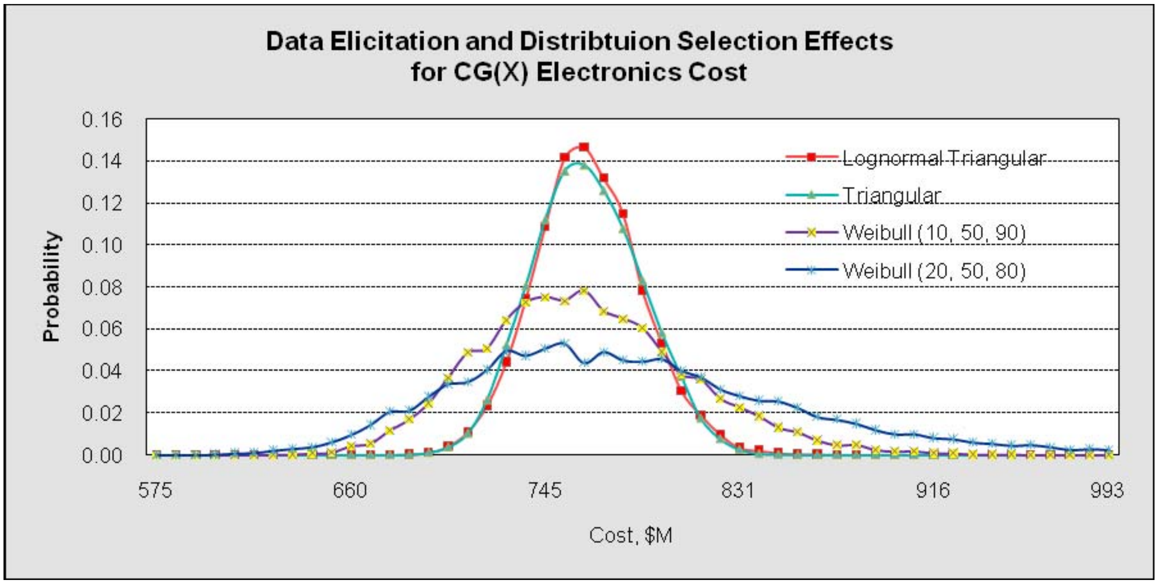


Figure 7. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Based on Different Distribution Selections

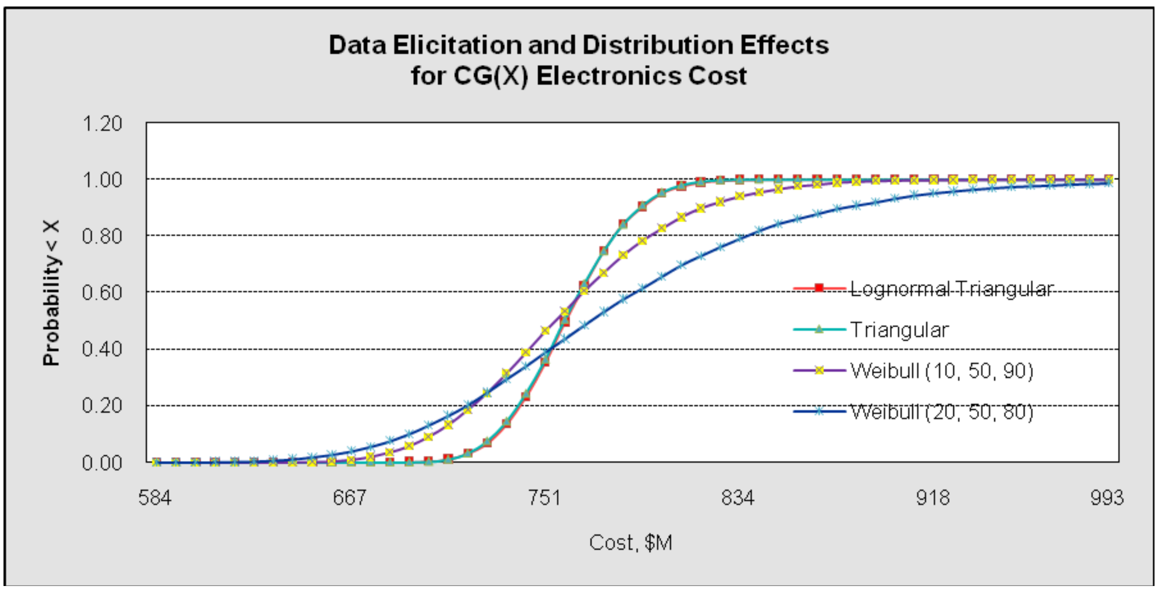


Figure 8. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Based on Different Distribution Selections in Cumulative Probability Form

2. Effects of Correlation on Cost

As discussed in Section II.B.1, two types of correlations are modeled in this paper: (1) Correlations among cost elements within the radar suite, and (2) correlations among cost elements in the entire electronics suite. This paper uses the following three correlation coefficient factors to show the correlation between the radar suite elements and the rest of the electronics suite components:

- Radar suite correlation coefficient = 0.5, electronics suite correlation coefficient = 0.5
- Radar suite correlation coefficient = 0.5, electronics suite correlation coefficient = 0.2
- Radar suite correlation coefficient = 0.8, electronics suite correlation coefficient = 0.5.

The choice of the values listed above simulates an environment that is not a perfectly correlated or no-correlated situation. The (0.5, 0.5) correlation assumes there is an equal correlation relationship between the subcomponents of the radar suite and the elements of the electronics suite. The (0.5, 0.2) correlation illustrates the effects of having a stronger correlation between the elements of the electronics suite than between elements of the entire electronics suite. The (0.8, 0.5) correlation shows the impact of a stronger correlation between components of one system than between different systems. These correlation coefficients represent a limited set of parameters for investigation in this paper. Further research in the determination of appropriate correlation coefficients and their effect is needed to provide a more complete analysis.

The impact of correlation effects is seen in Figures 9 and 10. These overlays show the different distributions that are a result of a 10,000-run Monte Carlo simulation for the correlated distributions in cumulative distribution form (Figure 9) and PDF form (Figure 10). The blue PDF is the reference Weibull (20%, 50%, 80%) distribution with no correlation effects. This distribution has the most narrow cost range when compared with the correlated distributions. The cost ranges of the Weibull distribution increases as the correlation factors increase. Also, in the cumulative probability distribution shown in Figure 9, all the distributions intersect at the mean value for the cost.

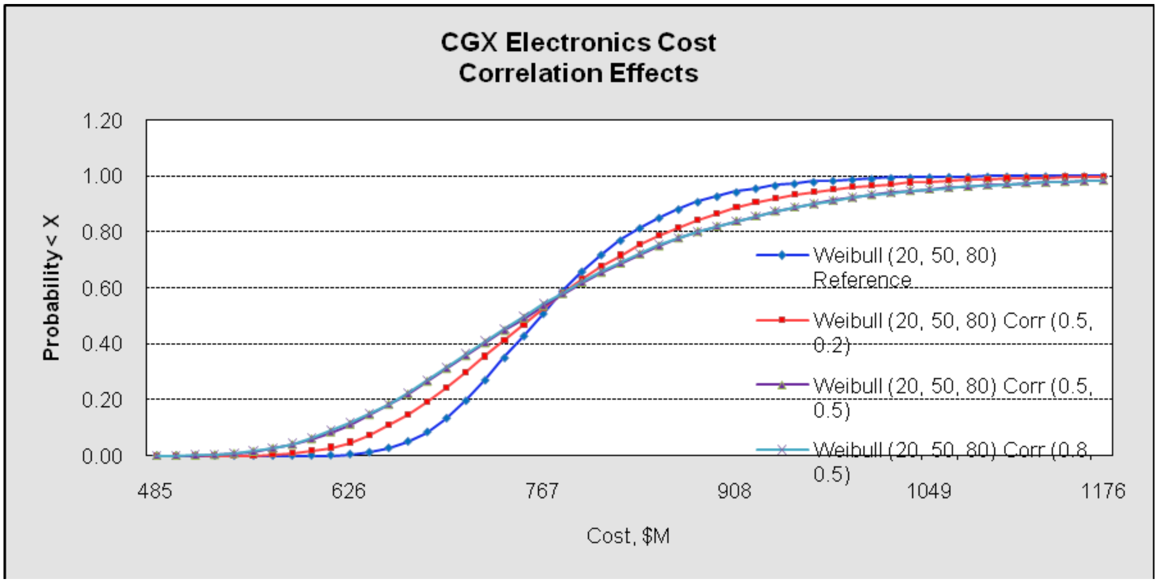


Figure 9. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Showing the Impact of Different Correlation Effects

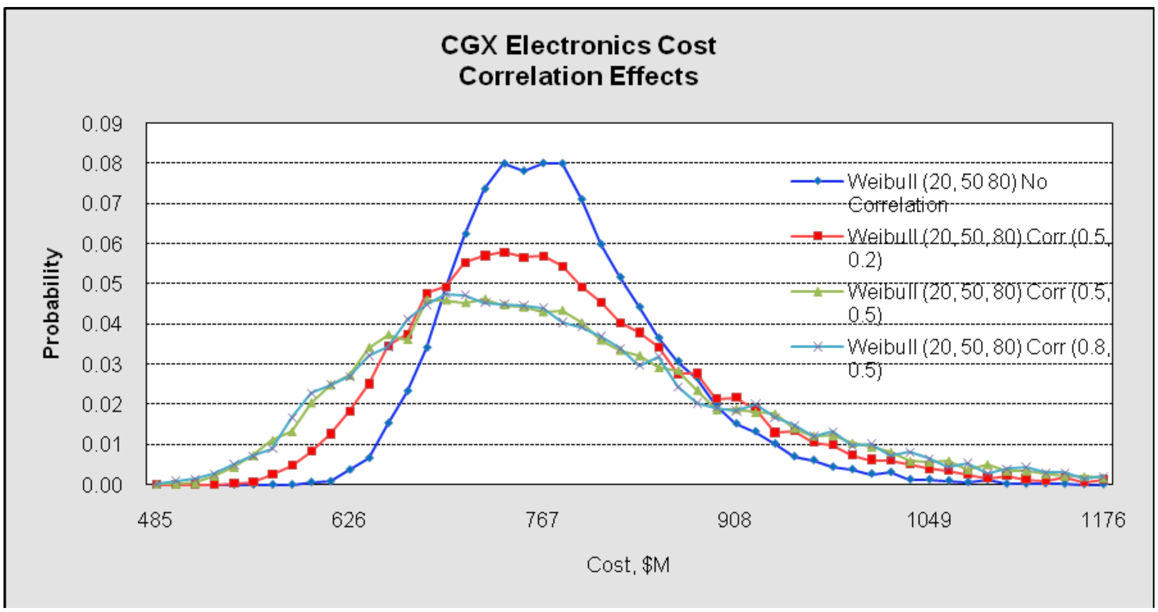


Figure 10. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Based on Different Correlation Effects in Cumulative Probability Form

As expected, the (0.5, 0.2) correlation being the smallest has the least effect on the total cost distribution. It is interesting to note that the distribution resulting from the (0.5, 0.5) correlation does not differ much from the (0.8, 0.5) distribution, but both of these correlations have a more significant effect than the (0.5, 0.2) correlation. This indicates that a change in the correlation factor for the radar suite from 0.5 to 0.8 is not as significant as a change in the correlation factor from 0.2 to 0.5 for the different components of the entire electronics suite. These results suggest that the correlation effects are important for probability values midpoint between the mean and the extremes, but there is little difference for values beyond 0.5. The results in Figure 10 are consistent with theoretical predictions of positive correlation effects in that the total cost becomes broader than for uncorrelated total cost (Kujawski et al., 2004). Further investigations are recommended to quantify correlation effects.

3. MAIMS Effects on Cost

The MAIMS modified cumulative probability and density density distributions for the electronics suite cost are shown in Figures 11 and 12. Characteristics of the MAIMS modified PDF is that they will never have a value less than the chosen value of modification. So, for the MAIMS 50th percentile modified distribution in Figure 11, the distribution has no value less than the 50th percentile baseline cost level. In Figure 12, the spikes or delta functions normally associated with the individual MAIMS distributions are not seen as they are modulated when summed.

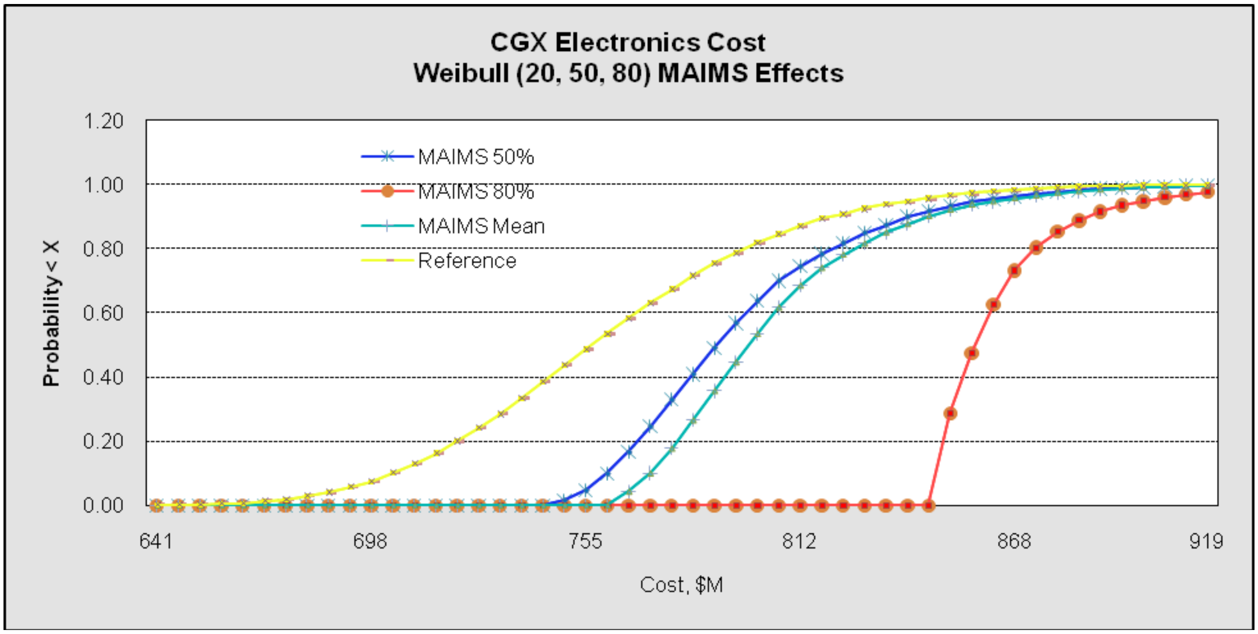


Figure 11. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Showing the MAIMS Effects in Cumulative Probability Form

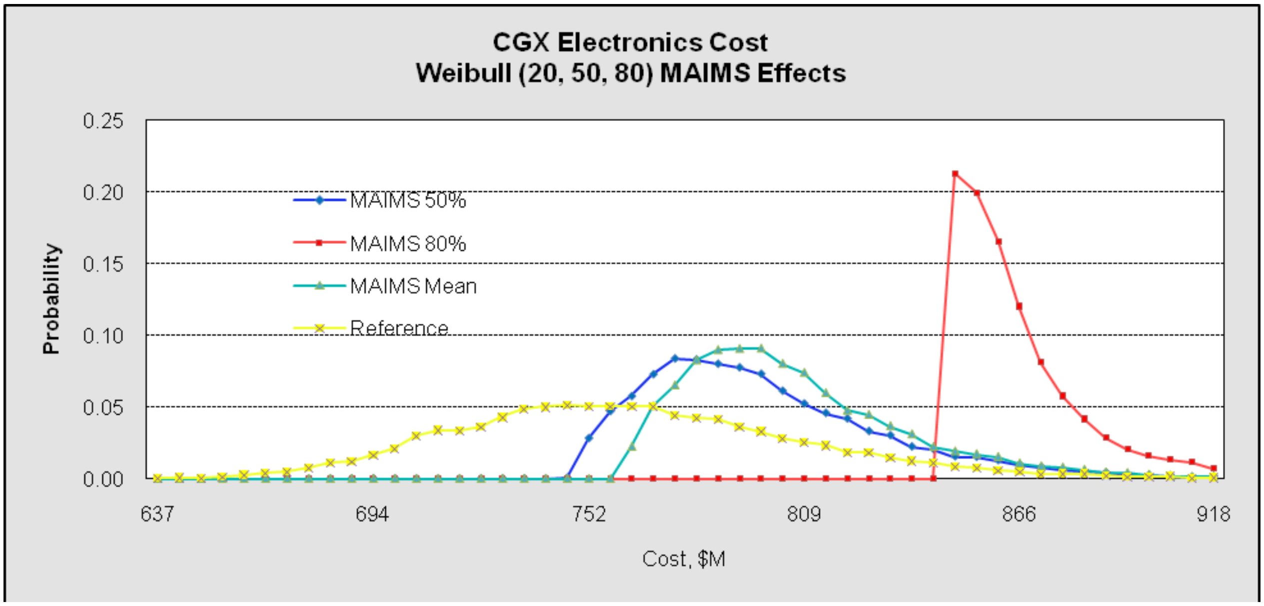


Figure 12. CG(X) Crystal Ball® Analysis, 10,000 Runs, Overlay of Electronics Suite Cost Showing the MAIMS Effects in PDF Form

It is important to note the significant rise in cost curve that occurs as the MAIMS modification value increases. The mean value of the distribtion increases as the funding level increases, and this is very clear in Figure 11. The curve representing the MAIMS 80% distribution shows how the budget is always high when comparing it to the MAIMS 50% or MAIMS mean distribution. This effect is because once money has been allocated to a WBS element, it is almost never seen in cost savings as underruns because cost account managers never return money to the project. Any remaining money from one WBS is subsequently spent on a different existing WBS that has cost overruns.

These simulations can be considered with other cost factors in making program management decisions regarding budgets. Funding projects at a level too low to cover costs will lead to cost overruns, while funding at a level that is too high leads to money not being recouped as savings later. Allocating reasonable budgets is the goal.

E. Chapter Summary

The research for this paper is based on the NAVSEA 05C CG(X) model provided by Mr. Chris Deegan and his CG(X) analysts. The CG(X) model encompasses all factors considered for cost of the entire program, including labor rates, material cost, overhead cost, planning cost, and other factors. Because of the complexity of the model and the numerous factors to consider, one portion of the model was chosen for analysis. The Electronic Suite and its nine elements are specifically targeted as the focus for analysis.

The steps used in the analysis of the CG(X) model include:

1. Analyze the cost factors used by NAVSEA 05C to develop the electronics cost.
2. Analyze the PDFs used for the electronics cost elements.
3. Identify what data elicitation methods were employed.
4. Determine if correlation factors were used in the cost analysis.

5. Develop cost factors to be modeled in a new model.
6. Decide which PDFs to use in the new model.
7. Develop a new cost model using correlation factors, chosen PDFs, and MAIMS influenced distributions.

Identified cost factors include NAVSEA 05C's probability distribution choice—a method used for developing the low, most-likely, and high cost values for the electronics suite elements, data elicitation methods, and correlation effects. This paper explores the methodology in choosing different probability distribution functions and their applicability to the model. Specifically, triangular, lognormal, and two variations of the three-parameter Weibull distribution are considered.

Methods of data elicitation are explored and the use of a DFA method is recommended for future use, although the research in this paper did not involve data acquisition. To simulate the use of a DFA methodology, Weibull distributions are employed to account for uncertainty associated with SME estimation of data. A Weibull (10%, 50%, 90%) distribution is used to simulate a more optimistic view of the uncertainty of data, while a Weibull (20%, 50%, 80%) distribution models a more pessimistic, but probably more realistic, view of the uncertainty associated with data from the SMEs.

Two types of correlation effects are considered and modeled in this paper. The first is the correlation between subcomponents of the radar suite, and the other is the correlation between the elements of the electronics suite. The radar suite is one of the elements that makes up the electronics suite. Analysis shows that a more significant effect is experienced with higher correlation between the elements of the electronics suite than between the subcomponents of the radar suite.

MAIMS modified probability distributions are modeled to show the significance of budget allocation level. These distributions are truncated at the baseline budget with a delta function at the baseline. This is based on the principle that once a budget is allocated, money is almost never seen in the form of cost under runs as the project progresses. As the MAIMS modification value increases, overall distribution cost rises with increasing probability of success.

III. Conclusions

A. Summary

This paper begins by exploring the definitions of risk and how it applies to the guidance set forth by current Navy leadership. Admiral Gary Roughead, Chief of Naval Operations, states that, "We manage risk" (Roughead, 2007). The need to develop effective acquisition and shipbuilding methods to successfully deliver an "affordable future fleet" (McCoy, 2008) is imperative if the Navy is to meet the goal of a 313-ship Navy by 2020. Cost risk analysis is one tool of many that can be used to help attain this goal.

This paper then proceeds to examine the probabilistic cost analysis approach that NAVSEA 05C currently uses to predict new naval vessel construction costs and to develop a method that better predicts the ultimate cost risk. Cost factors analyzed in this paper include the effect of data elicitation, distribution choice, the impact of the MAIMS principle, and the effect of correlation factors. Data elicitation and MAIMS have significant impact. Correlation effects vanish at the minimum, mean, and maximum values. PDF selection has a small impact as long as the distributions fit the three specified percentiles.

The model provided by NAVSEA 05C encompasses all aspects of the ship's cost and only the nine elements of the electronics suite were chosen for analysis in this paper. Using data obtained from SMEs for low-, most-likely, and high-cost values, experiments were conducted for the noted cost factors in the Excel® Monte Carlo simulation add-in Crystal Ball®.

Triangular, lognormal, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%) distributions are modeled and simulated to show the impact that each distribution can have on budget considerations for program managers. Both the triangular and lognormal distributions show narrow cost ranges when compared to the Weibull distribution cost range. The Weibull (10%, 50%, 90%) represents a more optimistic distribution than the more pessimistic Weibull (20%, 50%, 80%) distribution. The Weibull (20%, 50%, 80%) distribution accounts for the optimism bias commonly associated with SMEs. Data elicitation effects are modeled through the use of the Weibull distributions.

Correlation among cost elements in the electronics suite is modeled with the use of the Correlation Matrix function in Crystal Ball®. This paper uses three sets of two correlation coefficients to model the correlation between the radar suite elements and the rest of the electronics suite components. The results suggest that the correlation effects are important for probability values midpoint between the mean and the extremes, but there is little difference for values beyond 0.5. Further investigations are recommended to quantify correlation effects.

MAIMS principle modified distributions are modeled with the 50th percentile cost value, mean, and 80th percentile cost value to show the impact of funding at these different levels. The MAIMS principle is based on the observation that for a given budget, any money allocated is considered money spent. Very rarely are cost underruns experienced on a project once the budget has been allocated. The MAIMS modified distributions in this paper show the impact of either under-funding a budget or over-funding. Under-funding leads to cost overruns and over-funding leads to an overall higher cost, since money allocated is unlikely to be recouped.

B. Recommendations and Areas for Further Research

The analysis conducted in this model is only a starting point for improvements in the area of cost analysis for naval vessels. Although the methodology used in this paper provides a framework for obtaining more accurate predictions of cost than those in use with current probabilistic cost analysis, more work is required to develop a more complete and tested model. Recommendations for future research in the area of probabilistic cost analysis for shipbuilding include:

- Use of the DFA method to obtain data for cost assessment. Recommend eliciting data from SMEs at the 10th, 50th, and 90th percentiles, at a minimum, for relatively optimistic view of the data quality, and at the 20th, 50th, and 80th percentiles if a more pessimistic view of the quality of data is present. Take into consideration the overconfidence of estimates provided by experts in their field and use this knowledge when calibrating data for analysis.
- Select flexible and realistic probability distribution functions for cost analysis. Create probability distribution functions from historical data and adjust for expected differences in new programs.

- Incorporate the use of correlation among cost elements of a system. Aim to use a range of correlation coefficients that is realistic. A reasonable range for correlation coefficients is between 0.3-0.6, with some room for variation. Overly optimistic correlation coefficients that assume independence and overly pessimistic correlation coefficients that assume perfect correlation rarely exist in real data.
- Use the "Money Allocated is Money Spent" (MAIMS) principle to model budget management behavior. The MAIMS function will not allow the system cost to be a lesser amount than the budgeted cost baseline.
- Investigate further capabilities available with advanced modeling software such as Crystal Ball® or @Risk.
- Incorporate systems engineering methodologies and thinking into the development of probabilistic cost analysis. Kujawski et al. (2004) state that this is the single greatest challenge to the development and use of improved cost models.

Continuing with the development of improved cost models is an important step in helping the Navy to ensure the successful acquisition of the 313-ship Navy it desires. Improved cost models can give project managers the ability to develop more realistic and successful plans for their projects, while enabling them to make better budget decisions. The cost analysis methodology presented in this paper can serve as a starting point for further advanced research in this area that can be used by different programs across the Navy.

Acknowledgements

I thank Dr. Edouard Kujawski for his time and mentoring throughout the research and writing of this paper. I also thank Dr. Diana Angelis for her guidance and assistance in the development of this paper. Additionally, I thank Mr. Chris Deegan, the former Director of Cost Engineering and Industrial Analysis, and his staff for providing the data used in this paper; supporting travel to their office in Washington, DC; and for discussions regarding the CG(X) model. Specifically, the help provided by Mr. Morris Fields and Mr. Aaron Ratliff with the CG(X) model is greatly appreciated.

I would also like to thank my special friends Lynne and Charlie Denley for making me a part of their family and their support during my time at the Naval Postgraduate School. In addition, I thank the members of the Wednesday Night Laundry Runners and my dogs for their friendship and good times.

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- Capital Budgeting for DoD

- Energy Saving Contracts/DoD Mobile Assets
- Financing DoD Budget via PPPs
- Lessons from Private Sector Capital Budgeting for DoD Acquisition Budgeting Reform
- PPPs and Government Financing
- ROI of Information Warfare Systems
- Special Termination Liability in MDAPs
- Strategic Sourcing
- Transaction Cost Economics (TCE) to Improve Cost Estimates

Human Resources

- Indefinite Reenlistment
- Individual Augmentation
- Learning Management Systems
- Moral Conduct Waivers and First-tem Attrition
- Retention
- The Navy's Selective Reenlistment Bonus (SRB) Management System
- Tuition Assistance

Logistics Management

- Analysis of LAV Depot Maintenance
- Army LOG MOD
- ASDS Product Support Analysis
- Cold-chain Logistics
- Contractors Supporting Military Operations
- Diffusion/Variability on Vendor Performance Evaluation
- Evolutionary Acquisition
- Lean Six Sigma to Reduce Costs and Improve Readiness
- Naval Aviation Maintenance and Process Improvement (2)
- Optimizing CIWS Lifecycle Support (LCS)
- Outsourcing the Pearl Harbor MK-48 Intermediate Maintenance Activity
- Pallet Management System
- PBL (4)
- Privatization-NOSL/NAWCI
- RFID (6)
- Risk Analysis for Performance-based Logistics
- R-TOC Aegis Microwave Power Tubes

- Sense-and-Respond Logistics Network
- Strategic Sourcing

Program Management

- Building Collaborative Capacity
- Business Process Reengineering (BPR) for LCS Mission Module Acquisition
- Collaborative IT Tools Leveraging Competence
- Contractor vs. Organic Support
- Knowledge, Responsibilities and Decision Rights in MDAPs
- KVA Applied to Aegis and SSDS
- Managing the Service Supply Chain
- Measuring Uncertainty in Earned Value
- Organizational Modeling and Simulation
- Public-Private Partnership
- Terminating Your Own Program
- Utilizing Collaborative and Three-dimensional Imaging Technology

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