ADVANCED ESTIMATING METHODOLOGIES FOR CONCEPTUAL STAGE DEVELOPMENT

Keywords: Conceptual Stage, Technology Development, Systems Development, Cost Estimating, Parametric Modeling, Cost Estimating, Bayesian Uncertainty, Statistical Analysis

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Executive Summary

Industry Challenges. *One of the prominent challenges for conceptual phase technology and systems development in industry, government, and institutional sectors continues to be the lack of effective methods and historical data with which to produce reliable estimates. Forecasting the cost and duration of early stage development is very difficult for numerous reasons. The nature of new or immature technologies suggests there is a lack of truly analogous systems available from which to generate a basis of estimate (BOE). Traditional micro-parametric estimating models are also driven by fundamental engineering, design, or performance criteria that are generally unavailable in immature development phases. These models are also frequently focused on narrow technology areas and frequently based upon very limited historical project data. This is exacerbated by the protected nature of these efforts, often containing proprietary intellectual property or classified information. A comprehensive risk-adjusted solution is therefore needed that may be applied across technology areas, leveraging a full complement of primary technical, cost and risk drivers.*

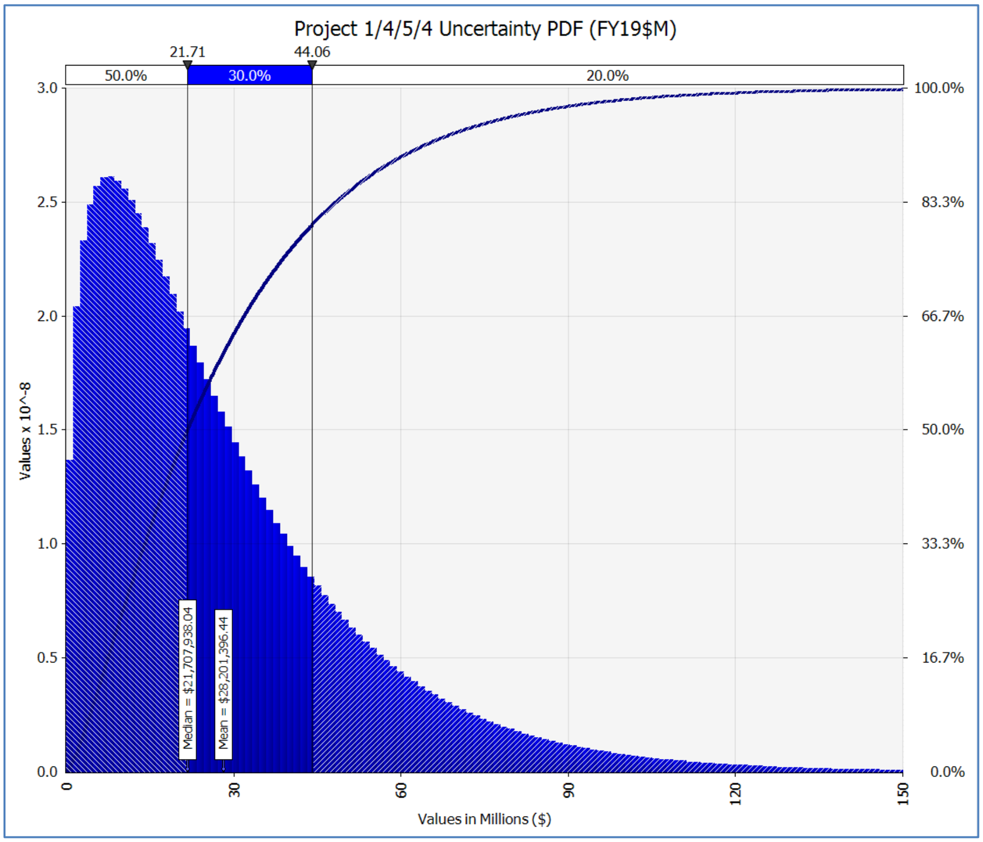
Current Investigation. *This research expands and refines an earlier investigation introduced in 2017* (Alexander, 2017) *that developed a first generation of parametric cost and schedule models based on technology readiness levels (TRL) and systems hierarchy level (SHL) macro-parameters. Second generation cost models from this extended analysis are developed by augmenting the base TRL Improvement & SHL independent predictors with other macro-parameters including research and development (R&D) degree of difficulty (RD^3) and technology area (TA). The two greatest underlying drivers of cost, schedule and risk for any development, are measures of project scale and complexity (i.e., both technological and system). Inclusion of these key measures more directly associated with system function, complexity, development difficulty, and level of integration, significantly enhances the estimating methodology by reflecting a more diverse and complete set of underlying cost and risk drivers. Model fidelity is further advanced by development of Gaussian uncertainty distributions, which provide probability-based functions of project cost variability, custom fit to independent macro-parameter levels. Leading methods to aggregate composite macro-parameter measures for multi-technology programs and system development efforts are also presented.*

To extend these estimating capabilities further, a standard development framework is constructed with which total development estimates can be broken down into major constituent activities and milestones for investment analysis and budget planning. This framework also provides utility since it is based on common technology and systems development life cycle stages, acquisition milestones and standard R&D budget activities (BA). A typical development cost profile is introduced relating cost expenditure levels with key acquisition milestones and TRL benchmarks. This profile is woven into the estimating framework providing a utility to breakdown or extrapolate costs across the primary development activities. It is further used to refine the monolithic TRL Improvement (TIL) parametric costs with discrete TRL_{Start} to TRL_{end} adjustment factors.

Methodology Results. *The range of improvements introduced fundamentally transform and expand capabilities of baseline development cost models, capturing a substantially broader perspective of essential cost attributes. The development cost landscape undergoes a vast increase in forecasting*

*power and precision from a coarse 25 point two-dimensional (2D) grid to a 4D high-resolution topography of 9,000 possible SHL-TIL-*RD^3*-TA project datum. An example probability density function (PDF) plot for just one of these project data points (for SHL = 1, TIL = 4, RD^3 = 5 and TA = 4) is provided in **Figure E-1**. Collectively, these advancements provide a comprehensive, integrated estimating solution set for conceptual phase technology and systems development.*

Figure E-1: PDF Uncertainty Output for Project: SHL = 1, TIL = 4, RD^3 = 5 and TA = 4

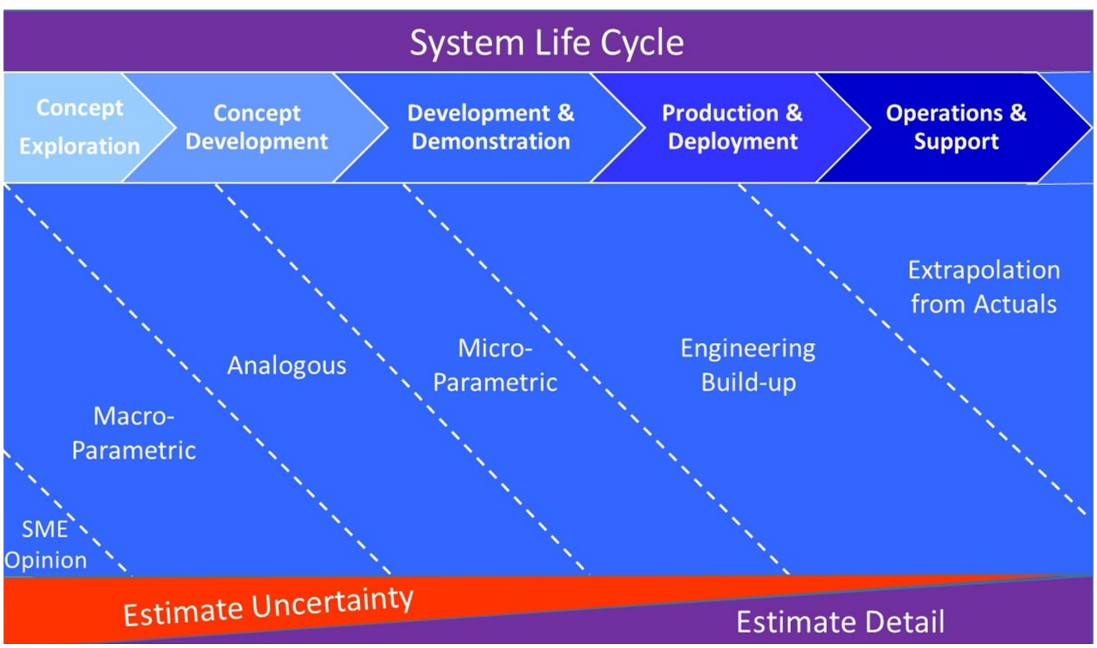


Future Considerations. *Federal agencies, major research institutions and industry technology leaders are beginning to more broadly endorse the development, measurement and capture of standardized forms of macro-parameters to enhance project planning, estimating and performance measurement. Several recent research papers have also focused on the need for use of readiness and integration measures early in the development process. System readiness level (SRL), integration readiness level (IRL), manufacturing readiness level (MRL), and programmatic readiness level (PRL) are associated with various aspects of development maturity and readiness. These measures all have potential to compliment TRL-based macro-parametric forms of technology and system estimating. Complexity is affiliated with a variety of the underlying dimensions of TIL, SHL, RD^3 and TA macro-parameters. The development of an explicit standard measure of overall system complexity however, capturing all its key attributes, may produce the most influential relationship to development program cost and duration. These parametric measures hold substantial promise to advance parametric estimating capabilities but more project level cost and schedule information will be needed to reach their full potential in resource planning and investment decision making.*

1. Background

Viable cost and schedule estimating methods available in conceptual stages of development of the system life cycle primarily include analogous systems, macro-parametrics and to a lesser extent, micro-parametric techniques as illustrated in **Figure 1-1**. Due to the general lack of analogous technologies, traditional technical, design or performance micro-parameters, and related cost data, estimating methodologies for this research were pursued using macro level predictor variables more readily available in this immature phase. A previous investigation into early technology development estimating produced a series of preliminary cost and schedule models presented in an initial research paper (Alexander, 2017). The two key input variables applied in the original analysis are the TIL [1] from project start to completion and SHL (see definitions in **Appendix A**). For that research, several hundred cost and schedule models were evaluated traversing a spectrum of forms including a range of linear, non-linear, simple and multiple regressions and custom curve fits of the TIL and SHL independent predictors. An example of one of the higher performing of these first generation cost models is presented in **Appendix B**. This multiple regression model is of the form: **Total Cost = f [c_i + TIL+ SHL]^2**, where c_i represents the regression constant intercept term. Model mean cost output results for the 5 SHL x 5 TIL matrix are also displayed in **Table 1-1**[2].

Figure 1-1: Estimating Methods over the System Life Cycle



Attributes of the two initial independent variables relate directly to technology scale and maturity but with much more limited affiliation to other common cost drivers such as technology and system

[1] TIL = TRL improvement from state at project completion or end, less the TRL state at project start ($TRL_{End} - TRL_{Start}$).

[2] Source data project costs are from the NASA Technology Cost and Schedule Estimating (TCASE) tool which defines total cost as total dollars required to complete a technology development project. This cost is provided by year and represents the total cost of labor, materials, travel, testing, equipment, and any needed facilities infrastructure investments made as part of the research project. Mean project costs shown in Table 1-1 are in FY19$ converted from the initial analysis performed in FY15$.

complexity, level of integration, development difficulty, and technology form or function. One of the principal recommendations from the baseline analysis was therefore to develop relationships for other prospective factors that could round out the full field of key cost drivers to capture the missing portions of the development estimating domain.

Table 1-1: SHL-TIL Multiple Regression Model Cost Output

Mean Project Cost (CY$19)					
TI Level	System Hierarchy Level (SHL)				
	1	2	3	4	5
1	1,465,102	1,669,178	2,667,033	4,880,072	201,910,868
2	2,690,085	2,964,254	4,255,307	6,963,384	214,308,183
3	4,736,434	5,098,058	6,754,939	10,080,685	230,294,450
4	15,391,037	16,037,575	18,886,263	24,224,271	286,362,944
5	173,836,568	175,993,723	185,161,369	201,168,389	685,592,966

As displayed in **Table 1-1** there are significant cost escalations at both SHL 5 and TIL 5. Reasons driving this behavior for SHL include factors such as the aggregation of major components & subsystems and the exponential growth in the number of internal and external nodal interfaces and communication paths.[3] This includes internal hardware and software system modifications & interfaces as well as external legacy platforms or command, control and communications (C^3) system interfaces, each with potential nonlinear compound impacts on system complexity, engineering, design, integration, test and demonstration. Possibly the greatest factor driving this cost growth however, is the extremely broad range in the scope of SHL level 5 (i.e., the System level) that encompasses very large "System of Systems" programs. This phenomenon suggests that segregating an SHL 6 for Systems of Systems development projects may be appropriate and worthy of investigation. TIL 5 similarly implies large, long term, extensive technology and system developments where costs can accelerate sharply at peak levels.

2. Introduction:

This research examines parameters and explores techniques to extend the capabilities and overall utility of earlier technology and systems development estimating methodologies. In-depth analysis was performed generating profound improvements to the forecasting capacity, strength, precision and reliability of preliminary TIL and SHL based models. More powerful custom solutions were produced via an array of advancements including:

1) Augmentation of first generation cost models with supplemental macro-parameters tailored to reflect a more comprehensive set of common cost drivers. Original models are vastly expanded from a limited 25 point, two dimensional (2D) project space to a four dimensional (4D) macro-parametric composite topography of 9,000 available data points.

[3] Both of these relationships can grow at a rate approaching a theoretical limit of $(n^2 – n) / 2$, where n represents the number of nodes. This second order function parallels the second order regression model demonstrative of one of the fundamental drivers of cost.

2) Development of enhanced uncertainty models reflecting substantially larger and more diverse project datasets
3) Construction of a standard technology and systems development framework integrated with key development activities, processes, acquisition milestones and TRL achievement
4) Building of historical development cost benchmarks tied to the framework milestones & TRLs that:
    a. Provide a method to segment total development estimates into a full range of common research and development (R&D) stages, milestones and activities, and;
    b. Refine uniform project TIL cost metrics with unique incremental TRL start / end cost adjustment factors

A variety of complementary independent macro-level predictors were first assessed and two primary variables selected to broaden and magnify the scope of limited baseline technology development models. An examination of the chosen R&D degree of difficulty (RD^3) and technology area (TA) variables was conducted, and estimating methods explored to incorporate them into the analysis. Two primary techniques were identified, one involving formulation of mean cost factors and an alternative employing geometric means. These methods were assessed uniting the additional parameters with the first generation SHL-TIL models resulting in marked improvements to forecasting performance and uncertainty analysis.

A standard technology development framework with associated cost benchmark profile was then constructed. Common high level research, development, test and evaluation (RDT&E) milestones from the DoD Acquisition Management Process and standard RDT&E budget activity (BA) category definitions were examined to develop a general development work breakdown structure (WBS). Cost estimating relationships aligned with the proposed development framework milestones and TRL achievement were then introduced based on an investigation of industry studies and historical R&D budget research. Research findings and historical budget metrics were collectively employed to produce a “typical” R&D cost benchmark landscape mapped to critical acquisition milestones and TRLs. This profile is applied to calculate and allocate costs for major elements of development, generate cost factors to refine uniform TILs into specific TRL start and end states and also serve as an alternate cost estimate validation method.

3. Expanded Parametric Data Investigation

To pursue the research objective, additional project data was examined from the National Aeronautics Space Administration (NASA) Technology Cost and Schedule Estimating (TCASE) database (Wallace, 2015), used for the initial research. TCASE is a unique resource developed in early 2013 by the prior NASA HQ Cost Analysis Division and SpaceWorks Enterprises, Inc., consisting of a database of nearly 3,000 development projects with integral user interface and query utility. The TCASE data was assessed to search for additional macro-parameters to complement the preliminary TRL and system hierarchy based independent variables to strengthen and enhance base model power and performance. Principal candidates identified from this exploration were TCASE data fields for technology area (TA), research and development degree of difficulty (RD^3), key performance parameters (KPP), and the advanced degree of difficulty (AD^2). These parameters showed potential to augment prior model predictors since they relate more directly to complementary cost drivers such as system complexity, performance, functionality, reliability, level of integration and development difficulty.

The AD^2, KPP, TA, and RD^3 parameters were each screened for viability as supplemental measures. AD^2 resulted in an insufficient population of projects to effectively apply. In addition, since the KPPs in TCASE are not standardized system attributes but rather manual entries of factors and qualities often specific to a particular project or technology, they were eliminated from contention. Definitions for the remaining TA and RD^3 project characteristics are found in **Tables 3-1** and **3-2**. For TAs, NASA breaks down R&D projects into 15 standard categories[4]. Since the range of technologies investigated and developed by NASA is extensive, going well beyond just space and flight systems, it includes a diversity of relevant platforms, applications and systems spanning scientific, military, intelligence and commercial sectors. RD^3 is the five level qualitative scale of the degree of difficulty anticipated to achieve R&D objectives and associated probability of success over the course of a development project.

Table 3-1: Technology Areas (TA)[5]

No.	Description
TA01	Launch propulsion systems
TA02	In-space propulsion technologies
TA03	Space power and energy storage
TA04	Robotics, telerobotics, autonomous systems
TA05	Communication and navigation
TA06	Human health, life support, habitation systems
TA07	Human exploration destination systems
TA08	Science instruments, observatories, sensor systems
TA09	Entry, descent, and landing systems
TA10	Nanotechnology
TA11	Modeling, simulation, information tech
TA12	Materials, structures, mechanical systems, manufacturing
TA13	Ground and launch systems processing
TA14	Thermal management systems
(+) 1	Aeronautics

[4] Note that Aeronautics, added later as TA No. (+) 1, has been labeled as TA15 for purposes of this analysis.

[5] The list of space technology areas and their supporting roadmaps was developed by NASA, and reviewed and validated by the National Research Council (NRC). (Reference: Technology Estimating Research Project - Introduction and Definitions, June 21, 2013).

Assessing TCASE projects for TA and RD^3 values, a broader, more diverse collection of available project cost data was available than those with the original composite TIL & SHL parameter models containing 221 project records. TA categories were found in well over 1,700 project records and RD^3 measures were discovered in over 400. This provided both parameters substantial sample sizes as candidate predictor variables; therefore, associated project data containing each macro-parameter was extracted for analysis. However, an insufficient number of projects containing all four independent variable measures (i.e., TIL, SHL, RD^3 and TA) were available to develop statistically significant multiple regression models. Therefore, alternate techniques were explored to incorporate the additional parameters in the analysis that are presented in **Section 4**.

Table 3-2. Research and Development Degree of Difficulty (RD^3) [6]

Level	Definition
5	The degree of difficultry anticipated in achieving R&D objectives for this technology is so high that a fundamental breakthrough is required [$P_{success}$ = 0.2]
4	A very high degree of difficulty anticipated in achieving R&D objectives for this technology [$P_{success}$ = 0.5]
3	A high degree of difficulty anticipated in achieving R&D objectives for this technology [$P_{success}$ = 0.8]
2	A moderate degree of difficulty should be anticipated in achieving R&D objectives for this technology [$P_{success}$ = 0.9]
1	A very low degree of difficulty is anticipated in achieving R&D objectives for this technology [$P_{success}$ = 0.99]

4. RD^3 and TA Data Analysis and Cost Modeling

TIL, SHL and RD^3 independent variables each use progressive ordinal category level definitions based on qualitative assessments. Therefore, they are not designed to follow any particular linear or nonlinear continuous mathematical algorithm. This does not mean the ordinal or categorical level costs cannot observe natural mathematical functions. However, there is no need to fit overall continuous functions, since the ordinal inputs are discrete integer values and interim fractional TRLs, SHLs or RD^3 values are both meaningless and unnecessary.[7] Similarly, TAs are not continuous variables but distinct independent categorical values that relate to cost through secondary effects such as system complexity, level of integration required, et.al.

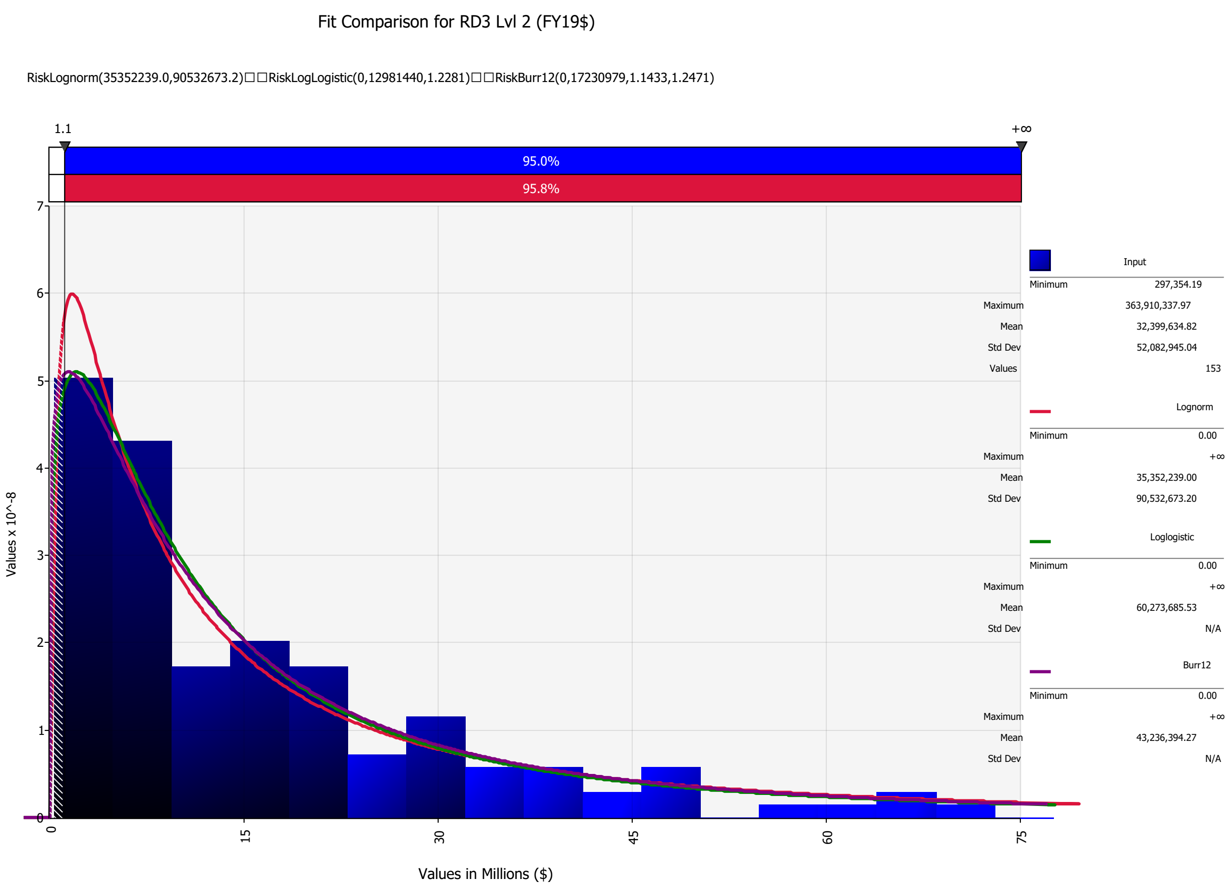
Statistical analysis was first performed on the RD^3 and TA data to assess the viability of each parameter as a complementary independent variable. This evaluation included strong regression coefficient of determination (R^2 adjusted) cost response in the 0.7 to 0.8 range for RD^3 and TA

[6] "RESEARCH & DEVELOPMENT DEGREE OF DIFFICULTY (R&D³) A White Paper" by John C. Mankins, NASA Headquarters Office of Space Flight, Advanced Projects Office, March 10, 1998

[7] For a further discussion of ordinal, categorical and other data types see **Appendix E.**

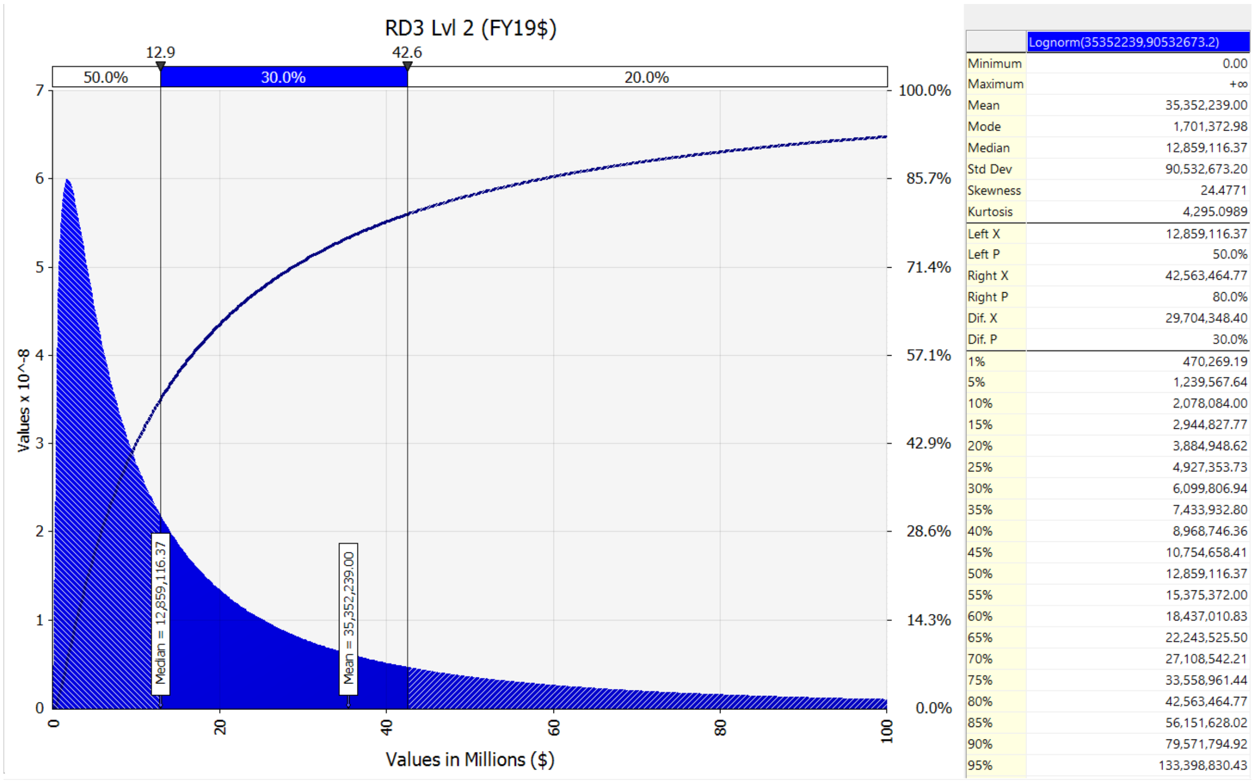
predictors (described in **Appendix C)**. Multicollinearity, residual autocorrelation and independence measures such as the Durbin Watson (DW) statistic, variance inflation factor (VIF), and low correlation coefficients between predictor variables also produced favorable results as demonstrated in **Appendix D**. Following this analysis, tailored cost curve fits for each RD^3 ordinal level and selected TA categories were modeled. Example curve fit probability density function (PDF) plots for RD^3 = 2 is provided in **Figure 4-1**. The highest performing or "best fit" of these functions for RD^3 = 2 resulting in a Lognormal function is shown in **Figure 4-2** with cumulative probability distribution (CPD) and markers for a typical planning range (50^{th} to 80^{th} percentile). The best fit PDF for each RD^3 level and TA category were selected based on statistical selection criteria and guidelines using Palisade's @RISK software tool as described in **Appendix F.**

Figure 4-1: Example Project Cost Curve Fit PDFs for RD^3 = 2 (FY19$M)[8]



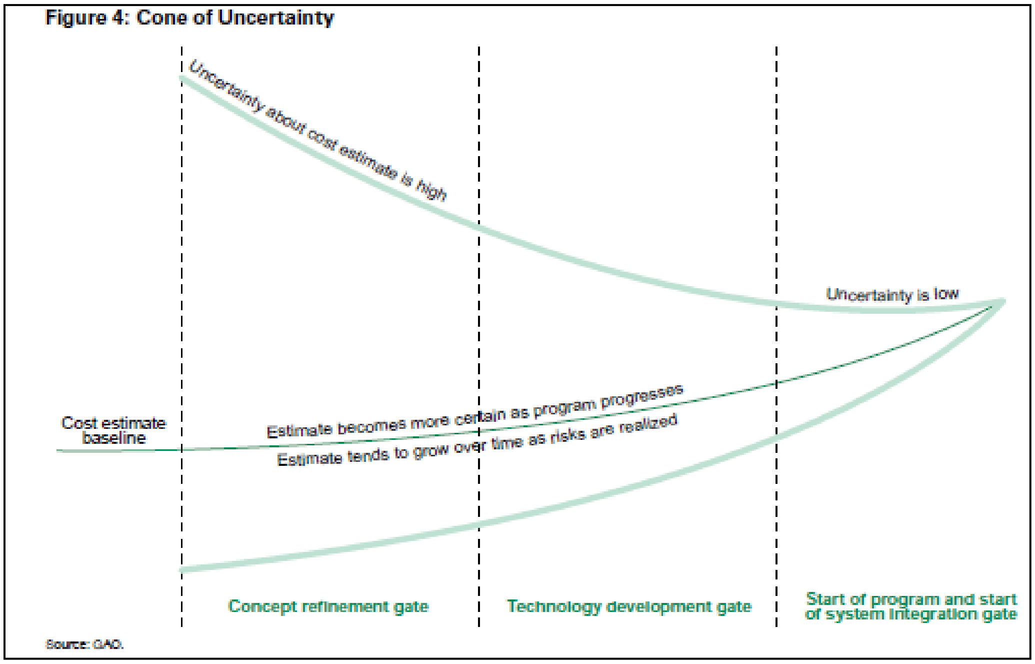
[8] Vertical Y axis of @RISK PDF uncertainty charts for curve fits and functions shown in this paper represent a relative scale of probability similar to relative frequency densities for a histogram. X axis represent units in US dollars in the FY shown in the Figure Titles.

Figure 4-2: Project Cost Data Best Fit PDF for RD^3 = 2 (FY19$M)



The resulting RD^3 cost curve PDFs are generally highly right-skewed distributions with large standard deviations and relatively wide dispersion around the central measures. This form of uncertainty distribution is expected and appropriate for project resource, cost and schedule data, especially for highly uncertain environments that accompany early stage technology and systems development. This result is consistent with GAO's suggested uncertainty behavior in conceptual stage development shown in **Figure 4-3** (from GAOs Cost Estimating and Assessment Guide-March 2009) (GAO, 2009) as well as the right-skewed uncertainty distributions considered practical for cost estimating by the Joint Agency Cost Schedule Risk and Uncertainty Handbook (JACSRUH) (NCCA, 2014). In this manner, **Figure 4-2** effectively represents a probability based vertical cross section of the GAO plot for RD^3 = 2. Numerous reasons drive this phenomenon especially in conceptual stages including cost growth due to the large range of unknowns, significant potential for requirements creep, technology & design changes, operational threat & environment changes, or organizational / staffing changeover. Supply chain disruptions, budget or resource priority realignments, legal / regulatory / political environment changes and poor management execution can also increase upside uncertainty. Also underlying this uncertainty effect is the bounded low end and essentially unbounded upper end nature of cost.

Figure 4-3: GAO System Acquisition Uncertainty



With this statistical information, methods of aggregating the impact of the TA and RD^3 macro-parameters with the base model SHL-TIL parametric cost models were explored. Two primary approaches were identified and assessed to incorporate the available RD^3 and TA project data: 1) a relative Mean Cost Index (MCI) application method and, 2) a technique merging the cost curve fit functions of the various independent predictors using a geometric mean. Both methods have the advantage of tailoring individual functions fit to each ordinal level or category, eliminating the constraint of an arbitrary forcing function across subjective ordinal parameter levels.

a. Mean Cost Index (MCI) Method

This estimating technique both extends and refines the preliminary base regression cost model results by establishing cost relationships between the SHL-TIL model cost data and each of the corresponding RD^3 and TA project data. To accomplish this, the SHL-TIL project cost data and RD^3 and TA project datasets were first evaluated to establish that they are based on essentially equivalent mean project costs. In support of this premise, the three subject samples come from a common project population, each with sufficiently large diverse sample sizes (SHL-TIL = 221, RD^3 = 425, TA = 1730) with some overlapping project commonality and sharing very similar sample means[9]. Establishing a common sample equivalence would formally support the practical application of a means based cost relationship to model the relative impact of the additional RD^3 and TA macro-parameters. Therefore, equivalence testing was conducted using the widely accepted two one-sided test (TOST) and Welches t-test (see analysis provided in **Appendix G**). This

[9] TIL-SHL vs RD^3 trimmed sample means fall within 0.25% of one another and TIL-SHL vs TA trimmed samples within 1.4% (see **Appendix G**).

analysis resulted in demonstration of practical sample equivalence between the overall SHL-TIL project data cost mean and the corresponding TA and RD^3 project data cost means.

MCI Central Point Estimate Values. MCI values relating the mean project costs for the RD^3 levels and TA categories to the SHL-TIL sample project mean were developed and assessed to determine the relative impact of both parameters on project development costs. To calculate the MCIs, RD^3 and TA project mean cost factors (MCFs) for each project were first formulated. These cost adjustment factors are calculated as the ratio of the individual project cost to the SHL-TIL dataset mean cost. The project data MCFs were then aggregated into summary statistical MCI measures (mean, median, standard deviation) for each RD^3 ordinal level and TA nominal category, as shown in **Tables 4-1** and **4-2.** These MCIs can be applied directly (i.e., multiplied) to the first generation SHL-TIL parametric cost model outputs to refine results for RD^3 level and TA impacts.

Table 4-1: RD^3 Project Data MCI Statistics

RD^3 Project Data Mean Cost Index (MCI)			
RD3 Lvl	Mean	Median	Std Dev
1	0.4083	0.2352	0.4412
2	0.7759	0.3171	1.2473
3	1.0690	0.4770	2.6810
4	1.3620	0.6360	2.0470
5	1.9081	0.7929	1.7566

Table 4-2: TA Project Data MCI Statistics

TA Mean Cost Index (MCI)				
No.	Technology Area (TA)	Mean	Median	Std Dev
1	Launch Propulsion Systems	1.0940	0.0333	4.6480
2	In-Space Propulsion Technologies	0.8300	0.0416	2.5320
3	Space Power and Energy Storage	0.7940	0.0296	5.0520
4	Robotics, Telerobotics, Autonomous Systems	0.9603	0.4905	1.5894
5	Communication and Navigation	0.3125	0.0360	0.8966
6	Human Health, Life Support, Habitation Systems	1.9740	0.5900	3.2410
7	Human Exploration Destination Systems	1.8098	0.9807	2.3102
8	Science Instruments, Observatories, Sensor System	0.3310	0.0344	1.4660
9	Entry, Descent, and Landing Systems	13.2360	0.9640	24.8020
10	Nanotechnology	0.1025	0.0149	0.2023
11	Modeling, Simulation, Information Tech	1.4730	0.0552	6.5440
12	Materials. Structures, Mechanical Systems, Mfg.	0.4390	0.0298	1.2510
13	Ground and Launch Systems Processing	1.8550	0.5010	4.6850
14	Thermal Management Systems	0.7125	0.0981	1.3793
15	Aeronautics	0.2186	0.0146	0.6291

As with the RD^3 cost functions, the RD^3 MCI statistics demonstrate a progressive incremental relationship with RD^3 across all five levels. TA category MCIs similar to the TA Cost Curve fits in

Appendix C produced reasonable MCI values for ten of the fifteen TAs with the remaining five TA categories yielding questionable results, exhibiting very low or high MCI values (TA #'s 5, 8, 9, 10 and 15). As noted in **Appendix C,** these results are driven by the nature of the broad uniform TA categories spanning the full range of project scale, complexity and maturity in combination with limited sample sizes and in some instances TA inter-categorical project size concentrations. Since small sample sizes and a lack of project data diversity can result in biased statistical measures, these TA categories were therefore discarded and not applied for estimating purposes.

MCI Uncertainty. In the same manner as for the RD^3 and TA Cost curve fit PDFs, MCI curve fits were also produced for both parameters and the best performing overall function fits selected. The resulting RD^3 level PDF @RISK functions are provided in **Table 4-3**. These PDFs are consistent with the lognormal, gamma, Weibull and betaPERT type PDFs commonly recommended for estimating uncertainty by the JACSRUH. Continuing with the RD^3 Level 2 example, cost curve fits from **Figures 4-1** and **4-2**, example MCI curve fit PDFs and best fit selection (i.e., Lognorm) are provided in **Figures 4-4** and **4-5**. **Appendix H** also contains all TA and RD^3 and MCI PDF @RISK functions including the corresponding plots for the other RD^3 levels (1, 3, 4, and 5). Similar to the RD^3 cost PDFs, the RD^3 MCI PDFs produced highly right-skewed distributions with relatively large standard deviations. As noted previously these types of uncertainty distributions are expected and common for cost data, especially with the high level of unknowns and cost growth risk in early development stages.

Table 4-3: RD^3 MCI Curve Fit PDFs

RD^3 Mean Cost Index (MCI)			
RD3 Lvl	**PDF Type**	**Function**	**@RISK PDF Formula**
1	Gamma	0.4083	=RiskGamma(0.59877,0.68192,RiskName("RD3 Lvl 1 MCI"))
2	Lognorm	0.8466	=RiskLognorm(0.84662,2.1681,RiskName("RD3 Lvl 2 MCI"))
3	Pearson6	1.0687	=RiskPearson6(1.1572,1.7721,0.71302,RiskName("RD3 Lvl 3 MCI"))
4	Gamma	1.3620	=RiskGamma(0.71451,1.9062,RiskName("RD3 Lvl 4 MCI"))
5	Gamma	1.9081	=RiskGamma(1.3688,1.394,RiskName("RD3 Lvl 5 MCI"))

Similar to the TA project cost data, several TA category MCIs also produced very large cost ranges and significant standard deviations with most exhibiting very large coefficients of variation (CV). As previously noted, this result is primarily due to the fact that each TA category spans a full range of project scale, complexity and maturity and does not reflect graduated measurement with respect to cost. Therefore, the TA MCI PDFs contribute little value to uncertainty estimating in the analysis, and are shown in **Table H-2** for demonstration purposes only and not applied or recommended for modeling purposes. This does not create estimating limitations however, since their central values still fall within reasonable ranges of overall population means, and project cost uncertainties are more effectively captured by RD^3 MCI PDFs. Attempting to model project cost uncertainty by compounding multiple perspectives (i.e., RD^3 and TA segmentations) of the same costs is also invalid since that artificially amplifies or "double counts" the impact of those uncertainties. Therefore, to avoid distortion of cost risk, RD^3 MCI PDFs alone are suitable and effective for modeling total cost uncertainty. This approach provides central cost adjustment factors for applicable TA MCI categories but avoids redundant uncertainties caused by overlaying expansive TA MCI PDFs on top of the tailored RD^3 PDFs.

Figure 4-4: Example MCI PDF Curve Fits for RD^3 Level = 2

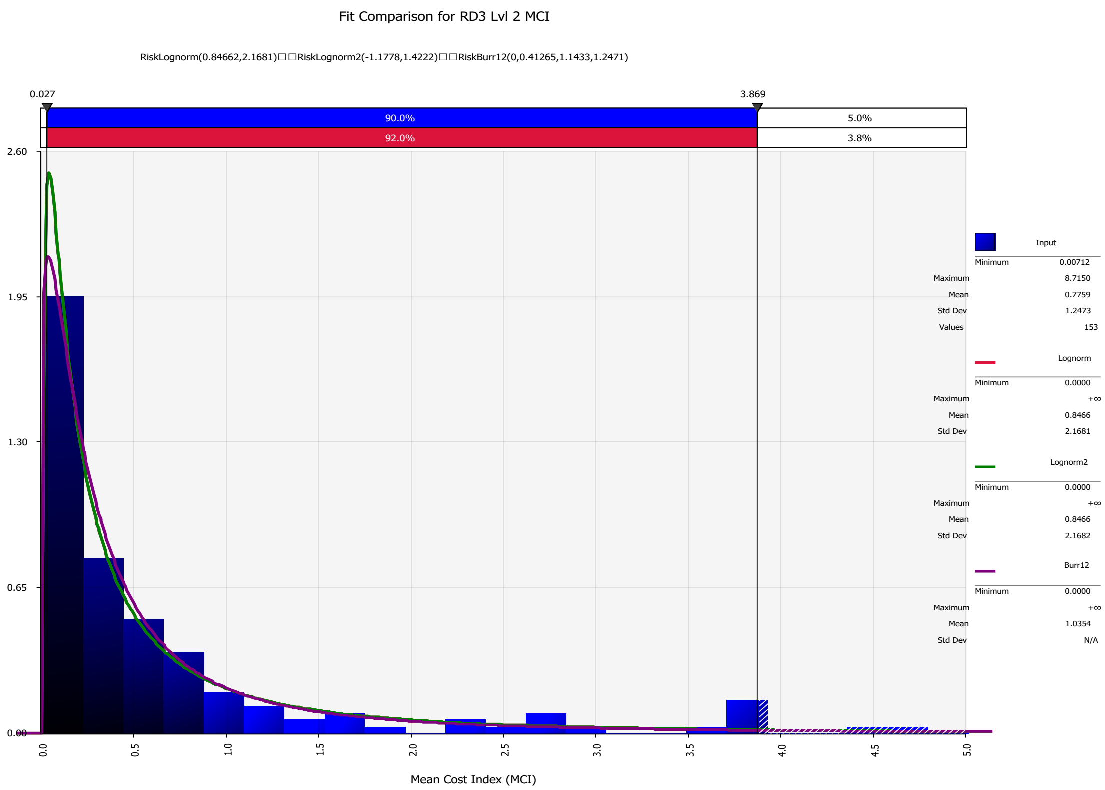
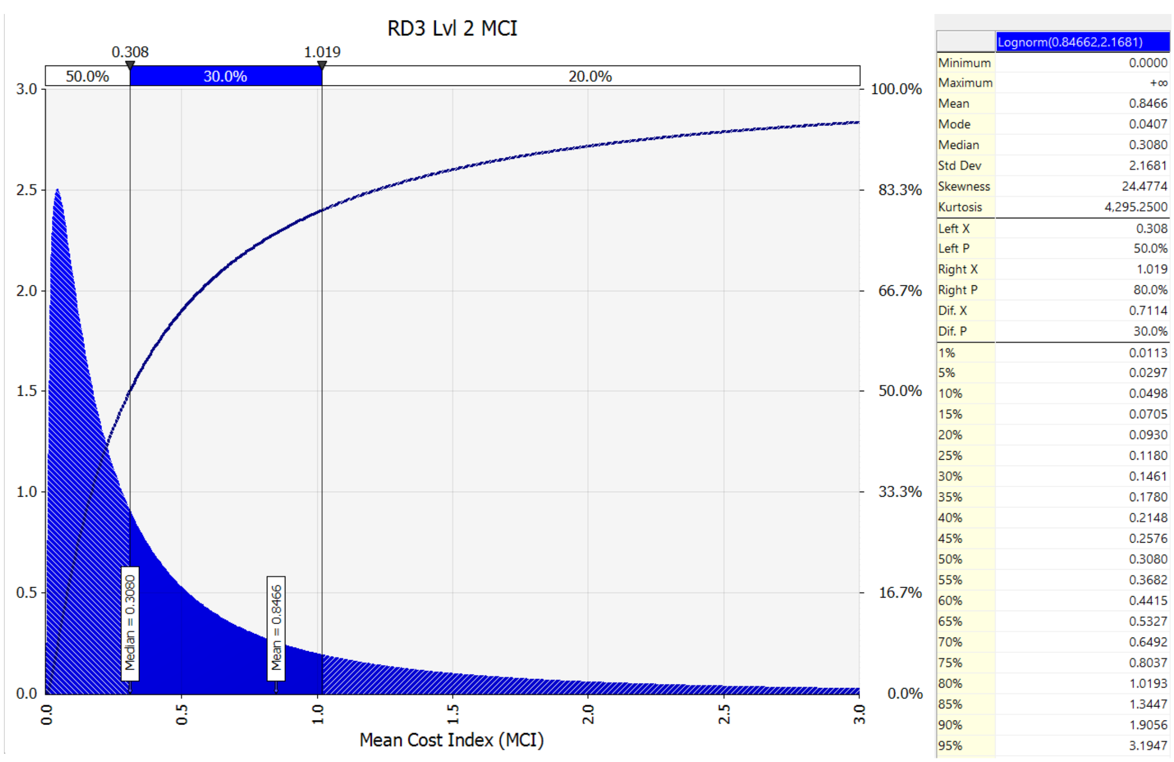


Figure 4-5: Selected Best Fit MCI PDF for RD^3 Level = 2



The resulting TA and RD^3 MCI stats in concert with the RD^3 uncertainty functions can therefore be applied directly to the range of first generation SHL-TIL regression model variants developed in the initial research to fine-tune them for the influence of the additional RD^3 and TA attributes.

b. Geometric Mean Curve Fit Method

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. The average impact of individual custom cost curve fits for each independent parameter level are estimated by taking the geometric mean of their expected values (i.e., root of their product) sampled from the individual PDFs in Monte Carlo simulation. In a similar manner as the MCI technique, the best performing SHL-TIL curve fits from the baseline research were applied. For this method, RD^3 and TA category project cost curve fits were applied instead of their respective static MCIs. Therefore, outputs represent the blended average of the three or four selected constituent macro-parameter groupings. This approach is fully delineated in **Appendix I**. However, results do not effectively capture the aggregate or compound impact of the independent parameters and relatively low project costs were predicted with rather large residuals vs. project actuals. Therefore, this method was abandoned as a viable option for estimating purposes.

5. Cost Model Results

Using the MCI method enhances modeling capabilities unifying the available RD^3 and TA project MCF data with legacy SHL-TIL parametric regression and curve fit models. Estimating power and precision are improved with extensive growth in the overall development project cost geometry. Three or four parameter cost estimates can be generated as either multifaceted point estimates or composite functions with uncertainty. With a foundation of the highest performing first generation SHL-TIL regression model (from **Appendix B)**, the RD^3 and TA MCI values from **Tables 4-1** and **4-2** and uncertainty functions from **Table 4-3** can be applied in product combinations to produce families of three or four parameter project estimates.

First, augmenting the base SHL-TIL models with just the RD^3 independent parameter MCI means from **Table 4-1**, results in 125 model configurations (25 SHL-TIL x 5 RD^3). The resulting project mean point estimates for these three parameter models are displayed in **Table J-1** of **Appendix J.** An overall contour 3-dimensional (3D) surface plot for the array of this SHL-TIL / RD^3 / Cost data is shown in **Figure 5-1.** As previously noted, each data point is a separate estimate for a unique parametric model combination. The X-axis two digit numbers represent the 25 distinct SHL-TIL (i.e., “XY”) level combinations and not a continuous variable. For example, the value “42” represents a project with SHL = 4 and TIL = 2. Therefore, this plot does not represent a continuous function, but rather serves as an illustration of the relative impact of the variables ranges on cost scale. Similarly specific 3D SHL-TIL x RD^3 Mean cost plots such as this can be generated by TA. A detailed SHL / TIL / RD^3 PDF model for each project configuration can be also be produced by substituting the RD^3 MCI cost PDFs from **Table 4-3** with the MCI mean values from **Table 4-1** and running the resulting compound function through Monte Carlo simulation. A resulting PDF estimate example for this type of 3-parameter model is presented in **Figure 5-2** representing the project attributes SHL = 4, TIL = 3 and RD^3 = 5 (i.e., model # 4/3/5).

Figure 5-1: SHL-TIL x RD^3 Mean Development Cost Model Topography Plot[10]

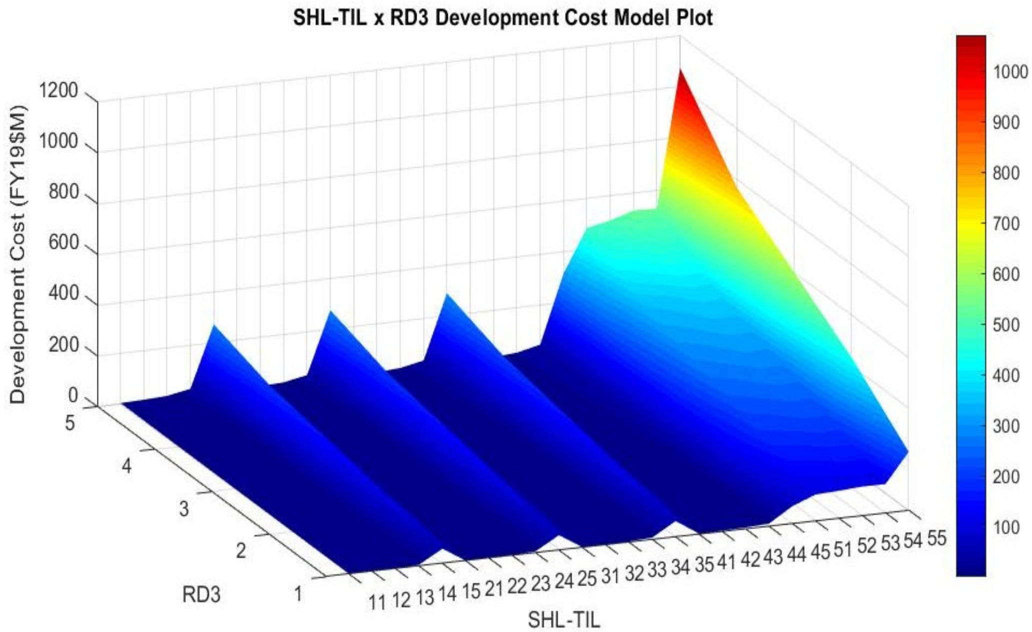
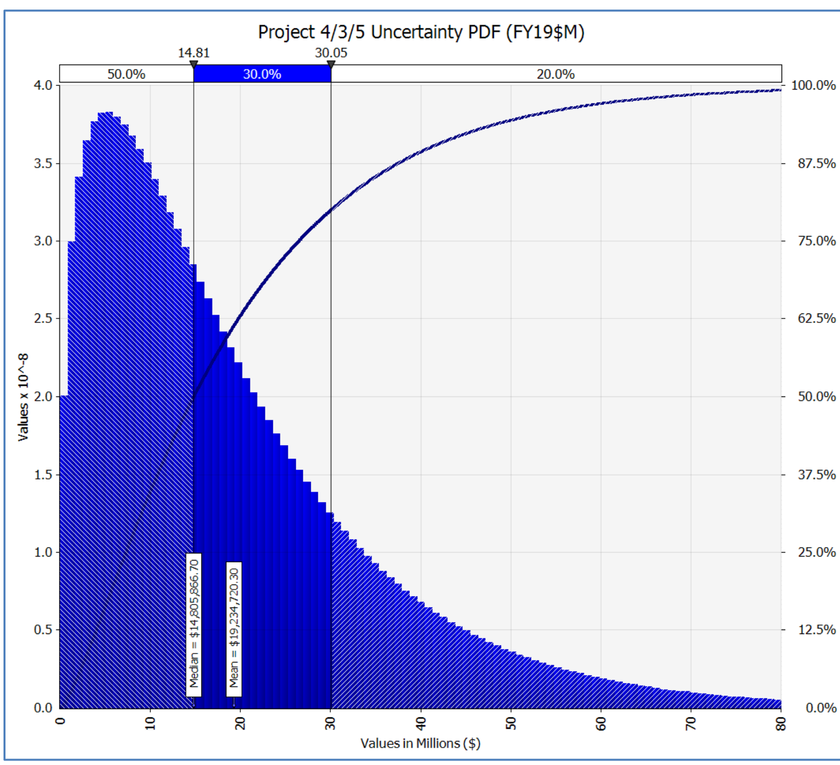


Figure 5-2: PDF Uncertainty Output for Project: SHL = 4, TIL = 3, and RD^3 = 5

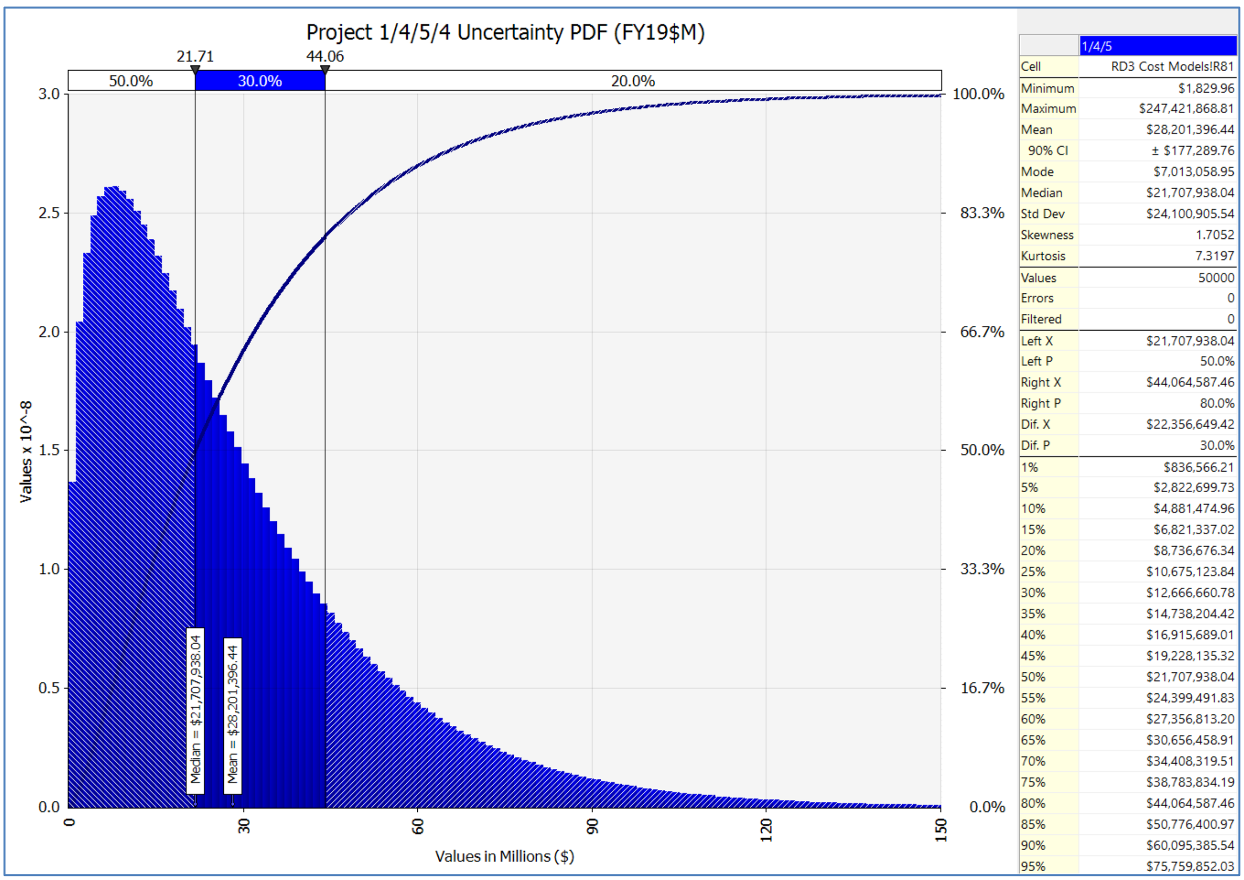


	4/3/5
Cell	RD3 Cost Models!R71
Minimum	$1,248.12
Maximum	$168,753,715.86
Mean	$19,234,720.30
90% CI	± $120,920.22
Mode	$4,783,246.38
Median	$14,805,866.70
Std Dev	$16,437,986.61
Skewness	1.7052
Kurtosis	7.3197
Values	50000
Errors	0
Filtered	0
Left X	$14,805,866.70
Left P	50.0%
Right X	$30,054,186.02
Right P	80.0%
Dif. X	$15,248,319.32
Dif. P	30.0%
1%	$570,578.74
5%	$1,925,218.13
10%	$3,329,402.70
15%	$4,652,482.72
20%	$5,958,837.04
25%	$7,280,952.26
30%	$8,639,277.06
35%	$10,052,170.30
40%	$11,537,320.41
45%	$13,114,520.96
50%	$14,805,866.70
55%	$16,641,636.94
60%	$18,658,673.56
65%	$20,909,191.98
70%	$23,468,142.90
75%	$26,452,456.15
80%	$30,054,186.02
85%	$34,631,968.40
90%	$40,987,967.90
95%	$51,671,893.86

[10] The X-axis two digit numbers represent the 25 distinct SHL-TIL (i.e., XY) level combinations and not a continuous variable. For example the value 23 represents a project with SHL = 2 and TIL = 3. Therefore, this plot does not represent a continuous function, but rather serves as a perspective illustration of the relative impact of the variables across their ranges vs. cost scale.

Similarly, 250 three parameter SHL/TIL/TA model variants are produced by a product of the 25 SHL-TIL regression model output with the 10 TA category MCI cost data. The resulting mean costs for these three parameter configurations are provided in **Table J-2** of **Appendix J.** Finally, the four independent macro-parameter product applied concurrently produce additional tailored composite functions reflecting the combined influence of all four variables. This expands the development cost topography to a full complement of 1,250 unique cost model variants (25 SHL-TIL x 5 RD^3 x 10 TA). These project estimates can be produced with the parametric cost data in **Appendix B,** and **Tables 4-1** & **4-2** but are too numerous to display in this paper. Again, substituting the RD^3 MCI cost PDFs from **Table 4-3** for the RD^3 MCI mean point estimate values from **Table 4-1** within the compound functions and running the results through Monte Carlo simulation produces a detailed multifactor model PDF for each SHL/TIL/RD^3/TA combination. An example resulting output PDF plot for one of these 4 parameter model variants for project dimensions SHL = 1, TIL = 4, RD^3 = 5 and TA = 4 (model # 1/4/5/4) is shown below in **Figure 5-3**.

Figure 5-3: PDF Uncertainty Output for Project: SHL = 1, TIL = 4, RD^3 = 5 and TA = 4



In summarizing this analysis, establishing cost data relationships for the RD^3 and TA parameters advance and refine the estimating ability of the baseline parametric models and increase the segmentation of the technology development project space. Marked model forecasting capacity and fidelity improvements are generated by tailoring the analysis to a broader array of fundamental predictors with greater representation of primary technical, cost, and risk factors. RD^3 MCI PDFs also produce an enriched understanding of cost uncertainty as they embody much larger project datasets. Two methodologies that further extend these forecasting capabilities are developed in following **Sections 6** through **8.** The first involves a technique to allocate total development costs to primary development activities and milestones via a standard framework tied to historical cost benchmarks. The second applies this refines TIL estimates by actual TRL start and end allocation cost factors, also derived from the development benchmarks.

6. Standard Development Framework

The use of a product-oriented WBS is advantageous for systems acquisitions but Development activities can differ significantly from Production processes with respect to the system architecture. Therefore, it is beneficial to utilize a Development phase WBS with common process breakdown spanning the major technology and systems development stages. An integrated framework for the total R&D phase using a standard set of "typical" development activities and milestones aligned with key macro-parameters can facilitate new technology and systems development investment scoping, estimating and budget planning. Depending on the application and type of economic analysis, some macro-parameters that may be well suited for this purpose include TRL, system readiness level (SRL), integration readiness level (IRL), and manufacturing readiness level (MRL). See industry definitions for SRL, IRL and MRL in **Appendix A**.

Common development and demonstration activities related to the standard DoD acquisition process provide an extensible basis for this type of breakdown. Several authorities have linked standard R&D processes to acquisition phases and milestones as well as general recommended levels of technology maturity, system readiness and manufacturing readiness. **Figures 6-1, 6-2** and **6-3** (Copeland & Holzer, The Effects of System Prototype Demonstrations on Weapon Systems, 2015) are illustrative of this type of mapping. **Figure 6-1** demonstrates the relationship of the acquisition milestone process to suggested TRLs and MRLs (OSD, 2016). **Figure 6-2** provides a similar yet slightly different perspective that includes incremental technology and system demonstrations. **Figure 6-3** offers a more descriptive characterization of the demonstration environments and state of technology vs. suggested TRL progression. **Table 6-1** contains acronyms for the associated Acquisition milestone and Development process terms presented.

These constructs along with the descriptions of processes and suggested technical achievements for the standard DoD RDT&E Budget Activities (BA) (OUSD - Comptroller / CFO, 2019) vary slightly but are in general agreement for technology maturity at key acquisition milestones. Based on this general consensus, a high level standard development framework is proposed in **Table 6-2** that can be applied across a range of platforms, system architectures and applications. This concept fuses WBS elements based on progressive development and demonstration processes or technical reviews with acquisition milestones and suggested TRLs and MRLs reached at the milestone or completion of a major activity.
A more detailed 4-level WBS for this framework containing a data dictionary and suggested element descriptions associated with corresponding RDT&E BAs (OUSD - Comptroller / CFO, 2019) is also

provided in **Appendix L**. This detailed WBS is not intended to be prescriptive but instead serve as general guidance in identifying the full range of activities in development, yet allowing for specific product orientation or system architectures to be threaded in where appropriate. This structure provides a comprehensive basis to help assure relevant design, development, integration, test and demonstration requirements are effectively identified and captured for estimate development and budget planning.

Figure 6-1 Relationship of Decision Points, Milestones and Technical Reviews to MRLs & TRLs

(Source: Manufacturing Readiness Level (MRL) Deskbook, 2016)

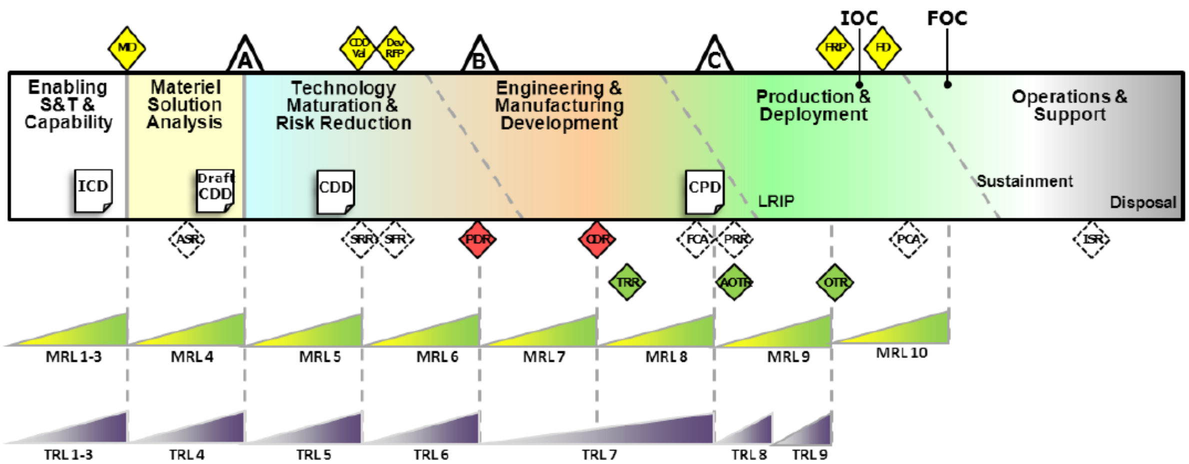


Figure 6-2: Level of Prototype Demonstrations, Venue and Technology Maturity (Source: The Effects of System Prototype Demonstrations on Weapon Systems-DAU Defense Acquisition Research Journal (ARJ)-Jan 2015, Figure 2)

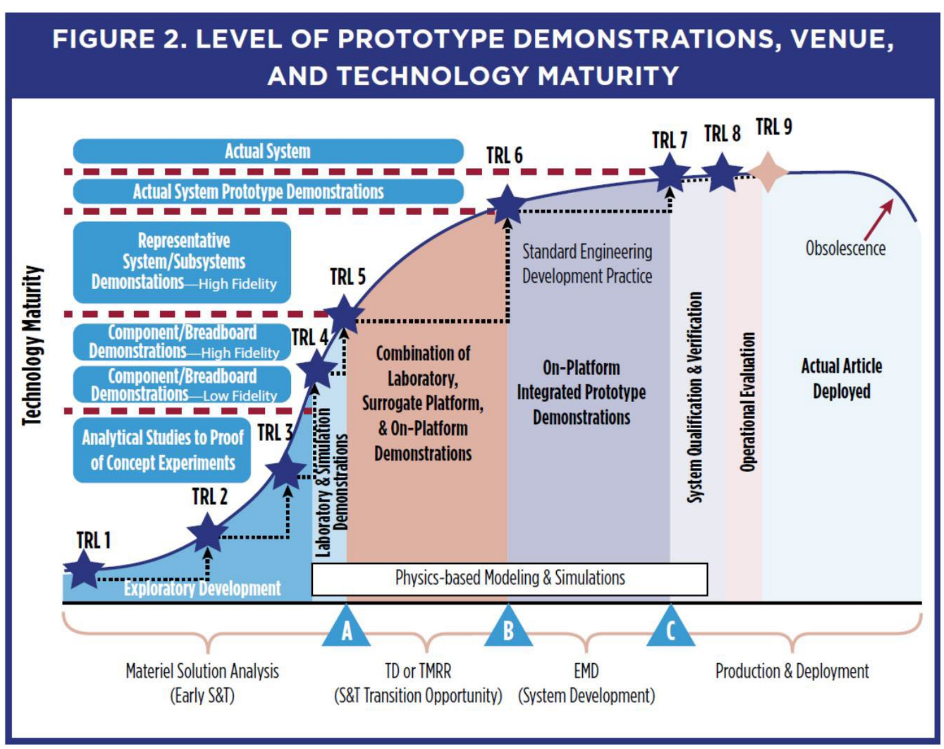


Figure 6-3: TRL Mapping to Prototype Demonstration Attributes (Source: The Effects of System Prototype Demonstrations on Weapon Systems-Defense ARJ-Jan 2015, Figure 3)

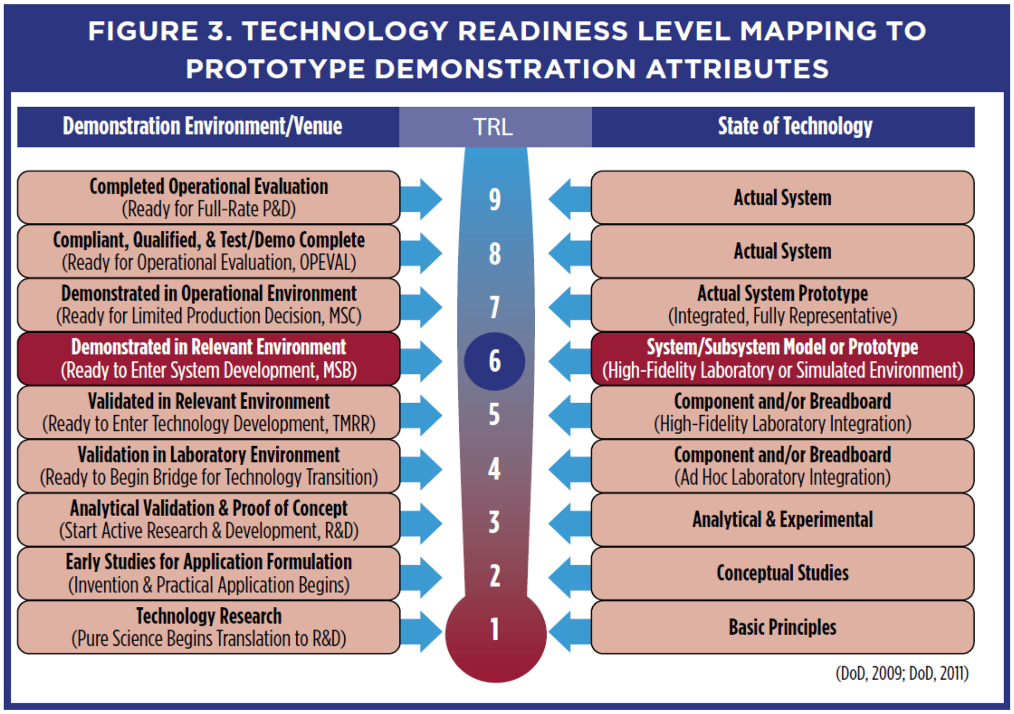


Table 6-1: Acquisition Milestone and Development Process Acronyms

ACRONYMS	
CDR	Critical Design Review
DOE	Demonstrated in an Operational Environment
DRE	Demonstrated in a Relevant Environment
EMD	Engineering and Manufacturing Development
FOC	Full Operational Capability
FRP	Full Rate Production
IOC	Initial Operating Capability
LRIP	Low Rate Initial Production
MDD	Materiel Development Decision
MSA	Materiel Solution Analysis
OPEval	Operational Evaluation
OT&E	Operational Test and Evaluation
P&D	Production & Deployment
PDR	Preliminary Design Review
PoC	Proof of Concept
S&T	Science and Technology
SRR	System Requirements Review
T&E	Test and Evaluation
TMMR	Technology Maturation and Risk Reduction
VLE	Validation in a Laboratory Environment
VRE	Validation in a Relevant Environment

Table 6-2: Proposed Development Framework – Standard R&D WBS Activities vs Acquisition Phases / Milestones and Suggested TRLs & MRLs

Development WBS		Acquisition Phase	DoD Acq'n. Milestone	TRL	MRL
No.	Name				
1.1	Technology Development	Various			
1.1.1	Basic Research	Enabling S&T Capability	N/A	1	1
1.1.2	Technology Research	Enabling S&T Capability	CBA / ICD	2	2
1.1.3	Analytical Proof of Concept (PoC) Validation	Enabling S&T Capability	MDD	3	3
1.1.4	Validation in a Laboratory Environment (VLE)	Materiel Solution Analysis (MSA)	A	4	4
1.1.5	Validation in a Relevant Environment (VRE)	TMRR	VRE / SRR	5	5
1.1.6	Prototype Demo in Relevant Environment (DRE)	TMRR	B (PDR)	6	6
1.2	Systems Development	Various			
1.2.1	Systems Prototype Demo in Oper'l Environment (DOE)	Engineering and MFG Dvlp (EMD)	C	7	8
1.2.2	Full Scale Systems Dvlp. & Demonstration (SDD)	Prod'n & Deployment (P&D)	LRIP	8	8+
1.2.3	Operational Systems Evaluation (OPEval)	Prod'n & Deployment (P&D)	IOC (FRP)	9	9
1.2.4	Operational Systems Development	Operations & Support (O&S)	FOC	9+	10

7. Cost Benchmarks by Development Milestone and TRL

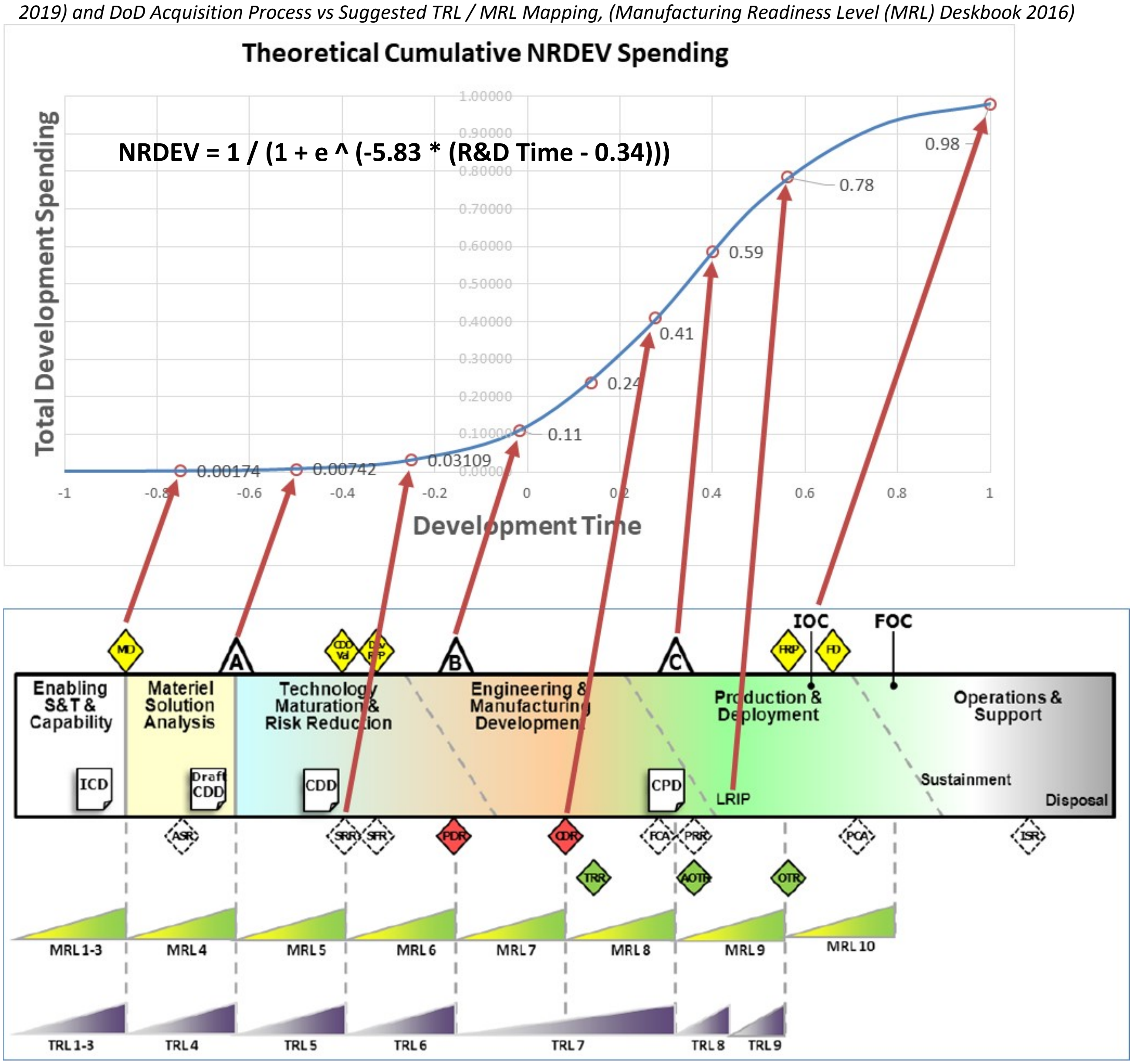
Investigation was conducted for ways to align cost with the development framework by bridging the progression of investment with development phases and acquisition milestones. This examination identified two research papers / presentations that relate historical program costs with major acquisition milestones. This arrangement provides historical cost profiles spanning the full development life cycle to produce progressive benchmarks at key milestones. In both analyses, corresponding functions were further fit to the resulting cost benchmarks. Expenditures can thereby be mapped to the corresponding general TRL and MRL macro-parameter achievement.

Cost Benchmark Study No. 1. The first study titled "Methodology to assess cost and schedule impact using System and Technology Readiness Level (SRL/TRL)" by Dr. Nate Sirirojvisuth of PRICE® Systems was presented at the 2019 International Cost Estimating Analysis Association (ICEAA) SoCal Workshop (Sirirojvisuth, 2019). This analysis applied historical selected acquisition report (SAR) data from over 140 Major Defense Acquisition Programs (MDAP) programs to generate relative cost and schedule factors traversing the acquisition milestones. Cumulative non-recurring development (NRDEV) spending cost benchmarks from this research were normalized (i.e., 0 to 1) over the full development life cycle and plotted across the timeline up through TRL 9. A cumulative NRDEV cost curve was fit to the equation: **NRDEV = 1 / (1 + e ^ (-5.83 * (R&D Time - 0.34))).** The plot of this exponential function and values for major acquisition and key development milestones are mapped to the progressive TRLs and MRLs in the acquisition milestone process from the OSD Manufacturing Readiness Level (MRL) Deskbook (OSD, 2016) in **Figure 7-1**.

In the original analysis, cost milestones were mapped slightly differently for TRLs 8 & 9 than suggested by the DAU DRJ and OSD Deskbook milestones, and general RDT&E budget activity descriptions. To maintain consistency with the consensus of reference documentation and resulting development framework, TRLs 8 and 9 are mapped to low rate initial production (LRIP) and initial operating capability (IOC) respectively. As described in RDT&E BA 6.7 with development upgrades exceeding FRP and demonstrated by the MRL / TRL / Milestone relationship exhibit in **Figure 6-1** from the OSD Deskbook, MRLs exceeding the extent of TRL 9 at full rate production (FRP) or IOC can continue through FOC. This implies some development activities can occur past TRL 9 and mapping of TRL to milestones up through FOC is needed. Some literature addresses this shortfall expressing the need for adding another TRL level to accommodate and capture post-IOC activities into extended operations (see "*In search of technology readiness level (TRL) 10*" by Jeremy Straub (Straub, 2015)).

Figure 7-1: Development Spending Benchmarks vs Development Milestones & TRL - Study 1

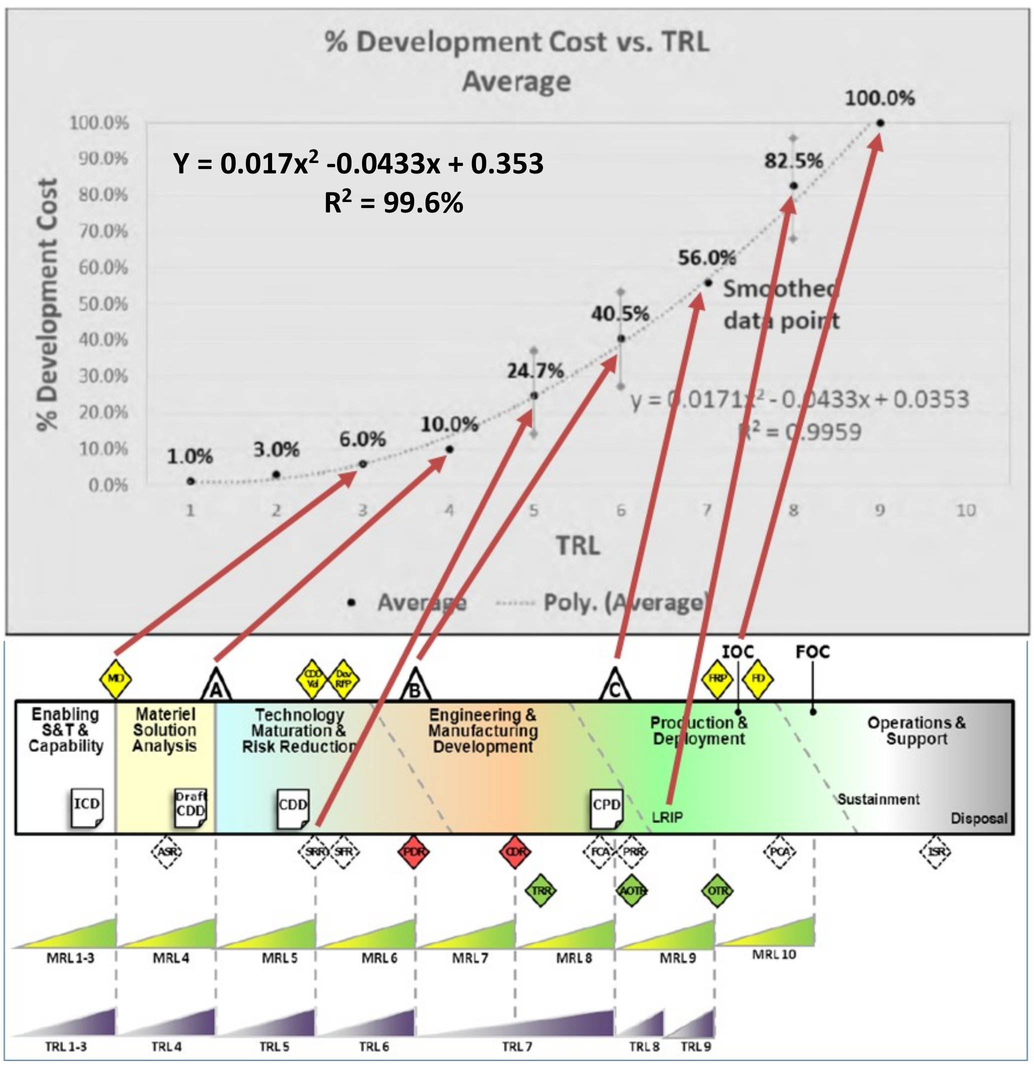
(Adapted from: "Methodology to assess Cost and Schedule impact using SRL and TRL-PRICE" (Sirirojvisuth, ICEAA SoCal, Mar20, 2019) and DoD Acquisition Process vs Suggested TRL / MRL Mapping, (Manufacturing Readiness Level (MRL) Deskbook 2016)



Cost Benchmark Study No. 2. A second analysis from a 2017 ICEAA conference presentation (Linick, 2017) similarly produced plots of percent development cost vs. TRL (see **Figure 7-2**). These results were based upon a curve fit to data from approximately 30 programs primarily from an earlier research paper titled “Estimating Technology Readiness Level Coefficients” by Dr. Ed Conrow (AIAA SPACE 2009 Conference & Exposition) (Conrow E. , 2009). The Conrow research examined Analytical Hierarchy Procedure (AHP) based TRL values using source data from a prior study (Lee, 2003). The source data included cost information for programs in NASA’s Resource Data Storage and Retrieval database (REDSTAR). The curve fit from this analysis similarly demonstrates a relationship between TRL and total development cost, normalized to a range of 0 to 1. A 2nd order function, **$Y = 0.017x^2 -0.0433x + 0.353$**, where **x** represents the current state of TRL, was fit to the data producing a very strong coefficient of determination (R^2) exceeding 99%. Percent (%) Development Cost points on the **Figure 7-2** graph are the actual project empirical values and not calculation approximations from the curve fit function.

Figure 7-2: Development Spending Benchmarks vs Development Milestones & TRL- Study 2

Adapted from Technology Development Level (TRL) vs. Percent Development Cost (Presentation by James Linick / BCF Solutions Inc., at ICEAA 2017 Professional Development & Training Workshop and DoD Acquisition Process vs Suggested TRL / MRL Mapping (Manufacturing Readiness Level (MRL) Deskbook 2016))



Development cost benchmark results from both studies are compared vs development phase acquisition milestones and associated TRLs & MRLs applying a consistent methodology up through IOC in **Table 7-1**. Examination of the outcomes demonstrates that the two methods produced very similar outcomes for TRLs 7-9 but rather divergent results for TRLs 1 through 6.[11]

Table 7-1: Study 1 vs 2 Cost Benchmarks by Development Milestone and TRL / MRL

Milestone	Macro-parameter		Sirirojvisuth Study		Linick Analysis	
@ end	MRL	TRL	% Total Dvlp	Cum % Ttl Dvlp	% Total Dvlp	Cum % Ttl Dvlp
N/A	1	1	Negl.	Negl.	1.0%	1.0%
CBA / ICD	2	2	Negl.	Negl.	2.0%	3.0%
MDD	3	3	0.17%	0.17%	3.0%	6.0%
A	4	4	0.57%	0.74%	4.0%	10.0%
VRE / SRR	5	5	2.36%	3.10%	14.7%	24.7%
B (PDR)	6	6	8.0%	11.1%	15.8%	40.5%
Interm.	6+	6+	12.4%	23.5%	N/A	N/A
CDR	7	6++	17.2%	40.7%	N/A	N/A
C	8	7	17.7%	58.5%	15.5%	56.0%
LRIP	8+	8	20.0%	78.4%	26.5%	82.5%
IOC (FRP)	9	9	19.6%	97.9%	17.5%	100.0%

Note: Negligible (abbreviated Negl.) comparative costs occur in some early stages while in other interim stages data were not available (N/A).

RDT&E Historical Budget Activity Data. To provide a third perspective on the progression of TRL based development costs, another method was employed using historical RDT&E BA cost data. BA categories characterize the continuous sequential steps in the advancement of the development process that are already aligned within the proposed development framework, associated acquisition milestones and TRL levels. Therefore RDT&E expenditures were applied by BA. Twenty-three (23) years of actual RDT&E R-1 Budget Exhibits by BA from FY1996 through FY2018 were analyzed to create historical BA cost profiles (OUSD - Comptroller / CFO, 1996-2018). With so many consecutive years of data being utilized, the statistical summaries effectively represent the development cycle of hundreds of DoD-wide programs of varying size and complexity. Statistics for % of total expenditures across BA categories 6.1 through 6.7 were created characterizing the weighted average development costs spanning all development programs and stages.[12] Summary statistics for these historical RDT&E R-1 BA expenditures corresponding to the completion of each

[11] *Sirirojvisuth paper cumulative total Development costs equal approximately 98% due to some post-IOC Development work not included in totals.*

[12] Expenditures include overseas contingency operations (OCO) RDT&E funding. BA 6.6 RDT&E Management Support was spread across the other 6 BA categories in proportion to annual expenditure amounts so did not alter or impact the effective % development calculations.

major BA category funding phase over the historical timeframe are linked with the acquisition milestones and suggested TRLs from the framework in **Table 7-2**. Annual expenditures are fairly consistent over the 23 year window with CVs by BA falling primarily in the 8% to 13% range.

Table 7-2: Annual DoD % RDT&E Expenditure % by BA (FY1996 to FY2018)

RDT&E Budget Activity (BA)		Milestone	TRL	Annual % Development		
Code	BA Category	@ end	Notional @ End	Average	StdDev	CV
6.1	Basic Research	N/A	1	2.9%	0.5%	17.6%
6.2	Applied Research	MDD	3	7.7%	1.0%	12.5%
6.3	Advanced Technology Development (ATD)	VRE / SRR	5	9.4%	1.2%	12.7%
6.4	Advanced Component Development & Prototypes	B (PDR)	6	20.5%	1.6%	7.8%
6.5	System Development & Demonstration (SDD)	C	7	23.0%	3.0%	13.0%
6.7	Operational Systems Development	IOC (FRP)	9	36.5%	3.8%	10.5%
	Total Development			100.0%		

Although only 6 BA categories are available to map to the 9 TRLs and corresponding Development milestones, they align well with 6 milestones based on the description of activities and technical achievements at the completion of each BA. **Table 7-3** charts those relationships, comparing the 6 shared or common RDT&E BA Milestones and TRL level cumulative % development cost benchmarks vs. the corresponding results from the two benchmark studies.

Table 7-3: RDT&E BA Category completion vs Study 1 & 2 Milestone / TRL Cost Benchmarks

RDT&E Budget Activity (BA)		Milestone	TRL	RDT&E R-1 Exhibit BA Budgets	ICEAA / Linick Analysis	ICEAA / Sirirojvisuth Paper
Code	BA Category	@ end	Notional @ End	Cum % Dvlp Phase Cost	Cum % Dvlp Phase Cost	Cum % Dvlp Phase Cost
6.1	Basic Research	N/A	1	2.9%	1.0%	Negl.
6.2	Applied Research	MDD	3	10.6%	6.0%	0.2%
6.3	Advanced Technology Development (ATD)	VRE / SRR	5	20.0%	24.7%	3.1%
6.4	Advanced Component Development & Prototypes	B (PDR)	6	40.5%	40.5%	11.1%
6.5	System Development & Demonstration (SDD)	C	7	63.5%	56.0%	58.5%
6.7	Operational Systems Development	IOC (FRP)	9	100.0%	100.0%	97.9%

Cost Benchmark Comparison. TRL cumulative % development cost benchmark data for the common milestones and TRLs demonstrate that the Linick & Conrow research and analysis are fairly well aligned with the RDT&E results. Lower relative total development expenditures in early stages of the Sirirojvisuth / PRICE Systems ICEAA presentation may be a reflection of the source data all being from large MDAP ACAT 1 programs vs a more diverse range of programs for the R-1 Exhibit BA data and the NASA project data used by the Linick ICEAA Conference presentation. This lower relative early expenditure characteristic of MDAP program data may be the result of initial technology development efforts for very large, complex systems being a smaller portion of total development due to economies of scale similar to the spread of fixed or overhead cost pools over a larger base. More conservative or risk averse existential technology selection to reduce overall developmental loss potential may also be an artifact of large investment programs.

Other factors underlying the Sirirojvisuth MDAP program development expenditure profile may include larger, more significant portions of early stage technology research (basic, fundamental, incubation) for MDAP programs being captured or funded under separate incremental projects or shouldered by a wider array of institutions. This could be the result of a desire to distribute workload or the ability to leverage more highly specialized skill sets and facilities needed. This strategy can also reduce or spread out overall budget risk exposure for large program efforts by allocating portions of critical early phase technology development to be more widely shared or burdened by various organizations. In this manner, the total associated development costs may not be effectively captured in MDAP SAR reporting for programs that involve substantial efforts by bodies such as government labs, university research institutions, industry research groups or vendors. An example is Internal Research and Development (IRAD) investments made by large defense contractors. These factors and others could potentially contribute to the TRL 1-6 cost deviation of the Sirirojvisuth study MDAP program data. Following TRL 6 however, the cumulative costs catchup and converge with the Linick findings as technology development transitions into broader overall systems development. As a result of these findings the Linick results were selected and applied for the parametric model TRL refinements introduced below.

8. Fine-Tuning TIL Estimates for Discrete TRL Start-End States

Another fundamental benefit to generating relative cost profiles across TRL levels is that these can be used to significantly enhance the fidelity and precision of the uniform TIL-based models. This can be accomplished because the incremental empirical cost benchmarks provide a means by which to calculate the relative size of all TRL start to end transitions. Homogeneous TIL costs from first generation models can thereby be fine-tuned to their discrete constituent project TRL start to end state costs via the relative cost adjustment weighting factors produced in **Table 8-1**. The upper section second column of this table shows the Cumulative % Development cost at the TRL_{End} achieved for that row that is taken from the last column of **Table 7-1** (ICEAA Linick / Conrow analysis). This study data was selected for application because it tracks well with results of the expansive DoD RDT&E BA program data, representing a very diverse range of projects in terms of scale, complexity, difficulty and uncertainty. The next column (3rd) shows the incremental % cost increase for the eight unitary TRL improvement transitions for TIL= 1 (e.g., 1-2; 2-3; 3-4; 4-5; 5-6; 6-7; 7-8; and 8-9). Percentages in the subsequent columns of the top section numbered 2 through 8 also represent the % Development Cost increase to achieve the TRL_{End} (first column) starting from TRL_{Start} determined by: $TRL_{Start} = TR_{End}$ - TIL. TIL increases up through the maximum possible value of 8 in the last column, for which only one possible transition exists (TRL 1 to 9).

The cost factors in green in the lower table section are simply the relative costs vs the TIL category average. They are calculated taking the category % from the matching category cell in upper table (i.e., % value for the combination TRL_{End} row and TIL column from the upper table) divided by the overall average % for that TIL category found in the row named "Average TIL % =". These relative weighting factors range from 0.16 to 2.14 and can be applied to tailor the uniform TIL costs from the first generation TI-based parametric models to arrive at discrete TRL_{Start} to TRL_{End} transition costs for all 36 possible transitions.[13] These cost adjustments further expand and refine the total development cost space to 9,000 possible data points (36 TRL start-end combinations x 5 SHLs x 5 RD^3s x 10 TA categories).

Table 8-1: Cost Adjustment Weighting Factors – Discrete TRL Transition Start-End to TIL Average %

TRL_{End}	Cum % Dev. Cost	Percent Total Development Cost between TRL_{Start} and TRL_{End}							
	TIL =	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1.0%								
2	3.0%	2.0%							
3	6.0%	3.0%	5.0%						
4	10.0%	4.0%	7.0%	9.0%					
5	24.7%	14.7%	18.7%	21.7%	23.7%				
6	40.5%	15.8%	30.5%	34.5%	37.5%	39.5%			
7	56.0%	15.5%	31.3%	46.0%	50.0%	53.0%	55.0%		
8	82.5%	26.5%	42.0%	57.8%	72.5%	76.5%	79.5%	81.5%	
9	100.0%	17.5%	44.0%	59.5%	75.3%	90.0%	94.0%	97.0%	99.0%
	TIL Average % =	**12.4%**	**25.5%**	**38.1%**	**51.8%**	**64.8%**	**76.2%**	**89.3%**	**99.0%**
	TIL =	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
TRL_{End}		**Relative Cost Adjustment Weighting to TI Level Average**							
1									
2		0.16				**$TRL_{Start} = TRL_{End} - TIL$**			
3		0.24	0.20						
4		0.32	0.27	0.24					
5		1.19	0.73	0.57	0.46				
6		1.28	1.20	0.91	0.72	0.61			
7		1.25	1.23	1.21	0.97	0.82	0.72		
8		2.14	1.65	1.52	1.40	1.18	1.04	0.91	
9		1.41	1.73	1.56	1.45	1.39	1.23	1.09	1.00
	TIL =	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**

TIL progressions above level 5 (i.e., TRL Improvements in the 6 to 8 range) as part of one continuous project was found to be extremely rare in the large project population of the NASA TCASE database

13 The nth triangular number or "termial function" of possible combinations for an interval range of 8 (i.e., 1 to 9) = $(n^2 + n) / 2$ = (64 + 8)/2 = 36.

(approaching 3,000 total project records). Therefore, there was only adequate data to model TILs 1 to 5 in the original TI-SHL parametric models. Even though it is very unlikely TILs 6 through 8 will occur or need to be calculated, this output also makes it possible to estimate these very large transitions by extrapolating beyond TIL level 5 using the Average TIL % values as relative weighting factors. The two estimates in **Appendix K** provide examples applying the discrete TRL adjustment factors to the 3 and 4 parameter TI-SHL, RD^3 and TA based estimate examples in **Section 5**.

9. Composite Project or System Macro-Parametric Measures

Development projects may range from an individual technology development up to a system with multiple technology development efforts at varying states of maturity, scale, and development difficulty (i.e., TRL, SHL and RD^3). The scope of possible development projects can also extend to portions or potentially even all of the development life cycle demonstrated in **Figures 6-1** through **6-3**, and the development WBS' in **Table 6-2** and **Appendix-L**. Projects that involve the advancement or progression of multiple technologies must include relevant integration, testing and demonstration of those technologies up through the applicable TRL and development milestones at completion. Depending on the overall project SHL and phases of development involved in the TRL transition(s), this may include internal integration and test (I&T) at the assembly, subsystem, and system levels. If project development progresses into broader system development, it may also involve integration to external platforms, applications, networks, command & control systems or processes up through operational test and demonstration.

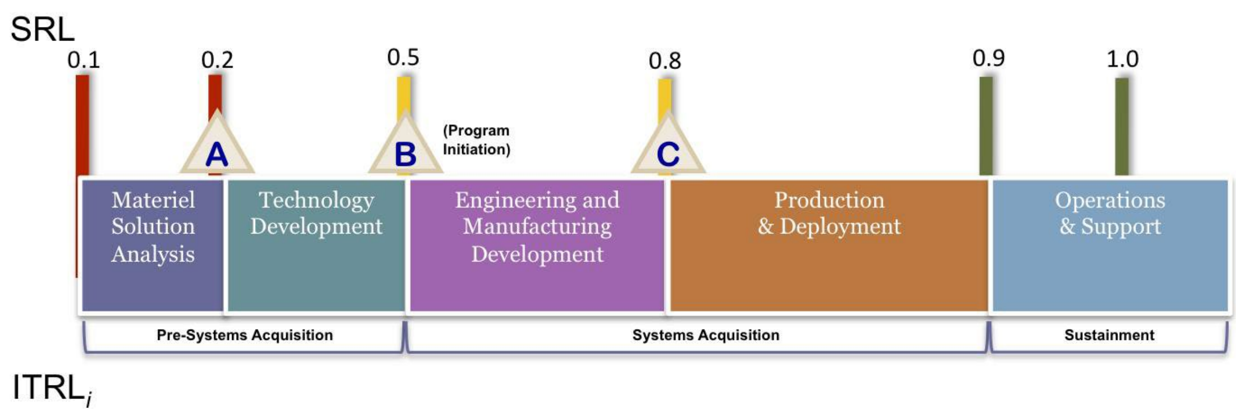
When applying a macro-parametric estimating approach to multi-technology developments that are part of one project or program, to the extent possible, each individual development should be estimated separately and rolled up or aggregated with progressive levels of integration, test, and demonstration. However if estimated together as one effort, an overarching SHL should be used to reflect the highest aggregate or predominant level of development. When aggregating the composite TRL & RD^3 independent macro-parameters must reflect the weighted average values across the overall project or system. Approaches have been proposed for methods to calculate compound system or program TRL measures. For instance, Lee and Thomas (Lee, 2003) estimated a cost-weighted TRL (WTRL), applying a component to total program percent cost weighting allocation. Sophisticated multifactor TRL calculators and utilities have also been devised based upon the weighted arithmetic or geometric mean of a range of attributes spanning TRLs. This includes the Air Force Research Laboratory's (AFRL) Transition Readiness Calculator[14] (see paper by Nolte and Dziegiel (Nolte, 2003) and NASA's TRL Workbook[15] (NASA-ESTO, 2010). Alternative techniques applying scalars such as technical design (e.g., size, weight and power (SWAP) requirements), performance, or complexity related metrics could also individually or collectively be

[14] AFRL Transition Readiness Level Calculator (aries.ucsd.edu/ARIES/MEETINGS/0712/Waganer/TRL%20Calc%20Ver%202_2.xls)
[15] NASA TRL Worksheet (https://esto.nasa.gov/files/TRL_Worksheet_11-30-10.xls)

applied as relative weighting coefficients for calculating overall system or project TRL or RD^3 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 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^3 and TA solutions. The addition of RD^3 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

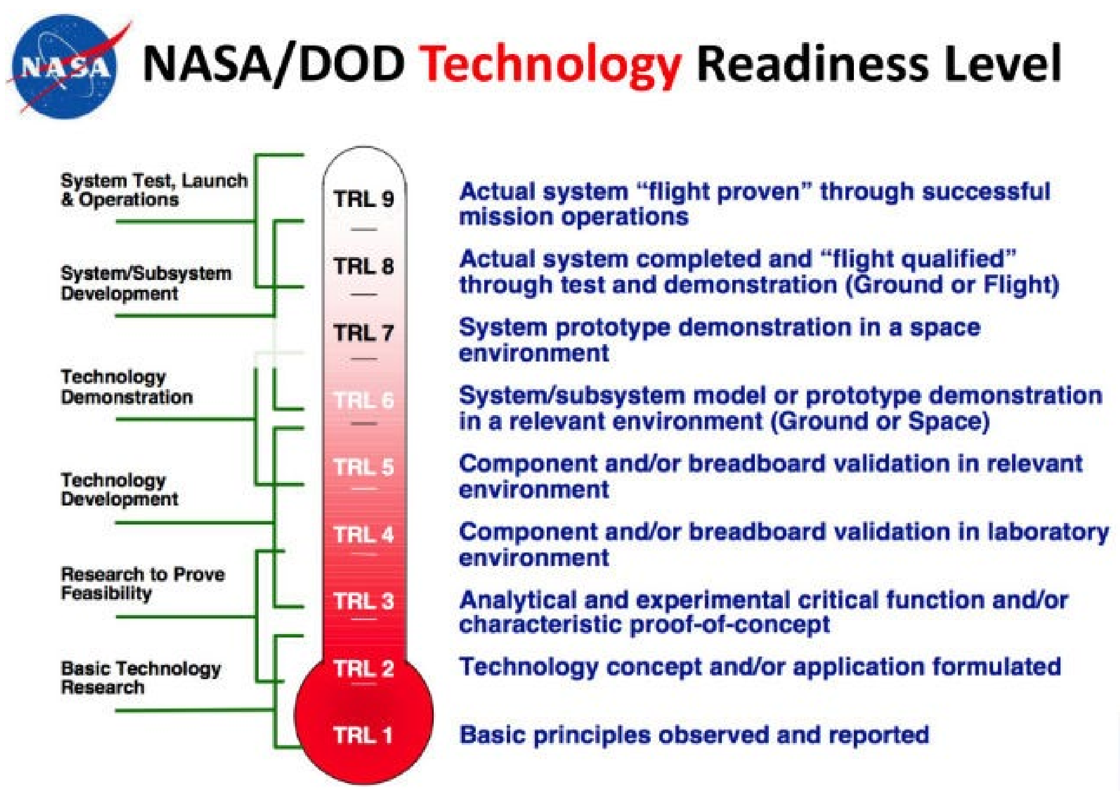
The expansion and enrichment of useful macro-parameters should continue to evolve early stage development estimating. This could take many forms including the addition of other TA categories and larger project datasets for all the key macro-parameters. Considerations for extending TRLs to level 10 mapped 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 underlying dimensions and attributes of TIL, SHL, RD^3 and TA macro-parameters. These characteristics are therefore implicitly inherent in the applied estimating formulae included with this analysis. The development of an explicit standard measure of overall system complexity, capturing all these various dimensions however, could produce an even more direct relationship to development program cost and duration.

The DoD, NASA, other civil agencies, major research institutions and industry technology leaders and system integrators are beginning to more broadly endorse the development, measurement and capture of standardized forms of macro-parameters to enhance project planning, estimating and performance measurement. Several important papers have expounded on the need for use of readiness and integration measures early in the development process. Among these are two Defense Acquisition Research Journal (ARJ) papers including one from AFRL titled "Application of System and Integration Readiness Levels to DoD R&D" (Ross, 2016) and another titled "Beyond Integration Readiness Level (IRL)" (Eder, 2017). Other significant work on this topic include the Conference on System Engineering Research (CSER) Procedia Computer Science papers by Uzdzinski, Grove and Atwater (Grove & Uzdzinski, 2013) (Atwater & Uzdzinski, 2014). These various measures hold substantial promise to advance parametric estimating capabilities but more project level cost and schedule information will be needed for their application in resource planning and investment decision making to reach their potential. Government, industry and institutional organizations with significant development program or project history may have the greatest opportunity to contribute to model advancements and impact progress of the estimating discipline through greater sharing of project technical and cost data, even if in a non-attributional or sanitized form.

Appendix A – Macro-Parameter Definitions for TRL, SHL, SRL, and IRL

NASA TRL Technology Readiness Level (TRL) Scale (Cole, 2013) [16]



NASA System Hierarchy Levels (SHL) (Cole, 2013) [17]

System Hierarchy Table			
No.	**Tier**	**Definition**	**Example**
5	System	An integrated set of constituent elements that are combined in an operational or support environment to accomplish a defined objective	A spacecraft or launch vehicle stage
4	Subsystem	A portion of a system	A satellite's propulsion system or launch vehicle's propulsion system
3	Assembly	A set of components (as a unit) before they are installed to make a final product	A satellite's thruster or launch vehicle's engine turbo-machinery
2	Component / Part	A portion of an assembly	A satellite's propellant valve or a launch vehicle's engine injector
1	Hardware / Material	An item or substance used to form a component	Alloy, polymer, screws, bolts, pipes, semiconductor chips

Note: Adapted from (Cole, 2013) *- numbers in the first column are inverted from the original table to correspond to the progressive ordinal numbers necessary to perform the analysis.*

[16] Source document from: https://www.nasa.gov/directorates/heo/scan/engineering/technology/txt_accordion1.html.

[17] Source document from: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20140005476.pdf,

System Readiness Levels (SRL) (Sauser & Ramirez-Marquez , 2006)

SRL	Name	Definition
5	*Operations & Support*	Execute a support program that meets operational support performance requirements and sustains the system in the most cost-effective manor over its total life cycle.
4	*Production & Development*	Achieve operational capability that satisfies mission needs.
3	*System Development & Demonstration*	Develop a system or increment of capability; reduce integration and manufacturing risk; ensure operational supportability; reduce logistics footprint; implement human systems integration; design for producibility; ensure affordability and protection of critical program information; and demonstrate system integration, interoperability, safety, and utility.
2	*Technology Development*	Reduce technology risks and determine appropriate set of technologies to integrate into a full system.
1	*Concept Refinement*	Refine initial concept. Develop system/technology development strategy

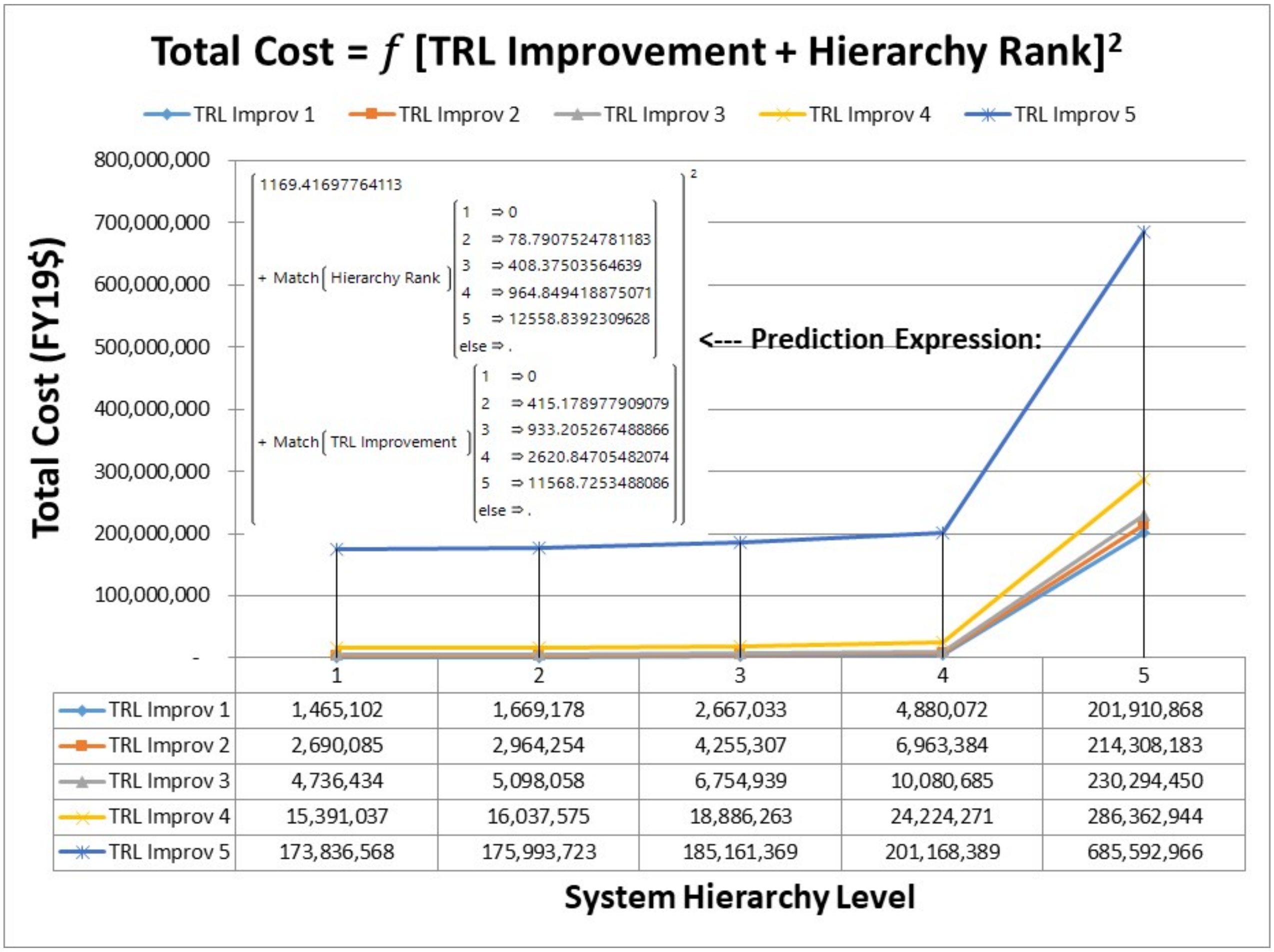
Integration Readiness Levels (IRL) (Sauser & Ramirez-Marquez , 2006)

IRL	Definition
7	The integration of technologies has been ***verified and validated*** with sufficient detail to be actionable.
6	The integrating technologies can ***accept, translate, and structure information*** for its intended application.
5	There is sufficient ***control*** between technologies necessary to establish, manage, and terminate the integration.
4	There is sufficient detail in the ***quality and assurance*** of the integration between technologies.
3	There is ***compatibility*** (i.e. common language) between technologies to orderly and efficiently integrate and interact.
2	There is some level of specificity to characterize the ***interaction*** (i.e. ability to influence) between technologies through their interface.
1	An ***interface*** (i.e. physical connection) between technologies has been identified with sufficient detail to allow characterization of the relationship.

Manufacturing Readiness Levels (MRL (OSD, 2016)

MRL 1	Basic manufacturing implications identified
MRL 2	Manufacturing concepts identified
MRL 3	Manufacturing proof of concept developed
MRL 4	Capability to produce the technology in a laboratory environment
MRL 5	Capability to produce prototype components in a production relevant environment
MRL 6	Capability to produce a prototype system or subsystem in a production relevant environment
MRL 7	Capability to produce systems, subsystems or components in a production representative environment
MRL 8	Pilot line capability demonstrated. Ready to begin low rate production
MRL 9	Low Rate Production demonstrated. Capability in place to begin Full Rate Production
MRL 10	Full Rate Production demonstrated and lean production practices in place

Appendix B – Highest Performing First Generation TI-SHL Cost Model



	1	2	3	4	5
TRL Improv 1	1,465,102	1,669,178	2,667,033	4,880,072	201,910,868
TRL Improv 2	2,690,085	2,964,254	4,255,307	6,963,384	214,308,183
TRL Improv 3	4,736,434	5,098,058	6,754,939	10,080,685	230,294,450
TRL Improv 4	15,391,037	16,037,575	18,886,263	24,224,271	286,362,944
TRL Improv 5	173,836,568	175,993,723	185,161,369	201,168,389	685,592,966

Reference: First Generation Model No. 9 *– Mean Total Cost vs. f [TRL Improvement + Hierarchy Level]* (Alexander, 2017). *Highest performing of several hundred Cost Curve Fit and Regression models evaluated in the initial research study (costs escalated to FY19$). Color coded TRL Improvement (TIL) lines do not represent continuous functions but are shown to illustrate the progression of costs within and across SHLs and TILs. Uncertainty PDFs for each SHL-TIL project data point were also constructed using Lognorm functions in the original study.*

Appendix C – RD^3 and TA Data Relationship Screening

Total project cost data was parsed into the range of RD^3 levels and TA categories for the two datasets to perform initial data relationship screening between the RD^3 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^3 data) the project cost statistics for the deconstructed RD^3 level and TA categorical data are shown in **Tables C-1** & **C-2**[18]. Linear regressions of cost vs RD^3 produce adjusted coefficient of determination (R^2 Adj.) values over 0.7 and cost vs TA regression R^2 Adj. exceeding 0.8, both implying relatively durable relationships may exist.

Table C-1: RD^3 Total Project Data Cost Statistics

RD^3 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^3 categories contained somewhat limited project sample sizes, project cost statistics demonstrate a direct and progressive incremental relationship to RD^3 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

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18 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).

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^3 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.

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^3 and TA parameters), multiple regression CC and VIF were assessed. Multiple regression models were formulated to perform these tests between the RD^3/TIL/SHL, TA/TIL/SHL and, RD^3/TA independent cost variables.

For the RD^3/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^3/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^3 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^3/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^3-SHL-TIL variables, 2.1 for TA-SHL-TIL variables and 1.8 for the RD^3-TA variables. These results suggest no autocorrelation issues are evident.

Appendix E – Data Types

The Development Cost response variable applied in this analysis is a continuous quantitative variable, TIL, SHL and RD^3 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^3, 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).

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 50th (i.e., median), 70th and 80th 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.

Appendix G – Project Data Sample Equivalence Investigation

A data relationship between either the RD^3 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^3 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 McLaughin (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^3 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^3 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 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^3 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^3 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^3 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^3 Sample Mean Cost Data

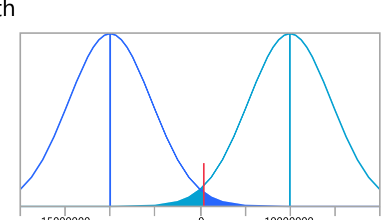
Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1 (SHL-TIL)	186	29304292	75771209	5555814.6	20119798	38488786
3 (RD^3)	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^3 (#3) and SHL-TIL (#1) Samples

Null Hypothesis	DF	t Ratio	p-Value
Mean Difference ≥ 1000000	600	-2.0674	0.0196*
Mean Difference ≤ -1000000	600	2.245442	0.0126*
Max over both			0.0196*

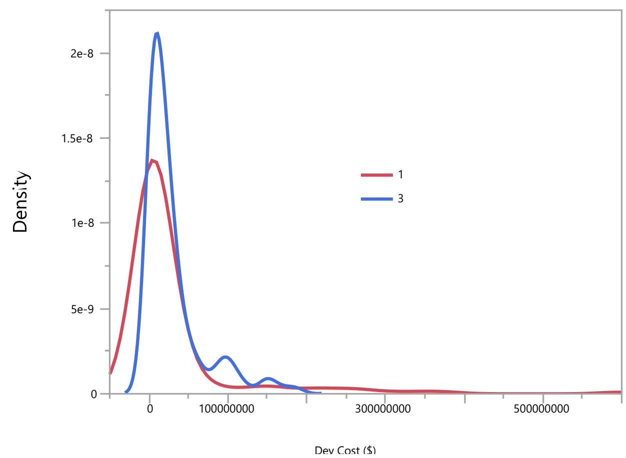


Welch's Test

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

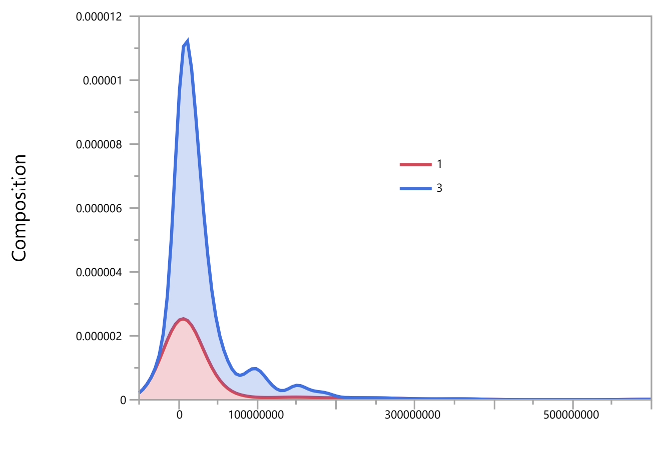


Figure G-2 Trimmed Equivalence Tests of TI-SH vs TA Sample Mean Cost Data

Means and Std Deviations

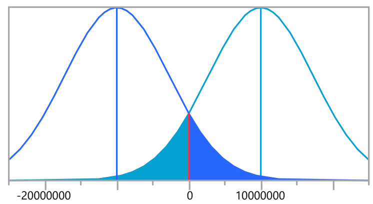
Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1 (SHL-TIL)	221	27052654	77816153	5234480.9	18406290	35699018
2 (TA)	1703	27059297	104306493	2527574.8	22899542	31219052

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

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 ≥ 1000000	1922	-1.37535	0.0846
Mean Difference ≤ -1000000	1922	1.377176	0.0843
Max over both			0.0846

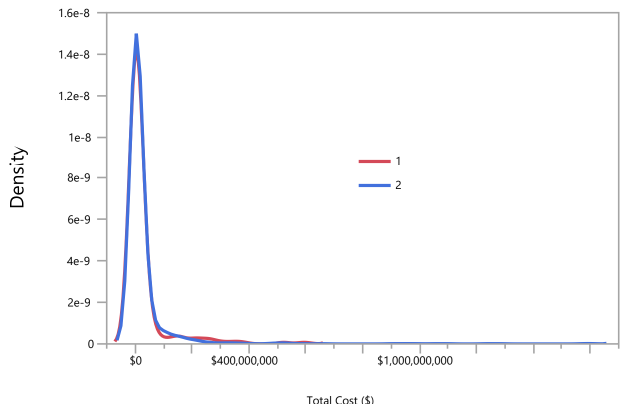


Welch's Test

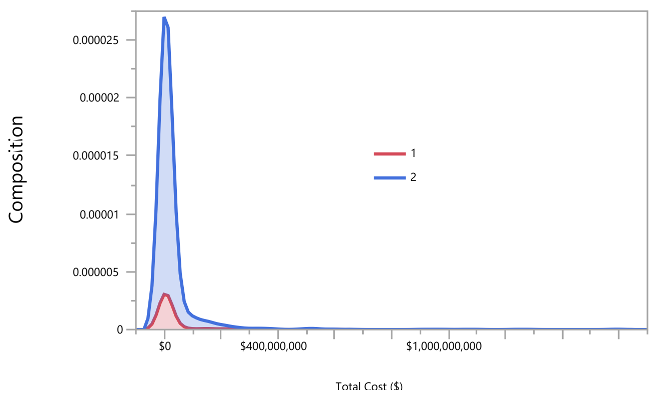
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0000	1	332.22	0.9991

Compare Densities



Composition of Densities



Appendix H – RD^3 and TA MCI Curve Fit PDF Formulas and Plots

Table H-1: RD^3 MCI Curve Fit PDFs

RD^3 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"))

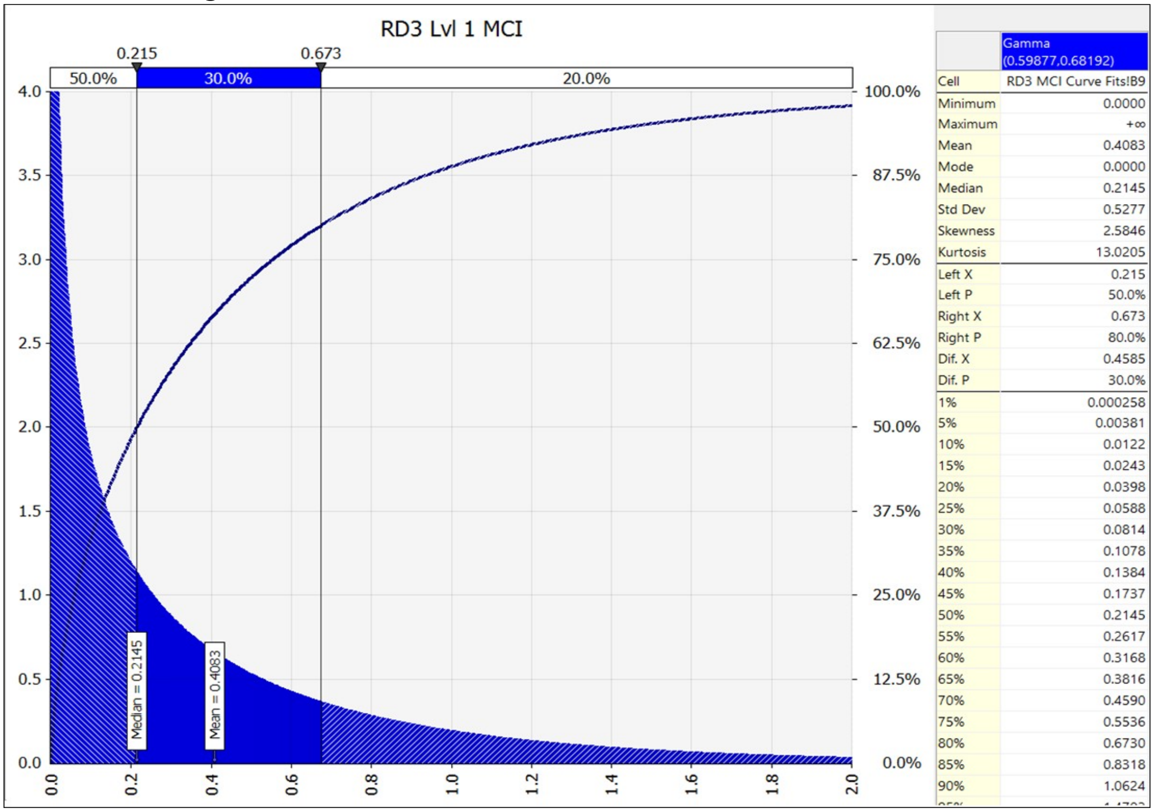
Table H-2: TA MCI Curve Fit PDFs

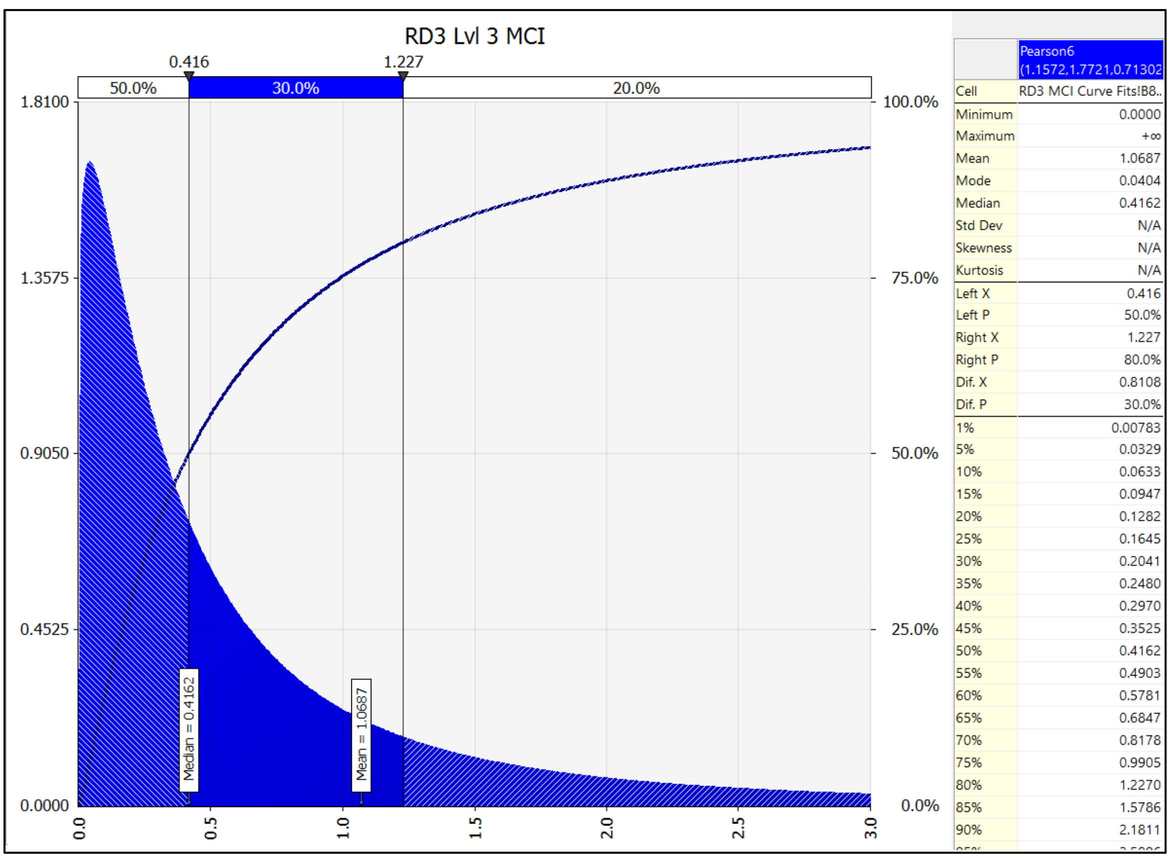
TA Mean Cost Index (MCI) Curve Fit PDFs			
No.	Technology Area (TA)	PDF Type	@RISK PDF Formula
1	Launch Propulsion Systems	Frechet	=RiskFrechet(0,0.016039,0.60073,RiskName("TA1 Mean Cost Index"))
2	In-Space Propulsion Technologies	Lognorm	=RiskLognorm(1.0673,18.846,RiskName("TA2 Mean Cost Index"))
3	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:

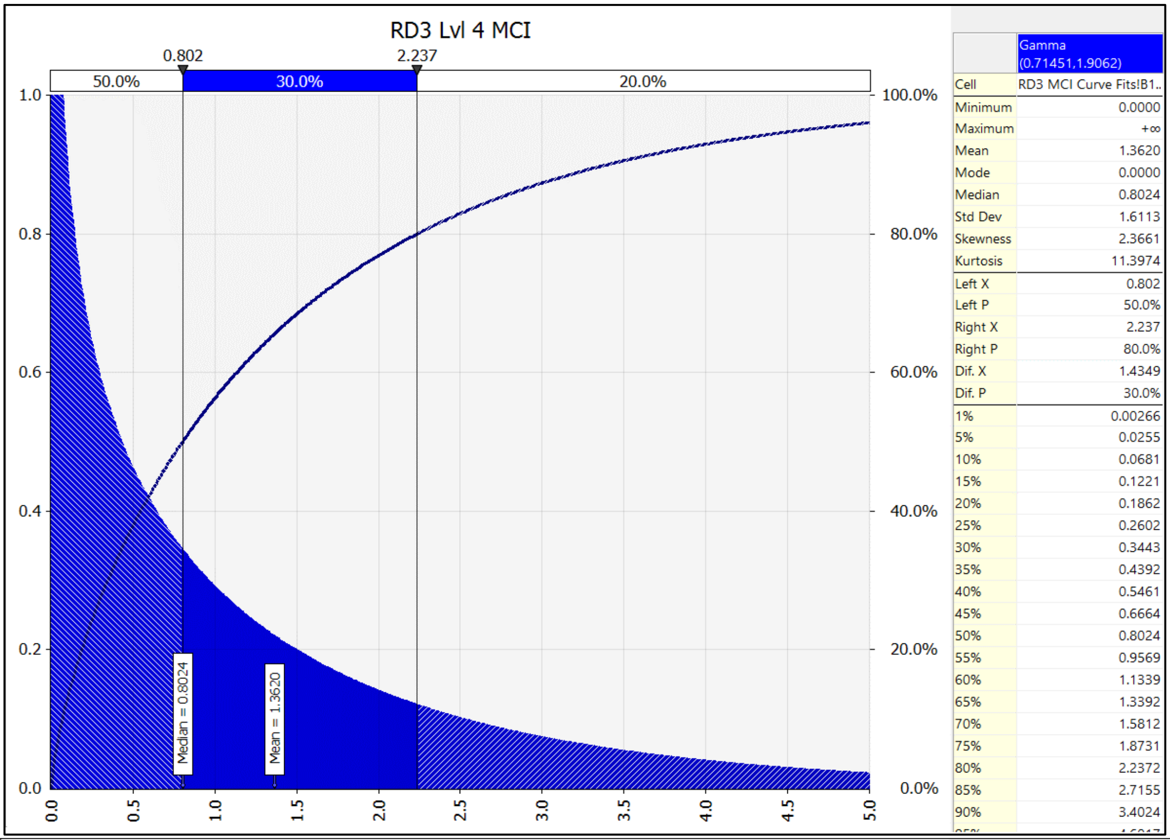
- ***Table H-1*** *and* ***H-2*** *PDFs are consistent with the right-skewed lognormal, gamma, Weibull and betaPERT type PDFs commonly recommended for estimating uncertainty in the Joint Agency Cost Schedule Risk and Uncertainty Handbook (JACSRUH).*
- ***Table H-2*** *is provided for analysis demonstration purposes only as these PDFs are not recommended for application in modeling due to reasons explained in Section 5.a.*
- *The following RD^3 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 50th to 80th percentiles generally applied in budgeting and investment decision making. For a more detailed explanation of the Curve Fit Methodology see* ***Appendix F****.*

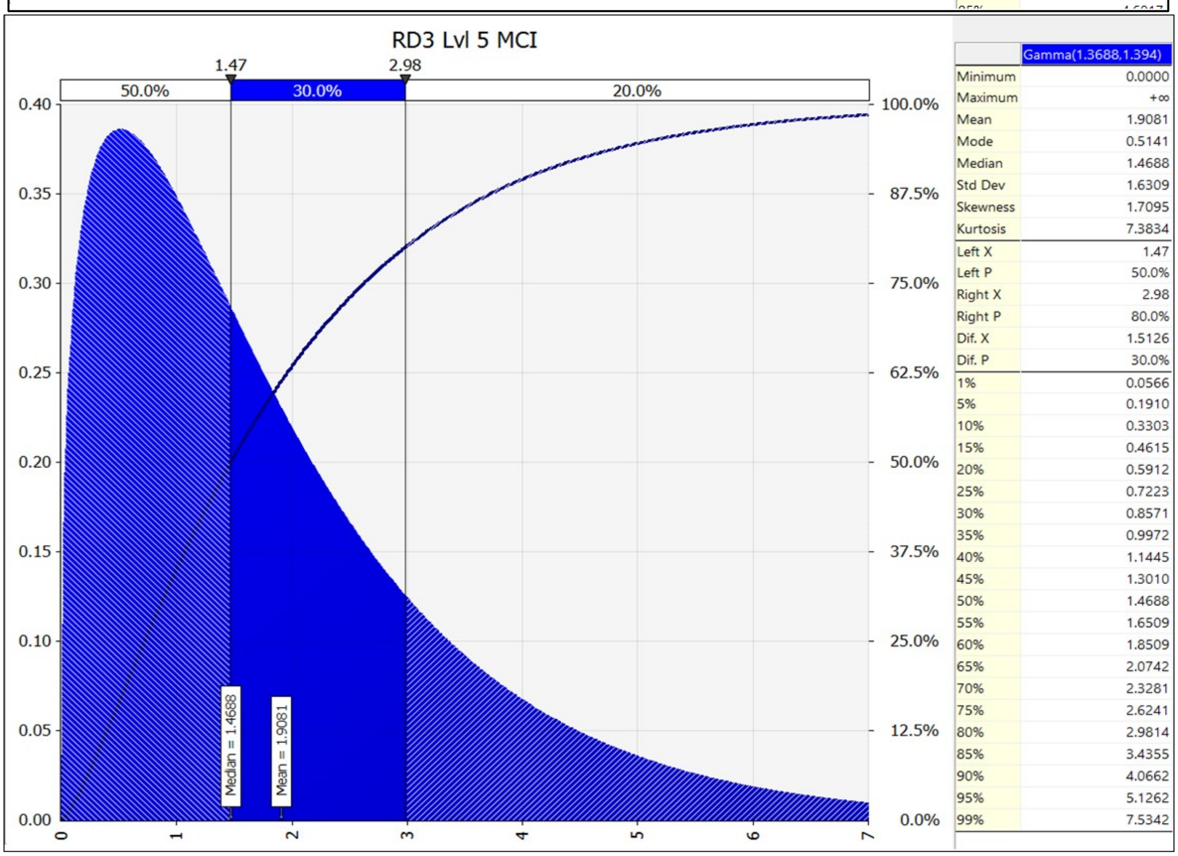
Figures H-1 and H-2: MCI Curve Fit PDFs for RD^3 Levels 1 and 3





Figures H-3 and H-4: MCI Curve Fit PDFs for RD³ Levels 4 and 5





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:

$\boldsymbol{Geometric\ Mean} = \left(\prod_{i=1}^{n} a_i\right)^{1/n} = \sqrt[n]{a_1 a_2 a_3 \ldots\ldots a_n}$ (Roenfeldt, 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^3 level and TA category cost PDF curve fits (see **Table I-1** for the RD^3 cost curve fit PDFs). The GM of the Project Development Cost included combinations of the 4 parameters => (PDF_{SHL} x PDF_{TIL} x PDF_{RD3} x 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^3/TA), were performed. Output from the simulations therefore represent a blended average of the 3 selected constituent macro-parameters.

Table I-1: RD^3 Project Sample Cost Data Curve Fit Functions

RD^3 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.

Appendix J – Table J-1: SHL-TIL-RD^3 Composite Model Mean Project Costs (FY19$)

Model No. (SHL / TIL / RD^3)	Mean Project Pt. Estimate Cost (FY19$)
1/1/1	$ 598,201
1/1/2	$ 1,136,772
1/1/3	$ 1,566,194
1/1/4	$ 1,995,468
1/1/5	$ 2,795,560
2/1/1	$ 681,525
2/1/2	$ 1,295,115
2/1/3	$ 1,784,351
2/1/4	$ 2,273,421
2/1/5	$ 3,184,959
3/1/1	$ 1,088,950
3/1/2	$ 2,069,351
3/1/3	$ 2,851,059
3/1/4	$ 3,632,499
3/1/5	$ 5,088,966
4/1/1	$ 1,992,533
4/1/2	$ 3,786,448
4/1/3	$ 5,216,797
4/1/4	$ 6,646,658
4/1/5	$ 9,311,665
5/1/1	$ 82,440,208
5/1/2	$ 156,662,643
5/1/3	$ 215,842,718
5/1/4	$ 275,002,603
5/1/5	$ 385,266,128
1/2/1	$ 1,098,362
1/2/2	$ 2,087,237
1/2/3	$ 2,875,701
1/2/4	$ 3,663,896
1/2/5	$ 5,132,952
2/2/1	$ 1,210,305
2/2/2	$ 2,299,965
2/2/3	$ 3,168,787
2/2/4	$ 4,037,314
2/2/5	$ 5,656,093
3/2/1	$ 1,737,442
3/2/2	$ 3,301,693
3/2/3	$ 4,548,923
3/2/4	$ 5,795,728
3/2/5	$ 8,119,551
4/2/1	$ 2,843,150
4/2/2	$ 5,402,890
4/2/3	$ 7,443,858
4/2/4	$ 9,484,130
4/2/5	$ 13,286,834
5/2/1	$ 87,502,031
5/2/2	$ 166,281,719
5/2/3	$ 229,095,448
5/2/4	$ 291,887,745
5/2/5	$ 408,921,444

Model No. (SHL / TIL / RD^3)	Mean Project Pt. Estimate Cost (FY19$)
1/3/1	$ 1,933,886
1/3/2	$ 3,674,999
1/3/3	$ 5,063,248
1/3/4	$ 6,451,023
1/3/5	$ 9,037,589
2/3/1	$ 2,081,537
2/3/2	$ 3,955,583
2/3/3	$ 5,449,824
2/3/4	$ 6,943,554
2/3/5	$ 9,727,604
3/3/1	$ 2,758,042
3/3/2	$ 5,241,157
3/3/3	$ 7,221,030
3/3/4	$ 9,200,227
3/3/5	$ 12,889,099
4/3/1	$ 4,115,944
4/3/2	$ 7,821,604
4/3/3	$ 10,776,253
4/3/4	$ 13,729,894
4/3/5	$ 19,234,956
5/3/1	$ 94,029,224
5/3/2	$ 178,685,464
5/3/3	$ 246,184,767
5/3/4	$ 313,661,041
5/3/5	$ 439,424,841
1/4/1	$ 6,284,160
1/4/2	$ 11,941,905
1/4/3	$ 16,453,018
1/4/4	$ 20,962,592
1/4/5	$ 29,367,637
2/4/1	$ 6,548,142
2/4/2	$ 12,443,555
2/4/3	$ 17,144,168
2/4/4	$ 21,843,177
2/4/5	$ 30,601,297
3/4/1	$ 7,711,261
3/4/2	$ 14,653,851
3/4/3	$ 20,189,415
3/4/4	$ 25,723,090
3/4/5	$ 36,036,878
4/4/1	$ 9,890,770
4/4/2	$ 18,795,612
4/4/3	$ 25,895,745
4/4/4	$ 32,993,457
4/4/5	$ 46,222,331
5/4/1	$ 116,921,990
5/4/2	$ 222,189,008
5/4/3	$ 306,121,987
5/4/4	$ 390,026,330
5/4/5	$ 546,409,134

Model No. (SHL / TIL / RD^3)	Mean Project Pt. Estimate Cost (FY19$)
1/5/1	$ 70,977,471
1/5/2	$ 134,879,793
1/5/3	$ 185,831,291
1/5/4	$ 236,765,406
1/5/5	$ 331,697,555
2/5/1	$ 71,858,237
2/5/2	$ 136,553,530
2/5/3	$ 188,137,290
2/5/4	$ 239,703,451
2/5/5	$ 335,813,623
3/5/1	$ 75,601,387
3/5/2	$ 143,666,706
3/5/3	$ 197,937,504
3/5/4	$ 252,189,785
3/5/5	$ 353,306,409
4/5/1	$ 82,137,053
4/5/2	$ 156,086,553
4/5/3	$ 215,049,008
4/5/4	$ 273,991,345
4/5/5	$ 383,849,403
5/5/1	$ 279,927,608
5/5/2	$ 531,951,583
5/5/3	$ 732,898,881
5/5/4	$ 933,777,620
5/5/5	$ 1,308,179,939

Estimating Methodology:

Three Parameter Estimates: *Tables represent the expected mean point estimate costs (FY19$) for the 125 possible three parameter (SHL-TIL-RD^3) 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^3 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^3 PDF x TA MCI). This results in 1,250 possible four parameter model variants (25 TIL-SHL x 5 RD^{3}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***

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

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:

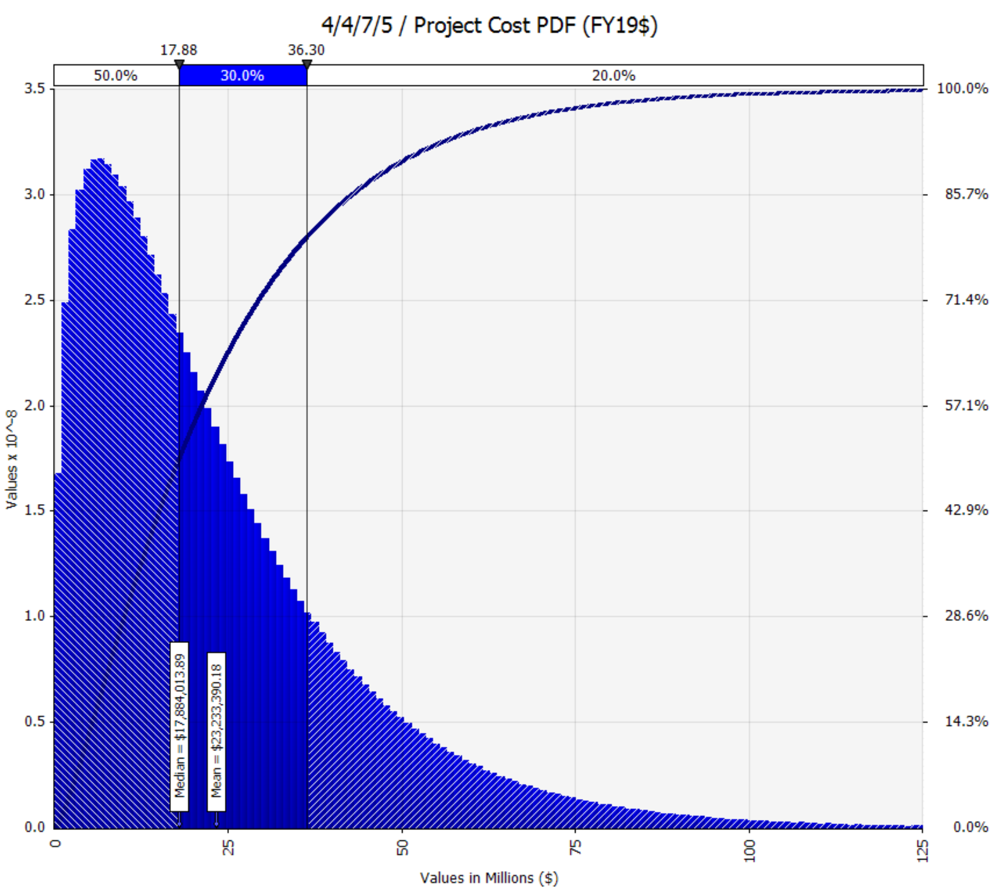
*To produce models including all four parameters simply include another factor for the applicable RD^3 MCI PDF from **Table H-1** in the product in Monte Carlo simulation (e.g., TIL-SHL mean x TA MCI x RD^3 PDF). This results in 1,250 possible four parameter model variants (25 TIL-SHL x 10 TAs x 5 RD^{3}s). 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^3 x 10 TA).*

Appendix K – Macro-Parametric Model Project Estimating Examples

Project 1: 3 Parameter Estimate for SHL = 4, TRL $_{Start}$ = 4, TRL $_{End}$ = 7 (TIL = 3), and RD^3 = 5

The first sample project estimate is for one of the 125 three parameter SHL-TIL-RD^3 models with a project configuration of SHL = 4, TRL $_{Start}$ = 4, TRL $_{End}$ = 7 (TIL = 3), and RD^3 = 5 (model no. 4/4/7/5 representing SHL/TRLs/TRLe/RD^3/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 $10,080,685 (FY19$k). 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^3 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^3 = 5 MCI from **Table H-1** (@RISK formula = RiskGamma (1.3688,1.394,RiskName ("RD^3 Lvl 5 MCI")) and **Figure H-4** of **Appendix H**, producing the project cost uncertainty distribution shown in **Figure K-1.** The resulting 50th to 80th percentile cost planning range for these project attributes is ~ $18M to ~$36M with a 70th 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^3 = 5

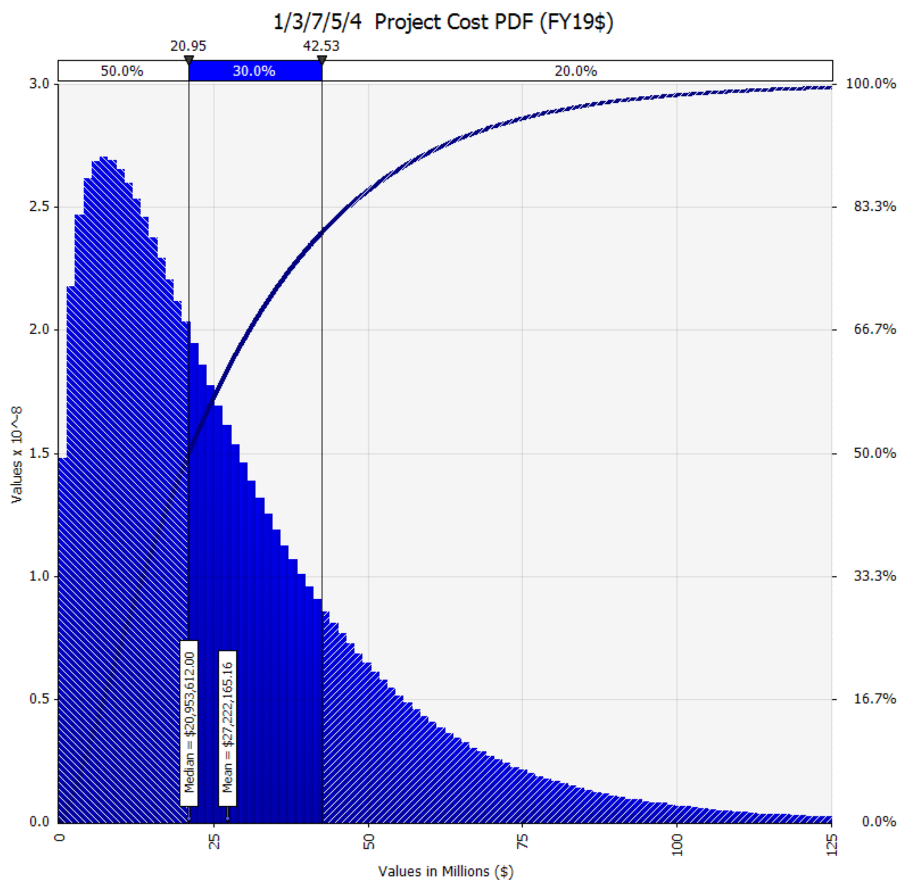


	16584016.401
Cell	RD3 Cost Models!N71
Minimum	$6,739.42
Maximum	$205,860,084.42
Mean	$23,233,390.18
90% CI	± $146,068.56
Mode	$6,408,521.02
Median	$17,884,013.89
Std Dev	$19,856,671.43
Skewness	1.7067
Kurtosis	7.3381
Values	50000
Errors	0
Filtered	0
Left X	$17,884,013.89
Left P	50.0%
Right X	$36,301,281.59
Right P	80.0%
Dif. X	$18,417,267.70
Dif. P	30.0%
1%	$689,071.21
5%	$2,325,994.32
10%	$4,021,760.96
15%	$5,619,308.47
20%	$7,198,086.71
25%	$8,794,420.27
30%	$10,435,319.29
35%	$12,142,284.40
40%	$13,935,734.58
45%	$15,840,402.05
50%	$17,884,013.89
55%	$20,101,073.50
60%	$22,536,900.51
65%	$25,255,584.01
70%	$28,347,565.98
75%	$31,951,060.77
80%	$36,301,281.59
85%	$41,829,692.30
90%	$49,508,556.20
95%	$62,417,222.44
99%	$91,707,898.79

Project 2: 4 Parameter Estimate for SHL = 1, TRL_{Start} = 3, TRL_{End} = 7 (TIL = 4), RD^3 = 5 TA = 4

Similarly, a four parameter SHL-TIL-RD^3-TA macro-parametric model estimate is demonstrated for a hypothetical project characterized by SHL = 1, TRL_{Start} = 3, TRL_{End} = 7 (TIL = 4), RD^3 = 5 and TA = 4 (i.e., Robotics, Telerobotics, Autonomous Systems) (model no. 1/3/7/5/4 representing SHL/TRL_{start}/TRL_{End}/RD^3/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^3 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^3 MCI point estimate with the corresponding RD^3 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^3 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^3 = 5 MCI from **Table H-1** (@RISK formula = RiskGamma (1.3688,1.394,RiskName ("RD^3 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 80th percentile cost planning range for these project characteristics is ~ $21M to ~$42.5M with a 70th percentile of $33.2M, as illustrated in the PDF plot and table.

Figure K-2: Project 2 Uncertainty PDF: SHL = 1, TRL_{Start} = 3, TRL_{End} = 7 (TIL = 4), RD^3 = 5 and TA = 4



	1/3/7/5/4 Project Cost PDF (FY19$)
Cell	RD3 Cost Models!Q81
Minimum	$7,412.56
Maximum	$265,944,812.20
Mean	$27,222,165.16
90% CI	± $171,180.74
Mode	$7,508,584.92
Median	$20,953,612.00
Std Dev	$23,270,440.58
Skewness	1.7121
Kurtosis	7.4186
Values	50000
Errors	0
Filtered	0
Left X	$20,953,612.00
Left P	50.0%
Right X	$42,532,402.68
Right P	80.0%
Dif. X	$21,578,790.67
Dif. P	30.0%
1%	$807,383.73
5%	$2,724,636.57
10%	$4,711,686.60
15%	$6,584,173.67
20%	$8,433,727.76
25%	$10,304,289.80
30%	$12,226,864.20
35%	$14,226,605.84
40%	$16,327,817.04
45%	$18,560,038.96
50%	$20,953,612.00
55%	$23,551,190.23
60%	$26,405,612.39
65%	$29,591,299.44
70%	$33,212,452.12
75%	$37,435,584.41
80%	$42,532,402.68
85%	$49,011,825.21
90%	$58,005,891.29
95%	$73,127,540.29
99%	$107,460,563.28

Appendix L – Detailed Standard Development Framework WBS Elements

WBS #	WBS Name	WBS Description *(Note: general WBS guidance only and not intended as prescriptive, tailor WBS to system architecture and project requirements)*
1.0	**DEVELOPMENT**	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).
1.1	**Technology Development**	Proof of concept (PoC) or feasibility demonstration in simulation and laboratory environment
1.1.1	**Basic Research**	Basic research is systematic study directed toward greater knowledge or understanding of the fundamental aspects of phenomena and of
1.1.2	**Technology Research**	Incubation stage scientific investigation with translation to basic principles & early exploratory development during pre-material solution analys
1.1.3	**Analytical Proof of Concept (PoC) Validation**	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.
1.1.4	**Validation in a Laboratory Environment (VLE)**	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
...	...	...
1.1.5	**Validation in a Relevant Environment (VRE)**	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
...	...	...
1.1.6	**Prototype Demo in Relevant Environment (DRE)**	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 (IA	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 proper
1.2	**Systems Development**	Advancing technology from Prototype to full scale system functional integration, test and demonstration with operational system through IOC
1.2.1	**Systems Prototype Demo in Oper'l Environment (DOE**	Systems Prototype Demo in Oper'l Environment
1.2.2	**Full Scale Systems Dvlp. & Demonstration (SDD)**	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 Desi	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&	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 righ
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
1.2.3	**Operational Systems Evaluation (OPEval)**	Full system operational evaluation (OPEval) through full rate production (RFP) approval, concluding with initial operational capability (IOC)
1.2.4	**Operational Systems Development**	Development efforts such as engineering or design modifications to resolve manufacturing or production issues for fielded systems up to FOC

Acronym List

ACRONYM	
advanced degree of difficulty	AD^2
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^3
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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