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Total Ownership with Life-Cycle Cost Model Under Uncertainty

October 19, 2020

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Abstract

In this research, we look at answering the following primary question: Would an advanced analytical model be a more effective metric to estimate total ownership cost (TOC) with life-cycle cost under uncertainty and risk than the current method of life-cycle cost estimates for Surface EO/IR Sensors? To accomplish this, the research developed and analyzed a computational model for Total Ownership with Life-Cycle Cost Model Under Uncertainty for Surface Electro-Optical Infrared Sensors. During the development of the model, we identified the required data and examined the current Department of Defense (DoD) method for determining system life-cycle costs for defense systems and determined that the proposed model is a useful alternative to the current method of determining the life-cycle costs for EO/IR Sensors on surface ships. Finally, we concluded that the developed model can be applied to cost estimating in other sectors of DoD cost projections.

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Introduction to the Total Ownership with Life-Cycle Cost Model

Research Purpose

The purpose of this research is to develop a model to estimate total ownership with life-cycle costs under uncertainty associated with Surface Electro-Optic Infrared (EO/IR) sensors. We examine the basics of Total Ownership Cost modeling over the life cycle of the EO/IR sensors, including the inception phase of Acquisition Costs, followed by annual Operations and Maintenance (O&M) expenses, along with a final set of Disposition Costs at the end of life of the sensor. This model will allow managers to have better decision analytics of the costs of said sensors for use in subsequent cost comparisons across sensor platforms, return on investment analysis, portfolio allocation of resources, and analysis of alternatives.

Research Focus

In this research, we answer the following primary question: Would an advanced analytical model be a more effective metric to estimate total ownership with life-cycle cost under uncertainty than the current method of life-cycle cost estimates for surface EO/IR sensors? To accomplish this, we develop and analyze a Total Ownership with Life-Cycle Cost Model Under Uncertainty for Surface Electro-Optical Infrared Sensors. In the development of the model, we determine what data is required to implement our proposed model for surface ship EO/IR sensors. We also examine the current Department of Defense (DoD) method for determining system life-cycle costs for defense systems and consider whether the proposed model is a useful alternative to the current method of determining the life-cycle costs for EO/IR sensors on surface ships. Finally, we consider whether the developed model can be applied to cost estimating in other sectors of DoD cost projections.

Research Summary

While executing a standard life-cycle-based total ownership cost analysis, we assume that before the system is operational, there are substantial acquisition costs. These costs are usually referred to as Year 0, followed by the operational years where operation and maintenance costs will apply. The final price analyzed is the salvage cost, or the cost to properly dispose of, sell, or render the system inoperable. The sum of these three expenses is called the life-cycle cost.

Unfortunately, the accurate calculation of these costs is not as straightforward as their descriptions. To accurately incorporate these three factors, it is essential to consider economic theory. The elements of time valuation of money are critical in the analysis of alternatives. The economic growth, annual discount rate, inflation, and opportunity cost of investing in a specific system are essential to our study. Other factors include budgetary cutbacks and changes in technology. The model will allow the user to input these changes to manually adjust for each of these. Utilizing this model will serve as a proof of concept to understand how this approach could be used to reduce cost overflow and prevent budget overruns. It will provide greater insight into the true nature of the cost of cash outflow and the life cycle of the product and its associated costs. These results would give leaders a more effective metric to analyze total ownership cost under uncertainty, therefore allowing leadership to make more informed decisions in the DoD acquisition process.

Literature Review

Introduction

This background and literature review provide a comprehensive overview of the topics pertinent to our project. We first examine the concepts and best practices in the field of cost and cost estimation, and their application inside of the DoD. We then look into the DoD's acquisition process as a whole to analyze how the DoD can utilize cost estimation to influence decision-making. After covering basic cost estimation and the acquisition system, we then discuss total ownership cost and life-cycle cost estimations, and how these factors play a role in calculating the overall cost of a system. The review also covers the topics of risk and uncertainty to explain the relationship and the differences between the two, as well as to highlight the importance of properly accounting for both factors. We conclude with an overview of our model's subject, the electro-optical infrared sensor (EO/IR). We give a brief rundown of the capabilities as well as the applications that these sensors have on Navy surface vessels, along with their rapidly changing technology, and state why it is imperative that the Navy continues to buy these sensors while ensuring the cost stays at a rational price point.

Cost Estimation

The DoD receives a limited amount of funds every fiscal year and must decide how those funds are used in support of U.S. national strategies and goals. Specifically, those decisions fall into one of three categories: long-term planning, budgeting, or choosing among alternatives (Mislick & Nussbaum, 2015). The government is tasked with spending taxpayers' dollars effectively and efficiently. This means that the DoD decision-makers must ensure they make strategic investments, including the acquisition of new programs and systems. Before a program is implemented or system purchased, decision-makers must understand the full cost that will be incurred and its effect on the DoD's limited budget.

The projected costs of major acquisitions are produced through a process known as *cost estimation*. Cost estimation is defined as "the process of collecting and analyzing historical data and applying quantitative models, techniques, tools, and databases in order to predict an estimate of the future cost of an item, product, or task" (Mislick & Nussbaum, 2015, p. 11). In basic terms, cost estimation is performed by running relevant data from the past through a model or database to predict what an item will cost in the future. It is important to note that reliable historical data is fundamental to this process.

In order to produce cost estimates, we must first gather available historical data. Collecting data is often the most time-consuming and costly step of the entire cost estimation process (Mislick & Nussbaum, 2015). Only after the historical data has been obtained can the cost analyst start the "organization, normalization, and management of that historical data" (Mislick & Nussbaum, 2015, p. 11). *Normalization* refers to taking the historical data and "applying adjustments to that data to gain consistent, comparable data to be used in your estimates" (Mislick & Nussbaum, 2015, p. 78). Normalizing the data set allows the analyst to compare data across different periods of time by adjusting for different factors. The data set must be normalized three different ways: for content, for quantity, and for inflation (Mislick & Nussbaum, 2015). Normalizing for content ensures comparison across the same category or type of data (Mislick & Nussbaum, 2015). Normalizing for quantity ensures comparison of data at the same point on the learning curve of production and of equal quantities (Mislick & Nussbaum, 2015). Finally, the data is adjusted to account for inflation when comparing data from different years (Mislick & Nussbaum, 2015).

The second component of cost estimation is the quantitative model that is used to turn normalized historical data into a future cost estimate. Mislick and Nussbaum (2015) explain that the "profession of cost estimating is scientifically grounded by using transparent, rationally defensible and reviewable quantitative methods" (p. 12). The development of a high-quality quantitative model is key in cost estimation. If a poor quantitative model is used, then the quality and reliability of the cost estimate will also be poor. This highlights the importance of the quality cost models for EO/IR sensors.

The third part of Mislick and Nussbaum's (2015) definition of cost estimation is to predict. The ultimate goal of cost estimation is to predict a future cost. The prediction is based on the information available at the time. We can only "estimate the conditions that will pertain later when the project is executed" and must rely on the information available in the present (Mislick & Nussbaum, 2015, p. 12). While no one can forecast the future with 100% accuracy, through historical data and quantitative models, we are able to provide a more accurate prediction that, while not perfect, is still a useful tool for decision-makers in the acquisition process.

Mislick and Nussbaum (2015) explain that the overall objective of cost estimation is to provide a complete, reasonable, credible, and analytically defensible estimation of future costs—a quality estimate—that can be used by decision-makers. They provide a breakdown of characteristics essential to a quality cost estimate, and we explore some of these characteristics in the following paragraphs.

One of the most important characteristics of a quality cost estimate is that it must be understandable to the user or decision-maker in order to be an efficient decision-making tool (Mislick & Nussbaum, 2015). To this end, a complex approach to cost estimation should be avoided and a simpler approach should be used (Mislick & Nussbaum, 2015). An understandable estimate also clearly lays out the assumptions and ground rules that were used in the process (Mislick & Nussbaum, 2015). With the diversity among people's background and experiences, there can be differing underlying assumptions in the cost estimation process. Therefore, the assumptions used must be clearly stated and a sensitivity analysis should be performed to accommodate additional variations of assumptions (Mislick & Nussbaum, 2015).

Another characteristic of a quality cost estimate is that it is "anchored in historical program performance" (Mislick & Nussbaum, 2015, p. 13). We previously stated that cost estimations use historical data to predict future cost. Therefore, an important aspect of the historical data is its relation to the future costs we are trying to predict. The cost estimation must be based on data from a similar system or program (Mislick & Nussbaum, 2015). For example, if we are trying to estimate the cost of a new class of surface ship, we should not be using historical data from a submarine program, as such data would not produce a quality estimate. Instead, we should use the historical data from a past class of surface ship that has features similar to the new class. Although we are using historical data as a base, we must also account for "current and potential future process and design improvements" (Mislick & Nussbaum, 2015 p. 13). We are trying to predict the cost of a new future system, which may have updated designs and processes with no historical data. These updates and improvements still need to be accounted for in our estimation and are often accomplished by subject matter experts (SMEs) and their professional judgment (Mislick & Nussbaum, 2015). Finally, cost estimates are about predicting the future, and with the future comes uncertainty. In order to produce quality estimates, cost analysts must address the uncertainties and risk associated with the program (Mislick & Nussbaum, 2015). We go into more detail about how risk and uncertainties are addressed in cost estimation later.

Cost Overview

Before comprehending cost estimation methods, it is important to become familiar with the terms associated with cost estimation. To begin with, an understanding of "cost" provides a solid foundation in the cost estimation process. If we do not understand what we are trying to predict, then we will not produce a quality or credible estimation. The term *cost* is often used interchangeably with the term *price*; however, they do not have the same meaning. There is an important distinction between the two terms. Mislick and Nussbaum (2015) define cost as the total amount of money needed to produce a certain item, or a quantitative measurement that accounts for all resources needed to produce an item. However, they refer to price as the amount of money that a person must pay for an item. When we go into a store, we normally ask the salesperson "What does this item cost?" Answering the literal question of what an item costs would encompass every resource that went into the development and production of that item. Instead, the accurate question is, "What's the item's price?" or "How much money must I exchange to receive that item?"

Because the term *cost* can refer to a number of different types or categories, the type of cost is important to understand during the cost estimation process. One of the first distinctions is between recurring and nonrecurring costs. A recurring cost is "repetitive and occurs each time a company produces a unit" (Mislick & Nussbaum, 2015, p. 26). When a bottling company produces a bottled beverage, each bottle cap has an associated cost. The cost of each bottle cap is recurring. In contrast, a nonrecurring cost is "not repetitive and cannot be tied to the quantity of the items being produced" (Mislick & Nussbaum, 2015, p. 26). The cost associated with purchase of the bottling machine would be consider nonrecurring. Closely related to recurring and nonrecurring costs are fixed and variable costs. Variable costs are associated and vary with the level of production (Mislick & Nussbaum, 2015). The more units produced, the more the total variable cost. However, fixed costs are unaffected by the level of production and are "generally associated with nonrecurring costs" (Mislick & Nussbaum, 2015, p. 27). No matter how many units are produced, the fixed cost will remain unchanged.

Another distinction between types of cost is direct and indirect costs. A direct cost can be "reasonably measured and allocated to a specific output, product, or work activity" (Mislick & Nussbaum, 2015, p. 26). The material used to produce an item is a direct cost. An indirect cost "cannot be attributed or allocated to a specific output, product, or work activity" (Mislick & Nussbaum, 2015, p. 27). The maintenance required for the upkeep of a machine used in production is indirect. Operating costs that are not direct labor or material, such as electricity and property taxes, are classified as overhead costs (Mislick & Nussbaum, 2015).

Other cost classifications are sunk costs and opportunity costs. A sunk cost is a cost that has already been incurred, as it occurred in the past. These costs are considered irrelevant to decision-makers, as the money spent cannot be retrieved (Mislick & Nussbaum, 2015). If someone walks into a car dealership and purchases a car, the cost of that car is not used in considering future upkeep or upgrades. The buyer cannot get the money they spent back and reallocate it; therefore, it is sunk. Opportunity cost arises when there is more than one option to be considered. *Opportunity cost* is the measure of the value lost when one alternative is chosen over another (Mislick & Nussbaum, 2015). In the car dealership scenario, the buyer has the option of buying several different cars. Each of those cars has different features and value. In order to buy one car, the buyer must decide not to buy the others. This means the buyer is giving up some features or value. Opportunity costs are important for decision-makers when determining the best available option among multiple alternatives.

The Theory of Predictive Modeling in Cost

Generally, forecasting can be divided into quantitative and qualitative approaches (see Figure 1). Qualitative forecasting is used when little to no reliable historical, contemporaneous, or comparable data exist. Several qualitative methods exist, such as the Delphi or expert opinion approach (a consensus-building forecast by field experts, marketing experts, or internal staff members), management assumptions (target growth rates set by senior management), as well as market research or external data or polling and surveys (data obtained through third-party sources, industry and sector indexes, or active market research). These estimates can be either single-point estimates (an average consensus) or a set of prediction values (a distribution of predictions). The latter can be entered into Risk Simulator as a custom distribution and the resulting predictions can be simulated; that is, running a nonparametric simulation using the prediction data points as the custom distribution.

For quantitative forecasting, the available data or data that need to be forecasted can be divided into time-series (values that have a time element to them, such as revenues at different years, inflation rates, interest rates, market share, failure rates, and so forth), cross-sectional (values that are time-independent, such as the grade point average of sophomore students across the nation in a particular year, given each student's levels of SAT scores, IQ, and number of alcoholic beverages consumed per week), or mixed panel (mixture between time-series and panel data; e.g., predicting sales over the next 10 years given budgeted marketing expenses and market share projections, which means that the sales data are time-series but exogenous variables such as marketing expenses and market share exist to help to model the forecast predictions). Here is a quick review of each of the most commonly used forecasting methodology.

- *ARIMA.* Autoregressive integrated moving average (ARIMA, also known as Box–Jenkins ARIMA) is an advanced econometric modeling technique. ARIMA looks at historical time-series data and performs back-fitting optimization routines to account for historical autocorrelation (the relationship of a variable's values over time, that is, how a variable's data is related to itself over time). It accounts for the stability of the data to correct for the nonstationary characteristics of the data, and it learns over time by correcting its forecasting errors. Think of ARIMA as an advanced multiple regression model on steroids, where time-series variables are modeled and predicted using its historical data as well as other time-series explanatory variables. Advanced knowledge in econometrics is typically required to build good predictive models using this approach. Suitable for time-series and mixed-panel data (not applicable for cross-sectional data).

- *Auto-ARIMA.* The Auto-ARIMA module automates some of the traditional ARIMA modeling by automatically testing multiple permutations of model specifications and returns the best-fitting model. Running the Auto-ARIMA module is similar to running regular ARIMA forecasts, the differences being that the required P, D, Q inputs in ARIMA are no longer required and that different combinations of these inputs are automatically run and compared. Suitable for time-series and mixed-panel data (not applicable for cross-sectional data).

- *Basic Econometrics.* Econometrics refers to a branch of business analytics, modeling, and forecasting techniques for modeling the behavior or forecasting certain business, economic, finance, physics, manufacturing, operations, and any other variables. Running basic econometrics models is similar to regular regression analysis except that the dependent and independent variables are allowed to be modified before a regression is run. Suitable for all types of data.

- *Basic Auto Econometrics.* This methodology is similar to basic econometrics, but thousands of linear, nonlinear, interacting, lagged, and mixed variables are automatically run on the data to determine the best-fitting econometric model that describes the behavior of the dependent variable. It is useful for modeling the effects of the variables and for forecasting future outcomes, while not requiring the analyst to be an expert econometrician. Suitable for all types of data.

- *Combinatorial Fuzzy Logic.* Fuzzy sets deal with approximate rather than accurate binary logic. Fuzzy values are between 0 and 1. This weighting schema is used in a combinatorial method to generate the optimized time-series forecasts. Suitable for time-series only.

- *Custom Distributions.* Using Risk Simulator, expert opinions can be collected, and a customized distribution can be generated. This forecasting technique comes in handy when the dataset is small, when the Delphi method is used, or the goodness-of-fit is bad when applied to a distributional fitting routine. Suitable for all types of data.

- *GARCH*. The generalized autoregressive conditional heteroskedasticity (GARCH) model is used to model historical and forecast future volatility levels of a marketable security (e.g., stock prices, commodity prices, oil prices, etc.). The dataset has to be a time series of raw price levels. GARCH will first convert the prices into relative returns and then run an internal optimization to fit the historical data to a mean-reverting volatility term structure, while assuming that the volatility is heteroskedastic in nature (changes over time according to some econometric characteristics). Several variations of this methodology are available in Risk Simulator, including EGARCH, EGARCH-T, GARCH-M, GJR-GARCH, GJR-GARCH-T, IGARCH, and T-GARCH. Suitable for time-series data only.

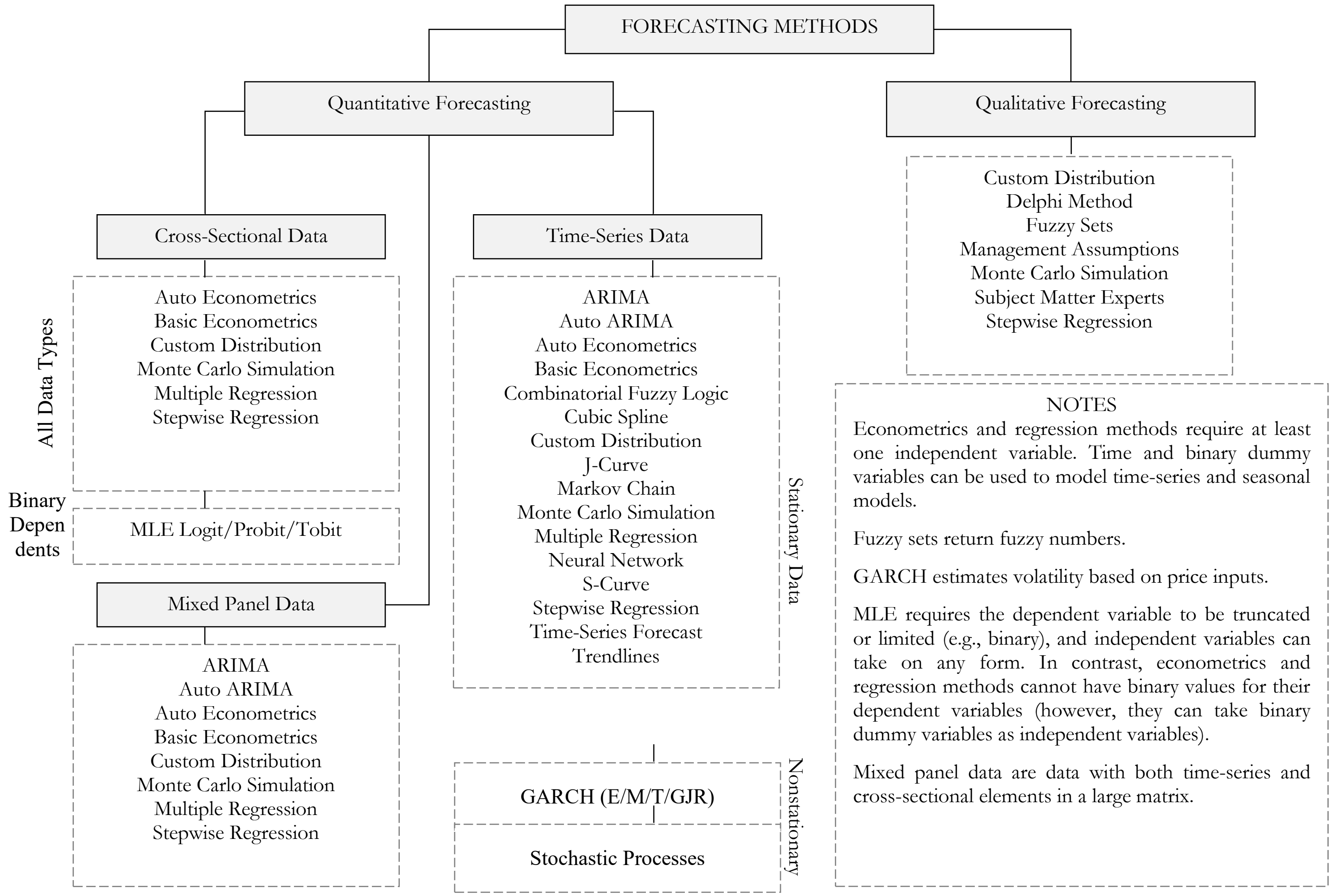


Figure 1. Forecasting Methods

- *J-Curve*. The J-curve, or exponential growth curve, is one where the growth of the next period depends on the current period's level and the increase is exponential. This phenomenon means that over time, the values will increase significantly, from one period to another. This model is typically used in forecasting biological growth and chemical reactions over time. Suitable for time-series data only.

- *Markov Chains*. A Markov chain exists when the probability of a future state depends on a previous state and when linked together forms a chain that reverts to a long-run steady state level. This approach is typically used to forecast the market share of two competitors. The required inputs are the starting probability of a customer in the first store (the first state) returning to the same store in the next period, versus the probability of switching to a competitor's store in the next state. Suitable for time-series data only.

- *Maximum Likelihood on Logit, Probit, and Tobit*. Maximum likelihood estimation (MLE) is used to forecast the probability of something occurring given some independent variables. For instance, MLE is used to predict if a credit line or debt will default given the obligor's characteristics (30 years old, single, salary of $100,000 per year, and total credit card debt of $10,000), or the probability a patient will have lung cancer if the person is a male between the ages of 50 and 60, smokes five packs of cigarettes per month or year, and so forth. In these circumstances, the dependent variable is limited (i.e., limited to being binary 1 and 0 for default/die and no default/live, or limited to integer values such as 1, 2, 3, etc.) and the desired outcome of the model is to predict the probability of an event occurring. Traditional regression analysis will not work in these situations (the predicted probability is usually less than zero or greater than one, and many of the required regression assumptions are violated, such as independence and normality of the errors, and the errors will be fairly large). Suitable for cross-sectional data only.

- *Multivariate Regression*. Multivariate regression is used to model the relationship structure and characteristics of a certain dependent variable as it depends on other independent exogenous variables. Using the modeled relationship, we can forecast the future values of the dependent variable. The accuracy and goodness-of-fit for this model can also be determined. Linear and nonlinear models can be fitted in the multiple regression analysis. Suitable for all types of data.

- *Neural Network*. This method creates artificial neural networks, nodes, and neurons inside software algorithms for the purposes of forecasting time-series variables using pattern recognition. Suitable for time-series data only.

- *Nonlinear Extrapolation*. In this methodology, the underlying structure of the data to be forecasted is assumed to be nonlinear over time. For instance, a dataset such as 1, 4, 9, 16, 25 is considered to be nonlinear (these data points are from a squared function). Suitable for time-series data only.

- *S-Curves*. The S-curve, or logistic growth curve, starts off like a J-curve, with exponential growth rates. Over time, the environment becomes saturated (e.g., market saturation, competition, overcrowding), the growth slows, and the forecast value eventually ends up at a saturation or maximum level. The S-curve model is typically used in forecasting market share or sales growth of a new product from market introduction until maturity and decline, population dynamics, and other naturally occurring phenomenon. Suitable for time-series data only.

- *Spline Curves*. Sometimes there are missing values in a time-series dataset. For instance, interest rates for years 1 to 3 may exist, followed by years 5 to 8, and then year 10. Spline curves can be used to interpolate the missing years' interest rate values based on the data that exist. Spline curves can also be used to forecast or extrapolate values of future time periods beyond the time period of available data. The data can be linear or nonlinear. Suitable for time-series data only.

- *Stochastic Process Forecasting*. Sometimes variables are stochastic and cannot be readily predicted using traditional means. Nonetheless, most financial, economic, and naturally occurring phenomena (e.g., motion of molecules through the air) follow a known mathematical law or relationship. Although the resulting values are uncertain, the underlying mathematical structure is known and can be simulated using Monte Carlo risk simulation. The processes supported in Risk Simulator include Brownian motion random walk, mean-reversion, jump-diffusion, and mixed processes, useful for forecasting nonstationary time-series variables. Suitable for time-series data only.

- *Time-Series Analysis and Decomposition*. In well-behaved time-series data (typical examples include sales revenues and cost structures of large corporations), the values tend to have up to three elements: a base value, trend, and seasonality. Time-series analysis uses these historical data and decomposes them into these three elements, and recomposes them into future forecasts. In other words, this forecasting method, like some of the others described, first performs a back-fitting (backcast) of historical data before it provides estimates of future values (forecasts). Suitable for time-series data only.

- *Trendlines*. This method fits various curves such as linear, nonlinear, moving average, exponential, logarithmic, polynomial, and power functions on existing historical data. Suitable for time-series data only.

Parametric Cost Model Approach

It is assumed that the user is sufficiently knowledgeable about the fundamentals of regression analysis. The general bivariate linear regression equation takes the form of $Y = \beta_0 + \beta_1 X + \varepsilon$, where β_0 is the intercept, β_1 is the slope, and ε is the error term. It is bivariate as there are only two variables, a *Y* or dependent variable, and an *X* or independent variable, where *X* is also known as the regressor (sometimes a bivariate regression is also known as a univariate regression as there is only a single independent variable *X*). The dependent variable is named as such as it *depends* on the independent variable. For example, sales revenue depends on the amount of marketing costs expended on a product's advertising and promotion, making the dependent variable sales and the independent variable marketing costs. An example of a bivariate regression is seen as simply inserting the best-fitting line through a set of data points in a two-dimensional plane, as seen on the left panel in Figure 2. In other cases, a multivariate regression can be performed, where there are multiple or *k* number of independent *X* variables or regressors, where the general regression equation will now take the form of $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 ... + \beta_k X_k + \varepsilon$. In this case, the best-fitting line will be within a *k + 1* dimensional plane.

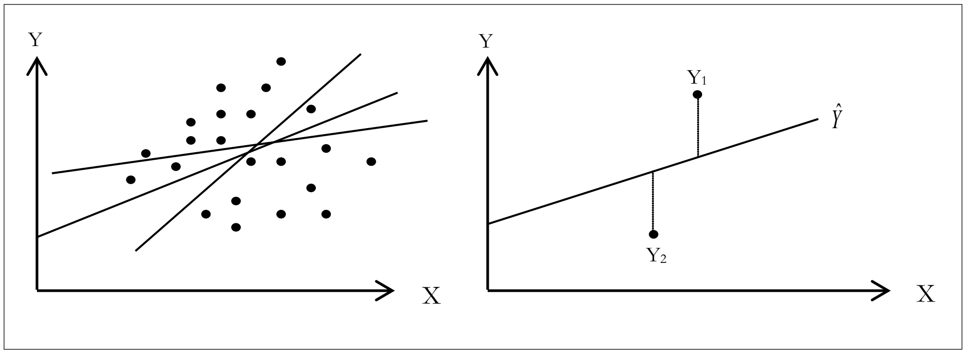


Figure 2. Bivariate Regression

However, fitting a line through a set of data points in a scatterplot, as in the left panel of Figure 2, may result in numerous possible lines. The best-fitting line is defined as the single unique line that minimizes the total vertical errors, that is, the sum of the absolute distances between the actual data points (Y_i) and the estimated line ($\hat{Y}$), as shown on the right panel of Figure 2. To find the best-fitting unique line that minimizes the errors, a more sophisticated approach is applied using regression analysis. Regression analysis finds the unique best-fitting line by requiring that the total errors be minimized, or by calculating

$$Min\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

where only one unique line minimizes this sum of squared errors. The errors (vertical distances between the actual data and the predicted line) are squared to avoid the negative errors from canceling out the positive errors. Solving this minimization problem with respect to the slope and intercept requires calculating first derivatives and setting them equal to zero:

$$\frac{d}{d\beta_0}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 = 0 \;\; and \;\; \frac{d}{d\beta_1}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 = 0$$

which yields the bivariate regression's least squares equations:

$$\beta_1 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sum_{i=1}^{n}(X_i - \overline{X})^2} = \frac{\sum_{i=1}^{n} X_i Y_i - \frac{\sum_{i=1}^{n} X_i \sum_{i=1}^{n} Y_i}{n}}{\sum_{i=1}^{n} X_i^2 - \frac{\left(\sum_{i=1}^{n} X_i\right)^2}{n}}$$

$$\beta_0 = \overline{Y} - \beta_1 \overline{X}$$

For multivariate regression, the analogy is expanded to account for multiple independent variables, where $Y_i = \beta_1 + \beta_2 X_{2,i} + \beta_3 X_{3,i} + \varepsilon_i$ and the estimated slopes can be calculated by

$$\hat{\beta}_2 = \frac{\sum Y_i X_{2,i} \sum X_{3,i}^2 - \sum Y_i X_{3,i} \sum X_{2,i} X_{3,i}}{\sum X_{2,i}^2 \sum X_{3,i}^2 - \left(\sum X_{2,i} X_{3,i}\right)^2}$$

$$\hat{\beta}_3 = \frac{\sum Y_i X_{3,i} \sum X_{2,i}^2 - \sum Y_i X_{2,i} \sum X_{2,i} X_{3,i}}{\sum X_{2,i}^2 \sum X_{3,i}^2 - \left(\sum X_{2,i} X_{3,i}\right)^2}$$

In running multivariate regressions, great care must be taken to set up and interpret the results. For instance, a good understanding of econometric modeling is required (e.g., identifying regression pitfalls such as structural breaks, multicollinearity, heteroskedasticity, autocorrelation, specification tests, nonlinearities, and so forth) before a proper model can be constructed.

Potential Issues in Parametric Models

The following six assumptions are the requirements for a parametric multiple regression analysis to work:

- The relationship between the dependent and independent variables is linear.
- The expected value of the errors or residuals is zero.
- The errors are independently and normally distributed.

- The variance of the errors is constant or homoskedastic and not varying over time.
- The errors are independent and uncorrelated with the explanatory variables.
- The independent variables are uncorrelated to each other, meaning that no multicollinearity exists.

One very simple method to verify some of these assumptions is to use a scatterplot. This approach is simple to use in a bivariate regression scenario. If the assumption of the linear model is valid, the plot of the observed dependent variable values against the independent variable values should suggest a linear band across the graph with no obvious departures from linearity. Outliers may appear as anomalous points in the graph, often in the upper right-hand or lower left-hand corner of the graph. However, a point may be an outlier in either an independent or dependent variable without necessarily being far from the general trend of the data.

If the linear model is not correct, the shape of the general trend of the X-Y plot may suggest the appropriate function to fit (e.g., a polynomial, exponential, or logistic function). Alternatively, the plot may suggest a reasonable transformation to apply. For example, if the X-Y plot arcs from lower left to upper right so that data points either very low or very high in the independent variable lie below the straight line suggested by the data, while the middle data points of the independent variable lie on or above that straight line, taking square roots or logarithms of the independent variable values may promote linearity.

If the assumption of equal variances or homoskedasticity for the dependent variable is correct, the plot of the observed dependent variable values against the independent variable should suggest a band across the graph with roughly equal vertical width for all values of the independent variable. That is, the shape of the graph should suggest a tilted cigar and not a wedge or a megaphone.

A fan pattern, like the profile of a megaphone, with a noticeable flare either to the right or to the left in the scatterplot, suggests that the variance in the values increases in the direction where the fan pattern widens (usually as the sample mean increases), and this in turn suggests that a transformation of the dependent variable values may be needed.

Life-Cycle Cost

In developing a cost estimate, we first must understand a program's or project's life cycle. A life cycle follows the project or program from its inception to its disposal, or "cradle to grave." It includes "the various stages of activity or phases through which the project progresses on its way from beginning to completion" (Rendon & Snider, 2008, p. 3). The life cycle starts at a program's development, flows through its production, operation, and maintenance, and finally concludes after proper disposal. The costs associated with this process are classified as the program's life-cycle cost (LCC).

The Defense Acquisition University defines *life-cycle cost* as the direct cost of the acquisition program, as well as the indirect cost that can be logically attributed to the program over the entire life cycle (DAU, n.d.-b). It includes the cost to the government to "acquire, operate, support (to include manpower), and where applicable, dispose" of a system or program (DAU, n.d.-b). There are multiple stakeholders in the DoD, such as Congress, the program manager and office, and contractors, that view a program's life-cycle cost from different perspectives. These multiple perspectives have led to three different methods of breaking down and displaying LCC.

The first method is breaking down program life-cycle costs by five different appropriation categories (DAU, n.d.-b): Research, Development, Test, and Evaluation (RDT&E); Procurement; Operations and Maintenance (O&M); Military

Construction (MILCON); and Military Personnel (MILPERS). This method is used to develop and submit budget requests to Congress (DAU, n.d.-b).

However, program managers and program offices would not find the first method as useful as Congress does. Instead, they utilize program life-cycle costs that are broken down by Work Breakdown Structure (WBS; DAU, n.d.-b). The DAU describes a *Work Breakdown Structure* as a framework that displays "the total system as a product-oriented family tree composed of hardware, software, services, data, and facilities" (DAU, n.d.-b). The WBS relates all of the work elements to each other and eventually to the final product (DAU, n.d.-b). A WBS encompasses all of the work necessary to produce a product (Huynh & Snider, 2008). This breakdown shows the relationship between costs and different elements of a system, which is a useful tool for program managers and contractors.

The Office of the Secretary of Defense (OSD) for Cost Assessment and Program Evaluation (CAPE) outlines the third display method in their *Operating and Support Cost-Estimating Guide* (DoD, 2014). OSD-CAPE defines a program's *life-cycle cost* as the summation of four different cost categories or phases: Research and Development (R&D), Investment, Operating and Support, and Disposal. Figure 3 provides a graphical representation of the four cost categories over a program's life cycle.

R&D is the initial cost category or phase in a program's life cycle. These costs are the first incurred in the research, design, and development of a new system or program. They can also include the "system design and integration; development, fabrication, assembly, and test of hardware and software for protypes and/or engineering development models" (DoD, 2014, pp. 2–3).

Following R&D is the investment cost category. These costs are incurred from "procurement and related activities from the beginning of low rate initial production (LRIP) through completion of deployment" (DoD, 2014, pp. 2–3). *Low rate initial* *production* refers to the production of the minimal number of a product or system that is required for initial operational test and evaluation (IOT&E; DAU, n.d.-c). Investment costs can include program management, initial spares, technical publications, and equipment training (DoD, 2014).

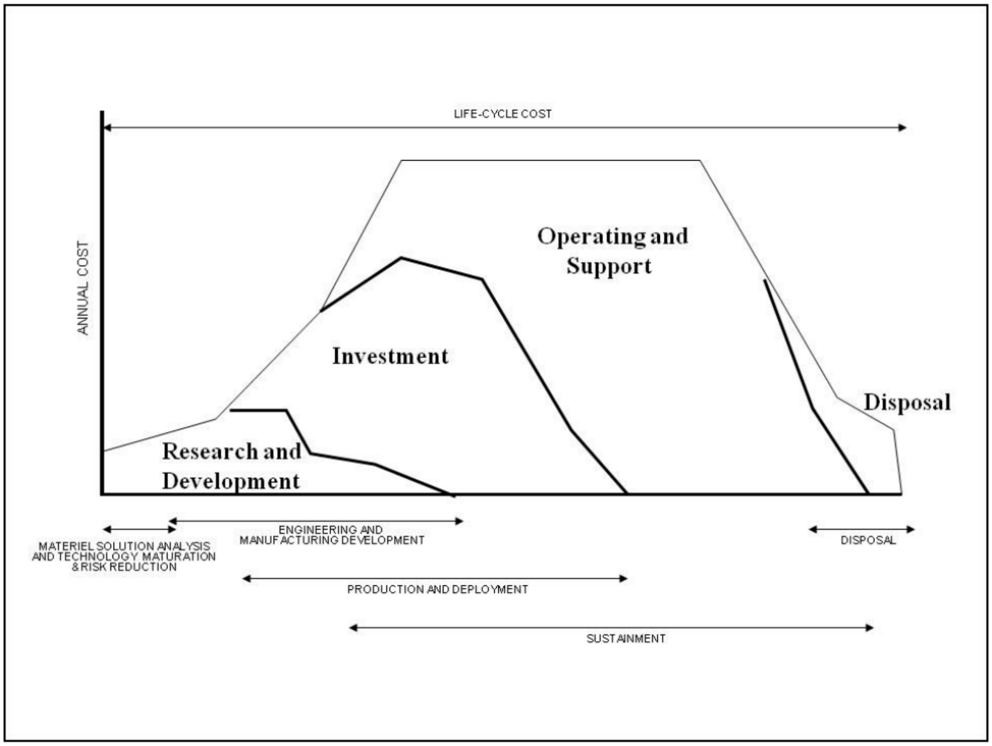


Figure 3. Notional Profile of Annual Program Expenditures by Major Cost Category over the System Life Cycle. Source: OSD CAPE (DoD, 2014).

The Operating and Support (O&S) phase is the third phase in the OSD-CAPE definition of LCC. The O&S phase normally accounts for a majority of a project's life-cycle costs (DoD, 2014). O&S consists of all of a system's operation and sustainment cost from initial deployment to the end of its operational life. This includes all the costs associated with "operating, maintaining, and supporting a fielded system" (DoD, 2014, pp. 2–3). Specifically, costs can include "personnel, equipment, supplies, software, and services associated with operating, modifying, maintain, supplying, and otherwise supporting a system" (DoD, 2014, pp. 2–3).

The fourth and final OSD-CAPE cost category is disposal. Disposal costs are those associated with the proper disposal or demilitarization at the end of a system's operational life (DoD, 2014). These costs can include "disassembly, materials processing, decontamination, collection/storage/disposal of hazardous materials and/or waste, safety precautions, and transportation of the system to and from the disposal site" (DoD, 2014, pp. 2–5). However, disposal costs can also be incurred during the sustainment phase due to unplanned system losses. (DoD, 2014). We revisit this method of life-cycle costing in our discussion of total ownership costing.

Department of Defense Acquisition Process

To comprehend how life-cycle costs and cost estimations are used in the DoD, we first must have a basic understanding of the DoD acquisition process. One version of the *DoD Directive 5000.01* defines the purpose of the acquisition process as the ability to "acquire quality products that satisfy user needs with measurable improvements to mission capability and operational support, in a timely manner, and at a fair and reasonable price" (DoD, 2007, p. 3) In acquiring a new system or program, the DoD uses the Defense Acquisition System (DAS), which is defined in *Directive 5000.01* as a "management process by which the Department of Defense provides effective, affordable, and timely systems to the users" (DoD, 2007, p. 2). However, the DAS is not the only part of the acquisition process. It is used in conjunction with two other DoD decision support systems (Ambrose, 2017a): The Joint Capabilities Integration and Development System (JCIDS) and the Planning, Programing, Budgeting, and Execution process (PPBE). These support systems identify and document the operational requirements or needs and guide the program's financing process. We are providing a brief overview of both support systems because they are fundamental to the overall DoD acquisition process.

Dealing with identifying, assessing, and prioritizing military operational requirements, JCIDS represents the foundation of the defense acquisition program process. It uses a top-down approach stemming from the National Military Strategy and flows into joint concepts and joint capabilities. The Defense Acquisition University describes the process as a “collaborative effort that uses joint concepts and integrated architectures to identify prioritized capability gaps and integrated doctrine, organization, training, material, leadership and education, personnel, and facilities (DOTmLPF) solutions (materiel and non-materiel) to resolve those gaps” (DAU, n.d.-a). The JCIDS process starts with the identification of an operational capability gap and the requirements needed to fill the associated gap. This can be achieved through a capabilities-based assessment (CBA) and two different potential solutions: materiel or non-materiel (DAU, n.d.-a). If a materiel solution is decided on, then the DoD acquisition process proceeds. As an example, if a commander discovers their Sailors are unable to combat a new threat with the ship’s current systems, a capability gap has been identified. The DoD will address this gap and the need for a solution through the JCIDS process. If the solution is a new or updated system, then a new program will be developed through the defense acquisition process. Once the need for a new system or program has been identified, we can transition to the financing side of the acquisition process.

The Planning, Programming, Budgeting, and Execution process (PPBE) is the second acquisition support system. The DAU defines the PPBE process as the DoD’s “internal methodology used to allocate resources to provide capabilities deemed necessary to accomplish the Department’s missions” (DAU, n.d.-d). The process focuses on how resources are allocated in the DoD to support both current and future acquisition programs, more specifically, on how the DoD finances those programs. The PPBE process is broken down into four phases.

In the first phase, planning, the required capabilities to support and complete the missions outlined in the national policy are developed. This phase produces the Joint Programming Guidance (JPG), which provides guidance and establishes priorities for the Program Objective Memorandum (POM; Candreva, 2008). However, the JPG does not account for any fiscal constraints. The next phase in the PPBE process is programming. This phase entails applying fiscal constraints to the objects produced in the planning phase and results in the production of the POM, which outlines the plan for the allocation of funding to programs (Candreva, 2008). The third part of the PPBE process in the budgeting phase. The goal of this phase is converting the information contained in the POM into the budget format required by Congress and Office of Management and Budget (OMB; Candreva, 2008). The budget outlines what the money is for, why it is needed (justification), and the monetary amount. The budget represents a request for spending authority. The appropriations from Congress grant that authority and give the power to obligate funds from the U.S. Treasury to an objective (Candreva, 2008). After the Authorization and Appropriations Bill has been signed, we can enter the execution phase, the fourth phase of the PPBE process (Candreva, 2008). Execution refers to the act of exercising the authority granted by the appropriation or the spending of the money (Candreva, 2008). The PPBE is an important part acquisition process. Without the “funding” piece, the DoD would not be able to acquire the new programs and systems that have been identified as a “need” through the JCIDS process.

Now that the two support systems, JCIDS and PPBE, have identified capability need and established program funding, we can turn to the DAS. The DAS is governed by the DoD’s Instruction 5000 series, which provides policy and principles, as well as a foundation of management for the DAS. The DAS serves a five-phase framework for defense acquisition programs. It takes the capability need identified through the JCIDS process and develops it into a working system. The process follows the system from the program’s conception, through its operational phase, and ends with its disposal. Figure 4 from the older version of *DODI 5000.02* (DoD, 2015) shows the DAS process for a hardware-intensive product.

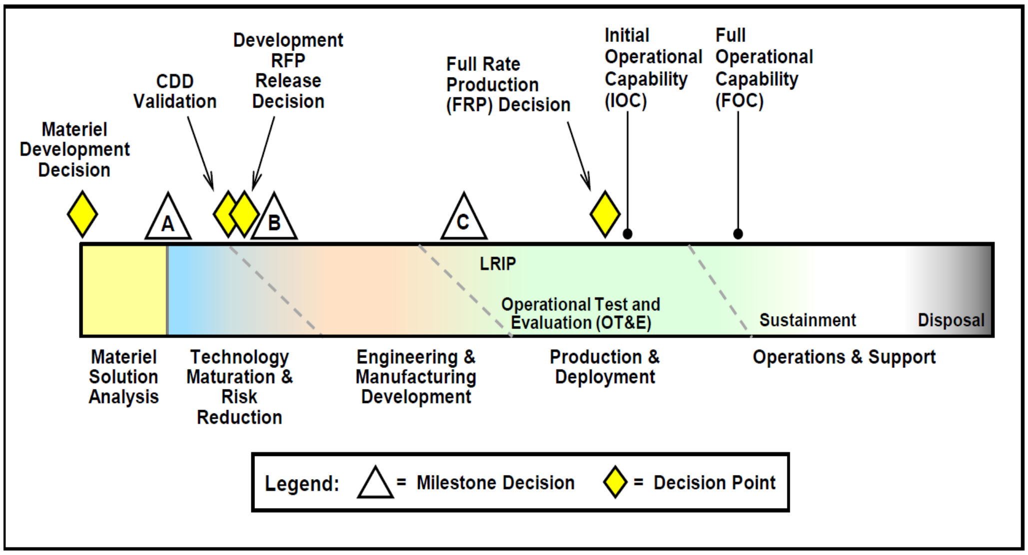


Figure 4. Hardware-Intensive DAS. Source: DoD (2017).

Material Solution Analysis (MSA) is the first phase of the DAS. *DODI 5000.02* describes the MSA's purpose as "conduct[ing] the analysis and other activities needed to choose the concept for the product that will be acquired, to begin translating validated capability gaps in system-specific requirements" (DoD, 2017, p.18). This phase takes the identified capability gaps and needs from the JCIDS process and translates them into the requirements for the desired acquisition. Then numerous technologies are analyzed and evaluated to determine which one best fulfills those needs and requirements (Ambrose, 2017b).

The second phase of the DAS is Technology Maturation and Risk Reduction (TMMR). The purpose of this phase, as defined by DAU, is "to reduce technology, engineering, integration, and life-cycle cost risk to the point that the decision to contract for Engineering and Manufacturing Development (EMD) can be made with confidence for the successful program execution of development, production, and sustainment" (DAU, n.d.-e). The goal of this phase is to reduce the risks associated with the product that will be developed (DoD, 2017).

Following the TMMR phase, the process enters the EMD phase of the DAS. The goal of this phase is to develop, build, and test a product in order to verify that all the operational and other requirements have been fulfilled (DoD, 2017). The hardware and software designed are being completed and prototypes are built during this phase. These prototypes will undergo a Developmental Test and Evaluation (DT&E) to verify that the capability requirements have been met (DoD, 2017). These results will support the decision to enter into the next phase.

Production and Development (P&D) is the fourth phase of the DAS. The purpose of this phase is “to produce and deliver requirements-compliant products to receiving military organizations” (DoD, 2017, p. 30). In this phase, the product undergoes testing, including Operational Test & Evaluation (OT&E), to verify that the product meets the operational requirements before full production and deployment (DoD, 2017). After successful testing, the product can be produced and then fielded for use by operational forces. The phase also encompasses low rate initial production, limited deployment, full-rate production decision, and eventually full-rate production and deployment (DoD, 2017).

The last phase of the DAS is Operation and Support (O&S). Its purpose is to “execute the product support strategy, satisfy materiel readiness and operational support performance requirements, and sustain the system over its life cycle (to include disposal)” (DoD, 2017). The phase consists of two main stages, sustainment, and disposal. Sustainment continues the full-rate production, deployment, and operational support of the product throughout its life (DoD, 2017). This phase also includes proper disposal at the end of the product’s operational life, at which time it will be “demilitarized and disposed of in accordance with all legal and regulatory requirements” (DoD, 2017, p. 32). After a product’s disposal, the DAS is complete.

Cost Estimation in the Department of Defense

Cost estimation is an important and required tool used by decision-makers in defense acquisitions. The requirement for a cost estimation is outlined in the *Department of Defense Instruction 5000.02, Operation of the Defense Acquisition System*. Specifically, the instruction mandates that the

> DoD Component will develop a DoD Component Cost Estimate that covers the entire life cycle of the program for all Major Defense Acquisition Programs (MDAPs) prior to Milestone A, B, and C reviews and the Full-Rate Production Decision; and for all Major Automated Information System (MAIS) programs at any time an Economic Analysis is due. (DoD, 2017, p. 135)

This means that before the acquisition process can move beyond the MSA, TMRR, and EMD phases and ultimately continue on to full production, a cost estimate encompassing the entire program life cycle must be produced. In addition to the DoD's Component Cost Estimate, a separate, independent cost estimate is also required. *DODI 5000.02* requires the Milestone Decision Authority to consider an "independent estimate of the full life-cycle cost of a program, prepared or approved by the Director of Cost Analysis and Program Evaluation (DCAPE)" (DoD, 2017, p. 135). The DoD Component and DCAPE cost estimates are typically classified as Life-Cycle Cost Estimations (LCCEs). Mislick and Nussbaum (2015) describe an LCCE as a "a cost estimate for the totality of the resources that will be necessary throughout the product's life cycle" (p. 18).

There are four main cost estimating techniques used in the DoD to develop an LCCE, and they can be used in different phases of a program's life cycle (Ambrose, 2017a). The first method is parametric cost estimating and involves the use of statistical inferences to generate an estimate based on system performance and design (Ambrose, 2017a). Using historical data from similar systems, cost estimation relationships (CERs) and patterns are identified. Those patterns are assumed to hold true in the future and are used to predict cost (Mislick & Nussbaum, 2015). The second method is analogy cost estimating, whereby a new system is compared to a similar existing system. The analogy method is a relatively quick and inexpensive method; however, it may not be as precise as other methods (Ambrose, 2017a). The parametric and analogy methods are normally used early on in the acquisition process during the MSA, TMMR, and EMD phases (Ambrose, 2017a). The third and most time-consuming method is engineering cost estimation. In this method, the system is broken down into its WBS elements in which individual detail estimates are conducted. These estimates are then summed together to create the overall estimate (Mislick & Nussbaum, 2015). The engineering method is used during the TMRR phase and through the remaining acquisition process (Ambrose, 2017a). The last main method used by the DoD is actual costing. This method uses the actual costs from a system that were incurred in the past to predict the cost of producing that system in the future (Ambrose, 2017a). This method can be used after a program has entered the P&D phase.

Total Ownership Cost

While LCCEs are a useful tool for decision-makers, they present a narrower scope when a broader perspective may be more beneficial (Kobren, 2014). Thus, we introduce the concept of total ownership cost (TOC). The DAU defines *total ownership cost* as including the "elements of life-cycle cost as well as other infrastructure or business process costs not normally attributed to the program" (Kobren, 2014). Infrastructures refers to "all military department and defense agency activities that sustain the military forces assigned to the combatant and component commanders" (Kobren, 2014). The major infrastructure categories are support to equipment, support to military personnel, and support to military bases (Kobren, 2014). Not normally included in a traditional LCCE, other support activities to consider in a cost estimate are recruiting, environmental and safety compliance, management headquarters functions, and logistics infrastructure activities (Kobren, 2014).

DoD Directive 5000.01 states that

> DoD Components shall plan programs based on realistic projections of the dollars and manpower likely to be available in future years. To the greatest extent possible, the MDAs shall identify the total costs of ownership, and at a minimum, the major drivers of total ownership costs. (DoD, 2007)

This requires the DoD to expand beyond the basic life-cycle cost estimation and include the support activities and infrastructure costs. To support the DoD directive, the Department of the Navy (DoN) issued its *Total Ownership Cost (TOC) Guidebook* in which it describes "new departmental and naval processes" that support the DoD policy of the identification of total costs of ownership (DoN, 2014, p. 6). Specifically, the guidebook assists the DoN and its organizations in developing, understanding, and applying the TOC requirements of the DoD.

The DoN outlines the importance of TOC: "As the DoD (and Navy) funding remains constant or declines, and as Navy's purchasing power declines as a result, increasing the decision weight priority for alternatives that can mitigate and reduce TOC becomes our clearest path to a capable an optimally affordable Fleet" (DoN, 2014, p. 8). For this reason, we focus on our model on TOC instead of a standard life-cycle cost.

Risk and Uncertainty

A key point that we need to understand in cost estimating is that the future is uncertain. Therefore, an essential pillar in developing a defensible and credible cost estimate is ensuring that risk and uncertainty are incorporated. A cost estimate can be severely affected by factors such as technological maturity, schedule slips, software requirements, or any other unforeseen event (Mislick & Nussbaum, 2015). Unknown factors make any "point estimate" or any exact answer extraordinarily unlikely (Mislick & Nussbaum, 2015). A more accurate estimate uses a central tendency centered on the original point estimate and a range both higher and lower to define the bounds of the estimate.

Though similar and related, risk and uncertainty are not synonymous. In the simplest terms, *risk* is the "probability" of the occurrence of a negative or unfavorable event, while *uncertainty* is the lack of certainty, or the realization that definitively knowing the outcome of any future event is completely impossible (Mislick & Nussbaum, 2015). Unlike risk, with uncertainty we are not able to predict the possibility of any future outcome. In Dr. Johnathan Mun's book, *Readings in Certified Quantitative Risk Management (CQRM),* he states,

> The concepts of risk and uncertainty are related but different. Uncertainty involves variables that are unknown and changing, but uncertainty will become known and resolved through the passage of time, events, and action. Risk is something one bears and is the outcome of uncertainty. Sometimes risk may remain constant while uncertainty increases over time. (Mun, 2015, p. 28)

A good way to think about risk and uncertainty is to imagine going on a sky diving trip with a friend. As the plane takes off, you and your friend realize that there is only one parachute and that parachute is looking like it is somewhat past its service life. Your friend, being slightly more adventurous than you, decides to grab the parachute and take the jump. Both you and your friend share the same level of uncertainty about whether the parachute will open, and if your friend will live to tell the story. However, only your friend will assume the risk of jumping out of the plane and falling to his death.

Though better than ignoring risk altogether, incorrect treatment of risk can significantly affect the estimate. Cost-estimating risk, schedule or technical risk, requirements risk, and threat risk are the four types of risk that will play a factor in the cost estimation for a life-cycle cost. Cost-estimating risk is the risk attributed to cost estimating error and uncertainty due to the numerical methodology used (Mislick & Nussbaum, 2015). Next, schedule or technical risk is the risk associated with the inability to accomplish schedule or technical objectives of the design or current specification, which stretches the timeline of the program completion (Mislick & Nussbaum, 2015). Requirements risk is the risk of the original requirements being shifted due to shortfalls in the original requirements documentation or due to the current design failing to complete the requirement. The final category, threat risk, is the risk of a new unforeseen threat due to a complete change in the original problem (Mislick & Nussbaum, 2015).

Even after a cost estimator does due diligence in looking at historical data, and normalizing data to build an analogy, parametric, engineering, or actual estimate, the multiple sources of uncertainty can still play a large factor in the estimate. Consider Figure 5 on the simplest way to take data and produce a cost estimate. Because cost estimators do not have a magic ball that they can use to tell the exact future, they must use assumptions.

Electro-Optical Infrared Sensors

Electro-optics (EO) are the field systems that convert electrons into photons (Driggers et al., 2012). These systems are designed to respond to wavelengths within the 0.4–.07 micrometer wavelength (Driggers et al., 2012). These systems deliver images that are analogous to human vision; some EO systems are even capable of processing the near or short infrared spectral region (Driggers et al., 2012). Figure 5 shows the basic components of an EO/IR sensor system.

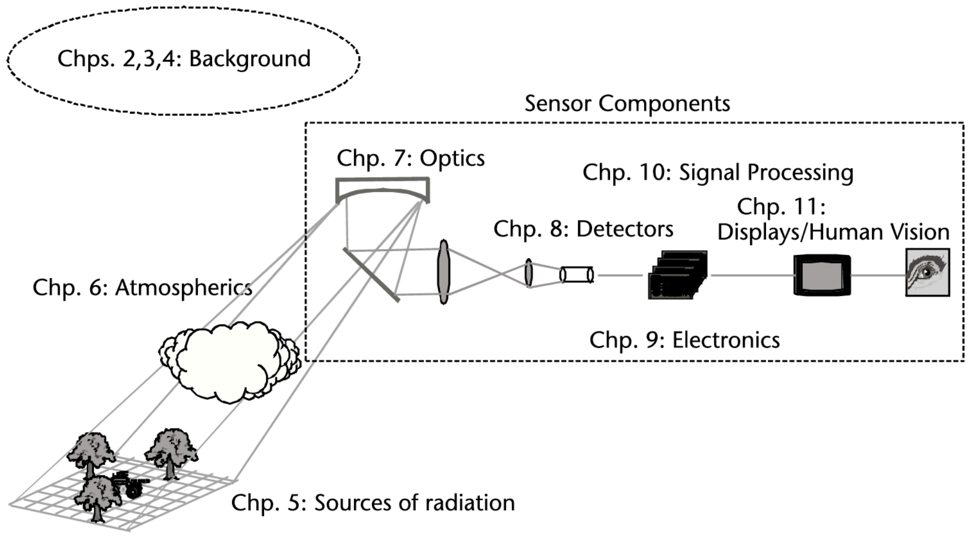


Figure 5. EO and IR Sensors. Source: Driggers et al. (2012).

The term *target* is used to describe the desired image that we are looking for with an EO sensor. The signal from a target usually has a large reflective component typically in the EO wavelength band. The target is provided this reflective component by moonlight, starlight, sunlight, or any artificial light source (Driggers et al., 2012). The light sources reflecting off of the background and the target are known as external radiation. Radiation reflected by targets and background does not go directly to the EO sensor. The reflected radiation must first transition through the atmosphere, where it experiences scattering, before being processed by the EO sensor (Driggers et al., 2012). Scattering is a phenomenon where particles in the atmosphere such as smoke, smog, or mist interfere with the reflection. Once the reflected radiation meets the EO sensor, it is passed through the sensing element, which could be detectors, tubes, or image intensifiers (low light situations) (Driggers et al., 2012). Next, the output of the sensor element is digested by the electronics and sent to a human interface for the operator (human) to gather some information from the process. This information could take a myriad of shapes such as detection, recognition, or identification of targets such as a warship. In short, EO sensors are essentially products of the light reflected from the scene (Driggers et al., 2012). Figure 6 represents a typical EO sensor scenario.

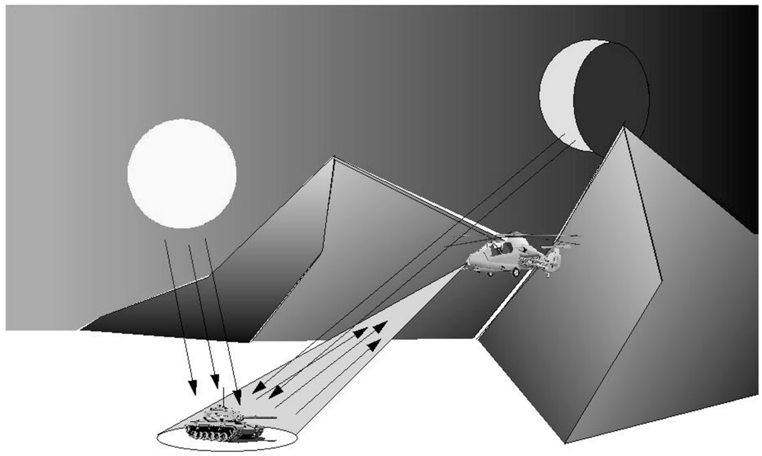


Figure 6. Typical EO Sensor Scenario. Source: Driggers et al. (2012).

Infrared is able to digest the spectral region from 0.7 to 14 micrometer wavelengths. Infrared is divided into four subregions:

> The near-infrared (NIR) region is from 0.7 to 1.1 mm, the short-wave infrared (SWIR) region is from 1.1 to 3 mm, the midwave infrared (MWIR) region is from 3 to 5 mm, and the long-wave infrared (LWIR) region is from 8 to 14 mm. Infrared is primarily used in night operations. (Driggers et al., 2012)

The science of infrared is based on the science supporting Planck's law, which states that all bodies above the temperature of absolute zero emit electromagnetic radiation. The electromagnetic radiation is exploited to uncover the electromagnetic signatures given off that do not correlate to the wavelengths visible by the human eye or EO sensors.

> As the temperature of the object gets hotter, the peak wavelength moves to shorter wavelengths so that at very hot temperatures the radiation is perceived by the eye as light. The emissive surface

> characteristics of the hot object determine the spectral emission weighting of the radiation. The radiation emitted travels through the atmosphere, where it will then meet the aperture of the sensor. (Driggers et al., 2012, p. 7)

Most IR sensors provide situational awareness for very low light situations such as night vision, surveillance of low-lit areas, and navigating through smoke-filled compartments (Driggers et al., 2012). Figure 7 shows the basics of an infrared sensor scenario.

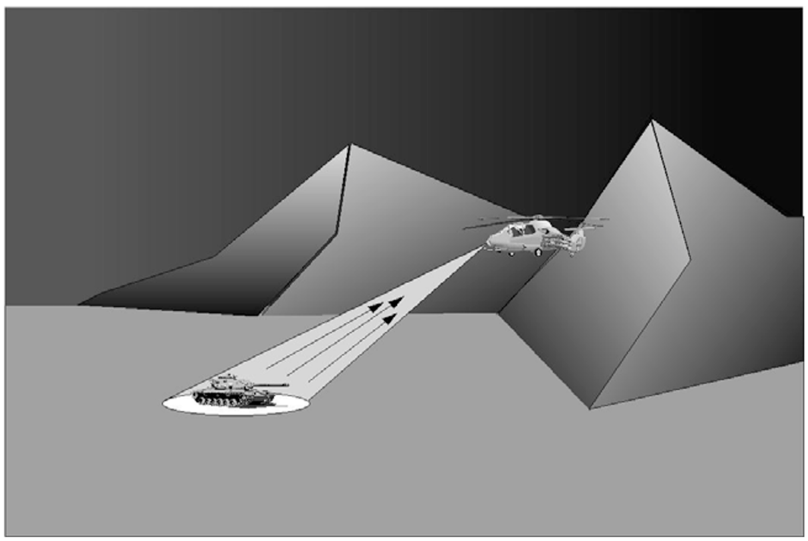


Figure 7. Typical IR Sensor Scenario. Source: Driggers et al. (2012).

The design of and EO and/or IR imaging is very dependent on the purpose of the sensor, and the performance of the system is predicated on the functions of the wavelength (Driggers et al., 2012). Factors such as the characteristics of the scene and the atmosphere will determine the quality of the image obtained by the sensor. For EO sensors, the largest factor is reflectivity, or how much of the external radiation from the scene is going to make it back to the sensor (Driggers et al., 2012). For IR sensors, the question is far more focused on the emissivity of the target or how much electromagnetic radiation the target creates that will get back to the sensor (Driggers et al., 2012).

EO/IR Sensors on Surface Ships

Before the advent of electro-optics, direct optics were a commander's main resource in support of tactical decision-making. Binoculars, stadimeters, and periscopes were the keys to situational awareness and obtaining fire control solutions for torpedoes and gun engagements (Davidson, 2015). With the invention of EO, warfighters are no longer restricted to the limitations of the human eye. The application of using television cameras and the discovery of light-sensitive semiconductor materials allow images to be converted into electrical signals that are fed into displays for humans to process information. EO sensors paired with the ability of infrared detection allow warfighters to discern a target in the most vast and unlit environments (Davidson, 2015).

In Stefan Nitschke's (2007) article "New Generation Naval Electro Optics," he states, "Electro Optical/Infrared technology is an invaluable aid for the 21st century battlespace arena. It provides surface warships, submarines, and maritime aviation operating in the varying naval environment with extensive image gathering, navigational, and targeting capabilities" (p. 87). The constant advances in EO/IR systems have developed sensors with integral lasers that are used to measure distances with extreme accuracy and are a fraction of the size of the range finders of legacy ships (Davidson, 2015). In the report given by the Institute of Defense Analyses entitled *A Tutorial on Electro-Optical/Infrared (EO/IR) Theory and Systems*, it is stated that "the performance of an EO/IR sensor depends on the optics, detector, display, target-background contrast and the intensity of the illumination source" (Koretsky et al., 2013, p. 5)

Technological advances have emphasized the importance of the opportunity and the necessity to re-invest in the newest technologies and systems. These advances in technology will drive future EO/IR systems purchases by the DoD. These system acquisitions will require credible and reliable cost estimations to ensure the DoD manages its budget effectively. With the complexity and uniqueness of EO/IR systems, an efficient cost estimation model is needed to account for all life-cycle costs. The additional aspect of uncertainty should also be considered in the estimation. The cost estimation model we are proposing considers total ownership costs and uncertainty for the acquisition of EO/IR systems for U.S. Navy surface ships. This model will serve as a proof of concept to help future DoD decision-makers understand the cost associated with EO/IR systems so they can make strategic investments.

Total Ownership Cost Model Overview

In standard life-cycle-based TOC analysis, a basic set of assumptions includes that there are significant acquisition costs prior to the system being operational, usually denoted as Year 0, followed by subsequent operational years (e.g., Year 1 to Year 10 in Figure 8), where O&M costs apply. In the last year of operations, additional disposition or salvage costs may be incurred to either dispose of the system or render it inoperable (e.g., Year 10 in Figure 9). Furthermore, the total costs can be computed as a simple summation of all expenses incurred and to be incurred throughout the life cycle of the system. Conversely, applying economic theory, these costs can be *discounted* annually at some prespecified discount rate to account for the time value of money (i.e., a dollar tomorrow is not equivalent in purchasing power to a dollar today, due to various factors such as economic growth rates, purchasing power parity, inflation, and interest rates, as well as opportunity cost of holding money). Finally, the O&M costs may be themselves subject to changes over time (e.g., due to inflationary pressures, budgetary cutbacks, periodic technology insertions, cost inflation, and the like), and the model allows for such manual adjustments.

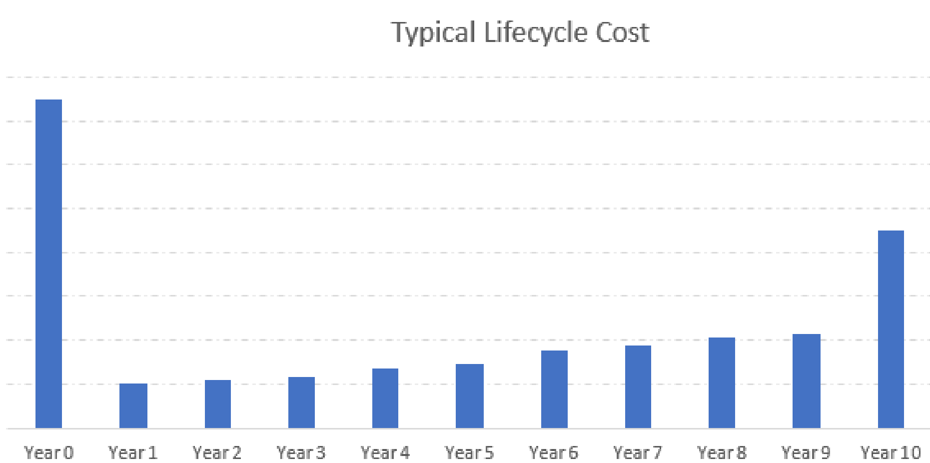


Figure 8. Typical Life-Cycle Cost Over Time

We assume that the reader is somewhat familiar with the basics of Microsoft Excel and understands the rudiments of Monte Carlo simulations to capture the future uncertainties of the cost structure. While this current section discusses the basics of the model, the next section covers the basic applications of Monte Carlo simulation techniques. Note that Risk Simulator does not have to be used in the model to obtain reasonable results. It is only used when uncertainty or risk analysis needs to be applied in the model, and when Monte Carlo simulations are applied to obtain the empirical probability distributions of the results.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1			*Name:*	**System A**			*Discount Rate:*	3.00%		*Economic Life:*	20 Years					
2		Select Uncertainty Range: Use Small +/- 5% Range	*Notes:*													
3			*Annual Growth or Decline Curve:*			1.50%										

	Categories	Number of Units per System	Number of Platforms	Acquisition Cost (Unit)	%	Operational Costs (Unit) Per Year	%	Maintenance Per Year	%	Replacement Per Year	%	Total Acquisition Cost	%	Total Annual O&M	%
5	**Grand Total**			**$125.00**		**$125.00**		**$125.00**		**$125.00**		**$125.00**		**$375.00**	
6	**Narrow-Medium Field of View (NFOV) Sensors**	**17**	**17**	**$17.00**	**13.6%**	**$17.00**	**13.6%**	**$17.00**	**13.6%**	**$17.00**	**13.6%**	**$17.00**	**13.6%**	**$51.00**	**13.6%**
7	NF-DIR (NFOV Director)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
8	NF-TIS (Thermal Imaging Sensor) - TIS #1	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
9	NF-TIS (Thermal Imaging Sensor) - TIS #2	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
10	NF-EOS (Electro-Optic Sensor) - EOS #1	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
11	NF-EOS (Electro-Optic Sensor) - EOS #2	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
12	NF-EOS (Electro-Optic Sensor) - EOS #3	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
13	NF-LRF (Laser Rangefinder)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
14	NF-LDR (Laser Designator/Rangefinder)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
15	NF-LDRFI (Laser Designator/Rangefinder/Illuminator)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
16	NF-LP (Laser Pointer)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
17	NF-LOI (Laser Optical/Ocular Interrupter)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
18	NF-LI (Laser Illuminator)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
19	NF-IRU (Inertial Reference Unit)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
20	NF-BSM (Boresight Module)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
21	NF-EU (Electronics Unit)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
22	Ancillary Material (cabling, mounting hardware, etc.)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
23	Other: ___________	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
24	**Wide Field of View (WFOV) Sensors**	**7**	**7**	**$7.00**	**5.6%**	**$7.00**	**5.6%**	**$7.00**	**5.6%**	**$7.00**	**5.6%**	**$7.00**	**5.6%**	**$21.00**	**5.6%**
25	WF-DIR (Director)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%
26	WF-TIS (Thermal Imaging Sensor)	1	1	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$1.00	0.8%	$3.00	0.8%

Figure 9. Input Worksheet

Figure 9 illustrates the first two dozen rows of the model while Figures 10 and 11 show the last two dozen rows of the model. The following list provides additional clarity and guidance to this worksheet:

- The Excel file has five worksheets (Systems A–E) where each worksheet is meant for a different system, or one of these can be set as the current or baseline system. If additional systems need to be included for analysis, we recommend creating a new file (simply perform a File | Save As to create a duplicate file).

- The figures in this document show a sample dataset where all unit and dollar inputs are set to 1 or $1, respectively. This was done intentionally to illustrate the location of data entry cells as well as to have some sample results to show how the model works. You can access the same results either by manually entering these unitary values or by opening the associated "TOC Model—Example Only (Repeated Data and Locked Sheets).xlsx" file to follow along.

- Row 1 is where you enter the name of the system. You can enter the system name in cell D1. Then, enter any discount rate value ≥ 0%. The discount rate is used to calculate the present value of all future cash flows. Use 0% if no present valuation is needed, or enter the annualized cost of money (e.g., from 3% for inflationary adjustments only to 15% to account for risks and reinvestment opportunity costs of the cash flows). Also, here you can select the economic or operational life of this current system. These inputs can be unique for each of the five systems under analysis.

- Row 2 allows you to select the uncertainty range on which to perform risk-based Monte Carlo simulations. You can select to not run any simulations, a small ±5% range, standard ±10% to ±20% range, wide ±25% to ±40%, or a highly uncertain ±45% to ±50% range. These ranges will be automatically computed and applied as probability distributions on the inputted costs (see the following bullet points) in order to run simulations. There is also a section where you can enter notes about the system under analysis (cells D2:O2).

- Row 3 allows you to enter an annual positive growth rate or an annual negative decline rate to be applied to the O&M over time, starting in the second year. This allows the user to increment the O&M over time or perform a similar reduction in costs over the lifetime of the system.

- The data input grid starts from row 6 to row 187, around columns B to P. All *white colored cells with borders* are user input cells. You can also make modifications to subsection headers (e.g., rows 6, 24, etc.) and line item titles (e.g., cells B7:B23). The subsections and line item titles are generic inputs and can be changed as required. There is also an “Other:” line item that can be used as required.

- Because the model has been structured to run simulations and other advanced analytics, it is highly recommended that the user does not make any structural adjustments and modifications (i.e., please do not delete worksheets or insert rows and columns unnecessarily). Also, the model has been optimized for printing and any major modifications will muddle the printing capabilities.

- The number of units per system and number of platforms (columns C and D) have to be ≥ 0 and are self-explanatory. The acquisition cost, operational cost, maintenance per year, and replacement per year are on a per unit basis. If you wish to enter the total replacement cost for the year, first take that value and divide it by the product of units with the number of platforms to obtain a per unit cost. Enter only per unit costs. Continue data entry until row 145.

- All grayed-out cells are computed values and should be left alone. If you wish to audit the calculations, first unlock/unprotect the worksheet and then select a cell to view its calculations.

- Area B147: D177 looks at nonrecurring costs to the acquisition process of this current system. All acquisition costs are summed and set as today’s (Year 0) cost.

- Area B179:D187 looks at the nonrecurring end of life or disposition costs. These costs will be incurred at the end of the selected economic life (droplist circa cell K2), and will be discounted appropriately based on the discount rate and term of life selected.

- Replicate the data entry described here for up to five systems as required. If fewer than five systems are needed, simply ignore the unused worksheets but remember not to delete them unnecessarily. If more than five systems are required, create a copy of the file, and apply these remaining systems as a separate file. Changing the structure of the file may invalidate some of the preset simulation models and assumptions.

	B	C	D
147	**Nonrecurring Acquisition and End of Lifecycle Costs**	**Total**	**%**
148	**Acquisition and Procurement**	**$29.00**	
149	Bid Specifications Development	$1.00	3.4%
150	Proposal Evaluation	$1.00	3.4%
151	Data Collection	$1.00	3.4%
152	Data Analysis	$1.00	3.4%
153	Contracts Development	$1.00	3.4%
154	Program Planning	$1.00	3.4%
155	Hardware Purchases	$1.00	3.4%
156	*Personal Computers*	$1.00	3.4%
157	*Peripherals*	$1.00	3.4%
158	*Storage*	$1.00	3.4%
159	*Networking*	$1.00	3.4%
160	*Related Equipment*	$1.00	3.4%
161	Other costs	$1.00	3.4%
162	Administrative Cost	$1.00	3.4%
163	Asset Management	$1.00	3.4%
164	Overseeing Contractor Services	$1.00	3.4%
165	In-House Training for Staff	$1.00	3.4%
166	Product Maintenance	$1.00	3.4%
167	Help Desk Support	$1.00	3.4%
168	IT Support for Database Management	$1.00	3.4%
169	Network Management Support	$1.00	3.4%
170	Software Upgrades	$1.00	3.4%

Analysis Notes

Analysis Assumptions

Figure 10. Input Worksheet (Nonrecurring Acquisition Cost)

	A	B	C	D
179		**Nonrecurring End of Lifecycle Costs**	**Total**	**%**
180		**End of Lifecycle**	**$7.00**	
181		Administrative Cost	$1.00	14.3%
182		Asset Management	$1.00	14.3%
183		Vendor Contract Procurement	$1.00	14.3%
184		Staging, Sanitizing, Testing	$1.00	14.3%
185		Follow-Up Support	$1.00	14.3%
186		Recycling and Disposal Fees	$1.00	14.3%
187		Value of Sold Products and Materials	$1.00	14.3%

Figure 11. Input Worksheet (Nonrecurring End of Life-Cycle Cost)

Figure 12 illustrates the Monte Carlo simulations section. This table summarizes the sections of the costs and created simulation variables (cells in green). Figure 13 shows how these simulated results will be used to generate the life cycle of the cost structure of the system, where the economic life of the system is accounted for, as well as any required discounting to generate the present value of the costs. Simulation will perturb the cells in green (Figure 12), and as these are input assumptions, the subsequent calculations based on these inputs will simulate and change (Figure 13).

Note that, by default, 10,000 simulation trials have been set because triangular probability distributions were applied on each of the subtotaled cost items, and the process is modeled to run without any predetermined seed values.

Risk-Based Monte Carlo Simulation on Uncertainty Ranges

	Acquisition Cost (Low)	Acquisition Cost (Mid)	Acquisition Cost (High)	Simulation	Operations and Maintenance with Replacement Costs (Low) Per Year	Operations and Maintenance with Replacement Costs (Mid) Per Year	Operations and Maintenance with Replacement Costs (High) Per Year	Simulation
Narrow-Medium Field of View (NFOV) Sensors	$16.15	$17.00	$17.85	$17.00	$48.45	$51.00	$53.55	$51.00
Wide Field of View (WFOV) Sensors	$6.65	$7.00	$7.35	$7.00	$19.95	$21.00	$22.05	$21.00
EO/IR Sensor Manager (ESM)	$5.70	$6.00	$6.30	$6.00	$17.10	$18.00	$18.90	$18.00
Human Machine Interface (HMI)	$4.75	$5.00	$5.25	$5.00	$14.25	$15.00	$15.75	$15.00
Product Support Management	$8.55	$9.00	$9.45	$9.00	$25.65	$27.00	$28.35	$27.00
Design Interface	$10.45	$11.00	$11.55	$11.00	$31.35	$33.00	$34.65	$33.00
Supply Support	$11.40	$12.00	$12.60	$12.00	$34.20	$36.00	$37.80	$36.00
Support Equipment	$7.60	$8.00	$8.40	$8.00	$22.80	$24.00	$25.20	$24.00
Packaging, Handling, Storage and Transportation	$3.80	$4.00	$4.20	$4.00	$11.40	$12.00	$12.60	$12.00
Computer Resources	$5.70	$6.00	$6.30	$6.00	$17.10	$18.00	$18.90	$18.00
Manpower and Personnel	$5.70	$6.00	$6.30	$6.00	$17.10	$18.00	$18.90	$18.00
Maintenance Planning and Management	$14.25	$15.00	$15.75	$15.00	$42.75	$45.00	$47.25	$45.00
Training and Training Support	$7.60	$8.00	$8.40	$8.00	$22.80	$24.00	$25.20	$24.00
Facilities and Infrastructure	$3.80	$4.00	$4.20	$4.00	$11.40	$12.00	$12.60	$12.00
Technical Data Management	$6.65	$7.00	$7.35	$7.00	$19.95	$21.00	$22.05	$21.00
Acquisition Costs	$27.55	$29.00	$30.45	$29.00				
End of Life Disposition Costs	$6.65	$7.00	$7.35	$7.00				

Figure 12. Monte Carlo Uncertainty Simulation

	Q	R	S	T	U	V	W	X	Y	Z	AA
25		**Year**	**Acquisition**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	
26		**Cash Flow**	$154.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	
27		**Present Value of Cash Flow**	$154.00	$364.08	$358.78	$353.55	$348.40	$343.33	$338.33	$333.40	
28		**Year**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	
29		**Cash Flow**	$416.19	$422.43	$428.77	$435.20	$441.73	$448.36	$455.08	$461.91	
30			$328.55	$323.76	$319.05	$314.40	$309.82	$305.31	$300.86	$296.48	
31		**Year**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	
32		**Cash Flow**	$468.84	$475.87	$483.01	$490.25	$497.61	$505.07	$512.65	$520.34	
33			$292.16	$287.91	$283.72	$279.58	$275.51	$271.50	$267.55	$263.65	
34		**Year**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**Disposition**	
35		**Cash Flow**	$528.14	$536.06	$544.10	$552.27	$560.55	$568.96	$577.49	$7.00	
36			$259.81	$256.03	$252.30	$248.62	$245.00	$241.44	$237.92	$7.00	
37		**Total Acquisition Cost for System A**	$154.00								
38			5 Years	10 Years	15 Years	20 Years	25 Years	30 Years			
39		**List of Total Lifetime Cost for System A**	$2,093.10	$4,174.52	$6,416.80	$8,832.38	$11,434.63	$14,238.01			
40		**List of Present Value Lifetime Cost for System A**	$1,928.17	$3,570.42	$5,096.58	$6,514.85	$7,832.85	$9,057.68			
41											
42		**Total Lifetime Cost for System A (20 Years)**	$8,832.38	20 Years							
43		**Total PV Lifetime Cost for System A (20 Years)**	$6,514.85								

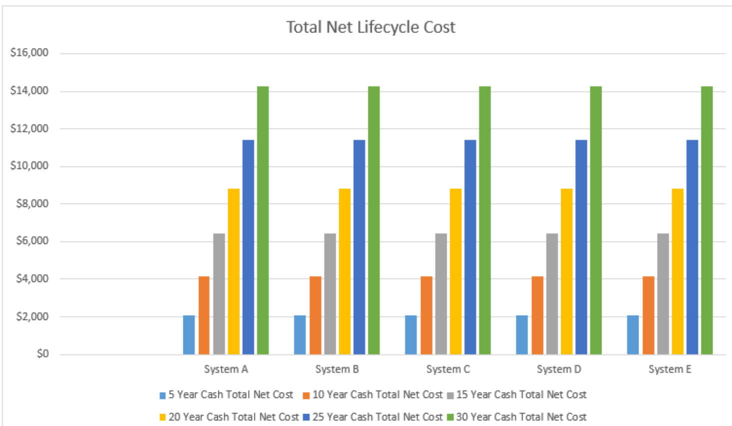
Figure 13. Life-Cycle Cost Cash Flow Calculations

In the summary worksheet, the total costs as well as present values of total costs for various economic and useful lives are tabulated (Figure 14). You can view the results as tables and charts. Here, a comparative cross-sectional analysis of alternatives assessment can be seen, and a growth of the costs can be seen in the charts. Note that these results and charts are single-point estimates and are calculated prior to any simulations.

Running the simulation will make changes to the cells in Figures 15 and 16 as previously discussed. If the other worksheets have populated inputs, these worksheets will also be run, and the results will be presented as probability distributions (Figure 17). Each system's calculated Total Cost and the Present Value of Total Costs will be shown (for the selected economic and useful life) as probability distributions and simulation statistics. Users can also perform comparative analysis by using Overlay Charts (bottom of Figure 17), generate reports of the statistical results (Figure 18), and run detailed reports of the analysis (Figure 19), as well as other analytics such as scenario analysis and sensitivity analysis.

Analysis Period/Type	System A	System B	System C	System D	System E
5 Year Cash Total Net Cost	$2,093.10	$2,093.10	$2,093.10	$2,093.10	$2,093.10
10 Year Cash Total Net Cost	$4,174.52	$4,174.52	$4,174.52	$4,174.52	$4,174.52
15 Year Cash Total Net Cost	$6,416.80	$6,416.80	$6,416.80	$6,416.80	$6,416.80
20 Year Cash Total Net Cost	$8,832.38	$8,832.38	$8,832.38	$8,832.38	$8,832.38
25 Year Cash Total Net Cost	$11,434.63	$11,434.63	$11,434.63	$11,434.63	$11,434.63
30 Year Cash Total Net Cost	$14,238.01	$14,238.01	$14,238.01	$14,238.01	$14,238.01

Analysis Period/Type	System A	System B	System C	System D	System E
5 Year Cash Cost in Present Values	$1,928.17	$1,928.17	$1,928.17	$1,928.17	$1,928.17
10 Year Cash Cost in Present Values	$3,570.42	$3,570.42	$3,570.42	$3,570.42	$3,570.42
15 Year Cash Cost in Present Values	$5,096.58	$5,096.58	$5,096.58	$5,096.58	$5,096.58
20 Year Cash Cost in Present Values	$6,514.85	$6,514.85	$6,514.85	$6,514.85	$6,514.85
25 Year Cash Cost in Present Values	$7,832.85	$7,832.85	$7,832.85	$7,832.85	$7,832.85
30 Year Cash Cost in Present Values	$9,057.68	$9,057.68	$9,057.68	$9,057.68	$9,057.68



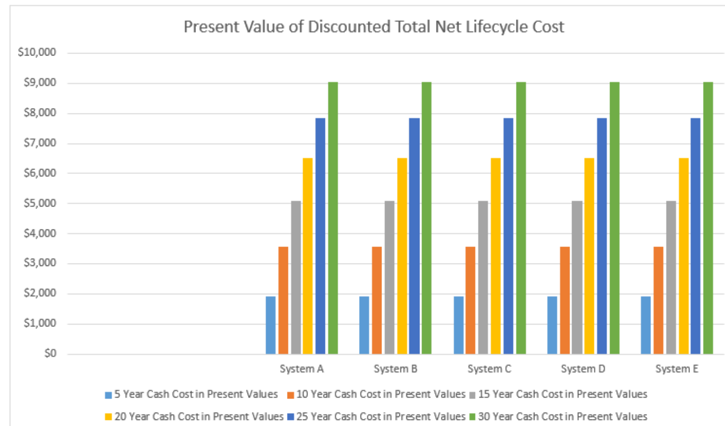


Figure 14. Life-Cycle Cost Cash Flow Results and Dashboard

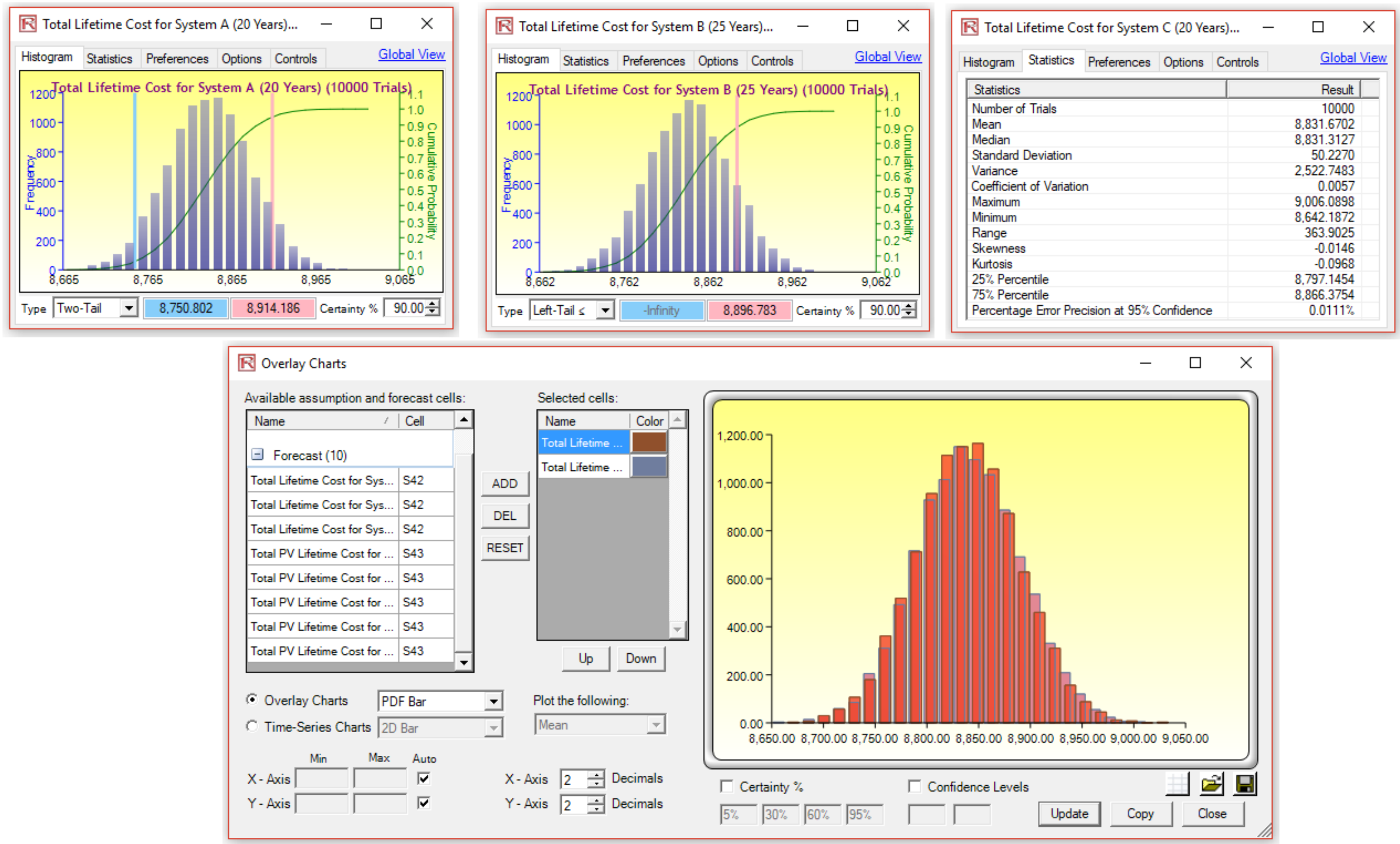


Figure 15. Example Simulation Results

Forecast Statistics Table - TOC Model

Cell	Total Lifetime Cost for System A (20 Years)	Total Lifetime Cost for System B (25 Years)	Total Lifetime Cost for System C (20 Years)	Total Lifetime Cost for System D (10 Years)	Total Lifetime Cost for System E (15 Years)	Total PV Lifetime Cost for System A (20 Years)	Total PV Lifetime Cost for System B (25 Years)	Total PV Lifetime Cost for System C (20 Years)	Total PV Lifetime Cost for System D (10 Years)	Total PV Lifetime Cost for System E (15 Years)
Name	S42	S42	S42	S42	S42	S43	S43	S43	S43	S43
Number of Datapoints	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Mean	$8,831.96	$8,832.11	$8,831.67	$8,832.22	$8,833.20	$6,514.55	$6,514.66	$6,514.34	$6,514.74	$6,515.45
Median	$8,832.09	$8,832.36	$8,831.31	$8,832.68	$8,833.84	$6,514.71	$6,514.79	$6,514.06	$6,515.10	$6,515.92
Standard Deviation	$49.60	$49.78	$50.23	$49.66	$50.31	$36.37	$36.49	$36.83	$36.41	$36.89
Variance	2460.2390	2477.5659	2522.7483	2465.9911	2531.3819	1322.4143	1331.8844	1356.4244	1325.8729	1360.8216
Coefficient of Variation	0.56%	0.56%	0.57%	0.56%	0.57%	0.56%	0.56%	0.57%	0.56%	0.57%
Maximum	$9,027.86	$9,011.75	$9,006.09	$9,009.43	$9,003.96	$6,658.10	$6,646.07	$6,642.13	$6,644.26	$6,640.59
Minimum	$8,655.82	$8,652.68	$8,642.19	$8,660.92	$8,665.34	$6,385.77	$6,382.97	$6,375.27	$6,389.07	$6,392.70
Range	$372.04	$359.07	$363.90	$348.51	$338.63	$272.33	$263.11	$266.86	$255.19	$247.90
Skewness	0.0074	-0.0160	-0.0146	-0.0251	-0.0198	0.0077	-0.0158	-0.0150	-0.0256	-0.0202
Kurtosis	-0.0662	-0.0987	-0.0968	-0.0796	-0.0914	-0.0653	-0.0993	-0.0963	-0.0786	-0.0916
25% Percentile	$8,798.40	$8,798.34	$8,797.15	$8,799.02	$8,798.81	$6,489.99	$6,489.93	$6,488.95	$6,490.41	$6,490.24
75% Percentile	$8,865.49	$8,865.74	$8,866.38	$8,865.77	$8,866.89	$6,539.05	$6,539.33	$6,539.87	$6,539.27	$6,540.17
Error Precision at 95%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
5% Percentile	$8,750.80	$8,749.88	$8,748.87	$8,750.02	$8,750.08	$6,455.09	$6,454.33	$6,453.63	$6,454.58	$6,454.45
10% Percentile	$8,768.11	$8,768.33	$8,767.45	$8,767.78	$8,767.83	$6,467.70	$6,467.94	$6,467.36	$6,467.41	$6,467.44
20% Percentile	$8,790.18	$8,789.76	$8,788.77	$8,790.54	$8,790.56	$6,483.91	$6,483.59	$6,482.92	$6,484.17	$6,484.13
30% Percentile	$8,805.71	$8,805.99	$8,804.53	$8,806.06	$8,806.62	$6,495.32	$6,495.49	$6,494.57	$6,495.54	$6,496.10
40% Percentile	$8,818.82	$8,819.88	$8,818.79	$8,819.62	$8,820.54	$6,504.97	$6,505.68	$6,504.87	$6,505.48	$6,506.12
50% Percentile	$8,832.09	$8,832.36	$8,831.31	$8,832.68	$8,833.84	$6,514.71	$6,514.79	$6,514.06	$6,515.10	$6,515.92
60% Percentile	$8,844.69	$8,844.76	$8,844.26	$8,845.26	$8,846.54	$6,523.91	$6,523.96	$6,523.52	$6,524.33	$6,525.27
70% Percentile	$8,858.16	$8,857.91	$8,858.11	$8,858.30	$8,859.69	$6,533.76	$6,533.60	$6,533.74	$6,533.85	$6,534.87
80% Percentile	$8,873.26	$8,874.27	$8,874.71	$8,874.33	$8,875.39	$6,544.78	$6,545.59	$6,545.98	$6,545.52	$6,546.35
90% Percentile	$8,896.26	$8,896.78	$8,896.86	$8,895.78	$8,897.90	$6,561.77	$6,562.09	$6,562.10	$6,561.33	$6,562.91
95% Percentile	$8,914.19	$8,914.12	$8,913.73	$8,914.62	$8,916.08	$6,574.83	$6,574.91	$6,574.50	$6,575.13	$6,576.09
99% Percentile	$8,946.27	$8,945.13	$8,946.00	$8,946.14	$8,950.41	$6,598.43	$6,597.55	$6,598.03	$6,598.03	$6,601.18

Figure 16. Example Simulation Statistics Tables (Only Sample Basic Results Shown)

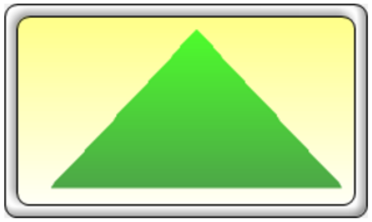
Simulation - TOC Model

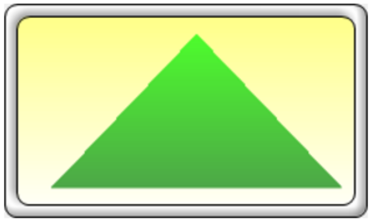
General

Number of Trials	10000
Stop Simulation on Error	No
Random Seed	Random
Enable Correlations	Yes

Assumptions

Name	**Field of View (NFOV) Sensors**	**Name**	**Wide Field of View (WFOV) Sensors**	**Name**	**O/IR Sensor Manager (ESM)**
Enabled	Yes	Enabled	Yes	Enabled	Yes
Cell	V6	Cell	V7	Cell	V8
Dynamic Simulation	No	Dynamic Simulation	No	Dynamic Simulation	No
Range		**Range**		**Range**	
Minimum	-Infinity	Minimum	-Infinity	Minimum	-Infinity
Maximum	Infinity	Maximum	Infinity	Maximum	Infinity
Distribution	Triangular	**Distribution**	Triangular	**Distribution**	Triangular
Minimum	16.15	Minimum	6.65	Minimum	5.7
Most Likely	17	Most Likely	7	Most Likely	6
Maximum	17.85	Maximum	7.35	Maximum	6.3





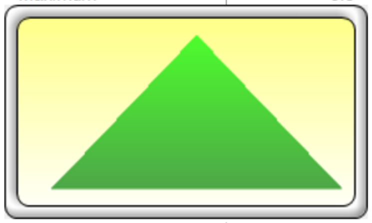


Figure 17. Example Simulation Report

Finally, in the Summary worksheet, users have the option to adjust the cost cash flow series by making ± $ adjustments in the empty cells with borders (Figure 18). This capability allows for any known factors to be applied every few years, such as technology insertion, foreseen major structural modifications, or any other such adjustments. The cash flows will be adjusted accordingly in this worksheet. Note that as of the current version, simulations will not be applied to any such modifications, only single-point results.

	C	D	E	F	G	H	I	J	K	L	M	N	O	P
37		Acquisition	Disposition	1	2	3	4	5	6	7	8	9	10	11
38	Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
39	Manual Adjustment													
40	Net Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
41	PV Cash Flows	$154.00		$364.08	$358.78	$353.55	$348.40	$343.33	$338.33	$333.40	$328.55	$323.76	$319.05	$314.40
42														
43														
44	System B	Discount Rate	3.00%											
45		Acquisition	Disposition	1	2	3	4	5	6	7	8	9	10	11
46	Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
47	Manual Adjustment													
48	Net Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
49	PV Cash Flows	$154.00		$364.08	$358.78	$353.55	$348.40	$343.33	$338.33	$333.40	$328.55	$323.76	$319.05	$314.40
50														
51														
52	System C	Discount Rate	3.00%											
53		Acquisition	Disposition	1	2	3	4	5	6	7	8	9	10	11
54	Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
55	Manual Adjustment													
56	Net Cash Flow	$154.00	$7.00	$375.00	$380.63	$386.33	$392.13	$398.01	$403.98	$410.04	$416.19	$422.43	$428.77	$435.20
57	PV Cash Flows	$154.00		$364.08	$358.78	$353.55	$348.40	$343.33	$338.33	$333.40	$328.55	$323.76	$319.05	$314.40

Figure 18. Manual Adjustments to Life-Cycle Cost Cash Flow

Model Application and Results

Introduction

The inputs for this model were sourced from the program components lists provided by the research sponsor, NAVSEA, for the (generic or specific) EO/IR sensor. The cost estimates for this model were sourced using rough of order magnitude (ROM) values. The values fluctuate slightly between the five different systems to illustrate the differing systems' costs between contract estimates. These values were explicitly created to further the proof of concept of the model and therefore do not necessarily reflect the accurate value for component, part, or salary of support team members. However, these values do show how the simulation can provide an estimate of an entire system and demonstrate how much impact each variable will have on the overall life-cycle cost estimate. In this example, we simulate a cost estimate of an EO/IR system being implemented on 55 platforms with a service life of 20 years.

Model Inputs and Data

The Total Ownership Cost is calculated by summing the initial Acquisition Cost, Operation Cost, Maintenance Cost, and Disposal Cost. The model accounts for these four phases, beginning with the Acquisition Cost. In a real-world scenario, a cost analyst would utilize the technical specifications given by the program office to enter the required values. From the technical specifications, the analyst would insert two crucial metrics. The first is the number of platforms that will receive the system, and the second is the number of components required in each system. Since real-world data is not available for this notional model, this research uses the ROM system to fill in the blanks.

In Systems A–E, the model uses 55 as the number of platforms. Though the number of platforms remains the same in the simulation, the technical specifications for the number of components required for each sensor are different. Figure 19 shows the input column for Number of Platforms and Number of Units per System.

Categories	Number of Units per System	Number of Platforms
Grand Total		
Narrow-Medium Field of View (NFOV) Sensors	**43**	**935**
NF-DIR (NFOV Director)	2	55
NF-TIS (Thermal Imaging Sensor) - TIS #1	3	55
NF-TIS (Thermal Imaging Sensor) - TIS #2	2	55
NF-EOS (Electro-Optic Sensor) - EOS #1	3	55
NF-EOS (Electro-Optic Sensor) - EOS #2	3	55
NF-EOS (Electro-Optic Sensor) - EOS #3	3	55
NF-LRF (Laser Rangefinder)	2	55
NF-LDR (Laser Designator/Rangefinder)	2	55
NF-LDRFI (Laser Designator/Rangefinder/Illuminator)	2	55
NF-LP (Laser Pointer)	5	55
NF-LOI (Laser Optical/Ocular Interrupter)	1	55
NF-LI (Laser Illuminator)	3	55
NF-IRU (Inertial Reference Unit)	2	55
NF-BSM (Boresight Module)	1	55
NF-EU (Electronics Unit)	2	55
Ancillary Material (cabling, mounting hardware, etc.)	3	55
Other: ___________	4	55

Figure 19. Number of Platforms and Units per System

The Acquisition Unit Cost accounts for all of the planning, design, and construction costs to make each component possible. The model also considers the estimated cost for a replacement component. The estimated cost for replacement parts should be considerably lower than the initial Acquisition Cost because developed technology will only need to be reproduced instead of being redeveloped. The Operational Cost per year is an estimate of the amount required to run the component for a year. The Operation Cost includes equipment depreciation, costs of the energy source used to power the component, cost of damage due to use, and so on. Similarly, the Maintenance cost is an estimate based on the amount required to maintain the equipment every year. Figure 20 shows the categories for Acquisition and Operation and Maintenance Costs.

Categories	Number of Units per System	Number of Platforms	Acquisition Cost (Unit)	%	Operational Costs (Unit) Per Year	%	Maintenance (Unit) Per Year	%	Replacement (Unit) Per Year	%	Total Acquisition Cost	%	Total Annual O&M	%
Grand Total			##############		**$217.00**		**$1,164.00**		**$42,391.00**		**$45,863,500.00**		**$15,308,443.00**	
Narrow-Medium Field of View (NFOV) Sensors	**43**	**935**	**$7,110.00**	**0.2%**	**$73.00**	**33.6%**	**$594.00**	**51.0%**	**$4,880.00**	**11.5%**	**$960,850.00**	**2.1%**	**$753,720.00**	**4.9%**
NF-DIR (NFOV Director)	2	55	$400.00	0.0%	$5.00	2.3%	$30.00	2.6%	$300.00	0.7%	$44,000.00	0.1%	$36,850.00	0.2%
NF-TIS (Thermal Imaging Sensor) - TIS #1	3	55	$350.00	0.0%	$6.00	2.8%	$23.00	2.0%	$150.00	0.4%	$57,750.00	0.1%	$29,535.00	0.2%
NF-TIS (Thermal Imaging Sensor) - TIS #2	2	55	$460.00	0.0%	$7.00	3.2%	$25.00	2.1%	$300.00	0.7%	$50,600.00	0.1%	$36,520.00	0.2%
NF-EOS (Electro-Optic Sensor) - EOS #1	3	55	$230.00	0.0%	$5.00	2.3%	$34.00	2.9%	$200.00	0.5%	$37,950.00	0.1%	$39,435.00	0.3%
NF-EOS (Electro-Optic Sensor) - EOS #2	3	55	$340.00	0.0%	$3.00	1.4%	$45.00	3.9%	$220.00	0.5%	$56,100.00	0.1%	$44,220.00	0.3%
NF-EOS (Electro-Optic Sensor) - EOS #3	3	55	$450.00	0.0%	$2.00	0.9%	$56.00	4.8%	$250.00	0.6%	$74,250.00	0.2%	$50,820.00	0.3%
NF-LRF (Laser Rangefinder)	2	55	$560.00	0.0%	$3.00	1.4%	$45.00	3.9%	$560.00	1.3%	$61,600.00	0.1%	$66,880.00	0.4%
NF-LDR (Laser Designator/Rangefinder)	2	55	$430.00	0.0%	$4.00	1.8%	$34.00	2.9%	$220.00	0.5%	$47,300.00	0.1%	$28,380.00	0.2%
NF-LDRFI (Laser Designator/Rangefinder/Illuminator)	2	55	$460.00	0.0%	$5.00	2.3%	$23.00	2.0%	$140.00	0.3%	$50,600.00	0.1%	$18,480.00	0.1%
NF-LP (Laser Pointer)	5	55	$450.00	0.0%	$6.00	2.8%	$45.00	3.9%	$270.00	0.6%	$123,750.00	0.3%	$88,275.00	0.6%
NF-LOI (Laser Optical/Ocular Interrupter)	1	55	$560.00	0.0%	$6.00	2.8%	$65.00	5.6%	$320.00	0.8%	$30,800.00	0.1%	$21,505.00	0.1%
NF-LI (Laser Illuminator)	3	55	$430.00	0.0%	$3.00	1.4%	$43.00	3.7%	$540.00	1.3%	$70,950.00	0.2%	$96,690.00	0.6%
NF-IRU (Inertial Reference Unit)	2	55	$430.00	0.0%	$3.00	1.4%	$34.00	2.9%	$450.00	1.1%	$47,300.00	0.1%	$53,570.00	0.3%
NF-BSM (Boresight Module)	1	55	$230.00	0.0%	$3.00	1.4%	$23.00	2.0%	$220.00	0.5%	$12,650.00	0.0%	$13,530.00	0.1%
NF-EU (Electronics Unit)	2	55	$670.00	0.0%	$3.00	1.4%	$23.00	2.0%	$330.00	0.8%	$73,700.00	0.2%	$39,160.00	0.3%
Ancillary Material (cabling, mounting hardware, etc.)	3	55	$430.00	0.0%	$3.00	1.4%	$23.00	2.0%	$200.00	0.5%	$70,950.00	0.2%	$37,290.00	0.2%
Other: __________	4	55	$230.00	0.0%	$6.00	2.8%	$23.00	2.0%	$210.00	0.5%	$50,600.00	0.1%	$52,580.00	0.3%
Wide Field of View (WFOV) Sensors	**23**	**385**	**$25,600.00**	**0.6%**	**$24.00**	**11.1%**	**$245.00**	**21.0%**	**$14,200.00**	**33.5%**	**$4,240,500.00**	**9.2%**	**$2,487,100.00**	**16.2%**
WF-DIR (Director)	2	55	$4,500.00	0.1%	$4.00	1.8%	$35.00	3.0%	$2,000.00	4.7%	$495,000.00	1.1%	$224,290.00	1.5%
WF-TIS (Thermal Imaging Sensor)	3	55	$3,500.00	0.1%	$3.00	1.4%	$43.00	3.7%	$1,200.00	2.8%	$577,500.00	1.3%	$205,590.00	1.3%
WF-EOS (Electro-Optic Sensor)	1	55	$4,500.00	0.1%	$2.00	0.9%	$23.00	2.0%	$3,200.00	7.5%	$247,500.00	0.5%	$177,375.00	1.2%
WF-IRU (Inertial Reference Unit)	2	55	$5,300.00	0.1%	$6.00	2.8%	$22.00	1.9%	$2,300.00	5.4%	$583,000.00	1.3%	$256,080.00	1.7%
WF-EU (Electronics Unit)	4	55	$1,000.00	0.0%	$3.00	1.4%	$55.00	4.7%	$1,000.00	2.4%	$220,000.00	0.5%	$232,760.00	1.5%
Ancillary Material (cabling, mounting hardware, etc.)	5	55	$2,300.00	0.1%	$2.00	0.9%	$45.00	3.9%	$2,100.00	5.0%	$632,500.00	1.4%	$590,425.00	3.9%
Other: __________	6	55	$4,500.00	0.1%	$4.00	1.8%	$22.00	1.9%	$2,400.00	5.7%	$1,485,000.00	3.2%	$800,580.00	5.2%
EO/IR Sensor Manager (ESM)	**17**	**330**	**$1,910.00**	**0.0%**	**$45.00**	**20.7%**	**$124.00**	**10.7%**	**$1,400.00**	**3.3%**	**$282,150.00**	**0.6%**	**$275,990.00**	**1.8%**
Processing Equipment	3	55	$340.00	0.0%	$4.00	1.8%	$15.00	1.3%	$150.00	0.4%	$56,100.00	0.1%	$27,885.00	0.2%
Processing Software	4	55	$230.00	0.0%	$6.00	2.8%	$23.00	2.0%	$230.00	0.5%	$50,600.00	0.1%	$56,980.00	0.4%
Recording Equipment	5	55	$240.00	0.0%	$5.00	2.3%	$40.00	3.4%	$430.00	1.0%	$66,000.00	0.1%	$130,625.00	0.9%
Docking Station Equipment	2	55	$350.00	0.0%	$5.00	2.3%	$21.00	1.8%	$230.00	0.5%	$38,500.00	0.1%	$28,160.00	0.2%
Ancillary Material (video converters, encoders, ethernet switches, racks, cabling, etc.)	1	55	$210.00	0.0%	$12.00	5.5%	$10.00	0.9%	$210.00	0.5%	$11,550.00	0.0%	$12,760.00	0.1%
Other: __________	2	55	$540.00	0.0%	$13.00	6.0%	$15.00	1.3%	$150.00	0.4%	$59,400.00	0.1%	$19,580.00	0.1%

Figure 20. Categories for Acquisition and Operation and Maintenance Costs

Once the cost analyst has entered the acquisition cost for the hardware and software required for the system, the analyst must remember to account for the human element. The analyst will need to ensure that the cost required to pay for those responsible for the design, logistics, management, and technology are represented in the model. This model uses the Acquisition Cost column to record the initial salary of each job. The Number of Platforms column describes the number of teams required for each system. The Number of Units per System column describes the number of people required on each team. The Operation Cost column is used to annotate the continuing salary for the human element for the remainder of the program's life. Essentially, this is how an analyst would annotate a recurring salary payment. Throughout the five systems, the number of people per team and the amount requested per salary will vary. Figure 21 shows an example of where salaries are input into the model.

Categories	Number of Units per System	Number of Platforms	Acquisition Cost (Unit)	%	Operational Costs (Unit) Per Year	%
Grand Total			$4,202,920.00		$1,907,716.00	
Manpower and Personnel	30	6	$321,000.00	7.6%	$240,000.00	12.6%
Program Management Office Team	8	1	$80,000.00	1.9%	$80,000.00	4.2%
Manning and military occupational series training	6	1	$40,000.00	1.0%	$40,000.00	2.1%
Depot Activation	5	1	$60,000.00	1.4%	$55,000.00	2.9%
Software Sustainment	4	1	$40,000.00	1.0%	$35,000.00	1.8%
Initial Fielding Support	4	1	$56,000.00	1.3%	$30,000.00	1.6%
Other: __________	3	1	$45,000.00	1.1%	$0.00	0.0%

Figure 21. Manpower and Personnel Salary Input Section

All of the costs mentioned previously are recurring costs, costs that will be multiplied by the number of years of the program and summed to get the total cost. Analysts must be sure not to forget to account for all of the one-time costs associated with the origins of any project. Figure 22 shows the list of nonrecurring costs accounted for in the model.

Nonrecurring Acquisition and End of Lifecycle Costs	Total	%
Acquisition and Procurement	**$467,800.00**	
Bid Specifications Development	$10,000.00	2.1%
Proposal Evaluation	$2,000.00	0.4%
Data Collection	$40,000.00	8.6%
Data Analysis	$12,000.00	2.6%
Contracts Development	$3,000.00	0.6%
Program Planning	$4,000.00	0.9%
Hardware Purchases	$10,000.00	2.1%
Personal Computers	$10,000.00	2.1%
Peripherals	$15,000.00	3.2%
Storage	$60,000.00	12.8%
Networking	$23,000.00	4.9%
Related Equipment	$35,000.00	7.5%
Other costs	$10,000.00	2.1%
Administrative Cost	$34,000.00	7.3%
Asset Management	$15,000.00	3.2%
Overseeing Contractor Services	$4,000.00	0.9%
In-House Training for Staff	$5,000.00	1.1%
Product Maintenance	$2,000.00	0.4%
Help Desk Support	$10,000.00	2.1%
IT Support for Database Management	$20,000.00	4.3%
Network Management Support	$42,000.00	9.0%
Software Upgrades	$12,000.00	2.6%
Hardware Upgrades	$2,100.00	0.4%
Internet and Network Access Cost	$14,000.00	3.0%
Furniture and Equipment	$10,000.00	2.1%
Energy Costs	$3,400.00	0.7%
Informal Training	$4,300.00	0.9%
Downtime Support and Outsource	$24,000.00	5.1%
Other costs	$32,000.00	6.8%

Figure 22. Nonrecurring Acquisition and Procurement Costs

Finally, we account for all of the disposal and end-of-life-cycle costs that will also be one-time costs. Figure 23 shows the nonrecurring end-of-life-cycle costs.

Nonrecurring End of Lifecycle Costs	Total	%
End of Lifecycle	**$109,000.00**	
Administrative Cost	$40,000.00	36.7%
Asset Management	$20,000.00	18.3%
Vendor Contract Procurement	$4,000.00	3.7%
Staging, Sanitizing, Testing	$10,000.00	9.2%
Follow-Up Support	$10,000.00	9.2%
Recycling and Disposal Fees	$5,000.00	4.6%
Value of Sold Products and Materials	$20,000.00	18.3%

Figure 23. Nonrecurring End-of-Life-Cycle Costs

Results and Analysis

Once the data have been manually inputted into the model, the cost analyst can utilize the multitude of charts, graphs, and tools to analyze the total ownership cost of the systems. These graphs, charts, and tools will allow the analyst to compare multiple cost estimates over the entire life of the system at the same time. This research analyzed the following tables and charts to highlight the functionality of the model: Total Net Life-Cycle Cost, Present Value of Discounted Total Net Life-Cycle Cost, Cash Total Net Cost at Five-Year Increments, Total Ownership Cost Forecast Statistic Table, Simulation Probability Charts, and the Tornado Analysis.

Total Net Life-Cycle Costs and Cash Total Net Cost at Five-Year Increments

Figure 24 shows the Total Net Life-Cycle Cost for all five systems over a span of 30 years. The table and graph show the cost for the systems broken down into 5-year estimates. The model projects the life span of the system past the 20-year expected service life. This extension allows the cost analyst to consider cost out to the 30-year point, as many DoD systems tend to exceed their expected service lives. However, the 5-year increments also allow a decision-maker to understand the total net cost of disposing of a system before its 20-year service life. The side-by-side comparison enables a decision-maker to graphically perceive the potential differences between the cost estimates of the multiple systems. When choosing between alternatives, Figure 24 can be a beneficial decision aid.

In the analysis table in Figure 24, the 20-Year Cash Total Net Cost ranges from $554 million (System C) to $771 million (System D). If cost was the determining factor, a decision-maker could quickly determine that System C should be selected. To make the comparison even easier to analyze, Figure 25 provides a side-by-side comparison of all five systems at each of the five-year increments. Looking at the 20-Year Total Net Cost Graph, it can be clearly seen that System C has the lowest Total Net Cost.

Cost analysis should only be one part of the picture when it comes to making the correct strategic decision. For example, each system's specifications and capabilities—its military benefits or returns—should also be computed, such that each system will have its own return on investment (ROI). Nonetheless, the major component of any ROI analysis is its cost. The focus of this research is to determine this cost computation. Another aspect of TOC analysis is its use in cost mitigation, cost savings, and cost deferred, which constitute another point of view of cost-based decision analytics.

Analysis Period/Type	System A	System B	System C	System D	System E
5 Year Cash Total Net Cost	$192,078,759.39	$199,950,888.59	$158,074,801.16	$206,656,401.49	$161,982,378.15
10 Year Cash Total Net Cost	$348,972,742.05	$366,909,094.54	$280,489,136.93	$381,039,284.24	$291,014,854.14
15 Year Cash Total Net Cost	$517,992,119.86	$546,770,499.13	$412,364,142.71	$568,899,174.37	$430,019,476.51
20 Year Cash Total Net Cost	$700,073,991.93	$740,532,313.22	$554,430,976.94	$771,277,628.99	$579,766,932.65
25 Year Cash Total Net Cost	$896,227,880.11	$949,268,816.09	$707,477,304.94	$989,296,700.88	$741,087,471.77
30 Year Cash Total Net Cost	$1,107,541,326.15	$1,174,137,311.67	$872,351,665.95	$1,224,165,159.57	$914,875,508.07

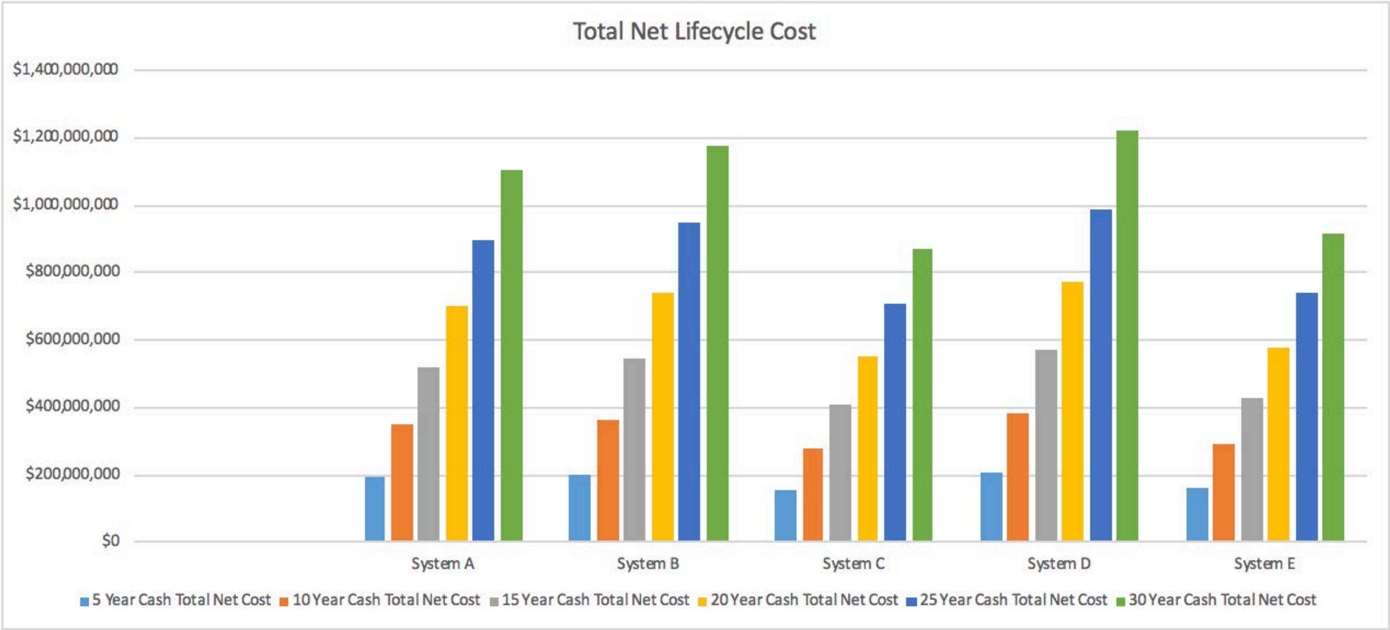


Figure 24. Total Net Life-Cycle Cost

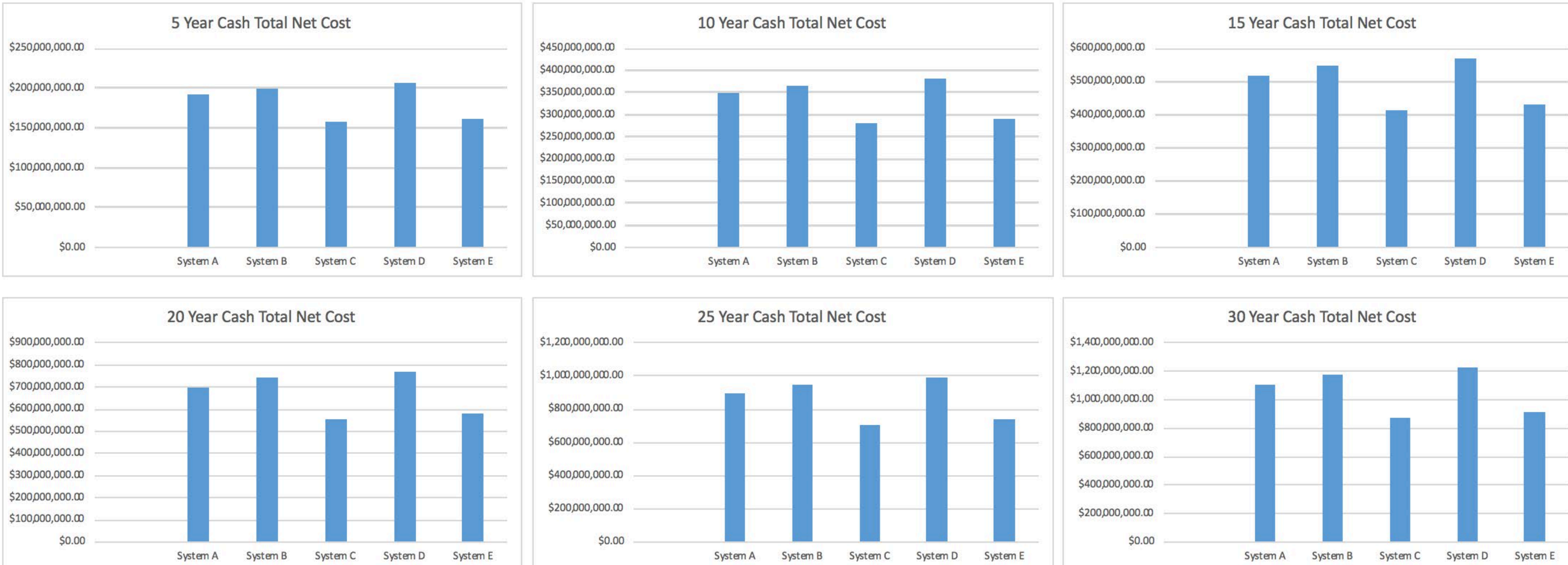


Figure 25. Five-Year Increment of Net Total Cost

Present Value of Discounted Total Net Life-Cycle Cost

While Figure 26 shows the Total Net Life-Cycle Cost, it does not include consideration of economic factors such as the time value of money and uncertainty risk. To mitigate these factors in the model, Figure 26 incorporates a Net Present Value Life-Cycle Cost estimate using a discount rate of 3% (i.e., the government's cost of money, where we can use 20-year and 30-year Treasury bond yields as proxies). In the analysis table in Figure 26, the 20-Year Total Net Cost ranges from $554 million (System C) to $771 million (System D), but when looking at the more realistic Present Value Discounted Net Life-Cycle Cost, the range between Systems C and D decreases to $418 million and $577 million. Not only do the estimates for the minimum and maximum values decrease when the discount factor is applied, but the delta of the range between the values also shrinks by $57.8 million. Incorporating the discount rate into the model gives the decision-maker a complete analysis of the costs. Specifically, it shows the value of the lifetime cost of a system in today's money, thereby putting all systems with different life cycles and life spans on an equal footing with each other, for a better cost comparison.

Analysis Period/Type	System A	System B	System C	System D	System E
5 Year Cash Cost in Present Values	$179,704,285.34	$186,783,594.12	$148,416,499.73	$192,904,219.83	$151,802,725.35
10 Year Cash Cost in Present Values	$303,544,126.37	$318,568,174.68	$245,037,964.84	$330,549,870.97	$253,648,577.73
15 Year Cash Cost in Present Values	$418,626,211.89	$441,033,105.19	$334,826,703.72	$458,461,345.77	$348,292,207.24
20 Year Cash Cost in Present Values	$525,569,818.93	$554,837,402.90	$418,265,845.06	$577,326,978.99	$436,242,875.34
25 Year Cash Cost in Present Values	$624,950,442.22	$660,593,492.07	$495,804,364.31	$687,786,438.92	$517,973,842.03
30 Year Cash Cost in Present Values	$717,302,888.41	$758,870,497.06	$567,859,497.04	$790,434,167.10	$593,924,909.86

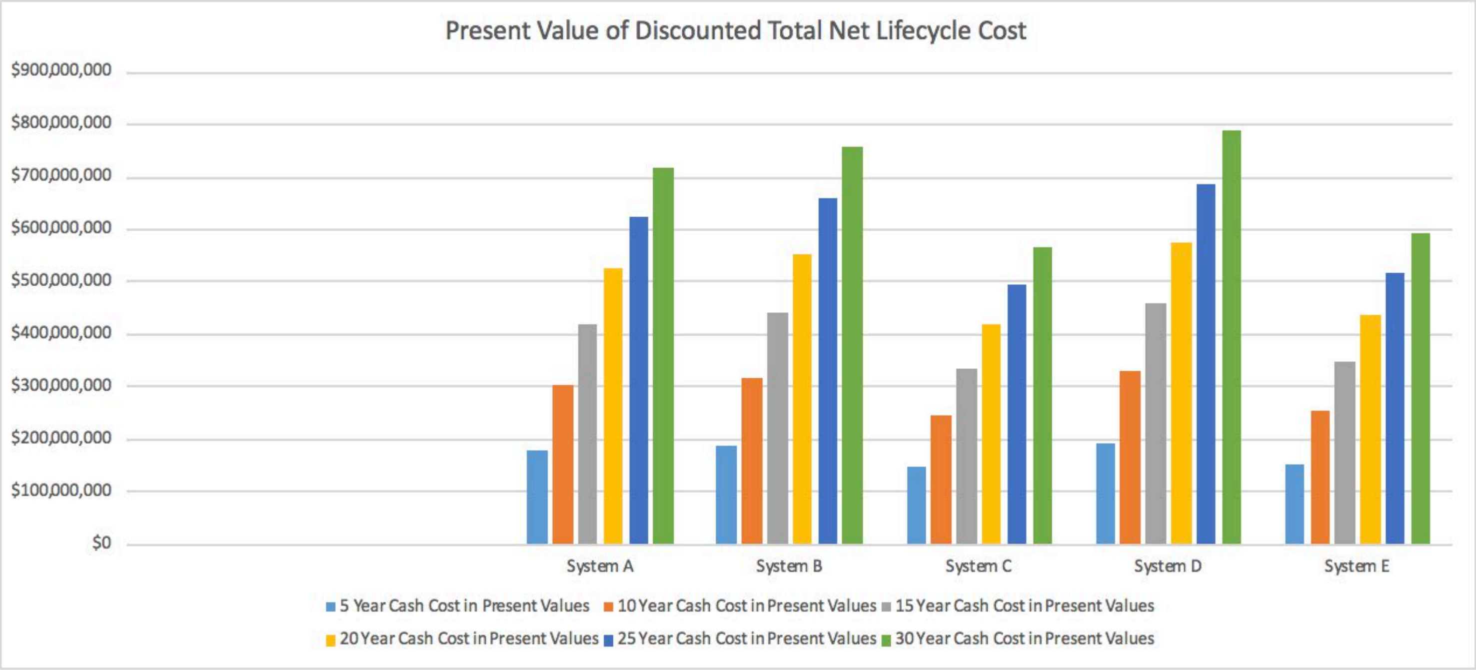


Figure 26. Present Value of Discounted Net Life-Cycle Cost

Stochastic Total Ownership Cost Forecast Statistics Table

The Forecast Statistics Table, shown in Figure 27, summarizes the distribution of the Total Life-Cycle Cost and the Total Present Value (PV) Life-Cycle Cost for the five systems at different points in the life cycle of the system based on risk-based simulation and stochastic TOC models used to value the alternative cost paths. Figure 27 highlights the outcomes of running 10,000 trials using the Monte Carlo Risk Simulator. The takeaways from this figure are the mean, standard deviation, maximum, minimum, and range data points. These metrics provide a decision-maker with a better understanding of how uncertainty can affect the Total Life-Cycle Cost and Total PV Life-Cycle Cost of a system.

System C looks at the cost over a 20-year life span. Using the Monte Carlo Risk Simulator, the maximum Total Life-Cycle Cost of the system is $568 million, while the minimum is $540 million. These values represent the worst- and best-case scenarios, respectively. The simulations produced a Total Life-Cycle Cost range of $28 million and a mean value of $554 million. The standard deviation of Total Life-Cycle Cost simulations for System C is $4.5 million, meaning 68.2% of the estimates will fall within ±$4.5 million of the mean if the distribution is somewhat normally distributed. Figure 27 also shows the same metrics for the PV of the Total Life-Cycle Cost for all systems.

Forecast Statistics Table - TOC Model

Cell	Total Lifetime Cost for System A (20 Years)	Total Lifetime Cost for System B (25 Years)	Total Lifetime Cost for System C (20 Years)	Total Lifetime Cost for System D (10 Years)	Total Lifetime Cost for System E (15 Years)	Total PV Lifetime Cost for System A (20 Years)	Total PV Lifetime Cost for System B (25 Years)	Total PV Lifetime Cost for System C (20 Years)	Total PV Lifetime Cost for System D (10 Years)	Total PV Lifetime Cost for System E (15 Years)
Name	S42	S42	S42	S42	S42	S43	S43	S43	S43	S43
Number of Datapoints	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Mean	$700,128,499.57	$740,532,963.43	$554,392,425.60	$771,338,025.77	$579,775,293.62	$525,611,374.46	$554,838,179.48	$418,238,633.17	$577,371,510.62	$436,248,097.08
Median	$700,141,006.85	$740,535,580.46	$554,384,371.67	$771,364,875.28	$579,759,448.54	$525,610,342.27	$554,835,058.62	$418,245,556.21	$577,382,472.47	$436,233,772.78
Standard Deviation	$6,257,100.80	$5,845,829.50	$4,467,888.27	$7,611,267.45	$4,630,641.37	$4,594,559.43	$4,292,302.35	$3,283,147.51	$5,583,858.78	$3,400,790.39
Coefficient of Variation	0.89%	0.79%	0.81%	0.99%	0.80%	0.87%	0.77%	0.78%	0.97%	0.78%
Maximum	$721,408,465.72	$760,794,257.46	$568,380,140.14	$792,265,719.52	$595,514,481.66	$541,361,082.89	$569,528,468.16	$428,545,963.69	$592,883,001.86	$447,659,644.97
Minimum	$679,850,811.09	$719,523,385.66	$540,339,232.67	$748,640,296.95	$564,025,304.82	$510,709,204.65	$539,393,598.53	$407,787,597.45	$560,676,945.01	$424,678,356.35
Range	$41,557,654.63	$41,270,871.80	$28,040,907.47	$43,625,422.57	$31,489,176.84	$30,651,878.24	$30,134,869.63	$20,758,366.24	$32,206,056.85	$22,981,288.62
Skewness	-0.0032	-0.0042	-0.0148	-0.0026	0.0087	-0.0023	-0.0028	-0.0144	-0.0026	0.0091
Kurtosis	-0.4009	-0.2633	-0.3281	-0.5003	-0.3088	-0.3995	-0.2616	-0.3249	-0.4998	-0.3093
25% Percentile	$695,719,253.67	$736,446,455.02	$551,284,478.55	$765,796,106.33	$576,509,002.84	$522,378,543.35	$551,839,791.47	$415,958,053.49	$573,311,007.82	$433,851,693.64
75% Percentile	$704,532,335.37	$744,600,466.38	$557,526,620.08	$776,618,455.92	$582,946,797.53	$528,851,703.11	$557,822,109.37	$420,545,180.57	$581,253,957.83	$438,577,466.99
Error Precision at 95%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
5% Percentile	$689,682,929.25	$730,959,587.63	$546,946,259.66	$758,769,396.90	$572,144,154.21	$517,951,178.33	$547,793,197.77	$412,759,859.00	$568,154,901.40	$430,640,138.12
10% Percentile	$691,747,640.51	$732,794,898.81	$548,533,001.64	$761,225,549.84	$573,689,454.88	$519,468,239.36	$549,181,125.39	$413,946,175.50	$569,990,913.70	$431,776,478.59
20% Percentile	$694,602,871.32	$735,367,935.12	$550,510,692.26	$764,515,420.38	$575,778,821.69	$521,563,700.07	$551,045,883.57	$415,386,396.82	$572,378,313.33	$433,315,521.79
30% Percentile	$696,704,619.98	$737,452,394.84	$551,979,547.59	$767,095,731.78	$577,226,617.51	$523,096,629.77	$552,578,355.90	$416,460,293.34	$574,253,331.14	$434,382,267.57
40% Percentile	$698,493,546.06	$739,011,582.52	$553,233,344.80	$769,309,931.15	$578,543,844.11	$524,394,394.43	$553,713,041.68	$417,379,609.28	$575,880,312.72	$435,341,189.38
50% Percentile	$700,141,006.85	$740,535,580.46	$554,384,371.67	$771,364,875.28	$579,759,448.54	$525,610,342.27	$554,835,058.62	$418,245,556.21	$577,382,472.47	$436,233,772.78
60% Percentile	$701,843,734.05	$742,099,383.62	$555,579,609.61	$773,403,235.14	$580,989,590.40	$526,887,691.99	$555,979,070.58	$419,103,492.37	$578,891,015.17	$437,139,948.28
70% Percentile	$703,601,587.76	$743,714,003.76	$556,847,632.09	$775,491,755.81	$582,222,603.44	$528,161,141.23	$557,172,586.27	$420,044,672.96	$580,410,041.35	$438,057,186.64
80% Percentile	$705,593,527.64	$745,597,406.41	$558,265,766.20	$778,104,442.05	$583,805,528.28	$529,626,241.70	$558,543,630.43	$421,090,371.98	$582,332,648.63	$439,205,172.05
90% Percentile	$708,345,917.64	$748,088,346.78	$560,256,120.90	$781,498,101.24	$585,875,474.23	$531,647,003.55	$560,385,422.61	$422,546,755.03	$584,823,963.64	$440,711,757.31
95% Percentile	$710,307,855.95	$750,205,085.99	$561,774,937.44	$784,001,472.92	$587,517,826.61	$533,116,251.14	$561,929,004.53	$423,658,279.36	$586,692,336.33	$441,943,293.84
99% Percentile	$713,991,274.06	$753,529,283.26	$564,370,570.06	$787,642,529.91	$589,971,521.84	$535,763,348.04	$564,406,101.50	$425,570,623.73	$589,320,737.18	$443,747,515.40

Figure 27. Total Ownership Cost Forecast Statistics Table

Simulation Probability Charts

A simulation probability chart is a histogram or frequency distribution of all of the total life-cycle costs of a system based on 10,000 simulation runs or trials. The probability chart produces a graphic representation of the information contained in the forecast statistics table. Figure 28 shows the frequency distribution of the total life-cycle cost for System A over a 20-year life. In the figure, it can be seen that System A's frequency distribution is shaped as a roughly symmetrical bell curve centered on a mean of $700 million. Using this chart, an analyst could confidently conclude the total life-cycle cost for this system will fall between $679 million and $721 million. The figure also shows the 90% confidence interval of the TOC to be between $690 million and $710 million. This means that there is a 90% chance that given all uncertainties that exist in each of the input assumptions, the 20-year total lifetime cost for System A will be between these two values. In addition, there is only a 5% chance that the cost can be below $690 million and a 5% chance it can exceed $710 million.

Figure 29 uses the same frequency distribution over the same 20-year system life as in Figure 28; however, Figure 29 takes into account the discount rate to better illustrate the economic factor of inflation over time. Similarly, the 90% confidence interval in present values is between $518 million and $533 million.

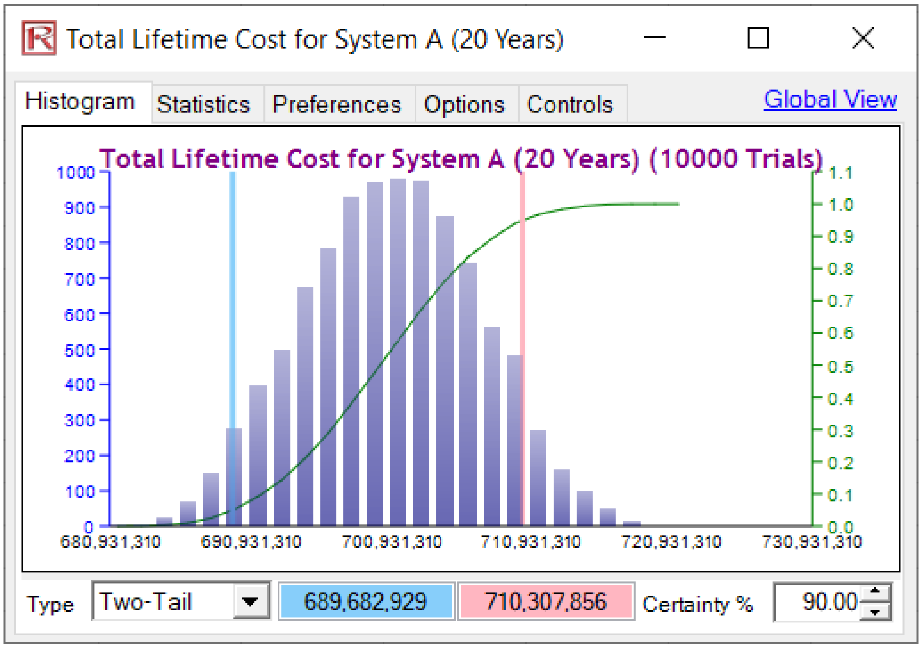


Figure 28. Total Life Cycle-Cost for System A (20 Years)

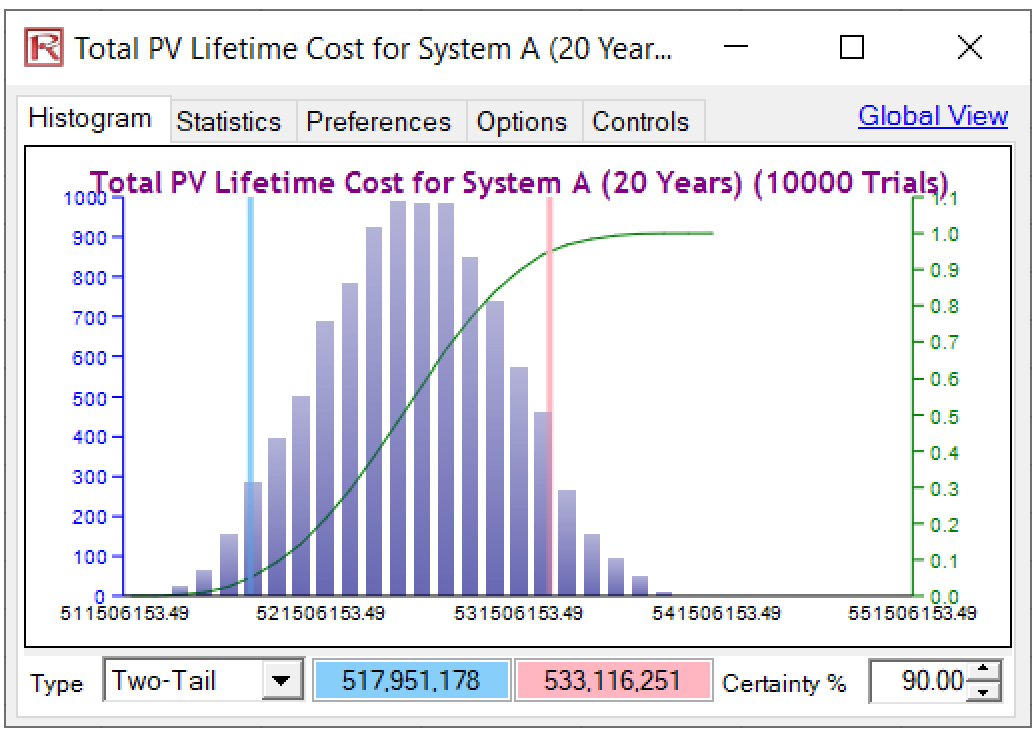


Figure 29. Total Present Value Life-Cycle Cost for System A (20 Years)

Figure 30 shows the total life-cycle cost for System B; however, the system's life span has been extended to 25 years versus 20 years. The probability charts allow cost analysts to graphically compare the frequency distributions of two different systems with varying life spans. As seen in a comparison between Figure 28 and Figure 30, System A has a shorter life span and lower total cost range. Through this analysis, a decision-maker can determine if the extended life span of System B is worth the higher total life-cycle cost. Figure 31 displays the total PV life-cycle cost for System B, which has been adjusted using a discount factor for inflation.

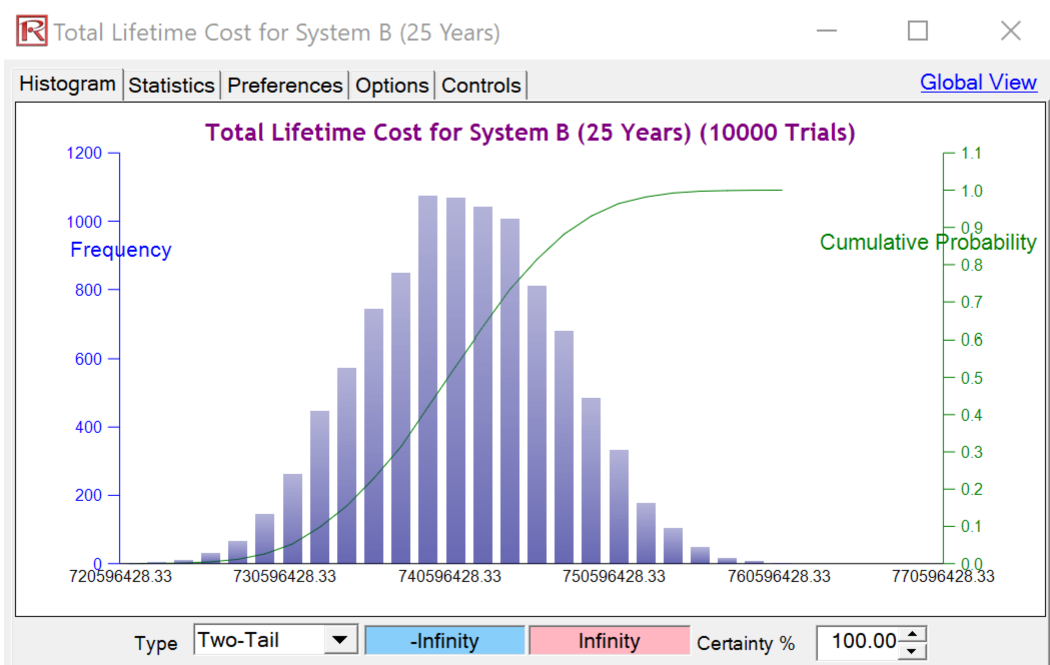


Figure 30. Total Life-Cycle Cost for System B (25 Years)

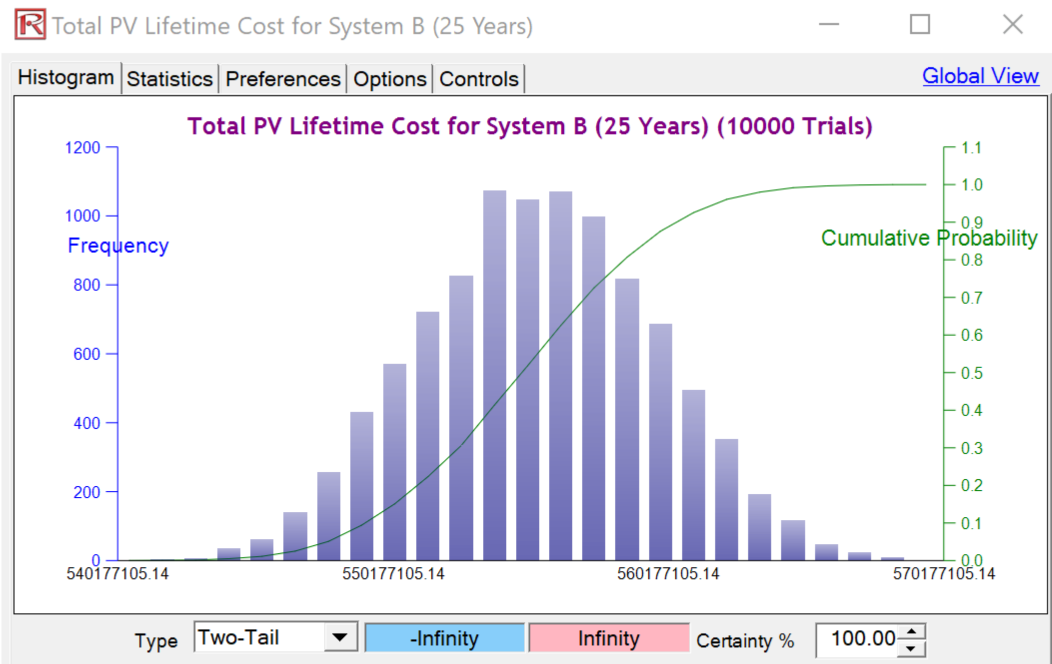


Figure 31. Total Present Value Life-Cycle Cost for System B (25 Years)

Figure 32 shows the total life-cycle cost for System D; however, the system's life span has been shortened to 10 years versus the original 20 years. The probability chart allows an analyst to compare the total life-cycle cost of a system with a shorter life span to systems with longer life spans. In a comparison between Figure 28 and Figure 32, System A has a longer life span and a lower total cost range than System D. This comparison illustrates that despite System D's shorter life span, the total life-cycle cost is higher than that of System A. This could be a vital metric for decision-makers to consider when determining which system has the best value. Figure 33 shows System D's total PV life-cycle cost to account for economic factors. These probability distributions can also be overlaid and compared against one another for a better view of the potential cost spreads, as shown in Figure 34.

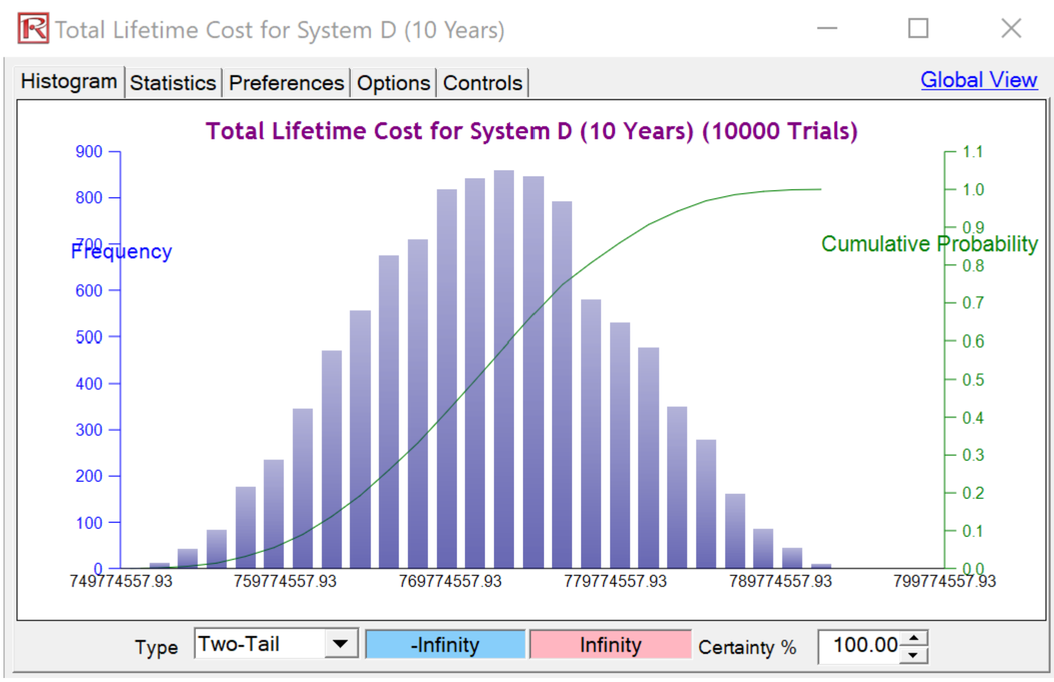


Figure 32. Total Life-Cycle Cost for System D (10 Years)

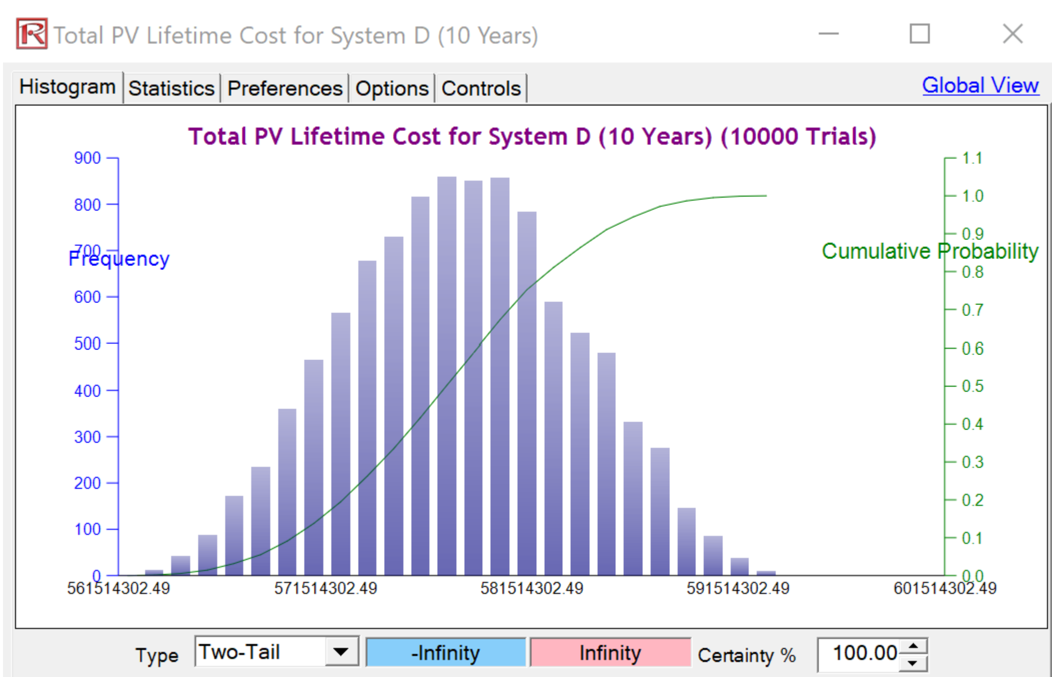


Figure 33. Total Present Value Life-Cycle Cost for System D (10 Years)

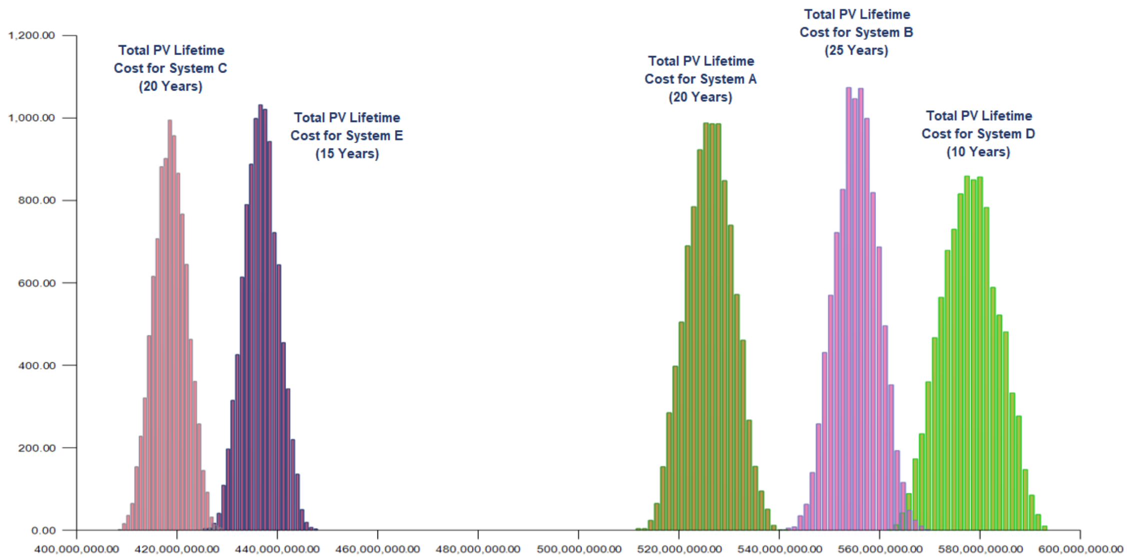


Figure 34. Probability Distribution Cost Overlay of the Five Systems

Tornado Analysis

The tornado analysis chart gives decision-makers the ability to break down which variables have the most significant impact on the overall outcome of the simulation. By focusing on the top critical factors, decision-makers can focus on cost reduction techniques in places that will have the most effect. The tornado analysis allows the decision-makers to adjust how many critical variables to display. Figure 35 shows the tornado analysis chart detailing the 20 most impactful variables on the TOC model. Based on the notional cost values inputted into the model, the number of platforms containing that ancillary material is the most critical factor.

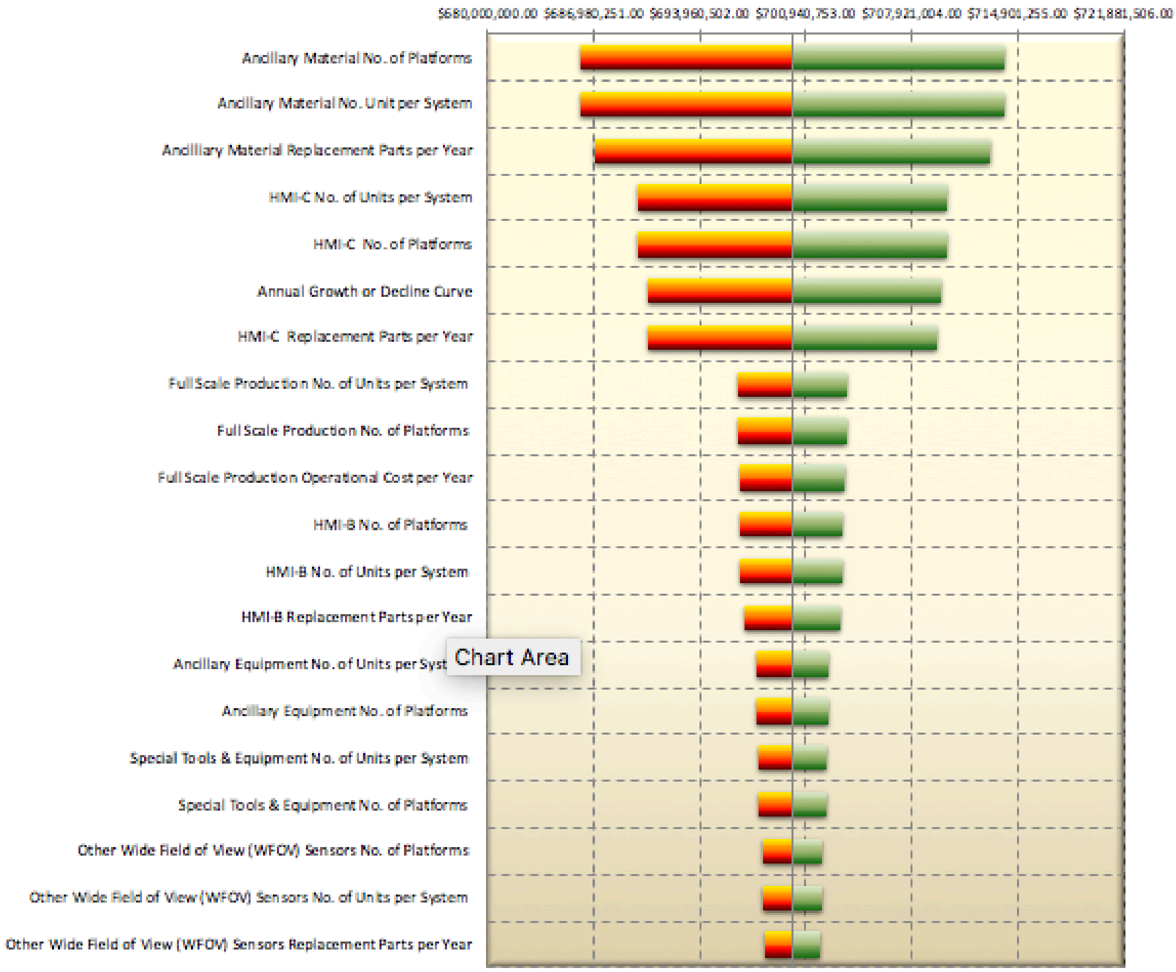


Figure 35. Tornado Analysis

Conclusion

Key Conclusions

The purpose of this report was to develop a total ownership with life-cycle cost model while considering uncertainty for EO/IR sensors on U.S. Navy surface ships. Through the examination of total ownership cost (TOC) modeling over the life cycle of EO/IR sensors, including the inception phase of Acquisition Costs, followed by annual Operations and Maintenance expenses, along with a final set of Disposition Costs, we were able to develop a useful model for TOC estimations. Using Monte Carlo risk simulation, our model accounts for risk and uncertainty when producing cost estimates. The model also provides analysts with a more realistic estimate by factoring in economic theory, such as economic growth, annual discount rate, and inflation.

As discussed, the cost analysis models presented should be only one part of a larger picture when it comes to making the correct strategic investment decisions. For example, each system's specifications, capabilities, military benefits, or financial and non-economic returns, should also be computed, such that each system will have its own return on investment (ROI). Nonetheless, the major component of any ROI analysis is its cost. The focus of this current research is to determine a suitable method to compute critical life cycle cost. Another use of TOC modeling is in determining cost mitigation, cost savings, and cost deferred, that is, what the cost differential might be or an Analysis of Alternatives, which constitutes another point of view of cost-based decision analytics.

The model allows decision-makers to have better decision analytics of the costs of EO/IR surface sensors. These analytics can be used in subsequent cost comparisons between different sensor platforms, Analysis of Alternatives, and portfolio allocation of resources. Specifically, PEO IWS (Integrated Warfare Systems) and NAVSEA can utilize this model in future program cost estimation development. Since the model is tailorable to different sensor configurations, it can provide clarity in analyzing different and complex alternative sensor systems to develop and outfit the fleet. The results of this model give decision-makers a more effective metric to analyze TOC under uncertainty; this can reduce cost overflow and prevent budget overruns. Ultimately, the model allows leadership to make more informed decisions in the DoD acquisition process and maximize the use of its limited resources.

Current Research Limitations and Follow-on Research

The main limitation of the current study is that notional cost data was used to provide a proof of concept that the model functions as designed. However, this presents an opportunity for future research whereby additional follow-on research with empirical data should be conducted. This model can analyze cost data in past, present, and future EO/IR models.

Beginning with historical data, a cost analyst could compile a list of program components associated with a system that is either retired or currently in use. Once the list of components is obtained, the analyst can then associate the estimated historical cost assigned to each component during the program’s initial cost estimate (e.g., a program cost estimate developed in 1992). Using the original cost data and component list, the analyst could then run the new total ownership with life-cycle cost model under uncertainty. This would produce a new cost estimate for the program, which could then be compared to the original estimate and the actual life-cycle cost of the program. Executing this study would determine whether the TOC model developed in this thesis is a superior method of cost estimation for the DoD.

Another follow-on study could be done using the data from a program that is currently undergoing its initial cost estimation. The cost estimate could be done in conjunction with the DoD's current methods of cost estimation. Another researcher could partner with PEO IWS and the new system's program office to complete a cost estimate using the TOC model developed in this thesis. This process would allow for real-time cost comparisons at different stages in the acquisition process. The comparison between the two estimates would provide decision-makers with another method of verifying assumptions and validating that their cost estimates are reasonable and credible. Concurrently conducting the cost estimates allows researchers and cost estimators to compare their estimates to actual cost data at the different increments throughout the program's life cycle. This comparison would determine which method of cost estimation was more accurate at different points in the system's life cycle.

These follow-on studies require real-world cost data from historical or current EO/IR programs. While data collection may prove difficult and time-consuming, this research would be beneficial to the DoD and well worth the investment. Working with PEO IWS and the program office's cost estimation teams could result in model improvements and provide an even more robust total ownership with life-cycle cost model under uncertainty.

Other Applications and Conclusions

This thesis focuses specifically on the application of this TOC model with regard to EO/IR sensors on surface ships; it barely scratches the surface of the model's potential. This model could be applied to any one of the thousands of acquisition projects in the DoD. The model's use is not confined to EO/IR sensors on surface ships but can be adjusted and developed for various programs. The process and the strength of the results that the model would provide would be the same; the only necessary change a cost analyst would need to make is to alter the list of components to reflect whichever system or program is being analyzed. In the same fashion, this model could also provide contractors and non-DoD organizations with an additional method of cost estimation.

Cost estimation is not an exact science; however, this model provides a coherent method of estimating the total ownership with life-cycle costs under uncertainty for EO/IR sensors on surface ships. It gives a decision-maker another tool when evaluating alternative programs and courses of action. The ultimate goal of this model is to provide a more effective tool in determining how the DoD spends its limited resources on competing priorities. While follow-on research needs to be conducted to validate the efficacy of the model, this thesis offers a proof of concept and takes a step towards DoD portfolio optimization.

Appendix A. A Primer on Integrated Risk Management

In earlier times, chance was something that occurred in nature, and humans were simply subjected to it as a ship is to the capricious tosses of the waves in an ocean. Even up to the time of the Renaissance, the future was thought to be simply a chance occurrence of completely random events and beyond the control of humans. However, with the advent of games of chance, human greed has propelled the study of risk and chance to ever mirror real-life events more closely. Although these games were initially played with great enthusiasm, no one actually sat down and figured out the odds. Of course, the individual who understood and mastered the concept of chance was bound to be in a better position to profit from such games of chance. It was not until the mid-1600s that the concept of chance was properly studied, and the first such serious endeavor can be credited to Blaise Pascal, one of the fathers of the study of choice, chance, and probability. Fortunately for us, after many centuries of mathematical and statistical innovations from pioneers such as Pascal, Bernoulli, Bayes, Gauss, LaPlace, and Fermat, and with the advent of blazing fast computing technology, our modern world of uncertainty can be explained with much more elegance through methodological rigorous hands-on applications of risk and uncertainty. Even as recent as two and a half decades ago, computing technology was only in its infancy, and running complex and advanced analytical models would have seemed a fantasy, but today, with the assistance of more powerful and enabling software packages, we have the ability to practically apply such techniques with great ease. For this reason, we have chosen to learn from human history that with innovation comes the requisite change in human behavior to apply these new methodologies as the new norm for rigorous risk-benefit analysis.

To the people who lived centuries ago, risk was simply the inevitability of chance occurrence beyond the realm of human control. Many phony soothsayers profited from their ability to convincingly profess their clairvoyance by simply stating the obvious or reading the victims' body language and telling them what they wanted to hear. We modern-day humans, ignoring for the moment the occasional seers among us, with our fancy technological achievements, are still susceptible to risk and uncertainty. We may be able to predict the orbital paths of planets in our solar system with astounding accuracy, or to predict the escape velocity required to shoot a man from the Earth to the Moon, or to drop a smart bomb within a few feet of its target thousands of miles away, but when it comes to, say, predicting a firm's revenues the following year, we are at a loss. Humans have been struggling with risk our entire existence, but through trial and error, and through the evolution of human knowledge and thought, we have devised ways to describe, quantify, hedge, and take advantage of risk.

In the U.S. military context, risk analysis, real options analysis, and portfolio optimization techniques are enablers of a new way of approaching the problems of estimating return on investment (ROI) and estimating the risk-value of various strategic real options. There are many new DoD requirements for using more advanced analytical techniques. For instance, the Clinger–Cohen Act of 1996 mandates the use of portfolio management for all federal agencies. The Government Accountability Office's (1997) *Assessing Risks and Returns: A Guide for Evaluating Federal Agencies' IT Investment Decision-Making* requires that IT investments apply ROI measures. DoD Directive 8115.01, issued in October 2005, mandates the use of performance metrics based on outputs, with ROI analysis required for all current and planned IT investments. DoD Directive 8115.bb implements policy and assigns responsibilities for the management of DoD IT investments as portfolios within the DoD enterprise where they defined a portfolio to include outcome performance measures and an expected return on investment. The DoD Risk Management Guidance Defense Acquisition guidebook requires that alternatives to the traditional cost estimation need to be considered because legacy cost models tend not to adequately address costs associated with information systems or the risks associated with them.

In this quick primer, advanced quantitative risk-based concepts will be introduced, namely, the hands-on applications of Monte Carlo simulation, real options analysis, stochastic forecasting, portfolio optimization, and knowledge value added. These methodologies rely on common metrics and existing techniques (e.g., return on investment, discounted cash flow, cost-based analysis, and so forth), and complement these traditional techniques by pushing the envelope of analytics, and not replacing them outright. It is not a complete change of paradigm, and we are not asking the reader to throw out what is tried and true, but to shift one's paradigm, to move with the times, and to improve upon what is tried and true. These new methodologies are used in helping make the best possible decisions, allocate budgets, predict outcomes, create portfolios with the highest strategic value and returns on investment, and so forth, where the conditions surrounding these decisions are risky or uncertain. They can be used to identify, analyze, quantify, value, predict, hedge, mitigate, optimize, allocate, diversify, and manage risk for military options.

Why Is Risk Important in Making Decisions?

Before we embark on the journey to review these advanced techniques, let us first consider why risk is critical when making decisions, and how traditional analyses are inadequate in considering risk in an objective way. Risk is an important part of the decision-making process. For instance, suppose projects are chosen based simply on an evaluation of returns alone or cost alone; clearly the higher-return or lower-cost project will be chosen over lower-return or higher-cost projects.

As mentioned, projects with higher returns will in most cases bear higher risks. And those projects with immediately lower returns would be abandoned. In those cases, where return estimates are wholly derived from cost data (with some form of cost in the numerator and denominator of ROI), the best thing to do is reduce all the costs, that is, never invest in new projects. The result of this primary focus on cost reduction is a stifling of innovation and new ways of doing things. The goal is not simply cost reduction. In this case, the simplest approach is to fire everyone and sell off all the assets. The real question that must be answered is how cost compares to desired outputs, that is, "cost compared to what?"

To encourage a focus on improving processes and innovative technologies, a new way of calculating return on investment that includes a unique numerator is required. ROI is a basic productivity ratio that requires unique estimates of the numerator (i.e., value, revenue in common units of measurement) and the denominator (i.e., costs, investments in dollars). ROI estimates must be placed within the context of a longer term view that includes estimates of risk and the ability of management to adapt as they observe the performance of their investments over time. Therefore, instead of relying purely on immediate ROIs or costs, a project, strategy, process innovation, or new technology should be evaluated based on its total strategic value, including returns, costs, and strategic options, as well as its risks. Figures A.1 and A.2 illustrate the errors in judgment when risks are ignored. Figure A.1 lists three mutually exclusive projects with their respective costs to implement, expected net returns (net of the costs to implement), and risk levels (all in present values). Clearly, for the budget-constrained decision-maker, the cheaper the project the better, resulting in the selection of Project X. The returns-driven decision-maker will choose Project Y with the highest returns, assuming that budget is not an issue. Project Z will be chosen by the risk-averse decision-maker as it provides the least amount of risk while providing a positive net return. The upshot is that, with three different projects and three different decision-makers, three different decisions will be made. Who is correct and why?

Why is Risk Important?

Name of Project	Cost	Returns	Risk
Project X	$50	$50	$25
Project Y	$250	$200	$200
Project Z	$100	$100	$10

Project X for the cost and budget-constrained manager
Project Y for the returns driven and nonresource-constrained manager
Project Z for the risk-adverse manager
Project Z for the smart manager

Figure A.1. Why Is Risk Important?

Figure A.2 shows that Project Z should be chosen. For illustration purposes, suppose all three projects are independent and mutually exclusive, and that an unlimited number of projects from each category can be chosen but the budget is constrained at $1,000. Therefore, with this $1,000 budget, 20 project Xs can be chosen, yielding $1,000 in net returns and $500 risks, and so forth. It is clear from Figure A.2 that project Z is the best project as for the same level of net returns ($1,000), the least amount of risk is undertaken ($100). Another way of viewing this selection is that for each $1 of returns obtained, only $0.10 of risk is involved on average, or that for each $1 of risk, $10 in returns are obtained on average. This example illustrates the concept of bang for the buck or getting the best value (benefits and costs both considered) with the least amount of risk. An even more blatant example is if there are several different projects with identical single-point average net benefit or cost of $10 million each. Without risk analysis, a decision-maker should in theory be indifferent in choosing any of the projects. However, with risk analysis, a better decision can be made. For instance, suppose the first project has a 10% chance of exceeding $10 million, the second a 15% chance, and the third a 55% chance. Additional critical information is obtained on the riskiness of the project or strategy and a better decision can be made.

Adding an Element of Risk…

Looking at bang for the buck, X (2), Y (1), Z (10), Project Z should be chosen–with a $1,000 budget, the following can be obtained:

Project X: 20 Project Xs returning $1,000, with $500 risk
Project Y: 4 Project Xs returning $800, with $800 risk
Project Z: 10 Project Xs returning $1,000, with $100 risk

Project X: For each $1 return, $0.5 risk is taken
Project Y: For each $1 return, $1.0 risk is taken
Project Z: For each $1 return, $0.1 risk is taken

Project X: For each $1 of risk taken, $2 return is obtained
Project Y: For each $1 of risk taken, $1 return is obtained
Project Z: For each $1 of risk taken, $10 return is obtained

Conclusion:
Risk is important. Foregoing risks results in making the wrong decision.

Figure A.2. Adding an Element of Risk

Military and business leaders have been dealing with risk since the beginning of the history of war and commerce. In most cases, decision-makers have looked at the risks of a particular project, acknowledged their existence, and moved on. Little quantification was performed in the past. In fact, most decision-makers look only to single-point estimates of a project's benefit or profitability. Figure A.3 shows an example of a single-point estimate. The estimated net revenue of $30 is simply that, a single point whose probability of occurrence is close to zero. Even in the simple model shown in Figure A.3, the effects of interdependencies are ignored, and in traditional modeling jargon, we have the problem of garbage-in, garbage-out (GIGO). As an example of interdependencies, the units sold are probably negatively correlated to the price of the product, and positively correlated to the average variable cost; ignoring these effects in a single-point estimate will yield grossly incorrect results. There are numerous interdependencies in military options as well; for example, the many issues in logistics and troop movements beginning with the manufacturer all the way to the warrior in the field.

In the following commercial example, if the unit sales variable becomes 11 instead of 10, the resulting revenue may not simply be $35. The net revenue may actually decrease due to an increase in variable cost per unit while the sale price may actually be slightly lower to accommodate this increase in unit sales. Ignoring these interdependencies will reduce the accuracy of the model.

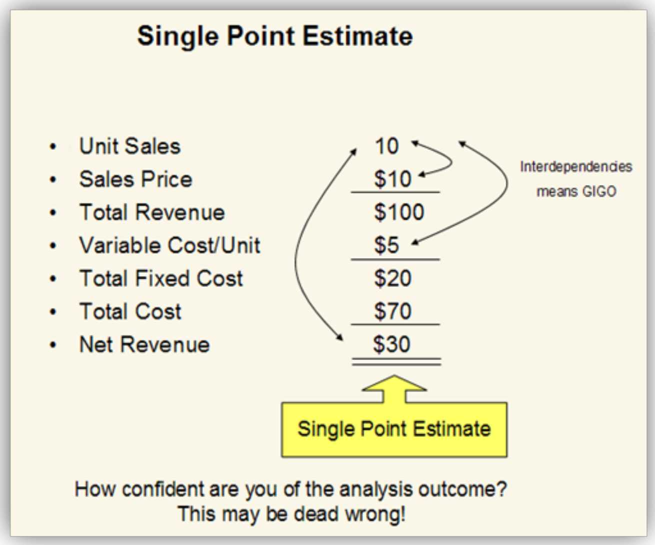


Figure A.3. Single-Point Estimates

One traditional approach used to deal with risk and uncertainty is the application of scenario analysis. For example, scenario analysis is a central part of the capabilities-based planning approach in widespread use for developing DoD strategies. In the previous commercial example, suppose three scenarios were generated: the worst-case, nominal-case, and best-case scenarios. When different values are applied to the unit sales, the resulting three scenarios' net revenues are obtained. As earlier, the problems of interdependencies are not addressed with these common approaches. The net revenues obtained are simply too variable. Not much can be determined from such an analysis.

In the military planning case, the problems are exacerbated by the lack of objective ways to estimate benefits in common units. Without the common-unit benefits analysis, it becomes difficult, if not impossible, to compare the net benefits of various scenarios. In addition, interdependencies must be interpreted in a largely subjective manner, making it impossible to apply powerful mathematical and statistical tools that enable more objective portfolio analysis. The problem arises for the top leaders in the DoD to make judgment calls, or selections among alternatives (often referred to as “trades”) about the potential benefits and risks of numerous projects and technologies investments.

A related approach is to perform a what-if or sensitivity analysis. Each variable is perturbed a prespecified amount (e.g., unit sales is changed ±10%, sales price is changed ±5%, and so forth) and the resulting change in net benefits is captured. This approach is useful for understanding which variables drive or impact the result the most. Performing such analyses by hand or with simple Excel spreadsheets is tedious and provides marginal benefits at best. A related approach that has the same goals but employs a more powerful analytic framework is the use of computer-modeled Monte Carlo simulation and tornado sensitivity analysis, where all perturbations, scenarios, and sensitivities are run hundreds of thousands of times automatically.

Therefore, computer-based Monte Carlo simulation, one of the advanced concepts introduced in this paper, can be viewed as simply an extension of the traditional approaches of sensitivity and scenario testing. The critical success drivers or the variables that affect the bottom-line variables the most, which at the same time are uncertain, are simulated. In simulation, the interdependencies are accounted for by using correlation analysis. The uncertain variables are then simulated tens of thousands of times automatically to emulate all potential permutations and combinations of outcomes. The resulting net revenues-benefits from these simulated potential outcomes are tabulated and analyzed. In essence, in its most basic form, simulation is simply an enhanced version of traditional approaches, such as sensitivity and scenario analysis, but automatically performed thousands of times while accounting for all the dynamic interactions between the simulated variables. The resulting net revenues from simulation, as seen in Figure A.4, show that there is a 90% probability that the net revenues will fall between $19.44 and $41.25, with a 5% worst-case scenario of net revenues falling below $19.44. Rather than having only three scenarios, simulation created 5,000 scenarios, or trials, where multiple variables are simulated and changing simultaneously (unit sales, sale price, and variable cost per unit), while their respective relationships or correlations are maintained.

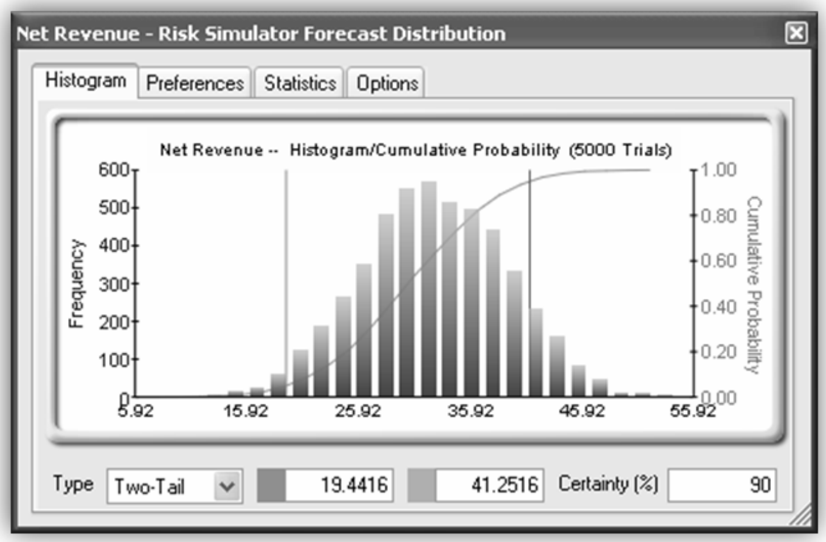


Figure A.4. Simulation Results

Monte Carlo simulation, named for the famous gambling capital of Monaco, is a very potent methodology. For the practitioner, simulation opens the door for solving difficult and complex but practical problems with great ease. Perhaps the most famous early use of Monte Carlo simulation was by the Nobel physicist Enrico Fermi (sometimes referred to as the father of the atomic bomb) in 1930, when he used a random method to calculate the properties of the newly discovered neutron. Monte

Carlo methods were central to the simulations required for the Manhattan Project, where, in the 1950s, Monte Carlo simulation was used at Los Alamos for early work relating to the development of the hydrogen bomb and became popularized in the fields of physics and operations research. The Rand Corporation and the U.S. Air Force were two of the major organizations responsible for funding and disseminating information on Monte Carlo methods during this time, and today there is a wide application of Monte Carlo simulation in many different fields including engineering, physics, research and development, business, and finance.

Simplistically, Monte Carlo simulation creates artificial futures by generating thousands and even hundreds of thousands of sample paths of outcomes and analyzes their prevalent characteristics. In practice, Monte Carlo simulation methods are used for risk analysis, risk quantification, sensitivity analysis, and prediction. An alternative to simulation is the use of highly complex stochastic closed-form mathematical models. For a high-level decision-maker, taking graduate level advanced math and statistics courses is just not logical or practical. A well-informed analyst would use all available tools at his or her disposal to obtain the same answer the easiest and most practical way possible. And in all cases, when modeled correctly, Monte Carlo simulation provides similar answers to the more mathematically elegant methods. In addition, there are many real-life applications where closed-form models do not exist and the only recourse is to apply simulation methods. So, what exactly is Monte Carlo simulation and how does it work?

Monte Carlo simulation in its simplest form is a random number generator that is useful for forecasting, estimation, and risk analysis. A simulation calculates numerous scenarios of a model by repeatedly picking values from a user-predefined probability distribution for the uncertain variables and using those values for the model. As all those scenarios produce associated results in a model, each scenario can have a forecast. Forecasts are events (usually with formulas or functions) that you define as important outputs of the model.

Think of the Monte Carlo simulation approach as picking golf balls out of a large basket repeatedly with replacement. The size and shape of the basket depend on the distributional input assumption (e.g., a normal distribution with a mean of 100 and a standard deviation of 10, versus a uniform distribution or a triangular distribution) where some baskets are deeper or more symmetrical than others, allowing certain balls to be pulled out more frequently than others. The number of balls pulled repeatedly depends on the number of trials simulated. Each ball is indicative of an event, scenario, or condition that can occur. For a large model with multiple related assumptions, imagine the large model as a very large basket, wherein many baby baskets reside. Each baby basket has its own set of colored golf balls that are bouncing around. Sometimes these baby baskets are linked with each other (if there is a correlation between the variables), forcing the golf balls to bounce in tandem whereas in other uncorrelated cases, the balls are bouncing independently of one another. The balls that are picked each time from these interactions within the model (the large basket) are tabulated and recorded, providing a forecast output result of the simulation.

As the U.S. military is not in the business of making money, referring to revenues throughout this paper may appear to be a misnomer. For nonprofit organizations, especially in the military, we require Knowledge Value Added (KVA), which will provide the required "benefits" or "revenue" proxy estimates to run ROI analysis. ROI is a basic productivity ratio with revenue in the numerator and cost to generate the revenue in the denominator (actually ROI is revenue-cost/cost). KVA generates ROI estimates by developing a market comparable price per common unit of output multiplied by the number of outputs to achieve a total revenue estimate.

KVA is a methodology whose primary purpose is to describe all organizational outputs in common units. It provides a means to compare the outputs of all assets (human, machine, information technology) regardless of the aggregated outputs produced. For example, the purpose of a military process may be to gather signal intelligence or plan for a ship alteration. KVA would describe the outputs of both processes in common units, thus making their performance comparable.

KVA measures the value provided by human capital assets and IT assets by analyzing an organization, process, or function at the process level. It provides insights into each dollar of IT investment by monetizing the outputs of all assets, including intangible assets (e.g., assets produced by IT and humans). By capturing the value of knowledge embedded in an organization's core processes (i.e., employees and IT), KVA identifies the actual cost and revenue of a process, product, or service. Because KVA identifies every process required to produce an aggregated output in terms of the historical prices and costs per common unit of output of those processes, unit costs and unit prices can be calculated. The methodology has been applied in 45 areas within the DoD, from flight scheduling applications to ship maintenance and modernization processes.

As a performance tool, the KVA methodology

- compares all processes in terms of relative productivity,
- allocates revenues and costs to common units of output,
- measures value added by IT by the outputs it produces, and
- relates outputs to cost of producing those outputs in common units.

Based on the tenets of complexity theory, KVA assumes that humans and technology in organizations add value by taking inputs and changing them (measured in units of complexity) into outputs through core processes. The amount of change an asset within a process produces can be a measure of value or benefit. The additional assumptions in KVA include the following:

- Describing all process outputs in common units (e.g., using a knowledge metaphor for the descriptive language in terms of the time it takes an average employee to learn how to produce the outputs) allows historical revenue and cost data to be assigned to those processes historically.

- All outputs can be described in terms of the time required to learn how to produce them.
- Learning Time, a surrogate for procedural knowledge required to produce process outputs, is measured in common units of time. Consequently, Units of Learning Time = Common Units of Output (K).
- A common unit of output makes it possible to compare all outputs in terms of cost per unit as well as price per unit, because revenue can now be assigned at the suborganizational level.
- Once cost and revenue streams have been assigned to suborganizational outputs, normal accounting and financial performance and profitability metrics can be applied (Rodgers & Housel, 2006; Pavlou et al., 2005; Housel & Kanevsky, 1995).

Describing processes in common units also permits market comparable data to be generated, which is particularly important for nonprofits like the U.S. military. Using a market comparable approach, data from the commercial sector can be used to estimate price per common unit, allowing for revenue estimates of process outputs for nonprofits. This approach also provides a common-unit basis to define benefit streams regardless of the process analyzed.

KVA differs from other nonprofit ROI models because it allows for revenue estimates, enabling the use of traditional accounting, financial performance, and profitability measures at the sub-organizational level. KVA can rank processes by the degree to which they add value to the organization or its outputs. This ranking assists decision-makers to identify how much processes add value. Value is quantified in two key metrics: Return on Knowledge (ROK: revenue/cost) and ROI (revenue-investment cost/investment cost). The outputs from a KVA analysis become the input into the ROI models and real options analysis. By tracking the historical volatility of price and cost per unit as well as ROI, it is possible to establish risk (as compared to uncertainty) distributions, which is important for accurately estimating the value of real options.

The KVA method has been applied to numerous military core processes across the services. The KVA research has more recently provided a means for simplifying real options analysis for DoD processes. Current KVA research will provide a library of market comparable price and cost per unit of output estimates. This research will enable a more stable basis for comparisons of performance across core processes. This data also provides a means to establish risk distribution profiles for Integrated Risk Management approaches such as real options, and KVA currently is being linked directly to the Real Options Super Lattice Solver and Risk Simulator software for rapid adjustments to real options valuation projections.

Appendix B. Understanding Probability Distributions

This appendix demonstrates the power of Monte Carlo risk simulation, but in order to get started with simulation, one first needs to understand the concept of probability distributions. This appendix continues with the use of the author's Risk Simulator software and shows how simulation can be very easily and effortlessly implemented in an existing Excel model.

To begin to understand probability, consider the following example. You want to look at the distribution of nonexempt wages within one department of a large company. First, you gather raw data—in this case, the wages of each nonexempt employee in the department. Second, you organize the data into a meaningful format and plot the data as a frequency distribution on a chart. To create a frequency distribution, you divide the wages into group intervals and list these intervals on the chart's horizontal axis. Then you list the number or frequency of employees in each interval on the chart's vertical axis. Now you can easily see the distribution of nonexempt wages within the department.

A glance at Figure A.5 reveals that the employees earn from $7.00 to $9.00 per hour. You can chart this data as a probability distribution. A probability distribution shows the number of employees in each interval as a fraction of the total number of employees. To create a probability distribution, you divide the number of employees in each interval by the total number of employees and list the results on the chart's vertical axis.

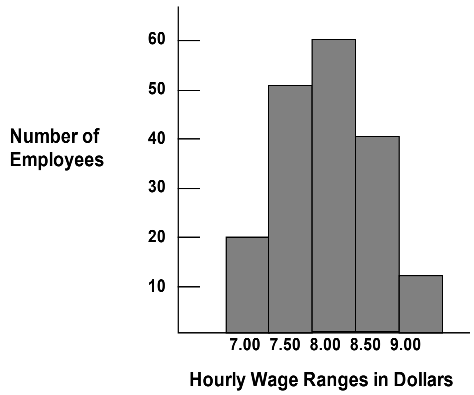


Figure A.5. Frequency Histogram I

Figure A.6 shows the number of employees in each wage group as a fraction of all employees; you can estimate the likelihood or probability that an employee drawn at random from the whole group earns a wage within a given interval. For example, assuming the same conditions exist at the time the sample was taken, the probability is 0.20 (a one in five chance) that an employee drawn at random from the whole group earns $8.50 an hour.

Probability distributions are either discrete or continuous. *Discrete probability distributions* describe distinct values, usually integers, with no intermediate values and are shown as a series of vertical bars. A discrete distribution, for example, might describe the number of heads in four flips of a coin as 0, 1, 2, 3, or 4. *Continuous probability distributions* are actually mathematical abstractions because they assume the existence of every possible intermediate value between two numbers; that is, a continuous distribution assumes there is an infinite number of values between any two points in the distribution. However, in many situations, you can effectively use a continuous distribution to approximate a discrete distribution even though the continuous model does not necessarily describe the situation exactly.

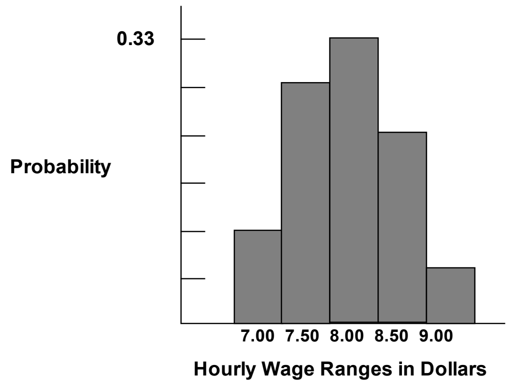


Figure A.6. Frequency Histogram II

Selecting a Probability Distribution

Plotting data is one method for selecting a probability distribution. The following steps provide another process for selecting probability distributions that best describe the uncertain variables in your spreadsheets.

To select the correct probability distribution, use the following steps:

- Look at the variable in question. List everything you know about the conditions surrounding this variable. You might be able to gather valuable information about the uncertain variable from historical data. If historical data are not available, use your own judgment, based on experience, listing everything you know about the uncertain variable.
- Review the descriptions of the probability distributions.
- Select the distribution that characterizes this variable. A distribution characterizes a variable when the conditions of the distribution match those of the variable.

Alternatively, if you have historical, comparable, contemporaneous, or forecast data, you can use Risk Simulator's distributional fitting modules to find the best statistical fit for your existing data. This fitting process will apply some advanced statistical techniques to find the best distribution and its relevant parameters that describe the data.

Probability Density Functions, Cumulative Distribution Functions, and Probability Mass Functions

In mathematics and Monte Carlo simulation, a probability density function (PDF) represents a *continuous* probability distribution in terms of integrals. If a probability distribution has a density of *f(x)*, then intuitively the infinitesimal interval of [*x, x* + *dx*] has a probability of *f(x) dx*. The PDF therefore can be seen as a smoothed version of a probability histogram; that is, by providing an empirically large sample of a continuous random variable repeatedly, the histogram using very narrow ranges will resemble the random variable's PDF. The probability of the interval between [*a, b*] is given by $\int_a^b f(x)dx$, which means that the total integral of the function *f* must be 1.0**.** It is a common mistake to think of *f(a)* as the probability of *a*, when, in fact, *f(a)* can sometimes be larger than 1—consider a uniform distribution between 0.0 and 0.5. The random variable *x* within this distribution will have *f(x)* greater than 1. The probability, in reality, is the function *f(x)dx* discussed previously, where *dx* is an infinitesimal amount.

The cumulative distribution function (CDF) is denoted as *F(x)* = *P(X ≤ x)* indicating the probability of *X* taking on a less than or equal value to *x*. Every CDF is monotonically increasing, is continuous from the right, and at the limits, has the following properties: $\lim_{x \to -\infty} F(x) = 0$ and $\lim_{x \to +\infty} F(x) = 1$. Further, the CDF is related to the PDF by $F(b) - F(a) = P(a \le X \le b) = \int_a^b f(x)dx$, where the PDF function *f* is the derivative of the CDF function *F*.

In probability theory, a probability mass function, or PMF, gives the probability that a *discrete* random variable is exactly equal to some value. The PMF differs from the PDF in that the values of the latter, defined only for continuous random variables, are not probabilities; rather, its integral over a set of possible values of the random variable is a probability. A random variable is discrete if its probability distribution is discrete and can be characterized by a PMF. Therefore, *X* is a discrete random variable if $\sum_u P(X = u) = 1$ as *u* runs through all possible values of the random variable *X*.

Normal Distribution

The normal distribution is the most important distribution in probability theory because it describes many natural phenomena, such as people's IQs or heights. Decision-makers can use the normal distribution to describe uncertain variables such as the inflation rate or the future price of gasoline.

The three main conditions underlying the normal distribution:

- Some value of the uncertain variable is the most likely (the mean of the distribution).
- The uncertain variable could as likely be above the mean as it could be below the mean (symmetrical about the mean).
- The uncertain variable is more likely in the vicinity of the mean than further away.

The mathematical constructs for the normal distribution are as follows:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad \textit{for all values of } x \text{ and } \mu\text{; while } \sigma > 0$$

Mean = μ

Standard Deviation = σ

Skewness = 0 (this applies to all inputs of mean and standard deviation)

Excess Kurtosis = 0 (this applies to all inputs of mean and standard deviation)

Mean (μ) and standard deviation (σ) are the distributional parameters.

Input requirements: Standard deviation > 0 and can be any positive value whereas mean can be any value

PERT Distribution

The PERT distribution is widely used in project and program management to define the worst-case, nominal-case, and best-case scenarios of project completion time. It is related to the beta and triangular distributions. PERT distribution can be used to identify risks in project and cost models based on the likelihood of meeting targets and goals across any number of project components using minimum, most likely, and maximum values, but it is designed to generate a distribution that more closely resembles realistic probability distributions. The PERT distribution can provide a close fit to the normal or lognormal distributions. Like the triangular distribution, the PERT distribution emphasizes the most likely value over the minimum and maximum estimates. However, unlike the triangular distribution, the PERT distribution constructs a smooth curve that places progressively more emphasis on values around (near) the most likely value, in favor of values around the edges. In practice, this means that we trust the estimate for the most likely value, and we believe that even if it is not exactly accurate (as estimates seldom are), we have an expectation that the resulting value will be close to that estimate. Assuming that many real-world phenomena are normally distributed, the appeal of the PERT distribution is that it produces a curve similar to the normal curve in shape, without knowing the precise parameters of the related normal curve. Minimum, most likely, and maximum are the distributional parameters.

The mathematical constructs for the PERT distribution are shown here:

$$f(x) = \frac{(x-Min)^{A1-1}(Max-x)^{A2-1}}{B(A1,A2)(Max-Min)^{A1+A2-1}}$$

$$where\ A1 = 6\left[\frac{\frac{Min+4(Likely)+Max}{6}-Min}{Max-Min}\right]\ and\ A2 = 6\left[\frac{Max-\frac{Min+4(Likely)+Max}{6}}{Max-Min}\right]$$

and B is the Beta function

Mean = $\dfrac{Min + 4Mode + Max}{6}$

Standard Deviation = $\sqrt{\dfrac{(\mu - Min)(Max - \mu)}{7}}$

Skew = $\sqrt{\dfrac{7}{(\mu - Min)(Max - \mu)}}\left(\dfrac{Min + Max - 2\mu}{4}\right)$

Excess Kurtosis is a complex function and cannot be readily computed.

Input requirements: Min ≤ Most Likely ≤ Max and can be positive, negative, or zero.

Triangular Distribution

The triangular distribution describes a situation where you know the minimum, maximum, and most likely values to occur. For example, you could describe the number of cars sold per week when past sales show the minimum, maximum, and usual number of cars sold.

The three main conditions underlying the triangular distribution:

- The minimum number of items is fixed.
- The maximum number of items is fixed.
- The most likely number of items falls between the minimum and maximum values, forming a triangular-shaped distribution, which shows that values near the minimum and maximum are less likely to occur than those near the most-likely value.

The mathematical constructs for the triangular distribution are as follows:

$$f(x) = \begin{cases} \dfrac{2(x - Min)}{(Max - Min)(Likely - \min)} & for\ Min < x < Likely \\ \dfrac{2(Max - x)}{(Max - Min)(Max - Likely)} & for\ Likely < x < Max \end{cases}$$

Mean = $\frac{1}{3}(Min + Likely + Max)$

Standard Deviation = $\sqrt{\frac{1}{18}(Min^2 + Likely^2 + Max^2 - Min\,Max - Min\,Likely - Max\,Likely)}$

Skewness = $\dfrac{\sqrt{2}(Min + Max - 2Likely)(2Min - Max - Likely)(Min - 2Max + Likely)}{5(Min^2 + Max^2 + Likely^2 - MinMax - MinLikely - MaxLikely)^{3/2}}$

Excess Kurtosis = -0.6 (this applies to all inputs of Min, Max, and Likely)

Minimum (Min), most likely (Likely) and maximum (Max) are the parameters.

Input requirements:

Min ≤ Most Likely ≤ Max and can take any value.

However, Min < Max and can take any value.

Uniform Distribution

With the uniform distribution, all values fall between the minimum and maximum and occur with equal likelihood.

The three main conditions underlying the uniform distribution:

- The minimum value is fixed.
- The maximum value is fixed.
- All values between the minimum and maximum occur with equal likelihood.

The mathematical constructs for the uniform distribution are as follows:

$$f(x) = \frac{1}{Max - Min} \quad \textit{for all values such that } Min < Max$$

Mean = $\frac{Min + Max}{2}$

Standard Deviation = $\sqrt{\frac{(Max - Min)^2}{12}}$

Skewness = *0* (this applies to all inputs of Min and Max)

Excess Kurtosis = -1.2 (this applies to all inputs of Min and Max)

Maximum value (Max) and minimum value (Min) are the distributional parameters.

Input requirements: Min < Max and can take any value.

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