Development of the Small Satellite Cost Model 2014 (SSCM14)

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Abstract—**Prompted by the rise in the use of small satellites throughout the space industry in the late 1980's, The Aerospace Corporation began to study small satellites to better understand the design principles that were being employed in their implementation. These studies highlighted the fact that cost models developed for traditional large satellites were not applicable to small satellites. This led to the development of the Small Satellite Cost Model (SSCM) in the mid-1990's. This model estimates subsystem- and system-level costs for satellites weighing less than 1000 kg, not including Cubesats, using cost estimating relationships (CERs) derived from actual costs and technical parameters. Over the years, SSCM has evolved to account for the increasing number of small satellites that have been launched, refine the CERs and increase the scope of the model. This paper will discuss the development of the current version of SSCM released in 2014 (SSCM14). The topics covered will include the history of SSCM, the CER generation process, updates from the previous version of SSCM, the application of the model, and future efforts to enhance the model.**

TABLE OF CONTENTS

1. INTRODUCTION

In the past two decades, developers of space systems have turned toward small satellites as vehicles for science and technology demonstration missions. Small satellites, defined as weighing less than 1000 kg, because of their functional and operational characteristics and comparatively low development and service costs, have provided access to space for more users than the large satellites prevalent over the last 30-40 years [1]. Relatively low acquisition costs and short development timelines offer space-related capabilities previously reserved only for highly-funded programs. Small satellites with sufficient power, pointing and tracking accuracy, on-board data compression, storage and processing capabilities, high-rate data downlinking, and associated ground segments for a variety of applications have been demonstrated by NASA, the DOD, the Centre National d'Études Spatiales (CNES), the European Space Agency (ESA), and various other organizations. However, due to the desire to use less expensive small launch vehicles, advanced and commercial technologies are increasingly being incorporated into small spacecraft to systematically reduce mass and increase performance, in some cases with minimal insight into the impacts to cost and assumed risk.

Small satellite studies at The Aerospace Corporation (Aerospace) have shown that cost-reduction techniques, including the use of commercial off-the-shelf hardware and software, employed on modern small satellite programs, result in system costs that are substantially lower than those estimated by traditional weight-based parametric cost estimating relationships (CERs.) [2]. Cost models based on historical costs and technical parameters of traditional large satellites are not applicable to this class of missions [3], [4]. Credible parametric cost estimates for small satellite systems require CERs derived from a cost and technical database of modern (post-1990) small satellites. The Small Satellite Cost Model (SSCM) was developed in response to this shift towards small satellites.

Industries continuously evolve and the satellite industry is no different. After the paradigm shift to the use of small satellites in the 1990's, the past decade has seen another paradigm in satellite development with the introduction of cubesats. Just as the cost models of the time were not applicable for small satellites when they became more prevalent and led to the need for SSCM, the same can be said for SSCM when it comes to estimating the costs cubesats. Cubesats are developed under a completely different paradigm that is not representative of the satellites that are used to develop SSCM and as such SSCM is not applicable to estimate the costs of cubesats.

This paper updates the last paper written on SSCM for the version released in 2002 (SSCM02) [16] covering many of topics and information which are common to all versions of SSCM while providing updates on the changes to SSCM since then and providing specifics about the new version released in 2014 (SSCM14). The paper is organized as follows: Section 2 discusses the history of SSCM; Section 3

describes the philosophy related to the development of the CERs used in the model; Sections 4 and 5 cover additional features in the user interface related to cost risk and funding profiles, respectively; and Section 6 steps through the use of the user interface in which SSCM14 is implemented.

2. HISTORY

Work on the development of CERs to estimate the costs of small satellites began in the early 1990's with funding from various DoD organizations. These early CERs only estimated system-level costs of spacecraft and were based on a very limited database. The CERs continued to be refined and were eventually implemented in a standalone DOS-based PC program known as The Aerospace Corporation's Small Satellite Cost Model (SSCM). These CERs estimated the total satellite bus cost as a function of spacecraft technical parameters (e.g., mass, power, pointing accuracy). In the mid-1990's, a new methodology for developing CERs was implemented with the introduction of the General-Error Regression Model (GERM) [5]. Additionally, work began on the first set of subsystem CERs.

At the same time, NASA began to seek better cost analysis methods and models specifically tailored to small satellite programs. This search was motivated by NASA's need to respond to increasingly frequent questions regarding small satellite concepts and system analysis. In 1995, NASA's Lewis Research Center (now Glenn Research Center) and NASA Headquarters (HQ) Code BC funded the first phase of an activity at Aerospace to gather information regarding capabilities and costs of small satellites and to develop a set of subsystem-level small satellite CERs. This effort involved an examination of technical and economic issues related to designing, manufacturing and operating small satellites. Programs either already completed or launching in the next year were targeted for data collection, so that the technical and cost data obtained were as close to final as was feasible. A cost and technical survey was generated and distributed to each of these programs. The data that were collected consisted not only of mass, power, technical parameters, and cost for satellites, but also impacts on cost such as schedule difficulties, funding interruptions, requirements changes, and cost-sharing among multiple contractors. From this data, Aerospace developed several stand-alone CERs that estimated recurring and non-recurring costs of small satellite subsystems. This model, along with other cost estimating tools and databases, provided the capability to estimate lifecycle costs for a variety of small mission concepts. The resulting form of the model, which used subsystem CERs to estimate the total cost of a small satellite, is the form that the model has to this day.

In 1998, Aerospace began funding SSCM development and upgrades through internal research and development funds, resulting in the release of an updated version that same year. This version was the first to include interplanetary spacecraft and incorporate NASA's technology readiness levels (TRLs) to generate risk-based estimates. Also, the model was moved from a DOS- to an Excel-based tool.

Work on SSCM has continued, leading to the release of new versions in 2000, 2002, 2005, 2007, 2010, and 2014. SSCM02 included a number of changes, including a more powerful and flexible graphical user interface (including the first deployment of the funding profile feature) and new approach to cost risk that was user driven as opposed to being based on TRLs. The change to the cost risk methodology was made as further review of the TRL-based approach highlighted that the inputs to the algorithm were too subjective for the exactness of the result that was provided. SSCM05 saw the introduction of two sets of CERs that sub-divided the available data into two classes: micro (≤100 kg mass) and small (>100 to ≤1000 kg mass). The micro CERs had been looked at for previous versions, as it had been noticed that micro satellite missions trended differently than satellites with masses greater than 100 kg, but due to limited data, had not been deemed usable. The addition of new data provided a large enough data set from which to generate micro CERs. Since then SSCM has not gone under any radical changes; the subsequent versions have been released to account for new data and new cost drivers.

The general cadence for updating SSCM is every two to three years. Typically an update does not occur sooner than two years, but can be more than three years as can be seen in the time between SSCM10 and SSCM14. The timing is a function of many factors: new/updated data, available funding, perceived model staleness, etc.

3. CER DEVELOPMENT

The first step in the development of new CERs for SSCM14 was reviewing the available data to make sure that it was properly categorized and normalized. This is a very important step as the CERs are only as good as the data from which they are generated. Once that was done, the actual CER development could be undertaken. This began by using a combination of statistics, engineering judgment, and often, common sense, to find which of the 200+ technical parameters within the database worked best for each subsystem. This included looking at parameters directly associated with a subsystem (e.g., beginning-of-life power for the electrical power subsystem) as well as parameters not directly associated with a subsystem (e.g., satellite wet mass for the attitude determination and control subsystem). This process is not a one-time occurrence and the search for parameters continued throughout the whole of the CER generation process.

As a starting point for the CER generation, all forms of CERs were considered from single variable linear and non-linear CERs to multi-variable linear and non-linear CERs. When looking at multi-variable CERs, care was taken to use non-correlated parameters. For example, little is gained by

regressing against both beginning-of-life power and end-of-life power, since the two are highly correlated. In general, throughout the history of the development of SSCM, higher-order non-linear CERs have tended to provide the best results, and that was once again the case for SSCM14. For SSCM, best is considered to encompass good statistical fit, low error, simple, and physically meaningful. While a good amount of data is available from which to generate the CERs, care was taken to not include too many parameters in the CERs. As each CER was developed, the results were examined for any statistical outliers and time was taken to identify whether the apparent discrepancies were attributable to numerical errors or possibly non-traditional ways of accounting for costs; based on this information, choices were made to exclude data points that were not in-family with the whole of the data set.

One other step in the CER generation process was to look for cases, where it might make sense, from an engineering perspective, to subdivide subsystems into separate categories to account for fundamentally different design approaches. An example is the attitude determination and control subsystem, where the primary approaches are spin-stabilized and 3-axis which can be significantly different and driven by distinct parameters. By segregating the data in such a way, the cost drivers for each type of design could be better explored, leading to more appropriate CERs.

Statistical Approach

The CER development effort takes advantage of developments in regression techniques applied to cost analysis. In regression, models are classified as one of two types: additive-error or multiplicative-error. In the simple linear case the model can be expressed in one of two ways:

$$y = a + bx + \varepsilon \qquad (1)$$

or

$$y = (a + bx) \times \varepsilon \qquad (2)$$

where y is the true cost, x is a cost-driving parameter, $a + bx$ is the estimated cost, and ε is the (random) error of estimation (a and b are referred to as "coefficients" of the model). The error model in (1) is known as an additive-error model, since the error is an additive term. The error model in (2) is known as a multiplicative-error model, since the error term is a multiplicative factor.

Analogous examples for a common nonlinear situation are

$$y = ax^b + \varepsilon \qquad (3)$$

or

$$y = ax^b \times \varepsilon \qquad (4)$$

where y is true cost, x a cost-driver, ax^b is the estimated cost, and ε the error of estimation.

In an additive-error model, each observed value of cost is assumed to be a function of cost-driving parameters plus a random error term that does not depend on the parameters. Unfortunately, this assumption is often not valid. A case in point is where the actual costs change by an order of magnitude or more as a function of the inputs, in which case the random error should be considered proportional to the cost. In such an instance, a multiplicative-error model can be assumed, where the error is proportional to the y-value, so that larger costs lead to larger dollar value errors.

The discussion to follow only focuses on multiplicative error, since that is the formulation used to derive the CERs for SSCM. The statistical framework is the equation

$$y = f(x) \times \varepsilon \qquad (5)$$

where y is the true cost, x is a cost-driving parameter, $f(x)$ is the estimated cost, and ε is the proportional error of estimation. Here, $f(x)$ can take on *any* functional form, linear or non-linear, single or multivariate, that is found to be appropriate. In theory, there is no limit to the number of forms that can be used; in practice, however, the forms are often "limited" to a smaller set of possibilities, due to the nature or shape of the data.

In the multiplicative-error model, one sample observation y_i corresponds to each x_i, and the error term ε_i equals the ratio of y_i to $f(x_i)$. Thus,

$$\varepsilon_i = \frac{y_i}{f(x_i)} \qquad (6)$$

where $\varepsilon_i = 1$ for all i would indicate no predictive error. Here, the least-squares problem is to find the coefficients (of f) that minimize the sum of squared relative deviations (errors) from the predictions. That is, once the functional form is chosen, the calculation consists of minimizing the sum of squared *percentage* errors:

$$\sum_{i=1}^{n}\left(\varepsilon_i - 1\right)^2 = \sum_{i=1}^{n}\left[\frac{y_i}{f(x_i)} - 1\right]^2 = \sum_{i=1}^{n}\left[\frac{y_i - f(x_i)}{f(x_i)}\right]^2 \qquad (7)$$

where x_i and y_i are the observed values. This minimization is achieved via numerical computation, yet some care must be exercised to ensure that one obtains the global minimum when employing such methods. This problem has been mitigated by developing and employing several powerful mathematical tools to assist in the minimization process. This form of regression has been termed General Error Regression and the model General Error Regression Model (GERM) [5].

3

Once the regression has been carried out, there are a number of ways to assess the quality of the CER:

Standard Error of Estimate (SEE): The root-mean-square (RMS) of all percentage errors made in estimating points of the data (a "one-sigma" number that can be used to bound the actual cost within an interval about the estimate). Note that this number is a *percentage*, rather than, say, a dollar value. The formula for the SEE is

$$SEE = \sqrt{\frac{1}{n-m}\sum_{i=1}^{n}\left(\frac{y_i}{f(x_i)}-1\right)^2} \qquad (8)$$

where n is the number of observed values and m is the number of parameters being estimated (not the number of independent variables). The SEE quantifies the accuracy to which the cost model represents its own underlying data under the various uncertainties.

Average Percentage Bias: The algebraic sum (positives and negatives included) of all percentage errors made in estimating points of the data averaged over the number of points; bias measures how well percentage over-estimates and under-estimates are balanced.

Pearson's Correlation Squared (R^2): The R^2 value measures the amount of correlation between estimates and corresponding database actuals; that is, the extent of linearity in the relationship between the two quantities.

Even within the GERM framework, there are two schools of thought on which types of CERs to derive: minimum percentage error (MPE) or minimum percentage error under zero percentage bias constraint (MPE-ZPB). All things being equal, an unbiased estimator is preferred over a biased one. Unfortunately, in general, a CER cannot be optimized with respect to two different criteria (SEE <u>and</u> bias, for example), so SSCM's CERs cannot be optimal with respect to all three above statistical criteria. In choosing to derive MPE-ZPB CERs for SSCM, zero bias was considered preferable to lower standard error, allowing the model to calculate an unbiased estimate of the entire spacecraft bus.

When it comes to the final selection of the CERs, both SEE and R^2 are used as part of the decision process for which CER to pick to represent a subsystem. In the case of SSCM, the goal is to develop a CER that has a SEE of 30% or less and a R^2 of 0.70 or greater. These are just guidelines that have been selected and are not hard limits that must be followed. The CER must also make physical sense and simple (as mentioned above). And there are cases where one or both cannot be met and the best possible CER is selected to represent the subsystem.

4. COST RISK

Technology and Heritage

One of several dilemmas in cost-estimation is the uncertainty inherent in parametric models, which includes such things as uncertainty associated with hardware design, inflation, labor rates, contractor accounting practices, and overhead rates. In the case of parametric cost models utilizing general-error regression, and with SSCM in particular, general cost-estimating uncertainty is quantified by the SEE.

Cost growth due to unforeseen technical difficulties has greater potential to cause costing uncertainty than any other single influence. Technical difficulties are often related to a project's attempt to inject new technologies with limited or no flight demonstration into the design of the spacecraft. Twelve major NASA projects initiated after 1977 and completed before 1993 experienced an average cost growth of 77%, with eight of them citing technical complexities as a major risk driver [6]. Unfortunately, quantification of technical risk is not nearly as straightforward as quantifying general cost-estimating uncertainty.

The level of design reuse (i.e., heritage) in a particular subsystem also impacts the amount of cost risk inherent in building that subsystem. Heritage is not the same as technology insertion; a system can exist where a previously developed design is utilized, but new technologies are also incorporated. A common example is an existing ADCS design that incorporates a new star tracker into a standard interface.

A simple scheme for adjusting the cost estimate based on technical risk and heritage is implemented in SSCM. This scheme uses a triangular cost probability distribution for each subsystem, where the most likely cost is the output of the CER and the upper and lower limits are user-defined (Figure 1). By identifying the lowest possible cost for the subsystem (e.g., 10% below the most likely estimate), as well as the highest possible cost (e.g., 150% greater than the most likely estimate), an appropriate distribution is calculated. A subsystem with very low design maturity and no flight heritage must have a much larger upper bound than a subsystem that has flight heritage and is very mature. This scheme allows modification of the cost risk parameters for each subsystem to properly take into account the cost uncertainty due to technology development and heritage. The user is left to determine the percentages to input for each subsystem based on engineering judgement, historical data, the planned design, etc.

Cost-Probability Distribution

Two sources of risk for each cost element have been defined: general cost-estimating uncertainty and uncertainty due to design implementation. General cost-estimating uncertainty is quantified by the SEE, while uncertainty due to design implementation is quantified by a triangular
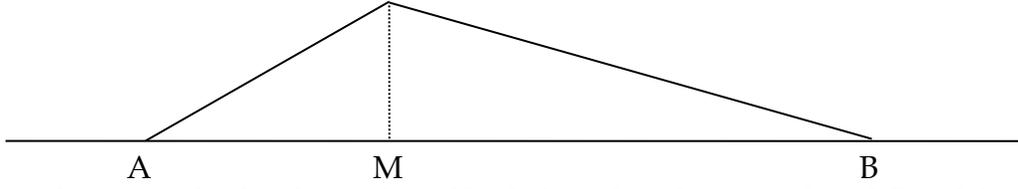
Figure 1. Example of triangular distribution defined by the lower bound, A, upper bound, B, and the "most likely" estimate, M, derived from the CER. Depending on the inputs, the triangle can have any shape, including a right triangle (A = M or M = B), isosceles (M – A = B – M), or even a single point (A = M = B).

distribution defined by A, B, and M (Figure 1). These two sources of cost risk are merged into one cost-probability distribution that has a mean equal to the mean of the triangular distribution

$$Mean_{ss} = \frac{1}{3}(A + B + M) \qquad (9)$$

and a variance that is equal to the sum of the variances from both sources of uncertainty

$$Var_{ss} = SEE^2 + \frac{1}{18}(A^2 + B^2 + M^2 - AB - AM - BM) \qquad (10)$$

The system-level variance is also affected by the correlation of the errors in individual subsystems. Cross-correlation coefficients are needed to accurately capture the statistical effects of adding uncertainties [7], [8]. Correlation coefficients can be calculated in two ways: linear (Pearson's product-moment) correlation and rank (Spearman's) correlation [9]. Pearson's product-moment correlation is a measure of the linearity between two random variables and Spearman's rank correlation is a measure of the monotonicity between two random variables. In SSCM, linear correlation coefficients are derived and used because the sum of random variables depends on Pearson's product-moment correlation and not Spearman's rank correlation.

Correlation coefficients are generated for the relationship between each subsystem- and system-level element. The coefficients are calculated using

$$\rho_{xy} = \frac{\sum_{i=1}^{n}(x_i - x_m)(y_i - y_m)}{\sqrt{\sum_{i=1}^{n}(x_i - x_m)\sum_{i=1}^{n}(y_i - y_m)}} \qquad (11)$$

where ρ_{xy} is the correlation coefficient between two elements, x and y are errors from each element, and x_m and y_m are the average errors from each element. Correlation coefficients range in value from −1 to +1. A coefficient of either −1 or +1 denotes that two subsystems are perfectly correlated; the error in one subsystem will be directly reflected in the error of the subsystem to which it is correlated.

The variance from the correlation coefficients is added to the variance for the CER and design implementation uncertainty to generate the variance for the total spacecraft and system according to [10]

$$Var_t = \sum_{i=1}^{n} Var_{ss} + 2\sum_{k=2}^{n}\sum_{j=1}^{k-1} \rho_{jk}\sigma_j\sigma_k \qquad (12)$$

where ρ_{jk} is the correlation coefficient between elements j and k, and σ_j and σ_k are the standard deviations for elements j and k calculated from the original variance equation. The first term represents the sum of the element variances, while the second term is the covariance calculated from the correlation coefficients.

With the total system variance calculated, a cost-probability distribution can be generated. Research by The Aerospace Corporation and the MITRE Corporation has shown that this distribution may be accurately approximated by a lognormal distribution [11]. This approximation technique, known as Formal Risk Assessment (FRISK), allows confidence percentiles to be computed without Monte Carlo simulation. The end product of the cost risk assessment in this framework is a total spacecraft cost-probability distribution, from which mean, standard deviation, percentiles, and other descriptive statistics can be read.

Error Estimation Outside the Range of Validity

Parametric cost models have certain advantages and disadvantages, as do all cost estimation techniques. One of the disadvantages of such models is that the CERs can only be reliably applied to inputs that fall within the range of the data used to create the CERs, which is termed the "range of validity." As a variable strays further from the range of validity, it would be expected that the CER estimate would be less reliable. For example, if a subsystem CER is based on subsystem mass and the mass range within the database is 5 kg to 50 kg, an estimate for a subsystem weighing 55 kg would be seen as more reliable than one weighing 80 kg.

Applying CERs outside the range of validity makes two assumptions: (1) the CER remains valid beyond the data range; and (2) the SEE does not change outside the data

5

range. The first assumption is not all that unreasonable, based on some studies done with data points outside the SSCM database. An in-depth analysis was made with one of the early SSCM versions using the planetary spacecraft NEAR (Near Earth Asteroid Rendezvous), which went beyond the SSCM database range in several cases, and provided decent correlation between the model results and the actual spacecraft costs [3]. Furthermore, in the absence of additional information, there is little reason to doubt the CER trend in the vicinity of the data range, although the trend may be less certain further away from the range of validity. However, the second assumption is questionable at best and unreasonable at worst, as the uncertainty should increase as the input deviates further from the database range. The SEE is a statistical measure whose value is based on the underlying data. By the very nature of the problem, there is no way to analytically compute a new value outside the range of validity. Further, the SEE is a measure of cost-estimating uncertainty, not CER-applicability uncertainty. The problem here is one of data-insufficiency, since there is simply not enough data available to make an analytical estimate of the behavior of the variance outside the range of the database.

Previously, research was done at Aerospace to look into new methods for addressing this problem by estimating the SEE based on the spread of the input data, but no solution was found. Therefore, in SSCM, the SEE is not adjusted outside the range of validity of the input data. Thus, the user needs to take great care to examine cases where the input data is outside the range of validity and make a sound engineering decision about whether the CER remains applicable.

5. FUNDING PROFILE

To aid in project planning and milestone development, a funding profile function is included in SSCM. This function spreads the total development cost to generate a funding profile for the spacecraft for the formulation (Phase B) and implementation (Phases C and D) phases. Phase B starts when the project is given the go ahead to start detailed design and Phase D ends at launch plus 30 days. This profile can be used as a tool to look at various ways to spread costs. It is only meant to be a guideline in planning project spending since it spreads only the spacecraft portion of the total project costs and does not account for other programmatic issues such as yearly funding caps.

The funding profile is generated using the equation below taken from [12]

$$F(S) = A[10 + S((15 - 4S)S - 20)]S^2$$
$$+ B[10 + S(6S - 15)]S^3$$
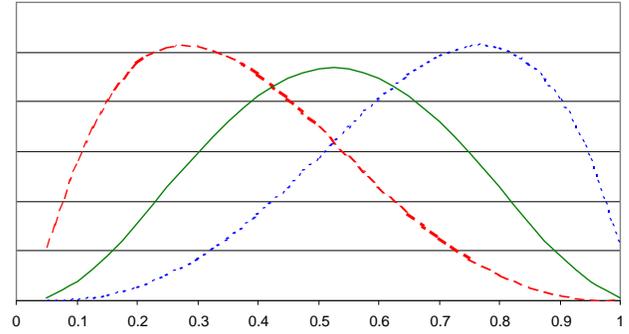$$+ [1 - (A + B)](5 - 4S)S^4 \qquad (13)$$

Figure 2. Various funding profiles; dashed line represents front-loaded (e.g., engineering), solid line represents evenly distributed (e.g., manufacturing), and dotted line (e.g., flight testing) represents back-loaded.

where $F(S)$ represents the fraction of the funding spent up to time S, S is the fraction of development time elapsed, and A and B are coefficients based on the desired rate of spending.

The coefficients A and B are selected based on the desired spreading of the costs, based on the percentage expenditure of costs at the schedule midpoint. Figure 2 shows examples of front-loaded spending, evenly distributed spending, and back-loaded spending.

SSCM generates an estimate for Phases C and D of the spacecraft development, yet the funding profile spreads costs over Phases B, C, and D. Therefore, the SSCM estimate must be augmented to account for the amount of funding spent in Phase B. According to the NASA Systems Engineering Handbook, the costs in Phase B should typically be between six and 10 percent of the development costs [13]. Based on this, SSCM adds 10 percent to the Phase C/D estimate prior to generating the funding profile.

6. MODEL APPLICATION

SSCM14 is implemented in Microsoft Excel as a standalone workbook. The workbook is backed up by Visual Basic for Applications modules that perform many of the model functions. Inside the workbook are worksheets that provide the all the necessary information to generate an estimate with the model, including five user worksheets and three information worksheets. The user worksheets are Inputs, Cost Estimate, Cost Risk, Funding Profile, and Inflation Factors, and the information worksheets are Glossary, Drivers, and CERs.

Inputs

The **Inputs** worksheet shown is the data primary user interface for the model. This worksheet provides the area in which to input values for the parameters used in the CERs and information on how the inputs compare to the data set used to generate the CERs.

6

Figure 3 shows the Technical Parameter area that lists all the parameters that can be used to generate a cost estimate and allows the user to input values for those parameters. Some parameters listed are only required under certain conditions, defined by the satellite wet mass and by the choices made in the drop-down boxes; parameters that are not required are grayed out. There is also a Notes space to where comments about the inputs can be entered.

The information in the Range area is used to identify input values that are outside the range of the CERs, as shown in Figure 4. Each CER was generated from a specific data set and is only intended to be valid within this range (see Section 4). Many parameters that will be used to generate SSCM estimates will not fall within their respective ranges and it is up to the user to determine whether the CERs are valid for the input data. The Range area consists of Minimum and Maximum columns that show the lower and upper limits for each parameter. Included with these values are the inputs for those parameters and a comparison of the input values to the valid data ranges for the CERs. This area also informs the user as to whether all the necessary parameters to generate an estimate have been supplied. To aid the user when inputting parameter values, when the value cell for a parameter is selected in the Technical Parameter area, the corresponding row(s) related to the parameter in the Range area are highlighted to show the user the range of validity. As with the Technical Parameter, when a parameter is not required, it is grayed out.

Technical Parameter	Units	Value	Notes
Programmatic			
Fiscal Year for Estimate	YYYY	2016	
Inflation Methodology	---	NASA	
Development Time	months	60.0	
Calendar Year for Phase B Start	YYYY	2016	
Design Life	months	60.0	
System			
Destination	---	Earth-Orbiting	
Satellite Wet Mass	kg	800.0	
Spacecraft Bus Dry Mass	kg	600.0	
Number of Instruments	#		
Power			
Solar Array Mounting Type	---	Deployed – Fixed	
Solar Cell Type	---	Gallium Arsenide	
Battery Type	---		
Power Subsystem Mass	kg	80.0	
BOL Power	W	1000	
Solar Array Area	m^2	10.00	
Structure			
Primary Structure Material	---	Aluminum	
Structure Subsystem Mass	kg	100.0	
ADCS			
Star Tracker?	---	Yes	
ADCS Subsystem Mass	kg	40.0	
Pointing Control	deg	0.003	
Propulsion			
Monopropellant or Bipropellant?	---	Monopropellant	
Propulsion Subsystem Dry Mass	kg	100.0	
TT&C/C&DH			
Communications Band	---		
TT&C/C&DH Subsystem Mass	kg	40.0	
Transmit Power	W	5	
Data Storage Capacity	MB	10000	
Thermal			
Thermal Subsystem Mass	kg	25.0	

Figure 3. Inputs Area. The inputs for the parameters used in the CERs (left-hand column) are entered in the center column and notes on each input can be placed in the right-hand column.

Technical Parameter	Range				
	Low	Minimum	Value	Maximum	High
Development Time (ATLO)					
Development Time (PM/SE)		12.0	60.0	92.2	
Design Life		0.2	60	96.0	
Spacecraft Bus Dry Mass (ATLO)		52.0	600.0	778.0	
Spacecraft Bus Dry Mass (PM/SE)		52.0	600.0	699.4	
Number of Instruments					
Power Subsystem Mass		22.3	80.0	160.8	
BOL Power (Power)					
BOL Power (Structure)					
BOL Power (Thermal)		141	1000	10500	
Solar Array Area		1.15	10.00	36.42	
Structure Subsystem Mass		16.8	100.0	298.0	
ADCS Subsystem Mass		0.6	40.0	59.2	
Pointing Control	32.4%	0.004	0.003	3.000	
Propulsion Subsystem Dry Mass		7.1	100.0	118.2	
TT&C/C&DH Subsystem Mass		4.7	40.0	106.7	
Transmit Power		1	5	100	
Data Storage Capacity		0.3	10000	96000	
Thermal Subsystem Mass		1.0	25.0	53.0	

Figure 4. Range Area. Displays information on whether an input for a parameter is within the valid range for the CER, is not being used, has not yet been entered, or is outside the range of validity. Parameters that are used for different CERs are broken out by CER.

Cost Estimate

The **Cost Estimate** worksheet displays the results produced by the CERs for the given inputs, including a table of the cost estimate broken out by subsystem and two graphs that provide detailed information on the estimate. This worksheet requires no user interaction; it strictly displays the estimate results.

The cost estimate table (Figure 5) shows the estimated cost for each subsystem. Non-recurring and recurring costs are presented, as well as the development and first unit total. The subsystem costs are summed into a Spacecraft Bus subtotal, which is added to the system-level programmatic costs to create the Spacecraft Development & First Unit total. The Range area displays messages as to whether any of the input parameters for a particular subsystem are out of range.

Two additional columns display how the total costs are split as a percentage by subsystem. The Sub-level column shows how the Spacecraft Bus costs are divided among each subsystem, while the System-level column shows how the Spacecraft Development & First Unit costs are divided among the spacecraft bus and system-level. These data are also presented in graphic form below the cost estimate table, as shown in Figure 6.

Cost Risk

The **Cost Risk** worksheet is where the subsystem estimates from the Cost Estimate worksheet are rolled-up via the FRISK methodology. The cost risk table shown in Figure 7 has separate areas to input the high and low percentages and display the triangular probability distribution of the user-

| | Estimate (FY16$K) | | | | % of | % of | |
	Non-rec	Rec	Total	Std Error	Sub-level	Sys-level	Range
Spacecraft Bus Subsystems							
Power	3,481	5,550	**9,031**	4,362	21.5%		
Structure	3,304	3,045	**6,350**	2,273	15.1%		
ADCS	1,897	2,162	**4,060**	1,514	9.7%		Pointing Control is 32.4% low.
Propulsion	3,086	5,975	**9,061**	4,340	21.6%		
TT&C*	1,848	1,877	**3,725**	5,804	8.9%		
C&DH*	3,820	3,881	**7,701**		18.4%		
Thermal	1,052	981	**2,033**	850	4.8%		
Spacecraft Bus	18,489	23,472	**41,961**	8,930	100%	61.1%	
IA&T*	4,095	4,594	**8,689**	5,314		12.7%	
PM/SE	6,679	7,891	**14,570**	7,941		21.2%	
LOOS*	0	3,444	**3,444**			5.0%	
S/C Development & First Unit	29,263	39,401	**68,664**	13,078		100%	

*TT&C/C&DH and IA&T/LOOS costs are generated from single CERs and standard error is presented as such. Per subsystem cost presented is based on database data.

Figure 5. Cost Estimate Table. The section to the left includes details on the estimate for the spacecraft generated by the CERs including non-recurring/recurring costs, total costs, and percentage distributions at the subsystem-level and system-level. The section to the right highlights inputs that are out of the valid range of the CERs for each estimate.
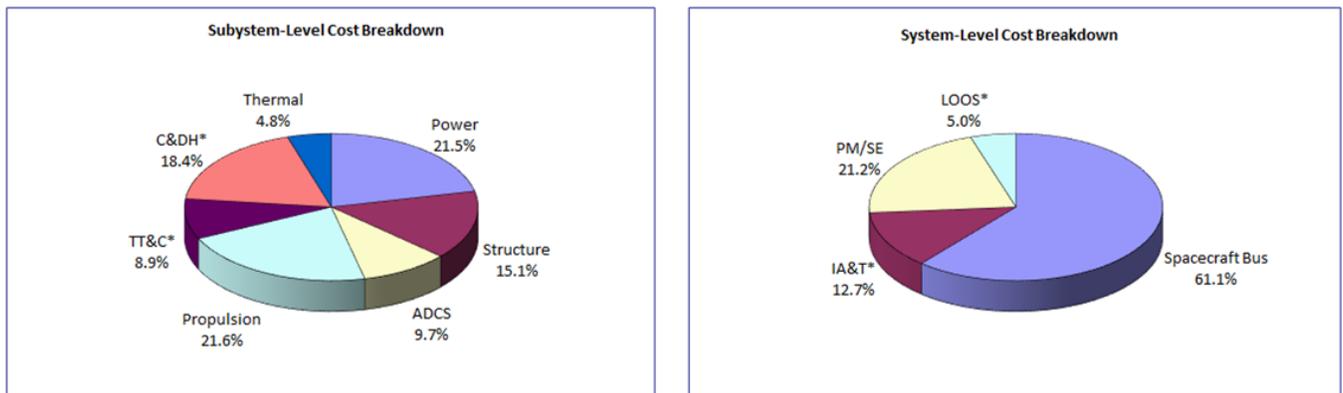

Figure 6. Cost Breakdown Plots. The chart on the right shows the subsystem-level cost breakdown. The chart on the right shows the system-level cost breakdown.

| | Percentages | | Distribution Points | | | Estimate (FY16$K) | |
	Low	High	Low	Most Likely	High	Mean	Std Dev
Spacecraft Bus Subsystems							
Power	10%	40%	8,128	9,031	12,643	**9,934**	4,896
Structure	5%	10%	6,032	6,350	6,985	**6,455**	2,319
ADCS	10%	40%	3,654	4,060	5,683	**4,466**	1,722
Propulsion	5%	15%	8,608	9,061	10,421	**9,364**	4,502
TT&C/C&DH	15%	40%	9,712	11,426	15,996	**12,378**	6,426
Thermal	5%	20%	1,931	2,033	2,440	**2,135**	899
Spacecraft Bus			38,065	41,961	54,168	**44,731**	13,436
ATLO	10%	50%	10,920	12,133	18,200	**13,751**	6,230
PM/SE	10%	30%	13,113	14,570	18,941	**15,541**	8,560
S/C Development & First Unit			62,099	68,664	91,309	**74,024**	20,642

Figure 7. Cost Risk Table. The user inputs sets a triangular distribution for the cost risk of each subsystem by setting the lowest and highest possible cost as a percentage of the CER estimate. The mean and standard error for each subsystem are calculated and used to generate system-level values for use in the cost probability distribution.

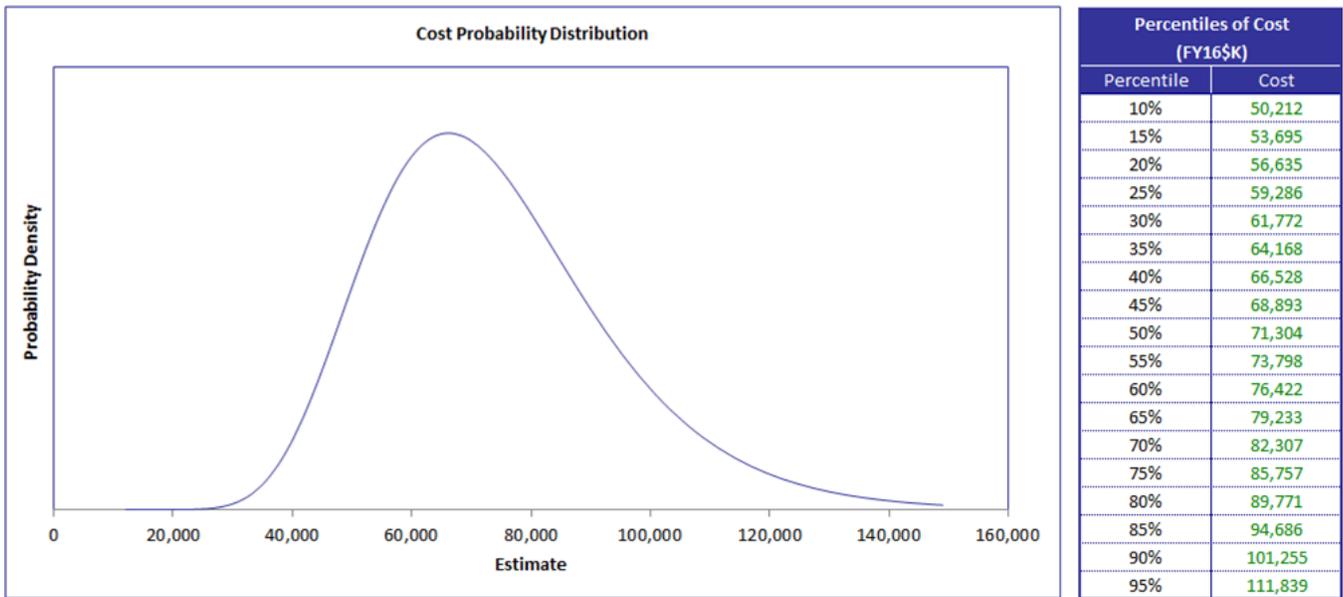| Percentiles of Cost (FY16$K)	
Percentile	Cost
10%	50,212
15%	53,695
20%	56,635
25%	59,286
30%	61,772
35%	64,168
40%	66,528
45%	68,893
50%	71,304
55%	73,798
60%	76,422
65%	79,233
70%	82,307
75%	85,757
80%	89,771
85%	94,686
90%	101,255
95%	111,839

Figure 8. Cost Risk Plot. The graph on the left shows the cost probability distribution function as a lognormal distribution. The table on the right shows cumulative probability.

defined cost risk and the combined mean and standard error of the estimate (see Section 4).

The Most Likely column is the result of the CER for that particular subsystem. The shape of the triangular probability distribution is determined by the high and low percentages defined by the user on this worksheet.

The Mean is the risk-impacted mean of the triangular distribution, while the Standard Error includes both the variance from the CER and the variance from the triangular distribution. The means are summed and the standard errors are combined along with cross-correlation terms (see Section 4) to create a system-level mean and standard error, respectively. The cost probability distribution is displayed below the cost summary in graphical and tabular format, as shown in Figure 8.

It should be noted that the model has a great amount of flexibility in adjusting the estimate based on the user's understanding of the subsystem technology readiness, subsystem heritage, and the cost risk methodology.

Funding Profile

The **Funding Profile** worksheet generates the monthly spending levels for the development of the spacecraft based on the development time, model estimate, and several user-defined inputs (Figure 9). The funding profile spreads costs from the beginning of Phase B to the end of Phase D (launch plus 30 days). The inputs are the launch date, the cost estimate to spread, and the percentage of funding spent at the schedule midpoint, which is a measure of how the funding will be distributed. The development start date is calculated based on the development time defined on the

Inputs worksheet along with the launch date. The user is afforded a handful of estimates to spread: either the primary estimate for the Cost Estimate worksheet or some of the cost risk estimates from the Cost Risk worksheet. Then, based on the choice of constant or real-year dollars, monthly and cumulative plots of funding are generated (Figure 10).

Launch Date (MM/DD/YYYY)	Jul-21
Estimate Choice	Base Estimate
Funding Spent at Schedule Midpoint (%)	50
Basis for Funding Profile	◉ Constant Year ○ Real Year

Milestone	Date
Development Start	Aug-16
Development End	Jul-21

Funding Profile (FY16$K)	FY16	FY17	FY18	FY19	FY20	FY21
Yearly Funding	27	6,524	21,885	27,337	17,078	2,681
Cumulative Funding	27	6,550	28,435	55,772	72,850	75,531

Figure 9. Funding Profile Inputs and Outputs. The top section shows the Funding Profile inputs. The middle section shows the calculated start and end points of the spacecraft development period. The bottom section shows the yearly and cumulative funding by fiscal year.

These costs are summarized by fiscal year in the Funding Profile table (not shown).

Inflation Factors

The **Inflation Factors** worksheet defines the inflation factors that will be used to convert from the FY14 base to some other constant year dollars (for the cost estimate) or to real year dollars (if needed for the funding profile), as shown in Figure 11. This worksheet contains NASA and Air Force values for inflation from 2004 to 2014, along with each organization's projected inflation from 2015 to 2034 [14], [15]. In addition, a customizable field offers the capability to input a set of user-defined inflation factors.
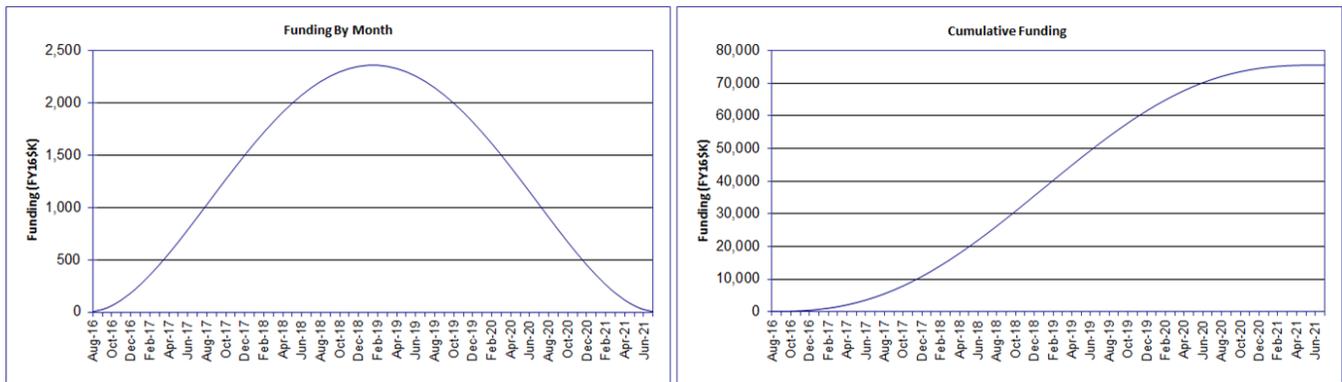
Figure 10. Funding Profile Plots. The plot on the left shows the funding required per month, while the plot on the right shows the cumulative funding for Phases B, C, and D. The y-axis label indicates if the funding profile is in constant year or real year dollars.

Year	NASA	OSD	Custom
2004	4.19%	2.00%	0.00%
2005	3.80%	2.80%	0.00%
2006	4.20%	3.10%	0.00%
2007	3.59%	2.70%	0.00%
2008	2.87%	2.40%	0.00%
2009	1.32%	1.50%	0.00%
2010	2.32%	0.80%	0.00%
2011	2.04%	2.00%	0.00%
2012	0.99%	1.80%	0.00%
2013	1.85%	1.50%	0.00%
2014	2.21%	1.50%	0.00%
2015	2.38%	1.70%	0.00%
2016	2.57%	1.90%	0.00%
2017	2.80%	2.00%	0.00%
2018	2.75%	2.00%	0.00%
2019	2.61%	2.00%	0.00%
2020	2.58%	2.00%	0.00%
2021	2.57%	2.00%	0.00%
2022	2.56%	2.00%	0.00%
2023	2.57%	2.00%	0.00%
2024	2.65%	2.00%	0.00%
2025	2.60%	2.00%	0.00%
2026	2.60%	2.00%	0.00%
2027	2.60%	2.00%	0.00%
2028	2.60%	2.00%	0.00%
2029	2.60%	2.00%	0.00%
2030	2.60%	2.00%	0.00%
2031	2.60%	2.00%	0.00%
2032	2.60%	2.00%	0.00%
2033	2.60%	2.00%	0.00%
2034	2.60%	2.00%	0.00%

Figure 11. Inflation Factors. The user can use NASA or Air Force standard inflation factors or input user-defined values.

Information

The model also provides three worksheets that provide additional information about the cost estimating methodology. The **Glossary** worksheet describes what hardware is estimated by each CER. The **Drivers** worksheet shows the cost drivers for each CER. The **CERs** worksheet shows the exact form for each CER. The **Graphs** worksheet plots each of the CERs over the range of data for the parameters used in the CERs; given the multi-dimensional nature of the many of the CERs, some parameters are not varied and a representative input value is used.

7. SUMMARY

Traditional cost-estimating models based on historical data from large civil and military programs overestimate costs of modern small satellites. Over the past 25 years, numerous small satellites have been procured by NASA, the DOD, CNES, ESA and various other organizations. These projects have often strived to reduce non-recurring development costs by making use of existing hardware and off-the-shelf components and by reducing contractor oversight and reporting requirements. In an attempt to credibly estimate the costs of such programs, Aerospace has developed a set of subsystem-level cost-estimating relationships based on the actual costs and physical and performance parameters of small and micro satellites.

CERs were derived using a generalized error regression model and assuming constant relative error. Implicit in this method is the assumption that cost estimating error is a percentage of the estimated costs, rather than a particular dollar value independent of the estimate. Cost drivers and CER function forms were chosen based on engineering judgment and statistical quality of regression results with the latter measured primarily by standard error and Pearson's correlation squared under the constraint of zero percent bias.

A cost risk methodology allows the user to define the cost probability distribution for each subsystem. A funding profile spreads the estimated costs over Phases B, C, and D to give the user an idea of what the potential yearly funding requirements will be for the spacecraft over the course of the development.

While quite useful as it stands, this model should always be considered as a work in progress. Small satellite programs are continually being launched and targeted for inclusion in future CER development efforts.

FURTHER INFORMATION

For more information on SSCM, or to learn how to obtain a copy of SSCM, visit the SSCM website at http://www.aerospace.org/expertise/technical-resources/small-satellite-cost-model/ or send an email to sscm@aero.org.

ACKNOWLEDGEMENTS

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BIOGRAPHY

Eric Mahr is a Senior Engineering Specialist in the Space Architecture Department at The Aerospace Corporation. His expertise is in spacecraft and architecture development. He has worked on a number of architecture and mission developments, studies and evaluations for NASA, the Air Force, and commercial organizations. He has a B.S. in Aerospace Engineering from the University of Arizona and a M.S. in Aerospace Engineering from the University of Colorado.

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Anil Gupta is a Senior Project Leader in the Economic and Market Analysis Center at The Aerospace Corporation. He has developed business models for various Government agencies in the areas of life cycle cost analysis, cost-risk analysis, financial planning, delay and disruption, resource allocation and acquisition analysis. He has a Ph.D. in Business Administration from the University of Southern California, Los Angeles; an M.S. in Industrial Engineering and Operations Research from Kansas State University and a Bachelor of Technology degree in Mechanical Engineering from Indian Institute of Technology, New Delhi, India.