

NASA Instrument Cost/Schedule Model

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Abstract—NASA’s Office of Independent Program and Cost Evaluation (IPCE) has established a number of initiatives to improve its cost and schedule estimating capabilities.^{1,2} One of these initiatives has resulted in the JPL developed NASA Instrument Cost Model. NICM is a cost and schedule estimator that contains: A system level cost estimation tool; a subsystem level cost estimation tool; a database of cost and technical parameters of over 140 previously flown remote sensing and in-situ instruments; a schedule estimator; a set of rules to estimate cost and schedule by life cycle phases (B/C/D); and a novel tool for developing joint probability distributions for cost and schedule risk (Joint Confidence Level (JCL)). This paper describes the development and use of NICM, including the data normalization processes, data mining methods (cluster analysis, principal components analysis, regression analysis and bootstrap cross validation), the estimating equations themselves and a demonstration of the NICM tool suite.

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1. INTRODUCTION

The NASA Cost Analysis Division (CAD) and the Independent Program Assessment Office (IPAO) initiated the NASA Instrument Cost Model (NICM) development task with JPL in October 2003. NICM enhances current instrument cost modeling capabilities by providing cost estimates at both the system and subsystem level. Under the ONE NASA cost management initiative, NICM is used by all NASA centers to support agency-wide proposal activities

and program-directed missions. The JPL System Analysis and Model Development Group is the developer of NICM.

The NICM Version I that was published in January 2007 included both system and subsystem level cost estimating relationships (CERs) and supporting databases. In August of 2009, NICM II was released after more instrument data were collected and the CERs were re-estimated and re-validated. In NICM II, the number of subsystem CERs was expanded from six to twelve: antenna and optics subsystems are separately estimated, electronic subsystems are now estimated separately for planetary and earth orbiting instruments, three types of detectors are modeled and the thermal subsystem now includes an additional CER for cryocoolers. In April of 2010, NICM III was released, with a main focus on improving the tools, leaving the CERs unchanged from version II. In September 2010, NICM IV was released, which now includes the ability to estimate cost for in-situ instruments, while moving all of the NICM tools into a single Excel workbook. NICM V, planned to be released in January 2011, will be augmented with phased (i.e. development Phases B, C and D) cost and schedule rules of thumb and a calculation of the instrument joint cost and schedule probability distribution (JCL).

This paper summarizes the scope and processes that were used to develop the NICM databases, CERs, cost and schedule rules of thumb and the instrument joint cost and schedule probability distribution calculation. Section 2 begins with a description of the NICM development schedule and the data collection and normalization process. Section 3 describes the processes for the development of the system and subsystem CERs and their validation. Section 4 presents the subsystem and system cost models. Section 5 presents the data and model used to estimate schedule. Schedule and cost rules of thumb for each development phase are discussed in Section 6. Section 7 describes the high-level parametric joint cost and schedule estimation process. Section 8 concludes with a tour of the NICM tool set.

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² IEEEAC paper#1158, Version 2, Updated 2010:10:29

2. DATA COLLECTION AND NORMALIZATION PROCESS

The NICM development had four major steps:

- 1) Instrument Data Collection: Cost, programmatic, and technical data from previously flown NASA instruments were collected. These parameters describe the instrument at both the system and subsystem levels.
- 2) Instrument Data Evaluation and Normalization: The collected instrument data was normalized to scale for uniformity, ensure completeness of costs, and correct for known biases and inconsistencies.
- 3) Cost Model Development and Validation: Statistical techniques were applied to the normalized data to establish and validate Cost Estimating Relationships (CERs).
- 4) NICM Tool Development: Finally, the validated CERs and a search engine were incorporated into Excel based software tools.

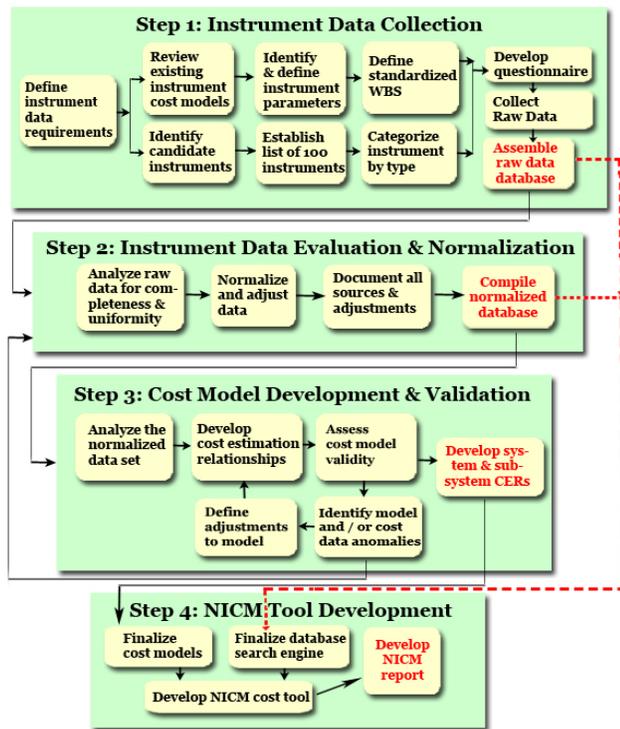


Figure 1 NICM Development Process Flow

These four steps were repeated as new data were collected throughout the NICM development cycle. This iterative process is shown in detail with each step broken into subtasks in Figure 1

During FY04, the NICM team spent the first few months defining user requirements and reviewing the capabilities of the existing instrument cost models that are available within the government (NASA and DoD) and the industry. Once the requirements were developed, the entire effort was focused on the data collection for the rest of FY04.

By the end of FY04, the team collected the initial sample of instrument data and the data evaluation and normalization began. The data collection and normalization activities continued throughout the development cycle.

Around the mid-point of the development cycle (second quarter of FY05), the model development and validation activities began. The model development and validation phase was an iterative process that was concluded at the end of FY06 for the first official release of NICM.

In FY06, the team initiated the NICM cost tool development that consisted of the database search engine, the system and the subsystem cost tools. At the same time, formal documentation of the development effort was also initiated. A draft NICM report was developed at the end of FY05. The official report was finalized at the end of FY06. NICM Version I documentation was published in January 2007. Model maintenance/updates and NICM training were begun in FY07. New instruments and data collection were continued in FY08 and FY09. During this period the cost models and tools were updated and improved based on new information and feedback from many users. NICM Version II was finalized and delivered. NICM III and IV improvements were begun in FY10, with release of NICM III occurring in April of 2010 and NICM IV in September 2010.

A substantial data collection effort began in the early phases of the NASA Instrument Cost Model development lifecycle. The data collection effort was composed of four major activities. The first activity identified a complete set of recent NASA space flight instruments. The second activity developed a common instrument work breakdown structure (WBS) to standardize data collection and simplify model development. The third activity identified reliable sources of information at various NASA centers, international space agencies, universities and aerospace contractors. The final activity compiled all the raw instrument technical and programmatic data and documentation that were collected into a single data set.

NICM IV utilized cost and technical data from 144 instruments. In order to collect instrument data that would be relevant to future instrument estimates, only NASA flight instruments launched after 1985 were used. To ensure the applicability of all cost data, 100% foreign built instruments were not considered. Also, to ensure that the model would be applicable throughout NASA, instruments built at many different NASA centers, as well at universities and aerospace contractors, were incorporated. Of the instruments

used in NICM IV, 38% were JPL-led developments, 21% University-led, 14% GSFC-led, 10% System Contractor-led, and 9% APL-led. Also, there are 8% under the “Other” category where the instrument development leads do not fall into any of the above groupings, e.g., other NASA centers, DoD, NOAA, FFRDC’s, etc

Work Breakdown Structure

A work breakdown structure was defined and the instrument data were collected in accordance with this standardized WBS that includes system and subsystem level elements. The details of the WBS are provided in Figure 2.

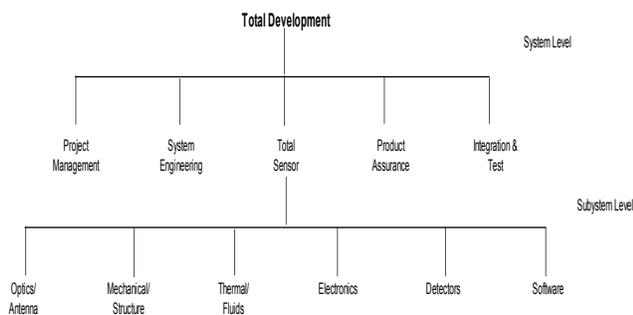


Figure 2 NICM Instrument WBS

For each WBS element, the associated costs were collected. In addition, technical parameters were collected, where applicable, at the system and subsystem levels including: Mass (kg), Maximum Power (W), Wavelength (μm), Peak Data Rate (kbps), Number of Bands, Number of Channels, Technology Readiness Level (TRL), Dust Environment, Number of Samples/Deployments, Planetary Protection Level, Volume, Temperature Range, Thermal Control System, Number of Mechanical Actuators/Degrees of Freedom, Number of Instruments in Suite, Delivery Mechanism, Platform.

A full definition of each of these terms as used by NICM can be found in the NICM IV Report. Additional information was also collected beyond the scope of the system and subsystem WBS parameters described above. This information included programmatic data such as design life, development schedule, and design inheritance.

Instrument Classification

In order to ensure the accuracy of the model, individual CERs were constructed from similar instruments with common characteristics. The instruments selected had the full range of applications, measurement types and destinations for NASA missions. Differences provided the basis for grouping and subsequent analysis for CER development. Homogeneous instrument groups were formed by dividing the instruments into instrument types, destination types and specific instrument types. Each instrument was classified by one of 2 instrument types,

Remote Sensing or *In-situ*. The definition for an in-situ instrument within NICM is any instrument that is onboard an in-situ platform, i.e., any instrument that is on a rover, lander or atmospheric probe. Instruments which operate on a spacecraft operating in space were classified as remote sensing instruments.

Remote Sensing Instrument Classification

Each Remote Sensing instrument was grouped into the following two destination types, Earth Orbiting or Planetary. The earth orbiting group includes all instruments on spacecraft in geocentric orbits. The planetary type was meant for instruments visiting planets other than Earth. This definition was expanded to include any instrument not in a geocentric orbit for its primary mission. This includes missions with heliocentric orbits, deep space missions, and non-geocentric-orbiting missions to moons, comets and asteroids.

Each Remote Sensing instrument was also grouped into one of the following five remote sensing instrument types: Optical (cameras, spectrometers, interferometers, etc.), Active Micro/Sub-Millimeter Wave (radars, altimeters, scatterometers, etc.), Passive Micro/Sub-Millimeter Wave (sounders, GPS receivers, etc.), Particles (plasma detectors, plasma wave detectors, etc.), and Fields (electric field detectors, magnetic field detectors, etc.).

In-situ Instrument Classification

For *in-situ* instruments two classifications were developed. The first *in-situ* type, Science Type, defined the scientific category of the instrument investigation. The definitions were as follows:

1. Chemical/Elemental w/Contact: Instruments that required direct contact with the desired samples either through arm based manipulation or delivery of a sample via acquisition hardware or sample processor.
2. Chemical/Elemental w/out Contact: Instruments that can make a measurement at a stand-off distance from a sample
3. Atmospheric/Environmental: Instruments that monitor environmental parameters such as pressure, temperature, and radiation environment
4. Sample Acquisition/Distribution: Instruments that gain possession or deliver a sample.

The second in-situ type, Mounting Type, was defined with respect to where on a spacecraft the instrument is mounted. The definitions were as follows:

1. Probe Mounted: Any instrument that is located on a probe that slowly descends through the atmosphere and comes to a static landing (Examples: NMS, GIM, GSWC).

2. Arm/Mast Mounted: Instruments where the main part of the instrument is located outside of the environmentally controlled structure (Examples: APXS, RAT, MET, SSI).

3. Body Mounted: Instruments where the majority of the instrument structure is held within a centrally located structure. These tend to be larger type instruments (Examples: TEGA, RA, MECA)

After completing the cluster analysis as described in Section 3 below it was determined that the mounting type was a good indicator to use for assigning *in-situ* instrument groupings for CER development.

Data Collection Questionnaire

A questionnaire was developed to standardize the data collection process. This questionnaire included a description of the mission and instrument, those responsible for managing and building the instrument, as well as the cost, technical and programmatic parameters described in the sections above. A Comments and Assumptions section was developed to provide additional information, including the data sources and a log of recent updates. The following data collection assumptions were made to ensure uniformity in the collected data:

- 1) Development Phases: The costs for this database were limited to Instrument Development Phases B through D. This excluded the large variability of scope and cost associated with Phase A and Phase E.
- 2) Inflation: All cost data dollar values were converted to a common base year dollars (FY 2004) from the reported year dollars to the base year dollars using NASA New Start Inflation Index.
- 3) Technology Development: Advanced Technology development costs were excluded (i.e. those beginning with a TRL of 1, 2, or 3).
- 4) The total instrument development cost does not include science, ground and mission operations related instrument support costs.
- 5) First Unit Cost: Cost models are based on the development cost of the 1st unit only

Cost Data Security

JPL is obligated by non-disclosure agreements to treat the cost data as discreet. This is to protect the business of the data providing organizations. NASA Headquarters has developed guidelines and policies to determine authorized recipients of the NICM database for which data may be shared and those which should be protected.

Data Normalization

Before the database could be used to develop CERs, the data in the questionnaires required normalization to scale for uniformity, ensure completeness of costs, and correct for known biases and inconsistencies. For example, delays due to the Challenger accident caused substantial cost increases for many instruments which were not attributable to their design, development or fabrication, therefore these costs were removed. The data originally assembled using the questionnaires is considered to be raw historical data, whereas the data after the normalization process is referred to as normalized data. Normalization of the data for each instrument was performed by groups of experienced experts who had direct knowledge of the specific instrument development. These adjustments and rationales were documented in the Comments and Assumptions section of the questionnaire. Adjustments were made to costs for expended instrument development resources which did not appear in cost accounting systems or external sources which were beyond the control of the instrument developer.

The following items were adjusted in the normalization process:

1. Civil Service Workforce: Where the cost of effort contributed by civil servants did not appear in the accounting system, equivalent costs were determined and added based on estimates of workforce from the civil service developer.
2. Government-Furnished Equipment (GFE)/Inherited Equipment: Where existing equipment was furnished without charge and utilized, its value was added based on a best estimate from the source or by the expert.
3. External Sources: Where resources from an outside organization did not appear in the developer's accounting system, equivalent costs were added based on a best estimate from the source or by the expert. For example, hardware supplied by a partnering organization was added to the cost reported in the developer's accounting systems.
4. By-pass Funding: Sponsor funding supplied directly to organizations supporting the development, which did not appear in the developer's accounting, were estimated and added. For example, funding sent directly to a University in support of the instrument development would be estimated and added to the total development.
5. Costs Beyond the Developer's Control: Where additional costs were incurred due to unexpected events, such as delayed sponsor funding or launch system problems, these costs were estimated and subtracted.
6. Mission Class: Scaling of selected cost elements to account for stringency of risk allowance as reflected in mission assurance and reliability requirements.
7. TRL Level/Heritage: TRL was adjusted to reflect relative level of technology and design inheritance at the time development was initiated.
8. WBS Allocations: Costs were combined or disaggregated by experts to better reflect the standard WBS.
9. First Unit Cost Only: Costs were adjusted to reflect the

1st unit cost.

10. Suites of Instruments: dividing an instrument into “sub-instruments,” then estimating each “sub-instrument” with NICM and totaling all to determine the original instrument estimate will result in an overestimate due to the non-linear nature of the NICM CERs.

An audit trail was created to track all adjustments made during the normalization process. Electronic copies of the data sheets were archived before any adjustments were made. The rationale for each adjustment was documented. Also, when possible, backup materials supporting the normalization steps, and materials supporting the original data collection, were archived.

As of NICM IV, the data for 144 instruments have been normalized, including 104 remote sensing instruments and 40 in-situ instruments.

The normalized cost data were developed by JPL for the sole purpose of cost model development and validation. They are not intended to represent the developer’s cost performance for their particular instrument project and/or instrument.

3. DATA MINING AND ANALYSIS

The empirical relationships between the system and subsystem level costs and the database technical and programmatic parameters (or characteristics) were determined by using two data mining techniques, cluster analysis and principal components analysis, augmented where applicable by ordinary least squares regression analysis. The CERs were then validated using bootstrap cross-validation methods.

Cluster Analysis

Cluster analysis is used for identifying and grouping similar instruments using a distance measure (metric) defined between each pair of instruments. The distance metric is a function of the values of the technical and programmatic parameters for each pair of instruments. A clustering algorithm is then applied to the matrix of distances between instruments. Outputs were groups of similar instruments. Cluster analysis groups were compared with instrument descriptive categories (instrument types, etc.) for consistency.

Cluster analysis inputs were the technical and programmatic parameters from the instrument database that were continuous or integer valued numbers. These inputs were expected to be measures of similarity or closeness in characteristics. These inputs were all quantitative, distinguished from the discrete descriptive variables like instrument type or destination that have no obvious quantitative relationship. The descriptive variables were

examined after cluster analysis to test the association of instruments within clusters. When all instruments of a particular type fell within the same cluster, this indicated that the group was homogeneous and should be grouped together for CER development.

Cluster analysis requires a similarity metric to be defined between objects – the higher the number the more similar the instruments are. A dissimilarity measure (the higher the number the further apart) can also be used to the same effect. The dissimilarity metric selected is analogous to the Euclidean metric from linear algebra. The distance between two instruments is defined as

$$d(i, j) = \sqrt{\sum_A \left[\log \left(\frac{A_i}{A_j} \right) \right]^2}$$

where i and j are instruments, A_i and A_j are the values of parameter A (e.g. mass, max power, etc.) for instruments i and j and $\log()$ is the natural logarithm and the sum is over selected technical and programmatic variables. For example, an instrument i with a 5% higher cost than instrument j (and all other attributes equal) is closer to instrument j than is an instrument with a 10% higher cost. For small deviations the effect is linear when using the log function. Between attributes, the Euclidean metric treats all dimensions equally, i.e. a 10% distance in one attribute dimension has the same impact on dissimilarity as a 10% distance in another. Weighting factors for each parameter can be applied, if desired. Trial runs suggest that the resulting output classes are robust to reasonable variations in weighting factors on parameters.

Once the distance matrix is defined for each pair of instruments, there are a number of different clustering objectives that can be used to group them. The method selected is called Complete Clustering. It defines the distance between two clusters as the maximum distance found from all possible pairs of elements, one selected from each cluster. Figure 3 displays an example cluster tree.

There are many commercial and public domain tools available to do the clustering, using as input the distances between instruments. In addition, many statistical packages can execute the Complete Clustering algorithm. A JPL Excel program for cluster analysis and the display of cluster trees was developed.

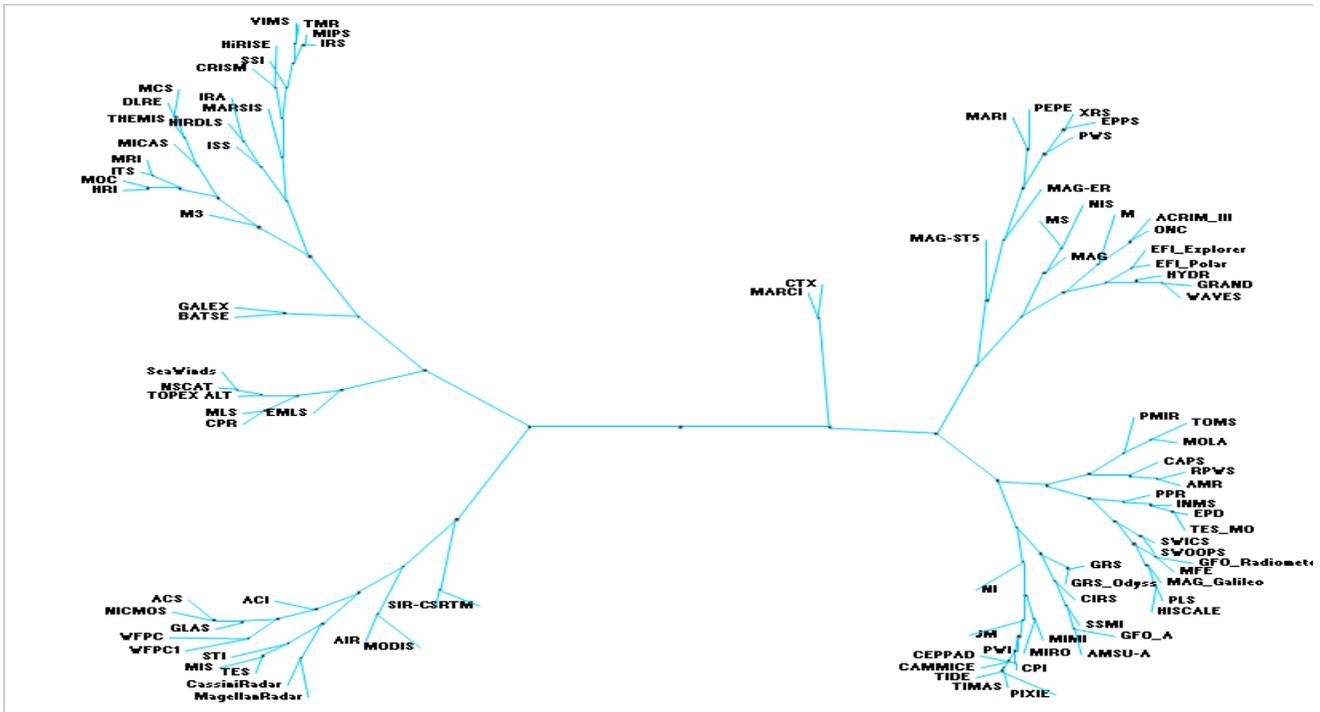


Figure 3 Remote Sensing Instrument Clusters

Principal Components Analysis

Principal components analysis (PCA) is a linear regression technique that decomposes the data structure of the instrument technical and programmatic parameters to find the most significant linear relationship among the parameters. From the identified significant principal components, a CER can be constructed.

Principal Components Analysis overcomes a number of regression model defects when used in a data mining context. Linear regression analysis posits a model (e.g. linear, log-linear) of how cost varies with a given set of parameters such as mass and power:

$$C_i = a_0 + a_1 * M_i + a_2 * P_i + \epsilon_i$$

where C_i is the cost, M_i is the mass and P_i is the max power for instrument “i”, and ϵ_i is an error term, typically assumed to be normally distributed with constant variance. In this pedagogical example cost is displayed as a linear function of mass and power. Actual cost models are generally scaling relationships between instrument attributes – for these models logarithms of continuous valued variables are used when building models. In application of the regression-based PCA, the means of the logged variables are subtracted and divided by the standard deviation (called standardization) before estimating and validating.

This *assumed* linear model is traditionally solved by least squares when there is a data set $\{C_i, M_i, P_i\}$ of attributes for the instruments of interest. The sum of the squared residuals to be minimized is:

$$\chi^2 = \sum_i (C_i - a_0 - a_1 * M_i - a_2 * P_i)^2$$

defined over parameters $\{a_0, a_1, a_2\}$. That is, χ^2 is to be minimized over all possible choices of a_0, a_1, a_2 .

Linear least squares regression analysis does not generally make a good data mining tool. It over emphasizes cost and performs poorly when outliers are present in estimating models and produces poor results when residual errors are not from the same distribution (the case of heteroscedasticity). Instrument technical and programmatic variables like cost, mass and max power are the outputs of a complicated instrument design and development process. As such they are determined jointly, with no obvious causal model structure to guide a proper causal analysis. Principal components analysis avoids these problems by treating the model residuals of these parameters as equally important. Using the prior formulation, the model equations are re-written.

$$C_i = a_{i1} * c_1 + a_{i2} * c_2 + a_{i3} * c_3$$

$$M_i = a_{i1} * m_1 + a_{i2} * m_2 + a_{i3} * m_3$$

$$P_i = a_{i1} * p_1 + a_{i2} * p_2 + a_{i3} * p_3$$

Here all the original data is on the left hand side of the equation and the parameters to be determined on the right side. Additional parameters representing idealized values of the instrument attributes (i.e. latent variables) are added in addition to the usual location and scale parameters in the linear regression models. Re-written in a more compact notation, the equations to be solved are:

$$X_{ik} = \sum_q U_{iq} D_q V_{kq} + \varepsilon_{ik} \text{ for all } i \text{ and } k$$

where X_{ik} is the parameter type k data value (e.g. cost, mass, ...) for instrument i and ε_{ik} is the error term. This right-hand side is the singular value decomposition of the matrix X in terms of the U , V and D matrices for which standard linear algebra algorithms exist. Due to the inherent noise in the data, the selection of a statistically significant number of principal components Q (where $q = 1, \dots, Q \leq \text{minimum}(K=\#\text{attributes}, N=\#\text{Instruments})$) is determined by two independent methods: the scree chart and bootstrap cross-validation. The scree chart is a plot of the number of included principal components Q by the total reduction in model variance provided by the principal components as they range from 1 to Q . This plot is called a scree chart because it looks like a steep mountain with scree (debris) piled up at the bottom; there is a kink in the curve where the noise in the data takes over and the curve flattens for high Q . In determining the point of the kink in the chart we apply PCA to random model input data of the same dimension as the original data (K by N). This provides a comparison set of fictitious data points created from noise. When plotted together the “peak of the mountain” from the real data stands out in comparison to the noisy data “scree”. This comparison selects a significant number of principal components to consider for the model. By variation in the selection of model parameters and the number of principal components selected, *bootstrap cross-validation* provides confirmation of the statistically significant parameters and appropriate grouping of instruments based on the predictive ability of the identified model. A CER expressing the cost of an instrument as a function of the other parameters describing the instrument is derived from the first order conditions that define the U and V matrices.

$$X_{ic} = \sum_k X_{ik} \left[\frac{\sum_q (V_{kq} V_{cq})}{1 - \sum_q (V_{cq} V_{cq})} \right] + \frac{\varepsilon_{ic}^Q}{1 - \sum_q (V_{cq} V_{cq})}$$

where the prime on the sum over k is to denote that c is not included. The terms in the bracket are analogous to the usual

regression coefficients from a linear least squares regression of cost against the other variables.

Bootstrap Cross-Validation

Bootstrap cross-validation is a resampling based technique for validating statistical models. The basic cross-validation procedure divides the original data set into two parts, a subset that is used to estimate model coefficients (called the training set) and the remaining subset (called the testing set) that's used to test the model predictions using the estimated coefficients. In *bootstrap* cross-validation this procedure is repeated for many different random selections of training and testing sets. A goodness of fit statistic, the average prediction error variance (also called the “632” bootstrap cross-validation error variance), is calculated for the ensemble of randomized data splits. This “632 error” in simulation studies has been found to be the most accurate estimate of the true model prediction error. When selecting the appropriate PCA model the number of principal components to include in the final model is varied and potential outliers in the original set of instruments are identified and removed. Better models are those whose prediction errors are smaller than those of alternative models.

4. COST ESTIMATING RELATIONSHIPS

Subsystem Level CERs

The subsystem cost estimating relationships and statistics are presented below. Note that the significant figures shown here have been rounded; non-rounded equations for these parameters are utilized in the tools. Error terms are lognormal and multiply the right hand side. R^2 is the *coefficient of determination*, the reduction in cost variability due to the regression model. PE is the prediction error used to calibrate each lognormal error distribution (i.e. which equals the exponential of a Normal distribution with mean = zero and standard deviation = PE). All costs are in FY04\$K.

a) $\text{AntennaSubsystemCost} = 758 * (\text{AntennaMass}[\text{kg}])^{0.92}$

$$(R^2 = 0.87, \text{PE} = 57\%)$$

b) $\text{Optics Subsystem Cost} = 1424 * (\text{OpticsMass}[\text{kg}])^{0.56}$

$$(R^2 = 0.72, \text{PE} = 60\%)$$

c) $\text{Electronics Subsystem Cost, Earth Orbiting Instruments} = 771 * (\text{ElectMass}[\text{kg}])^{0.39} * (\text{MaxPower}[\text{W}])^{0.40}$

$$(R^2 = 0.77, \text{PE} = 71\%)$$

e) $\text{Electronics Subsystem Cost, Planetary Instruments} = 2047 * (\text{ElecMass}[\text{W}])^{0.57}$

$$(R^2 = 0.71, \text{PE} = 40\%)$$

f) Mechanical/Structures Subsystem Cost $(R^2 = 0.76, PE = 46\%)$
 $= 340 * (TotalMass[kg])^{0.69}$
 $(R^2 = 0.73, PE = 62\%)$

g) Detectors Subsystem Cost (part 1)
 $= 1002 * (DetectMass[kg])^{0.33}$ for Fields/Ion Detector
 $= 3498 * (DetectMass[kg])^{0.33}$ for Photovoltaic/Photodiode/PMT
 $(R^2 = 0.57, PE = 72\%)$

h) Detectors Subsystem Cost (part 2)
 $= 1659 (DetectMass[kg])^{0.87}$ for CCD Detectors
 $(R^2 = 0.84, PE = 86\%)$

i) Thermal/Fluids Subsystem Cost
 $= 562 * (ThermalMass[kg])^{0.517}$, Passive Systems
Add Cost $= 40099 * (LowTemperature[°K])^{-0.15}$,
, for Active w/Two or More Stages or Dewars
 $(R^2 = 0.61, PE = 73\%)$

k) Software Subsystem Cost
 $= 4.3\% * SensorCost$,
For a Low Level of Software Development Intensity
 $= 12.3\% * SensorCost$,
For a High Level of Software Development Intensity
 $(R^2 = 0.92, PE = 39\%)$

System Level CERs

The system level cost estimating relationships and statistics are presented below. Note that the significant figures shown here have been rounded; non-rounded equations for these parameters are utilized in the tools. Error terms are lognormal and multiply the right hand side. R^2 is the *coefficient of determination*, the reduction in cost variability due to the regression model. PE is the prediction error used to calibrate each lognormal error distribution (i.e. which equals the exponential of a Normal distribution with mean zero and standard deviation PE). All costs are in FY04\$K.

a) Planetary Optical Instruments Sensor Cost $= 277 * (TotalMass[kg])^{0.426} * (MaxPower[W])^{0.414} * (DesignLife[months])^{0.375}$

b) Earth Orbiting Optical Instrument Sensor Cost $= 979.9 * (TotalMass[kg])^{0.328} * (MaxPower[W])^{0.357} * (DataRate[kbps])^{0.092}$

$(R^2 = 0.89, PE = 59\%)$

c) Active/Passive Microwave Sensor Cost $= 19899 * (TotalMass[kg])^{0.284} * (MaxPower[W])^{0.325} * (DataRate[kbps])^{0.090} * (TRLevel)^{-1.296}$
 $(R^2 = 0.88, PE = 48\%)$

d) Fields Instruments Total Development Cost $= 952 * (TotalMass[kg])^{0.184} * (MaxPower[W])^{0.238} * (DesignLife[months])^{0.274}$
 $(R^2 = 0.87, PE = 43\%)$

e) Particles Instruments Total Development Cost $= 825 * (TotalMass[kg])^{0.327} * (MaxPower[W])^{0.525} * (DesignLife[months])^{0.171}$
 $(R^2 = 0.65, PE = 33\%)$

In-situ System Level CERs

The *in-situ* system level cost estimating relationships and statistics are presented below. Note that the significant figures shown here have been rounded; non-rounded equations for these parameters are utilized in the tools. Error terms are lognormal and multiply the right hand side. R^2 is the *coefficient of determination*, the reduction in cost variability due to the regression model. PE is the prediction error used to calibrate each lognormal error distribution (i.e. which equals the exponential of a Normal distribution with mean zero and standard deviation PE). All costs are in FY04\$K.

a) Probe Mounted In-Situ Instrument Cost $= 579 * (TotalMass[kg])^{0.607} * (MaxPower[W])^{0.425}$
 $(R^2 = 95\%, PE = 31\%)$

b) Body Mounted Instrument Cost $= 700 * (TotalMass[kg])^{0.39} * (MaxPower[W])^{0.33} * (#Samples)^{0.22}$
 $(R^2 = 78\%, PE = 52\%)$

#Samples = Planned number of samples over planned life of instrument.

c) Arm/Mast Mounted Instrument Cost $= 688 * (TotalMass[kg])^{0.469} * (MaxPower[W])^{0.492}$
 $(R^2 = 79\%, PE = 46\%)$

System Level Wrap Factor CERs

System level wrap factor costs for Management, Systems Engineering, Product Assurance and Integration and Test were determined by regression analysis. Each wrap CER uses Sensor Cost as the independent variable. The system wrap factors cost estimating relationships and statistics are presented below. Note that the significant figures shown here have been rounded; non-rounded equations for these parameters are utilized in the tools. Error terms are lognormal and multiply the right hand side. R^2 is the *coefficient of determination*, the reduction in cost variability due to the regression model. PE is the prediction error used to calibrate each lognormal error distribution (i.e. which equals the exponential of a Normal distribution with mean zero and standard deviation PE). All costs are in FY04\$K.

a) Management Cost = $0.071 * (\text{SensorCost})^{1.032}$

($R^2 = 0.85$, PE = 54%)

b) Systems Engineering Cost = $0.493 * (\text{SensorCost})^{0.865}$

($R^2 = 0.75$, PE = 71%)

c) Product Assurance Cost = $0.143 * (\text{SensorCost})^{0.942}$

($R^2 = 0.91$, PE = 57%)

d) Integration and Test Cost = $0.146 * (\text{SensorCost})^{1.007}$

($R^2 = 0.87$, PE = 56%)

5. SCHEDULE AND COST RULES OF THUMB

Data Collection and Normalization

Remote sensing instrument cost and schedule data for Phases B, C and D were collected for a subset of NICM instruments that were JPL developed, both remote sensing and in-situ. Various JPL science and spacecraft project databases, on-line web sites and archived data sources from JPL project records were collected. Instrument developers and technical experts were used to develop and normalize the data as was described above. The instruments were grouped as before by instrument type and their mission's type, either Flagship or Nominal planetary or Earth orbiting.

Within the normalization process, anomalies to normal instrument development were identified and corrections were made to phased costs and schedules for:

1. Extensive design changes imposed from outside the project on the instrument development.
2. Mission launch slips from external causes that impacted the instrument development schedule ("Acts of God").

3. Unrealistic schedules imposed by programs and projects ("Faster, Better, Cheaper").
4. Problems with the spacecraft or its other instruments which impacted the instrument's development.
5. Unexpected problems associated with the coordination of multiple agency or foreign partners.
6. Adjustments for accounting and engineering practices that blurred the definition of phase boundaries.
7. Delays due to programmatic budgeting issues where development was delayed by re-phasing of funding.

The process for converting raw cost data to normalized cost data was as follows. The burn rate for each phase and total project was defined as cost divided by schedule. The normalization process starts by adjusting schedule by increasing or reducing months in each phase to account for anomalies, then using the burn rates from the raw data to calculate the normalized cost (= schedule * burn rate) in each phase. For each type of instrument the averages of normalized cost, schedule and burn rate were calculated after removing outliers.

Data Analysis and Rules of Thumb

Cluster analysis and visual inspection suggested the groupings of instruments. Within each group average values for cost and schedule by phase and burn rate were used to calculate the rules of thumb. *Rules of thumb* are the suggested schedule and cost percentages to be allocated to each phase for an instrument when given total cost and total schedule estimates. Table 1 displays the resulting normalized instrument cost and schedule rules of thumb. Each row in the figure is identified by associated mission type and instrument subtype. For mission type there are two classes: *EarthOrbiting/FlagshipPlanetary* and *Nominal Planetary* (i.e. all non-Flagship planetary missions). The instrument subtypes are Camera, Photometer, Chemical, Mechanical, Particles, Spectrometer, Radar and Radiometer. Costs percentages are percent of total cost by

Mission Class / Instrument Type	Phase B	Phase C	Phase D	100%	Phase B	Phase C	Phase D	100%	Phase B	Phase D	
	Cost Percent	Cost Percent	Cost Percent		Schedule Percent	Schedule Percent	Schedule Percent		Burn Rate Percent of Phase C	Burn Rate Percent of Phase C	
Nominal Planetary Camera	3.4%	77.7%	18.9%	100%	14.5%	52.8%	32.7%	100%	19.5%	100%	38.1%
Flagship/EO Camera	5.7%	81.2%	13.1%	100%	12.7%	64.3%	22.9%	100%	49.3%	100%	64.6%
Flagship/EO Photometer	4.4%	79.9%	15.6%	100%	14.3%	54.3%	31.4%	100%	21.0%	100%	33.8%
Nominal Planetary Chemical	4.7%	73.8%	21.5%	100%	16.5%	47.9%	35.6%	100%	26.8%	100%	40.4%
Flagship/EO Chemical	2.8%	85.9%	11.3%	100%	9.8%	62.2%	28.0%	100%	22.6%	100%	27.7%
Nominal Planetary Mechanical	2.8%	81.1%	16.0%	100%	11.4%	54.2%	34.3%	100%	18.4%	100%	30.0%
Flagship/EO Mechanical	2.0%	87.8%	10.2%	100%	8.5%	62.0%	29.6%	100%	16.4%	100%	24.5%
Nominal Planetary Particles	5.3%	74.4%	20.3%	100%	16.9%	51.9%	31.2%	100%	23.7%	100%	56.5%
Flagship/EO Particles	4.1%	80.2%	15.8%	100%	12.4%	63.4%	24.2%	100%	26.6%	100%	55.5%
Nominal Planetary Spectrometer	5.0%	76.3%	18.8%	100%	12.4%	54.1%	33.5%	100%	27.0%	100%	41.7%
Flagship/EO Spectrometer	5.4%	83.4%	11.2%	100%	16.4%	59.8%	23.8%	100%	25.4%	100%	34.6%
Flagship/EO Radar	6.8%	72.2%	21.0%	100%	14.7%	57.8%	27.5%	100%	33.6%	100%	62.1%
Flagship/EO Radiometer	5.7%	79.7%	14.6%	100%	18.3%	54.8%	26.9%	100%	21.5%	100%	41.4%

Table 1 Cost and Schedule Rules of Thumb

phase, schedule percentages are percent of total schedule by phase and the burn rate percentage columns are Phase B burn rate as a percent of Phase C burn rate and Phase D burn rate as a percent of Phase C burn rate. Give a total cost and total schedule duration, phased costs and schedules can be developed.

EarthOrbiting/FlagshipPlanetary instruments have longer phase lengths and higher burn rates than *NominalPlanetary* because of their greater mass and capability. Earth orbiting instruments also tend to accrue higher costs due to the possibility of delay to defer costs because of frequent, non-binding launch windows. The data were normalized to some extent for this effect. For planetary instruments Phase D is shorter and has a higher cost fraction because of their more schedule-driven launch window.

In an earlier paper we showed how the availability of cost and schedule information by phase allows a top level joint cost and schedule probability distribution analysis. Parametric methods for estimating the joint probability distribution are useful in the early stages of instrument cost and schedule prediction. They do not require a detailed WBS with associated resource loading and contingency plans to generate plausible schedule and cost probabilistic results. The following two sections describe another more parsimonious parametric JCL model that accepts as input a cost risk S-curve and implements a simple schedule estimation regression model.

of Thumb normalized total cost and total schedule data used in the estimation of regression parameters. The SER model calculates Schedule as a simple power law fit to *Total Instrument Cost* times an element from the matrix of parameters ($=A$) that depends on *Instrument Subtype* and *Mission Type*. The regression lines in Figure 3 are calculated using the nominal parameter values for a *Spectrometer*, the third row in Table 2, the Instrument SER Parameter Matrix. The regression lines for other subtypes yield lines parallel to these. R^2 is the *coefficient of determination*, the reduction in cost variability due to the regression model. PE is the prediction error used to calibrate the lognormal error distribution (i.e. which equals the exponential of a Normal distribution with mean zero and standard deviation PE). Note that Total Cost is in units of FY04\$M, not FY04\$K.

$$\text{Schedule [months]} = A(\text{Mission Type, Instrument Subtype}) * (\text{Total Cost[FY04\$M]})^{0.096}$$

$$(R^2 = 0.87, PE = 17\%)$$

6. SCHEDULE ESTIMATING RELATIONSHIP

Figure 3 displays the *Schedule Estimating Relationship* (SER) regression results plotted with the above *NICM Rules*

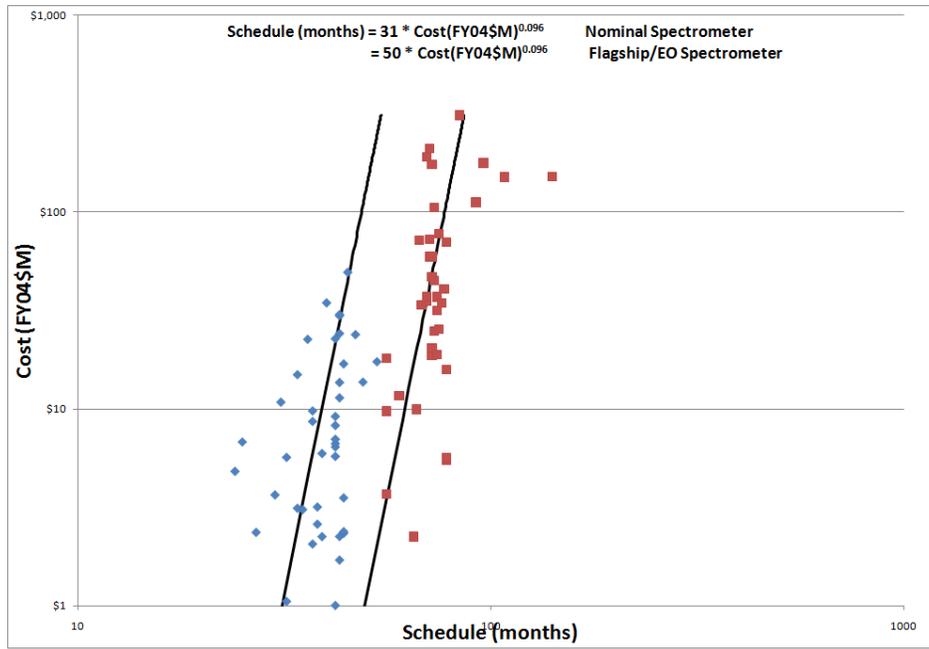


Figure 3 Schedule Estimating Relationship (SER)

The motivation for this schedule model is simply that the associated mission type will drive the total schedule length, as it must fit within the context of the overall mission schedule, with minor effects associated with the instrument subtype and the predicted final total instrument cost.

Schedule Estimation Relationship Instrument Subtype Parameters	non-Flagship Planetary	EO & Flagship Planetary
Mechanical	27.4	43.7
Radar	30.8	49.1
Spectrometer	31.5	50.2
Chemical	31.5	50.3
Camera	35.3	56.3
Particle	36.4	58.2

Table 2 Instrument SER Parameter Matrix (= *A*)

7. INSTRUMENT JOINT COST AND SCHEDULE RISK

The high-level parametric Joint Confidence Level Cost and Schedule probability distribution is calculated using the definition of conditional probability:

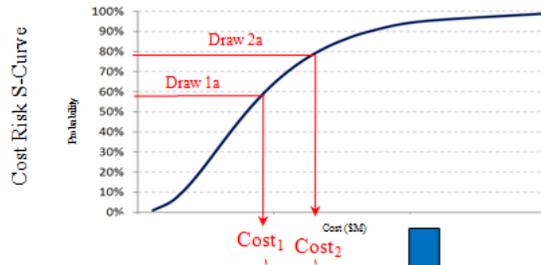
$$\Pr\{\mathit{Cost} \ \& \ \mathit{Schedule}\} = \Pr\{\mathit{Cost}\} * \Pr\{\mathit{Schedule} \mid \mathit{Cost}\}$$

Here, $\Pr\{\dots\}$ is the probability distribution of the Borel sets found within the brackets. The definition says, loosely, that we can calculate the probability of the schedule given that a particular cost has occurred as the probability that both the schedule and cost occur divided by the (unconditional) probability that cost occurs. The equation as written allows

us, in a Monte Carlo simulation, to first draw a random cost from the unconditional cost distribution, use that cost in calculation of the conditional distribution of schedule. We then draw a random schedule value from the resulting conditional schedule distribution. The availability of an unconditional total cost risk S-curve in NICM provides a starting point, as illustrated in Figure 4. As illustrated Monte Carlo simulation selects a Cost_1 value by inverting the S-curve for a uniform draw from the interval $[0,1]$ (i.e. the Draw_1 point on the Probability-axis). This Cost_1 value is inserted into the instrument SER – this selects a particular S-curve as illustrated on the lower chart. Different values of Cost inserted in the instrument SER model relationship yield a different S-curve from the family of S-curves. The prediction error (PE) determines the S-curve shape (i.e. lognormal).

Figure 5 illustrates the Monte Carlo draw for the schedule value. This process of creating a pair, the cost and schedule of a possible instrument development outcome, is repeated as many times as necessary to create the scatter plot in Figure 5.

Simulate cost from NICM Cost Risk S-Curve.



Simulated cost used to select a Schedule S-Curve based on historical schedule estimating relationship.

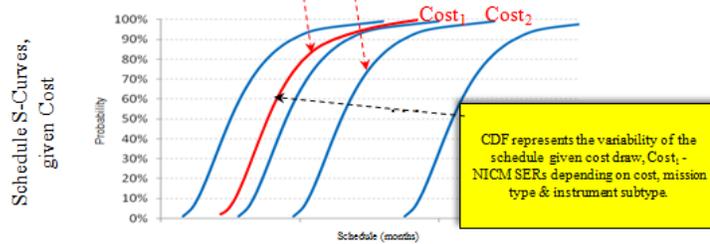
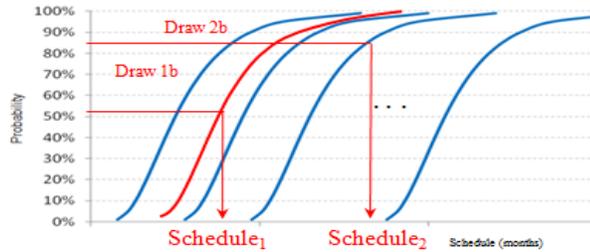


Figure 4 Schedule S-curve Selection from Cost Draw

Selected Schedule S-Curve used to simulate a schedule duration.



Simulated Cost-Schedule pair is plotted - Repeat 1,000 times.

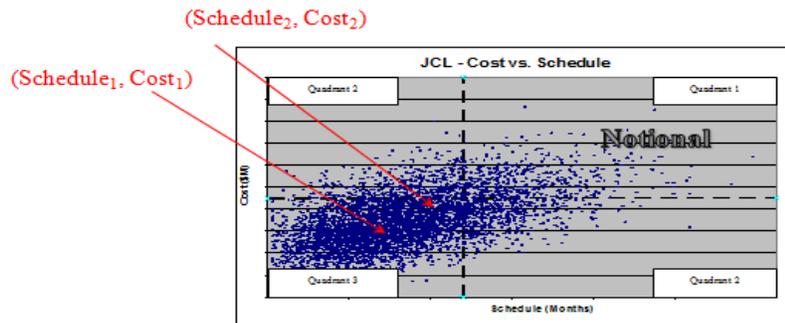


Figure 5 Schedule Draw, JCL Scatter Chart

From the scatter chart data performance statistics can be computed. In the figure, the fraction of pairs below and to the left of the specified dotted lines is the joint probability that the instrument development cost and schedule will be less than the values specified by the dotted lines. By varying inputs, i.e. the cost risk S-curve, mission type, and instrument subtype, this simple model provides a useful planning tool for conducting “what-if” budget studies. Should additional, detailed information concerning the cost risk S-curve, schedule model parameters and their uncertainty be available they can be incorporated easily into the model. This simple, high-level parametric method would be very useful during the instrument formulation phase, where limited detailed data and information are available.

8. NICM TOOLS

Three NICM Excel/VBA-based tools were developed: The NICM Subsystem Tool, the NICM System Tool and the NICM Search Engine. In NICM IV, each of these tools has been combined into one workbook. For the System and Subsystem tools, the user provides required parameter inputs as specified in the menu in the input section and the tool calculates the expected costs and their cumulative cost distribution functions in the output section. Should any user input value fall outside the applicable range, a warning will be displayed and the cost will still be estimated, however the user is encouraged to inspect the NICM database for analogy and appropriate input value ranges. The NICM Search Engine retrieves instrument information for use to create cost estimates by analogy. The user provides known parameter values and the tool returns those instruments in the database with similar features to the provided inputs.

NICM Subsystem Tool

The NICM subsystem tool provides instrument cost estimates at both the system and subsystem levels for remote sensing instruments (in-situ instruments currently not supported at the subsystem level). The NICM subsystem cost estimation tool has three basic elements: inputs, estimate outputs, and analogy outputs. Each area is described below, along with an overall description of how they interact. Figure 6 presents the subsystem estimator layout.

The NICM subsystem input area serves to collect the required parameters. Note that if a particular parameter is not needed for the instrument type being estimated, the tool will hide that parameter. Parameters are described as follows:

Instrument Name: A user-assigned name, and is used to identify the estimate. This input is not necessary to run the subsystem tool.

Costs are in: Base year for cost estimates.

Remote Sensing Instrument Type: Possible inputs include Optical, Active Microwave, Passive Microwave, Fields and Particles. Optical instruments sense frequencies from the infrared through x-ray. Active Microwave instruments sense and transmit in the microwave, millimeter, and sub-millimeter spectra. Passive Microwave instruments operate in the same spectra as active microwave but only sense. Field instruments sense in the radio and longer wavelengths. Particle instruments sense at frequencies higher than x-ray.

Environment: Select Earth Orbiting or Planetary.

Instrument Power: Total maximum (peak) power consumption in watts of all instrument subsystems during operations. This includes contingency.

System Mass: The total mass of the instrument in kilograms including structures, antenna, optics, electronics, thermal hardware, etc. Instruments with multiple sensors but common back-end electronics were treated as single instruments. This, and the remaining mass inputs, all include contingency.

Electronics Mass: The total mass of all instrument electronics in kilograms including power conditioning, signal processing, drive electronics, housekeeping sensors, data management, interface electronics, and electronics chassis. It does not include cables.

Optics/Antenna Mass: The total mass of the antenna and/or optical instrument elements in kilograms including all elements used in conditioning electro-magnetic fields and incident radiation prior to the sensor, and prior to conversion to an electrical signal. It also includes optical mounts, but does not include actuators (except filter wheels), and view-port covers.

Thermal Mass: The total mass of the passive thermal subsystem elements of the instrument. It does not include dewars or active thermal components.

Detector Mass: The total mass of the detectors including FPA filter elements in kilograms.

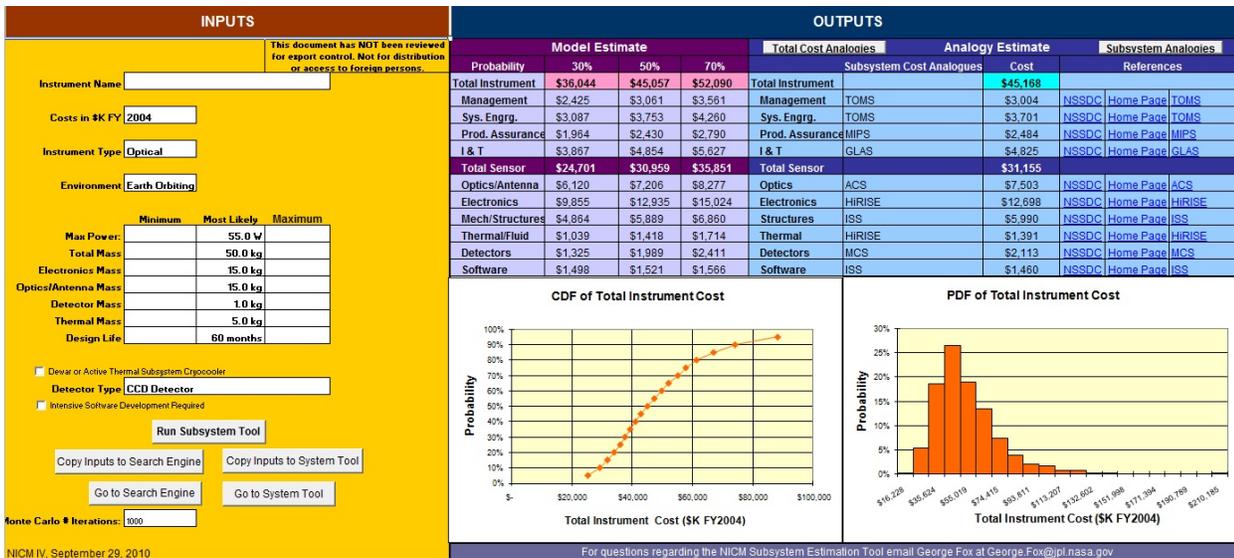


Figure 6 NICM Subsystem Tool Layout

Design Life: Time from launch in months until completion of the instrument baseline science objectives. Generally, this is the same duration for all instruments on a particular mission, but there are exceptions. For example, the Medium Resolution Imager (MRI) and High Resolution Imager (HRI) on the Deep Impact mission had design lives of 20 months while the Impactor Targeting Sensor (ITS) on Deep Impact had a design life of only 5 months. ITS needed only to survive until destroyed on impact, while MRI and HRI had to record that impact and observe the impact site for 15 more months.

Development Schedule: Time in months from start of Phase B through end of Phase D.

Dewar or Active Thermal Subsystem Cryocooler: Check box if this instrument or part of the instrument is deliberately cryogenically cooled to less than 80 Kelvin. Includes dewars and multiple stage active systems.

Low Operating Temperature: Minimum operating temperature in degrees Kelvin – used for estimating cryocooler cost when cryocooler is selected.

CCD, Photovoltaic/Photodiode/PMT, Fields/Ion Detector: Select the type of detector.

High Software Development Intensity: Check if this instrument’s software development is more intensive than average.

The model estimate output is built on a standardized WBS. Instrument hardware and software elements roll up into the sensor cost; management, system engineer,

I&T, and mission assurance (calculated using the formulas seen in section 5.4) are added to the sensor cost for the total instrument development cost. All subsystem costs are estimated as probability distributions then added through Monte Carlo simulation for the sensor and total instrument cost distributions. The instrument cumulative distribution function and probability density function graphs are presented along with the WBS based model estimate. The WBS elements are estimated at three prediction levels; nominally 30%, 50% and 70%, but these levels can be set to any multiple of 5%. Finally, graphs of a schedule cumulative distribution function based on a schedule CER, and a funding profile based on the launch date, 50% probability schedule, 50% probability instrument estimate, and the Beta factor are also presented.

In addition to the model WBS element estimates, the tool also sorts through its supporting data and orders the data for minimum statistical distance as the best internal analogues to the design being estimated. This is done for each WBS element when the “Subsystem Analogies” button is pushed, or is done only at the total instrument cost level when the “Total Cost Analogies” button is pushed. The user can scroll down the ordered list for the best user determined candidate. The actual element cost for the selected instrument is placed in the WBS and the totals are added arithmetically. Supporting information about these analogies can be found by clicking on the links/buttons in the reference section of the analogy estimates. Suggested analogues can be replaced with user provided analogues if desired. This then becomes an analogy estimate for the total instrument cost.

The subsystem tool operation is quite simple: enter the input parameters and click on the “Calculate Estimate” button to run the Monte Carlo simulation. Note that if the

user inputs happen to be out of the range of the database, a red color indicator will alarm the user. NICM will still provide an estimate; however, the user should be aware that the estimate will be an extrapolation of the database in these instances.

NICM System Tool

The NICM System Tool contains the CERs required to estimate system-level costs as well as the cumulative distribution function (CDF) calculation. As the data is entered the 50th percentile outputs change immediately. Figure 7 displays the System Estimator Layout.

The NICM system cost estimation tool has three basic elements: inputs, cost estimate outputs, and CDF display. The NICM system input area collects required parameters, which are described below. Note that if a particular parameter is not needed for the instrument type being estimated, the tool will hide that parameter.

Instrument Name: A user-assigned name, and is used to identify the estimate. This input is not necessary to run the subsystem tool.

Instrument Type: Select from Remote Sensing or In-situ

Remote Sensing Type: Select Optical, Active, Passive, Particles and Fields.

In-Situ Instrument Location: Select Arm/Mast, Body or [Atmospheric] Probe
Environment: Select Planetary or Earth Orbiting.

Mass: Total instrument mass in kilograms including structures, antenna, optics, electronics, thermal hardware, etc.

Power: Total maximum (peak) power consumption in watts of all instrument subsystems during operations.

Design Life: Design life is the time from launch, including calibration and checkout, until the completion of the instrument's baseline science mission objectives in months.

Data Rate: The total peak data rate of the instrument in kilobits per second. This is the data rate of the output of the instrument, not the sensor input data acquisition rate.

TRL: The numeric value of the NASA Technology Readiness Level at initiation of development.

Number of Samples: The number of samples (or deployments) a body-mounted, in-situ instrument is designed to select.

Model output is a buildup of system-level sensor and wrap costs. CERs are evaluated to calculate Sensor, Management, System Engineering, Integration and Test, and Product Assurance Costs. These are added together

to get Total Instrument Cost. In addition, the percent of total instrument cost of each system level wrap cost is displayed. Formulas for wrap costs and percentages are a function of Sensor Cost. Total Instrument and Sensor Cost CDF graph is presented alongside the model estimates.

The system tool operation is quite simple: enter the input parameters where specified and all 50th percentile outputs are automatically calculated. Hitting the button "Calculate Estimate" completes the calculation of the CDFs for sensor and total instrument cost. Note: Selection of different Instrument Types and/or Destinations may identify different parameters that must be supplied. Parameters that do not need to be supplied are blanked out on the input form. Values entered into these input cells have no effect on the calculation.

Note that if the user inputs happen to be out of the range of the database, a red color indicator will alarm the user. NICM will still provide an estimate; however, the user should be aware that the estimate will be an extrapolation of the database in these instances.

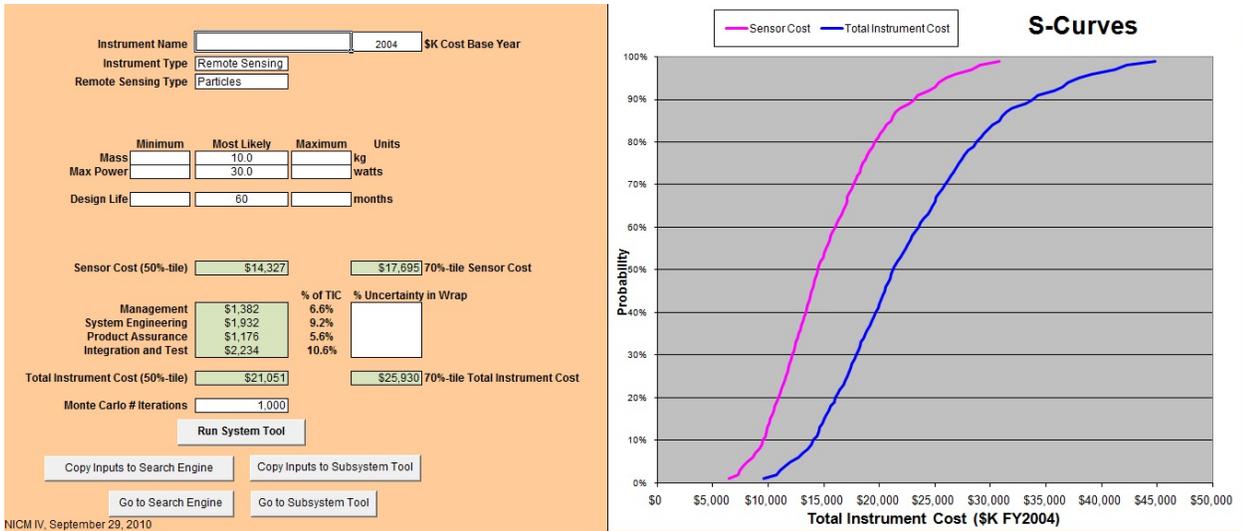


Figure 6 NICM Subsystem Tool Layout

NICM Search Engine

The NICM Search Engine is an Excel database search engine tool which was developed to retrieve instrument information to create cost estimates by analogy.

To use the tool, inputs known about the instrument to be costed are entered, and the tool returns similar instruments from the database. Inputs can be numerical or text, for numerical inputs, the degree of accuracy for the numerical inputs must be supplied.

For example, to cost an optical instrument with a mass of 55 kg and a total maximum power of 50 W, within an accuracy of +/- 25% on all numerical inputs, the search engine would return those selected instruments which meet the search criteria. Figure 8 displays search engine tool with example inputs.

As the following Table 3 indicates, three instruments met the criteria for the search parameters used in Figure 6. This example returns three instruments that met the specified criteria. For any search engine run, the following fields are always returned: B/C/D Cost, B/C/D Schedule and Destination. In addition to these fields, fields for the search are also returned for each instrument found (in the above example, total mass and the total maximum power were included). If the user is interested in seeing the rest of the data for a particular instrument, results are hyperlinked to the individual technology sheets. Clicking these hyperlinks will bring up the full NICM questionnaire.

The operation of the search engine operation is quite simple, as the following steps demonstrate:

1. Go to the "Search Engine" tab and push the "Start Search Engine" button which will display the NICM Search Engine Graphical User Interface (GUI).
2. Enter search criteria in the desired fields.
3. If you entered any numeric data, the "Result % Range" must be filled at the bottom. This will search for +/- x% on all numerical data you specify, where x = the "Result % Range" entered.
4. Press the "Search Database" button. The results will show up in the spreadsheet behind the GUI. You can now manipulate the results using Excel, and use the hyperlinks to bring up the full datasheets for the returned instruments.
5. Use the "Reset" button for a new search, or simply modify your previous entries.

NICM Remote Sensing and In-Situ Database Search Engine

NASA Jet Propulsion Laboratory California Institute of Technology JPL

General Information

Instrument Type

Remote Sensing
 In-situ

Optical
 Body Mounted

Active Microwave
 Arm/Mast Mounted

Passive Microwave
 Atmospheric Probe Mounted

Particles

Fields

Total Mass (kg) 55

Total Max Power (W) 50

Destination

Max Data Rate (kbps)

Instrument Name

Mission Name

Total Devel Cost (\$K FY04)

Total Sensor Cost (\$K FY04)

System Information

System Level Cost Inputs | System Level Technical Inputs

Management (\$K FY04)

System Engineering (\$K FY04)

Product Assurance (\$K FY04)

Integration & Test (\$K FY04)

Total FTEs

Subsystem Information

Subsystem Costs | Mass | Power | TRL | Other | Other 2 | Other 3

Thermal Temp Low (C)

Thermal Temp High (C)

Thermal Control System

Destination

of mech actuators/DOF

of instruments in suite

Delivery Mechanism

Platform

Filters

Result % Range 25

Launch Date Earliest

Launch Date Latest

NICM IV Rev 1, October 6, 2010

Reset Search Database

Figure 6 NICM Search Engine Tool with Example Inputs

Instrument Name	Mission Name	Destination	Inst. Type	B/C/D Cost (\$K FY04)	B/C/D Sched. (months)	TOTAL Mass (kg)	TOTAL Max Power (W)
HiRISE	MRO	Planetary	Optical	49843	48	65	60
HRI	Deep Impact	Planetary	Optical	23881	45	52	58
ISS	Cassini	Planetary	Optical	67478	60	58	56

Table 3 NICM Search Engine Example Results

CONCLUSIONS

The NASA Instrument Cost Model (NICM) allows users to produce cost estimates for space flight instruments at both the system and subsystem level using the parametric cost estimating relationships, or by analogy using the NICM database search engine.

ACKNOWLEDGEMENT

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REFERENCES

- [1] "NASA Instrument Cost Model (NICM) Version IV" JPL Report 982-0000 Rev. 4, September, 2010.
- [2] "NICM Schedule & Cost Rules of Thumb", Hamid Habib-Agahi , Gary Ball and George Fox, AIAA Space 2009, 14-17 September 2009, Pasadena, California.
- [3] A. C. Davison & D. V. Hinkley, Bootstrap Methods and their Application,
- [3] B. Efron & R. J. Tibshirani, An Introduction to the Bootstrap,
- [4] Donald F. Morrison, Multivariate Statistical Methods, McGraw-Hill Book Company. 1967. pps. 221-ff.
- [5] Gerhard Tintner, Jati K. Sengupta, Stochastic Economics. Stochastic Processes, Control, and Programming, Academic Press, 1972. p.56.
- [6] Henri Theil, Principals of Econometrics, John Wiley & Sons, Inc. 1971. pps. 46-56, 227, 532-533.
- [7] J. Johnston, Econometric Methods, 2nd Edition, McGraw-Hill Book Company, 1972. Chapter 11.
- [8] James T. McClave and P. George Benson, Statistics for Business and Economics, 4th edition, Dellen Publishing Company, 1988.
- [9] Jan Kmenta, Elements of Econometrics, Macmillan Publishing Co., Inc. 1971.
- [10] Maurice G. Kendall & Alan Stuart, The Advanced Theory of Statistics. Volume 3 Design and Analysis, and Time-Series, Macmillan Publishing, 1968. Chapter 43 Canonical Variables.

[11] N.R. Draper and H. Smith, Applied Regression Analysis, 2nd Edition, Wiley Series in Probability and Mathematical Statistics, 1981.

[12] Richard A. Johnson and Dean W.I Wichern, Applied Multivariate Statistical Analysis, 3rd Edition, 1992.

[13] S. Frosch Moller, J. von Frese, R. Bro, Robust Methods for Multivariate Data Analysis, Journal of Chemometrics, 2005. 19:549-563.

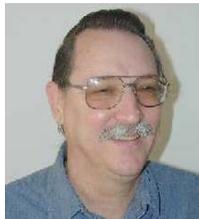
[14] S-Plus 7 Guide to Statistics, Volume 2, Insightful Corporation. Chapter 20 Principal Components Analysis.

[15] Takeshi Amemiya, Advanced Econometrics, Harvard University Press, 1985. pps.58-60.

BIOGRAPHY



Hamid Habib-Agahi: *Hamid's bio here once he returns from vacation.*



George Fox: *Engineers used slide rules when George entered Caltech as a freshman in 1965. After certification as a Quantum Mechanic & Micro Economist (Caltech PhD, Applied Physics and Economics, 1979) George joined JPL to determine the value of solar cell supplied power for the national PV solar energy program. When Ronald Reagan killed the program George changed sides, doing military acquisition policy analysis & war-gaming modeling for the highly successful JESS, validated during Gulf War (One!). As an original developer of the Space Station System Design Tradeoff Model and a founding analyst for JPL's Project Design Center, George failed in educating NASA and JPL about cost-performance-risk tradeoffs. Saddened, he moved on to develop reliability-based design models of complex systems (JPL's SIM and NSF's NEPTUNE). He has recently entered the quagmire of joint cost and schedule risk modeling to convince management that it can't (can?) be done without (irrelevant) historical data and (inappropriate) regression models. George is currently the statistical analyst for NICM.*



Joe Mrozinski is a systems engineer in JPL's Systems Analysis and Modeling group. Joe's roles on the NICM team include: software and tool creation, database management, data interviewing/collection and training NICM users. His other successes at JPL include technology-portfolio assessment, human-robotic task allocation for lunar/Martian/NEO applications, trade-tool software development for JPL's Team X design center, and several trade studies and mission/architectural optimizations. Joe's other professional experience includes five years of leadership positions in the field of residence education, supporting both the University of Michigan and the California Institute of Technology. Before joining JPL in 2004, Joe received his Masters in Space Systems Engineering at the University of Michigan, where he also earned a B.S. in Aerospace Engineering and a B.A. in Philosophy, with a focus on Ethics and Artificial Intelligence.