The JPL Cost Risk Analysis Approach That Incorporates Engineering Realism

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ABSTRACT

In recent years, there has been an increased desire to perform cost risk analyses on space exploration mission cost estimates presented for management review. Single point cost estimates are of limited value since they fail to capture uncertainty in the estimate and, in so doing, cannot provide proper context for comparison to other estimates. This uncertainty is important to capture, especially for cost estimates of complex space missions early in the project planning phase. There are many unknowns with high variances that must be captured in the estimation process (i.e., impacts of new technologies, the impact of unknown unknowns, etc.). Therefore, a cost risk assessment should include a range of likely costs with the probability of achieving that range.

Typically, this cost risk is best portrayed by a cumulative density function (CDF), or an S-curve, that illustrates the likelihood of achieving a particular cost. This S-curve should make engineering sense and provide realistic input to decision makers. By employing methodologies that are based on actual project cost data, the credibility of the analyses increases and decision makers will have better information upon which to make their assessments.

The fundamental problem associated with cost risk analysis is the accurate evaluation of three main elements that contribute to cost risk: uncertainty in cost estimation algorithms (model uncertainty), uncertainty in the inputs to the algorithms (technical risk), and the correlation between WBS elements. All three of these elements are important when adding distributions through simulation. Without proper representation of these factors, the resulting S-curve will understate the estimate uncertainty and, accordingly, understate the risk of overrunning the evaluated project's budget.

This paper discusses the JPL Cost Engineering Group (CEG) cost risk analysis approach that accounts for all three types of cost risk. It will also describe the evaluation of historical cost data upon which this method is based. This investigation is essential in developing a method that is rooted in engineering realism and produces credible, defendable results to aid decision makers.

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1. Introduction

In recent years, there has been an increased desire to perform cost risk analyses on space exploration mission cost estimates presented for management review. Single point cost estimates are of limited value since they fail to capture uncertainty in the estimate and, in so doing, cannot provide proper context for comparison to other estimates. This uncertainty is important to capture, especially for cost estimates of complex space missions early in the project planning phase. There are many unknowns with high variances that must be captured in the estimation process (i.e., impacts of new technologies, the impact of unknown unknowns, etc.). Therefore, a cost risk assessment should include a range of likely costs with the probability of achieving that range.

Typically, this cost risk is best portrayed by a cumulative density function (CDF), or an S-curve, that illustrates the likelihood of achieving a particular cost. This S-curve should make engineering sense and provide realistic input to decision makers. By employing methodologies that are based on actual project cost data, the credibility of the analyses increases and decision makers will have better information upon which to make their assessments.

This paper discusses the JPL Cost Engineering Group (CEG) cost risk analysis approach in detail and describes the evaluation of historical cost data upon which this method is based. This investigation is essential in developing a method that is rooted in engineering realism and produces credible, defendable results to aid decision makers.

2. History of Cost Risk Analysis in the CEG

The Cost Engineering Group resides in JPL's Mission System Concepts Section and its charter includes performing engineering cost trades and life cycle cost analyses for proposed JPL missions. Cost risk analysis became a standard task in the Cost Engineering Group with the addition of the Monte Carlo capability in the group's Parametric Mission Cost Model (PMCM).

PMCM is a total mission cost model that has been in use since 1998 and has included cost risk capability since 2003. The model is a full project estimation tool, with costs estimated at the subsystem level and then aggregated along a standard WBS. It has been verified to accurately estimate project costs using actual data from recent JPL missions. While PMCM has a built in Monte Carlo capability to perform a cost risk analysis on the parametrically generated cost estimate, the CEG also performs analyses on grassroots estimates using the @Risk software package to run the Monte Carlo simulation.

Another JPL model that incorporates cost risk capabilities is the NASA Instrument Cost Model (NICM). This model is currently in development and is earmarked for wider use throughout the Space Agency. It is based on about 70 NASA observational instruments launched since 1985. NICM estimates at the subsystem level, then aggregates to a total instrument cost through a standard WBS. Once development is completed, NICM will be integrated into PMCM for the instrument portion of the mission WBS.

The Cost Engineering Group has supported many project and proposal reviews by providing independent cost estimates and cost risk analyses. Table 1 describes just some of the cost risk analyses recently performed.

Table 1 CEG Cost Risk Analysis Support

Project Name	Date of Support
Discovery 2006 Proposals	March 2006
Aquarius PDR	June 2005
SIM Re-design	May 2005
Phoenix PDR	April 2005
Prometheus	April 2005
Juno PDR	February 2005
Discovery 2004 Proposals	June 2004

In addition, a large part of the work performed by the CEG is to support JPL's Advanced Projects Design Team (Team X) and other study development activities. The S-curves generated from a cost risk analysis can be used to support the sensitivity or trade studies performed during these design activities.

3. Understanding the Problem

The fundamental problem associated with cost risk analysis is the accurate evaluation of three main elements that contribute to cost risk: uncertainty in cost estimation algorithms (model uncertainty), uncertainty in the inputs to the algorithms (technical risk), and the correlation between WBS elements [1]. All three of these elements are important when adding distributions through simulation. Without proper representation of these factors, the resulting S-curve will understate the estimate uncertainty and, accordingly, understate the risk of overrunning the evaluated project's budget.

Model uncertainty is a result of the imprecision inherent in the cost estimating relationships (CERs). CERs are usually based on relationships derived from general cost dependence on input parameters such as mass, power, heritage, schedule, etc. While the CERs are validated against actual cost data, they will always have some amount of uncertainty that needs to be reflected in the cost risk analysis.

The technical inputs associated with cost algorithms or the technical risks associated with a grassroots estimate have their own uncertainty which has a significant impact on the likelihood of achieving the proposed cost estimate. The uncertainty of technical inputs is usually very indicative of the associated uncertainty of the cost estimate. A project proposing the use of new, untested designs will have more unknowns regarding the possible growth of mass, power, and other technical parameters upon which the baseline estimate is based. With a greater uncertainty of the inputs, a larger range of cost probabilities is expected.

Finally, it is generally agreed that there is some level of correlation between WBS elements and it must be accounted for in any justifiable cost risk analysis. Understating the correlation between WBS items may result in the cost risk analysis failing to account for possible ripple effects caused by an increase in a subsystem cost estimate.

As can be seen in Figure 1, the convolution of all the risk elements leads to an accurate cost estimate probability distribution. However, if all three elements are not accounted for, the correct probability distribution will be understated.

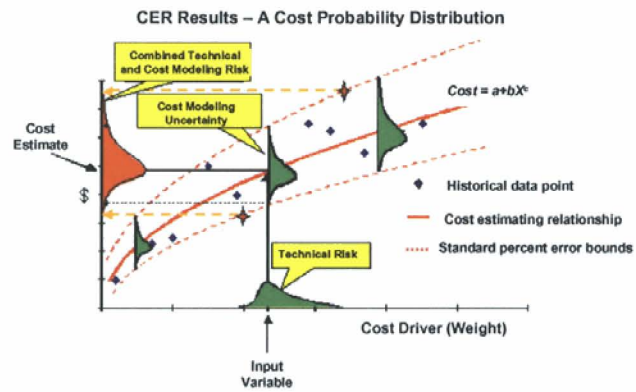

Figure 1 Convolution of Different Cost Risk Factors [2]

Unfortunately, several of the risk elements are easy to miscalculate. Many analyses fail to account for all the uncertainty or understate them. When unknown ranges are assumed to be zero or ranges are underestimated, the analysis results in an unrealistically steep S-curve, as illustrated in Figure 2. Additionally, most methods rely on some level of subjectivity, causing results to be different from one assessor to the next and introducing an additional error source.

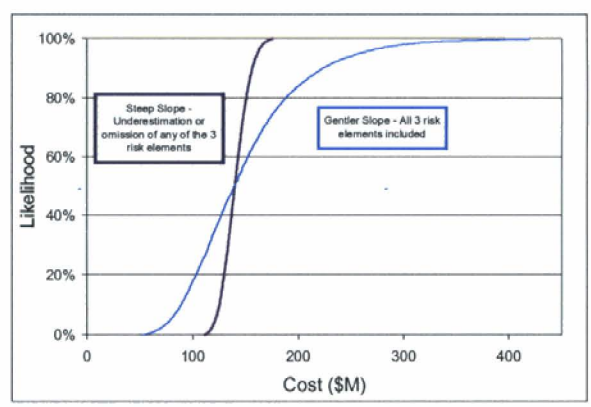

Figure 2 Comparison of S-Curve Slopes

A significant step towards an Agency-wide solution to these problems was taken with the JPL sponsored cost risk workshop held in January 2006. This workshop was attended by key cost risk personnel from NASA Headquarters, NASA's Independent Program Assessment Office (IPAO), significant contractors, and JPL.

In preparation, each attendee was requested to produce an S-curve based on a generalized example of a project's budget and risk information. Each methodology was then discussed, including the underlying assumptions and the interpretations of the data provided. The workshop confirmed that the main differences between the cost risk estimates lie in the assessments of correlation, probability distribution functions, and differences in interpretations of budget and reserve information. Because these assumptions drive the results of the cost risk analysis, efforts are being made to develop consistent definitions of terms and determine the applicability of certain assumptions based on the type of mission being evaluated and the level of detail available from the project at the time of the analysis.

4. Cost Engineering Group Methodology

General Methodology

The Cost Engineering Group at JPL has established a cost risk analysis approach that includes consideration of all three elements of risk and incorporates engineering realism. Cost risk analyses performed in PMCM allow distributions to be applied to the technical parameters to capture the uncertainty of the inputs. The validation of the model against historical actual cost data incorporates the CER uncertainty into the analysis; the standard deviations applied to the distributions on cost are established by the statistical results of the model validation. The correlation factors between WBS items are also accounted for and are based on the observed interactions between subsystem costs. As more and more historical cost data points become available, this methodology is refined to consistently fit the trends observed in actual costs.

Distributions

To perform the analysis, the CEG uses a log-normal distribution instead of the more commonly used triangular distribution. A triangular distribution requires a low, most likely, and high cost point to build the distribution around. A log-normal distribution, on the other hand, only requires a mean value (which the CEG method assumes to be the current best estimate) and a standard deviation to distribute costs around the mean. Thus, using the log-normal distribution eliminates the problem of guessing at the highest possible cost for missions that usually have significant unknown unknowns and that are using new technologies. This guess at a highest possible cost will likely be optimistic – it is usually not truly the highest cost possible, but rather the highest cost allowed.

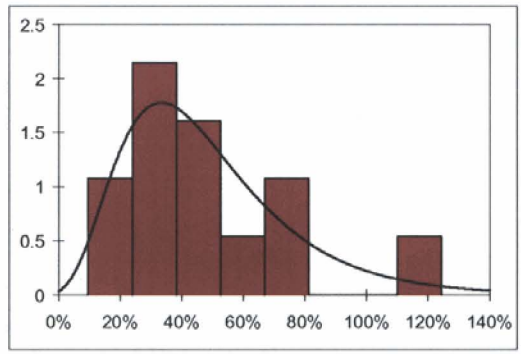

Figure 3 Actual Cost Growth Fits a Log-normal Distribution

Using a log-normal distribution also coincides with the historical cost growth of JPL missions, as shown in Figure 3. The number of projects that have cost overruns of more than 30% are significantly higher than those that have grown less than 30%, and the histogram of these project costs clearly fits a log-normal distribution. Yet another example is the actual cost growth of cost accounts within a project. Figure 4 shows the distribution of cost growth from the time of preliminary budgeting for a specific JPL project to the final actual cost; this example also fits a log-normal distribution. The CEG also assumes that the cost estimate provided is the Current Best Estimate (CBE) and is considered to be the mean of the log-normal distribution.

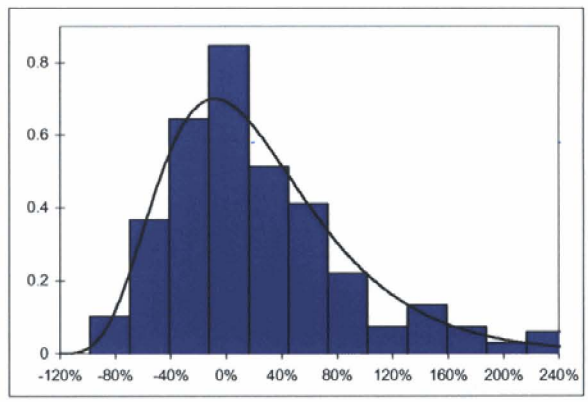

Figure 4 Cost Growth within a Project Fits a Log-normal Distribution

Standard Deviations

The standard deviations applied to the log-normal distribution are perhaps the most difficult element to standardize from one organization to the next. However, after tracking actual project costs over the last ten years, the CEG has studied cost growth data and uses standard deviation values that match those seen in reality.

The most compelling study has been the tracking of project cost growth from the proposed estimate at the Preliminary Mission and Systems Review (PMSR) or the Preliminary Design Review (PDR) up through fiscal year 2005. Thirteen projects were surveyed and their cost growth recorded (Figure 4). From this study, it is found that the average cost growth in total project cost has a standard deviation of 30%.

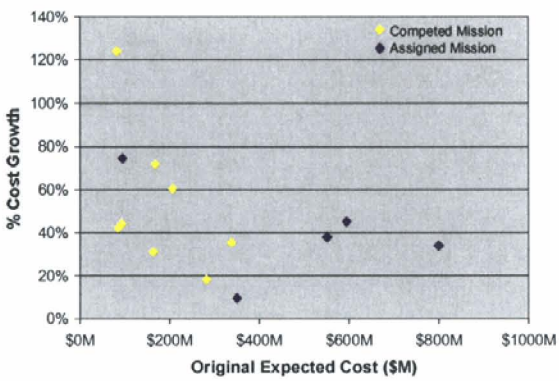

Figure 5 Results of JPL Cost Growth Study

The continuous validation of the PMCM model over the past several years has revealed similar statistics. In PMCM, each CER is validated against actual cost data and the uncertainty of the WBS distribution is set to the standard deviation of the result. From the findings of these validations shown in Table 2, the standard deviation is 36%, coinciding with the results of the cost growth study.

Table 2 PMCM Validation Results

Comparison	Version	Average Cost Delta	Average Standard Deviation
Actual Project Total Costs (1999)	PMCM 2	4.7%	35.2%
Actual Spacecraft Costs (2003)	PMCM 2	16.8%	42.5%
Actual Spacecraft Costs (2003)	PMCM 3	2.1%	31.0%
Average		**7.9%**	**36.2%**

During the preliminary validation efforts of NICM, there also seems to be a trend in the standard deviations of instrument costs. At this first stage of analysis, it appears that the deviation for instrument costs is closer to 50%, rather than the 30% for the spacecraft system or the total project costs.

In the face of all this evidence, the CEG uses a standard deviation of 25%-35% for most WBS items, including the flight system. The payload system is usually assigned a higher standard variation, around 50%. However, in recognition of the fact that some WBS items may carry more risk than others, and projects have a broad range of heritage and risk factors, the standard deviation may be varied – a higher standard deviation may be used to capture the higher cost risk elements and a lower standard deviation used for those items that are very well understood.

Correlation

Finally, the correlation factor used in the CEG methodology to relate a project's WBS items is 60%. This relatively high correlation is believed to reflect the close relation between subsystem designs. Some previous studies of aerospace industry missions have shown that a 20% correlation factor may be sufficient to capture most of the relationships between WBS items [3]. However, for JPL projects, which are almost exclusively one-of-a-kind missions, this factor may be too low. From observations of subsystem interactions in Team X and other JPL mission design activities, design changes in just one subsystem may have large ripple effects through the entire system. Often times, cost overruns are due to the failure to account for these effects across the various subsystems. For the CEG method, using a correlation factor of 60% is assumed to capture this high reliance of one subsystem on another more accurately. Additional research into correlation of space mission subsystems is on-going at JPL.

Reserve Recommendations

Once a cost risk analysis is complete and the probability of a project's estimate is determined, a recommendation for the amount of reserves necessary is made to bring the project estimate to a cost that has a 70% probability of success (Figure 5). Currently, the 70% probability cost is the recommended total cost for JPL projects and follows the guidelines provided in the NASA Cost Estimating Handbook [4]. A 70% probability is also assumed to account for possible unknown unknowns that cannot be captured in the analysis.

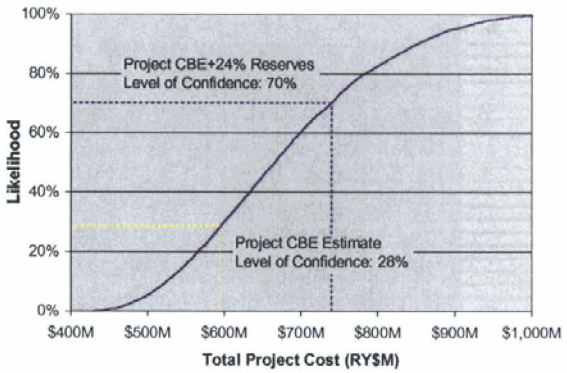

Figure 6 Example of Reserve Allocation Based on Cost Risk Result

Using the cost risk analysis as the basis for reserve allocations has the potential to improve on the current practice of assuming a flat reserve percentage over the project's life cycle. Another outcome of the cost growth study discussed earlier is that there does not appear to be a strong correlation between the proposed reserve percentage and the final project cost overrun. As seen in Figure 6, projects that propose 25% cost reserves may overrun just as much as projects that propose 10% cost reserves. Instead of a flat percentage requirement, which will not solve this disconnect, reserve levels should be based on the amount of risk associated with a project. The ability to characterize absolute cost risk will allow us to calculate a non-arbitrary cost reserve.

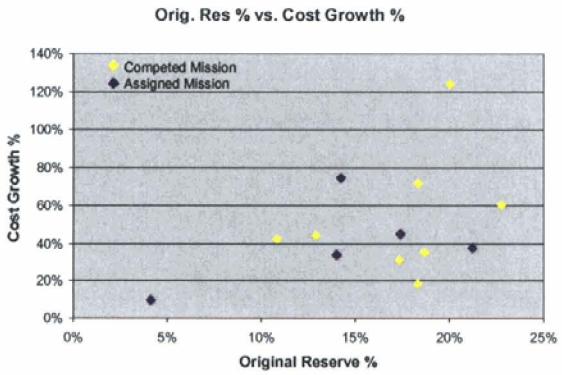

Figure 7 Cost Growth Trend

5. Future Work

The subject of cost risk analysis is only just now being studied in detail – there is still a large amount of work to be done to refine the methodologies. For the CEG, producing further statistics on the growth and uncertainty of input parameters, based on historical technical data, would be of significant importance. Developing a better understanding of the actual historic growth of these parameters would add even more fidelity to the CEG cost risk methodology. This task would be supported by two main sources of data: the actual technical and cost data at the time of a JPL mission's completion, and the Project Cost Analysis Data Requirement (CADRe)[1] which is specifically designed to track technical and cost data over the project's life cycle.

A further study of WBS correlations specific to JPL projects is also needed. This effort would be started by determining general correlations between Level 1 WBS items such as Project Management, Systems Engineering, Flight System, etc. Developing correlations at the subsystem level within the flight system would also be beneficial. For this task, the Team X database would provide a wealth of data – most of the studies performed by Team X consider specific subsystem design trades and capture the technical and cost deltas for each trade. These deltas will allow us to observe the ripple effects between subsystems as well as between higher level elements like the flight system, project management, etc. With a better understanding of how correlation between WBS items really operates, the CEG cost risk methodology will become more accurate.

6. Conclusion

A major step toward developing industry standards and definitions regarding cost risk analyses is to understand the various methodologies used and the assumptions associated with them. Here, we have presented the JPL CEG methodology, a defensible technique that is rooted in engineering realism. It is specifically tailored to JPL missions for maximum accuracy of analyzing cost risk for one-of-a-kind space missions.

This methodology is continuously refined based on actual historical cost data and observations of the numerous trade studies performed by JPL. The future work regarding correlation and technical inputs would add even more fidelity to the technique, improving the quality of cost estimates presented to decision makers.

7. References

[1] "The NASA 2004 Cost Engineering Handbook." pg 92

[2] "The NASA 2004 Cost Engineering Handbook." pg. 158

[1] CADRe is NASA's unified approach to collecting space mission data across all NASA centers, including JPL.

[3] Book, S. "A Theory of Modeling Correlation for Use in Cost-Risk Analysis." Proceedings of the International Society of Parametric Analysis Southern California Workshop. El Segundo, CA Dec. 2005.

[4] "The NASA 2004 Cost Engineering Handbook." pg. 93

8. Acknowledgements

The authors would like to acknowledge the System Analysis Models and Tools Group at JPL and their collaboration in hosting the JPL Cost Risk Workshop.

9. Biographies

Corey Harmon *is a member of the Cost Engineering Group in the Mission Systems Concepts Section at the Jet Propulsion Laboratory. She is a member of JPL's Advanced Project Design Team (Team X) and has participated in numerous studies as the Cost Engineering Chair and Deputy Systems Engineer. She has also been a member of the cost estimation team for Prometheus, and performs JPL internal Independent Cost Estimates (ICEs) and cost risk analyses for projects like Aquarius, Phoenix, and the Space Interferometry Mission. Corey received her B.S. in Aerospace Engineering from the University of California, Los Angeles, and is currently pursuing her M.S. in Astronautical Engineering at the University of Southern California.*

Leigh Rosenberg *is the Group Supervisor of JPL's Cost Engineering Group in the Mission Systems Concepts Section. He was also a charter member of JPL's Advanced Projects Design Team (Team X). He has worked at JPL in cost estimation and systems engineering for the last 28 years. He has developed JPL's engineering cost estimation methodology and has coordinated the cost estimation of various competitive proposals including the Stardust, Genesis, and Deep Impact projects. He created the Parametric Mission Cost Model which is used to generate parametric WBS mission costs for JPL space missions.*

Mr. Rosenberg has previously worked for the Federal Government at the Interstate Commerce Commission, and for the MITRE Corporation. He has an MS in Operations Research and Industrial Engineering from the University of Massachusetts and a BA in Mathematics from Queens College of the City University of New York.

In his spare time, he is currently a Boy Scout Assistant Scoutmaster. He completed an 8-day canoe trip with the Boy Scouts in 2004, and participated in National Boy Scout Jamboree in 2005 as a representative of NASA. Previously, he has been an active participant in Pasadena city government, running the City's Endowment Commission for 4 years, and participating on the City's Light Rail Task Force.

Keith Warfield *is a Senior Systems Engineer at the Jet Propulsion Laboratory working in proposals, advanced projects and tool development. He holds a B.Sc. in Engineering and Applied Science from the California Institute of Technology. Mr. Warfield has also worked in cost analysis and in engineering roles on several science instruments including the Satellite Test of the Equivalence Principle, the Mars Observer Pressure Modulator Infrared Radiometer, the TOPEX Microwave Radiometer, the UARS Microwave Limb Sounder, and particle detectors for the Stanford Linear Accelerator.*

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ISPA Conference
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JPL

Presentation Outline

- Introduction
- History of Cost Risk in the CEG
- Understanding the Problem
- Cost Engineering Group Methodology
  - Distributions
  - Standard Deviations
  - Correlations
  - Reserve Recommendations
- Future Work

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Introduction

- Why are we interested in cost risk analysis?
  - Decision makers want to know the likelihood of achieving a particular cost estimate
  - Single point cost estimates fail to capture uncertainty in the estimate and cannot provide proper context for comparison to other estimates
- The methodology needs to be well understood and justifiable in order to generate an S-curve that reflects reality

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History of Cost Risk Analysis in CEG

- Parametric Mission Cost Model (PMCM)
  - Developed in 1998, Cost Risk capability in 2003
  - Distributions placed on technical inputs and cost outputs
- NASA Instrument Cost Model (NICM)
  - In development, preliminary validation results
- Analysis of grassroots estimates using @Risk

Project Name	Date of Support
Discovery 2006 Proposals	March 2006
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Phoenix PDR	April 2005
Prometheus	April 2005
Juno PDR	February 2005
Discovery 2004 Proposals	June 2004

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Understanding the Problem

- Model uncertainty
  - Result of CER uncertainty
  - Accounted for by using validation statistics as a basis for standard deviations
- Technical risk or input uncertainty
  - Result of technical unknowns regarding changes in mass, power, etc. which have an effect on cost growth
- Correlation between WBS elements
  - An increase in cost of one element will likely be tied to the increase in cost of another element

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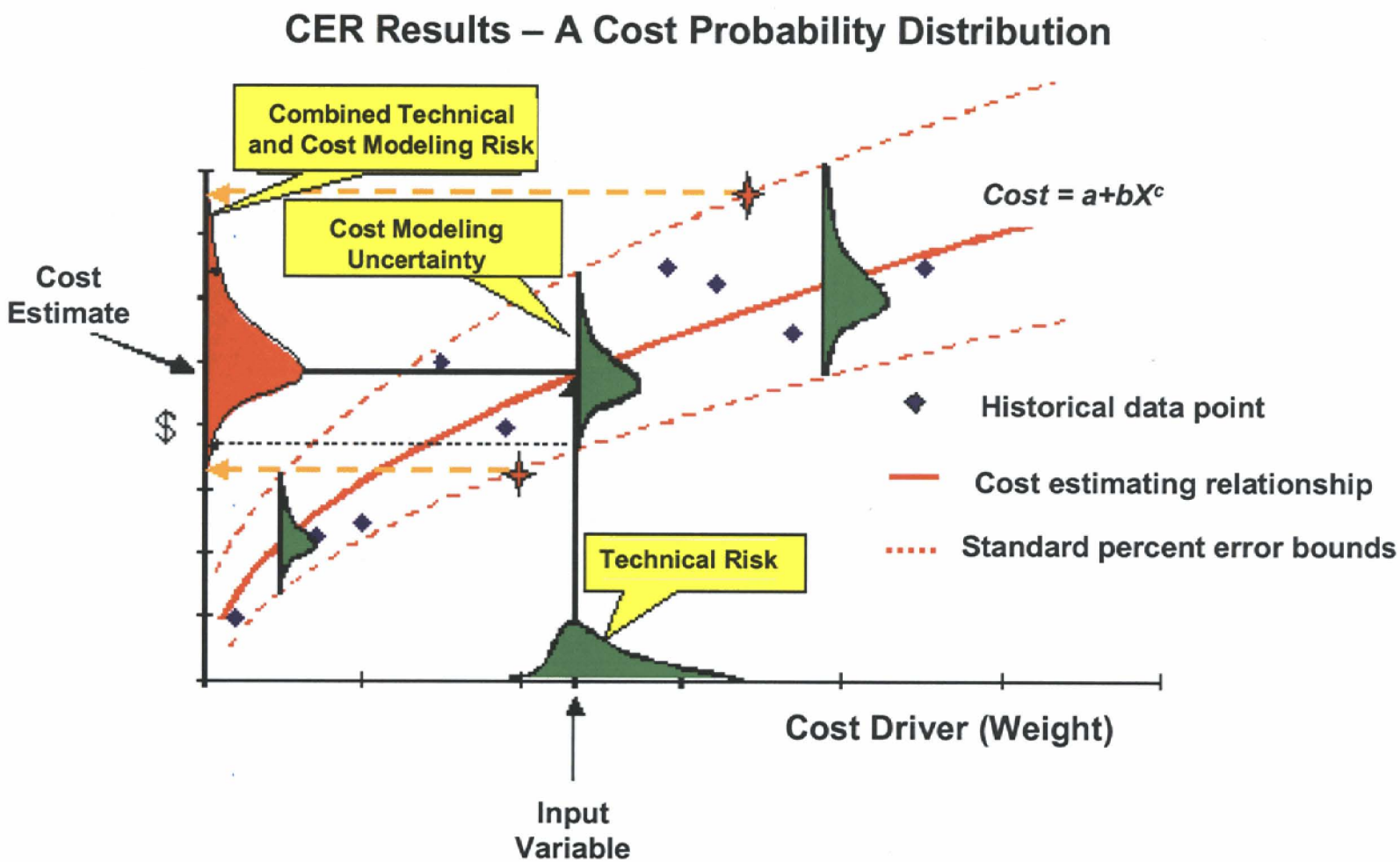
Convolution of Cost Risk Elements



NASA CEH pg. 158

A Step in the Right Direction

- Communication!
- JPL sponsored Cost Risk Workshop held in Jan. 2006
  - Each attendee was asked to generate an S-curve for a generalized example of a project's budget and risk information
  - Each methodology was presented and discussed
- The main differences between the cost risk estimates lie in assumptions regarding:
  - Correlation
  - Probability distribution functions
  - Interpretation of budget and reserve information

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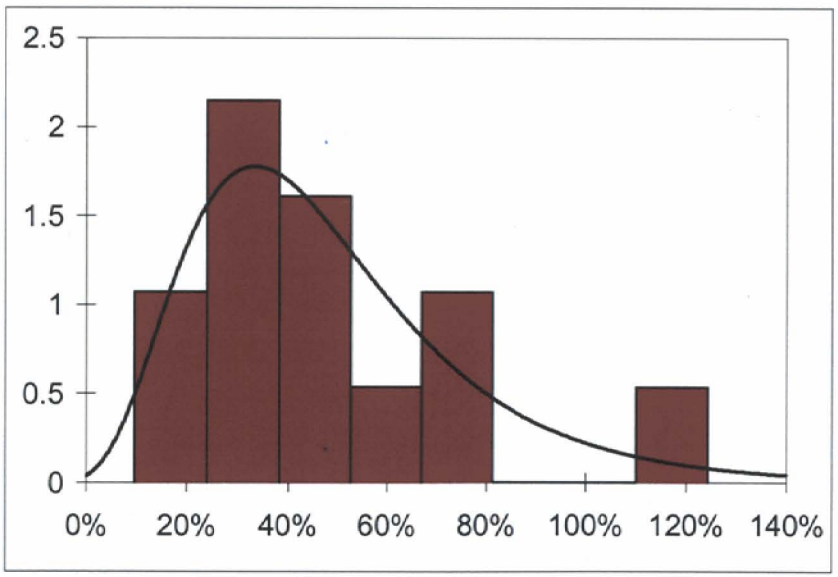
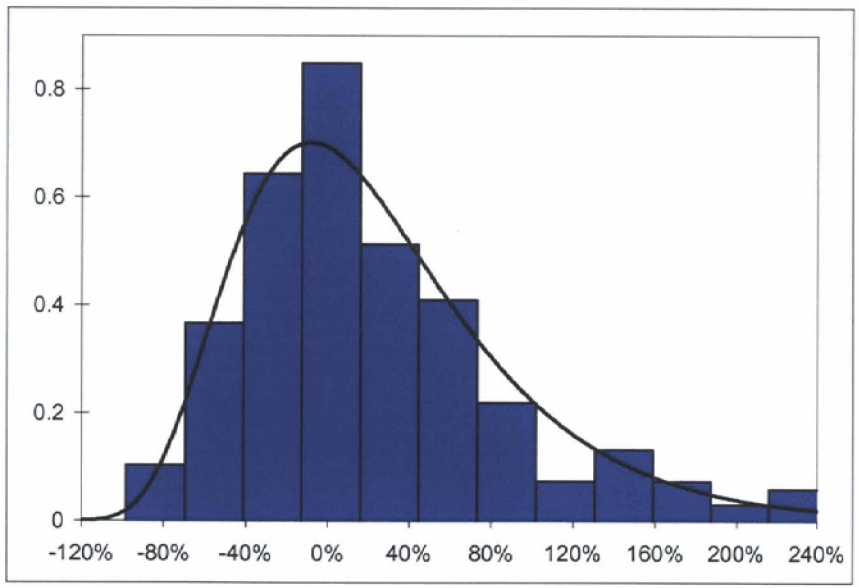
CEG Methodology - Distributions

- CEG uses log-normal distributions
  - Eliminates problem of guessing at highest possible cost
  - Fits historical cost growth of JPL missions
  - Assumes point estimate is the mean of distribution

Cost Growth of JPL Missions

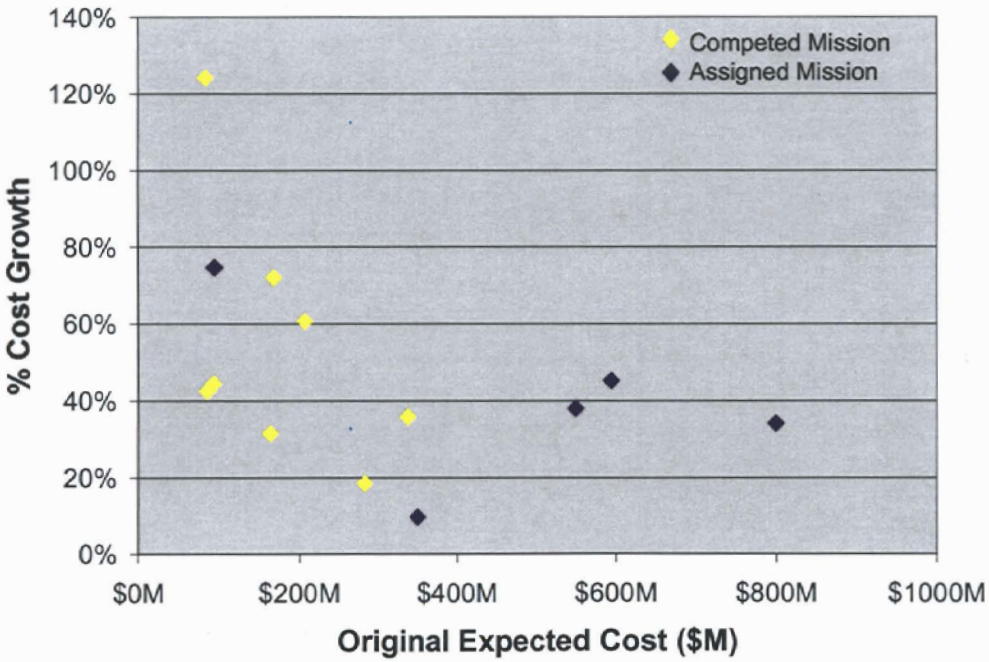


Cost Growth within a JPL Project



CEG Methodology – Standard Deviation

- Cost Growth Study
  - 13 projects tracked from proposed cost at PMSR or PDR to costs at 2005



- PMCM Validation

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Actual Project Total Costs (1999)	PMCM 2	4.7%	35.2%
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Average		**7.9%**	**36.2%**

CEG Methodology - Correlation

- CEG uses correlation factor of 60%
  - S. Book study recommends using at least 20%
- JPL missions are one-of-a-kind space missions that have subsystems with high dependence on one another
- Cost overruns of JPL missions are often due to failure to account for ripple effects between subsystems resulting from design changes
- A higher correlation is appropriate for the JPL method

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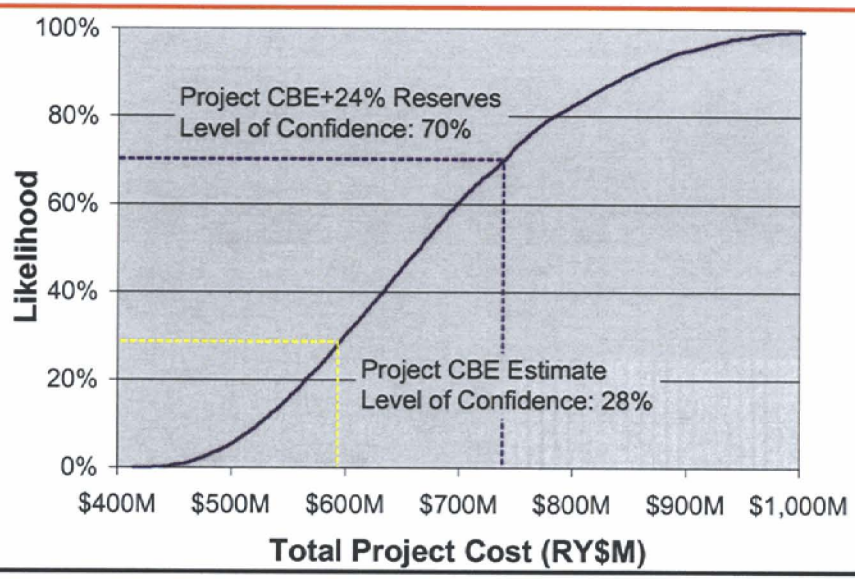
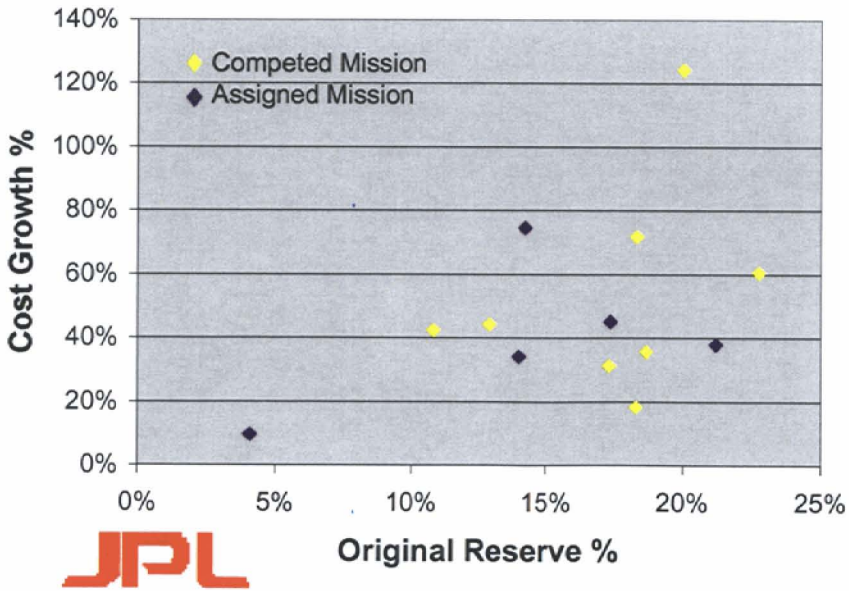
CEG Methodology - Reserves

- Reserves are recommended to bring estimate to a 70% probability of success
  - Guideline provided in NASA Cost Estimating Handbook (pg. 93)
  - Accounts for possible unknowns unknowns





- Flat reserve percentages do not provide an adequate reserve philosophy – reserves should be based on cost risk analysis

Future Work

- Better statistics on growth and uncertainty of technical input parameters
  - Study the growth of actual historical technical data
  - Use actual data from completed JPL missions
  - Use CADRe to track growth over a project's life cycle
- Correlation statistics
  - Develop correlation matrix of Level 1 WBS elements (Project Mgmt, Systems Eng, etc.) specific to JPL missions
  - Use Team X data to derive how element costs are affected due to changes in a specific subsystems

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