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ACQUISITION RESEARCH PROGRAM SPONSORED REPORT SERIES

Assessing the Accuracy of Cost Estimates using Statistical Techniques

December 2022

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Naval Postgraduate School

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ABSTRACT

Accurate cost estimates are vital to sustaining Navy Expeditionary Combat Command (NECC) operational forces. Currently, NECC needs a method to assess the accuracy of future cost estimates that will not disrupt its existing cost estimation process during the POM cycle. Accuracy is the sole metric used in this study to analyze and assess the effectiveness of a cost estimate. This research uses statistical techniques to assess the cost estimate's accuracy, including single variable linear regression, Monte Carlo simulation, and a proportional scale-down model. The sample of sustainment cost data spans from FY 2016 to 2021. The point estimates from the regression model revealed that the total aggregate cost decreases by just under $16.6 million in constant year 2018 dollars (CY18$) each fiscal year. I applied the point estimate and standard error to the Monte Carlo simulation to produce a normal probability distribution with a range of possible outcomes (i.e., probability of occurrence linked to each value within that range). For the FY2025 scenario simulation, the mean value representing the most likely estimate is $303,649,744 (CY18$), and the standard deviation is $7,767,962 (CY18$). The proportional scale factor model breaks down the aggregate estimate to a lower level of programmatic detail for additional analysis. Applying statistical techniques to the existing process will help ensure that operational forces receive sufficient resources to accomplish the mission.

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This paper is dedicated to my amazing husband, Kyle, for his steadfast support; to my sister, Jessica, for her mentorship and inspiring creativity; to my mother, Monica, for her strength and sacrifice; and to my late father, John, for his endless encouragement and kindness.

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LIST OF ACRONYMS AND ABBREVIATIONS

APPN	Appropriation
BSO 60	Commander, United States Fleet Forces
BSO 70	Commander, United States Pacific Fleet
BSO	Budget Submitting Office
CCM	Capability Cost Model
CER	Cost Estimating Relationship
CRF	Coastal Riverine Force
CV	Coefficient of Variation
CY	Constant Year
EOD	Explosive Ordnance Division
FY	Fiscal Year
GRG	Generalized Reduced Gradient
JIC	Joint Inflation Calculator
JON CIVPERS	Civilian Personnel
JON	Job Order Number
MDSU	Mobile Diving and Salvage Unit
MESF	Maritime Expeditionary Security Force
NAVELSG	Navy Expeditionary Logistics Group
NCF	Naval Construction Force
NECC	Navy Expeditionary Combat Command
NECE	Navy Expeditionary Combat Enterprise
NEIC	Navy Expeditionary Intelligence Command
NRP	Navy Research Program
OFRP	Optimized Fleet Response Plan
OMN	Operations and Maintenance, Navy
OMNR	Operations and Maintenance, Navy Reserve
OPNAV N834	Expeditionary Readiness

PB	President’s Budget
Pillar E	Equipment
Pillar P	Personnel
Pillar S	Supply
Pillar T	Training
POM	Program Objective Memorandum
SIC	Special Interest Code
VBA	Visual Basic for Applications

I. INTRODUCTION

This thesis aims to assess the accuracy of the Navy Expeditionary Combat Command (NECC) cost model estimates by applying statistical techniques, quantitative analysis of the findings, and recommendations to improve the accuracy of future NECC cost model estimates. The method validates the efficacy of cost estimates produced by the current NECC cost model using a top-down technique to test the statistical significance, likelihood, cost implications, and spending behavior at various programmatic levels based on historical execution.

The United States military service components, which include the Army, Navy, Air Force, and Marine Corps, formulate their budget using modeling techniques such as mathematical models to estimate the cost of resources needed to execute their respective mission. These estimates inform their annual budget requests in the programming phase of the POM cycle (Congressional Budget Office, 2012). This research focuses on the OPNAV N834 (Expeditionary Readiness) cost estimation process, which currently "uses an N81-accredited cost model to inform the annual sustainment requirements for the Navy Expeditionary Combat Enterprise (NECE)" (Reich et al., 2022).

Previous research focuses on dissecting the existing Capability Cost Model (CCM) to evaluate technical factors (i.e., code) as well as programmatic elements (i.e., cost drivers, constraints, and design) to assess the computational and analytical performance of the model and explore avenues for model enhancement (Reich et al., 2022). A significant finding during the project was that, currently, there is no way to assess the statistical accuracy of the CCM cost estimate. This paper extends the previous work by providing a way to mitigate this issue through a straightforward, short-term solution that supplements the CCM process until a more permanent redesign solution is developed, tested, and implemented.

This research uses a single variable linear regression model based on FY2016 to FY2021 historical expenditures to forecast future cost estimates. It then uses Monte Carlo simulation to model the risk and uncertainty of the cost estimates due to their inherent variability. All costs are subject to variability due to cost risk and uncertainty (Mislick & Nussbaum, 2015) caused by changes to assumptions (i.e., changes to the resource requirement based on deployment schedule or missions, the amount of budget appropriated by Congress, the amount of funding allocated to the service component). The simulation addresses uncertainty by using a normal probability distribution of cost to calculate the most likely estimate and understand the probability that cost may occur within a range or confidence interval. The research concludes with a proportional scale-down model to analyze the likelihood of the cost estimate and cost implications of reductions to requirements, such as budget cuts, based on the simulation results. This technique transforms the top-level cost estimate selected and proportionally distributes it down to a lower level of programmatic data to allow stakeholders to analyze the cost estimate more granularly to understand spending behavior and cost implications through sensitivity analysis.

This research found that the total aggregate cost point estimate decreases by just under $16.6 million in constant year 2018 dollars (CY18$) each fiscal year, as shown in the single variable regression model. I applied the regression values to the Monte Carlo simulation to produce a normal probability distribution indicating an array of possible outcomes. In the FY 2025 scenario simulation, the mean value is $303,649,744 (CY18$), representing the most likely estimate, and the standard deviation is $7,767,962 (CY18$). The proportional scale factor technique breaks down the total cost aggregate estimate (i.e., FY2025 scenario simulation's most likely estimate) at a lower level of programmatic detail for additional analysis during the POM cycle.

The quantitative analysis in this research will enable stakeholders to validate whether the current CCM cost estimate accurately captures the total budget required for a given FY. The budget process for military service components possesses inherent variability due to external factors such as the state of the economy or congressional budgetary authorizations, as well as internal factors such as investment in equipment upgrades and future technologies to respond to crises and emerging threats. An effective cost model is vital as it informs the annual sustainment requirements for the Navy Expeditionary Combat Enterprise (NECE).

II. BACKGROUND

A. EXISTING COST MODEL

The existing NECC cost model, developed in Visual Basic for Applications (VBA) programming language, uses the Generalized Reduced Gradient (GRG) Nonlinear method to solve optimization problems. GRG uses the objective function slope as the input values change and calculates the optimal solution when the partial derivatives equal zero. The optimization problem objective is to minimize the squared difference between total cost, which are actual dollars executed, and the optimized cost allocation rate by the lowest level of programmatic data (i.e., Job Order Number or JON). The model then applies the optimized rates to a forecasted deployment schedule to produce a cost estimate representing the total cost of the POM requirements. There is a significant amount of uncertainty in determining the accuracy of this estimate. One factor attributing to this uncertainty is the requirement to forecast the estimate at least two years before funds are spent or executed. Another contributing factor to this uncertainty is that the original CCM model was designed several years ago; thus, there is a discontinuity of personnel (i.e., original model developers) and a lack of documentation available (Reich et al., 2022). Lastly, uncertainty also exists, given that the current cost estimation process lacks an objective method to assess the accuracy of its estimates.

Previous studies dissected the existing cost model (Reich et al., 2022). Although the NECC cost model is accredited, it is still unclear whether there is a statistically significant relationship between unit phase counts and cost. As mentioned above, the uncertainty surrounding the originally developed constraints is due to factors such as the lead time required to forecast the estimate (i.e., two or more years), a lack of knowledge surrounding the original model design, and a process to assess in the cost estimate's accuracy (i.e., statistical significance or likelihood) during the current POM cycle. Thus, the uncertainty makes it difficult to validate whether the model is over- or under-constrained, which may affect the accuracy of the cost estimate. I recommend conducting further research to examine the significance of the phase counts as independent variables to cost and the associated constraint relationships.

This research aims to develop a supplementary, short-term solution that can be integrated into current processes to validate the accuracy of the cost estimate generated by the CCM. Validating the accuracy of the cost estimate is paramount since it provides objective, data-driven analysis to assist stakeholders in making an informed decision while ensuring that the cost estimate captures the total requirement.

B. EFFECTIVENESS METRIC

For this analysis, accuracy is the sole measure to determine cost model effectiveness. Therefore, an effective cost model produces a more accurate cost estimate by minimizing the variance between the predicted estimate and the actual cost. The probability of producing a reasonable cost estimate depends on how close the estimate is to the actual cost. An estimate is more accurate with a lower variance between the actual cost and the predicted estimate. The goal is to develop an objective validation process with process controls that will assist stakeholders in developing a credible, relevant, and justifiable cost estimate.

This research demonstrates a supplementary, short-term solution to validate the accuracy of the cost estimate through the first two sets of techniques: simple linear regression and Monte Carlo simulation. This validation process will help mitigate the inherent uncertainty and risk caused by rapidly changing external factors and conditions (e.g., fluctuating resource management and allocation decisions, strategic and service guidance, national economy, crisis, conflict, Continuing Resolution, and budget constraints).

Specifically, Monte Carlo simulation is a decision analysis technique that allows stakeholders to choose the future cost estimate by simulating various factors to assess all possible outcomes. The simulation enables stakeholders to understand the uncertainty and risk of selecting a specific cost estimate through sensitivity analysis using the probability distribution, which contains many *Cost* variable outcomes at different probabilities. The Monte Carol simulation inputs use the outputs produced by the simple linear regression. These techniques will give stakeholders insight into the cost estimate and informs programmatic decision-making by improving the accuracy of the CCM cost estimate.

III. DATA

A. SCOPE AND NORMALIZATION

The cost data used in this research stems from an OPNAV N834 Expeditionary Readiness-sponsored project through Naval Research Program. The primary data source is the Master Execution cost data which provides the total cost spent by NECC for a given timeframe. For this research, I tested sample data from historical cost execution between FY2016 and FY2021 since those were the only years of historical cost data available.

The cost data in this analysis represents the funding executed during a given FY. The scope of data consists of six NECC programs, CRF, EOD, NCF, NAVELSG, MDSU, and NEIC, across two budget submitting offices encompassing the four pillars of readiness (i.e., Personnel [P], Equipment [E], Supply [S], and Training [T]). JON CIVPERS is filtered out since it is phase agnostic according to NECC and not used to develop the estimate for this specific dataset. MESF was merged into CRF historical cost data since they are the same program; however, a program name change occurred during the timeframe. The cost data is normalized for inflation using the Joint Inflation Calculator (JIC) inflation factor from the PB-23 JIC reflecting CY18$.

B. SUMMARY STATISTICS

I collected the unclassified data from a NECC sponsor sourced from the Master Execution database containing actual budget execution from FY 2016 to FY 2021. The raw data consists of 30,308 individual cost lines comprised of five levels of programmatic detail by FY and month. The total aggregate cost is a summation of that raw data and indicates the dollars spent or executed for a given FY, with values reflecting CY18$.

Table 1 provides the descriptive summary statistics for the cost aggregate values based on six years of historical cost execution data from FY 2016 to FY 2021. The mean for this sample dataset is $411,505,670 (CY18$), and the median is $411,078,465 (CY18$). Since the mean and median are relatively close together, with a variance of approximately 0.1%, the data is likely rather symmetrically distributed. This sample dataset's total cost aggregate values range from $365,961,803 (CY18$) to $446,591,295 (CY18$). The standard deviation of $31,804,792 (CY18$) represents the amount of dispersion in the sample data from the mean (Mislick & Nussbaum, 2015).

Table 1. Summary Statistics of Cost (CY18$)

Mean	411,505,670.30
Standard Error	12,984,251.92
Median	411,078,465.33
Mode	#N/A
Standard Deviation	31,804,791.90
Sample Variance	1.01154E+15
Kurtosis	-1.087905091
Skewness	-0.209787568
Range	80,629,491.75
Minimum	365,961,803.16
Maximum	446,591,294.90
Sum	2,469,034,021.82
Count	6

Notes: All values above reflect CY18$.

The coefficient of variation (CV) is 7.73% (i.e., CV = 31,804,791.90 ÷ 411,505,670.30) representing the "average" percent estimating error when the mean is used as the estimated cost (Mislick & Nussbaum, 2015). This sample dataset CV means I expect the estimate to be off an average of 7.73% when using the mean of $411,505,670.30. This sample dataset has only six observations due to the limited availability of NECC cost data.

Figure 1 represents the aggregate cost by FY from FY 2016 to FY2021 in CY18$. The scatterplot shows a negative correlation between *Cost* and *FY* (i.e., the total aggregate cost decreases each FY. Additionally, there appears to be a possible linear relationship, so linear regression analysis could be an ideal technique to describe the statistical significance between these variables.

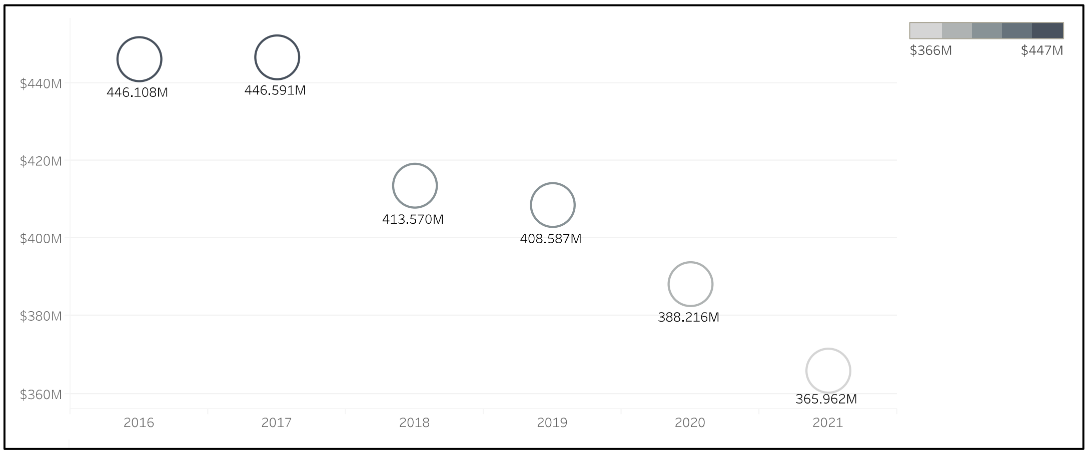

Figure 1. Aggregate Total Cost Over Time

Figure 2 shows the percent change of aggregate cost by FY and the percent difference from the previous FY. The percent change values in Figure 2 are highly correlated with the limited sample of POM funding to requirement values (i.e., POM 2018 through POM 2020), with an average variance of less than 0.4%. Future research should consider analyzing potential causal factors, such as the reduction to requirement percentage values, to explain the negative correlation in cost consistently occurring each year.

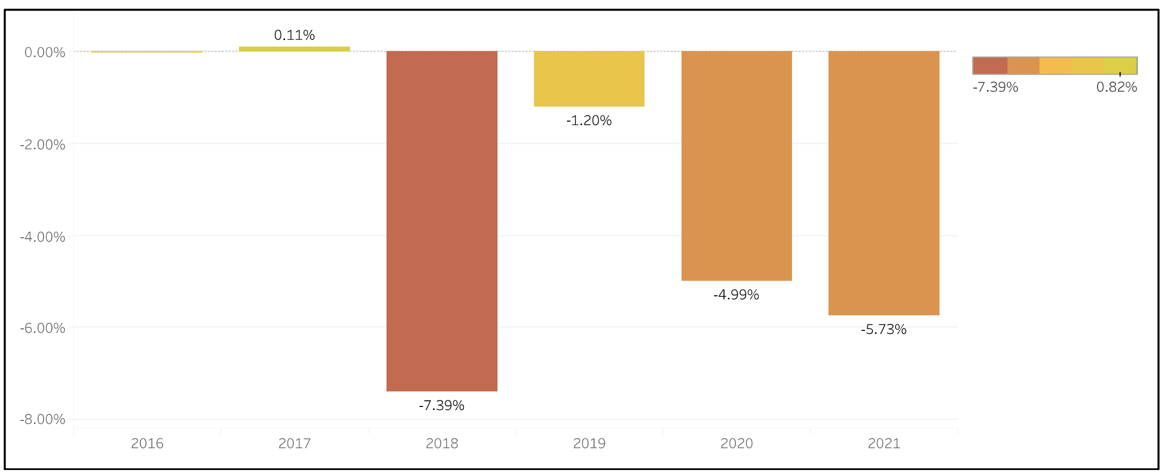

Figure 2. Percent Change of Aggregate Total Cost and Percent Difference Over Time

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IV. ANALYSIS

A. REGRESSION ANALYSIS

This paper uses regression analysis to describe the statistical relationship between Cost and FY. The regression analysis formulates an aggregate cost estimate for a given FY based on actual historical budget execution data. In the regression equation, also known as a Cost Estimating Relationship (CER), *Cost* is the dependent variable. *FY* is the independent variable, also referred to as the cost driver. The CER uses a single cost driver, in this case, known as single variable linear regression (Mislick & Nussbaum, 2015).

1. Single Variable Linear Regression Model

I used the time series single variable linear regression to analyze the impact of FY on Cost based on six years of historical cost data in order to forecast a statistically significant cost estimate. This model is shown below in Equation (1).

$$\text{Cost}_t = \alpha + \beta_1 \text{FY}_t + \varepsilon_t \quad (1)$$

where Cost is the aggregated execution cost as outlined in the Data section in time period *t*. FY_t represents a linear time trend for fiscal years. In addition, the equation includes a constant term, α, and an idiosyncratic error term, ε_t. The empirical model estimated uses two specifications of $Cost_t$ in the analysis, which includes the level effects of *FY* and the log of *FY*. β_1 is the coefficient of interest which can be interpreted as the FY's predicted effect on cost.

2. Linear Regression Model Limitations

Due to the inherent uncertainty in making future predictions based on historical data, the linear regression equation is limited in terms of robustness. Therefore, the relatively high level of confidence surrounding this model based on past data may not withstand the inevitable variability due to changing key assumptions affected by shifts in requirements, military strategy, priorities, and policy. NECC can mitigate the robustness shortfall by updating actual cost data to the regression as it becomes available in subsequent

FYs. “The Central Limit Theorem states that, for a large number of *n* observations from a population with a finite mean and variance, the sampling distribution of the sum or mean of samples of size *n* is approximately normal.” (Anderson, 2010). Thus, adding more observations (i.e., actual cost data in subsequent FYs) will provide more accurate mean cost estimates.

Another limitation of top-down linear regression is that the rolled-up point estimate does not inform lower-level spending behavior. The proportional scale-down technique was provided in this research as a possible solution to mitigate the top-down model limitation.

Another assumption is that the significant uncertainty in understanding the cost model design (i.e., constraints) due to lack of documentation from original model developers and discontinuity in personnel puts into question the credibility of the cost estimate the CCM produces. Integrating a process to assess the cost estimate’s accuracy is vital as it helps ensure adequate resource allocation.

This technique can enhance the existing cost estimation process to help prevent undue risk to mission accomplishment due to overly severe budget reductions or improper resource allocation to lower priority requirements. Future research into a potential redesign of the cost model may resolve this issue regarding the credibility of CCM cost estimates due to unknown cost model factors.

3. Linear Regression Results

Table 2 displays the estimates of the impact of FY on Cost as described in Equation (1). See Lavin et al. for modeling and specification details (Lavin et al., 2017). Both specifications show positive values for the intercepts and negative values for the FY coefficients. All specifications are statistically significant at the standard conventional levels. The results from Equation (1) show that, for the standard specification, the point estimate suggests that an increase in FY by one year decreases the predicted cost by approximately $16,595 million (CY18$). For the logarithmic specification, the point estimate suggests that cost decreases at a rate of 0.041 or 4.1% per year. Stakeholders can use Equation (1) coefficients to forecast future cost estimates. For example, the model predicts a cost estimate of $303,635,907.34 (CY18$) if FY is 2025 since Cost equals 33,939,215,906.68 (intercept) minus 16,595,348.15 (coefficient of interest) times 2025 (FY).

Table 2. The Effect of FY on Cost (CY18$). Adapted from Lavin et al. (2017).

	(1) Cost	(2) log(Cost)
Intercept	33,909,215,907***	101.87***
	(3,722,918,750)	(9.33)
FY	-16,595,348***	-0.041***
	(1,844,398)	(0.005)
Observations	6	6
R^2	0.9529	0.9507

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively
Standard errors are in parentheses.

B. MONTE CARLO SIMULATION

Monte Carlo simulation is the method used to describe the impact of risk and uncertainty in prediction models (Mislick & Nussbaum, 2015). This analysis uses Monte Carlo simulation to model the probability that a cost estimate is accurate by analyzing the results of many possible outcomes to find the most likely cost estimate.

1. Simulation Model

The Monte Carlo simulation was performed in Oracle's Crystal Ball using inputs from the linear regression values (predicted cost estimate and standard error). In this study, I assumed that the mean cost estimate generated in the simulation represents the most likely cost. This assumption allows for the expansion of the dataset to compare the accuracy of the current POM cycle estimate using funding execution estimates in the future that have not yet occurred.

Stakeholders can apply the CCM cost estimate to the probability distribution based on the assumption that the "most likely" point estimate should be the most accurate. Given this assumption, they could determine the accuracy of the CCM cost estimate after comparing and analyzing the results. This methodology reveals important cost implications, like the impact on sustainment efforts and readiness, by reducing the requirement below the "most likely" point estimate.

2. Simulation Results

The FY2025 scenario used Oracle's Crystal Ball to perform the Monte Carlo simulation. The simulation output produced a cost estimate distribution to provide insight into significant factors that affect risk and the range of all possible costs with their associated probabilities. The criteria set for the defined assumption was a normal distribution with the linear regression output, a point estimate of $303,635,907 (CY18$), and a standard error of $7,715,671 (CY18$).

Figure 3 illustrates a simple histogram with cost estimates generated during 10,000 iterations. The chart shows the probability distribution of cost estimate values grouped into 50 intervals (or bins). The x-axis shows the range of possible cost estimates. The highest value on the right side of the chart (440) represents the group interval frequency that contains the greatest number of forecast values – or the mode of the frequency distribution. The chart's scale on the left shows the probability of any particular interval, the greatest being above 0.04 or 4%. The top of the chart shows the number of trials run and the trials displayed. The chart did not present the remaining eight trials since they were extreme outliers. Removing these outliers keeps the visual from being skewed to maintain readability; however, the program includes them in all statistical calculations.

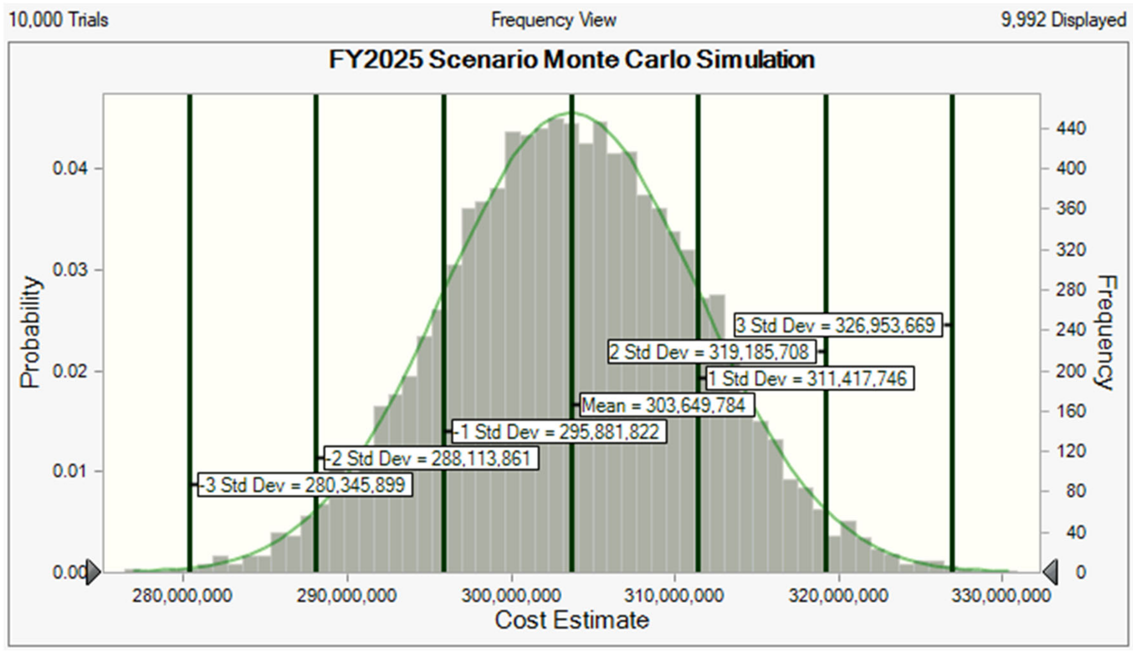

Figure 3. FY2025 Scenario Monte Carlo Simulation Forecast Chart (CY18$).

Specifically, Figure 3 illustrates the simulation results for the FY2025 scenario, including the point estimate mean of $303,649,784 (CY18$) and the standard deviation of $7,767,962 (CY18$). According to the Empirical Rule, 68.27% of the data falls between one standard deviation from the mean. So, there is an approximate confidence level of 68% that the cost estimate will be between $295,881,822 (CY18$) and $311,417,746 (CY18$). Following this rule, 95.45% of the data falls between two standard deviations from the mean. Hence there is an approximate confidence level of 95% that the cost estimate will be between $288,113,861 (CY18$) and $319,185,708 (CY18$). Lastly, this rule states that 99.73% of the data falls between three standard deviations from the mean. Therefore, there is an approximate confidence level of 99% that the cost estimate will be between $280,345,899 (CY18$) and $326,953,669 (CY18$).

Statistically, a higher confidence level results in a wider interval or range of possible values, in this case, cost estimates. Applying the CCM cost estimate to this probability distribution allows stakeholders to understand the statistical significance of a given estimate. For example, if the FY2025 CCM cost estimate falls outside the range of two standard deviations from the Monte Carlo simulation mean, it may indicate a possible issue with the derivation or assumption(s) regarding the estimate and should be examined further.

C. PROPORTIONAL SCALE-DOWN TECHNIQUE

The final step is optional; however, it provides value by enabling stakeholders to analyze spending behavior at lower levels of detail.

1. Proportional Scale-Down Model

This method scales down the linear regression point estimate, or the CCM cost estimate, to lower programmatic levels based on the proportional average of the previous three years of historical cost data. I used Tableau to compute the proportional scale factor to scale down the total aggregated cost estimate to lower levels of programmatic data.

Breaking down the total cost aggregate estimate allows stakeholders to analyze the cost estimate at a more granular level to understand the cost implications of requirement reductions, prioritize those reductions at various levels, and understand programmatic spending behavior better. For example, for programmatic data down to the program and BSO level for program CRF and BSO 60 in FY2016, the scale factor is the actual cost for those programmatic parameters (i.e., CRF and 60) divided by the total cost in FY2016. The proportional scale factor can be applied to the "most likely" estimate to analyze the data at lower levels of granularity.

Stakeholders can apply these scale factors to the most likely estimate to view the forecast at any programmatic level of detail, analyze the cost, and understand the impact of changes in budget allocation (i.e., reduction to the total requirement). The value of the Proportional Scale Down model is the ability to provide decision-makers with more granular cost data.

2. Proportional Scale-Down Results

Table 3 shows an example of the "most likely" cost estimate ($303,649,784.15) in the FY2025 scenario broken down at lower levels of programmatic data (i.e., at the Program, BSO, and APPN level). The 3-year average field represents the average of the last three years (i.e., 2019, 2020, and 2021). The unit cost shows the corresponding cost for the specific programmatic level of data derived from applying the aggregate cost estimate (i.e., $303,649,784.15) to the 3-year average percentage. For example, in the FY2025 scenario, the unit cost for program EOD/BSO 70/Appn OMN equals $59,489,904.11.

Table 3. Cost Aggregate Estimate Scaled Down to the Program, BSO, APPN Level (CY18$)

Program	BSO	Appn	2016	2017	2018	2019	2020	2021	3-year Avg	Unit Cost
EOD	70	OMN	26.2%	27.8%	23.6%	18.5%	20.4%	19.9%	19.6%	59,489,904.11
EOD	60	OMN	20.3%	16.4%	21.4%	18.4%	18.2%	17.6%	18.1%	54,899,789.56
NCF	70	OMN	16.7%	13.3%	13.6%	15.1%	16.2%	18.8%	16.7%	50,737,497.10
CRF	60	OMN	11.1%	12.5%	14.2%	13.3%	13.9%	13.0%	13.4%	40,749,077.95
NCF	60	OMN	6.3%	8.5%	10.4%	11.7%	11.8%	11.7%	11.8%	35,718,867.65
CRF	70	OMN	9.5%	13.0%	8.0%	11.3%	8.1%	7.2%	8.9%	26,939,655.04
NAVELSG	60	OMN	2.6%	3.4%	3.5%	3.6%	3.7%	3.0%	3.5%	10,486,512.19
CRF	70	OMNR	2.0%	1.5%	0.9%	1.1%	1.5%	2.3%	1.6%	4,852,216.22
MDSU	60	OMN	0.6%	0.6%	0.5%	1.1%	1.4%	1.4%	1.3%	3,860,455.55
NCF	70	OMNR	1.3%	0.4%	0.5%	1.4%	1.0%	1.0%	1.1%	3,392,704.01
NEIC	60	OMN	0.6%	0.7%	1.1%	0.8%	0.8%	1.2%	0.9%	2,787,162.42
CRF	60	OMNR	0.6%	0.5%	0.7%	1.0%	1.1%	0.7%	0.9%	2,786,555.24
MDSU	70	OMN	1.3%	1.0%	0.8%	0.9%	0.9%	0.7%	0.8%	2,464,056.17
NCF	60	OMNR	0.3%	0.2%	0.6%	0.7%	0.7%	0.9%	0.8%	2,296,881.04
NAVELSG	60	OMNR	0.7%	0.4%	0.3%	1.1%	0.4%	0.7%	0.7%	2,188,449.88
			100.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**303,649,784.15**

This table provides lower levels of programmatic cost data to inform the analysis of cost behavior and cost implications at various levels due to budget constraints. For example, suppose there is a reduction to the requirement captured by the cost estimate. In that case, stakeholders can identify the impact and risk of those reductions at lower programmatic levels (i.e., program, budget submitting office (BSO), appropriation (APPN), pillar, and job order number (JON).

The Proportional Scale Down technique provides stakeholders with a method to transform the cost estimate from a top-level aggregate value to a granular, programmatic-level value which informs stakeholders to improve risk-based decision-making. NECC budgets for various programs with different unit-specific requirements to sustain operational forces. Understanding cost behavior at lower levels is critical to ensuring that programmatic decision-making allows these forces to accomplish the mission and conduct emerging crisis operations.

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V. RECOMMENDATION

I recommend immediately implementing concrete process controls to assess the statistical accuracy of the CCM cost estimate. Since a cost estimate always contains uncertainty, it is subject to variability (Mislick & Nussbaum, 2015). The risk of uncertainty may be mitigated using various models, such as those in this study which provide an estimate accuracy range or confidence interval. It is important to note that the confidence interval may change depending on the model used. This estimate accuracy range allows for better monitoring and oversight of the existing CCM process based on the confidence level accepted by stakeholders. It will also enable them to quickly identify significant anomalies outside of the accuracy range to explore further as an indication of a possible error (i.e., manual or automated). As a result, this process control will assist in producing a more accurate cost estimate to inform data-driven, programmatic decision-making.

The set of techniques outlined in this paper provides NECC with one of many ways to ensure that the command captures the total requirement during the Program Objective Memorandum (POM) process. This research does not invalidate the current CCM cost estimation process. Instead, it aims to provide a temporary solution (i.e., process control) through a set of statistical techniques to determine the accuracy of the cost estimates and improve future forecasts. I recommend further research on developing a permanent control process for the CCM since this three-step technique (i.e., simple linear regression, Monte Carlo simulation, and the Proportional Scale Down method) requires continuous, manual application and analysis to remain relevant. Future researchers should develop a permanent validation process that can seamlessly integrate into the cost model process to ensure cost estimates are credible and accurate.

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VI. CONCLUSION

The mathematical models used to develop cost estimates must be as accurate as possible since they can directly affect the operational readiness of programs and forces within a military service (CBO, 2012). OPNAV N834 (Expeditionary Readiness) "uses an N81 accredited cost model to inform the annual sustainment requirement for NECC during the POM process" (Reich et al., 2022) to capture the entire requirement represented by a total aggregate cost estimate.

The primary focus of the analysis is to develop a short-term process to validate the statistical accuracy of the CCM cost estimate using simple linear regression and Monte Carlo simulation. The current CCM cost model helps predict the optimized requirement rate based on historical cost and the OFRP schedule phases and then applies the future deployment schedule to that optimized rate to calculate the total cost estimate. Unfortunately, the current cost estimation process cannot validate the accuracy of the CCM cost estimate during the POM cycle. The current process must assess the credibility of the cost estimate to ensure proper and sufficient allocation of resources to sustain their operational forces.

The linear regression method generates an equation to calculate the point estimate and the standard deviation for a future FY. In equation (1), the regression results for the standard specification suggest that an increase in *FY* by one year decreases the *Cost* by approximately $16,595 million (CY18$). The results in the logarithmic specification suggest that *Cost* decreases at a rate of 0.041 or 4.1% per *FY*. Stakeholders can use Equation (1) coefficients to forecast future cost estimates. For example, the model predicts *Cost* to equal $303,635,907.34 (CY18$) if FY is 2025 since Cost equals 33,939,215,906.68 (intercept) minus 16,595,348.15 (coefficient of interest) times 2025 (FY).

The Monte Carlo simulation uses the regression values to develop a normal distribution. The normal distribution is used to describe the uncertainty and risk associated with the CCM estimate, reducing the requirement and the effect on sustaining operational forces, and ultimately selecting the final cost estimate given the associated risks based on a data-driven, statistical approach. According to the Empirical Rule, 68.27% of the data falls between one standard deviation from the mean. Based on this theory, the results Monte Carlo simulation suggest an approximate confidence level of 68% that the cost estimate will be between $295,881,822 (CY18$) and $311,417,746 (CY18$). Furthermore, following this rule, 95.45% of the data falls between two standard deviations from the mean. Thus, the simulation results suggest an approximate confidence level of 95% that the cost estimate will be between $288,113,861 (CY18$) and $319,185,708 (CY18$). Finally, this theory states that 99.73% of the data falls between three standard deviations from the mean. Therefore, the results suggest an approximate confidence level of 99% that the cost estimate will be between $280,345,899 (CY18$) and $326,953,669 (CY18$).

Statistically, a higher confidence level results in a wider interval or range of possible values, in this case, cost estimates. Applying the CCM cost estimate to this probability distribution allows stakeholders to understand the statistical significance of a given estimate. For example, a future CCM cost estimate outside of two standard deviations from the Monte Carlo simulation mean point estimate may indicate a possible issue with the estimate's derivation or assumption(s) and should be examined further.

The proportional scale-down model provides stakeholders with a means of reviewing and analyzing the cost estimate at a lower level of granularity. Although this technique does not contribute to the cost estimate validation process, it is a value-added step for the stakeholders familiar with viewing costs at lower levels of detail. Therefore, it is included in the research as it provides a simple solution to mitigate the limitation of only viewing cost at an aggregate, top level.

Future research should focus on efforts to redesign the CCM model and incorporate a validation method in the cost estimation process. These efforts will significantly improve programmatic decision-making since the cost model was originally designed with constraints likely containing outdated assumptions that are largely unknown. The uncertainty surrounding the CCM model constraint values is due to a lack of documentation from the original model developers and a discontinuity of personnel. Future studies should integrate a method within the redesigned cost model proposal that provides a process to validate the credibility of the estimate and the effectiveness of the model. Redesign proposals need to provide phased, incremental improvements with actionable solutions, such as a concrete plan for implementation, since the resource allocation process is ongoing and cannot afford to be disrupted. Future research can build on the verification of technical specifications surrounding the cost model works initially conducted in previous studies (Reich et al., 2022) to update the outdated original design that may no longer be operationally relevant.

This paper provides a concrete, short-term solution to supplement the CCM process. It will assist stakeholders in identifying and resolving errors by assessing the CCM cost estimate's accuracy. These tools will help detect errors caused by manual data entry errors (i.e., deficiencies in the CCM code) or an overreliance on expert judgment based on experience not supported by objective, data-driven analysis. The techniques demonstrated in this analysis provide a proof of concept to serve as a starting point for incorporating CCM redesign improvement in future studies. These efforts to improve cost estimate accuracy will ensure NECC operational forces receive sufficient sustainment funding to accomplish the mission.

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