Cost and Risk Analysis of Small Satellite Constellations for Earth Observation

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Abstract—**Distributed Space Missions (DSMs) are gaining momentum in their application to Earth science missions owing to their ability to increase observation sampling in spatial, spectral, temporal and angular dimensions. Past literature from academia and industry have proposed and evaluated many cost models for spacecraft as well as methods for quantifying risk. However, there have been few comprehensive studies quantifying the cost for multiple spacecraft, for small satellites and the cost risk for the operations phase of the project which needs to be budgeted for when designing and building efficient architectures. This paper identifies the three critical problems with the applicability of current cost and risk models to distributed small satellite missions and uses data-based modeling to suggest changes that can be made in some of them to improve applicability. Learning curve parameters to make multiple copies of the same unit, technological complexity based costing and COTS enabled small satellite costing have been studied and insights provided.**

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1. INTRODUCTION

Distributed Space Missions (DSMs) are gaining momentum in their application to Earth science missions owing to their ability to increase observation sampling in spatial, spectral, temporal and angular dimensions. DSMs include homogenous and heterogeneous constellations, autonomous formation flying clusters [1] and fractionated spacecraft [2]. While DSMs aim at improving science performance and at reducing cost and risk by increased mission flexibility, scalability, evolvability and robustness, there is significant likelihood of increased costs and risks associated with launch and operations costs. To avoid being cost prohibitive, small satellites will be required to enable DSMs, especially those with large numbers. However, costing small satellite DSMs is challenging because of the following reasons:

- There is no standard cost-to-copy database or learning curve model established for multiple satellites. NASA prescribes an 85% learning curve [3] which will be investigated in this paper.
- Standard models including the Small Satellite Cost Model or SSCM [4] (parametric costs) and the RAND Models [5] (analogical costs) range from at least 20 kg to 500 kg of satellite mass. There is a large class of small satellites including the cubesat standard that falls out of range for both such traditional models.
- Constellations especially formation flying missions have more programmatic overhead and need more ground station support for orbit maintenance. This translates to operations cost more than what parametric percentages estimate.

There is, therefore, a need to assess the applicability of current cost models to small satellite DSMs and to formulate reliable cost model components to fill up the existing gaps. The improved cost model should efficiently differentiate between costs of the different architectures for designing a DSM toward a particular Earth observation goal and therefore serve as a tool to understand the cost impact of increased performance. Such a cost tool is especially important for DSM design because of the larger number of variables than traditional spacecraft design (e.g. number of satellites, inter-satellite

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distances) and because DSMs are theoretically optimized using value centric system design [6].

2. LITERATURE REVIEW

Small Satellite Nomenclature

First, it is important to define the scope of 'small satellites' that this paper intends to address. In Europe, the need for standardization of small satellite nomenclature was fist captured in an IAA review paper [7]. ESA defined small (350-700 kg), mini (80-350 kg) and micro (50-80 kg) satellites while EADS Astrium defined miniXL (1000-13000 kg), mini (400-700 kg) and micro (100-200 kg) satellites. The review discussed other small and large satellite nomenclatures, their typical revisit times, ground sample distances and Earth observation applications. In the US, the National Academy of Sciences published a report in 2000 [8] defining the core observational needs (required measurements, data continuity, etc.), payload characteristics and buses but size nomenclature was not assessed. The first size based classification was in 1991 by Sweeting [9] and refined further by Kramer et al in 2008 [10] into nano, micro, mini, small and large. Konecny [11], and later reviewed by Xue et al [5], extending the range of mini-satellites from 100 to 1000 kg, abolishing the medium satellite class which was originally 500-1000 kg. Almost 50% nanosatellites (<10 kg), investigated in 2010 [12] had the cubesat form factor while others were spherical, rectangular or cylindrical.

The late 1990's brought in the CubeSat era in the space industry. While most earlier CubeSats were used for technology demonstration and educational outreach [13], they have been used for scientifically significant Earth observation missions over the last decade. Nanosatellites such as the SPHERES have been used simultaneously for science, engineering testing, algorithm testing [14] as well as outreach [15]. Cubesats with scientifically important payloads leading on important results in Earth science have also been flown [10], [16]. Most cubesats till date have been launched as secondary payloads by the P-POD launcher. NASA funds a few dozen every year through the NASA and the Launch Services Program [17](ELaNa). Satellites over 100 kg use the ESPA (EELV Secondary Payload Adapter) ring to fit inside large launch vehicles and are also launched as the secondary payload. NASA funds a few launches every year through the University Nanosatellite Program (UNP) for this class of satellites. QB50, a constellation of 50 2U cubesats, is scheduled for a dedicated launch in 2015 using the Russian Shtil 2.1 and will be the first primary cubesat payload launched. [13] has looked at monolithic cubesat technologies for Earth observation while [18] plotted the typical altitude-inclination options available for secondary cubesat launches. As expected, maximum opportunity is seen between 400-800 km and inclinations corresponding to the International Space Station or Sun Synchronous orbits.

Table 1: Examples of recent Cubesats for Earth Observation Missions

Cubesat Type	Mass (kg)	Volume (cmXcmXcm)	Examples
1U	1.33	10X10X10	CanX-1, CanX-ArduSAT, PhoneSAT, Compass-1
2U	2	10x10x20	ION, CubeSTAR, QB50 constellation
3U	3.99	10x10x30	QuakeSat, geneSat-1, O/OREOS, CanX-2, Aalto-1, ExoplanetSat
6U (dev)	~10	10x20x30	ChipCube, and other interplanetary cubesats
12U (dev)	~15	N/A	N/A

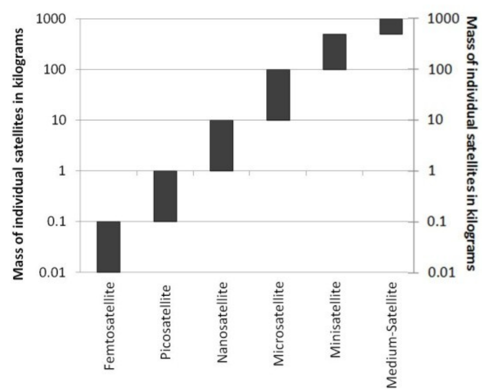


Figure 1 - top panel - defines the small satellite nomenclature to be used in this paper and for the models developed in this research. The nanosatellite class (1-10kg) is the home for currently active cubesats, 1U being 1 kg up to 3U being 3 kg. As larger cubesats are developed, such as 6U at 10-12 kg or 12U and 27U, the cubesat standard will be pushing the bounds of nanosatellites into the microsatellite category. Figure 1 – bottom panel – shows the examples of small satellite missions, as reviewed in [10] up to 2008, categorized into the above defined classes as vertical columns arranged by mass of their satellites. While mini-satellites dominate the space, over the last four years, nanosatellites have increased greatly in numbers owing to the cubesat form and launch opportunities.

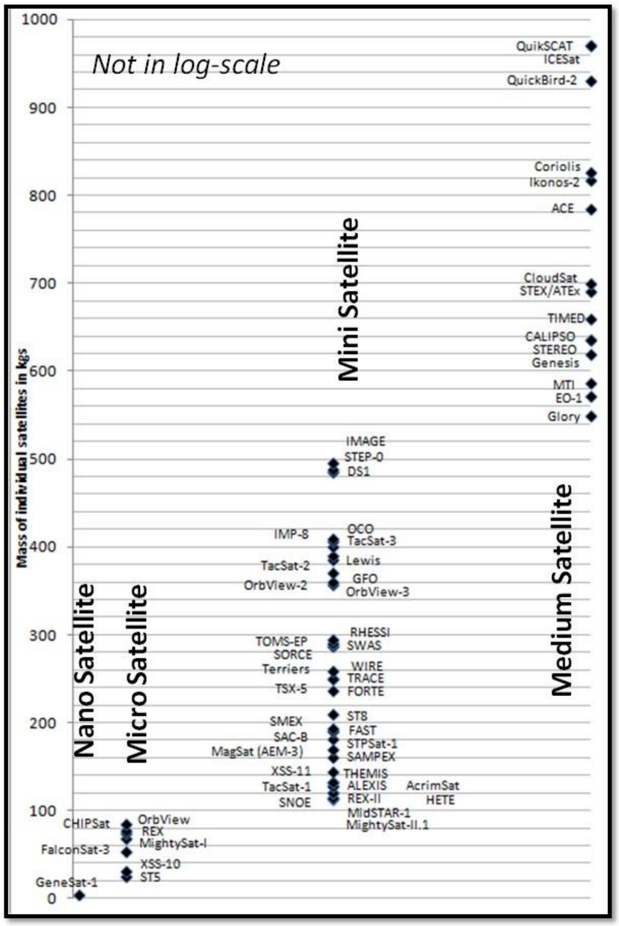


Figure 1: Small Satellite Nomenclature (top panel) and examples[10], [16] of Earth Observation Missions (bottom panel) grouped into vertical columns based on their size-based classification

Cost Modeling Literature

Formal cost modeling in the Phase A stage of the mission lifecycle was started by JPL after the formation of Team X more than10 years ago [19], [20]. TeamX is the JPL Advanced Projects Design Team, an interdisciplinary team of engineers that "utilizes concurrent engineering methodologies to complete rapid design, analysis and evaluation of mission concept designs"[1]. The TeamX model included costs through all phases of the mission lifecycle using data from 60 previous missions – for model prediction and validation [19], [20]. The payload model was exhaustive [21] and the spacecraft model was based on the cost per subsystem as a function of the mass of that subsystem. Wrappers as a percentage of the total cost of spacecraft and instrument development were used for the following Work Breakdown Structure (WBS) elements: program management, outreach, systems engineering, assurance testing, launch vehicle and integration, etc. The statistical tools that JPL used for cost model included: (1) Regressive fitting of polynomials (log or linear); (2) Residual analysis to find if there were correlations between residual cost and other variables that were not captured (e.g. design life) or if the distributions were normal, variances significantly different from the original population (using F or chi2 tests); (3) Model Validation where in the analysts kept 30% of the data aside for testing purposes and asked if the model predicted and actual populations differ with more than 95% confidence (T and chi2 tests); (4) Monte Carlo simulations to check the model output against probability of predictions, confidence intervals and possible forecast errors.

The RAND Corporation did an extensive survey of small satellite missions with the intent to derive a cost model through analogy. They used 12 NASA missions and Clementine [5] and evaluated total mission cost (or TMC) from conception to data analysis. Costs were collected and analyzed by phase (design, development, test, launch, operations) and spacecraft subsystems and labor rate assumed to be \$132k/professional year (FY 1998) [5]. They found the average NASA small satellite mission to cost \$145 million, take 3 years to develop and have a dry mass of 407 kg which accounted for 41% of the TMC. This was an average over different missions with different objectives. Technical specifications considered in [5] and [22]–[25] were design life, apogee, inclination, contractors #, instrument mass, propellant mass, dry bus mass, total wet mass, spacecraft volume, launch vehicle, upper stage, bus pointing accuracy, bus pointing knowledge, stabilization type, thrusters #, fuel type, thermal system mass, power system mass, solar array material, array area, array efficiency, Beginning-Of-Life (BOL) power, End-Of-Life (EOL) power, system power density, battery type, downlink Data Rate (DR), communication band, transmitter power, central processor Million Instructions Per Second (MIPS), memory, harness pinouts, and Source Lines of Code (SLOC). Finally, a Factor of complexity was calculated through a discrete scale [5], [23] cost per kg of the spacecraft was normalized using this factor and regression analysis, where S/C Cost (in \$K) = 64.37*m*FC + 9095 [5]. Complexity was accounted for quantitatively (vs. JPL which only used a binary variable). Complexity parameters considered included Technology Readiness Level (TRL), mission type, design life, spacecraft density, instrument mass fraction, bus pointing, solar array and power system efficiency, DR, proc, SLOC, memory.

[1] http://jplteamx.jpl.nasa.gov

The typical problems that RAND uncovered with respect to spacecraft costing [22] were data limited by the following: small sample sets because large scale production in spacecraft manufacturing does not exist, suppliers rarely making internal efficiency optimizations because delivering highly integrated payload requires very specific designs therefore no minimal generalizations and diverse stakeholders for every mission. Expert opinion proved superior to formal estimation in 33% cases (15 total), inferior in 33% and no difference in the last 33%. Unmitigated technical risk was identified as the biggest factor in cost overruns [22], cases studied being SBIRS and GPS, and the risks were primarily attributed to inadequate systems engineering, aggressive adoption of commercial standards for military applications, lack of process controls at contractors or their lack of domain knowledge and reduction in acquisition workforce due to budget cuts. In spite of the above problems, some projects did have risk assessment for each WBS but were limited by the following problems [22]:

- Little data availability (e.g. inadequate reviews of contractor work)
- Credibility (e.g. inadequate experience, judgment, independence)
- Limitations in risk quantification (e.g. analysts assumed 17% cost growth when historical data showed 50% growth and led to 250% in reality, expert subjectivity, erroneous cost-probability distributions for 'risks', random functions were used for probability distributions)
- Unavailability of methods for large cost growth (e.g. risk is defined as variance of prediction so low prediction implies low risk without any validation of such an assumption)

The RAND study of Air Force Missions found that most mission costs grew over their lifetimes or experienced mission creep. A metric called Cost Growth Factor or CGF was defined as the ratio of the final cost to the estimated costs using Milestone II estimates [23] where $CGF < 1$ represented underruns and $CGF > 1$ represented overruns. Uncertainties and cost growth [23] were identified to be caused by new technology, economic conditions or rare events after accounting for funding category, inflation, timeline/milestones and other such correlations. Recommendations included using many validation methods and having a consistent tracking method in place.

Table 2: Typical cost models available for pricing the development and operation cost of a LEO satellite mission [22]

Model	Content	Utility for SMC	Remarks
Unmanned Space Vehicle Cost Model	USAF/NASA/commercial spacecraft; communications payloads	Useful for ROM estimates; limited due to scope, age, data documentation	45 data points; many from 1970s; no non-COMM payload or ground segment
Passive Sensor Cost Model	Space sensor components	Limited due to age and quality of data	Older data; planned to be updated and incorporated into next USCM version
NASA/Air Force Cost Model	USAF/NASA; orbital/interplanetary/ manned spacecraft; instruments; launch vehicles; engines	Special cases	122 data points; integrated risk and phasing capabilities; heavily adjusted data
Small Satellite Cost Model	Spacecraft <1000 kg; orbital/ interplanetary	Special cases	35 data points
PRICE	Commercial general purpose model	Detailed comparisons of relative cost of alternatives	Various specialized modules available
SEER	Commercial general purpose model	Detailed comparisons of relative costs of alternatives	Various specialized modules available

There are several cost models available for costing satellites in low Earth orbit (LEO), as identified in Table 2 [26]. The major methods are categorized under top down estimations or parametric models, bottom up estimations or component models, analogy based estimations from historical missions and expert judgment. Specifically for Earth observation missions from LEO, instrument cost is a parametric function of mass, power and data rate. Bus cost is the sum of costs from different subsystems which is a parametric function of the subsystem mass. Integration, assurance and test (IAT) and systems engineering (SE) costs are a function of satellite mass (recurring) or satellite cost (non-recurring) while operations cost is a function of lifetime and spacecraft cost as obtained from the NASA Spacecraft Operations Cost model [27]. Operations cost of small satellites is 8% of TMC and 20% of bus cost, more than large satellites where operations is only 7% of bus cost [28]. This again is dependent on the human resource costs in the operating organization. Program overhead includes recurring and non recurring [26] costs with respective cost estimating relationships (CER) errors of 39% and 36% (lower for small satellites). Overall overhead is 8.9% and 9.3% of bus cost for small and large S/C respectively [5], [28].

Schedule slippage as percentage of total development time is a function of the TRL of the least mature component [26], [29], which in turn can map to cost overrun as a percentage of TMC [25]. Programmatic risks can be defined as a function of the sum of all TRLs below a threshold or to make them architecturally distinct [26]. Launch risks are significantly lower if distributed launch is used, therefore making a stronger case for DSMs with staged launches. Launch risks can be quantified either through a concave risk aversion curve or through the concept of entropy [26], [30]. Accounting for net present value and cost spreading improves the above cost estimates.

Costing multiple copies in DSMs

Cost modeling has been done and published publicly for a few planned DSMs, for example, GEOScan [31], TechSat 21 [32], [33], DARPA Phoenix [34].

The GEOScan (66 instruments of <5kg each for Iridium NEXT) mission proposed to minimize cost using standard John Hopkins University Applied Physics Lab (JHU APL) business practices and a streamlined management approach. Their studies initially assumed a cost copy factor of 35% [20], [21], performed regression analysis on Juno JEDI, Van Allen Probes RBSPICE and STEREO and validated a cost copy factor of 30-40% for their engineering practices.

The Generalized Information Network Analysis (GINA) tool was developed at MIT and applied to TechSat 21 [32] to evaluate performance and cost of a DSM. Complexity was not considered aside from the number of spacecraft. The author characterized capabilities of a DSM as a function of information isolation, rate, integrity and availability and performance as the probability that system satisfies requirements in terms of capability and used Markov states and integrate on lifecycle cost as a sum of baseline cost and failure compensation cost. The cost model captured program slip and adaptability metrics (e.g., changing configuration for the same mission, i.e., elasticity, or adapting for different mission goals, i.e., flexibility) could be added. The GINA model was combined with multi objective optimization to select the most suited architecture for any specific mission [33]. For example, in the Terrestrial Planet Finder case study, the trade was between acquiring a certain number of images and the cost as characterized by the GINA model.

The Phoenix project assessment [34] performed by JPL and Aurora Flight Sciences uses a complexity based cost model to estimate development costs ([30], [35]); it uses parametric equations for programmatic cost estimation and the usual 85% NASA learning curve estimate to calculate the cost of making many copies of the same spacecraft.

Launch Cost Modeling

Modeling launch costs for multiple spacecraft is difficult because of the complexity of choosing between single and staged launches and/or primary and secondary launches. TransCostSystems in Germany [36] used "cost engineering" applied to Launch Vehicles (LV) and minimized development and operations cost rather than the traditional approach of maximizing performance and minimizing weight. LV cost models demonstrated included PRICE-H, TRASIM, TRANSCOST and it was found that all CERs compute costs to be 15-25% higher than ideal cost. Cost was calculated as a function of payload capacity, engine technology, number of engine qualification tests, engines per stage, maintenance and refurbishment. Just lower weight did not mean lower cost. For example, thrusters were found to last longer if operated at 5-8% below max thrust therefore eliciting a trade between lifetime performance and deployment cost. Similarly, there was an automated optimizer to tap into different technologies to minimize cost.

Risk and Uncertainty Assessment

The RAND reports ([22], [23]) discussed in the previous sections highlight the critical impact of risk on cost, therefore more literature was reviewed to summarize available methods and statistically derived quantities quantify estimating uncertainty [23]. The studies concluded that uncertainty about technical and programmatic inputs need to be quantified. Expert opinion has biases stemming from information availability, representativeness, anchoring and adjustment and overconfidence. There may also be conflicts of interest or the process may be over-rushed. Cause-effect relationships can be quantified using Markov trees. Risks should be defined, understood and evolved with an evolving system.

Recommendations [23] on risk assessment included the use of multiple independent experts, asking experts to provide, at a minimum, upper, lower, and most-likely values for cost elements under consideration, fitting a triangle distribution to these three numbers and using the upper and lower values to bound 90 percent of the probability; eliciting other percentiles to counter the effect bias and providing feedback to expert in an iterative process that is documented.

Cost Risk methodologies [24] include qualitative and quantitative methods as shown in Figure 2. The following cautions apply to data collection and analysis methods mentioned in the figure. Historical analogies need credible data from similar projects which are hard to find and susceptible to large time scales. CGF may be data-based but it does not capture layers of influence that caused the growth. Sensitivity analysis needs exact CERs however, if the range of variation is not known a priori, select hazards should be identified. Probabilistic outputs as distribution functions instead of a deterministic point estimate should be encouraged. Error propagation is easy when CERs are linear, but complex relationships including precision of input and accuracy of computers need to be considered for probabilistic outputs.

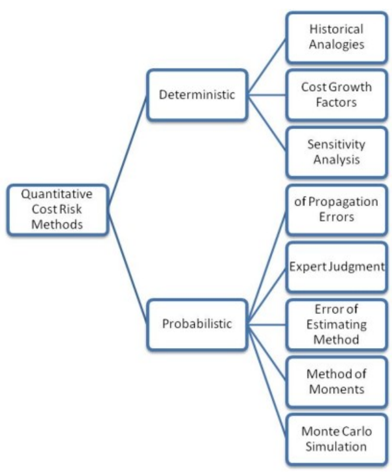


Figure 2: Summary of cost risk assessment methods suitable for spacecraft programs [24]

Subject matter experts capable of estimating cost and uncertainty, are very flexible but may be biased, thus careful, iterative, conduction and documentation is required. Different methods in Figure 2 should be combined to mitigate bias inherent to a single method. A method of moments is easy for normal distributions – means, variances add. For other distributions, percentiles are hard to calculate. For such cases, Monte Carlo (MC) simulation finds integrals and sums of random variables which are too complex for closed-form equations. MC methods may add and propagate variables, different distributions (Weibull, lognormal, triangular) can be used, expert opinion can be included, correlations captured and are well-understood numerically. It is a computationally expensive method and saved only for very high fidelity calculations.

Overall, methods to evaluate uncertainty are suggested in the RAND Cost Uncertainty Report for the USAF Weapon Systems [24]:

- Benefit-cost analysis (but benefits/risks difficult to quantify)
- Expert judgment (use Delphi method but experts can disagree)
- Fault tree analysis (for complex, correlated risks with specific hazards considered and cost risks rolled back into the WBS)
- Focus groups/one-on-one interviews (for individual behaviors, communication error warning esp. among decision makers)
- Root cause analysis or FMEA (examine the consequences of failures or risk and chains of them and make recommendations. Can also introduce the control system approach of STAMP)
- Behavior modeling (cognitive processes of humans in the loop)
- Data-based methods (tornado plots, regression analysis)
- Integrated assessment (precision, validity, bias, dominos, records so that credibility of methods can be validated)

Technical, economic, cost and schedule risks should be considered [24] and the method will depend on the program and potential risks, i.e. scenario driven analysis. There should be a preference for the more complex methods (probabilistic or sensitivity) because they can be tailored to the program. Historical analysis should be used in cases characterized by little time or information or as a supplement. Monte Carlo is not always the best because it lacks transparency, is subject to implementation errors and requires significant data and time.

Value centric risk methodology (or VCRM) was first mentioned in the context of the DARPA F6 Program in [2], [6] and [37] for value centric design in academia and industry.

Risk types considered were: technical (e.g. low TRL of a new component being deployed such as a polymer battery), cost (e.g. outsourcing not working out due to export control), and programmatic (e.g., the launch vehicle not ready). Risk management mechanisms suggested were: take, avoid, and mitigate. VCRM was given a stronger quantitative framework by de Weck when applied to the DARPA F6 Phase 2 [38]. The report quantifies probabilistic impact of individual risk items on project value using Value-at-Risk-Gain (VARG) curves. They recap the traditional approach of VCRM (Identify, Analyze, Plan, Track, Control) and typical tools (Layers of Risk Model based on influence on the risk, Risk Matrix). The management plan tracks the risks over time to ensure a “burndown path”. This model addresses the shortcomings of the traditional model where in the impact on mission value is not quantified and coupling and decoupling of risks not available. Risks are identified from and coupled to the uncertainty source. Probability of occurrence is available from a Markov Model S+ state transition matrix where robustness and adaptability measures can also be coded. Risk impact computed by turning input knobs, individual and coupled, VARG, probability and impact computed over lifetime (like Monte Carlo methods).

Capturing Complexity

Since all risk reports caution against technical and programmatic risks and small satellites pack state of the art technologies into a small form, it is very important to quantify complexity of small satellite DSMs and map this complexity to cost and risk. Typical spacecraft complexities discussed in the literature fall into three categories:

- Component-level complexity
  - Aerospace Corporation has a very evolved method of quantifying component complexity relative to existing flight components and claims it to be a better metric of mission “cost” than dollars ([39], [40])
  - Technical uncertainties can be factored into component complexities as a function of TRL as demonstrated in the DARPA META program [30]
- Structural complexity ([30], [35])
  - Complexity arising from complex dependencies within the system
  - Can be calculated from the design structure matrix of the system, captures emergent behavior and influences development cost of the system
- Dynamic complexity ([30], [35])
  - Representative of operational complexity during different mission stages
  - Each mission mode can be quantified in state space and the probability of success of each mode calculated

Eventually, the idea is to calculate the impact on cost of all the above complexities however such a mapping currently exists for only component and structural levels.

3. Data and Methods

From the literature review, we gathered the following insights for improving cost models for small satellite DSMs:

- To calculate cost to copy, cost data of an in-house DSM mission before and after CDR (Critical Design Review) will be needed. For example, the second copy of SwissCube [41] or SwissCube-2 is expected to be 45-60% of the original Swiss-Cube, depending on spares and assuming a new workforce. Regression analysis on other missions (especially NASA missions) will provide more insight.
- In the absence of openly available WBS data on small satellites, the available cost models cannot be improved to get more precise CERs for small satellites. Snatches of data available from online [42] and GSFC released sources can at most let us check the validity of the CER estimates for small satellites.
- Lifecycle risk modeling using techniques such as Monte Carlo and VARG is possible from a theoretical standpoint but model fidelity is questionable without risk-cost data for validation.

All the above techniques – cost to copy, single satellite modeling and lifecycle simulation – can be combined into a “system dynamics” or System Dynamics (SD) model of DSM operations. System Dynamics is a well-established field that draws inspiration from basic feedback control principles to create simulation models [43]. SD constructs (stocks, flows, causal loops, time delays, feedback interactions) enable investigators to describe and potentially predict complex system performance, which would otherwise be impossible through analytical methods. SD is argued to be superior for DSM modeling in comparison with other modeling tools such as discrete event simulation like VARG or Monte Carlo methods, because it is a robust, discrete time simulation that allows simultaneous simulation of quantitative and qualitative parameters, captures latencies and delays, captures non-linear processes through simple causal structures and physically explains complex feedback interactions based on these simple structures [43], [44].

The component interactions in the SD model (e.g. causal relationships) can be quantified using known parametric or physics-based equations obtained from the literature review and captured insights above. The behavior of each module of the model is benchmarked against data – whenever available, even if very sparse - from past and current DSMs. We have compiled a list of 60 DSMs – introduced in the next section - which can be used as reference modes to calibrate the SD model.

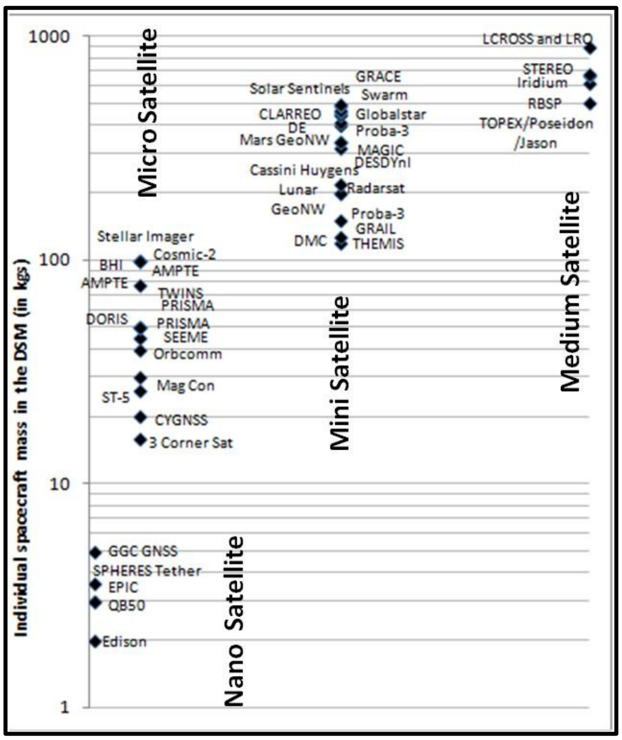


Figure 3: Examples of previous and planned DSMs sorted by their individual spacecraft masses (average when not homogeneous), grouped by the small spacecraft class defined in Figure 1

Collection of Data from Past Missions

The NASA GSFC Distributed Space Missions Group [45] gathered data from 59 DSMs – past, operational and planned – from publicly available sources. They spanned over many architectures such as constellations, clusters, formation flying, virtual telescopes, etc. and over a wide range of applications including science, commercial communications, defense and technology demonstrations. The data was sorted based on type of mission, spacecraft configuration, number of spacecraft, lifespan, cost, etc. so that insights could be drawn on DSMs. Figure 3 shows DSMs from this study grouped in vertical columns by the mass-based satellite classes defined in Figure 1's top panel. The average masses of the individual spacecraft determine the position on the Y-axis of the data point.

Unfortunately, cost data from public sources was not available for all the missions and WBS elements were not available at all. Reference [42] reported schedule slips and cost overruns for many of the above missions, especially those without fixed price contracts. Annual contracts were often re-negotiated for every year for every contractor leading intractable cost data collection issues as well as an incalculable creep. To avoid getting into unreliable details, only the total cost of the mission as it stands today was used.

Note that although the data has been primarily sorted by mass for regression analysis (for simplicity), small satellite mission costs are primarily driven by technology. For example, 20Mbit/s X-band transmitters by Axelspace in Japan at 1 kg mass cost $300,000 because the cost is driven up by shrinking a very high tech instrument into a small form. Cost is thus a factor of both the high tech *and* the small size. This implies that for a sufficiently advanced Earth observation mission, the benefits of cheaply launching a lower mass may be outweighed by fitting the technology into the lower mass. Cost models should be able to capture the conflicting effects of both variables to select the right monolithic architecture and therefore, DSM architecture.

4. RESULTS AND INFERENCES

Insights from analyzing the data from 59 DSMs and estimating costs using available cost models are presented in this section. The system dynamics modeling results to calculate development and operations cost and address the lifecycle risk gap in literature will be described in a later publication.

Regression Analysis of Past Mission Data

For regression analysis, we will revisit the DSMs from Figure 3. Twenty of the fifty nine studied DSMs, masses notwithstanding, have two homogeneous or heterogeneous spacecraft. The Earth observation missions or ones with science payload clearly show a decreasing mass with increasing numbers. The navigation and communication missions costing billions of dollars are the ones on the top right.

Thirty five of the fifty nine missions for which cost and mass data was available have been scatter plotted in Figure 4. The colors correspond to the size based classes of the DSM satellites. For each class, linear (top) and exponential (bottom) curves are fit to the cost vs. number of satellites data spread. Under the over-assumption, that the classes represent similar sizes and the same organizational framework developed and operated all the missions, linear curves represent non-recurring costs and exponential curves represent recurring costs. Nanosatellites and medium satellites are the only classes that show a high correlation for both types of fits, possibly owing to similar modus operandi of DSM development over the available data set. This also helps establish consistent data for the nano-satellite class.

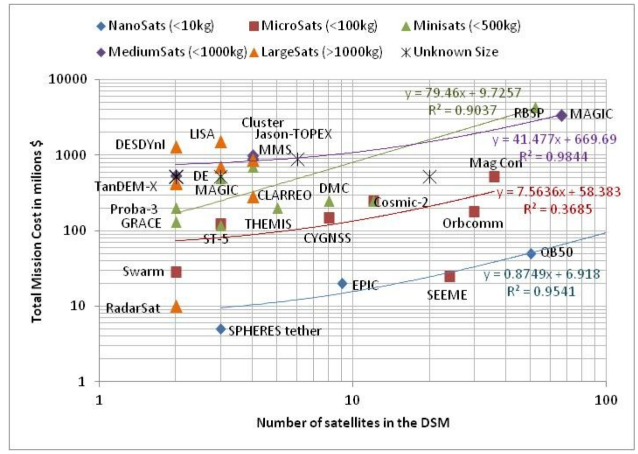
The scatter plot in Figure 4 was also sorted in terms of types of orbits, spatial relationship between the satellites, functional category, etc.; however none of those groupings produced a correlation coefficient higher than the size based sorting. Hence, the latter was used for further regression analysis.

While Figure 4 assumes the entire cost to be either non-recurring (top) or recurring (bottom), reality is a combination of the two where:

$$\begin{aligned} TMC &= NRE + RE \\ NRE &= NRE_0 * N \\ RE &= RE_0 * N^{\log_2 b} \end{aligned} \quad (1)$$

Non-recurring costs are one-time expenses and therefore do not follow the economies of scale. Recurring costs alleviated from having more units because learning reduces further costs. For example, ground system costs are considered entirely non-recurring costs while launch costs or integration and testing costs are entirely recurring costs [27]. Other WBS costs are a combination of both.

Non-linear least squares regression was then used with the TMC data to find RE_0 (theoretical first unit – TFU - recurring cost), NRE_0 (TFU non-recurring cost) and b (learning curve factor). The results for each mass-based class of satellites have been listed in Table 3, right panel. The learning parameter is 0.77 for nano-satellites and 0.79 for medium satellites, which is lower than the NASA prescribed value of 0.85 [3]. Under the assumption of TMC = RE, linear least squares regression may be used and the results are listed in the left panel. It is only under this assumption that we get the NASA prescribed learning factor of 0.85 or more. The analysis shows that the prescription possibly overestimates the cost of making multiple copies of a spacecraft.



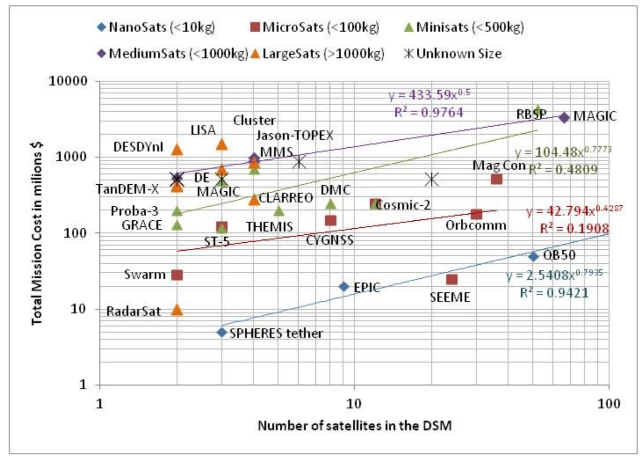


Figure 4: Scatter plot of previous and planned DSMs by the size of their individual spacecraft masses (average when not homogeneous) and number of physical entities in the DSM, grouped (in color) by the small spacecraft class defined in Figure 1. Linear (top) and exponential (bottom) regression curves for each size-based group shown

Table 3: Inversion of learning curve parameters using data shown in Figure 4. [Left] Linear inversion performed assuming only recurring costs, [Right] Non-linear inversion performed assuming sum of recurring and non-recurring costs

Satellite Class	Learning 'b'	RE0 $$ million
Nanosat (<10kg)	0.86	2.54
Microsat (<100kg)	0.67	42.79
Minisat (<500kg)	0.93	97
MedSat (<1000kg)	0.94	110

Satellite Class	Learning 'b'	RE0 $$ million	NRE0 $$ million
Nanosat (<10kg)	0.77	4.27	0
Microsat (<100kg)	0.56	28.5	7.93
Minisat (<500kg)	0.33	164.04	81.68
MedSat (<1000kg)	0.69	464.78	0

Learning Curve Calculations from Cost to Copy Factors

JHU APL published results of their analyses to find the cost to copy multiple copies of a spacecraft or instrument in 2013 [46]. APL has developed and manufactured the

JEDI (N=3), RBSPICE (N=2), STEREO (N=2) and Van Allen Probes (N=2). They published the cost to copy (C2C) to be 28%, 45%, 41% and 36% respectively [46]. This implies that it cost APL 28% of the first unit of JEDI to build the second or third unit. It can be seen that C2C decreases with decreasing N. Assuming that JEDI and RBSPICE were all copies of each other [46], the C2C for 2, 3 and 5 units was plotted in Figure 5 [46]. Assuming an initial learning curve factor (b=85%), if we fit the learning equation below to the data in Figure 5, the estimated learning parameter is b = 66.2%. This value will be used for costing multiple spacecraft in the next section, based on traditional models to estimate the cost of the first unit.

$$RE_{total} = (RE_{payload} + RE_{bus}) * N * N^{\log b/\log 2}$$

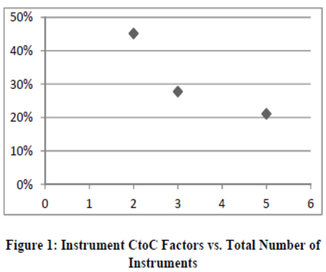


Figure 5: Cost to Copy (C2C) factors derived from cost data available within JHU Applied Physics Lab for instruments developed within their facility [46]

Applicability of Small Satellite Cost Models

This section discusses the application of traditional cost models, specifically the SSCM [47] and the RAND models [5], [25] to small satellite masses. Project reserves in keeping with the percentages of WBS elements that are used in NASA GSFC have also been included. A learning curve parameter of 0.662 from the previous section has been used and has been applied to only the recurring fractions of the TFU cost. Recurring fractions are obtained from reference [47], for example ground station support is 0 and IAT is 1.

Figure 6 compares the total mission cost minus launch costs of a 1, 2, 5, 9 and 13 satellite DSM using the SSCM (solid lines) and RAND models (dashed lines). In both cases, we used SMAD's parametric CERs to estimate bus and instrument cost as a function of mass, lifetime and data rate. All other values were model specific. No complexity, launch costs or extra ground operations costs were considered over the regular operations. Software costs were a function of lines of code only, which were very difficult to estimate; eventually values analogous to the MIT SPHERES satellites were used ([48], [49]) as currently functional on the International Space Station. (RAND, [5] and [25]). The coefficient of cost estimated in ground operations in the SSCM model is double that in RAND. Since ground operations have been assumed to be entirely non-recurring, the learning economies of scale do not apply. As a result, the cost predicted by SSCM is lower for few satellites but overshoots the RAND estimates for more satellites. Interviews with experts at NASA GSFC revealed that ground operations are more complex and cost more for DSMs than monoliths so the SSCM model seems intuitively more representative.

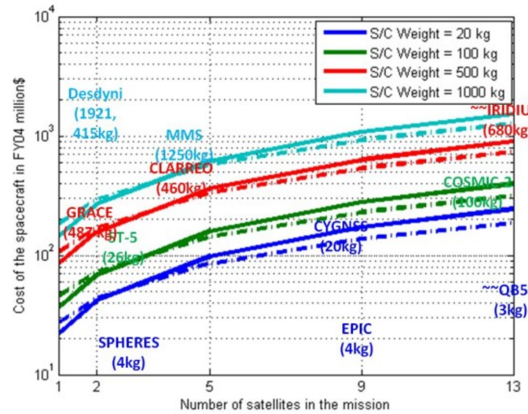
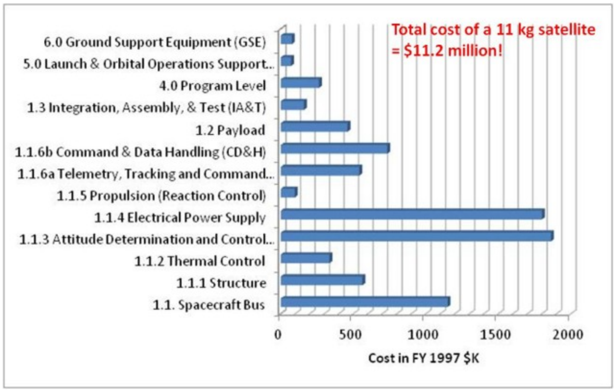


Figure 6: Comparison of costs estimated using RAND Corporation's analogous cost model applied to known S/C and instrument costs [19], [22] – dashed lines, SMAD's Small Satellite Cost model [4] – solid lines with data from real missions – text colored by the closest modeled spacecraft weights

A few candidate DSMs from Figure 4 have been highlighted on Figure 6 in the same color as the closest modeled spacecraft weight. While most of the data falls very close to the predictions, many precautions should be made. The GRACE mission was an international cooperation between USA and Europe and the cost here only includes the USA section. DesdYNI's two physical entities are so different that they could be two different missions rather than the same DSM, therefore no gain from the learning curve. DesdYNI has now been transitioned into the NASA-ISRO SAR mission. CYGNSS and CLARREO have are not yet operational so the cost cited is expected cost, and therefore not real data. Finally, since none of the models are applicable to model <10 kg spacecraft, the nano-satellites in Figure 6 do not have a curve to fit them. Again, total cost data is very hard to find, e.g. QB50's cost project does not include the internal costs incurred by the universities building the individual satellites.



INPUTS		
Day Power Required	10.0	W
EOL Array Power	10.0	W
Total COMMS Power	1.8	W
Total Payload Power	5.0	W
Total Power System Mass	2.0	kg
Array Area	0.5	m^2
Bus Mass	4.0	kg
Pointing Accuracy	0.0	deg
Telemetry/Comand Data Rate:	9600.0	bps
Propulsion System Mass	2	kg
Comand Data Handling Mass	1	kg

FIRST UNIT Cost Estimate		
	FY'97 $M	FY'10 $M
EOL Power, Pointing Accuracy CER	$ 51.09	$ 67.95
TT&C/CDS Mass,Payload Power CER	$ 1.40	$ 1.86
Downlink Rate,Power,Propulsion CER	$ 5.55	$ 7.39
Bus Mass,Pointing Accuracy CER	$ 1.30	$ 1.73
Array Area/ACS Type CER	$ 7.59	$ 10.09
Power Subsystem Mass CER	$ 1.08	$ 1.43
Average (Millions):	**$ 11.33**	**$ 15.08**

Figure 7: Cost estimated per subsystem (bar chart on top) of one spacecraft by the Aerospace Corporation's Small Satellite Cost Model (SSCM) based on inputs for a candidate nano-satellite mission (bottom excel spreadsheet)

The SSCM model was then used to calculate the total cost of developing and manufacturing only the first small satellite of mass 10 kg and other specifications listed under 'Inputs' in Figure 7. The cost calculated for every subsystem and the total cost of $15.08 million in FY 2010 is therefore a function of technological variables like power and pointing and not just mass.

To check the sensitivity of technology used to cost, we varied some of the input parameters and checked its effect on cost in FY97 $million. Changing the data rate from 10 kbps to 10 MBps to 1 GBps resulted in a cost of $11.35, $11.4 and $11.45 million respectively. Since COTS products will be used to support the communication link, these cost estimates imply that there will be only a $100,000 difference in deploying a radio transmitter (10 kbps) or deploying an optical transmitter (1 GBps) on the 10 kg nano-satellite. While previous proposals have certainly supported the availability for laser technologies [50], the optical demonstrations that are currently being developed by DLR in Germany and the Aerospace Corporation in the US [51] clearly demonstrate that the cost of optical technology is more than that. Similarly, changing the pointing accuracy from 0.1, 0.01 to 0.001 degrees resulted in the cost increasing from FY97 $ 6.45, 11.33 and 22.21 million respectively. The technology to support 0.1 degrees (sun sensors) is different from that to support 0.001 degrees (star trackers). However, current COTS quotations (e.g. Blue Canyon technologies XACT) show that it costs ~$100,000 for a nanosat star tracker system. Integration may cost a few additional thousands but estimating it to $18 million more sounds a bit too much.

The SSCM sensitivity study above highlights the need to have cost models that are more sensitive to different technologies and their associated complexities. Complexity and risk assessment has been proposed by the Aerospace Corporation in the form of their COBRA model. We used the COBRA model in our next study, where the methodology and data sets are detailed in ([39], [40], [52]). The data set relative to which complexities are calculated included 120 DoD and NASA missions from after FY89, excluded launch delays or failures and projects with heavy international cooperation. Complexity drivers include (Table 4 column 1) subsystem technical parameters (e.g. mass, power, performance, technology choices) and programmatic factors (e.g., heritage, level of redundancy, foreign partnership).

Forty such parameters are considered that are either continuous (e.g. mass, power), and represent a range of values bounded by a minimum and maximum, or discrete, such as propulsion type (none, cold gas, monopropellant, bipropellant or ion engine) that represent a finite number of choices.

For our smallsat case study, the factors corresponding to spacecraft complexity, as they proposed, are listed in Table 4 along with the minimum and maximum value that the component takes within their data set. The column 'data' represents the technical input parameters from a candidate nano-satellite which will be a part of a DSM that is tasked to measure the Earth's reflectance at different 3D angles from the same ground spot as it formation flies in LEO ([53],[54],[55]). For each factor, the complexity of the nanosat is calculated as a percentage of where the data point corresponding to the nanosat lies with respect to the data points for all the other space missions considered. For discrete data, the discrete rank of the data is assessed and then converted into a percentage. The average complexity of the proposed nanosat is calculated to be 21.64%.

Table 4: Cost estimated for a spacecraft as a function of the relative complexity of its components with respect to components used in previous missions, based on the Aerospace Corporation's Complexity Based Risk Assessment (COBRA) model. Inputs (Data in Column 3) are from a candidate nanosatellite mission

Factor	Min	Max	Data	Complex%
Payload Mass	0	6065	5	0.082440231
Payload Avg Power	0	6000	5	0.083333333
Payload Peak Power	0	13025	10	0.076775432
Payload DR	0	304538	2.34E+05	76.7063552
# Payload	0	23	0	0
Data Volume	0	21168000	10091520	47.67346939
Foreign Partnership	0	5	5	100
Design Life	0	240	2	0.833333333
Launch Margin	0	2	0	0
Launch Mass	17	18189	11	-0.03301783
Sat Mass	17	16329	11	-0.036782737
Bus dry mass	15	10264	10	-0.048785247
S/C heritage	0	100	0	0
Radiation	0	600	0	0
Redundancy	0	100	0	0
Orbit	0	5	1	20
BOL Power	12	12500	15	0.024023062
Orbit Ave Power	3	5342	7	0.074920397
EOL Power	3	9960	3	0
Solar Array Area	0	175	0.01	0.005714286
Solar Cell Type	0	4	1	25
Battery Type	0	4	1	25
Battery Capacity	1	1222	10	0.737100737
# Articulated Struct	0	13	0	0
# Deployed Structures	0	22	0	0
Solar Array config	0	3	0	0
Structures	0	3	0	0
ADCS type	0	6	3	50
Pointing Accuracy	1.90E-06	20	0.01	1.00E+02
Pointing Knowledge	1.90E-06	20	0.005	1.00E+02
Slew Rate	0	36	1.00E-03	0.002777778
#Thrusters	0	38	12	31.57894737
Propulsion Type	0	5	1	20
Delta V	0	5845	40	0.684345595
Comm Band	0	6	6	100
Downlink DR	1	1460926	1200000	82.13967178
Uplink DR	0	40000	1.00E+03	2.5
Transmitter Power	1	519	30	5.598455598
Central Proc	0	1600	1000	62.5
Software Code	2	1496	30	1.87416332
Flight SW Reuse	0	90	25	27.77777778
Data Storage	0	3.00E+06	1.50E+06	50
Thermal Type	0	4	0	0
			Average	21.64558227
			Cost	35.82402341
			DevTime	35.07406982

The map between complexity percentile and required mission cost and development time for successful missions (green triangles) is shown in Figure 8 using a green trend line. The missions plotted are among the 120 studied missions and equations are mentioned within the figure. COBRA's developers argue that if missions are attempted cheaper than or faster than this model predicts, then there is a large probability of failure as highlighted by the red and yellow crosses on Figure 8. Using the above model, the estimated cost for our candidate nano-satellite (10 kg) mission is \$35.824 million and the estimated development time is 35.074 months. The high cost is in keeping with the intuition expressed in the data collection section that the cost of LEO small satellites are driven more by technology than mass, so the utility of shrinking the satellite should be critically assessed and avoided if the mission technology is very state of art. In such cases, micro satellites would win the performance to cost ratio battle.

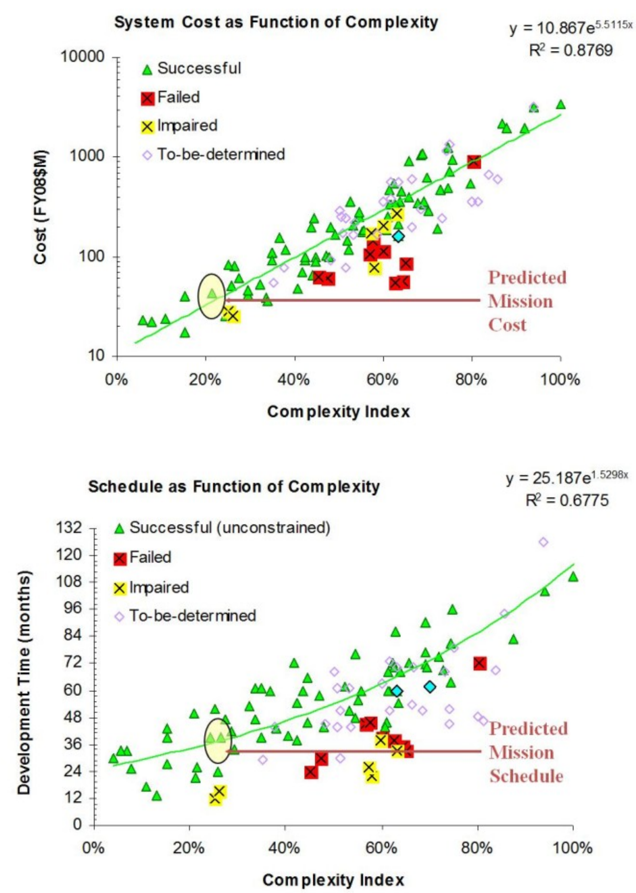


Figure 8: Predicted mission cost and development time as a function of relative mission complexity with respect to other missions evaluated by the Aerospace Corporation [39], [40], [52]. Mission complexity is a function of component complexities as calculated in Table 4. The candidate mission is a LEO satellite measuring passive Earth reflectance as part of a DSM

We ran a sensitivity analysis for the COBRA model by varying the deltaV and pointing accuracy required by the candidate satellite. It does a great job in predicting the increase in costs from 1 degree to 0.01 or 0.1 degree, by estimating a $ 200-250 increase. It overshoots the COTS quotations by a slight margin but is certainly better than the SSCM estimate of $ 18 million more. When the required delta-V is increased from none to 40 m/s to 80 m/s to 120 m/s, the respective costs are estimated to be FY97 $ 35.79, 35.82, 35.85 and 35.88 million. Quotations from a 3D cold gas propulsion system printing company called AustinSat revealed that their 1U propulsion unit capable of providing 40 m/s of delta V costs $100,000 with 6DOF thrusters included and would scale almost linearly as more 1U units are added for 40 m/s of more delta-V. The COTS systems therefore cost more than what the COBRA model predicts. The model can thus be improved and made more suitable for COTS-supported small satellites if COTS data and figures were included in the data set to calculate complexity. Since we do not have the data set (only the published Figure 8), we could not make the changes.

Since many small satellite missions are collaborations between many organizations, the COBRA model could be improved by adding a foreign partnership complexity factor that captures the number of collaborators, not just the nationality. For example, a recent paper [56] formulated a data supported method of capturing international cooperation related complexity using cyclometric complexity where CGF = 0.917 + 0.0575*CyclometricNumber and CyclometricNumber = f(nodes, edges, outputs).

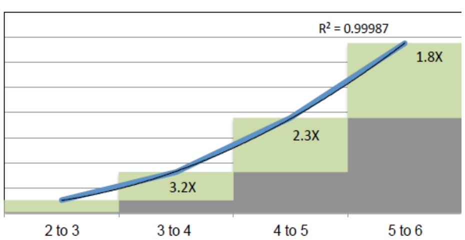


Figure 9: Cost growth required to support increasing TRL for any component as published in [57]

Small satellites are always pushing the boundaries of technology. It is very probable that some of its component values will fall out of range available from past missions. In such a case, cost models of TRL transition such as the one shown in Figure 9 [57] should be incorporated into the COBRA model for the relevant factors. Although TRL transition correlates to the spending, it does not follow traditional 80-20 rule. The COBRA model also does not capture the structural complexity of a small, tightly packed satellite which has been theoretically shown to drive development costs. Structural complexity can be quantified using a simple framework shown in Figure 10 ([35], [34]) and can be easily introduced in the COBRA model via a new factor and recalculating the data fit.

Capturing the above development costs is important for small satellites whose costs are driven more by technology than by mass. Again, since we do not have the data set (only the published Figure 8), we could not make the changes.

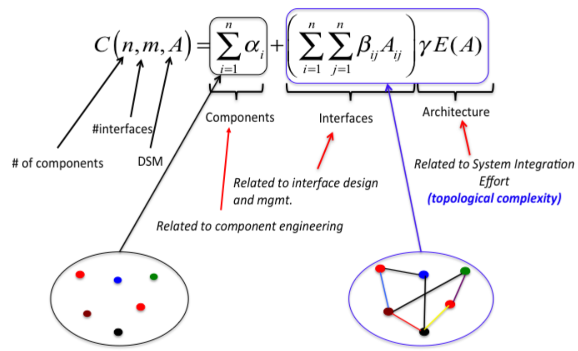


Figure 10: Structural complexity metric introduced and validated in [35] and [34]

5. Conclusions

We identify three major problems with current cost and risk models that limit their direct application to estimating the costs of DSMs. They are the absence of reliable learning curve factors, small satellite (<20 kg) costing tools and operations costing. Existing models and methodologies that may be applicable in part to DSMs have been identified and presented using an extensive literature survey. We selected some appropriate methods and applied them to estimate the cost of small satellites and small satellite DSMs. The exercise helped us point out valuable insights and/or inconsistencies in the results with respect to the data. We also suggest methods to modify the models so that they become more suitable for small satellite DSMs.

As future work, the operations cost model and dynamic complexity of the mission is expected to be captured by a Systems Dynamics Model. Results from model simulations can provide insight into the effect of design and operation decisions on lifecycle cost and risk, expected to improve upon the Monte Carlo results. The model results can guide the trade-off of cost with performance and can help in the selection of a final point design for any given DSM.

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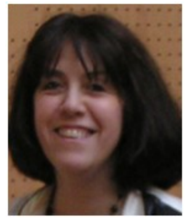

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