Parametric Cost and Schedule Modeling for Early Technology Development

Chuck Alexander
Technology Programs and Cost Group
National Security Analysis Department
Johns Hopkins University Applied Physics Laboratory (JHU/APL)
11100 Johns Hopkins Road, Laurel, MD 20723-6099

ABSTRACT: *One of the most formidable challenges in the disciplines of Investment Decision Analysis and Cost Estimating is found in the realm of technology development. In basic or even applied technology research there is often a lack of engineering design or conceptual technical requirements available in early life-cycle stages with which to drive parametric estimates or translate analogous system costs. Little or no comparable systems, design or performance parameters, or other objective basis are generally available from which to produce even rough order of magnitude cost and schedule models. Often compounding the availability of technology information is the proprietary or protected nature of technology research and development (R&D) efforts and related intellectual property (IP) information. This restriction contributes to the lack of data and objective models and methods that can be broadly applied in early planning stages.*

Consequently, executives, program managers, budget analysts, and other decision makers must often rely on historical information from related yet often very dissimilar systems or the subjective opinion or "best guess" of subject matter experts (SME). This capability gap creates a constant challenge for government and industry organizations' planning, investigating, and conducting technology R&D. As a result, there is a real need in the scientific, technology, and financial communities for economic forecast models that improve the ability to estimate new or immature technology developments. This paper first investigates applicable industry modeling concepts, frameworks, models and tools. A representative project data set is identified and selected for cost and schedule modeling, leveraging macro-parameters generally known or available in early technology development stages. A range of model forms are then created and evaluated based upon key performance criteria.

Keywords: Technology Development, Cost Estimating, Parametric Modeling, Schedule Estimating, Cost Uncertainty, Investment Decision Analysis, Statistical Analysis

1 Introduction

Industry and government models, tools, and contemporary research were explored for solutions to formulate cost and schedule estimates in early stage technology investment decision making. The investigation discovered a variety of proposed and extant methodologies. These solutions however, were found to be either focused on later life cycle phases, based upon narrow technology applications and limited source data sets, or required technical inputs not available in preliminary development stages. Common or wide-ranging system, platform, or application-level parameters are needed to serve as independent predictor variables driving cost and schedule forecasts when little engineering or performance information is available, potentially even before conceptual design has commenced. Therefore, a search for applicable source data and modeling approaches was initiated to address a range of technologies applying macro-level cost and schedule drivers available in development program initial research or planning stages. This examination was intended to assess existing solutions as well as identify a relevant data set, select parameters, and develop methodologies to produce viable models for broad-based early life cycle technology estimating.

2 Background - Literature, Model, and Source Data Search

In initial development project pre-concept and early conceptual stages, there is generally very limited design or performance information available that is typically applied in parametric cost and schedule models. These key attributes are often focused on subsystem or unit/assembly level characteristics or performance metrics that have not yet been determined. Therefore, macro level parameters applied at a broader system or platform level must be leveraged. Life cycle estimating investigations have identified this phenomenon as illustrated in Figure 1 developed by QinetiQ (Shermon & Barnaby, 2015).

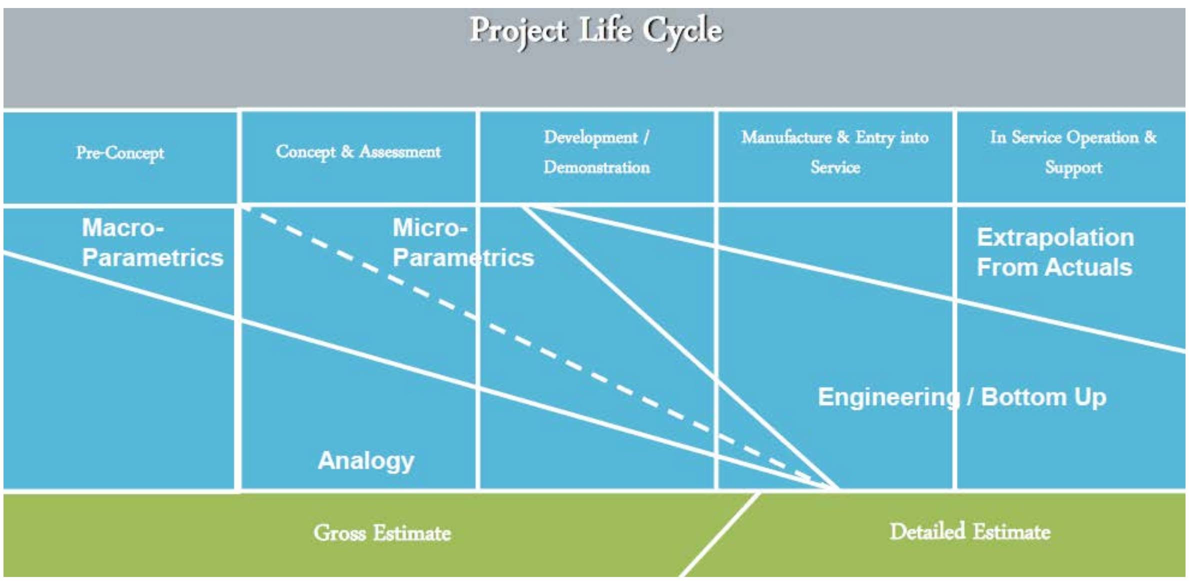

Figure 1: Estimating Methods over Project Life Cycle

In initial discovery, government and industry databases, repositories, and models were first examined for possible sources of technology development estimating solutions and applicable project information. This search considered leading commercial parametric cost estimating and analysis tools such as PRICE True Planning and the Galorath SEER tool suite. Others tailored to development phase estimating like the Constructive Technology Development Cost Model (COTECHMO) (Jones et al., 2014) were also explored. Commercial tools contain robust cost knowledge bases, and are driven by cost and schedule estimating relationships (i.e., CERs, SERs) that can be highly tailored or calibrated to a particular application, platform, or environment. For instance, the COTECHMO Resources (labor effort) and Direct Cost (hardware) Models are based upon a comprehensive list of cost drivers such as resource size, effort, complexity, process, and hardware requirements. The underlying algorithms within these parametric models therefore generally require detailed and sometimes extensive technical design, configuration, performance, and complexity metrics that are not yet available in initial development stages.

A literature search was also conducted for contemporary research and models addressing methods for early phase technology development estimating. Various frameworks, analysis, and modeling concepts have been proposed or developed including the application of Technology Readiness Level (TRL) based metrics. These papers and models offer insightful analysis, methods, and considerations for the use of TRL and other metrics to drive development program cost and schedule estimating. Approaches have included a comprehensive four-level assumptions-based framework (El-Khoury & Kenley, 2014) and several TRL-based cost and schedule models or empirical-based functions (Conrow, 2009; Hay et al., 2013; Jones et al., 2014; Malone et al., 2011; Stahl et al., 2010). Methodologies using Systems Readiness Levels (SRLs) and Integration Readiness Levels (IRLs) expanding upon TRL modeling concepts have also been introduced (Sauser, Ramirez-Marquez, Magnaye, & Tan, 2006; Sauser, Ramirez-Marquez, Verma, & Gove, 2008).

Current models deliver varying results but most are based upon limited data sets or concentrate on select technology areas or applications. These models often require historical baseline program information or metrics to drive them that are again, not generally available in early R&D phases. Various government sector repositories, databases, and models also exist but are usually focused on Procurement and/or Operations and Support (O&S) phases, and access is generally restricted. Other papers have also recognized the lack of available cost models or studies for forecasting technology development efforts, especially at the initial development stages (Curran et al., 2004; Hay et al., 2013; Jones et al., 2014). Except for certain technology-specific or proprietary forms, industry and government solutions designed to drive early life cycle R&D forecasts for general technology application, have consequently not been readily available.

Data Resource. During the course of this investigation, a key resource was identified with the scope, and extent of historical cost, schedule, and technical data being sought to develop broad-based technology development models. The National Aeronautics Space Administration (NASA) Technology Cost and Schedule Estimating (TCASE) tool was established partially in response to findings of the NASA Cost Community from the 2011 Cost Symposium. The Cost Community concluded, “No known good method to estimate the cost of TRL advancement [*exists*] that is supported by actual data” (Cole et al., 2013, p. 3). The TCASE beta version was developed and introduced by the NASA HQ Cost Analysis Division and SpaceWorks Enterprises, Inc. in early 2013. TCASE is a rather unique resource with a large project repository containing vital technology development information. At the core of this tool is an extensive technology database containing over 2,900 project records and covering 14 wide-ranging technology areas (TA), each with up to 164 available data fields. The resident project data was extracted from over 70 sources of historical technology project information including an array of databases, records, repositories, and portfolios, across NASA centers/directorates, missions, programs, and technology areas. The range of technologies investigated, researched, and developed by NASA as demonstrated by the 14 TAs is expansive, going well beyond just space and flight systems.

This TCASE data set contains information germane to both cost and schedule modeling for a broad scope of applications and systems relevant across the scientific, military, and intelligence sectors. It was therefore selected as the data source for generation of the technology development cost and schedule models presented below.

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3 Methods - Modeling Approach

An incremental process was applied to identify, screen, and select key source data for causal relationships to cost and schedule. Independent predictor variables and dependent response variables were then investigated, and primary project data sets relevant to each independent variable were identified, filtered, and normalized. Finally, a comprehensive field of model forms was developed and performance evaluated based upon the strength of association between predictor and response variables and closeness of fit to the underlying sample data.

Key Data Selection. One of the keys to modeling early life cycle technology development efforts is finding common system or project requirements, attributes, and parameters that drive cost and schedule and are readily available. These attributes must therefore be general or fundamental enough to apply across technology areas and not require a level of conceptual or engineering design analysis that has not yet been performed. Available TCASE project data fields were assessed as possible independent model parameters and dependent cost and schedule response variables. The dependent cost variable selected from the TCASE database is the **Total Cost ($)**[1] field and contains the total project costs normalized to government fiscal year 2015 dollars (FY15$). For schedule analysis, an overall **Project Duration (months)** field was created using the net difference in months between the available **Start Date** and **End Date** database fields for each project.

In parametric estimating, variables that relate to size or scale, performance, and complexity are often leading drivers of cost and schedule. These basic relationships are often found in various estimating applications including a broad range of weapon system platforms (e.g., sea, air, space, and land based), information technology systems, and standalone hardware and software development programs. Analysis of the available project attribute data fields for possible predictor variables was performed in anticipation of the development of stochastic or parametric based cost and schedule models. From an initial review of the available data fields, principal candidates showing the greatest potential as predictor variables for cost and schedule included[2]:

- System Hierarchy (SH) Level (1 to 5)
- Project Start / End TRL (1 to 9)
- R&D Degree of Difficulty (RD3) (Levels I to V)
- TA1 to TA14
- System Characteristics
- Key Performance Parameters (KPPs)
- Total Full time Equivalents (FTEs) of project labor
- Capability Demonstrations

In surveying the available data within the target data set, it was discovered that many of the database fields were too sparsely populated to provide significant sample sizes[3]. Unfortunately, this eliminated the RD3, System Characteristics, KPPs and Capability Demonstration variables as possible contenders. There were also insufficient data within the 14 TAs to parse models effectively

[1] Defined in the NASA TCASE tool 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, and equipment, etc. and also includes (and separately identified) facilities and infrastructure capital investments made as part of the research project (if any).
[2] For definitions of NASA TRL Levels, System Hierarchy, RD3 levels, and Technology Areas see Appendix A.
[3] Sample sizes of 30 observations are generally desirable for the means normality assumption under the Central Limit Theorem.

at the individual TA levels. For this investigation, total project labor in FTEs was also not considered a practical parameter to effectively contribute to the analysis due to the following: 1) labor is driven by requirements, and therefore, more of an outcome than a causal factor; 2) labor resources are essentially already included in or captured by the more comprehensive Total Project Cost response variable, and; 3) the mix of labor resources and corresponding burdened labor rates varies by project, thus distorting the affiliation with cost and schedule. Project Start / End TRL and SH level were therefore the remaining parameters available for analysis as potential predictor variables. Others were also formulated for analysis as described under **Schedule Forecast Models**.

Data Modeling. The Total Cost and Project Duration response variables are continuous quantitative variables (a.k.a. cardinal numbers), yet both the TRL and SH level predictor variables are discrete ordered categorical values. Categorical variables that have more than two categories 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 both TRL and SH levels, 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 large interval variance is possible between class rankings. Fortunately, statistical analysis tools employ a regression technique that leverages the ordinal *interval* values.

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) (Berry, 1993; Gertheiss, 2009; Stauner, 2014), 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 structure, known or unknown, such as architecture, functionality, common development processes and activities. As a result, a quantitative relationship often exists that can 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 (Conrow, 2009; Malone et al., 2011; Smoker & Smith, 2007).

The graduated SH category levels[4] were converted into ordinal values 1 through 5 and named **System Hierarchy Rank** for model development and testing as follows:

1. Hardware/Software/Material End Item
2. Component
3. Assembly
4. Subsystem
5. System

[4] Numbering is reversed from NASAs numbering shown in Appendix A to allow for progressive ordinal response.

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TRL Levels – Background. TRL levels were conceived at NASA in 1974 and formally defined in 1989. Mankins (1995) described the current nine-level system for the maturity of a technology based upon qualitative criteria of capabilities and the achievement or demonstration of related key milestones (see Appendix A). The Government Accounting Office (GAO) (1999) subsequently encouraged the application of TRLs by the Department of Defense (DoD) to have a systematic method for assessing technology maturity and recommended that a minimum of TRL level 7 be achieved before committing to the development and production of weapons systems (GAO, 1999). DoD (2009) adapted the NASA TRL level definitions for military acquisitions (Director, Defense Research and Engineering [DDR&E], 2009), and other federal agencies have also adopted the use of TRL metrics for managing new technology development and acquisitions including the Department of Homeland Security (DHS) (Homeland Security Institute (HSI), 2009) and the Department of Energy (DOE) (Sanchez, 2011). The GAO also subsequently developed a Technology Readiness Assessment Guide (Aug. 2016) that contains best practices for evaluating the technology readiness in acquisition programs and projects (Persons & Sullivan, 2016).

Metrics associated with project TRL Start to End levels are sometimes referred to as "TRL Transition" metrics. Empirical research and studies applying TRL metrics for cost and schedule have been relatively sparse, with somewhat inconsistent results. Models have generally been based upon small and often selective data sets for narrow technology areas, resulting in relatively weak data relationships. Of these, some studies have developed relative measures of cost or schedule like cost growth, relative transition cost, schedule slippage probability growth, et al. These models, therefore, usually require a baseline estimate or actual project history, such as early program TRL transition cost or schedule experience, to apply. Even fewer studies have produced absolute measures of cost or schedule necessary to provide estimate forecasts normally required for project approval prior to start up.

Macro level predictor variables like TRL and SH related metrics do not replace the fidelity available through a more detailed analysis using traditional design, performance, and complexity related cost and schedule drivers. They can however be effective proxies to capture the broad impact of those direct relationships when detailed level metrics are not available. SH levels largely address scale and complexity related development factors while the progression of TRL levels embodies more the maturity of a technology. Individually, TRL and SH parameters do not *directly* explain all cost or schedule variability; however, when modeling at the total development cost or duration level, they are effectively assigned and reflect the aggregate range and variability found in the dependent response variable. Underlying engineering design characteristics, performance parameters, and complexity factors that drive cost and schedule at lower subsystem or unit/assembly levels can therefore be reflected in models applying macro level variables, albeit in more indirect means. Multivariate modeling applying a combination of macro variables may also add predictive value if they possess complimentary causal relationships that do not overlap significantly as evidenced by the presence of substantial multicollinearity.

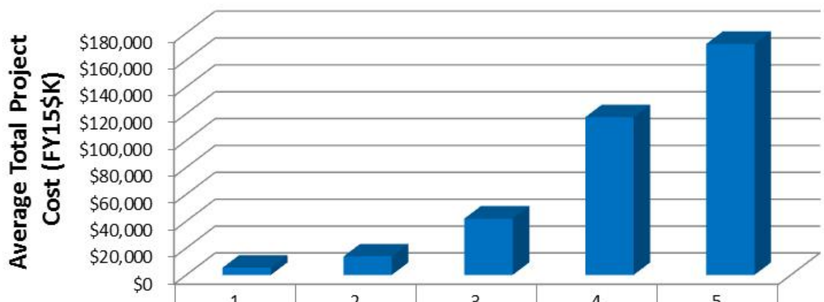
Preliminary Data Relationship Screening. Unlike SH levels that are straightforward, there are 36 possible Project Start and End TRL (i.e., TRL X-Y) combination pairings for TRLs one to nine[5]. Even though the overall TCASE data set is relatively large, in parsing the sample into 36 combinations,

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

only a few categories contain enough observations (i.e., individual projects) to effectively be considered "large" or "significant" sample sizes. Curve fits of TRL X-Y transitions for both cost and schedule also produced inconsistent results (Appendix B). Therefore, to provide a more complete solution and extend the analysis to leverage the available TRL transition category experience in the database, another method was necessary. Aggregating the TRL project information into larger, more robust data sets was an approach that could be accomplished by applying a parameter to capture the overall TRL level increase from project start to end. This measure, named **TRL Improvement (TI) Level** (sometimes referred to as TRL Transition Order[6]), was selected for evaluation. The TCASE database provided enough project data to evaluate the breadth of TI level experience (i.e., levels 1 through 5).[7] See Appendix B for more on the application of TI level as a predictor variable.

To perform an initial evaluation of possible associations between selected dependent and independent variables, scatterplots, correlation / summary statistics, and ordinal level cost and schedule metrics & charts were first assessed. These initial screening results are presented in Appendix B for both cost and schedule parameters. Summary statistic plots extracted from that analyses are presented below in Figures 2 through 5 in order to provide a general understanding of the relationships between the various predictor-response variables. See Appendix B for a more in-depth discussion of the preliminary data relationship analyses.

Cost Forecast Models. The direct nature of the cost to TI level relationship is evident from a columnar chart of the average total project costs by level (Figures 2). Cost growth appears to be relatively nonlinear with approximately 3x growth between successive TI levels 1 to 4 and tapering off somewhat at level 5.



	1	2	3	4	5
Mean (FY15$K)	$5,385	$13,716	$41,949	$117,418	$171,881

Figure 2: Average Total Project Costs vs. TRL Improvement Level

A chart of average total project costs by SH level (Figure 3) also demonstrates the progressive nature of cost, yet with more gradual growth at lower tiers and a dramatic, nearly order of magnitude increase at the System tier (level 5). This suggests a nonlinear, possibly exponential relationship of project cost to SH with relatively moderate impact up until reaching the system level

[6] For example a TRL Improvement level of 2 is also known as a 2nd order transition, a TI level of 3 a 3rd order transition, etc.
[7] Only a few records with TI above level 5 were found. Large TI progressions > five in a single project therefore appears to be rare as part of one project / effort; however they may also be modeled by integrating lower level TI steps in series.

(i.e., level 5). As with TRL related metrics, since SH is an ordinal variable, this steep cost surge could be attributable to various nonlinear quantitative or qualitative factors. For instance, the number of major subsystems found within a system as well as other effects like the integration, testing, demonstration, and communications activities that can escalate and compound significantly at higher levels of complex systems, could drive this substantial growth.

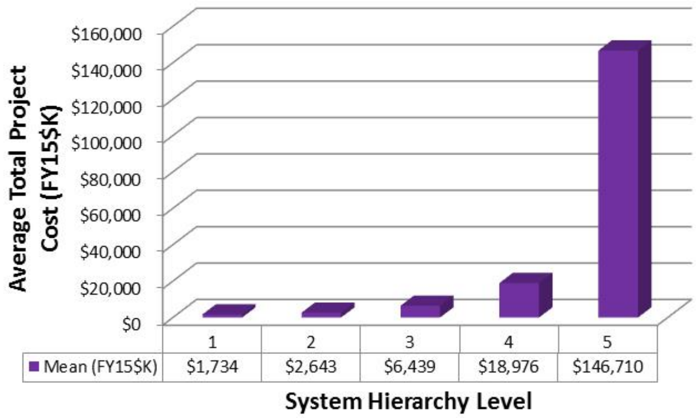


Figure 3: Average Total Project Costs vs. System Hierarchy Level

Based upon initial results, various cost models were formulated and tested in univariate and multivariate forms as a function of these two key parameters: *Total Project Cost = f {TRL Improvement, System Hierarchy, constant term}.*

Schedule Forecast Models. For schedule forecast models, preliminary assessments were performed looking at strength of possible data relationships to the **Project Duration (months)** response variable, developed as a data field for analysis. Similar to cost and SH level, the columnar chart in Figure 4 suggests that the mean project duration may also possess a direct functional relationship with SH level.

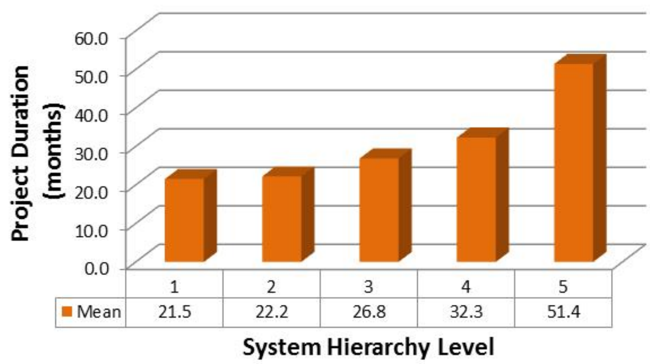


Figure 4: Average Project Duration vs. System Hierarchy Level

Finally, to assess a relationship between TI level and schedule, a columnar chart of average Project Duration by TI level is shown in Figure 5. Unlike SH level, a continuous functional association with the TI level is not indicated, peaking and then tailing off at level 3.

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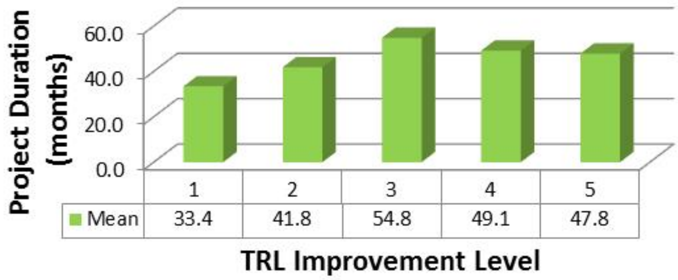

Figure 5: Average Project Duration vs. TRL Improvement Level

Despite the lack of strong initial results, various schedule models were developed to more thoroughly assess Project Duration. The Project **Spend Rate** (average $/mo.) variable, described in Appendix B, was also crafted specifically to enhance the project duration analysis. Univariate and multivariate forms of the three predictor variables were again applied: *Project Duration (months) = f {TRL Improvement level, System Hierarchy level, Spend Rate, constant term}.*

Data Set Construction: TCASE records were evaluated for analysis based upon several factors in the database. This involved filtering and removal of records containing estimated costs (vs. actual[8] historical costs) and blank or zero data field values. Three primary data sets emerged, centered on records with populated fields for the targeted independent variables. These data sets were used in the analysis of both cost and schedule models.[9]

- System Hierarchy levels 1 to 5 record set: available observation count = 603 for cost models and 551 for schedule models;
- TRL Improvement levels 1 to 5 record set: available observation count = 405 for cost models and 395 for schedule models, (*Note: Only a few records above TI level 5 were found, and therefore too sparse to evaluate*); and
- Combined SH and TI level record set (for multivariate models): available observation count = 221 for cost and schedule models;

It is noted that all project outcomes may not be captured within the available data set, including cancelled or non-productive projects (i.e., ones that did not improve TRL levels) with associated sunk costs for project failures. Over one-third of the total available project records showed no TRL improvement. It is not clear if this includes *all* terminated, failed, or unsuccessful projects during the source data period, but this percentage rate suggests that a significant amount, if not most of the projects initiated were included. To factor the expected costs of project cancellation or failure effectively, probability-based outcomes and related costs would need to be added to the forecasted cost of each project. Since these costs are probability based, similar to certain contingency or opportunity costs, they can be somewhat subjective in terms of interpretation and allocation. For singular development efforts, they are also only realized or incurred if the project is actually terminated and not a direct cost for successful projects. Consequently, most individual project cost models do not consider expected termination or failure costs, and they are not factored into

[8] Defined in NASA TCASE tool as data collected from realized, historical technology development projects.
[9] Note – not all records for each data set had available project start or end dates so total number of available records for schedule duration modeling were slightly less.

models presented here. They are however well suited for broader risk analysis or multiple program portfolio investment planning and may be a good topic for further study.

Core Model Development: In order to provide a diversity of perspectives for cost and schedule estimating, a variety of modeling techniques were examined. This approach explores the range of relationship types and uncertainty expected across the response variables as well as potential interval variance between predictor categorical levels. Several applicable modeling forms were investigated and assessed for their overall performance including:

1. Tailored curve fit models
2. Simple regression models
    a. Single predictor
    b. Composite variable (i.e., product of predictor variable terms)
    c. Transformed independent variable (single or composite variable transformations)
3. Multiple regression models
    a. Multiple predictor
    b. Transformed multiple predictor variables
4. Range of nonlinear (NL) models

TI- and SH-based Probability Density Function (PDF) cost curve fit models were first produced. To create these curve fits, the range of dependent variable sample data values across each predictor category / level were "fit" to a library of possible probability-based distribution functions using a distribution fitting utility and standard fit measurement techniques. These functions (or families of functions) included Beta, Chi-square, Erlang, Exponential, Gamma, Inverse Gaussian, Levy, LogLogistic, Lognorm, Pareto, Pearson, Program Evaluation and Review Technique (PERT), Raleigh, Triangular, Uniform, and Weibull. The distribution fit utility was applied initially 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)

Functions or curves with best results across these techniques were finally selected considering key statistical metrics vs the sample data such as fit of the estimate mean, a commonly applied budget and planning forecast range between the 50^{th} (i.e., median) and 80^{th} percentile, the standard deviation, and distribution shape characteristics (kurtosis, skewness, etc.).

Univariate and multivariate linear regression model forms were then developed. Linear model forms may seem contrary to the non-linear behavior exhibited between predictor and response variables in the initial data relationship screening. However the regression engine for the statistical analysis tool used (i.e., SAS JMP) codes and interprets ordinal predictor variables differently than continuous or nominal factors. Parameter estimates use indicator variables based upon the response *differences* between the ordinal tiers in development of least square functions, making "non-linear" output for variable intervals possible across the ordinal range.

In addition, various non-linear data transformations were also explored for both predictor and response variables to identify potential cost and schedule relationships. For every regression model form, up to 11 data transformation types were evaluated for each independent predictor and dependent response variable combination. These transformations included log, square, square root, exponential, reciprocal, logistic, and other data conversions. For both cost and schedule models, composite forms created by merging predictor variables into a single product variable (i.e., TI level x SH level) were also considered. Multiple regression cost and schedule models similarly examined a combination of TI and SH level predictor variables with transformations, yielding expressions with coefficients for each ordinal level. Finally, NL models were investigated, assessing up to 21 different forms for each predictor variable including various polynomial, sigmoid and logistic curves, exponential and peak models.

Preliminary analysis of both cost and schedule models investigated numerous candidates across the range of modeling techniques. For cost modeling alone, a broad field of well beyond 100 initial model candidates was explored from which approximately 40 different variants demonstrated some strength of association to cost. This field was further narrowed to approximately a dozen viable models, delivering the best overall performance across the range of model forms. Similarly, schedule models were developed and assessed using the range of curve fit regression and NL forms. As with cost modeling, a variety of data transformations, composites, and variants were examined.

Modeling Uncertainty: Once final model solutions were selected, uncertainty was applied to produce risk-adjusted estimates, and models assessed for overall fit. This was intended to help convey an understanding of cost risk across the possible range of model output. Since uncertainty is inherently built into curve fits, the actual sample data PDFs provide a perspective of expected ranges around predictor variable levels for both project cost and duration.

For the linear regression and nonlinear cost modeling techniques, to develop risk-adjusted estimates around response variable functions, commonly applied cost uncertainty probability distribution functions were investigated. This included an evaluation of normal, lognormal, PERT, and triangular forms where the underlying inputs necessary to drive those functions (e.g., sample mean, min, max, mode, standard deviation, etc.) were also more readily available. PERT and Lognormal functions were considered superior to normal curves since they more closely replicated the right skewed actual sample data distributions than the symmetrical normal distribution.[10] Lognormal and PERT functions also delivered more natural, continuous distributions within a relevant planning range[11] and less of a tendency to overemphasize the direction of skew than with non-continuous triangular distributions.

The Lognormal function was higher performing across ordinal curve fits and also closely resembled the other high performing Gamma and LogLogistic functions as shown in Section 5 (Table 2).

[10] See Section 5 and Appendices B, C, and D for some sample data distributions, resulting curve fits and discussion of right-skewed uncertainty distributions common to cost and schedule estimating.
[11] A normal planning range for investment or budgeting decisions generally falls within the 50th to 80th percentile, depending upon factors such as the expected level of overall risk.

Therefore, Lognormal PDFs correlated well with the right-skewed sample data and this function was selected to develop model uncertainty distributions for the linear and nonlinear models.

4 Model Selection Criteria - Measures of Performance

Overall model performance was evaluated based upon "best fit" type characteristics including:

1) A comprehensive list of statistical key performance measures (KPMs) provided below;
2) Additional measures tailored or relevant to the particular model form (e.g., curve fit goodness-of-fit statistical methods), and;
3) An overall assessment of the fit of the predicted model to the sample data using statistical benchmark metrics and methods previously mentioned. [12]

Statistical metrics were assessed at predictor variable ordinal levels when possible (vs at the aggregate model level) whenever that afforded greater fidelity for any measure.

The list of available KPMs applied for initial model screening includes the following:

- Error Variability and Dispersion Measures:
  - Coefficient of Determination - R^2 and Adjusted R^2
  - Root Mean Square Error (RMSE)
  - Coefficient of Variation (CV)
- Statistical Significance Measures:
  - F-ratio
  - t-stat (% of model terms with probability > |t|)
- Autocorrelation Measure:
  - Durbin-Watson test
- Data Reduction Measure:
  - Percent (%) of original data sample set unused

Detailed descriptions of these statistical measures are provided in Appendix E.

KPMs plus other performance measures applicable to or available for each particular model form were applied for overall performance assessment. For instance, several of the regression related performance categories do not apply or are not available for the curve fit or nonlinear models. Curve fit models were assessed based upon the five goodness-of-fit methods / techniques previously introduced (i.e., AIC, BIC, K-S, A-D, and Chi-Sq), applicable KPMs (RMSE, CV, and % Data Reduction metric) along with the key data statistics described above. For nonlinear models, available KPMs (R^2, Adjusted R^2, RMSE, CV, and % Data Reduction) as well as the key data statistics were used to gauge the closeness of fit. Multicollinearity was also evaluated for multivariate model forms using the variance inflation factor (VIF).

5 Cost Model Performance

Overall Results. A cross section of the higher performing cost models for each type, based upon just the assessed KPM category ratings is shown in Table 1. This includes two curve fit model series (TI and SH), four simple regression models (2 TI and 2 SH), three multivariate models, and four

[12] These metrics include fit of the predicted vs sample data values for the mean, a commonly applied budget and planning forecast range of the 50th (i.e., median) to 80th percentile, the standard deviation, distribution shape characteristics (kurtosis, skewness, etc.), and graphical methods such as plots of residuals and model forecasts vs actual sample data.

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nonlinear (2 TI and 2 SH based). Color coded ratings are notional and simply intended to assist with relative model comparison. Closeness of fit to the source data and other applicable statistical techniques were also applied to judge model performance. The resulting cost models produced progressive cost variable responses with largely favorable performance statistics. In general, costs increased steadily across predictor variable levels and were amplified significantly at the System level (SH 5) and higher TI levels (4 to 5). Intuitively this makes sense as critical scale and complexity factors, along with related process and resource impacts (e.g., technical, functional, organizational), can magnify or compound dramatically at the higher tiers. For System level technology developments, it appears essential to apply SH level variable models but much less important below level five, based upon relationship screening (Appendix B) and the detailed results in models below.

Table 1: Cost Model KPM Results [13, 14, 15]

Mdl. No.	Model Form / Method	Predictor Variable Form	Reference Model Name	Key Performance Measures (KPM)								
				R-Sq	Adj R-Sq	RMSE (000's)	Coef. of Variation (CV)	F-ratio	Prob. > F	t-stat: % of terms w/ Prob. > |t|	Durbin-Watson Stat	Data Reduction (%)
1	Tailored Curve Fits	TI Level	TI Curve Fits	N/A	N/A	40,929	0.736	N/A	N/A	N/A	N/A	2.5%
2	Tailored Curve Fits	SH Level	SH Curve Fits	N/A	N/A	26,724	0.711	N/A	N/A	N/A	N/A	3.2%
3	Simple Linear Regression	TI Level	TI Reg1	0.401	0.395	46,026	2.344	63.7	<.0001*	75%	1.519	4.9%
4	Simple Linear Regression	TI Level	TI Reg2	0.302	0.295	46,428	2.415	42.5	<.0001*	50%	0.767	1.7%
5	Simple Linear Regression	SH Level	SH Reg1	0.935	0.934	2,590	1.249	1893.2	<.0001*	75%	0.896	11.8%
6	Simple Linear Regression	SH Level	SH Reg2	0.659	0.657	29,132	2.486	280.8	<.0001*	50%	1.275	3.5%
7	Composite Linear Regression	$[TI \times SH]^2$	TIxSH Sqrd7	0.772	0.771	38,324	1.526	719.5	<.0001*	100%	1.433	3.6%
8	Multiple Linear Regression	TI + SH	TI+SH Reg14	0.823	0.816	33,397	1.226	116.7	<.0001*	100%	1.757	5.0%
9	Multiple Linear Regression	$[TI + SH]^2$	TI+SH Sqrd Reg15	0.788	0.780	2,621	0.617	90.4	<.0001*	50%	1.208	8.1%
10	Nonlinear - Quadratic	NL TI Level	TI NL Quad	0.610	0.609	32,685	1.606	N/A	N/A	N/A	N/A	15.3%
12	Nonlinear - Exponential 3P	NL SH Level	SH NL Exp 3P	0.744	0.743	24,966	2.070	N/A	N/A	N/A	N/A	11.3%
13	Nonlinear - Gompertz 4P	NL SH Level	SH NL Gpertz 4P	0.742	0.742	25,061	2.078	N/A	N/A	N/A	N/A	11.3%

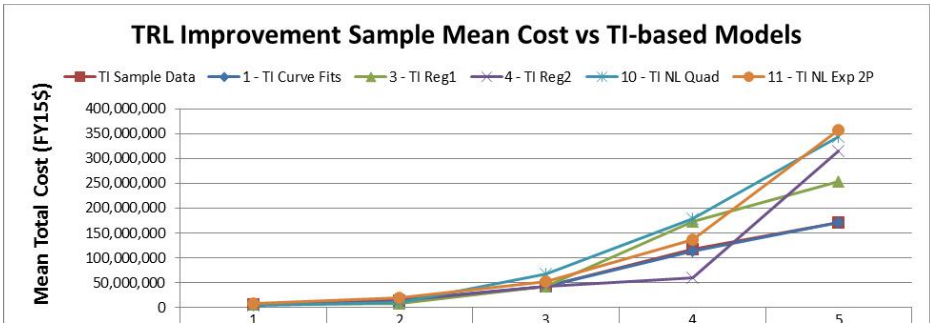
PERFORMANCE RATING			
Good	Fair	Marginal	Poor

Multivariate regression models (nos. 7, 8, and 9) performed best from KPMs alone. However, curve fit models (nos. 1 and 2) most tightly replicate the underlying sample data central values as illustrated in the plots in Figures 6 and 7. This curve fit model tracking substantially closer to the sample data than the univariate linear and nonlinear models may be due to the fact that curve fits are individually tailored to each predictor ordinal variable level. Curve fit models essentially neutralize the issue of interval ordinal scale variability, since each level is discretely modeled to align more directly with actual sample data uncertainty distributions. Linear regression and non-liner models generally employ more of a "one function fits all" approach. However, statistical regression engines also mitigate this concern by the method with which they handle predictor ordinal values as discussed under the Core Model Development section.

13 The custom TRL Start-End curve fit models discussed in Appendix B are an incomplete set of 14 of the 36 TRL X-Y transition categories. They are also based upon more limited sample sizes, producing inconsistent results and were therefore not presented as viable model solutions in Table 1.

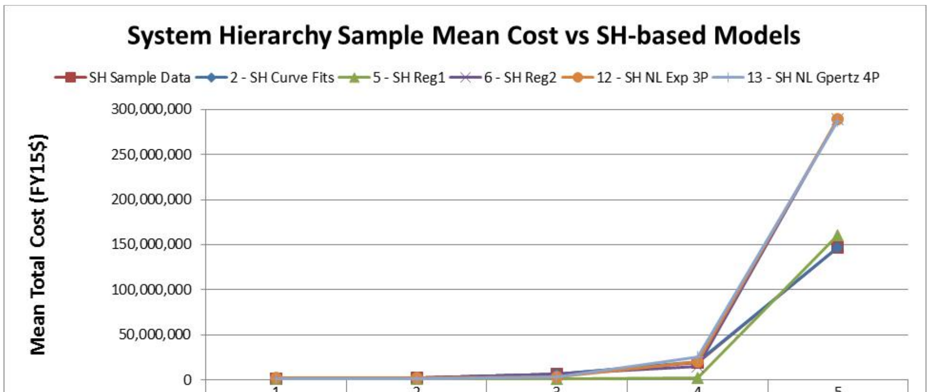
14 From initial analysis, the TI-based linear regression models (nos. 3 & 4) non-linear TI NL Model no. 11 (Exponential 2P) and were eliminated from further consideration due to poor KPM results.

15 In addition to KPMs, performance measures relevant to each model form, were also assessed. KPM categories that do not apply, cannot be generated or are not available to a particular model form are shown as N/A for not applicable.



	1	2	3	4	5
TI Sample Data	5,385,091	13,715,880	41,948,963	117,418,045	171,881,182
1 - TI Curve Fits	6,098,593	14,886,701	41,949,255	113,853,889	171,879,982
3 - TI Reg1	5,385,091	8,989,340	41,948,963	173,522,584	254,272,144
4 - TI Reg2	5,385,091	13,715,880	41,948,963	59,337,393	314,353,878
10 - TI NL Quad	4,331,991	9,551,810	67,957,831	179,550,054	344,328,479
11 - TI NL Exp 2P	7,552,009	19,819,678	52,015,246	136,510,080	358,260,387

Figure 6: TRL Improvement Sample Mean Cost vs. TI-based Models



	1	2	3	4	5
SH Sample Data	1,734,327	2,643,491	6,439,009	18,976,157	146,709,842
2 - SH Curve Fits	1,508,290	2,320,795	6,439,009	20,461,546	146,709,271
5 - SH Reg1	880,979	976,748	1,704,188	2,624,109	160,808,463
6 - SH Reg2	1,734,328	2,613,621	6,244,922	14,965,793	288,867,732
12 - SH NL Exp 3P	2,372,496	2,434,288	3,443,119	19,913,385	288,808,534
13 - SH NL Gpertz 4P	1,354,510	1,508,967	3,349,633	25,284,800	286,685,634

Figure 7: System Hierarchy Sample Mean Cost vs. SH-based Models

Response variable output for the all final cost models, including the multivariate forms, are provided in Appendix F. This includes key data benchmarks, regression results, functional prediction expressions, and uncertainty functions with corresponding PDF graphs.

Curve Fit Cost Models. The best performing cost curve fit functions with key output statistics for both the five TI and five SH levels are provided in Table 2. Curve fit plots for sample data at each ordinal level were developed and probability distributions for the highest performing functions selected for both TI and SH model forms, are provided in Appendix F. Two examples of these curve fit plots along with PDF and cumulative probability distributions (CPD) for the selected functions are presented in Figure 8 for TI level 1 and Figure 9 for SH level 1. The cost curve fit model output demonstrate progressive cost growth across predictor tiers with the Weibull, BetaGeneral, Exponential, Pearson6, Levy, Inverse Gaussian, and Raleigh functions generally producing good results. The three function types most commonly generating the best fits across both SH and TI predictor variables however, as shown in Table 2, were the Lognormal, LogLogistic, and Gamma distributions.

Table 2: Summary Cost (FY15$) Curve Fit Model Statistics

Predictor Level / Tier	Mean	Median	60th %ile	80st %ile	Curve Function Type
TRL Improvement Level					
TRL Improvement 1	6,098,593	1,352,186	2,098,994	5,827,153	Lognorm
TRL Improvement 2	14,886,701	2,937,018	4,636,000	13,379,843	Lognorm
TRL Improvement 3	41,949,255	17,585,237	28,194,724	68,557,068	Gamma
TRL Improvement 4	113,853,889	30,765,241	49,013,531	144,529,122	Lognorm
TRL Improvement 5	171,879,982	87,024,759	130,289,167	283,256,614	Gamma
Hierarchy Level					
Hardware / Software / Mat'l.	1,508,290	356,516	492,737	1,077,888	LogLogistic
Component / Part	2,320,795	427,230	600,295	1,366,661	LogLogistic
Assembly	6,439,009	855,392	1,308,794	3,661,668	LogLogistic
Subsystem	20,461,546	2,327,053	3,946,668	13,457,236	Lognorm
System	146,709,271	42,205,134	77,094,954	230,367,198	Gamma

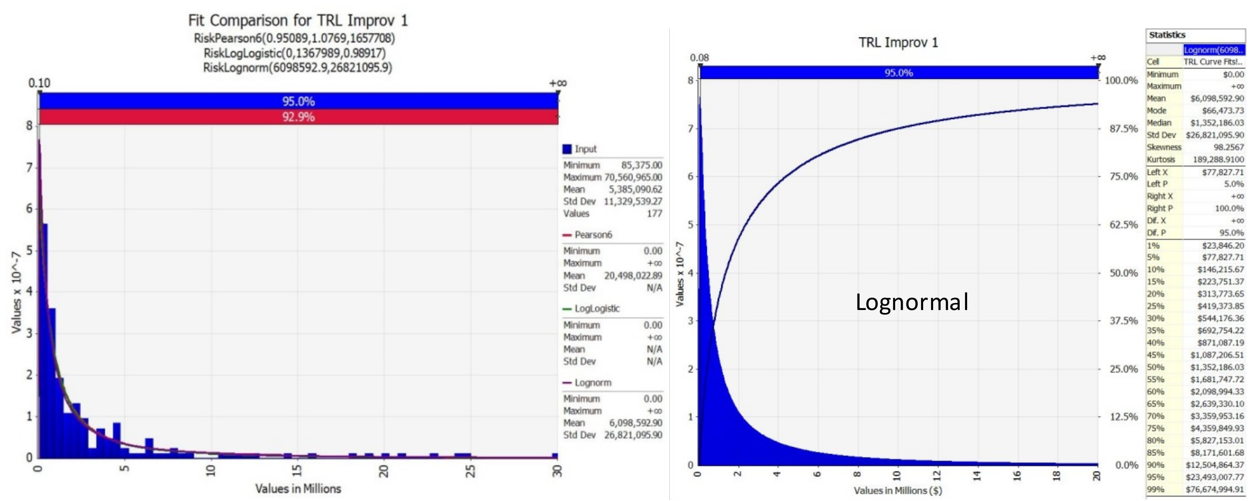


Figure 8: Example TI Cost Curve Fit Model PDF - Cost (FY15$) for TRL Improvement Level 1

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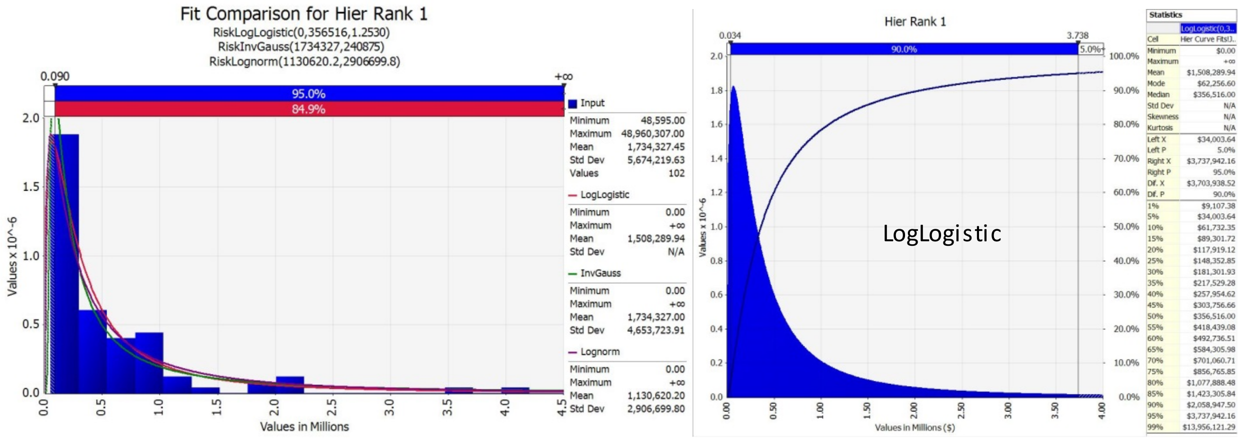


Figure 9: Example SH Cost Curve Fit Model PDF - Cost (FY15$) for System Hierarchy Level 1

Simple Linear Regression Cost Models. Simple linear regression models for the SH predictor variable (model nos. 5 & 6) produced consistent results with moderate statistical significance, but TI forms (model nos. 3 & 4) resulted in low R^2 values and were discarded. Two example uncertainty PDF plots along with CPDs for the SH Regression Models (SH level 1 for Model no. 5 and SH level 2 for Model no. 6) from Appendix F are shown in Figure 10.

Cost Model No. 5: System Hierarchy Rank 1 **Cost Model No. 6: System Hierarchy Rank 2**

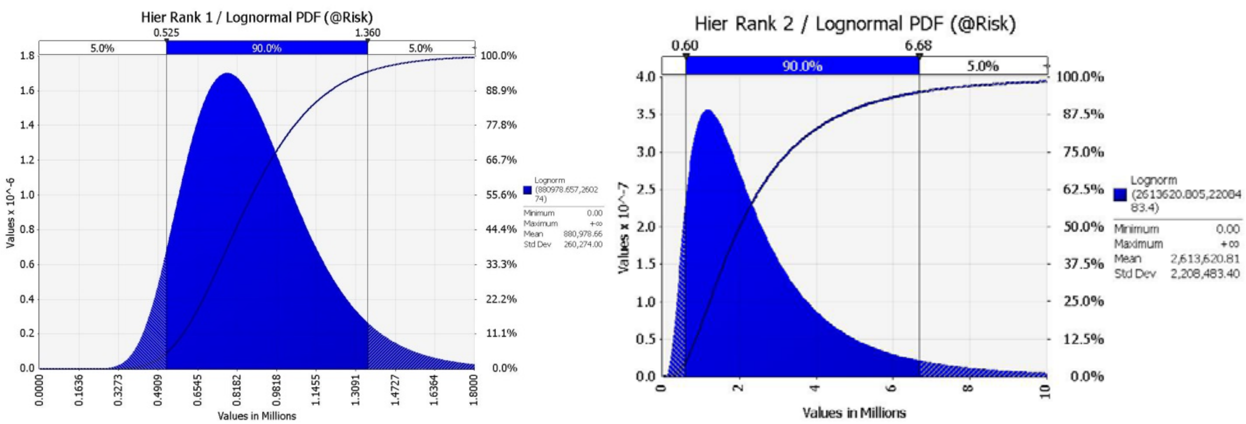
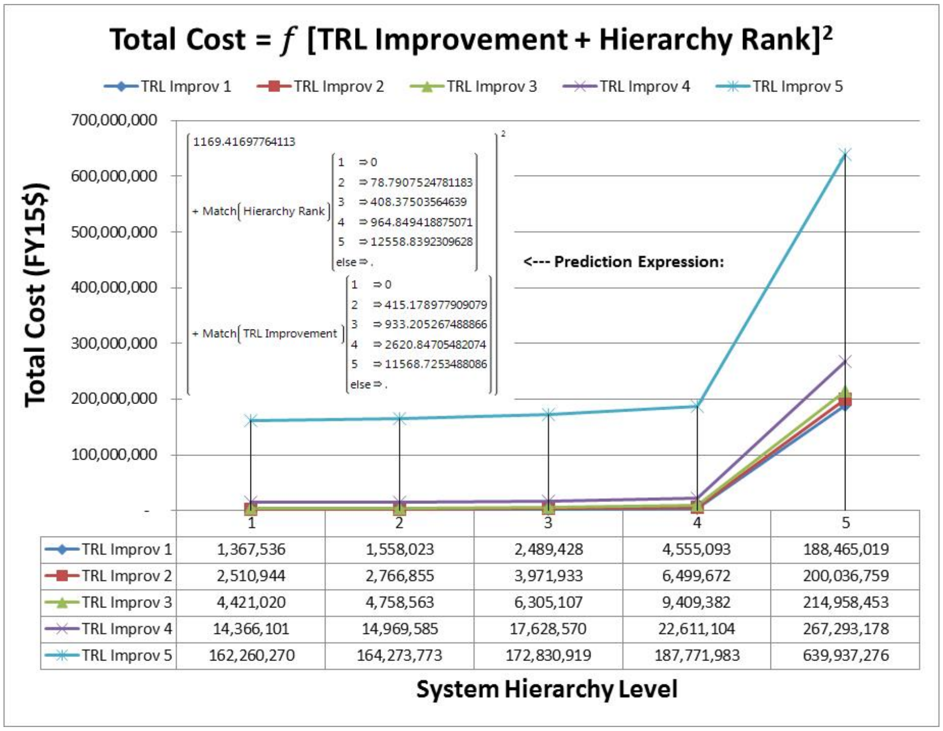


Figure 10: Example Linear Regression Model PDFs

Multivariate Linear Regression Cost Models. Multivariate linear regression cost models containing both TI and SH variables include composite linear regression model no. 7, of the form [TI level x SH level]^2 as well as two multiple regression models (nos. 8 & 9). These models exhibited progressive results across predictor levels and produced generally higher KPM performance. Output for Model No. 9, following the function, $f \alpha$ [TI level + SH level]^2, is presented in Figure 11. Model No. 8 is a more straightforward linear function of the two variables [TI level + SH level] and all three are detailed in Appendix F. Multivariate models performed well across KPM categories relative to other model forms. A smaller data set of 221 available observations were available however, that are spread across the twenty-five, 5 x 5 TI & SH level categories making sample sizes rather limited in some categories. Greater predictive power applying two variables related primarily to scalar and technical maturity dimensions, may help boost performance despite the smaller project data set. VIFs in the 1.1 to 1.8 range also indicate negligible multicollinearity reflecting a desired lack of correlation between the independent TI- and SH-level variables.

Parametric Cost and Schedule Modeling for Early Technology Development



	1	2	3	4	5
TRL Improv 1	1,367,536	1,558,023	2,489,428	4,555,093	188,465,019
TRL Improv 2	2,510,944	2,766,855	3,971,933	6,499,672	200,036,759
TRL Improv 3	4,421,020	4,758,563	6,305,107	9,409,382	214,958,453
TRL Improv 4	14,366,101	14,969,585	17,628,570	22,611,104	267,293,178
TRL Improv 5	162,260,270	164,273,773	172,830,919	187,771,983	639,937,276

Figure 11: Model No. 9 - Total Cost vs. *f* [TRL Improvement + Hierarchy Level]^2

Comparing coefficient values across the same TI and SH ordinal levels (1-5) in both models 8 & 9, it appears TI level is significantly more important than SH level below level 5. This suggests that SH level variables may not significantly augment explanation of response variable behavior or boost overall model performance below the System level (SH level 5). In situations where both TI and SH project inputs are known or available however, application of multivariate models may still be preferable since they apply more causal information in generating a forecast. [16]

Nonlinear Cost Models. Nonlinear cost models produced responses with desirable error variability measures and tracked fairly well to actual data at the lower TI and SH levels, but at the expense of considerable data reduction. The Newton-Raphson optimization method was applied for fitting nonlinear functions. As expected, these models resulted in significant escalation at the highest TI and SH tiers. This was demonstrated in Figures 6 and 7, where substantial geometric progression produced a divergence from the sample data at both TI and SH level 5. The best fits for nonlinear TI cost models arose from Quadratic, Mechanized Growth, and Exponential 2 Parameter (2P) fitted models. Best fits for the nonlinear SH cost models were generated by Exponential 3 Parameter (3P) and Gompertz 4 Parameter (4P) functional forms. A plot of SH NL models is presented in Figure 12 and an example uncertainty PDF / CPD graph for SH level 1 of SH Model 12 is provided as in Figure 13. TI NL model no. 11 was eliminated due to poor KPM results. Detailed TI and SH NL cost model results with all ordinal level PDFs are provided in Appendix F.

[16] Uncertainty PDFs for the 25 (5 x 5) TI & SH Level category combinations for each of multivariate models 7, 8 and 9 are too numerous to present in Appendix F but are available upon request.

Model Comparison

Model		AICc	AICc Weight	BIC	SSE	MSE	RMSE	R-Square
Exponential 3P		19748.669	0.9262116	19765.723	3.316e+17	6.233e+14	24966011	0.7436299
Gompertz 4P		19753.763	0.0725263	19775.061	3.335e+17	6.281e+14	25060990	0.7421611
Logistic 3P		19761.866	0.001262	19778.919	3.399e+17	6.389e+14	25275833	0.7372274

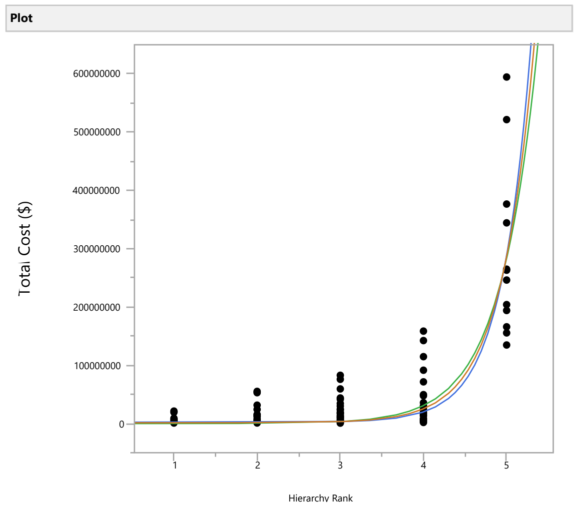


Figure 12: SH Nonlinear Model Statistics Data Table and Plot

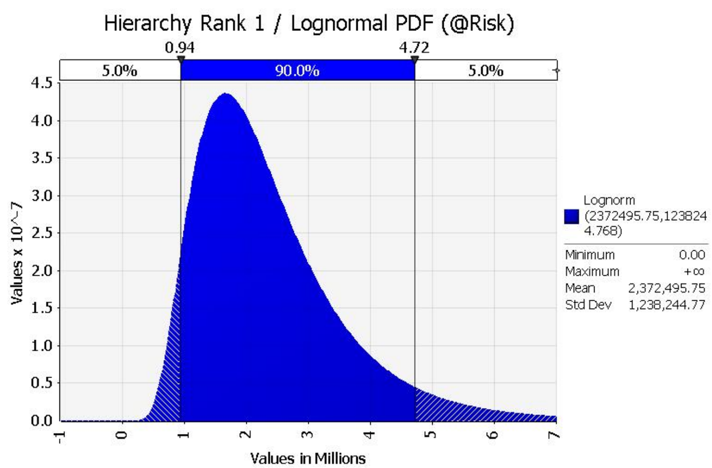


Figure 13: Cost Model No. 12 – SH level 1 Example

6 Schedule Model Performance

The same forms were developed and assessed for schedule-based modeling, as discussed in Appendices B & D. Schedule did not result in the same strength of relationship with the independent predictor variables as experienced with cost. Schedule curve fits produced the key TI and SH benchmark statistics are presented in Table 3. The SH based curve fits exhibited consistent cost growth across levels with best results coming from the Raleigh, Erlang, Pearson5, Weibull, and Inverse Gaussian distributions. An example sample input profile with curve fit plots and the selected function PDF/CPD for SH level 2 is also shown in Figure 14. See Appendix G for the complete set of SH schedule curve fit functions. SH curve fit model output is compared to the sample mean and median in Figure 15, with the mean plots approaching nearly an exact overlay of the sample data.

Parametric Cost and Schedule Modeling for Early Technology Development

Table 3: Summary Schedule Duration (months) Curve Fit Model - Key Benchmark Data

Predictor Level / Tier	Number of Observations	Mean	Median	60th %ile	80th %ile	Curve Function Type
TRL Improvement Level						
TRL Improvement 1	176	33.5	31.5	36.2	48.0	Rayleigh
TRL Improvement 2	133	41.1	38.6	44.4	58.8	Rayleigh
TRL Improvement 3	59	54.1	50.9	58.5	77.5	Rayleigh
TRL Improvement 4	21	49.1	45.5	51.4	67.0	Gamma
TRL Improvement 5	6	43.2	37.2	41.9	56.1	LogLogistic
	395	**0.0%**	**Data Reduction**			
System Hierarchy Level						
Hardware / Software / Mat'l.	98	21.8	17.8	20.4	28.5	Pearson5
Component / Part	169	22.5	19.7	23.6	34.0	Weibull
Assembly	173	26.8	20.0	24.4	38.6	InvGauss
Subsystem	86	32.3	27.1	32.7	48.3	Erlang
System	25	51.4	43.1	52.0	77.0	Erlang
	551	**0.0%**	**Data Reduction**			

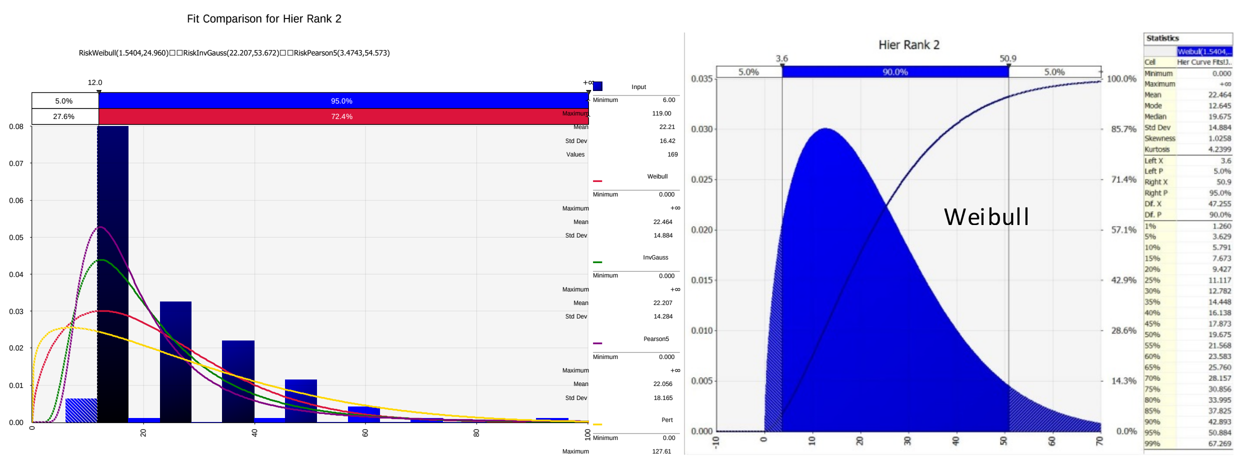


Figure 14: Example Schedule Curve Fits & Selected PDF - Project Duration (months) for System Hierarchy Level 2

	1	2	3	4	5
Sample Mean	21.5	22.2	26.8	32.3	51.4
SH Fit Mean	21.8	22.5	26.8	32.3	51.4
Sample Median	12.0	12.0	18.0	24.0	39.0
SH Fit Median	17.8	19.7	20.0	27.1	43.1

System Hierarchy Level

Figure 15: Schedule Duration (months) Curve Fit – System Hierarchy Summary Chart

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Similar to TRL X-Y cost models, only fourteen of the possible 36 TRL X-Y schedule curve fits contained minimum samples sizes, producing inconsistent results (see Appendix D). TI level-based schedule models however produced much weaker results than with cost. They experienced value degeneration at the higher category levels as demonstrated in Tables 4 & 10with data inversions at TI levels 4 & 5. The project Spend Rate predictor variable discussed earlier was introduced to supplement the analysis and help address this concern. This variable however did not solve the ordinal level inconstancies or boost performance appreciably when included with either the TRL or Hierarchy-based variables. This parameter may also be difficult to provide as an input unless investment budgets have already been established for a particular technology development. There was no clear or discernable affiliation with Schedule and TI levels for any of the model forms, and no strong results for SH was found using linear regression and nonlinear forms. Consequently, the only workable solution found for the schedule models was the SH-based curve fits in Appendix G.

Applicable KPM results for the SH tailored curve fit model (Schedule Model No. 1) are presented in Table 4. The much weaker performance in general for schedule models may be partly due to schedule often driven or constrained by the availability of limited resources and less strictly tied to technical or scaling related factors. The SH schedule curve fits nonetheless appear to contain useful predictability when compared to actual sample data and this area merits further study.

Table 4: Schedule Duration (months) Curve fit Model KPM Results

Model No.	Fit Model Type	Single / Multiple Predictor Variable(s)	Predictor Type	Reference Model Name	Predictor Variable(s)	Key Performance Measures (KPM)				
						RMSE (months)	Coef. of Variation (CV)	No. of Available Obs.	No. of Applied Obs.	Data Reduction (%)
1	Tailored Curve Fits	Single	System Hierarchy Level	Hier Curve Fits	Hierarchy Rank	20	0.755	551	551	0.0%

PERFORMANCE RATING			
Good	Fair	Marginal	Poor

7 Cost and Schedule Model Variability

Overall model output and performance variability can largely be linked to a few primary sources. Many of these factors relate to common data and analysis constraints that are often uncontrollable by researchers or analysts. Relatively significant RMSE, CV and standard deviation statistics for many of the cost models reflect the collective impact of these factors. This uncertainty is expected and appropriate however for early stage technology development and is reflected in the various associated uncertainty distributions.

1) **Source Data Characteristics**. Overall project data set sample sizes are generally good, exceeding several hundred observations; however, there are limited sample sizes for some of the higher ordinal levels. There is also some uncharacteristic or unexpected behavior in the underlying project source data. The large number of smaller projects across predictor variable levels, discovered in the screening process described in Appendix B, appears to be a primary driver of this variation, "dampening" progressive cost and schedule functions. There may be valid underlying reasons for this phenomenon explaining the behavior but in order to make a determination, a deeper investigation into the source data would need to be performed.

2) **Quantitative Measurement and Data Normalization**. Projects may sometimes involve multiple technologies or be funded partially by other projects / programs. Funding is also generally programmed or tracked by fiscal year or contract line items that may also not be aligned well with actual TRL transition level start / end. In addition, since federal government reporting does not follow a common set of cost accounting standards, the scope of what is captured in Total Project Costs can vary across projects. The type, level, and allocation of indirect costs such as support functions and overhead or general and administrative (G&A) activities included in the Total Project Costs may also vary considerably.
3) **Qualitative Measurement**. Since the gauged Start and End TRLs across the TCASE project database come from a variety of sources, there may be some variability in the interpretation of the appraised levels. As noted by Persons and Sullivan (2016), the quality of technology readiness assessment (TRA) in determining TRLs "*is contingent on the accuracy and relevance of the artifacts, test data, analytical reports, and other information used to support the evaluation. The artifacts, data, and other information collected to evaluate critical technologies may have dependency, functions, and interaction with other program elements that may be outside the evaluation scope or may not be available to the assessment team conducting the TRA*" (p. 36). There may also be similar considerations, to a lesser degree, for the somewhat less subjective SH level assessments.
4) **Range of Technologies in Project Data**. As discussed previously, the TCASE database contains a breadth of technologies. These diverse TAs may contain varying considerations for R&D activities that can drive both cost and schedule. The intent of this paper, however, is to provide general modeling solutions across TAs in early life cycle stages so greater variability is expected and the corresponding uncertainty has been built into model PDFs.
5) **Model Forms**. Output variability between or across model forms can also be related to the nature of particular model relationship characteristics or constraints. This includes things like function fitting at the unit predictor variable vs total aggregate level, the inherent shape of linear and nonlinear functions and transformations applied and the presence or absence of constant intercept terms.

8 Conclusions and Future Work

Cost and schedule models for estimating early life-cycle technology developments have not been readily available in both industry and government sectors. Traditional parametric cost and schedule models generally require a measure of technical design, performance and complexity that have not been established for new or immature technologies in pre-concept and early concept development stages. TRL and System Hierarchy-based parameters offer key macro-level cost and schedule drivers that are often available or determinable in these initial development phases. These parameters can also be effective surrogates that indirectly capture the impact of traditional causal metrics not yet determined. This was demonstrated through the strength of parametric relationships found in data screening and subsequent model performance assessment.

Using a broad-based technology development project dataset from NASA (TCASE) a field of curve-fit, linear regression, and nonlinear models applying TI- and SH-level predictor variables were developed and evaluated. This produced several models with solid statistical KPM and goodness-of-fit characteristics. These models can deliver forecasting value above very rough order-of-magnitude

(VROM) estimates often applied in early technology development that are based upon SME opinion, Delphi techniques or limited analogous programs with insufficient commonality. In addition, uncertainty modeling was conducted to convey expected probability ranges useful in understanding cost and schedule risk when performing resource planning, budgeting, and investment decision analysis.

The best performing cost and schedule models for each model form were presented in sections 5 & 6 and Appendices F & G. Mulitvariate cost models (nos. 8 & 9) produced generally better results in terms of available statistical KPMs, while univariate cost curve fit models (nos. 1 & 2) provided superior sample data fit quality. Some general guidance for cost model selection from this analysis in terms of performance and development project characteristics is provided in Table 5. Selection of applicable model(s) for a particular technology development should be based upon factors such as:

- The availability and quality of overall predictor variable data
- The planned level of the technology in the system hierarchy
- Contemporary and desired technology maturity levels for the application
- An assessment of any historical technical and cost drivers for similar technology programs
- Known or projected extent of technical, programmatic, and cost risks

Table 5: General Cost Model Applicability

Mdl. No.	Model Form / Method	Predictor Variable Form	Model Performance and Technology Development Attributes				
			Best Project Sample Data Fit	Generally Higher KPM Performance	System Level Development (SH level 5)	Below System Level Development (SH Level 1-4)	Generally Higher Cost or Uncertainty Levels*
1	Tailored Curve Fits	TI Level	✓			✓	
2	Tailored Curve Fits	SH Level	✓		✓		
5	Simple Linear Regression	SH Level			✓		
6	Simple Linear Regression	SH Level			✓		✓
7	Composite Linear Regression	$[TI \times SH]^2$		✓	✓	✓	
8	Multiple Linear Regression	TI + SH		✓	✓	✓	✓
9	Multiple Linear Regression	$[TI + SH]^2$	✓	✓	✓	✓	✓
10	Nonlinear - Quadratic	NL TI Level				✓	✓
12	Nonlinear - Exponential 3P	NL SH Level			✓		✓
13	Nonlinear - Gompertz 4P	NL SH Level			✓		✓

** May be more applicable for higher risk or volatile technology developments*

SH level cost impacts appear to be somewhat moderate up until the System level (SH level 5) at which point they become significant. This was evident from the relative size of TI- and SH-level ordinal level coefficients in multivariate models as well as data relationship screening findings in Appendix B. Therefore, for system level technology developments, models containing the SH level variable are more suitable. Below the system level, the TI level is much more dominant and models containing the TI parameter should more effectively explain response behavior. However, if planned SH-level and desired TRL start / end levels are known, multivariate models applying both predictor variables may improve performance, since they address both scalar and technical dimensions. For applications with greater potential risk or volatility, models exhibiting generally higher cost points and variability such as simple linear regression or nonlinear cost models, especially at the higher ordinal tiers, may be more applicable. Schedule modeling produced more limited results, but with reasonable SH-based duration curve fits and deserves further study.

If the TCASE database or other data sources can be expanded with key response and predictor variables like RD3, TAs, and Capability Demonstrations, additional project data may be available to improve model robustness and accuracy and reduce output variability. Beyond RD3, TAs, and Capability Demonstrations, additional macro cost and schedule parameters to consider that may enhance early stage technology development forecasting include:

- Advanced Degree of Difficulty (AD2)
- System Readiness Level (SRL)
- Integration Readiness Levels (IRL)
- Implementation Readiness Level (ImpRL)
- Manufacturing Readiness Level (MRL)
- System level or broad-based technology scalar, performance or complexity factors

Leveraging these types of metrics to better integrate cost and schedule modeling with technology road mapping, early systems engineering, and conceptual design efforts should help generate more consistent development estimates. This could produce better investment and design decisions with greater cost impact early in the life cycle.

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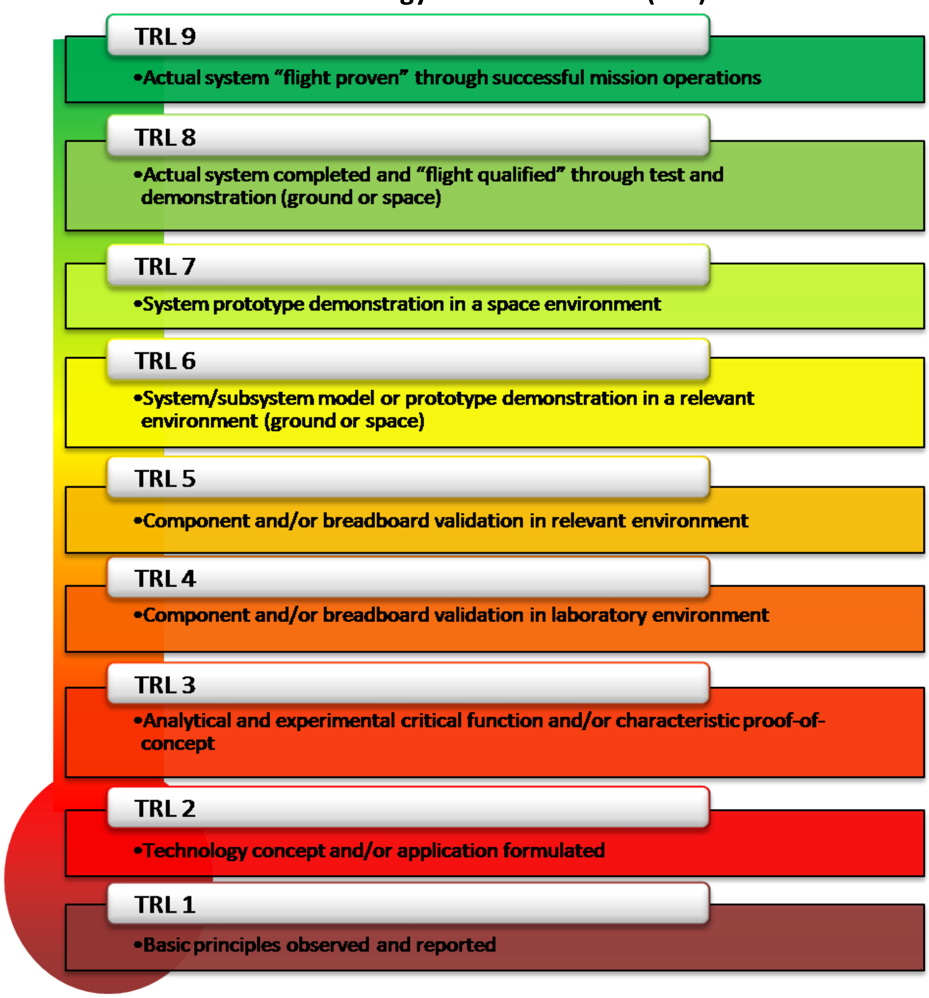
Appendix A

Definitions: NASA System Hierarchy Levels / TRL Levels / RD3 levels / TAs

NASA System Hierarchy Levels

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

NASA TRL Technology Readiness Level (TRL) Scale



Appendix A, cont.
Research & Development Degree of Difficulty (RD^3)

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]

NASA Technology Areas (TAs)[17]

14+1 TECHNOLOGY AREAS Table 2	
TA #	**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

[17] 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).

Parametric Cost and Schedule Modeling for Early Technology Development

Appendix B
Preliminary Data Relationship Screening

Cost Forecast Models. To assess the Technology Readiness Level (TRL) Start-End (i.e., TRL X-Y) category costs, summary statistics (mean - μ, median, standard deviation- $\sigma_{\bar{x}}$) were first developed for each and organized by TRL Improvement (TI) level (see Appendix C - Table C-1). A total of 405 projects with TRL Start-End data and Total Project Costs were available. Categories with very small sample sizes of < 8 observations were considered too small to demonstrate statistical significance and show the significant volatility produced by limited inputs. Only 5 TRL X-Y categories contained "large" sample sizes (i.e., >30), but cost curve fits were developed for 14 of the out of the 36 possible categories (those with 8 or > observations) to provide a notion of the distributions for each sample grouping. A representative example of one of these distributions with a plot of the actual sample project cost frequencies and resulting curve fits for projects transitioning from TRL 2 to 3 (TRL 2-3) is presented below in Figure B-1.

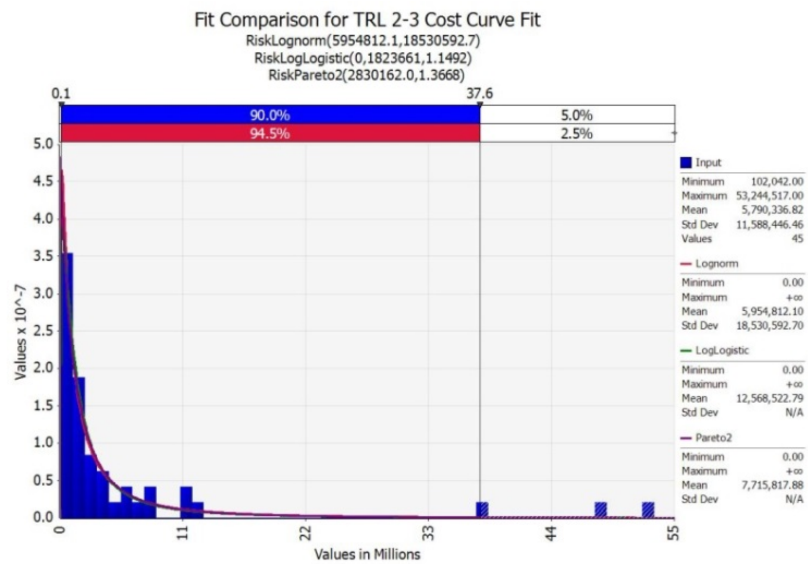
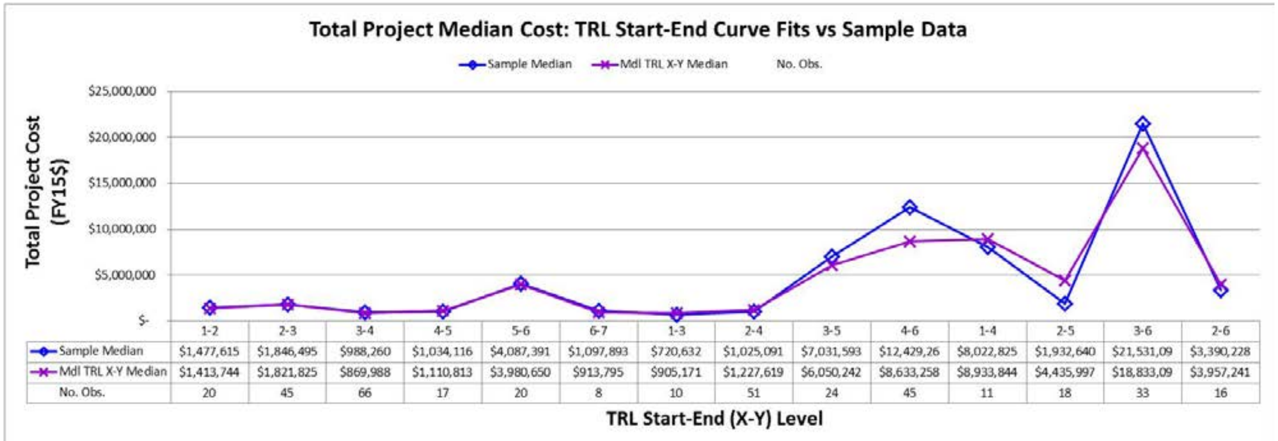


Figure B-1: Example "TRL X-Y" Cost Curve Fit for TRL 2-3

Figure B-1 is typical of the broader TRL X-Y curve fit results in that the general data plots and fitted probability density functions (PDF) reflect a significant right-skewness of the actual data (i.e., "Input" histogram in blue). This is commonly observed with both cost and schedule estimating due to various reasons but often attributed primarily to the following factors:

- Costs and cost or schedule drivers are generally bound on the low end and more "open ended" at the high end;
- Cost and schedule growth tends to occur over time from phenomena like requirements creep, design or engineering changes, and realization of "unknowns"; and
- Human tendency is to be overly optimistic and under inclusive (leave out items, understate or under-scope requirements and indirect costs), contributing to cost growth over time.

Due to this characteristic, median cost values may provide a better indication of central tendency as the highly skewed data sets drive mean values to disproportionally higher levels. A plot of median TRL X-Y Curve fit model Total Project Costs vs. the sample data values for the 14 available TRL X-Y categories up through TRL transition 2-6 is provided in Figure B-2. Plot lines here do not represent transitions but are just to assist visual acuity to better discern the closeness of model values with actual data. The plot demonstrates relatively tightly aligned model to sample data fits, however sample data project costs for TRL transitions 5-6, 1-3, 2-4, 2-5 and 2-6 appear to be somewhat erratic and inconsistent with surrounding transition results when normalized for TRL level improvement.



	1-2	2-3	3-4	4-5	5-6	6-7	1-3	2-4	3-5	4-6	1-4	2-5	3-6	2-6
Sample Median	$1,477,615	$1,846,495	$988,260	$1,034,116	$4,087,391	$1,097,893	$720,632	$1,025,091	$7,031,593	$12,429,26	$8,022,825	$1,932,640	$21,531,09	$3,390,228
Mdl TRL X-Y Median	$1,413,744	$1,821,825	$869,988	$1,110,813	$3,980,650	$913,795	$905,171	$1,227,619	$6,050,242	$8,633,258	$8,933,844	$4,435,997	$18,833,09	$3,957,241
No. Obs.	20	45	66	17	20	8	10	51	24	45	11	18	33	16

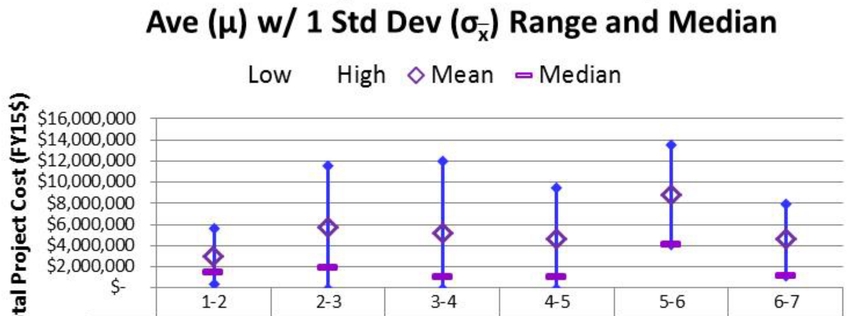
Figure B-2: Total Project Median Cost - TRL Start-End Curve Fits vs Sample Data

These mixed initial results along with the lack of TRL X-Y category data suggested another forecasting method was needed. Aggregating the TRL project information into larger, more robust data sets could be accomplished by applying a parameter that captures the overall TRL level increase from project start to end. This measure, named **TRL Improvement (TI) Level** (sometimes referred to as TRL Transition Order[18]), was selected for evaluation. The TCASE database containing TRLs 1 to 9, provided enough project data to evaluate TI levels 1 through 5.

In order to determine if TRL X-Y combination data possess enough commonality to be pooled for modeling by TI level, plots of cost ranges the various TRL X-Y combinations by TI level were developed. A sample, typical of the family of five TI range plots, for the TI level 1 group of TRL X-Y combinations is shown in Figure B-3 (the other 4 TI level plots are provided in Appendix C). These charts illustrate a cost range of one standard deviation around the mean, plus the median for each TRL X-Y. The horizontal axis thus represents the TRL X-Y combination based upon the TRL Start level and the TI tier (e.g., TRL 4-5 represents the available projects for TI tier = 1, TRL Start = 4 and TRL End = 5).[19] This plot, like others up through TI level 5 (i.e., 5th Order TRL transitions), demonstrates the absence of discernable continuous trends relative to starting TRL levels and large standard deviations relative to mean values. Similar findings have also been shown for project samples in other research (El-Khoury & Kenley, 2014; Hay et al., 2013, p. 7; Peisen, Schultz, Bolaszewski, Ballard, & Smith, 1999). A few studies have suggested continuous progressions within a limited range of TRL transition cost or schedule metrics. However, those studies' findings are based upon much smaller, selective samples in more narrowly focused technology areas and only applicable to TRL levels 2 through 5 or 6.

[18] For example a TRL Improvement level of 2 is also known as a 2nd order transition, a TI level of 3 a 3rd order transition, etc.
[19] Low values are truncated at zero when the standard deviation ($\sigma_{\bar{x}}$) produces negative cost values at the bottom of the range.

Parametric Cost and Schedule Modeling for Early Technology Development



	1-2	2-3	3-4	4-5	5-6	6-7
Low	$350,962	$-	$-	$-	$4,028,430	$1,370,923
High	5,583,833	11,584,560	12,024,121	9,498,699	13,561,723	7,904,513
Mean	$2,967,398	$5,790,337	$5,160,085	$4,680,995	$8,795,076	$4,637,718
Median	$1,477,615	$1,846,495	$988,260	$1,034,116	$4,087,391	$1,097,893

Figure B-3: TRL Improvement Level 1 Cost Range by TRL Start

The TRL X-Y transitions applicable to each TI level, were found to possess a general commonality or overlap in absolute scale and range. Significant correlation (coefficients ranging from 0.64 to 0.91) have also been found to persist among consecutive TRL X-Y transition level metrics of the same TI level in some studies (El-Khoury & Kenley, 2014, p. 170). These characteristics provide support for the hypothesis that applying a TI-level parameter by pooling applicable TRL X-Y transitions may produce consistent results if a viable, causal cost estimating relationship can be established. Due to a broader data range, aggregating TRL X-Y projects of the same TI level will also yield greater variance in cost ranges than the individual TRL X-Y data; however, this appropriately reflects the larger, more diverse project samples and will effectively be captured through uncertainty analysis. High uncertainty levels are also expected with forecasting in early or pre-concept technology development.

To assess the possible affiliation with cost, a scatterplot and correlation matrix of Total Project Cost vs. TI level was therefore developed (see Figure B-4). Nonparametric density ellipses and histogram counts[20] were included to help with the TI relationship screening. A visual pattern emerges in the plot that suggests a direct relationship, yet the correlation statistic ($r = 0.371$) implies a somewhat moderate association.[21] To better comprehend the relative number of data points at each TI level, scatterplot data points have been jittered into clusters with red-line data density ellipses and histograms provided in the correlation matrix. Nonparametric density ellipses in grey and red shading also shown on the plot, offer an understanding of where either an excess or shortage of data exists that could potentially hinder development of a parametric construction between the variables. These findings indicate a general overabundance of smaller projects across TI levels 2 through 5, potentially "pulling down" the relationship.

The direct nature of the cost to TI level relationship is also evident from a columnar chart of the average total project costs by level (see Figure B-5 below). Cost growth appears to be relatively nonlinear with approximate 3x growth between successive TI levels 1 to 4 and tapering off at level 5.

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[20] These are number of project observations or raw sample data counts by level.

[21] Note: Only a few TRL Improvement records above level 5 were available, and therefore too sparse to model.

Parametric Cost and Schedule Modeling for Early Technology Development

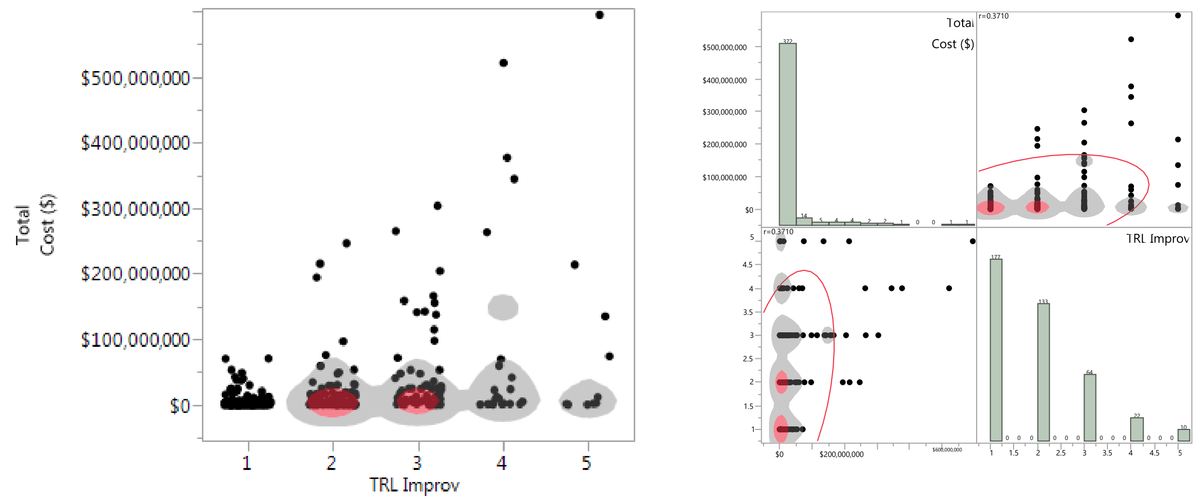

Figure B-4: Scatterplot and Correlation Matrix of Total Project Cost vs TRL Improvement Level

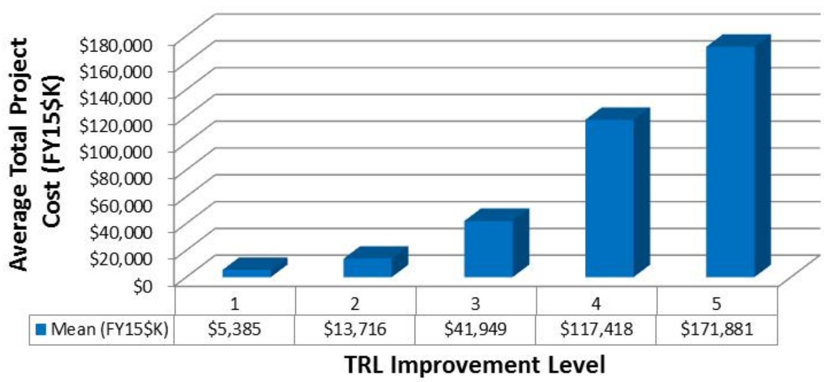

Figure B-5: Average Total Project Costs vs. TRL Improvement Level

Similarly, in assessing Total Project Costs vs SH level, a scatterplot and correlation matrix of these variables along with nonparametric density ellipses and histogram counts were developed (Figure B-6). The scatterplot again indicates a direct association with a moderate correlation (r = 0.3228) and a general excess of smaller projects across SH levels 2 through 5.

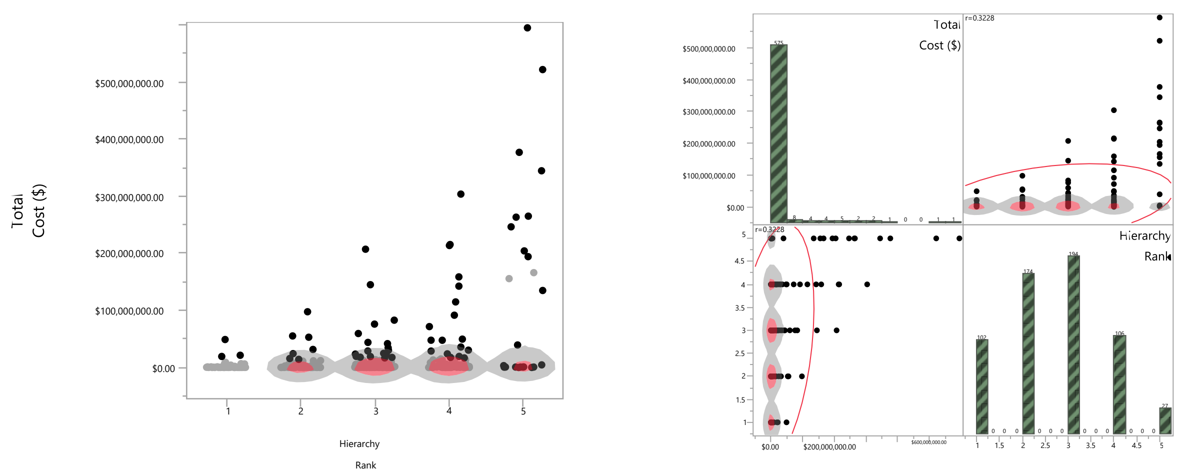

Figure B-6: Scatterplots and Correlation Matrix of Total Project Cost vs System Hierarchy Level

Parametric Cost and Schedule Modeling for Early Technology Development

A columnar chart of average total project costs by SH level (shown in Figure B-7), again demonstrates the progressive nature of cost, though with more gradual growth at lower tiers and a dramatic, nearly order of magnitude increase at the System tier (level 5). This suggests a nonlinear, possibly exponential relationship of project cost with SH. As with TRL related metrics, since SH is an ordinal variable, this steep cost surge could be attributable to certain qualitative or nonlinear quantitative factors. For instance, the number of major subsystems often found within a system as well as other effects like the integration, testing, demonstration and communications overhead that can escalate significantly at higher levels of complex systems, might drive this substantial growth.

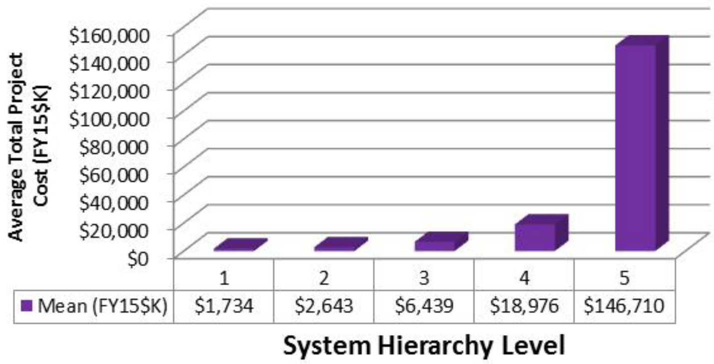

Figure B-7: Average Total Project Costs by System Hierarchy Level

Based upon this initial assessment, various cost models were formulated and tested in univariate and multivariate forms as a function of these two key parameters: *Total Project Cost = f {TRL Improvement, System Hierarchy, constant term}.*

Schedule Forecast Models. For schedule forecast models, a preliminary assessment was performed looking at strength of possible data relationships to the Project **Duration (months)** response variable. Similar to Cost Modeling, in order to consider project durations for each TRL Start-End (i.e., TRL X-Y) category, summary statistics (mean **-** μ, median, standard deviation- $\sigma_{\bar{x}}$) were calculated and organized into a table by TI level (Appendix D - Table D-1). From this table it is evident that, like cost, only 5 out of the 36 possible TRL X-Y categories contained large sample sizes and 22 of 36 contained very small samples (< 8 observations). Duration curve fits for the 14 cases with > 7 observations were developed. Similar to the TRL X-Y cost curve fits, the duration curve fits generally exhibited significant right-skewness, replicated the median sample values well and the cases with smaller sample sizes produced much greater volatility.

A plot of the resulting curve fits vs sample data medians for the 14 available cases in Figure B-8 however, again shows inconsistent behavior across transition levels when normalized for TI level. Just as with cost modeling, another method was needed to supplement the limited results and effectively extend them to cover the full band of TRL X-Y transitions. In order to assess whether TRL X-Y combination data are sufficiently comparable to be pooled for modeling by TI level, plots of duration ranges for the available TRL X-Y combinations by TI level were again developed. An example of one of these range plots for the TI level 1 family of TRL X-Y combinations is provided in Figure B-9 with remaining plots up through TI level 5 in Appendix D. Similar to the TI level cost

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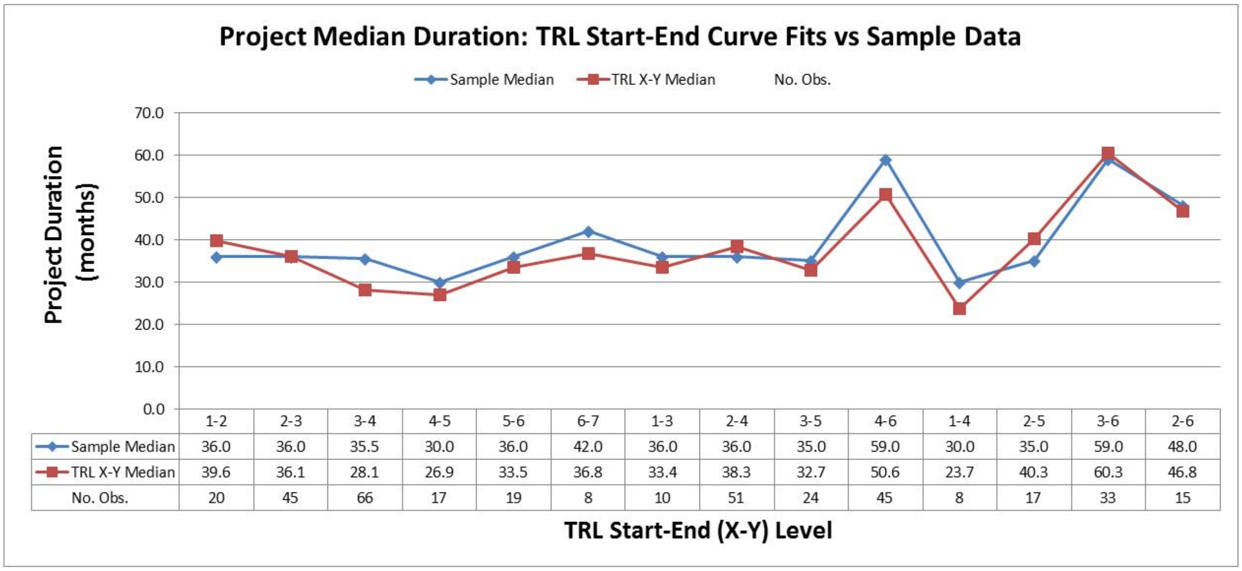
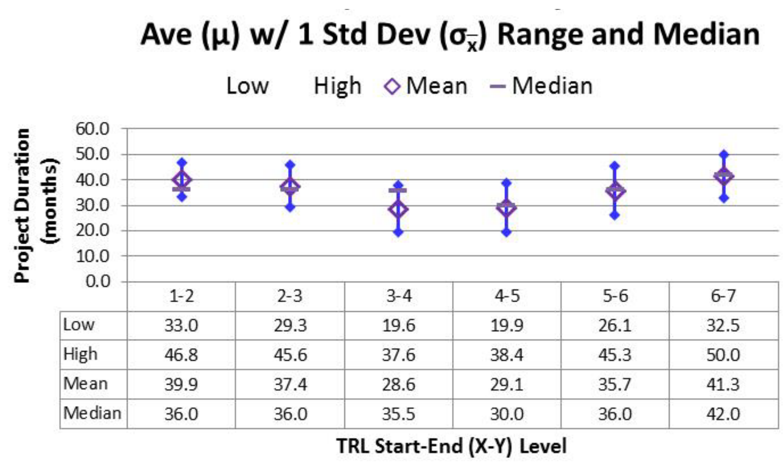
plots, overlap in ranges of the TRL Start-End categories and the lack of continuous trends, provide plausible support for applying a TI level parameter by pooling available TRL X-Y data.[22]



	1-2	2-3	3-4	4-5	5-6	6-7	1-3	2-4	3-5	4-6	1-4	2-5	3-6	2-6
Sample Median	36.0	36.0	35.5	30.0	36.0	42.0	36.0	36.0	35.0	59.0	30.0	35.0	59.0	48.0
TRL X-Y Median	39.6	36.1	28.1	26.9	33.5	36.8	33.4	38.3	32.7	50.6	23.7	40.3	60.3	46.8
No. Obs.	20	45	66	17	19	8	10	51	24	45	8	17	33	15

Figure B-8: Total Project Median Duration - TRL Start-End Curve Fits vs Sample Data



	1-2	2-3	3-4	4-5	5-6	6-7
Low	33.0	29.3	19.6	19.9	26.1	32.5
High	46.8	45.6	37.6	38.4	45.3	50.0
Mean	39.9	37.4	28.6	29.1	35.7	41.3
Median	36.0	36.0	35.5	30.0	36.0	42.0

Figure B-9: TRL Improvement Level 1 Duration Range by TRL Start

Looking for potential schedule data relationships, a scatterplot and correlation matrix of Project Duration vs TI Level is provided in Figure B-10 below. A rather weak affiliation is indicated by the random data distribution, lack of obvious visual patterns, substantial nonparametric density areas and moderate data correlation (r = 0.3238). The columnar chart shown in Figure B-11 below also suggests mean project duration does not possess a continuous association with the TI level, peaking and then tailing off at level 3. Based upon these results, TI level schedule models were abandoned.

[22] TI level 3 data as with other tiers, demonstrates a substantial overlap in duration ranges but is an exception in that it shows a gradual cost progression for TRL starts between 1 and 3. This could be the result of smaller sample sizes.

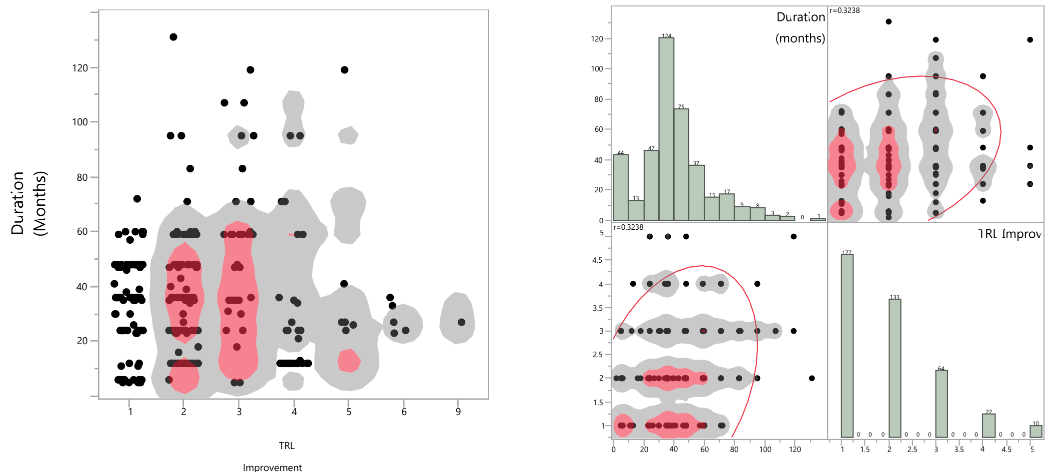


Figure B-10: Scatterplot and Correlation Matrix of Project Duration vs TRL Improvement Level

Figure B-11: Average Project Duration by TRL Improvement Level

Finally, to asses a relationship between SH level and schedule, a scatterplot and correlation matrix of Duration vs SH level was created (Figure B-12). The lack of structure in the plot along with extensive random scatter, no obvious visual patterns and significant nonparametric density areas and a relatively marginal correlation (r = 0.2869) suggest a weak affiliation. The columnar chart of average Project Duration by SH level shown in Figure B-13, however, does indicate a direct relationship exists.

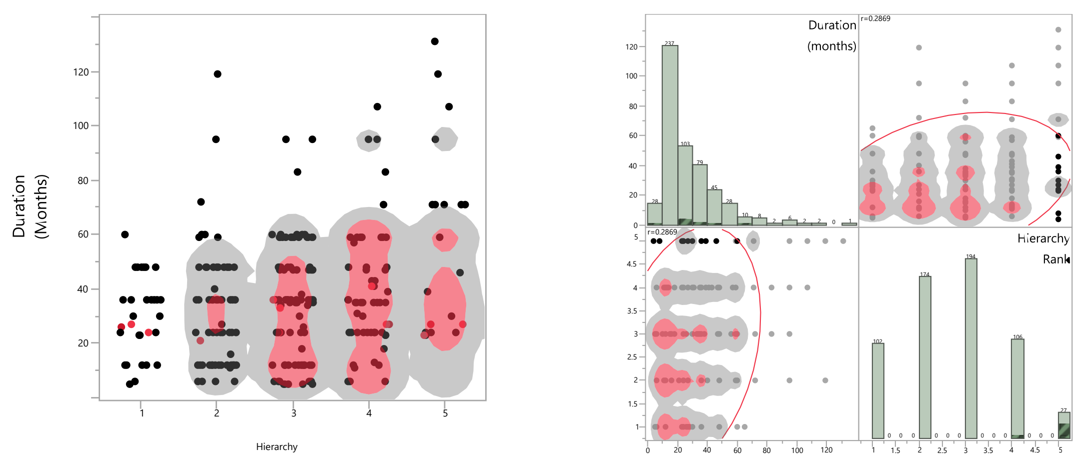


Figure B-12: Scatterplot and Correlation Matrix of Project Duration vs System Hierarchy Level

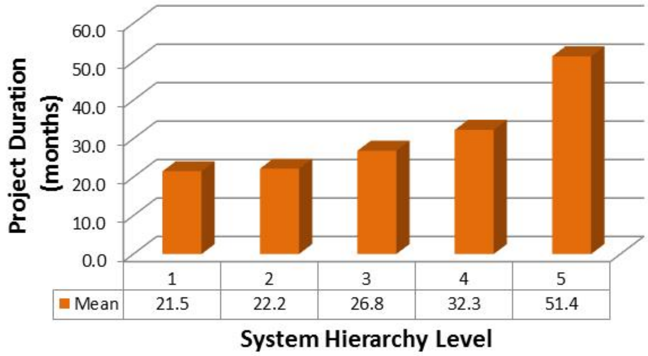


Figure B-13: Average Project Duration by System Hierarchy Level

In order to help enhance schedule modeling further, another parameter that also potentially drives schedule was formulated to measure project budget resource loading or burn rate. This parameter named **Spend Rate,** measures the average project financial expenditures over the life of the project in dollars per month ($/mo.) and is calculated as Total Project Cost divided by the Total Project Duration (months). The project Spend Rate is essentially designed to complement TI and/or SH levels in multiple regressions. This is because it tends to be a side effect of mission priority and the business, budgetary or programmatic environment and not a direct technical driver as such with project scale, complexity or performance related factors.

To screen for a potential association to project duration, a scatterplot and correlation matrix of project Spend Rate vs Duration was developed (Figure B-14). Correlation again was somewhat moderate at r = 0.3504 with substantial nonparametric density areas shaded in grey / red and red density ellipse and trend lines and trend line uncertainty bands shaded in light red. Although a proportional trend line is shown, the visual data plot appears somewhat random with an overabundance of lower Spend Rate projects under 60 months in duration, again over-anchoring the relationship. Despite strong initial screening results, SH- and TI-level and Spend Rate variables were assessed as schedule predictors across the range of modeling forms.

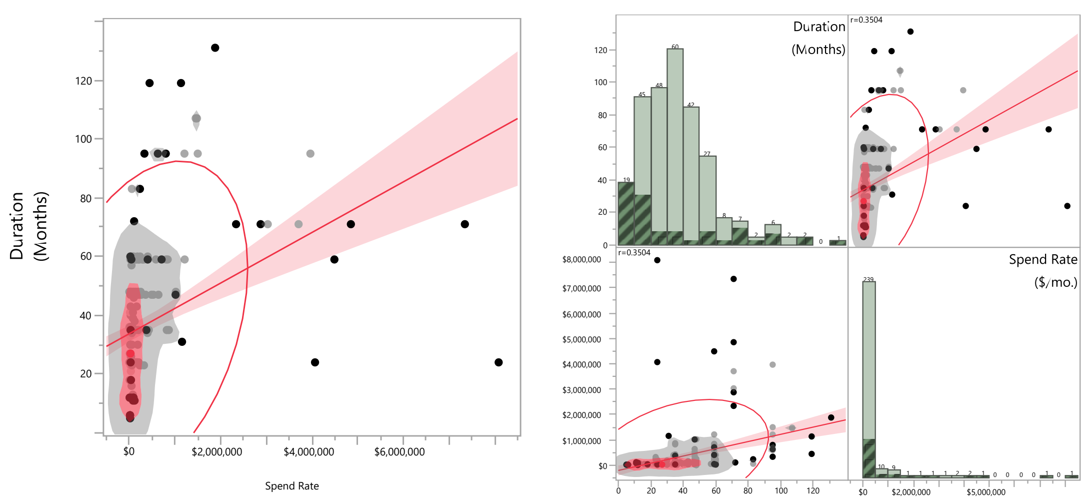


Figure B-14: Scatterplot and Correlation Matrix of Project Duration vs Spend Rate

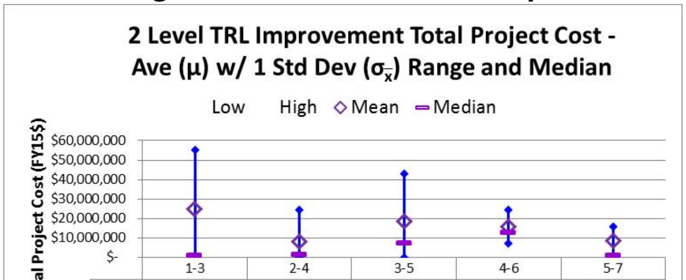
Appendix C

Table C-1 – Actual Project Costs by TRL Start / End[23]

Start TRL	End TRL	TRL X-Y	No. Obs.	Mean	Median
TRL Improvement Level 1			**176**		
1	2	1-2	20	$ 2,967,398	$ 1,477,615
2	3	2-3	45	$ 5,790,337	$ 1,846,495
3	4	3-4	66	$ 5,160,085	$ 988,260
4	5	4-5	17	$ 4,680,995	$ 1,034,116
5	6	5-6	20	$ 8,795,076	$ 4,087,391
6	7	6-7	8	$ 4,637,718	$ 1,097,893
7	8	7-8	1	$ 102,148	$ 102,148
8	9	8-9	0	N/A	N/A
TRL Improvement Level 2			**130**		
1	3	1-3	10	$ 24,775,284	$720,632
2	4	2-4	51	$ 7,901,939	$1,025,091
3	5	3-5	24	$ 18,275,863	$7,031,593
4	6	4-6	45	$ 15,758,338	$12,429,265
5	7	5-7	3	$ 8,571,468	$745,572
6	8	6-8	0	N/A	N/A
7	9	7-9	0	N/A	N/A
TRL Improvement Level 3			**62**		
1	4	1-4	11	$ 44,565,378	$8,022,825
2	5	2-5	18	$ 34,361,579	$1,932,640
3	6	3-6	33	$ 42,300,951	$21,531,093
4	7	4-7	1	$ 155,585,488	$ 155,585,488
5	8	5-8	0	N/A	N/A
6	9	6-9	0	N/A	N/A
TRL Improvement Level 4			**16**		
1	5	1-5	3	$ 135,751,924	$22,494,634
2	6	2-6	16	$ 80,649,554	$3,390,228
3	7	3-7	1	$ 59,465,169	59,465,169
4	8	4-8	1	$ 749,542	$ 749,542
5	9	5-9	1	$ 9,807,907	$ 9,807,907
TRL Improvement Level 5			**0**		
1	6	1-6	5	$ 18,095,038	$2,451,542
2	7	2-7	3	$ 45,435,638	$1,244,334
3	8	3-8	1	$ 594,678,801	$ 594,678,801
4	9	4-9	1	$ 213,567,134	$ 213,567,134
TRL Improvement Level 6			**0**		
1	7	1-7	0	N/A	N/A
2	8	2-8	0	N/A	N/A
3	9	3-9	0	N/A	N/A
TRL Improvement Level 7			**0**		
1	8	1-8	0	N/A	N/A
2	9	2-9	0	N/A	N/A
TRL Improvement Level 8			**0**		
1	9	1-9	0	N/A	N/A
36	**TRL X-Y types**	**Total Records**	**405**		

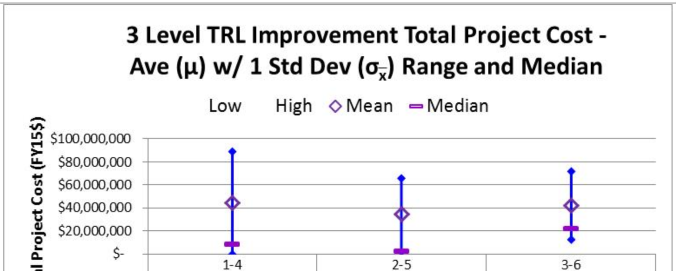
[23] TRL Start/End (TRL X-Y) combinations with < 8 observations were too limited to assess and demonstrate high volatility.

Appendix C, cont. – Cost Ranges for TRL X-Y Transition by TI Level



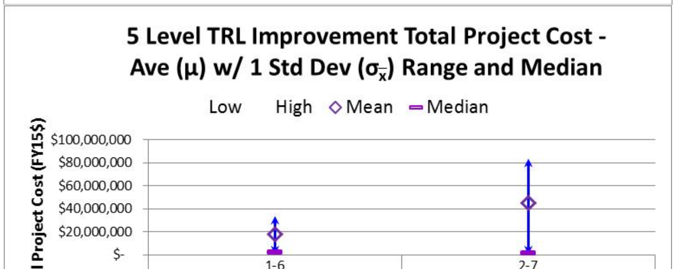
	1-3	2-4	3-5	4-6	5-7
Low	$-	$-	$-	$7,210,923	$1,513,599
High	55,406,553	24,166,150	42,838,679	24,305,752	15,629,337
Mean	$24,775,284	$7,901,939	$18,275,863	$15,758,338	$8,571,468
Median	$720,632	$1,025,091	$7,031,593	$12,429,265	$745,572

TRL Start-End (X-Y) Level



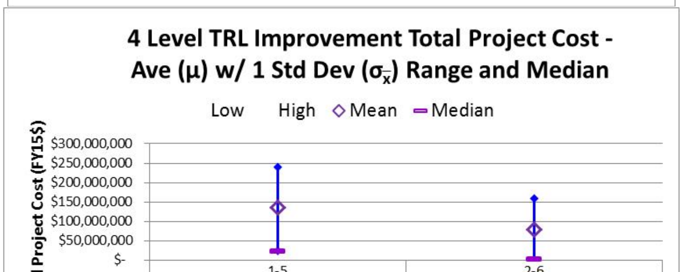
	1-4	2-5	3-6
Low	$-	$2,657,408	$12,652,924
High	89,795,629	66,065,750	71,948,977
Mean	$44,565,378	$34,361,579	$42,300,951
Median	$8,022,825	$1,932,640	$21,531,093

TRL Start-End (X-Y) Level



	1-6	2-7
Low	$2,302,319	$6,732,132
High	33,887,757	84,139,143
Mean	$18,095,038	$45,435,638
Median	$2,451,542	$1,244,334

TRL Start-End (X-Y) Level



	1-5	2-6
Low	$31,361,197	$2,847,005
High	240,142,650	158,452,103
Mean	$135,751,924	$80,649,554
Median	$22,494,634	$3,390,228

TRL Start-End (X-Y) Level

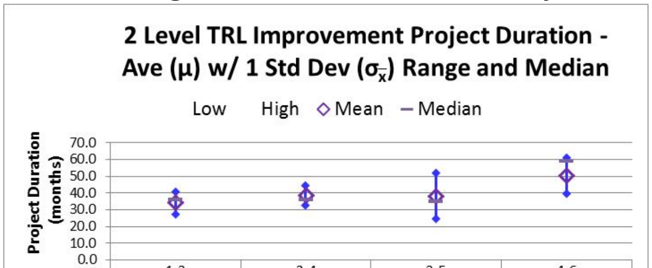
Appendix D

Table D-1 – Actual Project Duration by TRL Start / End[24]

Start TRL	End TRL	TRL X-Y	No. Obs.	Mean	Median
TRL Improvement Level 1			**176**		
1	2	1-2	20	39.9	36.0
2	3	2-3	45	37.4	36.0
3	4	3-4	66	28.6	35.5
4	5	4-5	17	29.1	30.0
5	6	5-6	19	35.7	36.0
6	7	6-7	8	41.3	42.0
7	8	7-8	1	6.0	6.0
8	9	8-9	0	N/A	N/A
TRL Improvement Level 2			**133**		
1	3	1-3	10	34.1	36.0
2	4	2-4	51	38.5	36.0
3	5	3-5	24	38.3	35.0
4	6	4-6	45	50.6	59.0
5	7	5-7	3	21.3	24.0
6	8	6-8	0	N/A	N/A
7	9	7-9	0	N/A	N/A
TRL Improvement Level 3			**59**		
1	4	1-4	8	30.4	30.0
2	5	2-5	17	47.4	35.0
3	6	3-6	33	62.9	59.0
4	7	4-7	1	107.0	107.0
5	8	5-8	0	N/A	N/A
6	9	6-9	0	N/A	N/A
TRL Improvement Level 4			**21**		
1	5	1-5	3	55.7	36.0
2	6	2-6	15	47.4	48.0
3	7	3-7	1	95.0	95.0
4	8	4-8	1	24.0	24.0
5	9	5-9	1	35.0	35.0
TRL Improvement Level 5			**6**		
1	6	1-6	3	32.0	24.0
2	7	2-7	3	63.7	36.0
3	8	3-8	0	N/A	N/A
4	9	4-9	0	N/A	N/A
TRL Improvement Level 6			**0**		
1	7	1-7	0	N/A	N/A
2	8	2-8	0	N/A	N/A
3	9	3-9	0	N/A	N/A
TRL Improvement Level 7			**0**		
1	8	1-8	0	N/A	N/A
2	9	2-9	0	N/A	N/A
TRL Improvement Level 8			**0**		
1	9	1-9	0	N/A	N/A
36	**TRL X-Y types**	**Total Records**	**395**		

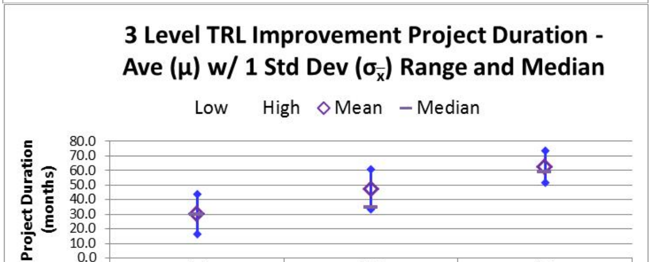
[24] TRL Start/End (TRL X-Y) combinations with < 8 observations were too limited to assess and demonstrate high volatility.

Appendix D, cont. – Duration Ranges for TRL X-Y Transition by TI Level



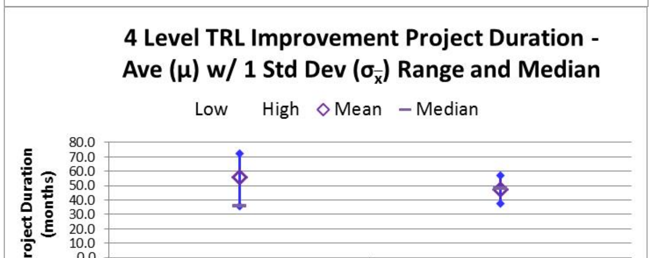
	1-3	2-4	3-5	4-6
Low	27.3	32.4	24.8	39.8
High	40.9	44.5	51.8	61.3
Mean	34.1	38.5	38.3	50.6
Median	36.0	36.0	35.0	59.0

TRL Start-End (X-Y) Level



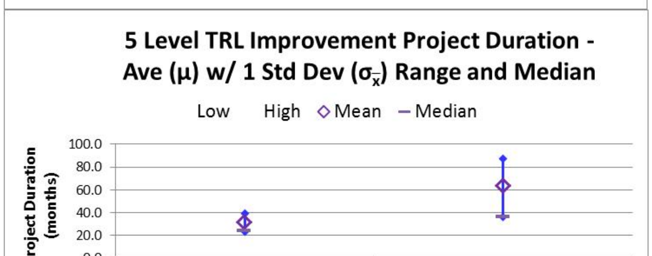
	1-4	2-5	3-6
Low	16.7	33.7	52.0
High	44.0	61.1	73.9
Mean	30.4	47.4	62.9
Median	30.0	35.0	59.0

TRL Start-End (X-Y) Level



	1-5	2-6
Low	38.6	37.5
High	72.7	57.3
Mean	55.7	47.4
Median	36.0	48.0

TRL Start-End (X-Y) Level



	1-6	2-7
Low	25.1	39.7
High	38.9	87.6
Mean	32.0	63.7
Median	24.0	36.0

TRL Start-End (X-Y) Level

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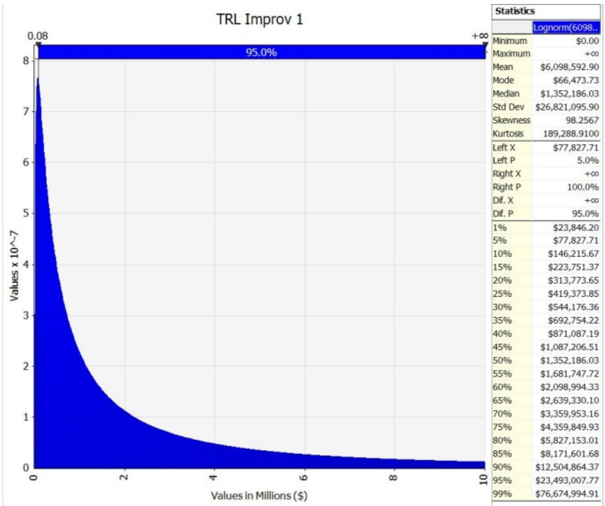
Appendix E – Key Performance Measure (KPM) Descriptions

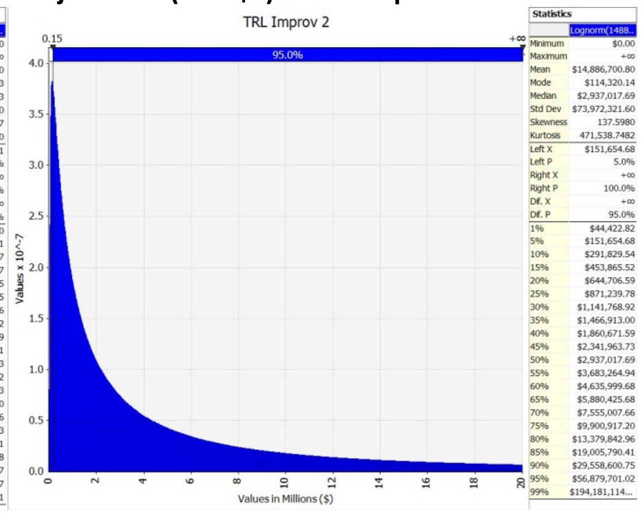
- **Error Variability and Dispersion Measures:**
  - **Coefficient of Determination - R^2 and Adjusted R^2.** Most commonly used measure of "goodness of fit." Relative measure of fit equal to the percent of the variation in the dependent variable (Y) explained by the independent variable (X) = SSR / SST[25].
  - **Root Mean Square Error (RMSE)** – absolute measure of fit or accuracy based upon the differences between sample and population values predicted by a model.
  - **Coefficient of Variation (CV)** – RMSE for models as applied here (Standard Deviation for individual variables) divided by mean of the Y-data, a unitless relative measure of estimating error. Using this convention, CV < 1 is considered low-variance and CV > 1 is considered high variance.
- **Statistical Significance Measures:**
  - **F-ratio** - tests if the entire regression equation is valid (i.e., how well the statistical model is fitted to a sample data set).
  - **t-stat** - tests if the individual hypothesized predictor (X-variables) values are valid. T-stat represents the calculated difference represented in units of standard error. The % of expression terms with probability > |t| was applied as an overall measure.
- **Autocorrelation Measure:**
  - **Durbin-Watson test** - measures independence of regression residuals.
- **Data Reduction Measure:**
  - **Percent (%) of original data sample set unused.** The extent of selectivity in actual data set applied, measured as the % of available sample observations filtered out due to outliers, large residuals or non-core data, etc.

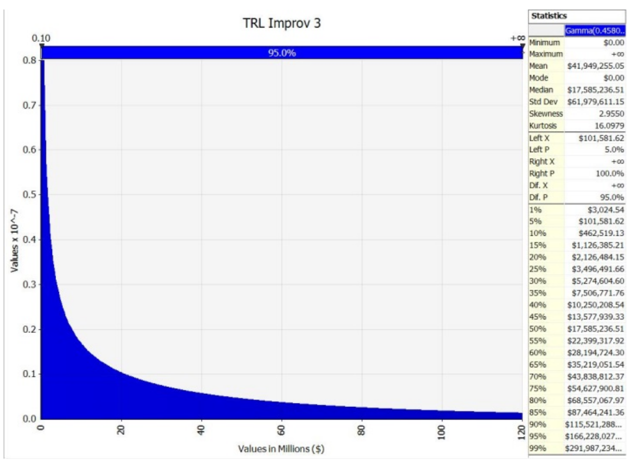
[25] SSR represents the sum of squares due to the regression and SST represents the sum of squares total.

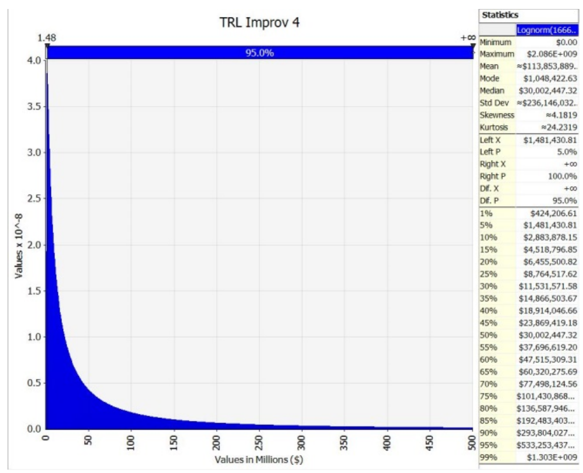
Appendix F – Cost Model Output *

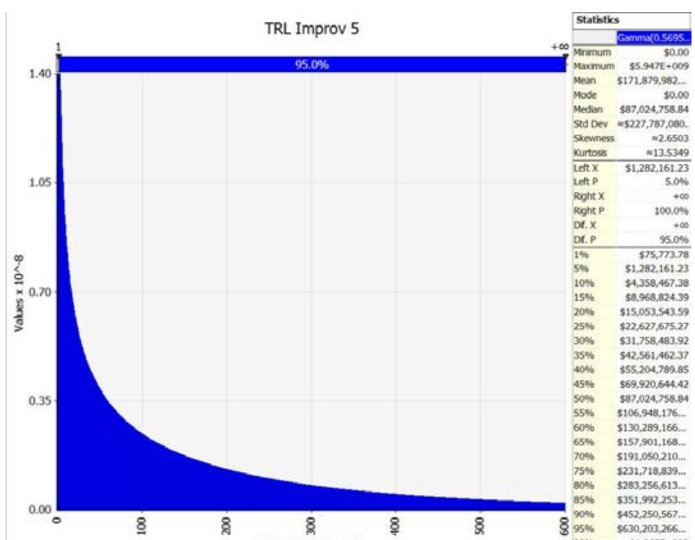
Cost Model No. 1 Selected Curve Fits – Total Project Cost (FY15$k) vs TRL Improvement Level









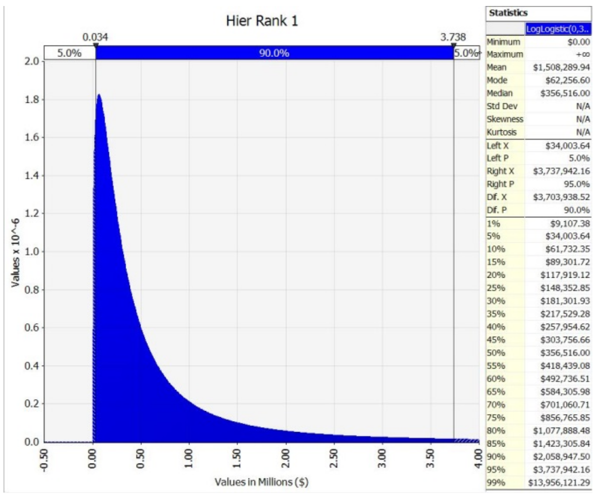


****Note**: Detailed model results are available upon request.*

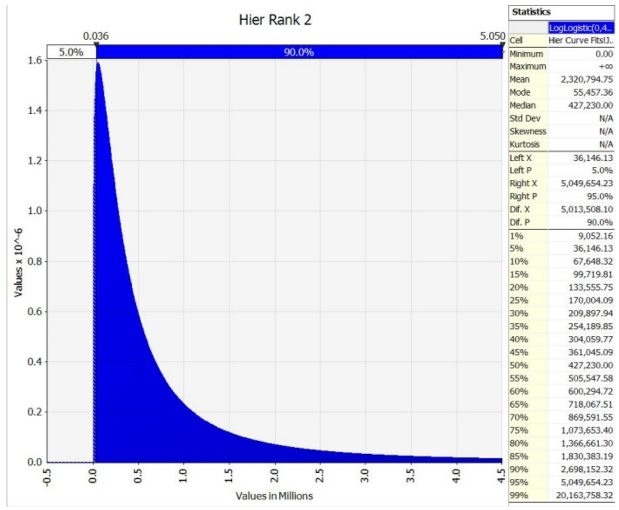
Parametric Cost and Schedule Modeling for Early Technology Development

Appendix F, cont.

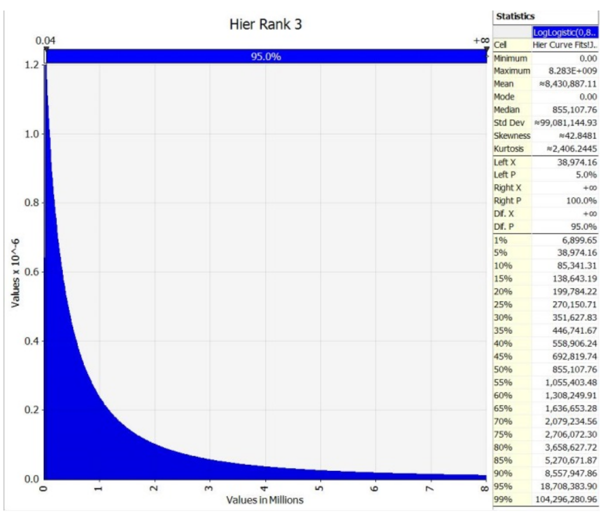
Cost Model No. 2 Selected Curve Fits – Total Project Cost (FY15$k) vs System Hierarchy Level



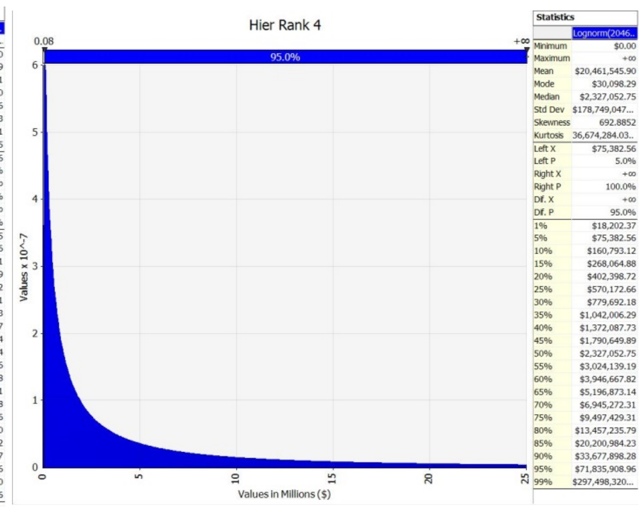
Statistics	LogLogistic(0,3..
Minimum	$0.00
Maximum	+∞
Mean	$1,508,289.94
Mode	$62,256.60
Median	$356,516.00
Std Dev	N/A
Skewness	N/A
Kurtosis	N/A
Left X	$34,003.64
Left P	5.0%
Right X	$3,737,942.16
Right P	95.0%
Dif. X	$3,703,938.52
Dif. P	90.0%
1%	$9,107.38
5%	$34,003.64
10%	$61,732.35
15%	$89,301.72
20%	$117,919.12
25%	$148,352.85
30%	$181,301.93
35%	$217,529.28
40%	$257,954.62
45%	$303,756.66
50%	$356,516.00
55%	$418,439.08
60%	$492,736.51
65%	$584,305.98
70%	$701,060.71
75%	$856,765.85
80%	$1,077,888.48
85%	$1,423,305.84
90%	$2,058,947.50
95%	$3,737,942.16
99%	$13,956,121.29



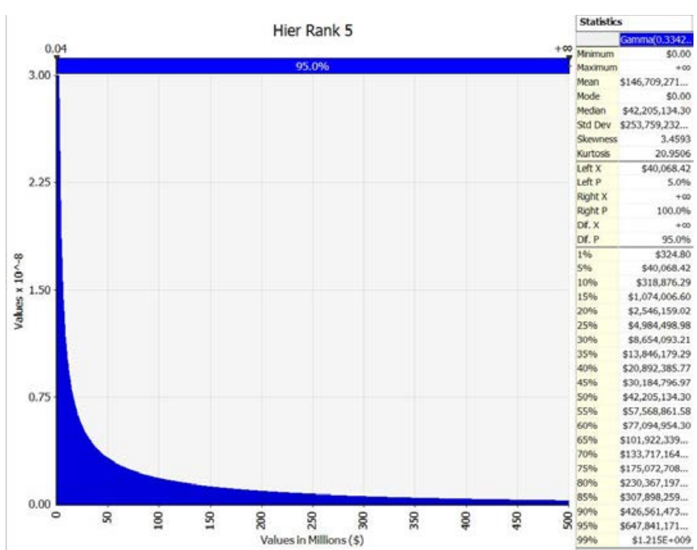
Statistics	LogLogistic(0,4..
Cell	Hier Curve Fits!J..
Minimum	0.00
Maximum	+∞
Mean	2,320,794.75
Mode	55,457.36
Median	427,230.00
Std Dev	N/A
Skewness	N/A
Kurtosis	N/A
Left X	36,146.13
Left P	5.0%
Right X	5,049,654.23
Right P	95.0%
Dif. X	5,013,508.10
Dif. P	90.0%
1%	9,052.16
5%	36,146.13
10%	67,648.32
15%	99,719.81
20%	133,555.75
25%	170,004.09
30%	209,897.94
35%	254,189.85
40%	304,059.77
45%	361,045.09
50%	427,230.00
55%	505,547.58
60%	600,294.72
65%	718,067.51
70%	869,591.55
75%	1,073,653.40
80%	1,366,661.30
85%	1,830,383.19
90%	2,698,152.32
95%	5,049,654.23
99%	20,163,758.32



Statistics	LogLogistic(0,8..
Cell	Hier Curve Fits!J..
Minimum	0.00
Maximum	8.283E+009
Mean	≈8,430,887.11
Mode	0.00
Median	855,107.76
Std Dev	≈99,081,144.93
Skewness	≈42.8481
Kurtosis	≈2,406.2445
Left X	38,974.16
Left P	5.0%
Right X	+∞
Right P	100.0%
Dif. X	+∞
Dif. P	95.0%
1%	6,899.65
5%	38,974.16
10%	85,341.31
15%	138,643.19
20%	199,784.22
25%	270,150.71
30%	351,627.83
35%	446,741.67
40%	558,906.24
45%	692,819.74
50%	855,107.76
55%	1,055,403.48
60%	1,308,249.91
65%	1,636,653.28
70%	2,079,234.56
75%	2,706,072.30
80%	3,658,627.72
85%	5,270,671.87
90%	8,557,947.86
95%	18,708,383.90
99%	104,296,280.96



Statistics	Lognorm(2046..
Minimum	$0.00
Maximum	+∞
Mean	$20,461,545.90
Mode	$30,098.29
Median	$2,327,052.75
Std Dev	$178,749,047...
Skewness	692.8852
Kurtosis	36,674,284.03..
Left X	$75,382.56
Left P	5.0%
Right X	+∞
Right P	100.0%
Dif. X	+∞
Dif. P	95.0%
1%	$18,202.37
5%	$75,382.56
10%	$160,793.12
15%	$268,064.88
20%	$402,398.72
25%	$570,172.66
30%	$779,692.18
35%	$1,042,006.29
40%	$1,372,087.73
45%	$1,790,649.89
50%	$2,327,052.75
55%	$3,024,139.19
60%	$3,946,667.82
65%	$5,196,873.14
70%	$6,945,272.31
75%	$9,497,429.31
80%	$13,457,235.79
85%	$20,200,984.23
90%	$33,677,898.28
95%	$71,835,908.96
99%	$297,498,320...

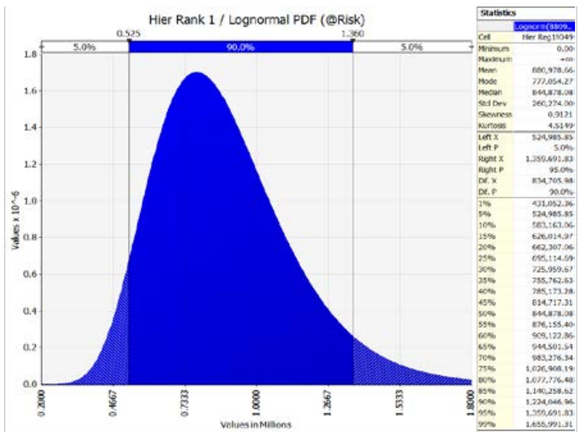


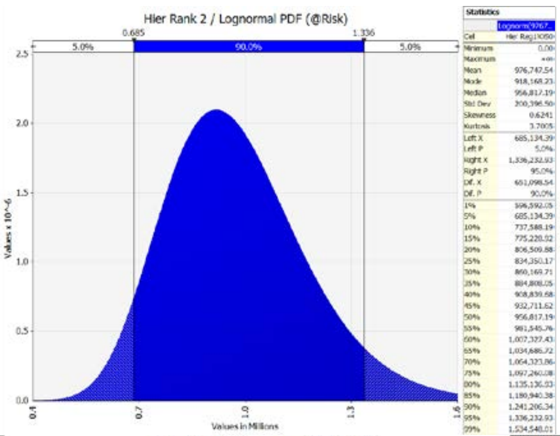
Statistics	Gamma(0.3342..
Minimum	$0.00
Maximum	+∞
Mean	$146,709,271...
Mode	$0.00
Median	$42,205,134.30
Std Dev	$253,759,232...
Skewness	3.4593
Kurtosis	20.9506
Left X	$40,068.42
Left P	5.0%
Right X	+∞
Right P	100.0%
Dif. X	+∞
Dif. P	95.0%
1%	$324.80
5%	$40,068.42
10%	$318,876.29
15%	$1,074,006.60
20%	$2,546,159.02
25%	$4,984,498.98
30%	$8,654,093.21
35%	$13,846,179.29
40%	$20,892,385.77
45%	$30,184,796.97
50%	$42,205,134.30
55%	$57,568,861.58
60%	$77,094,954.30
65%	$101,922,339...
70%	$133,717,164...
75%	$175,072,708...
80%	$230,367,197...
85%	$307,898,259...
90%	$426,561,473...
95%	$647,841,171...
99%	$1.215E+009

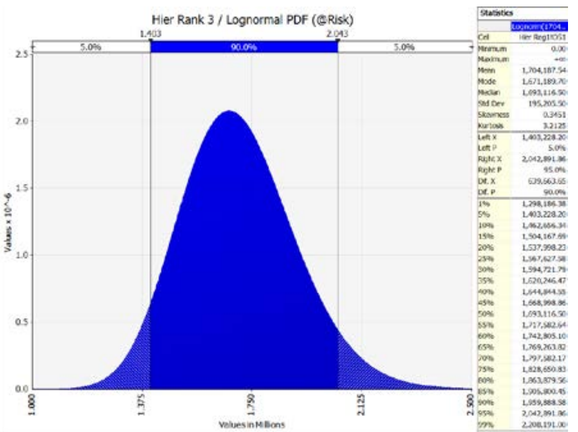
Parametric Cost and Schedule Modeling for Early Technology Development

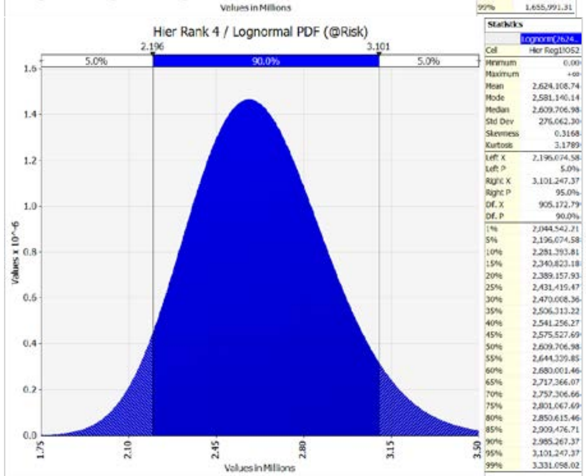
Appendix F, cont. - Cost Model No. 5 (Hier Reg1): Simple Linear Regression – System Hierarchy Level

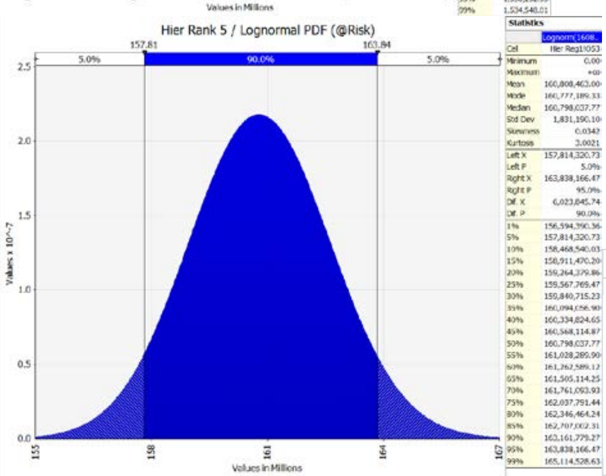
Model No.	Fit Model Type	Predictor Type	Single / Multiple Predictor Variable(s)	Predictor Variable(s)	Predictor Level / Tier	Predictor Level / Tier	No. of Obs.	Mean	Median	60th %ile	80st %ile	Std Error
5	Linear Simple Regression	Hierarchy Level	Single	Hierarchy Rank	Hardware / Software / I	1	99	880,979	844,878	909,123	1,077,776	260,274
	R-Sq =	0.934935	Durbin-Watson Stat =	0.8958787	Component / Part	2	167	976,748	956,817	1,007,327	1,135,137	200,397
	Adj R-Sq =	0.934441	DW AutoCorrelation =	0.5481	Assembly	3	176	1,704,188	1,693,117	1,742,805	1,863,880	195,206
	F-ratio =	1893.157	*Ref Model Name:*	*Hier Reg1*	Subsystem	4	88	2,624,109	2,609,707	2,680,001	2,850,615	276,062
	Prob. > F =	<.0001*			System	5	2	160,808,463	160,798,038	161,262,589	162,346,464	1,831,190
	RMSE =	2,589,694				Total Applied	532	11.8%	Data Reduction			
	Coef. of Variation (CV) =	1.249										











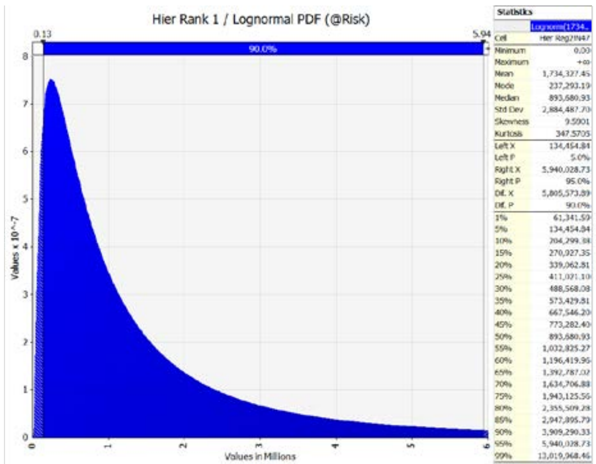
Prediction Expression

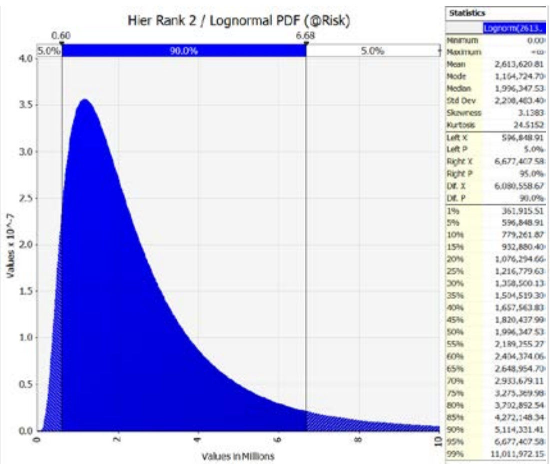
880978.656565697 + Match (Hierarchy Rank) [1 ⇒ 0; 2 ⇒ 95768.882356459; 3 ⇒ 823208.883207035; 4 ⇒ 1743130.08207067; 5 ⇒ 159927484.343434; else ⇒ .]

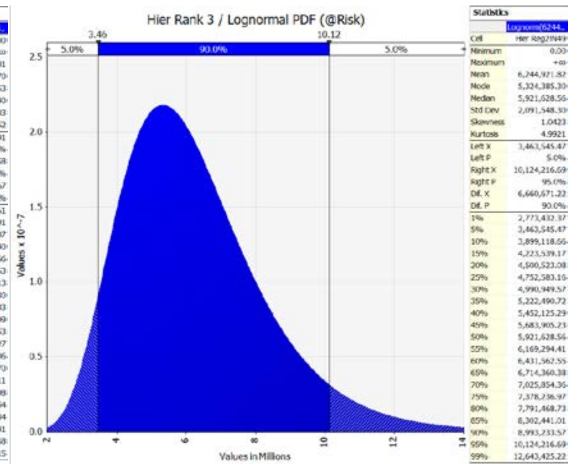
Parametric Cost and Schedule Modeling for Early Technology Development

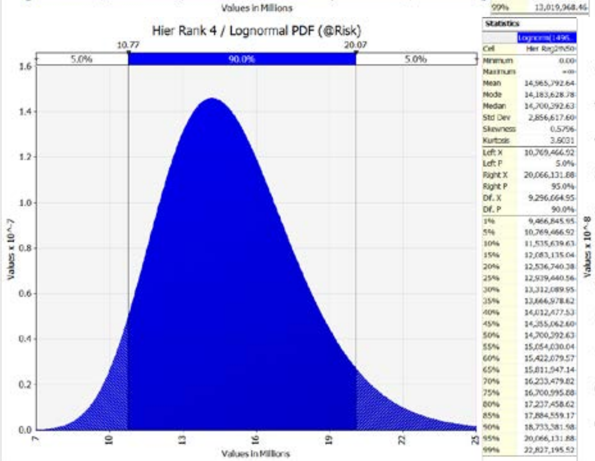
Appendix F, cont. - Cost Model No. 6 (Hier Reg2): Simple Linear Regression – System Hierarchy Level

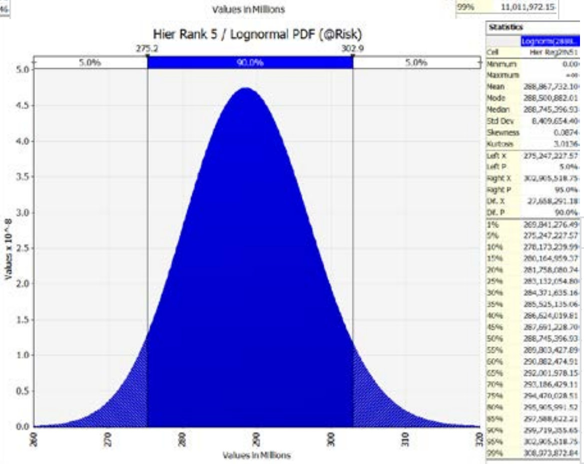
Model No.	Fit Model Type	Predictor Type	Single / Multiple Predictor Variable(s)	Predictor Variable(s)	Predictor Level / Tier	Predictor Level / Tier	No. of Obs.	Mean	Median	60th %ile	80st %ile	Std Error
6	**Linear Simple Regression**	**Hierarchy Level**	**Single**	**Hierarchy Rank**	Hardware / Software / I	1	102	1,734,328	893,681	1,196,420	2,355,509	2,884,488
	R-Sq =	0.659082	Durbin-Watson Stat =	1.2752178	Component / Part	2	174	2,613,621	1,996,348	2,404,374	3,702,893	2,208,483
	Adj R-Sq =	0.656735	DW AutoCorrelation =	0.3605	Assembly	3	190	6,244,922	5,921,629	6,431,563	7,791,469	2,091,548
	F-ratio =	280.8053	*Ref Model Name:*	*Hier Reg2*	Subsystem	4	104	14,965,793	14,700,393	15,422,080	17,237,459	2,856,618
	Prob. > F =	<.0001*			System	5	12	288,867,732	288,745,397	290,882,475	295,905,992	8,409,654
	RMSE =	29,131,897				**Total Applied**	**582**	**3.5%**	**Data Reduction**			
	Coef. of Variation (CV) =	2.486										









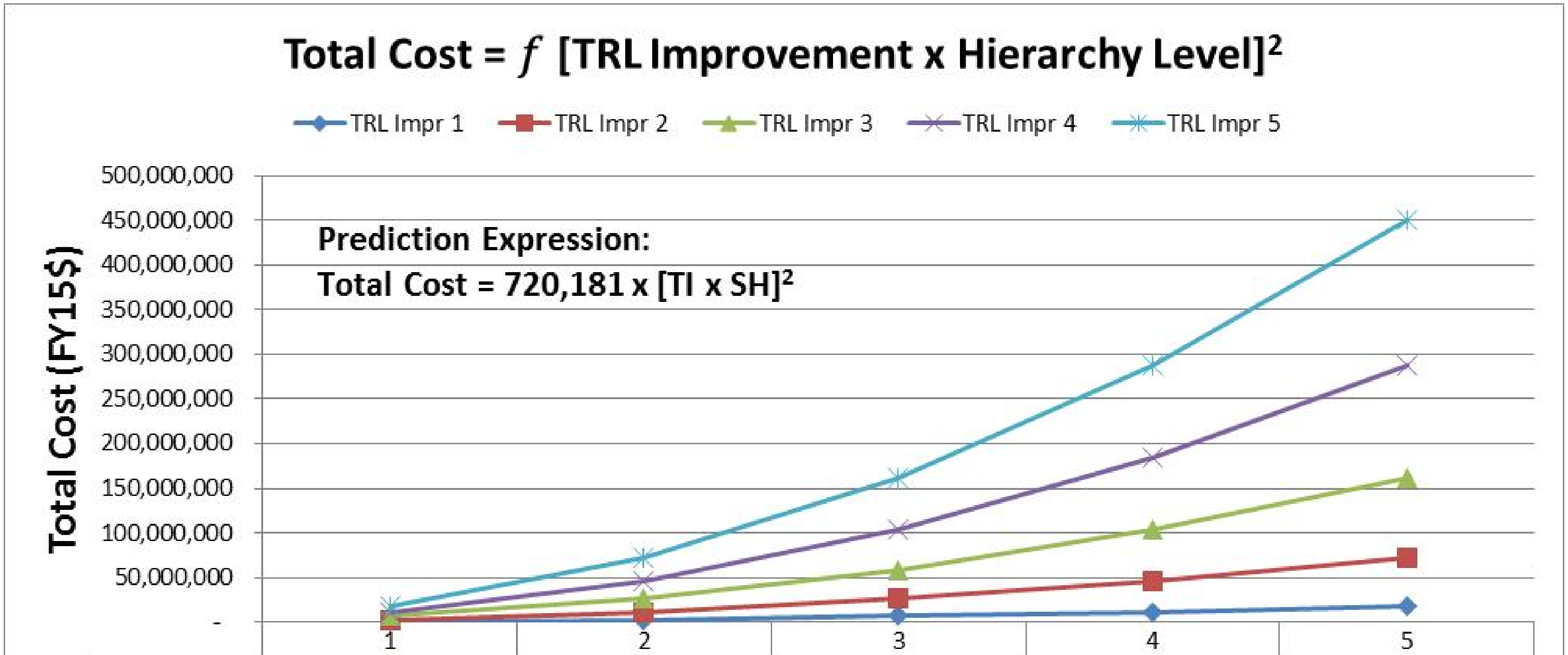


Prediction Expression

$$1734327.45098075 + \text{Match}\left(\text{Hierarchy Rank}\right)\begin{cases} 1 \Rightarrow 0 \\ 2 \Rightarrow 879293.353617182 \\ 3 \Rightarrow 4510594.36860685 \\ 4 \Rightarrow 13231465.1836346 \\ 5 \Rightarrow 287133404.632353 \\ \text{else} \Rightarrow . \end{cases}$$

Appendix F, cont.

Cost Model No. 7 (TRLxHier Sqrd7): Simple Linear Regression – [TRL Improv x Hierarchy]^2



	1	2	3	4	5
TRL Impr 1	720,181	2,880,722	6,481,625	11,522,890	18,004,515
TRL Impr 2	2,880,722	11,522,890	25,926,501	46,091,558	72,018,060
TRL Impr 3	6,481,625	25,926,501	58,334,628	103,706,006	162,040,634
TRL Impr 4	11,522,890	46,091,558	103,706,006	184,366,233	288,072,238
TRL Impr 5	18,004,515	72,018,060	162,040,634	288,072,238	450,112,873

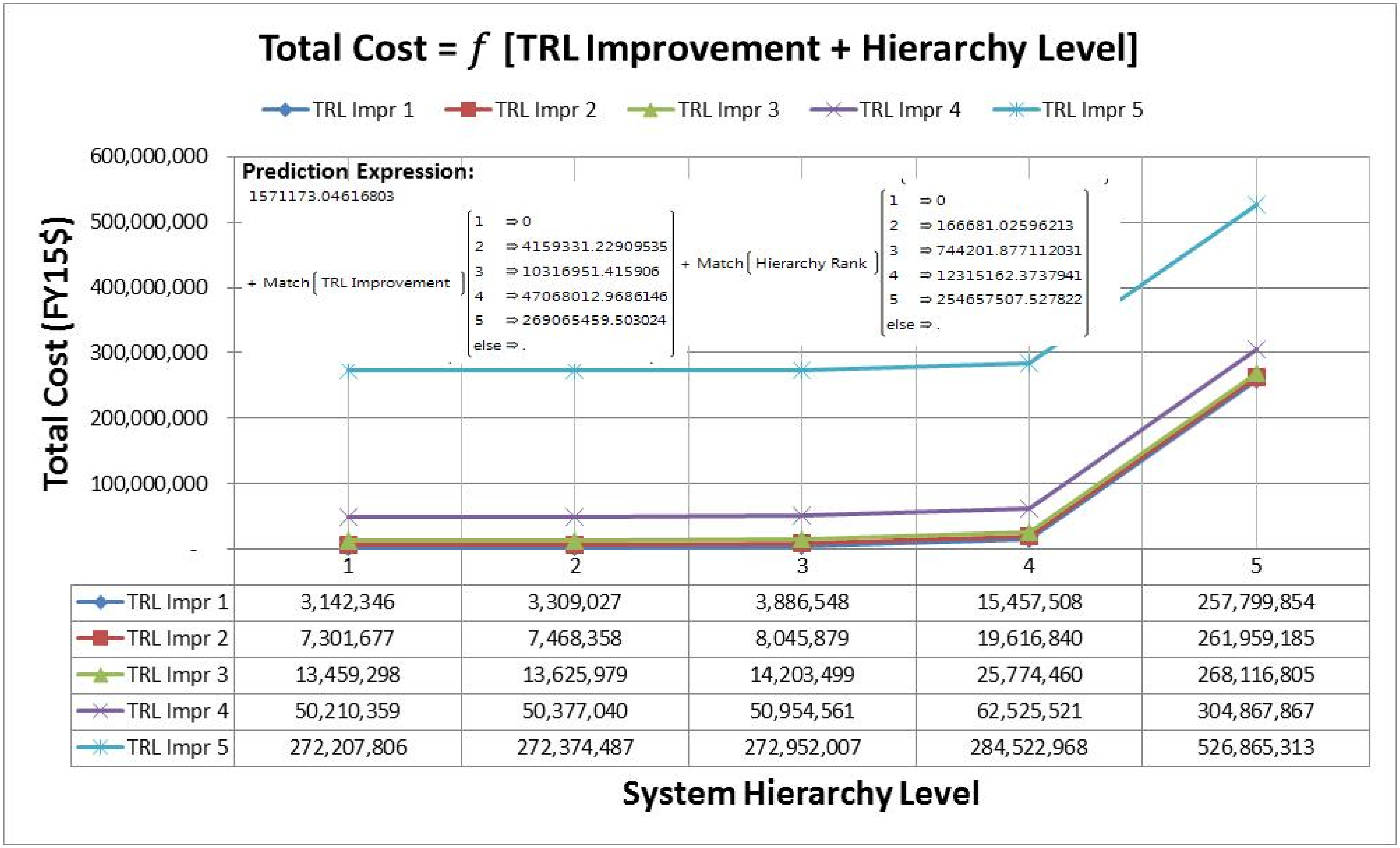
System Hierarchy Level

Note: Uncertainty PDFs for the twenty-five (5x5) TI x SH level categories are too numerous for presentation here are available upon request.

Parametric Cost and Schedule Modeling for Early Technology Development

Appendix F, cont.

Cost Model No. 8 (TRL-Hier Reg14): Multiple Linear Regression – TRL Improv + Hierarchy



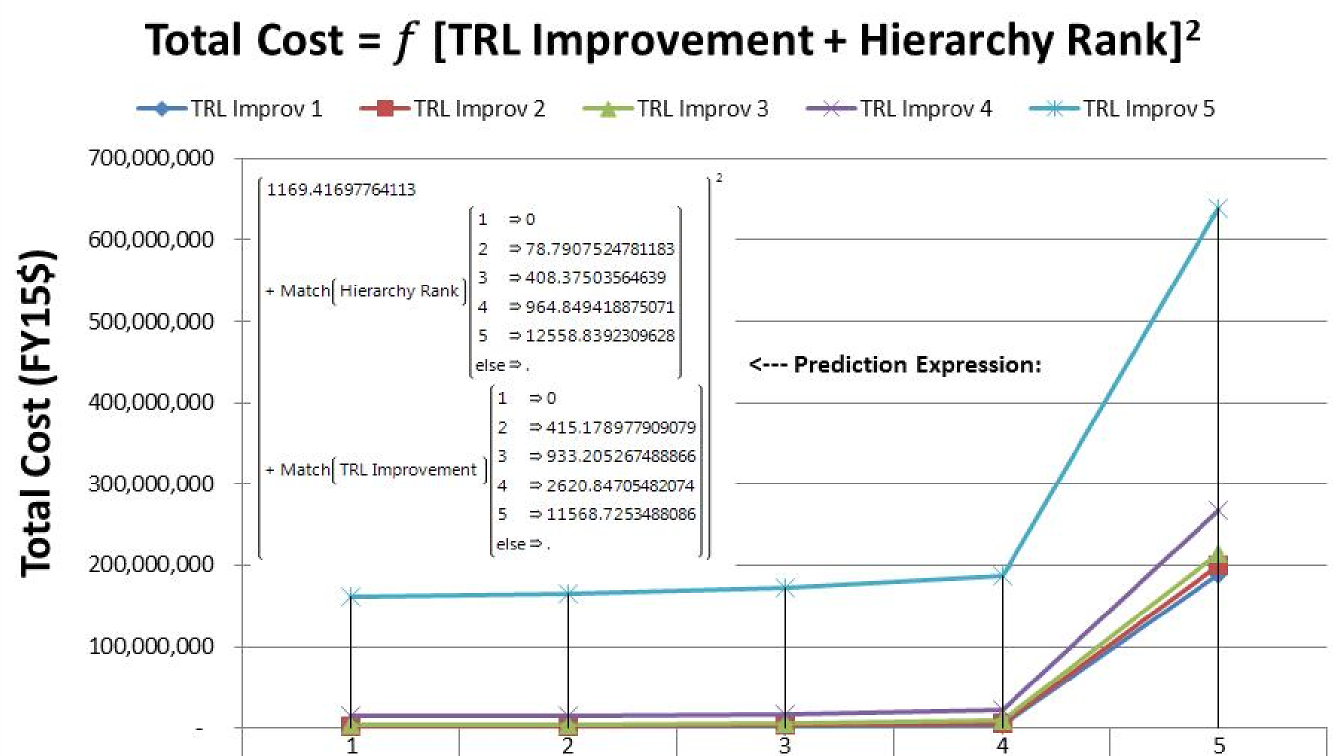
	1	2	3	4	5
TRL Impr 1	3,142,346	3,309,027	3,886,548	15,457,508	257,799,854
TRL Impr 2	7,301,677	7,468,358	8,045,879	19,616,840	261,959,185
TRL Impr 3	13,459,298	13,625,979	14,203,499	25,774,460	268,116,805
TRL Impr 4	50,210,359	50,377,040	50,954,561	62,525,521	304,867,867
TRL Impr 5	272,207,806	272,374,487	272,952,007	284,522,968	526,865,313

Note: Uncertainty PDFs for the twenty-five (5 x 5) TI & SH level categories are too numerous for presentation here but are available upon request.

Parametric Cost and Schedule Modeling for Early Technology Development

Appendix F, cont.

Cost Model No. 9 (TRL-Hier Sqrd Reg15): Multiple Linear Regression – [TRL Improv + Hierarchy]^2



	1	2	3	4	5
TRL Improv 1	1,367,536	1,558,023	2,489,428	4,555,093	188,465,019
TRL Improv 2	2,510,944	2,766,855	3,971,933	6,499,672	200,036,759
TRL Improv 3	4,421,020	4,758,563	6,305,107	9,409,382	214,958,453
TRL Improv 4	14,366,101	14,969,585	17,628,570	22,611,104	267,293,178
TRL Improv 5	162,260,270	164,273,773	172,830,919	187,771,983	639,937,276

System Hierarchy Level

Note: Uncertainty PDFs for the twenty-five (5 x 5) TI & SH level categories are too numerous for presentation here are available upon request.

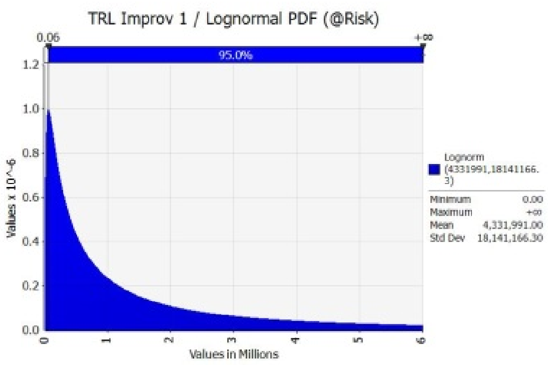
Parametric Cost and Schedule Modeling for Early Technology Development

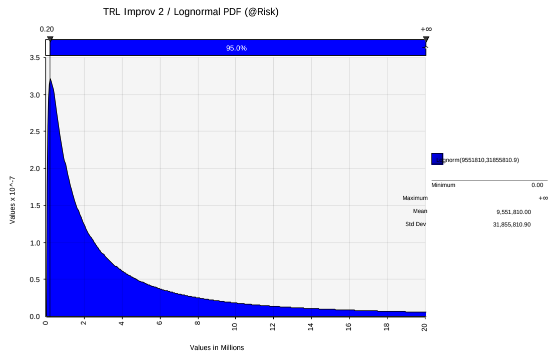
Appendix F, cont.

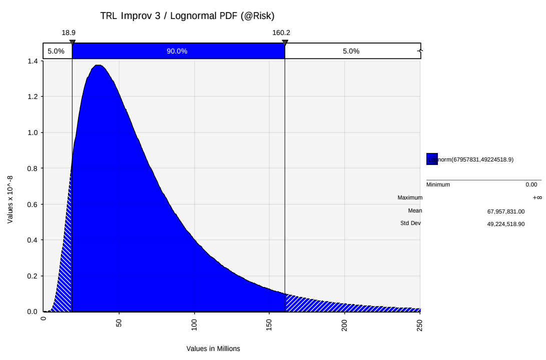
Nonlinear TI Level Cost Model No. 10 (TI NL-Quadratic)

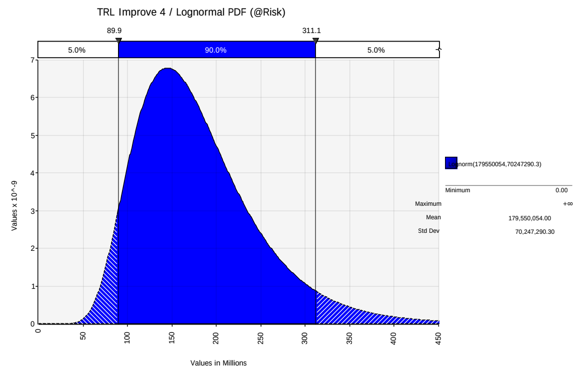
Model No.	Fit Model Type	Predictor Type	Single / Multiple Predictor Variable(s)	Predictor Variable / Parameter	Predictor Level / Parameter Name	Predictor Level / Parameter	Parameter Est. / No. Obs.	Prediction Estimate	Median	60th %ile	80st %ile	Mode
10	**Nonlinear - Quadratic**	**TRL Improvement Level**	**Single**	**TRL Improvement**	TRL Improvement 1	1		4,331,991	1,006,162	1,551,226	4,238,667	54,279
	Summary of Fit		*Ref Model Name:*	*TRL NL - Quadratic*	TRL Improvement 2	2		9,551,810	2,743,392	4,093,405	10,366,742	226,304
	AICc	12,885			TRL Improvement 3	3		67,957,831	55,036,648	64,879,635	95,067,227	36,097,482
	BIC	12,901			TRL Improvement 4	4		179,550,054	167,208,302	183,984,663	229,720,738	145,011,495
	SSE	3.643E+17			TRL Improvement 5	5		344,328,479	331,945,687	355,504,827	416,861,098	308,500,024
	MSE	1.068E+15		**Function**	Form	**Quadratic**						
	RMSE	32,684,768			Equation	Cost = a + b x TRL Improv + c x TRL Improv2				Lower 95%	Upper 95%	
	R-Square	0.6097699		**Parameters**	Intercept	a	52,298,374			36,460,718	68,136,030	N/A
	Coef. of Variation (CV) =	1.606			Slope	b	(74,559,484)			(90,696,944)	(58,422,023)	N/A
					Quadratic	c	26,593,101			23,012,184	30,174,017	N/A
						Total Applied	**343**	**15.3%**	**Data Reduction**			

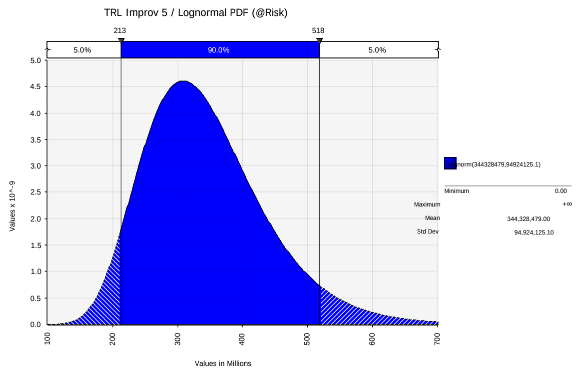
Nonlinear TI Level Cost Model No. 10 (TI NL-Quadratic) PDFs

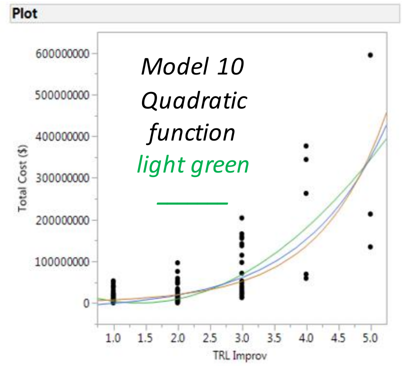












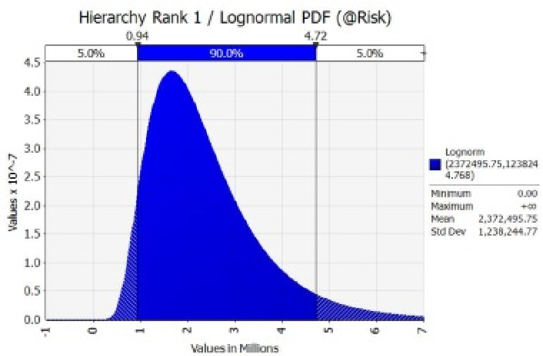
Parametric Cost and Schedule Modeling for Early Technology Development

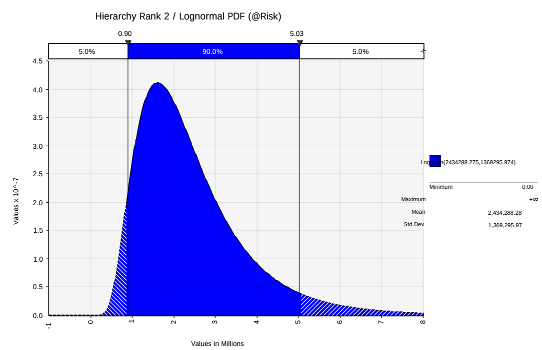
Appendix F, cont.

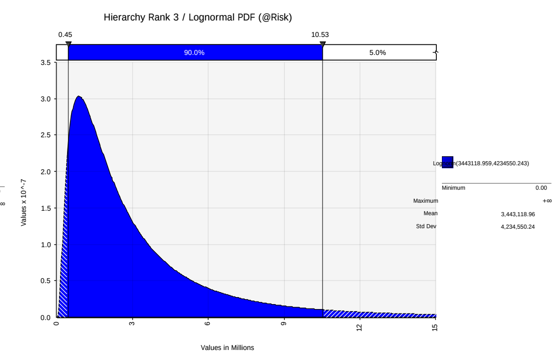
Nonlinear SH Level Cost Model No. 12 (SH NL-Exponential 3P)

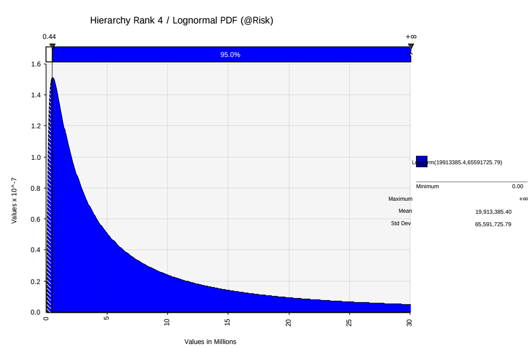
Model No.	Fit Model Type	Predictor Type	Single / Multiple Predictor Variable(s)	Predictor Variable / Parameter	Predictor Level / Parameter Name	Predictor Level / Parameter	Parameter Est. / No. Obs.	Prediction Estimate	Median	60th %ile	80st %ile	Mode
12	**Nonlinear - Exponential 3P**	**Hierarchy Level**	**Single**	**Hierarchy Rank**	Hardware / Software / Mat'l.	1		2,372,496	2,103,266	2,381,757	3,179,024	1,652,995
	Summary of Fit		*Ref Model Name:*	*Hier NL- Exponential 3P*	Component / Part	2		2,434,288	2,121,663	2,423,068	3,298,529	1,611,703
	AICc	19,749			Assembly	3		3,443,119	2,172,173	2,770,150	4,872,234	864,528
	BIC	19,766			Subsystem	4		19,913,385	5,784,901	8,615,831	21,727,389	488,200
	SSE	3.316E+17			System	5		288,808,534	59,985,261	93,997,585	266,732,460	2,587,698
	MSE	6.233E+14		**Function**	Form	**Exponential 3P**						
	RMSE	24,966,011			Equation	Cost = a+b x EXP(c x Hierarchy Rank)				Lower 95%	Upper 95%	
	R-Square	0.7436299		**Parameters**	Asymptote	a	2368463.9			-46553.5	4783481.2	N/A
	Coef. of Variation (CV) =	2.070			Scale	b	246.95741			-254.6162	748.53104	N/A
					Growth Rate	c	2.7927648			2.3862295	3.1993001	N/A
						Total Applied	**535**	**11.3%**	**Data Reduction**			

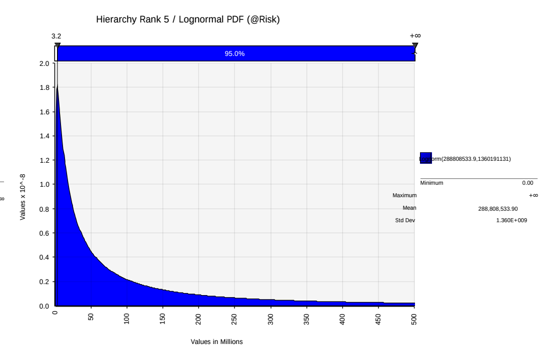
Nonlinear SH Level Cost Model PDFs - Model No. 12 (SH NL-Exponential 3P)











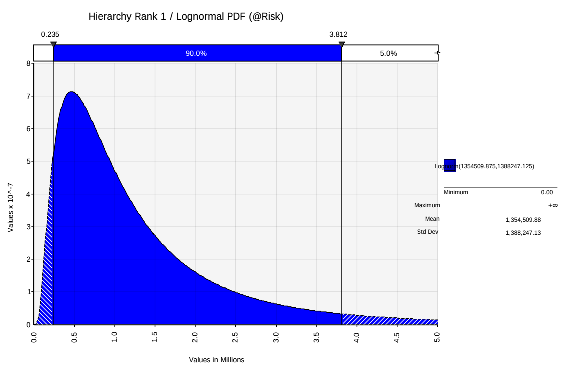
Parametric Cost and Schedule Modeling for Early Technology Development

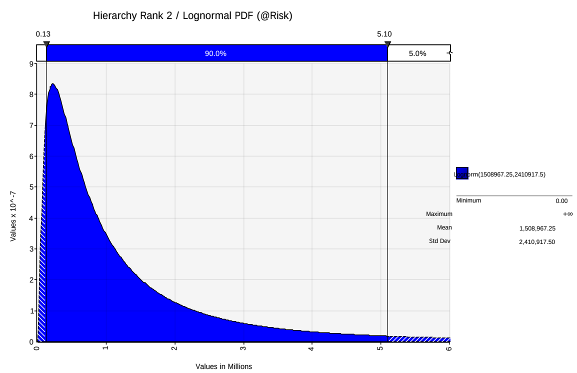
Appendix F, cont.

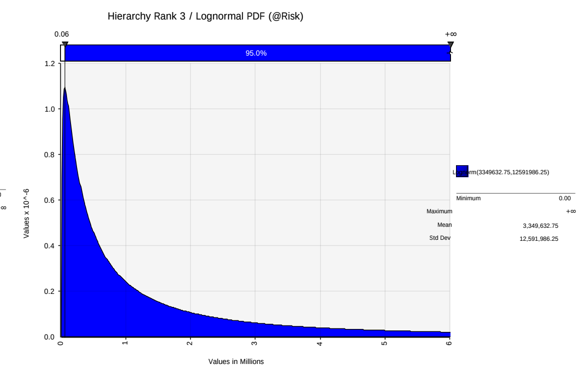
Nonlinear SH Level Cost Model No. 13 (SH NL-Gompertz 4P)

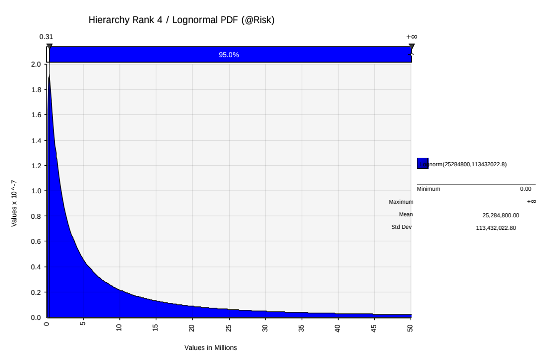
Model No.	Fit Model Type	Predictor Type	Single / Multiple Predictor Variable(s)	Predictor Variable / Parameter	Predictor Level / Parameter Name	Predictor Level / Parameter	Parameter Est. / No. Obs.	Prediction Estimate	Median	60th %ile	80st %ile	Mode
13	**Nonlinear - Gompertz 4P**	**Hierarchy Level**	**Single**	**Hierarchy Rank**	Hardware / Software / Mat'l.	1		1,354,510	945,930	1,172,449	1,930,128	461,332
	Summary of Fit		*Ref Model Name:*	*Hier NL-Gompertz 4P*	Component / Part	2		1,508,967	800,569	1,064,833	2,065,089	225,339
	AICc	19,754			Assembly	3		3,349,633	861,100	1,307,399	3,447,583	56,907
	BIC	19,775			Subsystem	4		25,284,800	5,501,148	8,562,946	23,924,522	260,400
	SSE	3.335E+17			System	5		286,685,634	71,940,045	109,630,329	291,585,161	4,530,021
	MSE	6.281E+14		**Function**	Form	**Gompertz 4P**						
	RMSE	25,060,990			Equation	Cost = a + (b -a) x Exp(-Exp(-c x(Hierarchy Rank - d)))				Lower 95%	Upper 95%	
	R-Square	0.7421611		**Parameters**	Lower Asymptote	a	8.24E+14			-6.76E+14	2.32E+15	N/A
	Coef. of Variation (CV) =	2.078			Upper Asymptote	b	1340361.5			-1157856	3838579	N/A
					Growth Rate	c	-2.477964			-2.780436	-2.175492	N/A
					Inflection Point	d	11.003063			11.003063	11.003063	N/A
						Total Applied	**535**	**11.3%**	**Data Reduction**			

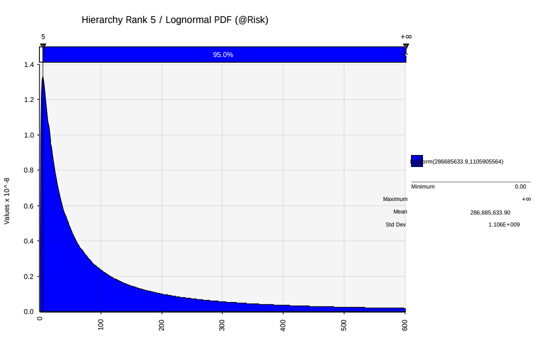
Nonlinear SH Level Cost Model PDFs - Model No. 13 (SH NL-Gompertz 4P)





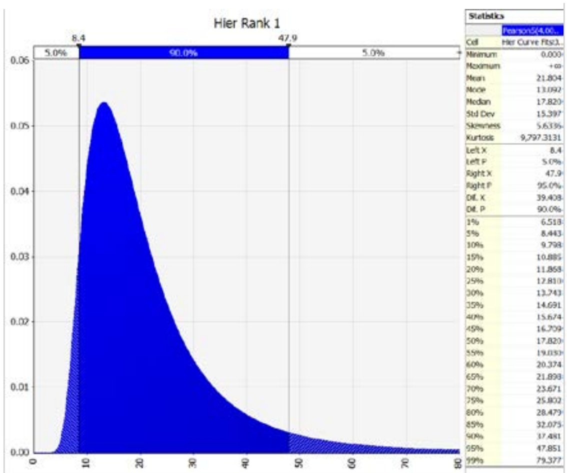


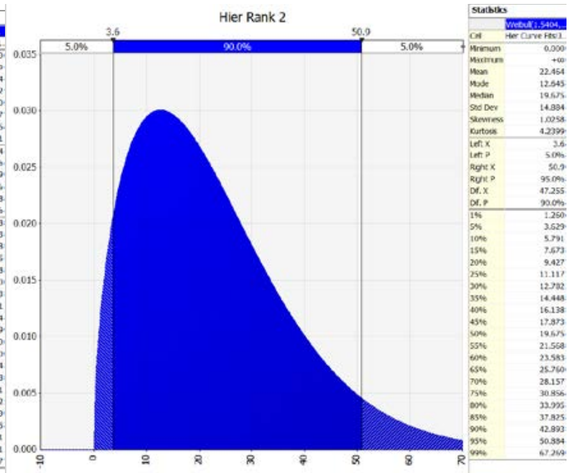


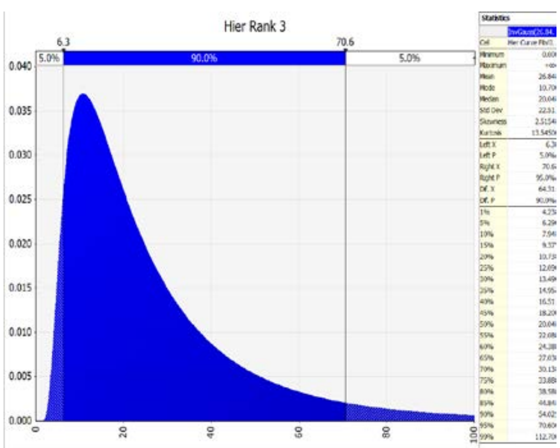


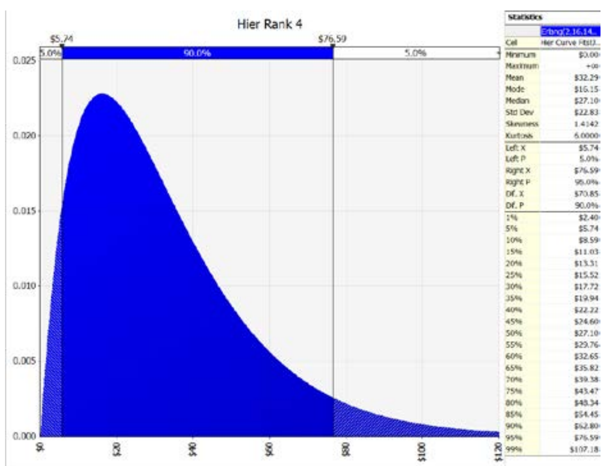
Appendix G - Schedule Model Output

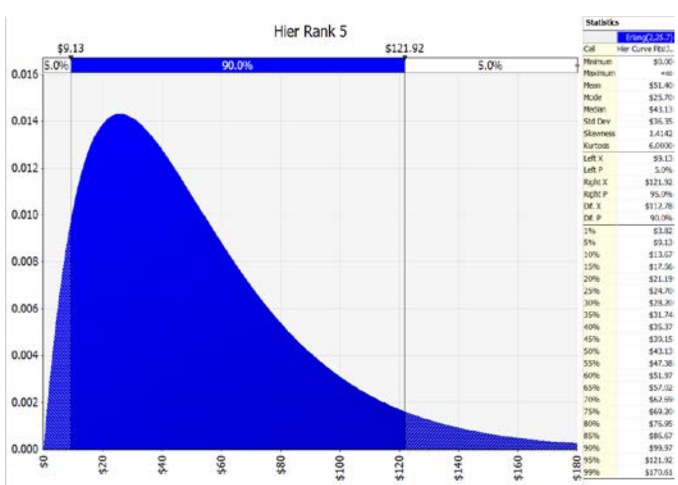
Schedule Model No. 1 Selected Curve Fits –
Project Duration (months) vs System Hierarchy Level











Note: *Detailed model results are available upon request.*

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Acronyms / Abbreviations

A-D	Anderson-Darling
AD2	Advanced Degree of Difficulty
AIAA	American Institute of Aeronautics and Astronautics
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BS	Bachelors of Science
CA	California
CCE/A	Certified Cost Estimator/Analyst
Chi-Sq	Chi-Squared Tests
COTECHMO	Constructive Technology Development Cost Model
CPA	Certified Public Accountant
CPD	Cumulative Probability Distribution
CV	Coefficient of Variation
DDR&E	Director Defense Research and Engineering
DHS	Department of Homeland Security
DoD	Department of Defense
DOE	Department of Energy
FTE	Full Time Equivalents
FY	Fiscal Year
G&A	General and Administrative
GAO	Government Accounting Office
HQ	Headquarters
HSI	Homeland Security Institute
ICEAA	International Cost Estimating and Analysis Association
ImpRL	Implementation Readiness Level
IP	Intellectual Property
IRL	Integration Readiness Levels
JHU/APL	The Johns Hopkins University Applied Physics Laboratory
KPM	Key Performance Measures
KPP	Key Performance Parameters
K-S	Kolmogorov-Smirnov
LLC	Limited Liability Corporation
MBA	Master's in Business Administration
MD	Maryland
MRL	Manufacturing Readiness Level
NASA	National Aeronautics Space Administration
NL	Nonlinear
NSAD	National Security Analysis Department
O&S	Operations and Support
P.E.	Professional Engineer
PDF	Probability Density Function
PE	Professional Engineer
PERT	Program Evaluation and Review Technique
R&D	Research and Development
R^2	Coefficient of Determination

RD3	R&D Degree of Difficulty
RMSE	Root Mean Square Error
SAIC	Science Applications International Corporation
SER	Schedule Estimating Relationships
SH	System Hierarchy
SME	Subject Matter Expert
SRL	Systems Readiness Levels
SSR	Sum of Squares due to Regression
SST	Total Sum of Squares
TA	Technology Areas
TCASE	Technology Cost and Schedule Estimating
TI	TRL Improvement
TRA	Technology Readiness Assessments
TRL	Technology Readiness Level
USA	United States of America
VA	Virginia
VIF	Variance Inflation Factor
VROM	Very Rough Order of Magnitude

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Author Biography

Chuck Alexander is a Senior Professional II with the JHU/APL National Security Analysis Department (NSAD), JTC Cost Analysis Team. Mr. Alexander performs economic and cost analysis for a variety of Sponsors across a range of applications, technologies, and system environments. He has over 30 years of professional experience in cost engineering, investment decision analysis, business operations & technology management and management consulting. Mr. Alexander is a licensed Professional Engineer (P.E.), Certified Public Accountant (CPA), former Certified Cost Estimator / Analyst (CCE/A) and holds an BS in Mechanical Engineering from Clarkson University and an MBA in Finance from the William & Mary Mason School of Business.