Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
May 3, 2018
A Regional Conference of the Society for Industrial and Systems Engineering

Determining Uncertainty Within Life Cycle Cost of Engineered Resilient Systems

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Author Note: The authors of this article consists of a Cadet Capstone Team and Capstone Advisor at the United States Military Academy. We would like to thank our client Mr. James Richards of the Engineer Research and Development Center and the Department of Systems Engineering at the United States Military Academy for funding this project.

Abstract: This article discusses how the Life Cycle Costing (LCC) component of Engineered Resilient Systems (ERS) can be utilized in order to create a more accurate and reliable process for predicting the costs of Department of Defense projects. While researching this project the Capstone team looked at multiple ways of predicting ERS project costs such as Bayes Theorem and Regression Analysis. Python, a computer program, provides the capability to isolate cost element structures and their respective cost estimating relationships in order to understand the propagation of uncertainty. In the end the team found that when given the mean and standard deviation of constants in cost estimating relationships that have been completed, there are commonalities between them that can be extracted and used to identify uncertainty. This will help predict future costs for similar systems.

Keywords: Engineer Research and Development Center (ERDC). Engineered Resilient System (ERS). Life Cycle Cost (LCC). Cost Estimating Relationships (CER). Uncertainty. Department of Defense (DoD)

1. Purpose

The purpose of this project is to give ERDC a tool that identifies areas of uncertainty within the CERs of a larger cost model so they can better understand the embedded uncertainty within LCC.

1.1 Background

For the purpose of this paper a few commonly used terms must be defined. An accurate and reliable process for predicting LCC is one that replicates the true expected system cost and consistently does so. LCC "is an important economic analysis used in the selection of alternatives that impact both pending and future costs" (U.S. General Service Administration). A CER is, "A mathematical relationship that defines cost as a function of one or more variables such as performance, operating characteristics, physical characteristics, etc" (Glossary of Defense Acquisition). The objective of this project is to research and help improve ways in which LCC is estimated when creating ERSs. ERDC states that "ERS seeks to create an integrated capability to increase the quality of acquisition decision-making information prior to the Milestone-A decision point." ERDC has been developing the ERS and is seeking ways to predict a more accurate LCC. There were many facets in which the Capstone Team looked to assess the validity of the current Life Cycle Cost methodology. The decision was to focus on the effects of uncertainty because the level of uncertainty of an ERS can vastly vary the resulting cost. Analyzing the uncertainty in the LCC gives ERDC the ability to assess which parameters have the greatest effects on the LCC. Through intensive research, the Capstone Team was able to find that a majority of the cost is predicted in the Pre-Milestone A phase of the Defense Acquisition Process (see Figure 1). Due to this discovery, our research has been primarily directed to this concept. There is past evidence of Department of Defense projects that have experienced extreme cases of poor cost estimation that ultimately led to project failure due to the uncertainty of predicting LCC. Refining and honing in on Pre-Milestone A uncertainty in cost factors allows for a more accurate Life Cycle Cost as a whole.

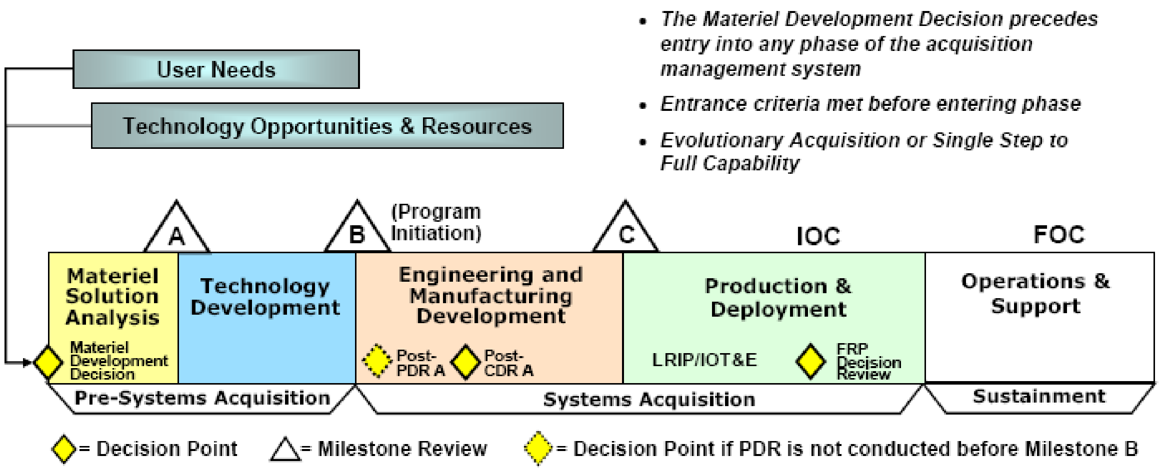

Figure 1. Defense Acquisition Process (DODI 5000.02)

1.2 Problem

ERDC is faced with the difficulty of estimating the LCC of the complex system that is ERS. Our team identified the problem as a need for a methodology that will give an accurate assessment of the uncertainty in an ERS LCC. It is important to acknowledge that stakeholders possess different sources and methodologies of determining CERs. We are seeking to create a tool that is user friendly to those in the Defense Acquisition community.

1.3 Other Approaches

One of the first methodologies explored by the group was attempting to use Bayes Theorem as a method to help determine the uncertainty of variables within life cycle costs of different projects. A major aspect of using this method is working with decision trees in order to find a dependent probability by flipping the decision tree. After using this methodology and conducting research and analysis of its benefits and drawbacks, the group decided that it would be too difficult to create a large decision tree dependent on so many factors and probabilities because the tree grew exponentially as more cost elements were considered in the LCC. We found that with a basic cost model of 20 elements, the cost model decision tree contained 160,000 different branches. It was not practical to pursue given the tools at our disposal, so the group moved on and decided to pursue different methods.

Another methodology we explored was to build different systems and track the different systems costs in a program called DragonFly. DragonFly is a Defense Acquisition University simulation that allows the user to create an Unmanned Ground Combat Vehicle with many different modeling aspects that influence life cycle cost. By doing this, we were able to determine the uncertainty of the models by changing the different system components. We thought this would be a good avenue due to the perceived relevance to our project. The virtual aspect would have been a useful simulation to the study, however DragonFly's foundation is narrow in terms of its data analysis. DragonFly's data was not robust enough to incorporate the uncertainty. Although we did not pursue this course of action, it showed us that the cost models in DragonFly where all linear and too basic to provide pertinent feedback about the levels of uncertainty in a complex system's LCC.

2. Methodology

Experts use many methods and sources to build CERs that attempt to accurately predict the costs of projects for stakeholders. Although these CERs provide great information, they do not always accurately predict cost. Depending on how each of the CERs were made, some have more uncertainty than others. One piece of the model that was identified as an area of uncertainty were the constants that are found to supplement the relationships between system elements and cost. Constants within CERs are often derived from a linear regression of historical data, such as in the case of the Light Reconnaissance Vehicle (LRV) LCC model provided by Technomics, a contractor working with ERDC on ERS. More specifically, these

ISBN: 97819384961-2-7

constants often come directly from raw data itself or an average of other constants from similar CERs. In both ways constants are derived to support a best fit model.

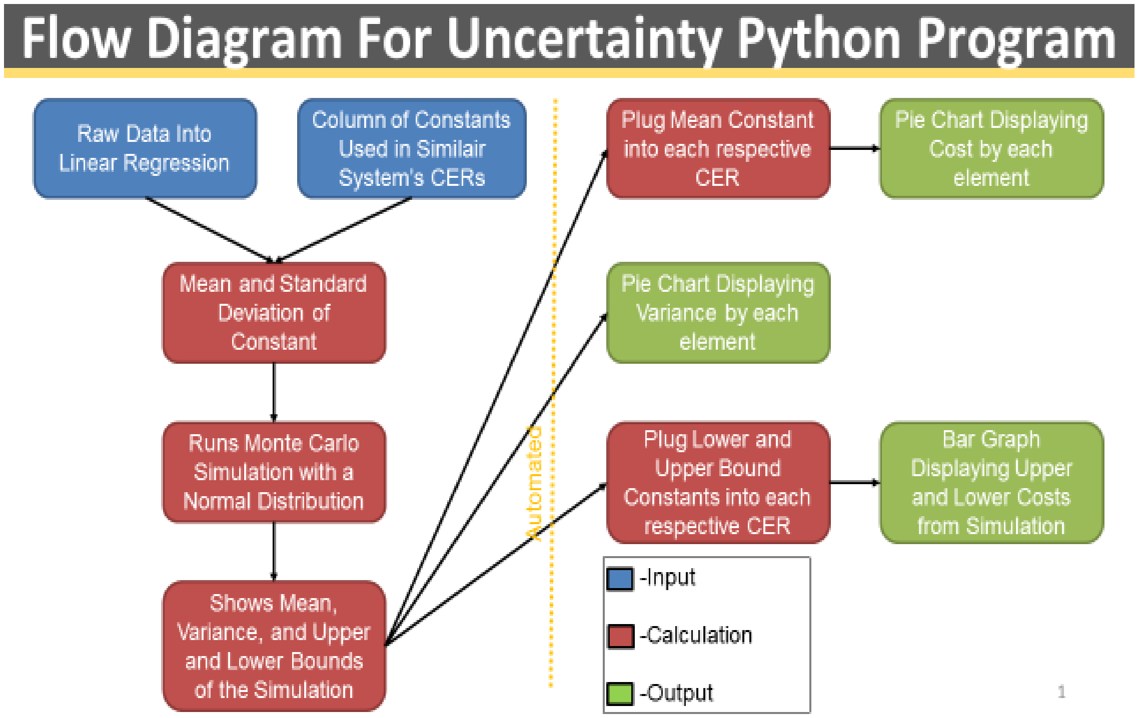

Figure 2. This chart displays a flow diagram that depicts the logical sequence of the Python script.

To begin testing the level of uncertainty of constants we created a Python script in Jupyter that uses simulation and statistical analysis to portray the effects of the constant's uncertainty on the LCC. The flow diagram above in Figure 2 depicts the logical sequence of the Python script that is described throughout the methodology and outcomes. Jupyter is a Python coding platform that is user friendly and has the mathematical imports necessary for such analysis. The script has the ability to read in one of two inputs. Equation 1 below shows an example of CER in the cost element structure 1.0, where the development engineering is dependent on both inputs and a constant. In equation 1, 9.1965 is the constant that is being tested for uncertainty.

$$Development\ Engineering = Unit\ Prototype\ Manufacturing\ Cost * 9.1965 * \#\ of\ contractors \quad (1)$$

First it can read in a two column set of raw data, perform the regression analysis, and determine the constant and standard deviation of the constant. The other is a single column list of other constants that are gathered from similar CERs, and then determines the mean and standard deviation of the constants. Both of these will yield a mean and standard deviation which is next used in a Monte Carlo simulation. The simulation assumes a normal distribution because it predicts many neutral, linear data sets well and then runs 1000 iterations based on the mean and standard deviation provided. Output consists of a mean, variance, and lower and upper bounds of the constant. The script is designed to isolate one cost element structure at a time, however once the code is automated it can run multiple, one after the other. This will allow for all of the results to be stored in the program instead of manually recording them.

Next the script will take all of the results of the cost element structure's constants and compare them in three different ways. The first display uses the variance of the simulation and creates a pie chart based on the levels of variance for each constant which can be seen in Figure 3. The second display is a similar pie chart as the first, however this time it is based on the cost of each element when the constants are reevaluated in the CERs. This is depicted by Figure 4. Lastly, the third display uses the lower and upper bounds of the constants found in the simulation. Each bound substituted into their original CER which results in the lower and upper limits of the element's cost. The script then displays these cost bounds in a bar graph for each respective cost element structure as depicted in Figure 5. The confidence in these bounds are based on the statistical analysis and are not the lowest and highest possibilities.

ISBN: 97819384961-2-7

3. Outcomes and Results

The outcomes of this project address the specific issue of identifying an area of uncertainty in predicting the LCC of an ERS. The proposed Python script, as explained in the methodology, is currently designed to output three different display options based on the choice of input data. Each of the displays provide different information for the stakeholder. In order to test the script, our team ran test sets of Excel documents full of mock data through the simulation. The mock data was specifically made to work into the cost element structure 1.0 of the LRV LCC model where there were CERs that contained constants. This tested both reliability and validity of the script. Once the run was complete, the script performed a similar analysis as the Monte Carlo simulation that was done in Excel on the LRV cost model. The script worked in the way it was intended and produced the information that was expected. In order to further test the reliability and validity of the script it is necessary to acquire the real data that was used to formulate the constants within the LRV model. If the simulation matches the statistics of the data sheet and the displays resemble the original costs of cost model, then we can say with a certain level of confidence what the estimated LCC will actually be. Although the script does not automatically store the statistics from each cost element structure, it can be modified in the future to do this. This will increase the usability of the code when providing the statistical information for the displays.

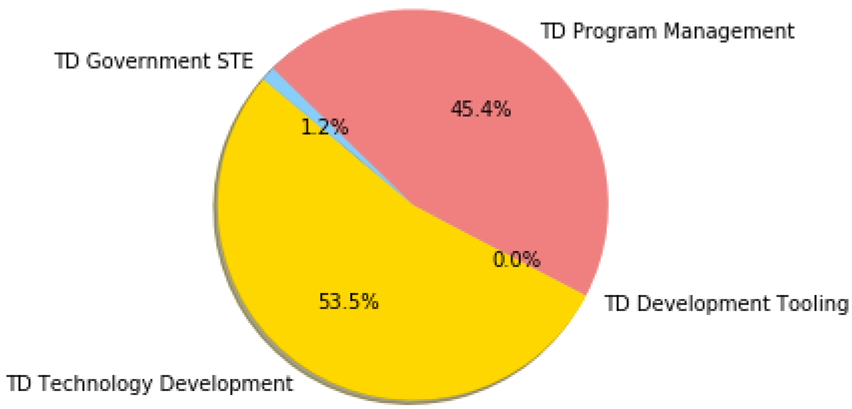

Figure 3. Display 1: Pie chart that shows the proportion of variance of four different elements in a cost element structure using the mock data.

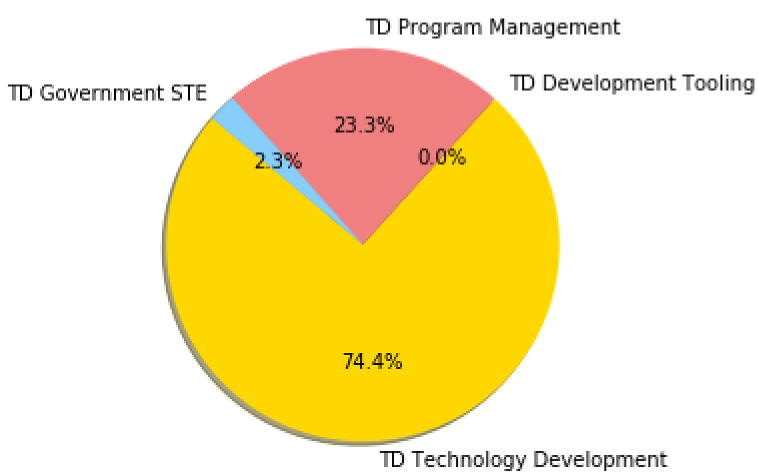

Figure 4. Display 2: Pie Chart that shows the proportion of LCC for four different elements in a cost element structure using the mock data.

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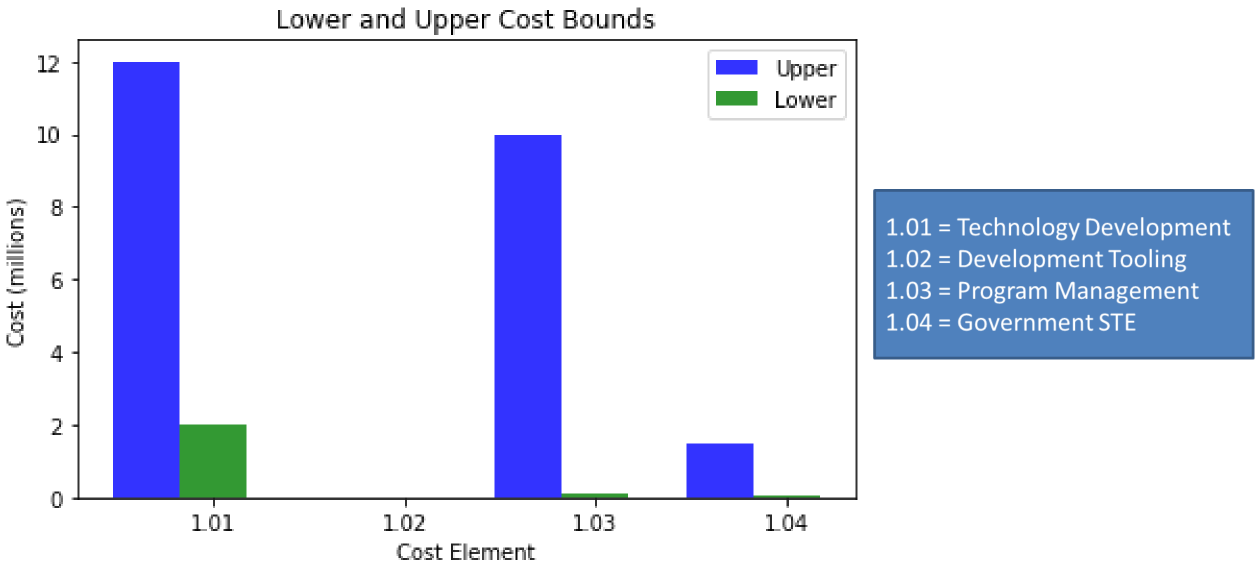

Figure 5. Display 3: Bar Graph that shows the lower and upper bounds of the LCC for four different cost element structures using the mock data.

4. Recommendations and Conclusions

The outcomes of the three displays provide the cost estimator and stakeholders with information that informs a recommendation based on one of four scenarios. The scenarios come from when a cost element structure has: small uncertainty and small cost, large uncertainty and small cost, small uncertainty and large cost, or large uncertainty and large cost. When there is a large uncertainty the cost element structure's constant will have a larger variance and thus a larger gap between its lower and upper bounds. This makes it more difficult to pinpoint the exact cost. Although the variance is important to identify, the weight of the cost is more important if the total cost for the element is deemed significant by the stakeholder. For instance, most would agree that a system element that costs $10,000 with a variance of 20% is not as influential as a system element that costs $100,000 with a variance of 5%.

The small uncertainty, small cost scenario is the least important element of the LCC. Not only is the total cost small, but it does not fluctuate. Large uncertainty, large cost is a red flag that identifies an area that needs improvement because a large cost factor in the LCC that has the potential to fluctuate may cause over or under budgeting. Both the large uncertainty, small cost and small uncertainty, large cost scenarios are more difficult to rank in importance. This comes down to what is available to address the uncertainty at hand. If there are resources and funding that can be attributed to minimizing the level of uncertainty in a cost element structure, then it should be allotted to the one that has a larger cost. However, if the uncertainty of an element causes its upper and lower bounds to overlap and surpass the cost of another element, then that element should become the new priority.

Overall, we see that the constants that make up CERs in a cost model contain useful statistical information about the uncertainty of predicting cost. By simulating this information, one can acquire a range of costs that their cost will fall under. Dividing the elements up separately and comparing them allows one to see which of the elements is the most important and then rank them based on order of need for improvement. This analysis applied to the trade builder tool of ERDC for ERS addresses the concept that uncertainty exists within their cost models and that it can be addressed to provide more useful information to its users.

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