























































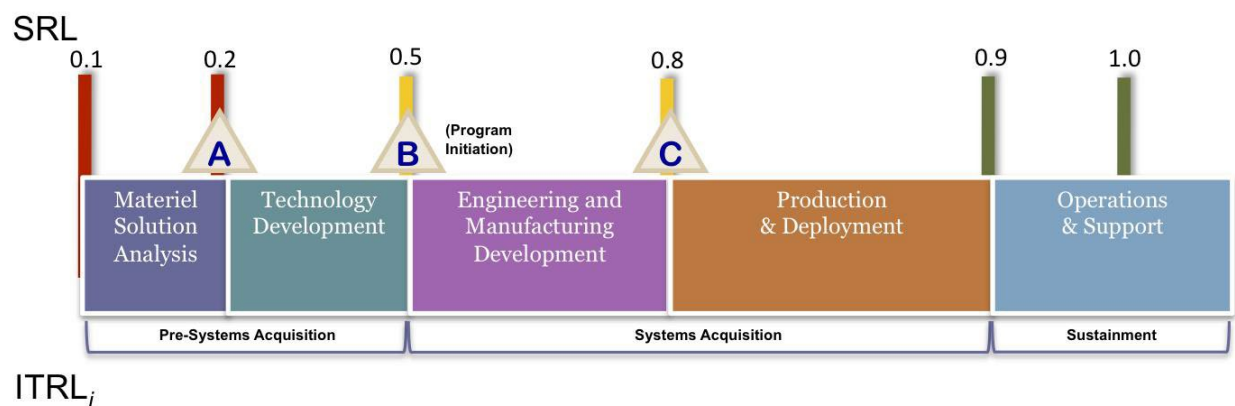


## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

applied as relative weighting coefficients for calculating overall system or project TRL or RD<sup>3</sup> development parameters.

Sauser and Ramirez-Marquez of Stevens Institute of Technology (Sauser B. J., 2011) also introduced a resourceful method to measure SRL as a function of TRL and IRL that deliberates both the technologies and integration elements along a numerical maturation scale to assess the maturity of the entire system. For this analysis, SRL is computed as a mathematical function using TRL and IRL matrices weighted on each technology within the system according to all of its integrations at a “system” level:  $[SRL]_{n \times 1} = [Norm]_{n \times n} \times [IRL]_{n \times n} \times [TRL]_{n \times 1}$  where in the TRL and IRL matrices the original (1,9) levels are normalized [Norm] to (0,1) (GridLAB-D, 2017). Like TRL, IRL is defined as a series of levels that relate to key maturity events for integration activities. Similar to TRL and MRL mapping presented in **Sections 6** and **7**, SRL is normalized across the DoD Acquisition Life Cycle in this analysis as shown below in **Figure 9-1**. NAVSEA PMS 420, with support by Northrop Grumman Corporation, have validated this SRL model monitoring development and integration progress in the Littoral Combat Ship Mission Module Program.

**Figure 9-1: SRL Mapped Against DoD Acquisition Lifecycle** (Sauser B. J., 2011)



## 10. Results and Conclusions

Conceptual stage technology and systems development has long been the most uncertain, volatile and challenging form of estimating for industry, government and institutional planning and investment decision analysis. This is primarily due to 1) the general lack of analogous systems 2) unavailable micro-level technical, design, or performance related parameters at this stage of development and 3) shortage of historical cost data. This investigation provided several methods to build a complete solution set for conceptual development estimating leveraging diverse empirical project data with risk-based Bayesian techniques.

Solutions demonstrating the greatest potential to effectively fill the estimating methodology void in early development stages are techniques applying key macro-parametric cost and schedule drivers that are readily available or determinable in pre-design stages. Limited first generation technology

## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

development models based on a coarse 2D TIL x SHL cost grid are transformed by a 360-fold increase in predictor data using comprehensive four dimensional TIL, SHL, RD<sup>3</sup> and TA solutions. The addition of RD<sup>3</sup> and TA parameters substantially augments the baseline analysis, providing a more complete picture of the key drivers of technological and system scale, complexity, functionality, maturity, difficulty, and integration. The high level of risks (known and unknown) associated with conceptual stage technology development are effectively captured by composite PDFs tailored to each project parametric configuration. Forecasting power, depth and precision are all greatly enriched, reflecting a comprehensive set of primary technological, programmatic, and cost risk factors.

A breakdown of common development process into WBS elements linked to standard acquisition milestones and readiness levels was introduced. This framework was associated to cost benchmarks employing empirical studies and historical DoD RDT&E data. This contributes value to TIL modeling capabilities and creates a useful method with which to estimate central processes and stages of development. In addition, the relative TRL transition cost factors deliver a method to refine the uniform 5 level TIL progressions into the full range of 36 discrete TRL start-end values. These improvements profoundly expand and transform gross initial 25 point TI-SHL cost forecasts into a 9,000 point high-definition rendering of the R&D landscape.

Composite system readiness and integration measures for IRL, SRL and MRL measures also hold potential to compliment TRL-based macro-parametric based forms of technology and system estimating in several respects. SRL and IRL measures, especially as modeled by Sauser and Ramirez-Marquez, may add greater value to Development phase estimating since they consider both technology and broader system development dimensions including critical integration requirements. The extensive enhancement to first generation development model fidelity, in concert with the development milestone cost benchmarking and other applied techniques from this research, yield improved estimating capabilities to conceptual stage development.

## 11. Future Considerations

The expansion and enrichment of useful macro-parameters should continue to evolve early stage development estimating. This could take many forms including the addition of other TA categories and larger project datasets for all the key macro-parameters. Considerations for extending TRLs to level 10 mapped to MRL level 10 at FOC as well as isolating and creating a "System of Systems" level 6 in the SHL scale, also deserve consideration. Composite system readiness and integration measures using as IRL, SRL, MRL, PRL and SML focused on various facets of maturity, also possess potential to compliment TRL-based macro-parametric forms of technology and system estimating.

Generally the two largest underlying drivers of cost, schedule and risk for any development, are measures of project scale and complexity (i.e., both technological and system). Project scale is effectively embodied by SHL but a comprehensive measure of complexity provides the dimension with greatest potential to improve modeling utility. Complexity is affiliated with a variety of the









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**Appendix C – RD<sup>3</sup> and TA Data Relationship Screening**

Total project cost data was parsed into the range of RD<sup>3</sup> levels and TA categories for the two datasets to perform initial data relationship screening between the RD<sup>3</sup> and TA predictors and the cost response variable. After filtering some outliers from the samples (1.1 % of TA project data and 2.3% of RD<sup>3</sup> data) the project cost statistics for the deconstructed RD<sup>3</sup> level and TA categorical data are shown in **Tables C-1 & C-2**<sup>18</sup>. Linear regressions of cost vs RD<sup>3</sup> produce adjusted coefficient of determination (R<sup>2</sup> Adj.) values over 0.7 and cost vs TA regression R<sup>2</sup> Adj. exceeding 0.8, both implying relatively durable relationships may exist.

**Table C-1: RD<sup>3</sup> Total Project Data Cost Statistics**

RD <sup>3</sup> Project Sample Cost Data Statistics (FY19\$)				
RD3 Lvl	Records	Mean	Median	Std Dev
1	17	\$ 18,072,037	\$ 9,799,623	\$ 18,436,153
2	153	\$ 32,399,635	\$ 13,242,734	\$ 52,082,945
3	174	\$ 44,543,794	\$ 19,864,101	\$ 111,674,939
4	76	\$ 56,739,467	\$ 26,485,469	\$ 85,282,868
5	6	\$ 79,677,118	\$ 57,605,894	\$ 73,348,093

**Table C-2: Technology Area (TA) Total Project Data Cost Statistics**

TA Project Cost Data Statistics (FY19\$)					
No.	Technology Area (TA)	Records	Mean	Median	Std Dev
1	Launch Propulsion Systems	159	\$ 29,482,594	\$ 896,999	\$ 125,232,312
2	In-Space Propulsion Technologies	111	\$ 22,420,479	\$ 1,122,812	\$ 68,386,702
3	Space Power and Energy Storage	229	\$ 21,455,560	\$ 800,408	\$ 136,454,438
4	Robotics, Telerobotics, Autonomous Systems	73	\$ 25,936,013	\$ 13,246,144	\$ 42,926,634
5	Communication and Navigation	182	\$ 8,439,804	\$ 972,011	\$ 24,215,606
6	Human Health, Life Support, Habitation Systems	224	\$ 53,192,277	\$ 15,891,281	\$ 87,320,195
7	Human Exploration Destination Systems	59	\$ 48,878,481	\$ 26,485,469	\$ 62,394,548
8	Science Instruments, Observatories, Sensor Systems	123	\$ 8,934,078	\$ 926,115	\$ 39,299,914
9	Entry, Descent, and Landing Systems	15	\$ 356,640,735	\$ 25,965,543	\$ 668,318,491
10	Nanotechnology	24	\$ 2,762,815	\$ 401,754	\$ 5,452,029
11	Modeling, Simulation, Information Tech	95	\$ 39,777,986	\$ 1,491,313	\$ 176,746,995
12	Materials, Structures, Mechanical Systems, Mfg.	229	\$ 11,845,815	\$ 803,508	\$ 33,782,225
13	Ground and Launch Systems Processing	23	\$ 50,093,679	\$ 13,529,154	\$ 126,535,384
14	Thermal Management Systems	85	\$ 19,242,667	\$ 2,648,547	\$ 37,251,256
15	Aeronautics	99	\$ 5,904,203	\$ 393,329	\$ 16,990,139

Although two of the RD<sup>3</sup> categories contained somewhat limited project sample sizes, project cost statistics demonstrate a direct and progressive incremental relationship to RD<sup>3</sup> across all 5 levels. Cost statistics for TA categories produced more mixed results with five categories being apparent outliers. TA #'s 5, 8, 9, 10 and 15 exhibit very low or high mean cost values vs the overall TA project

<sup>18</sup> Costs presented in this paper for TCASE source data and first generation model results have been escalated to FY2019\$ using the RDT&E Appropriation TY\$ indices from the current Joint Inflation Calculator (JIC) (available from The Naval Center for Cost Analysis (NCCA) at <https://www.ncca.navy.mil/tools/inflation.cfm>).

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sample and TA #'s 1, 3, 9, 11 and 13 contain extensive cost ranges with very significant standard deviations and most TAs also contained very large coefficients of variation (CV). The large category cost ranges and variability is primarily due to the fact that each TA category spans a full range of project scale, complexity and maturity and do not reflect any graduated measurement levels with respect to cost. Upon closer examination of the underlying project data, some of low and high central value behavior can also be largely attributed to limited sample sizes and a focus of similar small or large scoped projects in some categories. The reason for these project size concentration anomalies is unclear but are possibly related to repetitive type development efforts, project budgeting or execution policies or practices for particular technical areas. They may also simply reflect the way cost data was reported, captured or characterized by individuals providing historical project information for certain TA categories in the TCASE database.

As noted in the data investigation in **Section 3**, there were not enough projects containing all 4 variables to produce comprehensive multiple regression models, however other techniques were explored to leverage cost impacts from the additional parameters. To effectively apply these techniques, further screening tests and analysis were first conducted looking for multicollinearity and residual autocorrelation among the TIL, SHL, RD<sup>3</sup> and TA independent variables. First, regression analysis between combinations of the 4 independent parameters vs the cost response were performed. These tests produced favorable results with a Durbin Watson (DW) statistic in the range of 1.83 to 2.13 for all regressions, about 92 % of parameter category levels possessing a variance inflation factor (VIF) of < 4 and an average overall category level VIF of ~2.4 across models. For more detail on the DW and VIF statistics and specific results of tests conducted see **Appendix D**.

Lastly, the absolute value of correlation coefficients assessed between independent parameters fall under 0.1 for 85% of the category combinations, between 0.1 to 0.2 for 13% of cases, and between 0.2 to 0.4 for the remaining 2% of cases. All three indicators, DW statistic, VIF, and correlation coefficients therefore suggest no noteworthy residual autocorrelation or multicollinearity between the four predictor variables. This supports their independence and bringing the two additional parameters into the analysis should therefore not introduce any significant common influential affects or overlapping causal factors with respect to cost.

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**Appendix D – Independent Variable Multicollinearity and Residual Autocorrelation Testing**

Variance inflation factors (VIFs) and regression correlation coefficients (CCs) between independent predictor variables were assessed as indicators of potential multicollinearity. To check for autocorrelation among regression residuals used in independent variable screening, the Durbin-Watson (DW) statistic was also evaluated. A variance inflation factor (VIF) detects multicollinearity in regression analysis. Multicollinearity occurs when there's correlation between predictors (i.e. independent variables) in a model and its presence can adversely affect regression results. The VIF estimates how much the variance of a regression coefficient is inflated due to multicollinearity in the model. Variance inflation factors range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance (i.e. the standard error squared) is inflated for each coefficient. A rule of thumb for interpreting the variance inflation factor: In general, a VIF of 1 = not correlated; between 1 and 5 = moderately correlated and < 5 = highly correlated (Ref.: <https://www.statisticshowto.datasciencecentral.com/variance-inflation-factor/>).

The Durbin-Watson statistic tests the null hypothesis that the residuals from an ordinary least-squares regression are not autocorrelated. The statistic ranges in value from 0 to 4. A value near 2 indicates non-autocorrelation; a value toward 0 indicates positive autocorrelation; a value toward 4 indicates negative autocorrelation. A rule of thumb is that test statistic values in the range of 1.5 to 2.5 are relatively normal and even those in the 0.5 to 3.5 range are generally considered acceptable (Ref.: <https://www.statisticshowto.datasciencecentral.com/durbin-watson-test-coefficient/>).

To test for multicollinearity in the model forecasts of cost response to the 4 independent variable terms (TIL and SH levels from the original parametric models with the newly introduced RD<sup>3</sup> and TA parameters), multiple regression CC and VIF were assessed. Multiple regression models were formulated to perform these tests between the RD<sup>3</sup>/TIL/SHL, TA/TIL/SHL and, RD<sup>3</sup>/TA independent cost variables.

For the RD<sup>3</sup>/TIL/SHL independent cost variable multiple regressions, of the 32 independent variable term combinations, 20 CCs (63 %) fell in the -0.1 to 0.1 range, and 11 (34 %) in the -0.2 to -0.1 or 0.1 to 0.2 range, and 1 (3%) in the 0.3 to 0.4 range. VIFs for the various RD<sup>3</sup>/TIL/SHL terms range from 1.1 to 3.5 with an average of 1.68 and 67% falling under 2.0. For the multiple regression between the TA/TI/SHL independent cost variables, of the 144 independent variable combinations, 126 CCs (88 %) fell in the -0.1 to 0.1 range and 15 (10 %) fell in the -0.2 to -0.1 or 0.1 to 0.2 range and 3 (2%) fell in the 0.2 to 0.3 or -0.2 to -0.3 range. 95% of VIFs for the various TA/TIL/SHL fell under 4.0 with 1 TIL term at 5.3 and an average VIF of 2.51. Finally to test for multicollinearity between the two new variables introduced, RD<sup>3</sup> and TA, using multiple regressions, for the 48 independent variable cost term combinations, 44 CCs (92 %) fell in the -0.1 to 0.1 range, 3 CCs (6 %) in the -0.2 to -0.1 or 0.1 to 0.2 range, and 1 CC (2%) in fell the 0.2 to 0.4 range. 81% of VIFs for the various RD<sup>3</sup>/TA terms fell under 4.0 with an average of 3.22.

For the same cost regressions, these tests produced DW statistic values of 2.1 for RD<sup>3</sup>-SHL-TIL variables, 2.1 for TA-SHL-TIL variables and 1.8 for the RD<sup>3</sup>-TA variables. These results suggest no autocorrelation issues are evident.

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**Appendix E – Data Types**

The Development Cost response variable applied in this analysis is a continuous quantitative variable, TIL, SHL and RD<sup>3</sup> predictor variables are discrete ordered categorical values and Technology Area (TA) is simply a list of categorical class values. Categorical variables that have two or more incremental levels are often measured on an ordinal scale. This is done so that the characteristic or property described by the category levels or class (i.e., 1 through K) can be considered as ordered, but not as equally spaced. This is the case with TRL, SHL and RD<sup>3</sup>, as determination of those levels can involve various subjective criteria that span a wide range of scale and complexity both between and within categories.

Traditional linear regression models however, make no distributional assumptions about the independent predictor variables. Consequently, ordinal variables must be interpreted carefully when attempting to fit a continuous function especially if large or random interval variance is possible between class rankings. Fortunately, statistical analysis tools such as SAS JMP used for the first generation TI-SHL models, solve this potential issue by employing a regression technique that leverages response to the ordinal *interval* values. Further, since the dependent cost variable response in this analysis is being assessed at the discrete ordinal levels only and not as continuous functions, that completely neutralizes any concerns over a possible lack of a natural ordinal interval size structure impacting results.

Historically, ordinal *response* variables have been substantially investigated in regression modeling, but less research has been performed on ordinal *predictors*. Anderson (1984) notes there are two major types of ordinal categorical predictor variables, "grouped continuous variables" and "assessed ordered categorical variables." There have been various suggested techniques as to how to model ordinal predictor variables (e.g., quadratic penalization regression, ridge reroughing, 5-point Likert scales) (Stauner, 2014) (Gertheiss, 2009) (Berry, 1993) but no definitive method or approach was identified in the literature.

Ordinal qualitative measures nevertheless are ordered, and for technologies, this progression can be driven by certain underlying development structure, known or unknown, such as architecture, functionality, complexities, common development processes and support activities. As a result, a quantitative relationship can exist that may be modeled between an ordinal scale (or the variability in such a scale) and continuous numeric parameters. Since this relationship is not necessarily or even likely to be linear in nature, data transformations, coefficient / correction / adjustment factors, and nonlinear functions are often applied to normalize ordinal values to account for the variability in cost and schedule modeling (Malone, Smoker, Apgar, & Wolfarth, 2011) (Smoker & Smith, 2007) (Conrow E. , 2009).

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**Appendix F - Curve Fit Methodology**

All Probability Density Function (PDF) cost curve fits for this analysis were produced using the Palisade @Risk software. Sample data and calculated distribution data values were “fit” to a library of possible probability-based distribution functions using the tool’s distribution fitting utility and standard fit measurement techniques. Over 20 functions (or families of functions) are assessed including Beta, Chi-square, Erlang, Exponential, Gamma, Inverse Gaussian, Levy, LogLogistic, Lognorm, Pareto, Pearson, Program Evaluation and Review Technique (PERT), Raleigh, Triangular, Uniform, Weibull and several others. The distribution fit utility is applied to down select higher performing functions using the following commonly applied goodness-of-fit statistical significance methods / techniques:

- Akaike Information Criterion (AIC)
- Bayesian Information Criterion (BIC)
- Kolmogorov-Smirnov (K-S)
- Anderson-Darling (A-D) and
- Chi-Squared tests (Chi-Sq)

A lower bound of zero and unlimited upper bound were input as search range criteria to best replicate the highly right-skewed cost functions involved and that are common to cost and schedule behavior and related early life cycle estimating methodologies. Functions with best result consensus across these techniques are selected considering key statistical metrics vs the sample data such as fit of the estimate mean, a commonly applied budget planning and forecast range between the 50<sup>th</sup> (i.e., median), 70<sup>th</sup> and 80<sup>th</sup> percentile, the standard deviation, and distribution shape characteristics (skewness, kurtosis, etc.). The curve fits produced appropriately reflect the highly uncertain environments with relatively wide dispersion and large standard deviations around the central datum that are expected due to the high level of unknowns in conceptual stages of development.

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**Appendix G – Project Data Sample Equivalence Investigation**

A data relationship between either the RD<sup>3</sup> or TA sample project cost data and the SHL-TIL project cost data can be established via means translations (i.e., factor of the sample means). In addition to the data groups coming from a common population with a small difference in sample means and other empirical evidence described below, equivalence tests were also applied to demonstrate a degree of sample equivalence. These equivalence tests include the two one-sided test (TOST) and the Aspin-Welch test.

In a classical hypothesis test, the goal is to reject the null hypothesis of equality. As part of an equivalence test however, the goal is to validate the equivalence between two samples. TOST is a test of equivalence that is based on the classical t-test used to test the hypothesis of equality between two means. Therefore, equivalence tests differ from standard t-tests in that the null and alternative hypothesis are reversed:

- Null hypothesis ( $H_0$ ): The difference between the means is outside your equivalence interval. The means are not equivalent.
- Alternative hypothesis ( $H_1$ ): The difference between the means is inside your equivalence interval. The means are equivalent.

The TOST equivalence test can be used to validate the equivalence of the means of two groups by demonstrating they do not differ by more than a specified margin. When the sample sizes and variances of two groups are unequal (nonparametric), such as with the SHL-TIL, RD<sup>3</sup> and TA data samples being compared, Welch's t-test for unequal variance (also known as the Satterwaite's test, the Smith/Welch/Satterwaite test, the Aspin-Welch test, or the unequal variances *t*-test) is also commonly utilized to test sample equivalence (NCSS, 2015) (Ruxton, 2006) (Lakens D. , 2017).

Welch's t-test is more robust than the Student's t-test and maintains type I error rates close to nominal for unequal variances and for unequal sample sizes (Ruxton, 2006) (Lakens D. , 2015), as is the case for this analysis. Welch's t-test also remains robust for skewed distributions and large sample sizes (Fagerland, 2012), again present in this investigation. With unequal group sizes trimming a small proportion of outlying observations is commonly conducted to alleviate problems related to the skewness in underlying distributions. This was first proposed by Tukey and McLaughlin (1963) and later combined with Welch's test by Yuen (1974) (NCSS, 2015). The resulting trimmed Welch test is resistant to outliers and alleviates some of the problems that occur because of skewness in the underlying distributions. In applying this method, *G* represents the percent (%) of data trimmed, generally less than 25%, and often in the 5% to 10% range (NCSS, 2015) .

Sample equivalence testing was performed between the cost means for the SHL-TIL dataset and corresponding RD<sup>3</sup> and TA parameter samples using both the trimmed TOST and Welch's trimmed t-test assuming unequal variances in the SAS JMP software. The three datasets involved with the analysis each contain sufficiently large sample sizes with raw number of observations ( $n_i$ ) = 221, 425, and 1750 each, for the SHL-TIL sample (# 1), RD<sup>3</sup> sample (# 3) and TA sample (# 2) respectfully. All extracted data come from a common development project database population (i.e., the NASA TCASE) and include a degree of individual project commonality or overlap. The extreme cost data ranges and variance (CVs in the 1.7 to 3.8 range) within the project data can make equivalence

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testing more challenging. The actual G values for the final samples tested both fell well within the acceptable range with  $G = 2.8\%$  ( $=55/1971$  for  $n = 221 + 1750 = 1971$ ) for the SHL-TIL vs TA stacked project sample and  $G = 8.4\%$  ( $=55/656$  for  $n = 221 + 425 = 656$ ) for the SHL-TIL vs RD<sup>3</sup> stacked project sample. Due to extremely large overall project population cost variance, the sample data equivalence tests were performed at an alpha level of 0.10. Results of the trimmed TOST and Welch's trimmed test results, along with other evidence like sample density plot overlays are provided in **Figures G-1** and **G-2**.

For both sample dataset comparisons, TOST test p-values are smaller than alpha (0.1). Therefore, the difference in population means is located within the lower and upper confidence thresholds / limits and the sample means are practically equivalent. Both Welch tests also indicate that the Null Hypothesis can be rejected as the F Ratio is small and Prob > F is high and therefore no significant differences in the samples are detected (SAS Institute, Inc., 2019) (GraphPad Software, Inc., 2019) (Dawson, 2015). Other empirical support such as the very small % difference in sample means (only a 0.25% variability between the SHL-TIL vs RD<sup>3</sup> trimmed samples and 1.4% for the SHL-TIL vs TA trimmed samples) and the comparison and composition of density plots also provide rational support to demonstrate that the parameter sample means are similar enough to practically represent the same population. Based on this preponderance of evidence, it is therefore reasonable to extend RD<sup>3</sup> and TA influence on the SHL-TIL parametric models by applying statistical index values between sample means.

**Figure G-1 Trimmed Equivalence Tests of SHL-TIL vs RD<sup>3</sup> Sample Mean Cost Data**

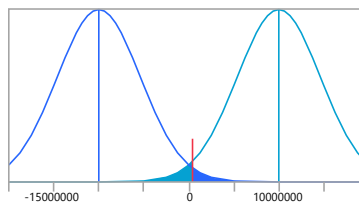
### Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1 (SHL-TIL)	186	29304292	75771209	5555814.6	20119798	38488786
3 (RD <sup>3</sup> )	416	29717115	37905496	1858469.9	26653365	32780865

Test	F Ratio	DFNum	DFDen	p-Value
Bartlett	136.0031	1	.	<.0001*
F Test 2-sided	3.9958	185	415	<.0001*

### Practical Equivalence between RD<sup>3</sup> (#3) and SHL-TIL (#1) Samples

Null Hypothesis	DF	t Ratio	p-Value
Mean Difference $\geq 1000000$	600	-2.0674	0.0196*
Mean Difference $\leq -1000000$	600	2.245442	0.0126*
Max over both			0.0196*



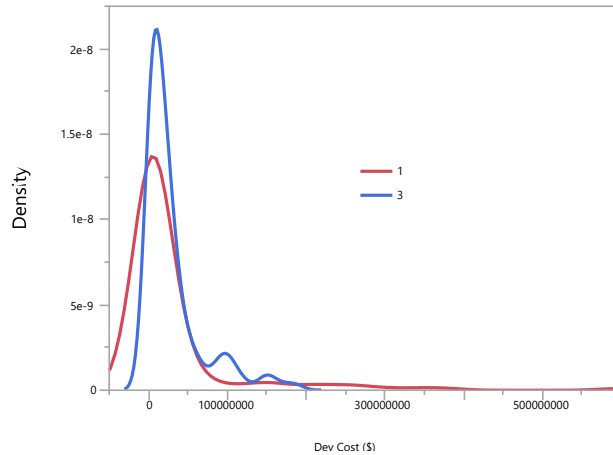
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**Welch's Test**

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0050	1	227.45	0.9439

**Compare Densities**



**Composition of Densities**

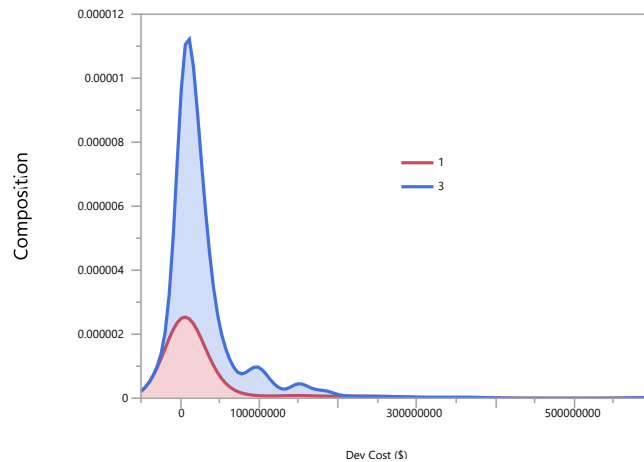


Figure G-2 Trimmed Equivalence Tests of TI-SH vs TA Sample Mean Cost Data

**Means and Std Deviations**

Level	Number	Mean	Std Dev	Std Err	Lower 90% Mean	Upper 90%
1 (SHL-TIL)	221	27052654	77816153	5234480.9	18406290	35699018
2 (TA)	1703	27059297	104306493	2527574.8	22899542	31219052

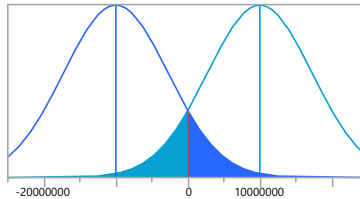
Test	F Ratio	DFNum	DFDen	p-Value
Bartlett	28.7506	1	.	<.0001*

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Test	F Ratio	DFNum	DFDen	p-Value
F Test 2-sided	1.7967	1702	220	<.0001*

**Practical Equivalence between TA (#2) and SHL-TIL (#1) Samples**

Null Hypothesis	DF	t Ratio	p-Value
Mean Difference $\geq$ 1000000	1922	-1.37535	0.0846
Mean Difference $\leq$ -1000000	1922	1.377176	0.0843
Max over both			0.0846

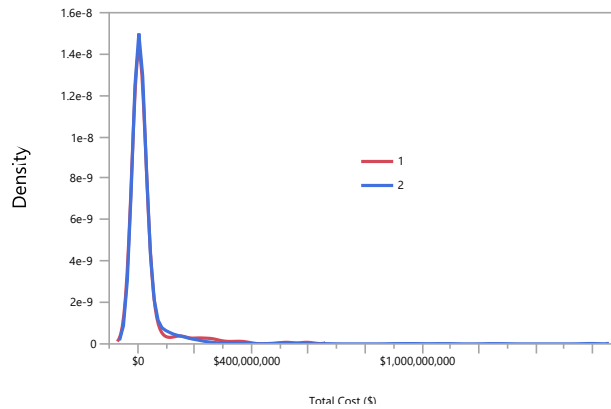


**Welch's Test**

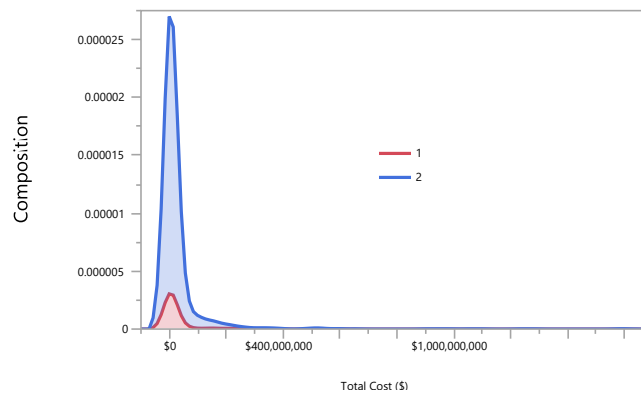
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0000	1	332.22	0.9991

**Compare Densities**



**Composition of Densities**



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Appendix H – RD<sup>3</sup> and TA MCI Curve Fit PDF Formulas and PlotsTable H-1: RD<sup>3</sup> MCI Curve Fit PDFs

RD <sup>3</sup> Mean Cost Index (MCI)		
RD3 Lvl	PDF Type	@RISK PDF Formula
1	Gamma	=RiskGamma(0.59877,0.68192,RiskName("RD3 Lvl 1 MCI"))
2	Lognorm	=RiskLognorm(0.84662,2.1681,RiskName("RD3 Lvl 2 MCI"))
3	Pearson6	=RiskPearson6(1.1572,1.7721,0.71302,RiskName("RD3 Lvl 3 MCI"))
4	Gamma	=RiskGamma(0.71451,1.9062,RiskName("RD3 Lvl 4 MCI"))
5	Gamma	=RiskGamma(1.3688,1.394,RiskName("RD3 Lvl 5 MCI"))

Table H-2: TA MCI Curve Fit PDFs

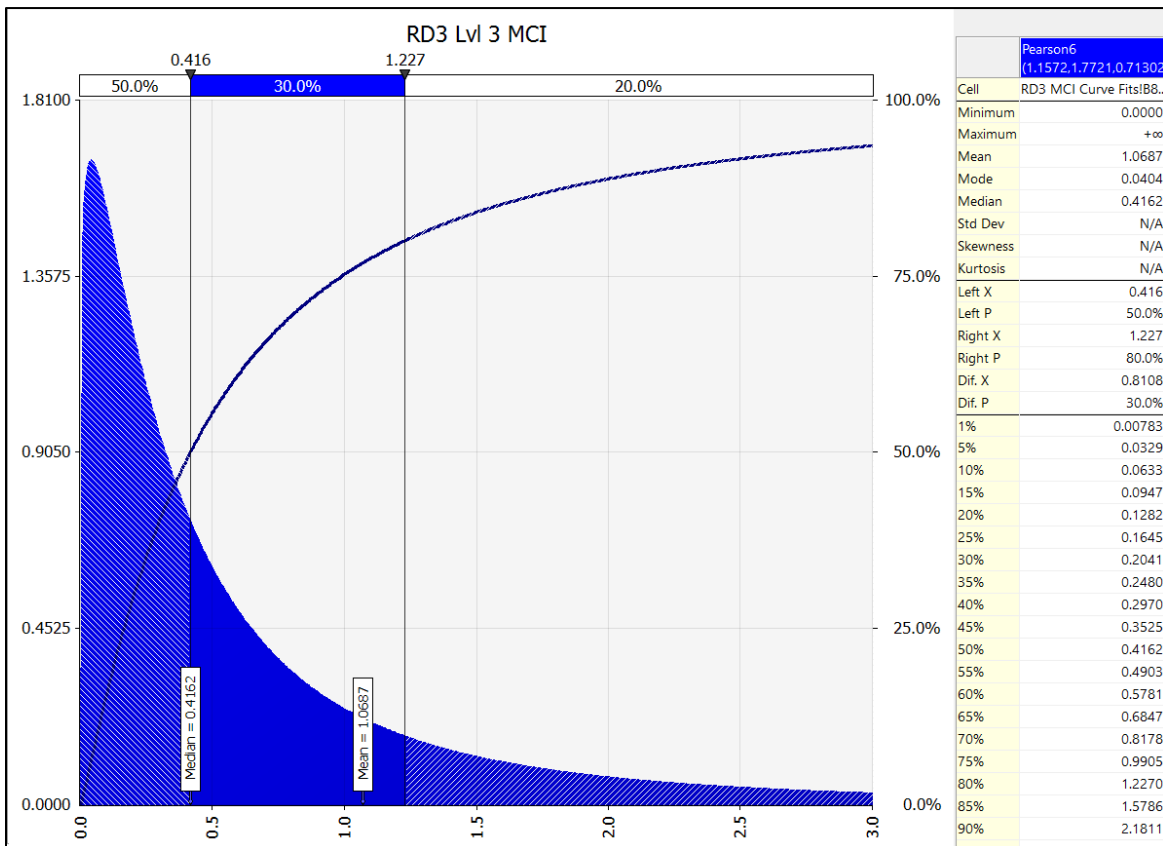
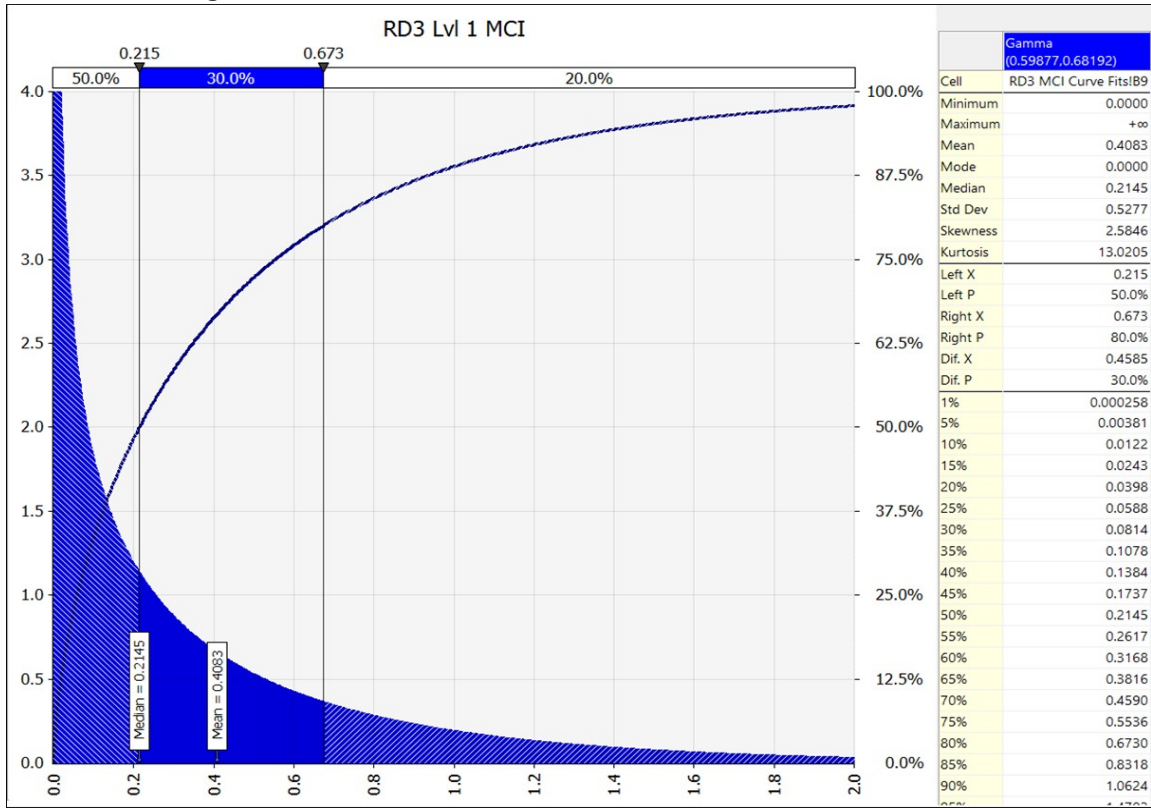
TA Mean Cost Index (MCI) Curve Fit PDFs			
No.	Technology Area (TA)	PDF Type	@RISK PDF Formula
1	Launch Propulsion Systems	Frechet	=RiskFrechet(0,0.016039,0.60073,RiskName("TA1 Mean Cost Index"))
2	In-Space Propulsion Technologies	Lognorm	=RiskLognorm(1.0673,18.846,RiskName("TA2 Mean Cost Index"))
3	Space Power and Energy Storage	Frechet	=RiskFrechet(0,0.014939,0.63461,RiskName("TA3 Mean Cost Index"))
4	Robotics, Telerobotics, Autonomous Systems	Gamma	=RiskGamma(0.33743,2.8459,RiskName("TA4 Mean Cost Index"))
5	Communication and Navigation	Lognorm	=RiskLognorm(0.32008,2.0834,RiskName("TA5 Mean Cost Index"))
6	Human Health, Life Support, Habitation Systems	Weibull	=RiskWeibull(0.57905,1.2756,RiskName("TA6 Mean Cost Index"))
7	Human Exploration Destination Systems	Gamma	=RiskGamma(0.50991,3.5492,RiskName("TA7 Mean Cost index"))
8	Science Instruments, Observatories, Sensor Systems	Loglogistic	=RiskLoglogistic(0,0.030355,0.8796,RiskName("TA8 Mean Cost Index"))
9	Entry, Descent, and Landing Systems	Levy	=RiskLevy(0,0.55536,RiskName("TA9 Mean Cost Index"))
10	Nanotechnology	Levy	=RiskLevy(0,0.0070262,RiskName("TA10 Mean Cost index"))
11	Modeling, Simulation, Information Tech	Lognorm	=RiskLognorm(1.156,16.677,RiskName("TA11 Mean Cost index"))
12	Materials. Structures, Mechanical Systems, Mfg.	Frechet	=RiskFrechet(0,0.015598,0.59836,RiskName("TA12 Mean Cost index"))
13	Ground and Launch Systems Processing	Pareto2	=RiskPareto2(0.49689,1.1179,RiskName("TA13 Mean Cost index"))
14	Thermal Management Systems	FatigueLife	=RiskFatigueLife(0,0.11763,3.1833,RiskName("TA14 Mean Cost Index"))
15	Aeronautics	Invgauss	=RiskInvgauss(0.21861,0.008011,RiskName("TA15 Mean Cost index"))

**Notes:**

- **Table H-1 and H-2** PDFs are consistent with the right-skewed lognormal, gamma, Weibull and betaPERT type PDFs commonly recommended for estimating uncertainty in the Joint Agency Cost Schedule Risk and Uncertainty Handbook (JACSRUH).
- **Table H-2** is provided for analysis demonstration purposes only as these PDFs are not recommended for application in modeling due to reasons explained in Section 5.a.
- The following RD<sup>3</sup> MCI Curve Fit PDFs for Levels 1, 3, 4, and 5 are plots of the continuous functions with the X-axis representing the Mean Cost Index (MCI) values. These functions can express larger concentrations as they approach at zero, however they are used because they replicate the typical range of interest in the sample data very closely. This area of interest is the planning range between the 50<sup>th</sup> to 80<sup>th</sup> percentiles generally applied in budgeting and investment decision making. For a more detailed explanation of the Curve Fit Methodology see **Appendix F**.

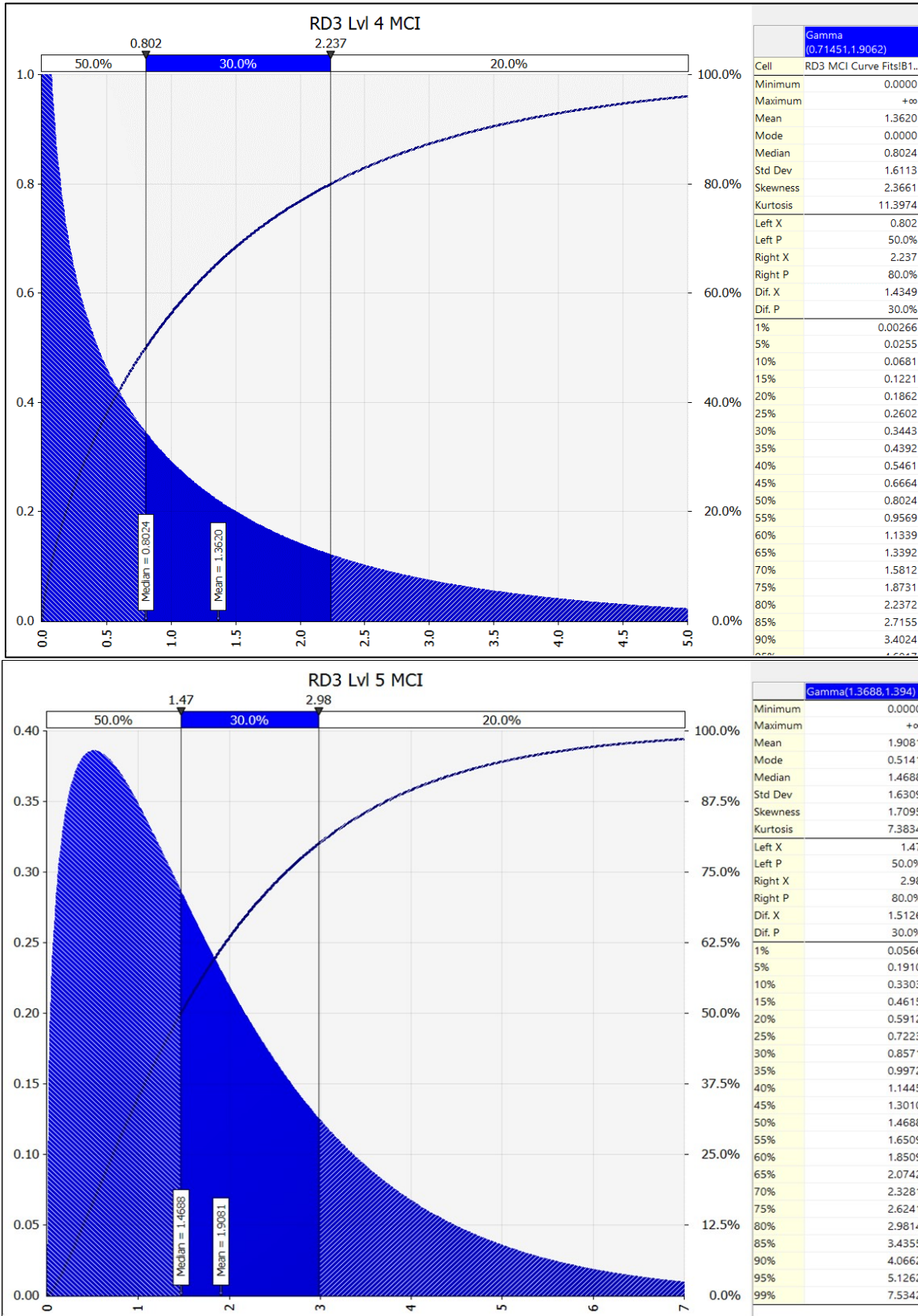
ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

Figures H-1 and H-2: MCI Curve Fit PDFs for RD<sup>3</sup> Levels 1 and 3



ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

Figures H-3 and H-4: MCI Curve Fit PDFs for RD<sup>3</sup> Levels 4 and 5



## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

**Appendix I - Geometric Mean Curve Fit Method**

GMs are considered preferable over arithmetic means since the GM form tends to minimize or dampen the influence of extreme data points such as large or small data values in the generally highly-skewed data distributions that are predominant in the technology project sample data) (Hu, 2010) (Clark-Carter, 2005). The geometric mean formula is represented as follows where a series of n data ( $a_1, .. a_n$ ) are compounded taking the nth root of the product:

**Geometric Mean** =  $(\prod_{i=1}^n a_i)^{1/n} = \sqrt[n]{a_1 a_2 a_3 \dots a_n}$  (Roefeldt, 2019). Much of the study data includes skewed lognormal or “lognormal like” distributions common to early life cycle cost data. With a true lognormal dataset, the median and GM are identical so with highly skewed data they can provide a substantially better indication of central tendency than the arithmetic mean (McChesney, 2019).

This technique involves creation of composite functions of the independent variables by merging the uncertainty distributions of the selected predictor variables for each parametric combination in a geometric mean (GM). The blended impact of individual tailored PDF cost curve fits for each independent parameter level are aggregated in a product (i.e., geometric mean) of their expected values sampling their individual values in Monte Carlo simulation. The highest performing SHL and TIL PDF cost curve fits from the initial study were used along with newly developed RD<sup>3</sup> level and TA category cost PDF curve fits (see **Table I-1** for the RD<sup>3</sup> cost curve fit PDFs). The GM of the Project Development Cost included combinations of the 4 parameters =>  $(PDF_{SHL} \times PDF_{TIL} \times PDF_{RD3} \times PDF_{TA})^{1/n}$ , where n represents the number of independent parameters actually applied (4 in this equation). Any combination of 2 to 4 of the parameters can be modeled in simulation applying the 1/n root power. Monte Carlo simulation runs calculating the expected GM for the full range of curve fit PDF combinations across the four independent variables (SHL/TIL/RD<sup>3</sup>/TA), were performed. Output from the simulations therefore represent a blended average of the 3 selected constituent macro-parameters.

**Table I-1: RD<sup>3</sup> Project Sample Cost Data Curve Fit Functions**

RD <sup>3</sup> Project Sample Cost Data Curve Fit Functions (FY19\$)		
RD3 Lvl	PDF Form	PDF Formula
1	Gamma	RiskGamma(0.81109,22281302,RiskName("RD3 Lvl 1 (FY19\$)"))
2	Lognorm	RiskLognorm(35352239,90532673.2,RiskName("RD3 Lvl 2 (FY19\$)"))
3	Burr12	RiskBurr12(0,27822346,1.1144,1.4889,RiskName("RD3 Lvl 3 (FY19\$)"))
4	Weibull	RiskWeibull(0.78281,48452157,RiskName("RD3 Lvl 4 (FY19\$)"))
5	Erlang	RiskErlang(1,79677117,RiskName("RD3 Lvl 5 (FY19\$)"))

Results however, did not effectively capture the compound or aggregate impact of the independent parameters and predicted relatively low project costs with rather large residuals. This method was therefore abandoned as a viable option for estimating purposes.

## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

**Appendix J – Table J-1: SHL-TIL-RD<sup>3</sup> Composite Model Mean Project Costs (FY19\$)**

Model No. (SHL / TIL / RD <sup>3</sup> )	Mean Project Pt. Estimate Cost (FY19\$)	Model No. (SHL / TIL / RD <sup>3</sup> )	Mean Project Pt. Estimate Cost (FY19\$)	Model No. (SHL / TIL / RD <sup>3</sup> )	Mean Project Pt. Estimate Cost (FY19\$)
1/1/1	\$ 598,201	1/3/1	\$ 1,933,886	1/5/1	\$ 70,977,471
1/1/2	\$ 1,136,772	1/3/2	\$ 3,674,999	1/5/2	\$ 134,879,793
1/1/3	\$ 1,566,194	1/3/3	\$ 5,063,248	1/5/3	\$ 185,831,291
1/1/4	\$ 1,995,468	1/3/4	\$ 6,451,023	1/5/4	\$ 236,765,406
1/1/5	\$ 2,795,560	1/3/5	\$ 9,037,589	1/5/5	\$ 331,697,555
2/1/1	\$ 681,525	2/3/1	\$ 2,081,537	2/5/1	\$ 71,858,237
2/1/2	\$ 1,295,115	2/3/2	\$ 3,955,583	2/5/2	\$ 136,553,530
2/1/3	\$ 1,784,351	2/3/3	\$ 5,449,824	2/5/3	\$ 188,137,290
2/1/4	\$ 2,273,421	2/3/4	\$ 6,943,554	2/5/4	\$ 239,703,451
2/1/5	\$ 3,184,959	2/3/5	\$ 9,727,604	2/5/5	\$ 335,813,623
3/1/1	\$ 1,088,950	3/3/1	\$ 2,758,042	3/5/1	\$ 75,601,387
3/1/2	\$ 2,069,351	3/3/2	\$ 5,241,157	3/5/2	\$ 143,666,706
3/1/3	\$ 2,851,059	3/3/3	\$ 7,221,030	3/5/3	\$ 197,937,504
3/1/4	\$ 3,632,499	3/3/4	\$ 9,200,227	3/5/4	\$ 252,189,785
3/1/5	\$ 5,088,966	3/3/5	\$ 12,889,099	3/5/5	\$ 353,306,409
4/1/1	\$ 1,992,533	4/3/1	\$ 4,115,944	4/5/1	\$ 82,137,053
4/1/2	\$ 3,786,448	4/3/2	\$ 7,821,604	4/5/2	\$ 156,086,553
4/1/3	\$ 5,216,797	4/3/3	\$ 10,776,253	4/5/3	\$ 215,049,008
4/1/4	\$ 6,646,658	4/3/4	\$ 13,729,894	4/5/4	\$ 273,991,345
4/1/5	\$ 9,311,665	4/3/5	\$ 19,234,956	4/5/5	\$ 383,849,403
5/1/1	\$ 82,440,208	5/3/1	\$ 94,029,224	5/5/1	\$ 279,927,608
5/1/2	\$ 156,662,643	5/3/2	\$ 178,685,464	5/5/2	\$ 531,951,583
5/1/3	\$ 215,842,718	5/3/3	\$ 246,184,767	5/5/3	\$ 732,898,881
5/1/4	\$ 275,002,603	5/3/4	\$ 313,661,041	5/5/4	\$ 933,777,620
5/1/5	\$ 385,266,128	5/3/5	\$ 439,424,841	5/5/5	\$ 1,308,179,939
1/2/1	\$ 1,098,362	1/4/1	\$ 6,284,160		
1/2/2	\$ 2,087,237	1/4/2	\$ 11,941,905		
1/2/3	\$ 2,875,701	1/4/3	\$ 16,453,018		
1/2/4	\$ 3,663,896	1/4/4	\$ 20,962,592		
1/2/5	\$ 5,132,952	1/4/5	\$ 29,367,637		
2/2/1	\$ 1,210,305	2/4/1	\$ 6,548,142		
2/2/2	\$ 2,299,965	2/4/2	\$ 12,443,555		
2/2/3	\$ 3,168,787	2/4/3	\$ 17,144,168		
2/2/4	\$ 4,037,314	2/4/4	\$ 21,843,177		
2/2/5	\$ 5,656,093	2/4/5	\$ 30,601,297		
3/2/1	\$ 1,737,442	3/4/1	\$ 7,711,261		
3/2/2	\$ 3,301,693	3/4/2	\$ 14,653,851		
3/2/3	\$ 4,548,923	3/4/3	\$ 20,189,415		
3/2/4	\$ 5,795,728	3/4/4	\$ 25,723,090		
3/2/5	\$ 8,119,551	3/4/5	\$ 36,036,878		
4/2/1	\$ 2,843,150	4/4/1	\$ 9,890,770		
4/2/2	\$ 5,402,890	4/4/2	\$ 18,795,612		
4/2/3	\$ 7,443,858	4/4/3	\$ 25,895,745		
4/2/4	\$ 9,484,130	4/4/4	\$ 32,993,457		
4/2/5	\$ 13,286,834	4/4/5	\$ 46,222,331		
5/2/1	\$ 87,502,031	5/4/1	\$ 116,921,990		
5/2/2	\$ 166,281,719	5/4/2	\$ 222,189,008		
5/2/3	\$ 229,095,448	5/4/3	\$ 306,121,987		
5/2/4	\$ 291,887,745	5/4/4	\$ 390,026,330		
5/2/5	\$ 408,921,444	5/4/5	\$ 546,409,134		

**Estimating Methodology:****Three Parameter Estimates:**

Tables represent the expected mean point estimate costs (FY19\$) for the 125 possible three parameter (SHL-TIL-RD<sup>3</sup>) model combinations. PDF uncertainty distributions for each model are also available by running Monte Carlo simulation for the product of TIL-SHL regression model output (Table 1-1 and Appendix B) x the applicable RD<sup>3</sup> MCI PDF functions in Table 4-3.

**Four Parameter Estimates:**

To produce models including all four parameters, simply include another factor for the applicable TA MCI mean value from Table 4-2 in the product in the simulation (e.g., TIL-SHL mean x RD<sup>3</sup> PDF x TA MCI). This results in 1,250 possible four parameter model variants (25 TIL-SHL x 5 RD<sup>3</sup>s x 10 TAs). Finally to adjust for actual TRL Start and End states use the adjustment factors found in the lower section of Table 8-1

## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

Appendix J – Table J-2: (Page 1 of 2) - TI-SHL-TA Composite Model Mean Project Costs (FY19\$)

Model No. (SHL/TIL/TA)	Mean Project Cost (FY19\$)	Model No. (SHL/TIL/TA)	Mean Project Cost (FY19\$)	Model No. (SHL/TIL/TA)	Mean Project Cost (FY19\$)
1/1/1	\$ 1,602,821	2/1/1	\$ 1,826,081	3/1/1	\$ 2,917,735
1/1/2	\$ 1,216,034	2/1/2	\$ 1,385,418	3/1/2	\$ 2,213,638
1/1/3	\$ 1,163,291	2/1/3	\$ 1,325,327	3/1/3	\$ 2,117,625
1/1/4	\$ 1,406,937	2/1/4	\$ 1,602,912	3/1/4	\$ 2,561,152
1/1/6	\$ 2,892,111	2/1/6	\$ 3,294,958	3/1/6	\$ 5,264,724
1/1/7	\$ 2,651,541	2/1/7	\$ 3,020,879	3/1/7	\$ 4,826,797
1/1/11	\$ 2,158,095	2/1/11	\$ 2,458,699	3/1/11	\$ 3,928,540
1/1/12	\$ 643,180	2/1/12	\$ 732,769	3/1/12	\$ 1,170,828
1/1/13	\$ 2,717,763	2/1/13	\$ 3,096,325	3/1/13	\$ 4,947,347
1/1/14	\$ 1,043,885	2/1/14	\$ 1,189,289	3/1/14	\$ 1,900,261
1/2/1	\$ 2,942,953	2/2/1	\$ 3,242,894	3/2/1	\$ 4,655,306
1/2/2	\$ 2,232,771	2/2/2	\$ 2,460,331	3/2/2	\$ 3,531,905
1/2/3	\$ 2,135,928	2/2/3	\$ 2,353,618	3/2/3	\$ 3,378,714
1/2/4	\$ 2,583,289	2/2/4	\$ 2,846,573	3/2/4	\$ 4,086,371
1/2/6	\$ 5,310,228	2/2/6	\$ 5,851,437	3/2/6	\$ 8,399,976
1/2/7	\$ 4,868,516	2/2/7	\$ 5,364,707	3/2/7	\$ 7,701,255
1/2/11	\$ 3,962,495	2/2/11	\$ 4,366,346	3/2/11	\$ 6,268,067
1/2/12	\$ 1,180,947	2/2/12	\$ 1,301,307	3/2/12	\$ 1,868,080
1/2/13	\$ 4,990,108	2/2/13	\$ 5,498,691	3/2/13	\$ 7,893,595
1/2/14	\$ 1,916,686	2/2/14	\$ 2,112,031	3/2/14	\$ 3,031,906
1/3/1	\$ 5,181,658	2/3/1	\$ 5,577,275	3/3/1	\$ 7,389,903
1/3/2	\$ 3,931,240	2/3/2	\$ 4,231,388	3/3/2	\$ 5,606,599
1/3/3	\$ 3,760,728	2/3/3	\$ 4,047,858	3/3/3	\$ 5,363,422
1/3/4	\$ 4,548,397	2/3/4	\$ 4,895,665	3/3/4	\$ 6,486,768
1/3/6	\$ 9,349,720	2/3/6	\$ 10,063,566	3/3/6	\$ 13,334,250
1/3/7	\$ 8,571,998	2/3/7	\$ 9,226,465	3/3/7	\$ 12,225,089
1/3/11	\$ 6,976,767	2/3/11	\$ 7,509,439	3/3/11	\$ 9,950,025
1/3/12	\$ 2,079,294	2/3/12	\$ 2,238,047	3/3/12	\$ 2,965,418
1/3/13	\$ 8,786,084	2/3/13	\$ 9,456,897	3/3/13	\$ 12,530,412
1/3/14	\$ 3,374,709	2/3/14	\$ 3,632,366	3/3/14	\$ 4,812,894
1/4/1	\$ 16,837,794	2/4/1	\$ 17,545,107	3/4/1	\$ 20,661,572
1/4/2	\$ 12,774,560	2/4/2	\$ 13,311,187	3/4/2	\$ 15,675,598
1/4/3	\$ 12,220,483	2/4/3	\$ 12,733,835	3/4/3	\$ 14,995,693
1/4/4	\$ 14,780,013	2/4/4	\$ 15,400,883	3/4/4	\$ 18,136,478
1/4/6	\$ 30,381,906	2/4/6	\$ 31,658,173	3/4/6	\$ 37,281,483
1/4/7	\$ 27,854,698	2/4/7	\$ 29,024,803	3/4/7	\$ 34,180,359
1/4/11	\$ 22,670,997	2/4/11	\$ 23,623,348	3/4/11	\$ 27,819,465
1/4/12	\$ 6,756,665	2/4/12	\$ 7,040,495	3/4/12	\$ 8,291,069
1/4/13	\$ 28,550,373	2/4/13	\$ 29,749,702	3/4/13	\$ 35,034,018
1/4/14	\$ 10,966,114	2/4/14	\$ 11,426,772	3/4/14	\$ 13,456,462
1/5/1	\$ 190,177,205	2/5/1	\$ 192,537,133	3/5/1	\$ 202,566,538
1/5/2	\$ 144,284,351	2/5/2	\$ 146,074,790	3/5/2	\$ 153,683,937
1/5/3	\$ 138,026,235	2/5/3	\$ 139,739,016	3/5/3	\$ 147,018,127
1/5/4	\$ 166,935,256	2/5/4	\$ 169,006,772	3/5/4	\$ 177,810,463
1/5/6	\$ 343,153,385	2/5/6	\$ 347,411,609	3/5/6	\$ 365,508,543
1/5/7	\$ 314,609,421	2/5/7	\$ 318,513,440	3/5/7	\$ 335,105,046
1/5/11	\$ 256,061,265	2/5/11	\$ 259,238,754	3/5/11	\$ 272,742,697
1/5/12	\$ 76,314,253	2/5/12	\$ 77,261,244	3/5/12	\$ 81,285,841
1/5/13	\$ 322,466,834	2/5/13	\$ 326,468,356	3/5/13	\$ 343,474,340
1/5/14	\$ 123,858,555	2/5/14	\$ 125,395,528	3/5/14	\$ 131,927,476

## ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

**Appendix J – Table J-2: (Page 2 of 2) - TI-SHL-TA Composite Model Mean Project Costs (FY19\$)**

Model No. (SHL/TIL/TA)	Mean Project Cost (FY19\$)	Model No. (SHL/TIL/TA)	Mean Project Cost (FY19\$)
4/1/1	\$ 5,338,798	5/1/1	\$ 220,890,490
4/1/2	\$ 4,050,459	5/1/2	\$ 167,586,021
4/1/3	\$ 3,874,777	5/1/3	\$ 160,317,230
4/1/4	\$ 4,686,333	5/1/4	\$ 193,895,007
4/1/6	\$ 9,633,261	5/1/6	\$ 398,572,054
4/1/7	\$ 8,831,954	5/1/7	\$ 365,418,290
4/1/11	\$ 7,188,346	5/1/11	\$ 297,414,709
4/1/12	\$ 2,142,351	5/1/12	\$ 88,638,871
4/1/13	\$ 9,052,533	5/1/13	\$ 374,544,661
4/1/14	\$ 3,477,051	5/1/14	\$ 143,861,494
4/2/1	\$ 7,617,942	5/2/1	\$ 234,453,152
4/2/2	\$ 5,779,609	5/2/2	\$ 177,875,792
4/2/3	\$ 5,528,927	5/2/3	\$ 170,160,697
4/2/4	\$ 6,686,938	5/2/4	\$ 205,800,148
4/2/6	\$ 13,745,721	5/2/6	\$ 423,044,354
4/2/7	\$ 12,602,333	5/2/7	\$ 387,854,950
4/2/11	\$ 10,257,065	5/2/11	\$ 315,675,954
4/2/12	\$ 3,056,926	5/2/12	\$ 94,081,292
4/2/13	\$ 12,917,078	5/2/13	\$ 397,541,680
4/2/14	\$ 4,961,411	5/2/14	\$ 152,694,581
4/3/1	\$ 11,028,270	5/3/1	\$ 251,942,129
4/3/2	\$ 8,366,969	5/3/2	\$ 191,144,394
4/3/3	\$ 8,004,064	5/3/3	\$ 182,853,794
4/3/4	\$ 9,680,482	5/3/4	\$ 221,151,761
4/3/6	\$ 19,899,273	5/3/6	\$ 454,601,245
4/3/7	\$ 18,244,025	5/3/7	\$ 416,786,896
4/3/11	\$ 14,848,850	5/3/11	\$ 339,223,725
4/3/12	\$ 4,425,421	5/3/12	\$ 101,099,264
4/3/13	\$ 18,699,672	5/3/13	\$ 427,196,205
4/3/14	\$ 7,182,488	5/3/14	\$ 164,084,796
4/4/1	\$ 26,501,352	5/4/1	\$ 313,281,061
4/4/2	\$ 20,106,145	5/4/2	\$ 237,681,244
4/4/3	\$ 19,234,071	5/4/3	\$ 227,372,178
4/4/4	\$ 23,262,567	5/4/4	\$ 274,994,335
4/4/6	\$ 47,818,710	5/4/6	\$ 565,280,452
4/4/7	\$ 43,841,085	5/4/7	\$ 518,259,657
4/4/11	\$ 35,682,351	5/4/11	\$ 421,812,617
4/4/12	\$ 10,634,455	5/4/12	\$ 125,713,333
4/4/13	\$ 44,936,022	5/4/13	\$ 531,203,262
4/4/14	\$ 17,259,793	5/4/14	\$ 204,033,598
4/5/1	\$ 220,078,217	5/5/1	\$ 750,038,705
4/5/2	\$ 166,969,763	5/5/2	\$ 569,042,162
4/5/3	\$ 159,727,701	5/5/3	\$ 544,360,815
4/5/4	\$ 193,182,004	5/5/4	\$ 658,374,926
4/5/6	\$ 397,106,399	5/5/6	\$ 1,353,360,516
4/5/7	\$ 364,074,550	5/5/7	\$ 1,240,786,151
4/5/11	\$ 296,321,037	5/5/11	\$ 1,009,878,439
4/5/12	\$ 88,312,923	5/5/12	\$ 300,975,312
4/5/13	\$ 373,167,361	5/5/13	\$ 1,271,774,953
4/5/14	\$ 143,332,477	5/5/14	\$ 488,484,989

**Estimating Methodology:*****Three Parameter Estimates:***

*Tables represent the expected mean point estimate costs (FY19\$) for the 250 possible three parameter (SHL-TIL-TA) model combinations. Costs are the product of TIL-SHL regression model output (Table 1-1 and Appendix B) x the applicable TA MCI values in Table 4-2.*

***Four Parameter Estimates:***

*To produce models including all four parameters simply include another factor for the applicable RD<sup>3</sup> MCI PDF from Table H-1 in the product in Monte Carlo simulation (e.g., TIL-SHL mean x TA MCI x RD<sup>3</sup> PDF). This results in 1,250 possible four parameter model variants (25 TIL-SHL x 10 TAs x 5 RD<sup>3</sup>s). Finally to adjust for actual TRL Start and End states use the adjustment factors found in the lower section of Table 8-1 producing up to 9,000 possible model variants (36 TRL Start-End x 5 SHL x 5 RD<sup>3</sup> x 10 TA).*

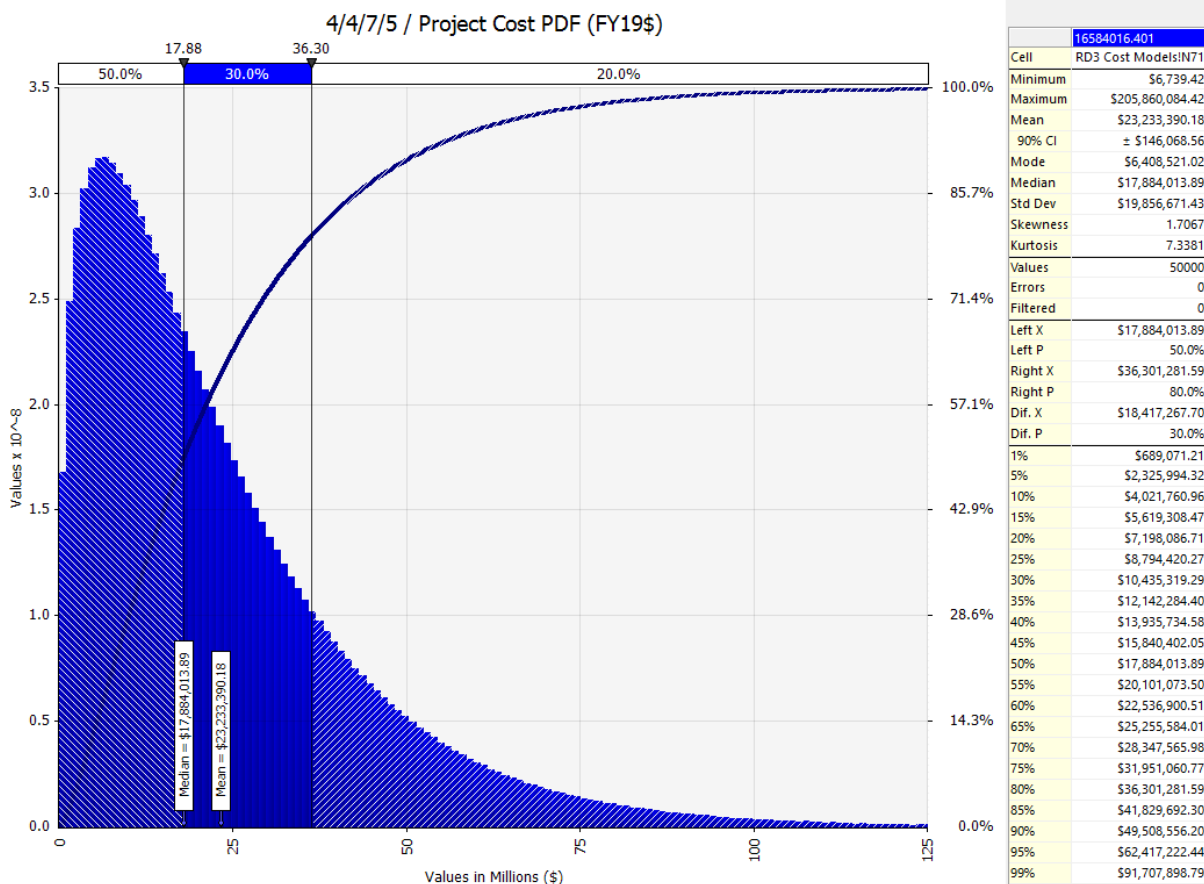
ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

**Appendix K – Macro-Parametric Model Project Estimating Examples**

**Project 1: 3 Parameter Estimate for SHL = 4, TRL<sub>Start</sub> = 4, TRL<sub>End</sub> = 7 (TIL = 3), and RD<sup>3</sup> = 5**

The first sample project estimate is for one of the 125 three parameter SHL-TIL-RD<sup>3</sup> models with a project configuration of SHL = 4, TRL<sub>Start</sub> = 4, TRL<sub>End</sub> = 7 (TIL = 3), and RD<sup>3</sup> = 5 (model no. 4/4/7/5 representing SHL/TRLs/TRL<sub>e</sub>/RD<sup>3</sup>/TA). The methodology starts with the SHL-TIL multiple regression model output for SHL = 4 and TIL = 3 from **Table 1-1** and **Appendix B** which results in a mean cost of \$10,080,685 (FY19\$<sub>k</sub>). This mean project value is adjusted to discrete TRL Start and End states of 3 and 7 (for a TIL = 7 – 4 = 3) applying cost factor from **Table 8-1** of 1.21 (rounded from 1.20788) and further refined by RD<sup>3</sup> MCI value = 1.9081 from **Table 4-1** producing a project mean point estimate of ~\$23,233,500. To provide a perspective of expected cost with uncertainty however, a Monte Carlo simulation was run substituting the PDF for the RD<sup>3</sup> = 5 MCI from **Table H-1** (@RISK formula = RiskGamma (1.3688,1.394,RiskName ("RD<sup>3</sup> Lvl 5 MCI"))) and **Figure H-4** of **Appendix H**, producing the project cost uncertainty distribution shown in **Figure K-1**. The resulting 50<sup>th</sup> to 80<sup>th</sup> percentile cost planning range for these project attributes is ~ \$18M to ~\$36M with a 70<sup>th</sup> percentile of \$28.3M, as illustrated in the PDF plot and table. Generating curve fits for this PDF produces and optimal function in @RISK of =RiskGamma(1.3689,16972745,RiskName("4/4/7/5 / Project Cost PDF Curve Fits (FY19\$)")).

**Figure K-1: Project 1 Uncertainty PDF: SHL = 4, TRL Start = 4, TRL End = 7 (TIL = 3), and RD<sup>3</sup> = 5**

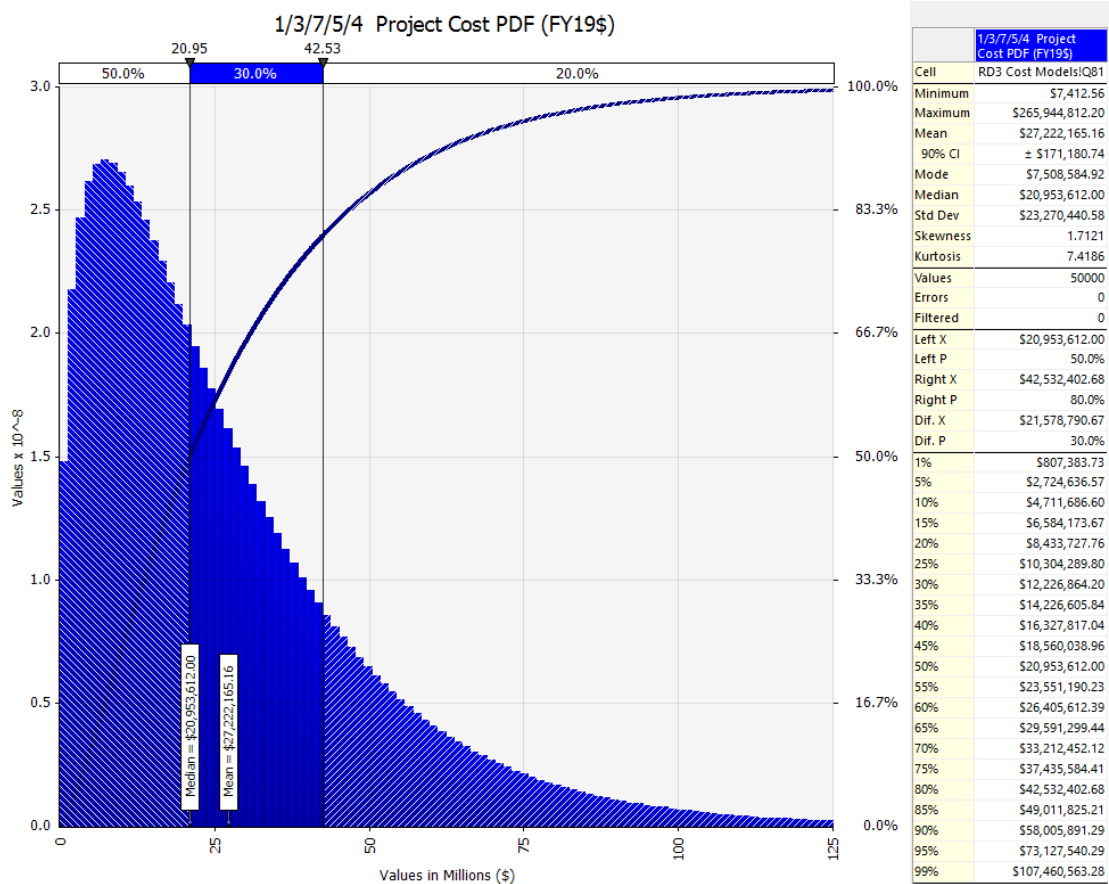


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**Project 2: 4 Parameter Estimate for SHL = 1, TRL<sub>Start</sub> = 3, TRL<sub>End</sub> = 7 (TIL = 4), RD<sup>3</sup> = 5 TA = 4**

Similarly, a four parameter SHL-TIL-RD<sup>3</sup>-TA macro-parametric model estimate is demonstrated for a hypothetical project characterized by SHL = 1, TRL<sub>Start</sub> = 3, TRL<sub>End</sub> = 7 (TIL = 4), RD<sup>3</sup> = 5 and TA = 4 (i.e., Robotics, Telerobotics, Autonomous Systems) (model no. 1/3/7/5/4 representing SHL/TRL<sub>start</sub>/TRL<sub>End</sub>/RD<sup>3</sup>/TA). This estimate is calculated starting with a base TI-SHL macro-parametric regression model and then fine-tuned by the discrete TRL Start / End cost factor and both the RD<sup>3</sup> MCI and TA MCI estimate values. Again to provide a perspective of estimate uncertainty the inputs are run in Monte Carlo simulation replacing the RD<sup>3</sup> MCI point estimate with the corresponding RD<sup>3</sup> MCI PDF. The SHL-TIL regression model returns a mean point estimate of \$15,391,037 (FY19\$), from **Table 1-1** and **Appendix B**. This mean project value is adjusted by a TRL Start/End (=3/7) to TIL (=4) average cost factor of 0.97 (rounded from 0.96525) from **Table 8-1**, an RD<sup>3</sup> MCI value of 1.9081 from **Table 4-1** and TA MCI = 0.9603 from **Table 4-2**, producing a project mean point estimate value of ~ \$27,221,700. To develop the overall expected cost with uncertainty, a Monte Carlo simulation is run utilizing the PDF for RD<sup>3</sup> = 5 MCI from **Table H-1** (@RISK formula = RiskGamma (1.3688,1.394,RiskName ("RD<sup>3</sup> Lvl 5 MCI"))) and **Figure H-4** of **Appendix H**, producing the project cost uncertainty PDF shown in **Figure K-2**. The resulting median to 80<sup>th</sup> percentile cost planning range for these project characteristics is ~ \$21M to ~\$42.5M with a 70<sup>th</sup> percentile of \$33.2M, as illustrated in the PDF plot and table.

**Figure K-2: Project 2 Uncertainty PDF: SHL = 1, TRL<sub>Start</sub> = 3, TRL<sub>End</sub> = 7 (TIL = 4), RD<sup>3</sup> = 5 and TA = 4**



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## Appendix L – Detailed Standard Development Framework WBS Elements

WBS #	WBS Name	WBS Description <i>(Note: general WBS guidance only and not intended as prescriptive, tailor WBS to system architecture and project requirements)</i>
<b>1.0</b>	<b>DEVELOPMENT</b>	Technology and Systems Development advancing and transitioning technology from conceptual scientific investigation through full systems development and demonstration in an operational environment to Full Operational Capability (FOC).
<b>1.1</b>	<b>Technology Development</b>	Proof of concept (PoC) or feasibility demonstration in simulation and laboratory environment
<b>1.1.1</b>	<b>Basic Research</b>	Basic research is systematic study directed toward greater knowledge or understanding of the fundamental aspects of phenomena and of
<b>1.1.2</b>	<b>Technology Research</b>	Incubation stage scientific investigation with translation to basic principles & early exploratory development during pre-material solution analysis
<b>1.1.3</b>	<b>Analytical Proof of Concept (PoC) Validation</b>	Analytical PoC or feasibility demonstrated in a simulated environment establishing initial practicality of proposed solutions to technological req
1.1.3.1	Development NRE	Development non-recurring Systems Engineering (NRE) including security considerations
1.1.3.2	Systems Hardware	Systems hardware development, modifications or purchases (COTS), needed for this phase of demonstration
1.1.3.3	Systems Software	Systems software development, modifications or purchases (COTS), needed for this phase of demonstration
1.1.3.4	Systems Integration	System integration activities including internal and external interfaces needed for this phase of demonstration
1.1.3.5	Testing	Testing including any applicable test labor, equip, labs/ranges, or platform costs and certification req'ts etc. needed for this phase of
1.1.3.6	Project Management (PM)	Project planning, management and oversight activities
1.1.3.7	Support Services	Other support services may include logistics support, configuration management, facilities, IT, security, etc.
1.1.3.8	Other Direct Costs (ODCs)	ODCs may include applicable subcontract services, network / communications costs, travel, etc.
<b>1.1.4</b>	<b>Validation in a Laboratory Environment (VLE)</b>	Component or breadboard validation or ad hoc demonstration testing in a laboratory environment (VLE)
1.1.4.1	Development NRE	Development non-recurring Systems Engineering (NRE) including security considerations
1.1.4.2	Systems Hardware	Systems hardware development, modifications or purchases (COTS), needed for this phase of demonstration
1.1.4.3	Systems Software	Systems software development, modifications or purchases (COTS), needed for this phase of demonstration
...	...	...
<b>1.1.5</b>	<b>Validation in a Relevant Environment (VRE)</b>	Component or breadboard high fidelity proof of concept validation or demonstration in a laboratory or relevant environment (VRE) (around SRR)
1.1.5.1	Development NRE	Development non-recurring Systems Engineering (NRE) including security considerations
1.1.5.2	Systems Hardware	Systems hardware development, modifications or purchases (COTS), needed for this phase of demonstration
1.1.5.3	Systems Software	Systems software development, modifications or purchases (COTS), needed for this phase of demonstration
...	...	...
<b>1.1.6</b>	<b>Prototype Demo in Relevant Environment (DRE)</b>	Prototype system/subsystem technology design, integration build, test and checkout for Demonstration a Relevant Environment (DRE)
1.1.6.1	Prototype System Design	Design of Prototype architecture functional product breakdown of primary HW, SW and all internal and external interfaces
1.1.6.2	Vendor NRE	Vendor non-recurring systems engineering (NRE)
1.1.6.3	Prototype System Build(s)	Build of Prototype architecture functional product breakdown of primary HW, SW and all internal and external interfaces
1.1.6.4	Support Platform(s) / Systems Modification Design	Platforms like sea/air/land/space assets and comms. systems that require modifications to support Conops
1.1.6.5	System Integration, Assembly, Test and Checkout (IAT&C)	Prototype Integration, Assembly, Test and Checkout (IAT&C)
1.1.6.6	Systems Data	Prototype data & doc'n including vendor system specs, drawings/diagrams and Opns manuals as well as gov't purchase of intellectual data property
<b>1.2</b>	<b>Systems Development</b>	Advancing technology from Prototype to full scale system functional integration, test and demonstration with operational system through IOC
<b>1.2.1</b>	<b>Systems Prototype Demo in Oper'l Environment (DOE)</b>	Systems Prototype Demo in Oper'l Environment
<b>1.2.2</b>	<b>Full Scale Systems Dvlp. &amp; Demonstration (SDD)</b>	System Test and Evaluation (T&E) - functional or operational system test and demonstration
1.2.2.1	Full Scale System (FSS) Design	Design of full scale architecture functional product breakdown of primary HW, SW and all internal and external interfaces
1.2.2.2	FSS Vendor NRE	Vendor non-recurring systems engineering (NRE)
1.2.2.3	FSS LRIP Build(s)	Build of low rate initial production (LRIP) full scale systems including primary HW, SW and all internal and external interfaces
1.2.2.4	FSS Support Platform(s) / Systems Modification Design	Platform modification and integration design and including sea/air/land/space assets and C3I systems to support Conops
1.2.2.5	FSS Integration, Assembly, Test and Checkout (IAT&C)	Full Scale System Integration, Assembly, Test and Checkout (IAT&C)
1.2.2.6	FSS Data	FSS data & doc'n including vendor system specs, drawings/diagrams and opns manuals as well as gov't purchase of intellectual data property right
1.2.2.7	FSS Test Labor	Government (Military and Civilian) and Contractor personnel to plan and perform the operational system field tests
1.2.2.8	FSS Test Equipment	Procurement or lease of all necessary FSS test equipment
1.2.2.9	FSS Test Support Organizations and Ranges	Costs for use of all test facilities, labs, ranges and associated ODCs
1.2.2.10	FSS Test Platforms	Procurement, lease or usage fees for test support platforms including sea/air/land/space assets and C3I systems that are part of the operational
1.2.2.11	FSS Pre-Test Certification	Costs associated with certification / approval to integrate development systems with operational systems for testing
1.2.2.12	FSS Demonstration Test	System T&E / demonstration testing
1.2.2.13	Project Management	Project planning, management and oversight activities
<b>1.2.3</b>	<b>Operational Systems Evaluation (OPEval)</b>	Full system operational evaluation (OPEval) through full rate production (RFP) approval, concluding with initial operational capability (IOC)
<b>1.2.4</b>	<b>Operational Systems Development</b>	Development efforts such as engineering or design modifications to resolve manufacturing or production issues for fielded systems up to FOC

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**Acronym List**

ACRONYM	
advanced degree of difficulty	AD <sup>2</sup>
Analytical Hierarchy Procedure	AHP
basis of estimate	BOE
budget activity	BA
coefficient of variation	CV
cumulative probability distribution	CPD
Durbin-Watson	DW
full scale system	FSS
integration readiness level	IRL
International Cost Estimating Analysis Association	ICEAA
joint inflation calculator	JIC
key performance parameters	KPP
low rate initial production	LRIP
Major Defense Acquisition Programs	MDAP
manufacturing readiness level	MRL
mean cost factor	MCF
mean cost index	MCI
Naval Center for Cost Analysis	NCCA
non-recurring development	NRDEV
overseas contingency operations	OCO
probability density function	PDF
R&D degree of difficulty	RD <sup>3</sup>
research and development	R&D
research, development, Test and Evaluation	RDT&E
Resource Data Storage and Retrieval Database	REDSTAR
size, weight and power	SWAP
system readiness level	SRL
systems hierarchy level	SHL
technology area	TA
Technology Cost and Schedule Estimating	TCASE
technology readiness level	TRL
three dimensional	3D
TRL improvement level	TIL
two dimensional	2D
two one-sided test	TOST
variance inflation factor	VIF
work breakdown structure	WBS

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