Sensitivity Analysis of the Advanced Missions Cost Model

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Strategic decisions with regard to system architecture, technology investment, and mission planning for complex projects must balance cost, risk, and performance – potentially across years of development and operation. Cost models are used to translate program and system elements into financial considerations. Oftentimes, different mission options will be analyzed to determine their costs relative to each other and inform development decisions. Cost estimates often forecast years into the future, and parameters are usually uncertain. As such, it is important to perform sensitivity analyses and examine how the results behave in response to changes in the underlying assumptions. Cost sensitivity to particular parameters can be used to illustrate programmatic risks – for example, by revealing that a small variation in a particular parameter can result in massive cost increases. Similarly, these analyses can illuminate areas where development of capabilities outside the specific system being developed can result in cost savings. This paper presents a sensitivity analysis of case studies comparing the cost of open- and closed-loop life support systems for a space station, moon base, Mars transit habitat, and Mars base building upon previous work by Jones using the Advanced Missions Cost Model. The response of the cost estimated for each of these different cases are examined, focusing on the impact of variation of difficulty, a subjective model input. The implications of the results are discussed along with general observations on the use of sensitivity analysis in life cycle cost analysis.

Nomenclature

B	=	Block
C	=	Cost
D	=	Difficulty
IOC	=	Initial Operational Capability
M	=	System dry mass
Q	=	Quantity
S	=	Specification

AMCM	Advanced Missions Cost Model
CAD	Cost Analysis Division
CER	Cost Estimating Relationship
DDT&E	Design, Development, Test, and Engineering
ECLS	Environmental Control and Life Support
JSC	Johnson Space Center
NAFCOM	NASA-Air Force Cost Model

I. Introduction

DEVELOPMENT of new systems must balance between performance, cost, schedule, and risk in order to accomplish a desired mission most effectively within a given set of constraints.[1] Cost estimation is an important tool that, used in conjunction with other system models, can give decision-makers the information required to trade between these high-level metrics in order to decide on the appropriate course of action in terms of

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system architecture, technology development, and mission design. However, cost estimation can also be challenging and subject to significant uncertainty. Subjective model inputs present a particular challenge since they can be difficult to verify and may be manipulated (consciously or unconsciously) so that the outputs of a model reflect the bias of the analyst. As such, it is important to understand the relationship between cost model inputs and outputs, especially when subjective inputs are involved.

This paper presents an illustrative sensitivity analysis of the estimated costs of Environmental Control and Life Support (ECLS) systems for a space station, moon base, Mars transit habitat, and Mars base, building on previous work by Jones.[2,3] This cost analysis uses the Advanced Missions Cost Model (AMCM), examining in particular the subjective input variable representing difficulty. Difficulty is selected as the focus of the sensitivity analysis precisely because of its subjectivity. Different analysts may have different perceptions of how "difficult" a project will be, and unlike other model inputs difficulty is not directly related to a physical, measurable parameter like dry mass.

The remainder of the paper is organized as follows. Section II provides a brief background on cost models, the AMCM in particular, and the importance of sensitivity analysis in cost modeling. Section III describes the source data for the cases examined here and discusses the particular methodology implemented. Section IV presents the results of a sensitivity analysis focusing on variation in the difficulty input, and Section V discusses these results. Finally, Section VI presents conclusions.

II.   Background

A. Cost Models
Three primary categories of cost estimation techniques exist for space systems: grassroots (or bottom-up), analogy, and parametric. Grassroots models develop detailed, low-level assessments of the costs of various mission elements (in terms of systems and tasks) and aggregate that information into an overall cost estimate. Analogy-based approaches estimate system cost via comparison to a similar system with a known cost. Finally, parametric cost models are analytical equations called Cost Estimating Relationships (CERs) relating a subset of system characteristics, such as mass, to overall cost. These parametric models are usually derived from statistical regression of the costs and characteristics of existing systems.[4,5]

While grassroots models provide a very high level of detail, they also require a high level of detail in system knowledge and can be very time-consuming to produce. Therefore they are often not appropriate for use during early-phase trade studies that require rapid examination of many different system concepts. Analogy-based cost models are limited by the availability of valid analogous systems, and are typically not flexible enough to examine a wide range of system concepts during trade studies. Therefore, early concept development and trade studies (i.e. Pre-Phase A and Phase A) typically utilize parametric cost models since they are quick to execute and can be applied to a wide variety of systems based upon a few key engineering metrics.[2,4,5]

In the past, NASA has primarily used three parametric cost models for crewed systems: the NASA-Air Force Cost Model (NAFCOM), PRICE-H, and the Advanced Missions Cost Model (AMCM).[2,4] A list of common cost models (both in-house and commercial) that are currently used by NASA is maintained on the Cost Analysis Division (CAD) website.[6] A full review of the various cost models in use is beyond the scope of this paper. This paper will focus on AMCM in order to illustrate the importance of sensitivity analyses during cost estimation. However, the concepts discussed here are in no way limited to AMCM and should be considered during cost estimation regardless of the specific model being applied.

B. Advanced Missions Cost Model
The Advanced Missions Cost Model (AMCM), initially developed in the late 1980s at Johnson Space Center (JSC), is a multivariate cost model that estimates total cost of acquiring flight hardware.[7] The model is based on statistical regression on a database of more than 260 historical programs.[4] In addition to uncrewed systems, the AMCM database includes data from eight NASA crewed spacecraft programs.[2]

AMCM outputs the total system acquisition cost C (in millions of FY 1999 dollars) as a function of six variables and seven parameters, and has the form given below:[4]

$$C = \alpha Q^{\beta} M^{\Xi} \delta^{S} \varepsilon^{\frac{1}{(IOC-1900)}} B^{\phi} \gamma^{D} \tag{1}$$

Table 1: Parameters and values for AMCM.[4]	
Parameter	Value
α	5.65×10^{-4}
β	0.5941
Ξ	0.6604
δ	80.599
ε	3.8085×10^{-55}
φ	-0.3553
γ	1.5691

Table 2: Specification values for AMCM.[4]	
Specification	S Value
Planetary Lander	2.46
Planetary	2.39
Human Reentry	2.27
Rovers	2.14
Human Habitats	2.13

The values of the seven parameters are given in Table 1. The six variables that serve as inputs to the model capture key system cost drivers, and are defined as follows:[4]

1) Quantity Q: The number of development and production units produced, including test articles and spares.
2) Mass M: System dry mass in pounds. (Note that this paper uses kilograms to measure mass, and therefore a factor of 2.2 lb/kg is applied for calculation.)
3) Specification S: The type of mission to be flown. This input takes one of a set of values, and values for crewed systems are listed in Table 2.
4) Initial Operational Capability IOC: The first year of system operations.
5) Block B: The system's block number, or level of design inheritance. For example, a completely new design has a block number equal to 1, while modifications to existing designs have block numbers of 2 or more.
6) Difficulty D: A subjective input describing the expected programmatic and technical difficulty of producing the system. Difficulty ranges from -2.5 to 2.5 in increments of 0.5, where -2.5 indicates "extremely easy" and 2.5 indicates "extremely difficult."

C. The Need for Sensitivity Analysis

It can be tempting to use cost models such as AMCM to produce a single estimate for system cost as a function of estimates of each of the input variables. Using this approach, a set of concepts can quickly be characterized to produce point estimates of cost, which can then be used for comparison and/or downselection. However, it is important to bear in mind that the results of cost models such as AMCM are estimates and forecasts, and their outputs are not exact predictions.

Moreover, the inputs themselves will likely also be uncertain, particularly when cost estimates are being produced for systems that will be deployed several decades in the future. As a result, it is important to not simply produce a single cost estimate – even if it is used with the understanding that it is an estimate with uncertainty. More information on the impact of uncertainty in the input variables can be determined if a sensitivity analysis is undertaken that examines the impact of variations in each input on the overall system cost. This type of sensitivity analysis can identify which of the cost drivers captured in a given cost model is having the greatest effect in the range of this particular cost estimate, and can provide understanding of how the cost of the system will behave in response to changes in system definition (e.g. reduced mass, delayed deployment, change in block number).

Sensitivity analysis is particularly important when models incorporate subjective inputs, as is the case with the difficulty variable D in AMCM. These inputs fundamentally rely on a judgment call that may or may not be supported by analysis, and are likely difficult if not impossible to validate. If the impact of subjective inputs is relatively large, the conscious or unconscious bias of the individual performing the analysis may have a strong influence on the output of the analysis. For example, a reference case reported by Jones[2] showed that variation in D can result in extreme variation of cost estimates. From a baseline of average difficulty ($D = 0$), Jones showed that adjustment of D while holding all other parameters equal could reduce system cost to as low as 32% of the baseline value, or increase it by a factor of 3.[2] As such, it is especially important to characterize and understand the impact of variations in subjective inputs so as to understand how the particular value chosen may or may not have influenced the result.

III. Methodology

This paper builds upon previous work by Jones[2,3] that presented a life cycle cost analysis of recycling and resupply approaches to ECLS for a space station, Mars transit vehicle, lunar base, and Mars base, all using AMCM. As the purpose of this analysis is to discuss the value of sensitivity analyses in cost estimates, the results presented in this paper will focus on the Design, Development, Test, and Engineering (DDT&E) cost of ECLS systems for these cases and how they vary around the baseline presented by Jones as the input variables are varied. The baseline

Table 3: AMCM input values and resulting cost estimate for the four systems examined here.[3]

AMCM Input	Space Station		Moon Base		Mars Transit		Mars Base	
	Recycling	Resupply	Recycling	Resupply	Recycling	Resupply	Recycling	Resupply
Q	1	1,825	1	1,216	3	122	3	167
M [kg]	660	37.3	440	37.3	440	37.3	440	37.3
S	2.13	2.13	2.46	2.46	2.13	2.13	2.46	2.46
IOC	2030	2030	2030	2030	2030	2030	2030	2030
B	2	1	2	1	1	1	1	1
D	-1	-2.5*	-1	-2.5*	1	-2	1	-2
Cost	151.2	1,277.6	492.4	4,273.0	699.7	320.8	2,978.5	1,645.6

*Difficulty values adjusted from -3 to -2.5 to remain within the valid domain of the model

system inputs and resulting DDT&E cost estimates are presented in Table 3.[3] A more detailed description of these systems and discussion of the derivation of the particular values given is presented by Jones.[3]

This table incorporates an adjustment from the original data presented by Jones, since it listed the difficulty of resupply hardware for the space station and moon base as having a value of -3, which is outside the domain of the difficulty variable in AMCM and is therefore not a valid assignment.[4] In this dataset, the minimum difficulty assignments are constrained to -2.5 ("extremely easy"). We note that this adjustment to return the input variables to the valid range of the model results in an increase of cost for each of these architectures. The space station estimate increases by $257.7 million, and the moon base estimate increases by $861.8 million. (Unless otherwise noted, costs described in this paper are presented in FY 1999 dollars.)

Starting from this baseline, we examine in particular the impact of the difficulty input *D*, due to its subjectivity. Since the input D has only 11 possible values, we calculate the DDT&E cost at each of these values for each of the architectures, holding all other inputs at the baseline values. These results are then plotted in order to illustrate the impact of the difficulty input on the resulting cost estimate.
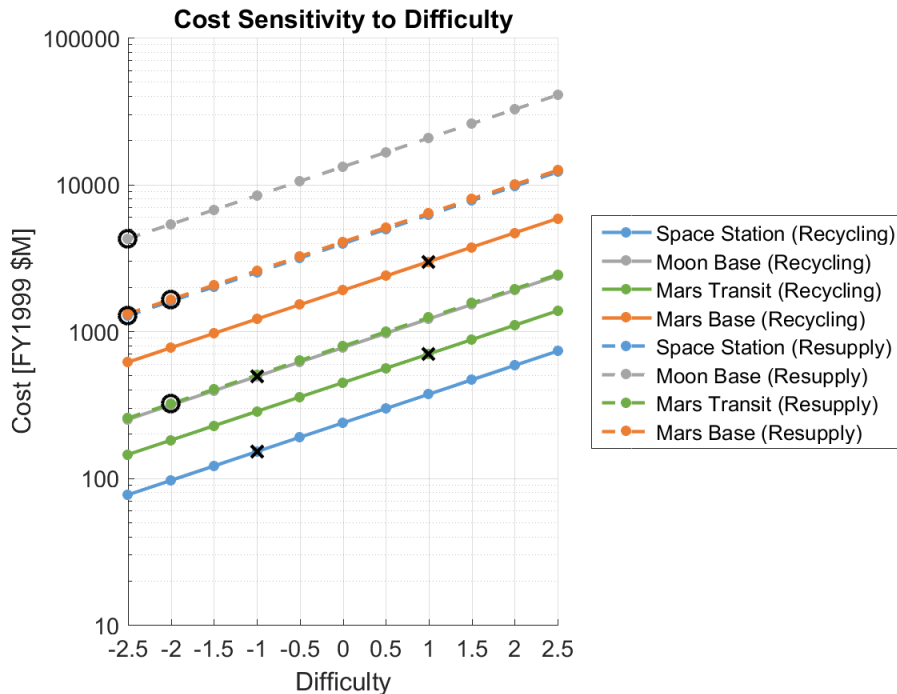
IV. Results

Figure 1: Sensitivity of AMCM cost estimates in response to changes in difficulty for recycling (solid line) and resupply (dotted line) architectures. Baseline difficulty levels are indicated with Xs for recycling cases and Os for resupply cases. Note that the y-axis uses a logarithmic scale.
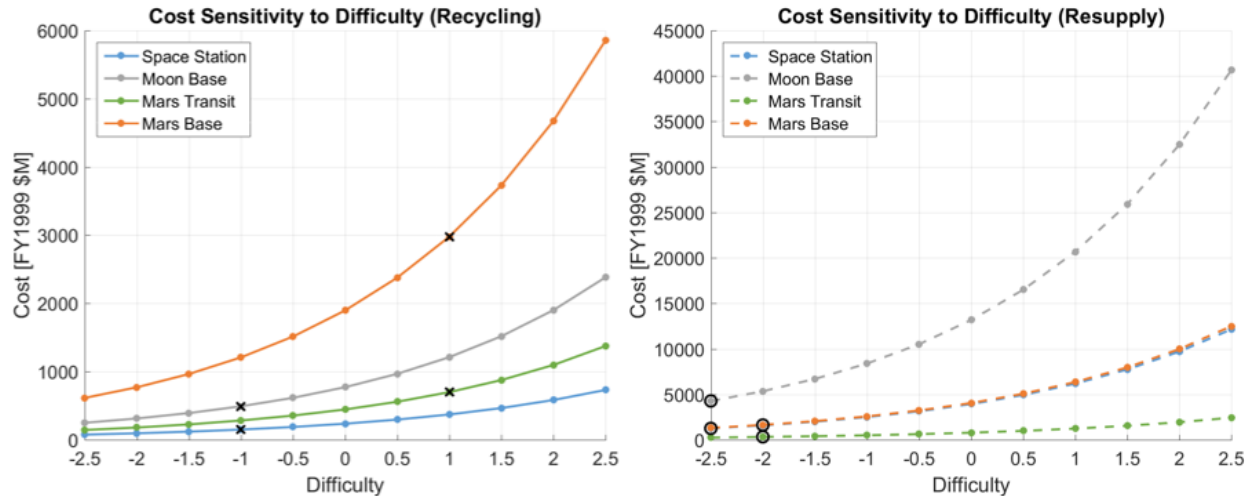
Figure 2: Sensitivity of AMCM cost estimates in response to changes in difficulty for recycling (left) and resupply (right) architectures. Baseline difficulty levels are indicated with Xs for recycling cases and Os for resupply cases. Note that the y-axes on each plot are scaled to the relevant data and are not at the same scale.

Figure 1 shows the variation in cost estimated by the AMCM for each system architecture examined by Jones[3] when difficulty is varied across its entire domain, from the the "extremely easy" -2.5 to the "extremely difficult" 2.5. Costs are presented on a logarithmic scale. The baseline difficulty level for each architecture is indicated with an X for recycling architectures and an O for resupply architectures. Figure 2 shows these same results on a more intuitive linear scale. The recycling and resupply cases are shown on separate plots (left and right, respectively) due to the nearly order of magnitude difference between the highest costs encountered in these two cases, and baseline difficulty levels are again marked with Xs and Os.

V.   Discussion

For the systems modeled here, the difficulty input has a very large effect on the resulting cost estimate. While the overall change in difficulty (from "extremely easy" to "extremely difficult") can result in an order of magnitude difference in cost estimate, even small changes in D can result in large changes to the overall cost estimate. For example, the baseline case for the Mars base using recycling systems (difficulty level 1) has a cost of $2.978 billion. If this difficulty estimate is varied downwards to 0.5, the cost drops to $2.377 billion, a reduction of over $600 million, or approximately 20%. If instead the difficulty is estimated to be 1.5 (one step higher on the scale), the cost rises to $3.731 billion, an increase of over $752 million – over 25% of the original cost. Similar effects appear in each of the other systems, though scaled by the other cost factors of that system.

It is important to note that the structure of the AMCM cost equation reveals these sensitivity impacts (in terms of multipliers on the original value) easily, since the equation itself is the product of several factors. However, this paper utilizes the more general approach of calculating cost estimates at various values for the given systems rather than exploiting the structure of the CER in order to maintain generality for application to other cost models and to focus on using these applications as example cases.

Since "difficulty" is a subjective parameter that has the potential to have an enormous impact on the final cost estimate, its application must be done with great care to ensure that the biases of the analyst (both conscious and unconscious) do not influence the output of the model, or at least that their effects are minimized. In application, this may mean that the difficulty input is used carefully not as an absolute input but as a relative judgment between two options. This may require that the same procedure be used to determine the value of the difficulty parameter for each case so as to ensure that each option is considered on even footing.

However, the plots shown in Figure 1 and Figure 2 illustrate another potential pitfall of this relative difficulty assessment. Though in general an increase in difficulty results in an increase in price for all types of missions (a conclusion supported by examination of the structure of the AMCM cost equation), the exponential nature of this increase results in divergence of cost estimates as difficulty moves towards the higher end of its domain. As a result, a set of difficulty estimates that are consistent in terms of relative relationships of the difficulty of different systems – for example, one that says that a Mars surface system is one point more difficult than a lunar surface system on the given scale – will produce different results depending on where in the difficulty scale those difficulty estimates are

anchored. Continuing the example, a cost model that puts the difficulty of a lunar base at 1 and therefore puts the difficulty of a Mars base at 2 will estimate a larger difference between the two than an estimate that puts them at -2 and -1, respectively.

The nonlinearity of the effect of the difficulty input means that the particular value of each difficulty input is important to the final result, not just the relative value between two systems being examined. As a result, cost estimates using AMCM must be careful not only to ensure that the various cases being examined by the model are not only considered on equal footing, but that they are pegged to the same reference value. This reference value may take the form of a baseline case that can be used as a reference for analysts to judge whether a particular case is more or less difficult, or perhaps it could be a set of (well-known or well-defined) cases representing key points in the scale to provide a reference not only for a specific value on the scale but also for the distance between points. For models like AMCM, which are based on statistical regression of a database of missions, it may be that these reference points could be specific missions from the database.

It is important to note that this analysis does not intend to imply that other parameters are unimportant, nor that other cost models do not share similar issues with subjectivity and strong sensitivity. The difficulty parameter of the AMCM is simply used as an example in order to illustrate the (potentially strong) sensitivity of cost estimates to input parameters, and the importance of considering sensitivity when using these results. In addition, These results are not intended to make the case that cost models such as the AMCM do not produce useful outputs, but they do illustrates the importance of consideration of the sensitivity of a cost model with respect to its inputs. Subjective inputs in particular have the potential to skew results and must be considered with great care. In these cases – where an input is not the result of a well-defined analytical approach and its effect is nonlinear – it is important to consider not only the validity of the relationship between subjective inputs (i.e. their relative positions in the input domain) but also their absolute position within the domain itself. However, validation of these subjective inputs can be difficult if not impossible. Therefore, results from models for which subjective inputs can have such a large impact, as is shown here, must be taken with a grain of salt. Decisions based on cost model outputs should be made with a full understanding of the sensitivity of those outputs to variations in model inputs.

VI. Conclusion

Cost models such as AMCM are an important part of decision-making for system development, since the financial cost of a given system may be the most important factor in the feasibility of its application to a particular mission. It does not matter how productive or safe a system is if it is too expensive to build in the first place. System architecture, technology development, and mission design efforts must be conducted with an understanding of the costs of the systems proposed. However, this understanding should not be based on a single point output by a cost model, particularly when subjective inputs are involved that can result in biased results.

This paper has presented a sensitivity analysis of AMCM with respect to the difficulty input D, showing that variation of this inherently subjective input can produce very large variations in cost estimate. The nonlinearity in the effect of D means that the magnitude of the difference between cost estimates for two systems depends not only on their relative D values, but also on where those values sit in the domain of D. In one of the cases examined here, one-step variation of D from the baseline value is demonstrated to produce a change of well over half a billion dollars in either direction. These results clearly illustrate the importance of understanding not only the point outputs of cost models such as AMCM, but also how those outputs behave in response to variation of the inputs.

Acknowledgments

References

[1]National Aeronautics and Space Administration, "NASA Systems Engineering Handbook," NASA/SP-2007-6105-Rev1, 2007.

[2]Jones, H. W., "Estimating the Life Cycle Cost of Space Systems," *45th International Conference on Environmental Systems,* ICES-2015-041, Bellevue, WA: International Conference on Environmental Systems, 2015.

[3]Jones, H. W., "The Life Cycle Cost (LCC) of Life Support Recycling and Resupply," *45th International Conference on Environmental Systems,* ICES-2015-295, Bellevue, WA: International Conference on Environmental Systems, 2015.

[4]Guerra, L., and Shishko, R., "Estimating the Cost of Crewed Space Systems," *Human Spaceflight: Mission Analysis and Design*, W.J. Larson and L.K. Pranke, eds., McGraw-Hill, 1999, pp. 933–960.

[5]Trivailo, O., Sippel, M., and Sekercioglu, Y. A., "Review of hardware cost estimation methods, models and tools applied to early phases of space mission planning," *Progress in Aerospace Sciences*, vol. 53, 2012, pp. 1–17.

[6]Keeter, B., "CAD Models & Tools," *NASA Cost Analysis Division*. Available at: http://www.nasa.gov/offices/ooe/CAD/Models_Tools.html#.Vx4r8PkrLRY.

[7]Cyr, K., "Cost Understanding (SAA-C-R-001)," *Exploration Studies Technical Report, vol. III (NASA-TM-4075-Vol-3)*, Houston, TX: Johnson Space Center, National Aeronautics and Space Administration, 1988, pp. 1296–1418.