

Data-Driven Guidelines for Correlation of Cost and Schedule Growth

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Abstract

When running Monte Carlo simulations, one of the most difficult issues to account for is correlation between the independent variables. Ignoring correlation generally reports overly optimistic analysis results; industry standard suggests that when no additional insight is available, a default value of 0.2 can be used. In an effort to develop better general correlation guidance, this study analyzed historical data of NASA programs, which suggest that a default correlation value closer to 0.6 can be used. Moving forward, this study can be replicated to other industries and organizations with critical schedules.

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1 Introduction

In his paper “Estimating System Cost” [3], Dr. Stephen A. Book suggests that in the absence of known correlation between elements of a WBS, a correlation value between 0.2 or 0.3 may be assumed to produce a “least wrong” representation of total-cost certainty. Dr. Christian Smart [17] mathematically minimized the total error under the assumption that the assumed and actual correlation are not equal and showed that, depending on one’s assumptions, the appropriate value may be .20, .40, or even .60.

In our research, we analyzed historical NASA cost-schedule data to produce a “magic correlation” number based on the data.

This paper is organized as follows. First, the various data sources are listed, followed by a characterization. We then analyze this data in three different approaches, each building upon the lessons learned from the previous trial(s). A methodology for cost correlation is presented. We then give recommendations and suggestions for additional analysis. A review of the relevant literature appears in the appendix.

2 Data Sources

Our sources included data files for 94 missions (3,836 folders containing 37,260 files; 94.1 GB of data) from NASA CADRe Checklists, NASA CADRe Parts A, B and C, Mission Milestone Reviews, Mission Quarterly Status Reviews, and Mission Monthly Status Reviews. We also used NRO high-level data for general guidance and validation.

We focused our attention on forty-five missions, which we partitioned into the categories of “Data Available,” “Data Insufficient,” and “Data Lacking.” “Data Available” referred to missions with scheduling data available at multiple milestones or periods, with either complete coverage of the mission lifecycle or at least 5 years of development, “Data Insufficient” referred to missions with scheduling data that was very close together, only spanning a few years or to missions that were not near completion, and “Data Lacking” referred to missions with data from only one milestone, year, or period or missions with large data gaps.

3 Correlation of Schedule Activity Durations

3.1 Methodologies

We tried three approaches. After testing our first approach, we decided that it yielded too few data points, and so decided on a second approach with more data. However, our second approach, while incorporating enough data, was too time costly to be plausible. The third method we tried found a sweet spot between these two extremes and gave us the results we were looking for. Details are described below.

Approach # 1

Our first approach was to find consistent milestones for two milestones (for instance, PDR, CDR, and Launch) while holding the missions constant. We focused on finding a correlation by activity (for instance, spacecraft development) between two missions. To accomplish this task, we would collect many correlation values for each activity across missions, pool these correlation results

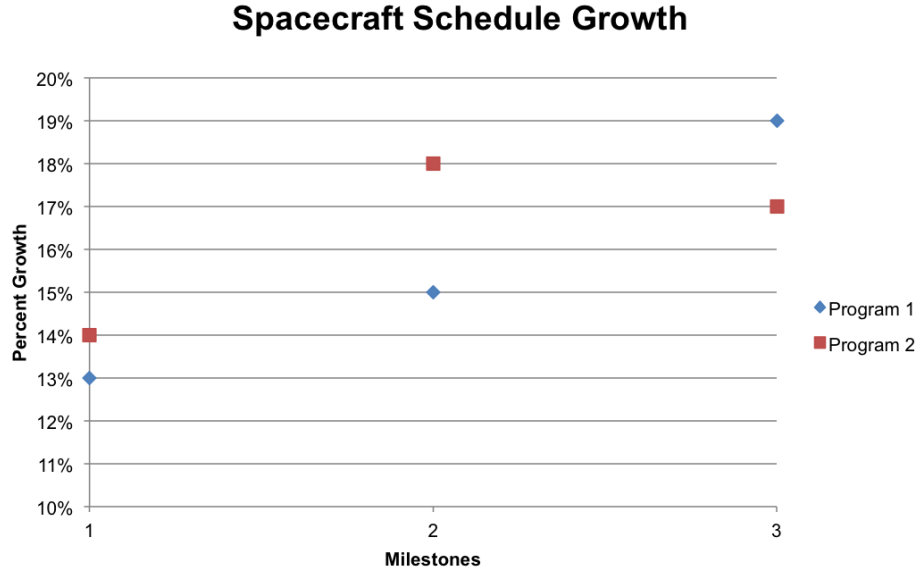


Figure 1: Approach #1

for that activity and compare to the correlation results for another activity (instrument development, say) to find the “magic correlation value.” See Figure 1.

We rejected this methodology due to three data points being too few to accurately capture correlation.

The approach afforded us several observations. First, not every mission had data for the same milestone reviews – over fifteen different milestone reviews identified. With such few data points, the correlation was very volatile and required the two missions to react in similar ways for each milestone. The lesson learned was to find a way to increase the number of data points captured.

Approach #2

To solve the problem of too few data points, we found multiple data points for one mission (either from multiple milestones or from multiple monthly status reviews) that captured two activities while holding activities constant. We then found a correlation between two activities (for instance, spacecraft and instrument development) within one mission. After identifying correlation values for many missions, we pooled correlation results for that activity (spacecraft development) and compare to correlation results for another activity (instrument development) to find the “magic correlation value.” See Figure 2.

We concluded that this method was extraordinarily time intensive. It also

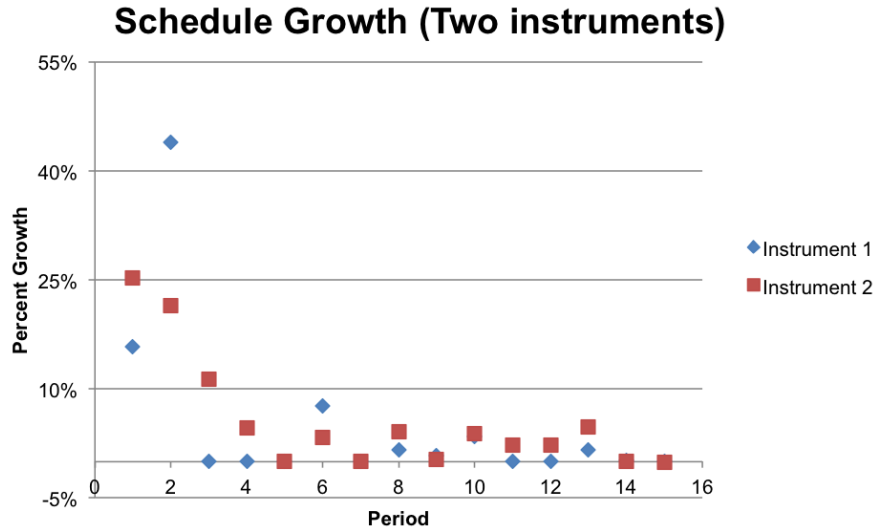


Figure 2: Approach #2

required every monthly or quarterly status review to show the same level of detail, which was often not the case, since when an activity was completed, no more changes were made and correlation data ended. The lesson learned: focus on “early” and “late” data.

Approach #3

For the final approach, we decided to find correlation of uncertainty distributions in schedule duration. This implies that schedule estimates have uncertainty distributions and furthermore, two estimates for two activities have correlated uncertainty distributions. We collected an early estimate, which incorporates a lot of uncertainty, and a late estimate, which will reflect little (or no, if actual) uncertainty. The difference in estimation was then the uncertainty that occurred (that is, the uncertainty distribution closed). We then compared the early-estimation to late-estimation differences. If the estimation differences were correlated then the uncertainty distributions were correlated. See Figure 3.

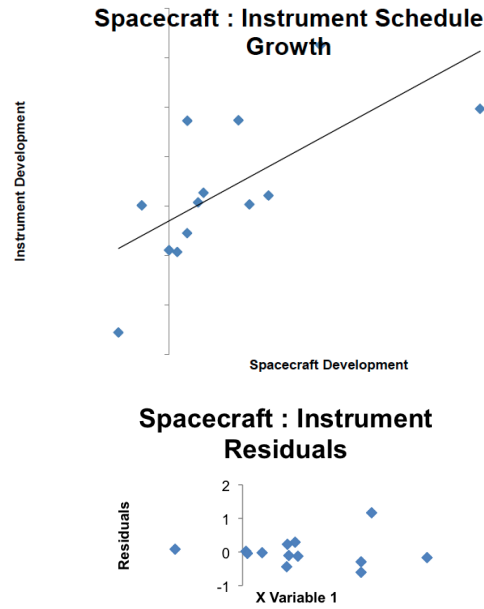


Figure 3: Approach #3

Mission	Instruments Comparison	Instrument X growth	Instrument Y growth
Mission 1	1:2	11.4%	16.4%
	1:3	11.4%	11.0%
	1:4	11.4%	3.4%
	1:5	11.4%	21.2%
	2:3	16.4%	11.0%
	2:4	16.4%	3.4%
	2:5	16.4%	21.2%
	3:4	11.0%	3.4%
	3:5	11.0%	21.2%
	4:5	3.4%	21.2%
Mission 2	1:2	54.4%	16.5%
	1:3	54.4%	-0.7%
	2:3	16.5%	-0.7%
Mission 3	1:2	24.2%	21.3%

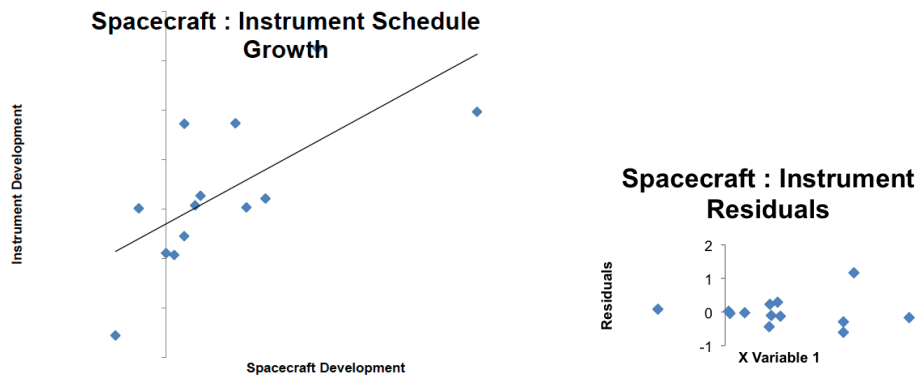
Figure 4: Approach #3 Table

3.2 Outcome

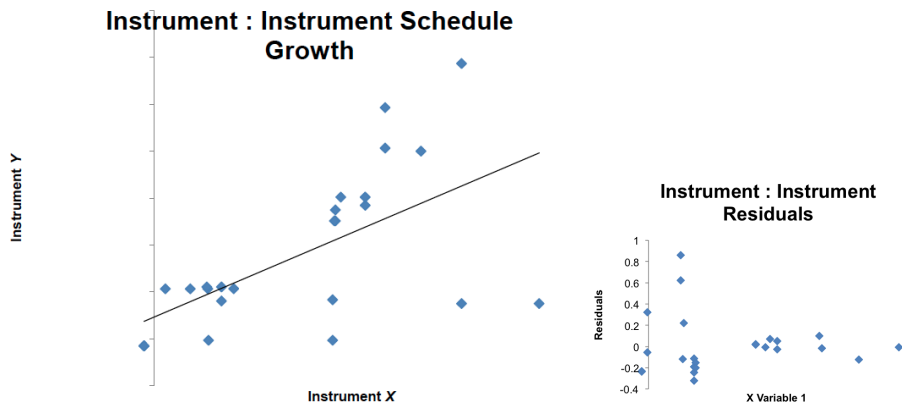
When missions are loaded with multiple instruments, there is an opportunity for greater instrument:instrument comparisons. A random sample of up to three data points per mission (instrument:instrument) was taken. Results are shown in Figure 4.

3.3 Empirical Results

For spacecraft (thirteen missions), instrument schedule growth had a Pearson's correlation coefficient of 0.679.



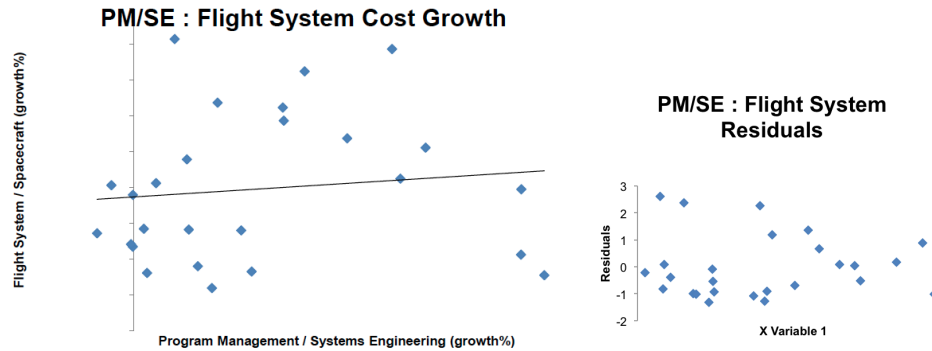
For spacecraft (thirty-four instruments across nine missions), instrument schedule growth had a Pearson's correlation coefficient of 0.605.



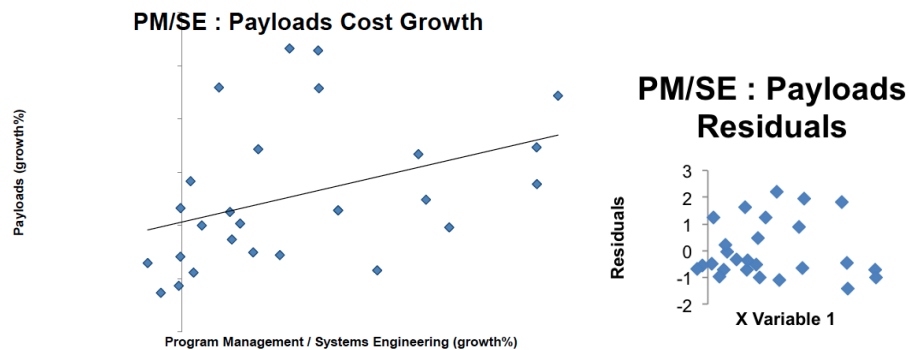
4 Correlation of Costs

The procedure for correlation of costs was as follows. First, we collected data from early milestone (CSR, SRR, or PDR) and a late milestone (Launch or Post-Launch). This produced an early cost estimate and a late cost actual. We compared cost growth and plotted points to find correlation of cost uncertainty. We then compared correlation from actuals against our simulation. We looked at correlation of cost growths between program management, spacecraft, instrument, I & T, ground segment, launch segment, and flight assurance. WBSs were categorized as either time-independent or time-dependent.

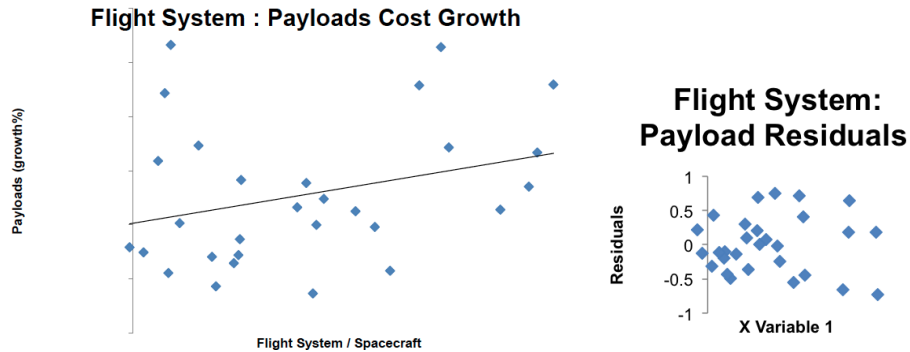
Over twenty-six missions, for PM / SE, the Flight System cost growth correlation had a Pearson's correlation value of 0.117.



The Payloads cost growth correlation PM/SE had a Pearson's correlation coefficient of 0.394.



For Flight System (twenty-nine mission), the payloads cost growth correlation had a Pearson's correlation coefficient of 0.303.



5 Recommendations

Our recommendations include the following. Accurately link cost elements to schedule elements to more consistently track cost-schedule impacts. This could be accomplished by pairing and consolidating WBS elements to CES elements to begin analysis on cost-schedule correlations. Leverage cost data from partner organizations for better analysis of true mission cost. Analyze which organizations are causing cost overruns or savings costs in the mission. Provide consistent and detailed scheduling to allow for a more comprehensive schedule with more accurate uncertainty distributions, which further allows JCL analysis. Ensure cost and schedule elements are consistent, and capture full mission cost across multiple organizations to allow all scheduling elements to be resource-loaded for JCL analysis.

Appendix A: Selected Literature Review

Magic Correlation Numbers

“Estimating Systems Cost” (Stephen A. Book) [3]

Summary. At the time this article was written, the traditional method of estimating the cost of a space system was to simply total the most likely costs of its elements. In this article, Stephen Book argues that the sum of the elements is in fact not equal to the most likely cost of the system, and that furthermore, this approach underestimates the cost of the total system. He proposes the solution to this problem is to employ the steps of statistical cost-risk analysis: establish probability distribution functions for the cost of each WBS item, estimate correlations among these distributions, and sum the distributions statistically (typically via a Monte Carlo simulation). The article provides the methods and theory for achieving each of these steps.

“Cost and Schedule Interrelationships” (Christian Smart) [18]

Summary. In this seminal presentation, Dr. Smart points out that cost and schedule are interrelated, and statistically correlated. Building from previous work (schedule algorithm in the Microgravity Experiments Cost Model and Matt Schaffers DOD experience), Dr. Smart argues for a data-driven detailed analysis of cost-schedule links. He provides algorithms for the effect of schedule expansion, schedule compression, and funding caps on cost, and explores other algorithms which are based on limited data. A companion Excel demo was given at the 2007 NASA Cost Symposium.

“Robust Default Correlation for Cost Risk Analysis” (Christian Smart) [17]
Summary. Because of the difficulty of determining correct correlation values between work breakdown structure elements can be challenging, a default correlation value of 20 percent (attributed to Dr. Book) is often used. In this paper, Dr. Smart discusses the basis of the 20 percent value, and shows that this default value is sensitive to error in the assumptions. After discussing the pros and cons of each assumption, Dr. Smart derives a new recommended value.

Time Dependent vs. Time Independent

“NASA Confidence Level Assessment Processes” (Harold S. Balaban et. al.) [1]
Summary. In 2009, NASA implemented the Joint Confidence Level (JCL) process which determines the probability that a project will stay within budget and be completed on time. At the behest of NASA, the Institute for Defense Analyses (IDA) performed an independent assessment of this process using two of the programs within its Constellation project, Ares and the Ground Operation Program. This report describes the JCL process, evaluation with NASA criteria (traceability, transparency, defensibility, and timeliness) and gives detailed analyses on the topics of network schedule model, correlation, and risk and uncertainty. Its overall conclusions include: compare the JCL process results with historical data (which, for instance, uncovers the flaw that the JCL models predictions for variance and schedule reserves are unrealistically low), determine annual funding requirements for a program (the Constellation JCL model failed to do this), model the connection between cost and schedule (fixable flaws in JCL), evaluate risks at the level of known information (which, contrary to criticism, does not lead to a lack of transparency in the Monte Carlo methods used in the model).

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