



COMPARISON OF DECISION ANALYSIS METHODS FOR A CUBESAT

PROPULSION SYSTEM

THESIS

Jared L. Pilcher, Captain, USSF

AFIT-ENV-MS-21-M-256

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government. This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

AFIT-ENV-MS-21-M-256

COMPARISON OF DECISION ANALYSIS METHODS FOR A CUBESAT
PROPULSION SYSTEM

THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the
Degree of Master of Science in Engineering Management

Jared L. Pilcher, BS

Captain, USSF

March 2021

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

COMPARISON OF DECISION ANALYSIS METHODS FOR A CUBESAT
PROPULSION SYSTEM

Jared L. Pilcher, BS

Captain, USSF

Committee Membership:

Lt Col Clay Koschnick, PhD
Chair

Alfred E. Thal, Jr., PhD
Member

Andrew S. Keys, PhD
Member

Bradley J. Ayres, PhD
Member

Abstract

Low Earth Orbit (LEO) is becoming an increasingly congested orbital regime. As a result, propulsion systems on CubeSats are becoming a more desirable feature to provide them with collision avoidance capabilities. To date, there have been very few CubeSat launches with a propulsion system on them. Due to the relatively high cost of a propulsion system compared to the budget of small educational organizations, a decision analysis model is needed so that these organizations can make the best decision between whether to purchase a Commercial-Off-The-Shelf (COTS) product or to develop one within the organization. This research applies three decision analysis methods: Simple Multi-Attribute Rating Technique with Swing weights (SMARTS), the Analytical Hierarchy Process (AHP), and Data Envelopment Analysis (DEA). A comparison of the strengths and weaknesses of these methods when applied to the propulsion system selection problem is then conducted.

Acknowledgments

I would like to express my gratitude to my faculty advisor, Lt Col Clay Koschnick, for the lengthy discussions that helped to push the boundaries of my critical thinking. His guidance and support were critical to the success of this thesis endeavor. My family has also been a constant source of motivation and inspiration on every step of this journey. I would, also, like to thank my fellow students in the Engineering Management degree program who have supported each other through a global pandemic. Their support uplifted the spirit despite the quarantine and social distancing.

Jared L. Pilcher

Table of Contents

	Page
Abstract	iv
Table of Contents	vi
List of Figures	ix
List of Tables	x
I. Introduction	1
General Issue	1
Problem Statement.....	3
Research Objectives	3
Research Question	4
Methodology.....	4
Assumptions and Limitations	5
Summary.....	6
II. Literature Review	8
CubeSats	8
Decision Analysis.....	9
Multi-Criteria Analysis.....	11
Decision Analysis Methods.....	13
Utility Theory	18
Utility Theory Examples	24
SMARTS	27
Analytical Hierarchy Process	29
Data Envelopment Analysis	31

Cost and Schedule Estimating	33
Summary.....	36
III. Methodology	37
Criterion Selection.....	37
Database	38
Simple Multi-Attribute Rating Technique with Swing Weights.....	41
Analytical Hierarchy Process	48
Data Envelopment Analysis	56
Composite Results	61
Summary.....	61
IV. Analysis and Results.....	63
SMARTS	63
Analytical Hierarchy Process	66
Data Envelopment Analysis	71
Combined Results.....	74
Summary.....	74
V. Conclusions and Recommendations	76
Conclusions of Research	76
Significance of Research	79
Recommendations for Future Research.....	79
Summary.....	80
Appendix A – Propulsion Vendor Trade Study.....	82
Appendix B – DSCM CERs and Schedule Parametric Relationship	83
Appendix C – SMARTS Scoring.....	84

Appendix D – SMARTS Sensitivity Iterations.....	84
Appendix E – AHP Comparison Matrices.....	86
Appendix F – DEA Sensitivity Analysis	89
References.....	93

List of Figures

	Page
Figure 1 - SBD and PBD in a Value versus Cost Tradespace (Parnell et al., 2018)	13
Figure 2 - CBRN R&S Objective Hierarchy Decision Tree (Barnes, 2017)	24
Figure 3 - MOE Thresholds and Objectives (Barnes, 2017)	25
Figure 4 - Propulsion System Selection Hierarchy	49
Figure 5 - Different RTS (Hui & Wan, 2013)	57
Figure 6 - DEA Frontier Free Data Format (Zhu, n.d.)	60

List of Tables

	Page
Table 1 - A Performance Matrix (Dodgson et al., 2009)	12
Table 2 - Comparison Intensity Scale (Saaty, 1982)	50
Table 3 - Example Alternative Comparison Matrix (Saaty, 1982)	51
Table 4 - Example Criteria Comparison Matrix	51
Table 5 - Consistency Matrix Calculations (Saaty, 1982)	53
Table 6 - Random Index Values (Saaty, 1982)	53
Table 7 – SMARTS Criteria Preferences	64
Table 8 – Total Utility Calculations	65
Table 9 – Random Weighting Sensitivity Analysis Results	66
Table 10 - Vector of Priorities	67
Table 11 - Eigenvalue, CI, CR Values	68
Table 12 - Cost Comparison Matrix	69
Table 13 - Cost Criterion Sensitivity	70
Table 14 - Schedule Criterion Sensitivity	71
Table 15 - Performance Criterion Sensitivity	71
Table 16 – DEA Efficiency Results	72
Table 17 - DEA Input Slacks	73
Table 18 - DEA Input Targets	73
Table 19 - Method Results Comparison	74

COMPARISON OF DECISION ANALYSIS METHODS FOR A CUBESAT PROPULSION SYSTEM

I. Introduction

General Issue

Small satellites, or SmallSats, face increasing attention as their rise in popularity for commercial applications continues to grow (Wekerle et al., 2017). SmallSats are defined as any satellite under 180 kg by the National Aeronautics and Space Administration (NASA) (Mabrouk, 2017). In educational organizations, SmallSats typically take the form of a CubeSat, which is a satellite with a form factor of 100x100x100mm. Increased congestion of the low earth orbit (LEO) environment is a growing concern for SmallSats. Even though space is massive, the number of objects in Earth's orbit continues to grow to over 20,000 trackable objects and many more that are too small to be tracked (National Aeronautics and Space Administration [NASA], 2019). Starlink, a project designed to provide high-speed internet anywhere in the world, hinges its operational ability on the use of over 12,000 satellites (space.com, 2020). Such projects led to the fear of a cascade effect, known as Kessler syndrome, where a single collision leads to more collisions until there is so much debris in orbit that satellites effectively can no longer operate (Kessler & Burton, 1978). A key feature to preventing such a scenario, and providing operational safety for any given satellite, is the ability to maneuver for collision avoidance and decommissioning at the end of the satellite's mission.

Propulsion systems have not seen much use on CubeSats other than as an attitude determination and control system (ADACS). Lemmer (2017) notes that as of 2017 only two publicly releasable missions have included a propulsion system. However, a brief search reveals over half a dozen commercial vendors with products on the market, and each vendor has multiple configurations or propulsion products to purchase. Propulsion methods for these products include cold gas, chemical reaction, electric propulsion, solar sails, and more. In addition, range safety and other requirements may limit the viable design space for a propulsion system built to purpose (Air Force Space Command, 2019). Determining which product is the best for a project requires a structured selection methodology.

Interest in CubeSats is not limited to the commercial market; educational and research facilities continue to be one of the most prominent groups that build and launch small satellites (Wekerle et al., 2017). The small satellite is attractive to this group due to its drastically reduced costs (both for development and launch) as well as because of its relatively simpler design and the construction skills needed (Wertz et al., 2018). Typically, these education and research groups do not include a propulsion system in their designs. Propulsion systems are relatively expensive compared to many of the other parts of a CubeSat. Costs for a CubeSat without a propulsion system can range from \$50,000 to \$250,000 (Straub, 2012). As the trade study conducted in this research shows, the low end of propulsion systems cost \$50,000 with the majority of them costing \$200,000 or more.

As the need for propulsion systems increase, these education and research organizations will require a simple and repeatable product selection method that their

management team can use for determining the most efficient use of their limited funds. Their product options include development of a system uniquely designed to meet the desired requirements, purchase of a Commercial-Off-the-Shelf (COTS) product from a vendor, or they can attempt to negotiate with a vendor to modify one of their COTS products to better meet the requirements.

Problem Statement

Educational and research organizations need a robust and effective method of determining which propulsion system will best meet the cost, schedule, and performance requirements of the project, whether that system comes from a selection of the current array of COTS products or is a bespoke design generated within the organization. These organizations lack a large pool of resources to draw from and as a result would benefit greatly from a method to make the determination of best choice. Additionally, the selection method should be auditable, reproducible, and logically sound so that the organization will be able to review the process and adjust if necessary.

Research Objectives

The primary objective is to develop several decision analysis models that can be applied to a desired small-satellite development program to inform the decision-maker of the best choice to make given the inputs that were supplied before performing the analysis. A primary output of the various models will be a ranked hierarchy of the various alternatives. Where a model is capable, the measured difference in preference between the alternatives will also be included. The intent behind using multiple decision analysis models is to provide increased confidence in any converged upon answer and to

determine if one of the models provides increased insight into the problem. Once the models have been developed, an educational research organization's CubeSat project requirements will be used to test the model for inconsistencies or sensitivity to any particular variable.

Research Question

The research performed primarily seeks to answer the research question, "Which decision model is best suited to be used in selecting a propulsion system for a CubeSat education and research project?" Reviewing the advantages and disadvantages inherent to each model when applied to the case study will help to identify the answer to this question. Additionally, this research answers the question, "Will different decision analysis models identify the same alternative as the best choice?" Comparing the results of the models will highlight the reasons why this is or is not the case.

Methodology

Three of the most common decision-making tools are used. The methods selected were chosen primarily based on their ease of application so that future project managers could conduct analysis without relying on an expert. Literature review guided the determination of which methods were easiest to apply. These methods are Simple Multi-Attribute Rating Technique with Swings (SMARTS), which is a form of Multi-Attribute Utility Theory (MAUT), the Analytical Hierarchy Process (AHP), and Data Envelopment Analysis (DEA). The common factor among them is that they all focus on dealing with multi-criteria problems. All of them approach the development of weights and criteria scoring differently.

To apply the decision-making tools above, a trade study conducted by the project staff on propulsion system products from a variety vendors is used. This provided the initial set of data that will be evaluated. The alternative set is further reduced based on dominance and author judgement to facilitate use of the AHP. To compare the bespoke design with these COTS products, a theoretical design with parameters that use mission requirements and estimation techniques is generated. Discussion with a propulsion SME identified the four most important propulsion criteria. Combined with cost and schedule, these provide the full set of criteria against which the alternatives are evaluated. Decision-maker preferences were solicited and recorded through use of Microsoft Excel and directions on how to complete the weighting process were provided. After translating these preferences into weights and scoring the alternatives, sensitivity analysis techniques are applied to determine the stability of the solution.

Assumptions and Limitations

The development of this model does not include external factors that could affect a decision-maker's choice. Examples of these factors include political pressure, prestige to be gained or lost by the organization, and the likelihood of an increase or reduction in funding for the program. These factors can render some alternatives un-selectable or elevate other alternatives to a higher level of preference; however, this research is focused on the cost, schedule, and technical performance aspects of making a selection.

In generating the criteria to be measured when evaluating the alternatives, a subject matter expert (SME) was consulted to ensure the full breadth of potential criteria was considered. As a result, if the models were applied to a different program than the

one considered in this research, the decision-maker could potentially, and indeed most likely, hold a different set of criteria to be necessary for evaluation. Different mission requirements will also induce a different set of criteria weights in addition to the potential for different requirements altogether. This limits the immediate applicability of the model to other programs, but this can be solved by having the decision-maker review the criteria and adjust it as necessary to match their preferences and mission requirements.

While performing the case study analysis, the performance data given by the manufacturer is used for input. Ideally, these performance metrics would be independently verified, but for this research they are assumed to be accurate. If this assumption fails to be true, the exact values obtained will be incorrect which could potentially alter the ranking of the alternatives.

Lastly, when developing the in-house design portion of the model, it is assumed that the design will fully meet the technical performance aspects of the mission requirements, given adequate funding and time. While this is not always guaranteed, this assumption satisfies the intent of a custom design. If there were COTS products that already fully met the performance requirements, then there would not be a need to develop a solution.

Summary

Using a decision analysis tool, educational and small research organizations can identify the most efficient use of their limited resources when deciding whether to purchase a propulsion system from a vendor or develop their own. The applicability of the various models being used in this research, their advantages and disadvantages, and

their historical use in other problems is explored in the literature review in Chapter II. Using this, a further discussion of the set-up of the different models, the underlying mathematics providing their functionality, and the generation of the input data is described in Chapter III. Chapter IV provides the results of using the models to generate their appropriate outputs and discusses the validity and sensitivity of the results. Finally, Chapter V draws conclusions based on the research and provides avenues for further research topics.

II. Literature Review

Determining which propulsion system is best suited to a mission requires a method that can account for various attributes, is able to handle different priorities of these attributes, incorporates risk, and is able to be used by decision-makers without extensive expert involvement. The field of decision analysis has been around for a long time and, as such, there are a large number of different methods to solving a decision problem. This chapter briefly reviews CubeSats, the field of decision analysis, particularly multi-criteria analysis, as well as many methods that have been applied to real-world problems. It then provides more depth on Utility Theory, the Analytical Hierarchy Process (AHP), and Data Envelopment Analysis (DEA) before completing the chapter with cost estimating models. Features of some of the most prominent forms of decision analysis in use today are described in-depth and example frameworks that have been created using established techniques are provided.

CubeSats

Satellites under 180kg is not the only working definition of a SmallSat, one example defines it to be satellites under 500 kg (Konecny, 2004); even without an exact cutoff point though, the usefulness of the term as a catch-all still endures. A specific subset of SmallSats in the nanosatellite range (1-10kg) are called CubeSats, which were originally created at California Polytechnic State University in 1999 by Robert Twiggs and Jordi Puig-Suari (Wertz et al., 2018). CubeSats use a standardized form factor called a “1U” which measures 100x100x100mm. Larger versions can be created in multiples of this standard unit, such as a 3U, 6U, or 12U.

CubeSats were initially born of a desire to provide a design program that university-level students could participate in. Designing and building the CubeSat would take one to two years and would cost less than \$100,000. The CubeSats would then be used to provide testing of new technologies or carry a scientific instrument (Wertz et al. 2018).

As of 2018, 855 CubeSat launches were recorded. It is projected that in 2021 as many as one thousand CubeSats will be launched. The most commonly used CubeSat configuration is the 3U, followed by 1U. Commercial applications account for 57% of CubeSat launches and academic institutions comprise 29%. Currently, remote sensing is the most common mission that CubeSats are used for and scientific missions are the second most common mission (Costa et al., 2019).

De-orbit requirements for CubeSats are currently 25 years or less (Wertz et al., 2018). This would not point to a need for propulsion systems on CubeSats. However, missions with strict pointing requirements, such as with testing new remote sensing equipment, or the requirement to provide collision avoidance will require the CubeSat to have a propulsion capability.

Decision Analysis

The field of decision analysis uses logical relationships and systematic techniques to analyze complex problems. Complex problems may have multiple objectives, risk and uncertainty, intangible factors, or value tradeoffs. When these features interact, the problem becomes difficult to assess without using structured techniques (Keeney, 1982). Decision analysis accomplishes this by decomposing a problem into parts to be evaluated

separately and then combined back together. Among all decision problems there are several commonalities. These include a need to accomplish some objectives, multiple alternatives with only one that can be selected, the consequences of the alternatives are different, there is uncertainty about the consequences, and the different consequences are not all equally valued. Determining which alternative to select should be based on the probability of a consequence occurring for each alternative and the preferences for those consequences.

Generally, the methodology of decision analysis can be described in four steps: structure the problem, assess the impacts of each alternative, determine the preferences or weights of the decision-makers, and evaluate and compare the alternatives (Keeney, 1982). When generating alternatives, it is helpful to eliminate clearly inferior options to reduce the field of potential competitors to a manageable size. On the other hand, if there is a dearth of attractive options, then a review of the objectives may be in order. Studying the objectives can help to generate innovative ideas to solve the problem by asking, “what type of solution can achieve this?”

An objectives hierarchy is the starting point for structuring the problem in a manner that is conducive to being studied. The top-level objectives will be broad in scope and address general concerns while lower-level objectives help define the meaning of the higher-level ones. An attribute that can be measured in terms of the lower-level objective is then required to assess how well an alternative achieves that objective. Professionals are valuable tools in creating these assessments as experience has shown they are reliable in creating forecasts of events within their fields of study.

Multi-Criteria Analysis

Multi-Criteria Analysis (MCA) encompasses decision analysis methods that structure the process of evaluating alternatives against multiple criteria. Specific methods are discussed elsewhere in this chapter so the review here will focus on the general topic of MCA. MCA methods are superior to informal judgements; they are explicit, leave an audit trail, and can serve as a communication mechanism for the decision-maker to other audiences and stakeholders (Dodgson et al. 2009).

The various MCA methods all share a common feature of requiring subjective input from decision-makers to identify objectives and the criteria to measure how effective an alternative is at achieving the objective. One of the limitations is that they do not contrast options against the choice of doing nothing, so they cannot tell us if the cost exceeds the benefits for the array of alternatives. MCA techniques typically have a performance matrix that lists all the criteria and how each alternative performs for each one. Often these performance values will not use consistent values, but follow-up methods can convert them to a unified system. One option is to transform all values to a common scale, such as 0 to 10 or 0 to 100. Weighting is often used for each criterion to value one parameter more than another based on decision-maker input. For finite option problems, the performance matrix forms the starting point of analysis.

The first step in conducting an analysis should be to look for dominance among the alternatives. This can potentially reduce the list of viable options without needing to develop any models or create preference weights. This is quickly and easily performed after a performance matrix has been assembled. A performance matrix is a standard feature wherein the rows list the alternative, and the columns hold the value of

performance by the alternative on each criterion, an example of which can be seen in Table 1. Even binary features can be recorded in this manner.

Table 1 - A Performance Matrix (Dodgson et al., 2009)

Options	Price	Reheat setting	Warming rack	Adjustable slot width	Evenness of toasting	Number of drawbacks
Boots 2-slice	£ 18.00				☆	3
Kenwood TT350	£ 27.00	✓	✓	✓	☆	3
Marks & Spencer 2235	£ 25.00	✓	✓		★	3
Morphy Richards Coolstyle	£ 22.00				☆	2
Philips HD4807	£ 22.00				★	2
Kenwood TT825	£ 30.00	✓			☆	2
Tefal Thick'n'Thin 8780	£ 20.00	✓		✓	★	5

When selecting a technique, the number of alternatives being considered is an important factor. Some techniques are better suited to handle an infinite design space while others may be unable to adjust for that at all. As the number of alternatives and criteria increases, the amount of data that is required to be collected begins to require considerable resources to process. MCA methods primarily differ in how they handle the input data. Leveraging the peculiarities of the various methods based on the circumstances of the problem will produce the best results.

Parnell et al. (2018) provide an example of developing an infinite number of alternatives; they use set-based design (SBD) to improve upon decision-making in the Analysis of Alternatives (AoA) process that is common to the DoD acquisition life-cycle. Traditional point-based design (PBD) uses selected points in a trade space to conduct a study, but SBD differs by being able to analyze a continuum of, and potentially the entire, trade space when evaluating optimal alternatives. Visually this can be explained with Figure 1.

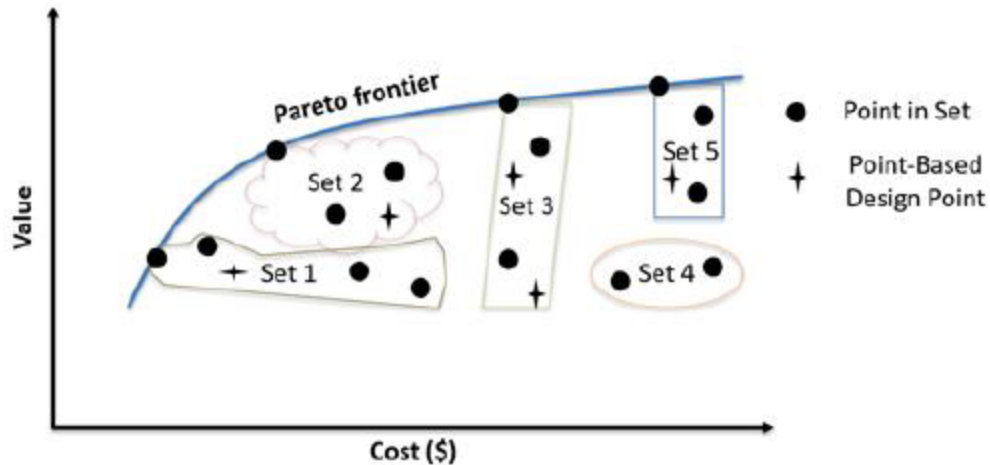


Figure 1 - SBD and PBD in a Value versus Cost Tradespace (Parnell et al., 2018)

As can be seen, there is a Pareto frontier that is described through portions of the points in a set. The main difference, and the improvement claimed by SBD, is that use of PBD, such as what might be expected in a DEA study, would generate a different, less-optimal Pareto frontier because it is not incorporating the best data possible. To facilitate the trade space study for SBD, ranges of design values are used to generate the sets. Enough information eventually allows for elimination of alternatives from consideration. Because this method generates large amounts of theoretical alternatives, use of computing systems to run simulations and calculate values is necessary in achieving results.

Decision Analysis Methods

This section provides an overview of eleven different decision analysis methods, conducted by Velazquez and Hector (2013), that have seen application to real-world problems; a brief discussion of their benefits and shortcomings is also included. More

commonly used and applied methods are focused on first before moving to less popular ones.

The most commonly used method is the Multi-Attribute Utility Theory (MAUT) method. It provides the advantage of readily incorporating uncertainty into its analysis. It has been applied to many different fields of study such as economics, energy management, and agriculture. To take advantage of MAUT, however a large amount of input and feedback from the decision-maker is required to accurately capture their preferences. Because the method relies heavily on the decision-maker's preferences, it is also susceptible to errors if those preferences are not precise.

Closely following MAUT in popularity is the AHP method. Historical applications of the AHP range from resource management to public policy, political strategy, and performance-type evaluations. One of the factors in AHP's popularity is that it is one of the easier methods to use. It is not as data intensive as MAUT and is able to scale to fit the size of the problem well. Despite its ease of use, it has several flaws that must be kept in mind. Because it relies on pairwise comparisons from the decision-maker, inconsistencies occur frequently and must be addressed before progressing. It also is unable to evaluate an alternative in isolation since it relies upon pairwise comparisons. Rank reversal, an effect in decision-making theory in which the rankings can be affected by including new alternatives or removing existing ones, is the biggest criticism that experts have with it.

Fuzzy Theory is an extension of classical set theory that excels at handling vague and imprecise inputs. Developing the rules to govern a fuzzy system can be somewhat difficult, however and often takes many iterations before it becomes useful for real-world

applications. Uses of fuzzy theory have covered engineering, management, and social problems.

Case-Based Reasoning (CBR) uses past data of similar cases to propose a solution. As a result of this, users do not have to acquire or generate additional data. CBR is sensitive to inconsistencies in the data. As cases are added to the database, the method improves over time. Because of this, it is best used in industries where there are a large number of previous cases to use as a foundational database such as vehicle insurance and medicine.

DEA is a newer method than MAUT, AHP and Fuzzy Theory but it has quickly gained popularity in areas such as economics, retail, and agriculture. DEA uses linear programming techniques to measure the relative efficiencies of alternatives. The best alternative will have a rating of 1.0 and the rest will be fractions of 1.0. This method can uncover relationships that may be hidden with other methods. It does not deal with imprecise data and assumes all data are exactly known. This leads to the results being strongly sensitive to the inputs and outputs.

MAUT, AHP, Fuzzy Theory, CBR, and DEA represented the majority of decision analysis methods, but Velazquez and Hester (2013) also looked at several less used methods. These additional methods, while less common, still have examples of their application in real-world problems. Due to their lower use rate, Velazquez and Hester's (2013) analysis of these techniques is not as in-depth.

Simple Multi-Attribute Rating Technique, or SMART, is a simplified form of MAUT that assumes criteria are both utility independent and preference independent. This means many of the advantages and disadvantages of MAUT carry over to SMART.

In addition, it allows for any weight assignment method such as relative or absolute.

Areas that SMART has been used in include military, construction, and manufacturing problems.

Goal programming selects a solution from an infinite number of alternatives. It can also handle large-scale problems; however, it is unable to weight coefficients. This can be overcome by using another method such as AHP to develop the weights. Many of the examples that elected to use goal programming did so to take advantage of the ability to choose from an infinite number of alternatives. This includes portfolio selection, scheduling, and energy planning.

ELimination Et Choix Traduisant la REalité (ELECTRE) is an outranking method based on concordance analysis. It can account for uncertainty and vagueness like with fuzzy set theory, but the results can be difficult to explain in simple terms. Due to the nature of its outranking method, the tradeoffs between choices are not explicitly defined. ELECTRE has been applied to problems in economics, water management, and transportation among other areas.

Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) is another outranking method that has had several iterations developed to handle various circumstances and provide different outputs. Examples include partial or complete ranking of the alternatives, ranking based on interval, and methods for handling segmentation constraints. It is an easy-to-use method that does not require its criteria to be on the same order of magnitude, but the method by which one assigns weights and values to the different parts of the problem is not clearly defined. Uses of

PROMETHEE include chemistry, hydrology and water management, and manufacturing and assembly.

Simple Additive Weighting (SAW) is a simple and direct method that is intuitive to decision-makers. It multiplies a criteria weight by the score for that criteria and sums the results to determine the value of an alternative. This is in essence the “classic” weighted performance problem. SAW has been used in business and financial management, but because it does not always reflect the realities of a problem, such as the results not being logical, it has seen limited wide-spread use.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) attempts to identify the alternative closest to the ideal solution and farthest from the negative ideal solution. The method is easy to use, simple, and programmable. A major advantage is that the process of using TOPSIS does not change based on the number of attributes being considered. Disadvantages include difficulty in determining weights of criteria, consistency problems, and the method does not consider correlation of criteria. Often, TOPSIS is used to confirm other Multi-Criteria Decision Making (MCDM) methods.

The many different methods explored have different advantages and disadvantages that can be exploited based on the problem being investigated. With the aid of computers in the modern day, almost any type of method can be used to solve any problem. However, oftentimes multiple methods are used in concert to overcome their disadvantages and leverage their unique benefits.

Utility Theory

Keeney and Raiffa (1976) set the foundation of the MAUT method with their work. They cover situations ranging from single attribute utility theory to multiattribute utility with uncertainty. The ability to deal with uncertainty is one of the strengths of the MAUT method over other options. Probability distributions and preference lotteries are used extensively to help determine the utility functions when uncertainty is present, but the method can also still generate value functions if there is no uncertainty.

Attributes have several properties (Keeney & Gregory, 2005). An attribute can be comprehensive if a decision-maker can understand how much an associated objective is achieved when the attribute is measured. An attribute is measurable if a probability distribution or point value can be obtained for the attribute and if the decision-makers preference for different measurements of the attribute is possible. Simplified, comprehensiveness represents the appropriateness of an attribute while measurability refers to the practical implementation of the attribute for use in assessment. Sometimes a proxy attribute, which does not directly measure an objective, must be used. Examples of proxy attributes include “profits” or “market share”, where these attributes may achieve an objective such as “power to implement decisions” indirectly.

A set of attributes should also be complete, operational, decomposable, nonredundant, and minimal (Keeney & Raiffa, 1976). Completeness means that the set of lowest-level attributes in a hierarchy include all areas of concern and the individual attributes at this level are comprehensive. An attribute is operational if the attribute is useful in helping the decision-maker choose the best alternative. A set of attributes is decomposable if the attributes can be broken down into smaller sets for assessment.

Nonredundancy refers to the case where a set of attributes does not duplicate the impact from any input. Finally, a set of attributes is minimal if it represents the smallest number of attributes that also still fulfill the other desired properties.

The concept of an involved decision-maker is very important to the MAUT method set out by Keeney and Raiffa (1976). It is necessary to involve the decision-maker in frequent feedback so that when inconsistencies in their judgements arise, adjustments that are satisfactory and representative of their preference can be made. However, care should be taken that changes are not made in order to achieve a specific result.

Mutli-Criteria Decision Analysis (MCDA) is a modified approach to MAUT. It uses the linear additive model of MAUT as its basis while assuming that the criteria are mutually preferentially independent of each other and that uncertainty is not formally built into the model (Dodgson et al., 2009). As a linear additive model, it follows the general process of scoring alternatives based on selected criteria, weighting the priority of the different criteria, and combining the weights and scores for each alternative to calculate an overall value. The method of scoring can be relative or another accepted method, then weighting is done with swing weights. Swing weighting prioritizes a criterion on both how much the criterion matters and how much the difference in its range of values matters. This means a very important criteria could still not have a large impact on the analysis if the difference between the best and worst values is very small.

Uncertainty can be handled in MCDA by using the formally defined approach in Keeney and Raiffa (1976) to use expected utility based on the probabilities of a consequence tree. If the tree becomes unmanageable due to a large amount of uncertainty

or too many possible outcomes, a bounding scenario can be constructed, and the MCDA conducted within each bound. Another option is to include a confidence criterion in the value tree that is defined as the probability that the other benefits will be obtained. Each alternative will then be scored on this criterion, and it is used as a penalty by subtracting the score from the total utility instead of adding it, representing a reduced likelihood of the benefits being realized.

Multi-attribute utility models have been applied to many problems and have been the subject of many research articles (Huber, 1974). First, studies involving the linear additive model have been used in the Air Force as early as 1963 by Madden (1963). This model takes the form

$$U = \sum_{n=1}^N b_n x_n \quad (1)$$

where U is the total utility, x_n is the score of an alternative on the n th attribute and b_n are weights determined through multiple regression. This model proved highly predictive of the utility of alternatives. Versions involving higher-order additive functions in place of x_n and interactive models that include $b_{r,s} * x_r * x_s$ terms have also seen use. These versions have seen the same success as the standard form but are less straightforward and have seen less use as a result. In summary about the linear additive models, Huber (1974) states that they have been shown to be an accurate method of prediction and that the different versions may have statistically identifiable differences but still produce similar results.

Next, studies using a multiplicative model, termed the conjunctive model, were used to review performance evaluations in medical professionals and in graduate students (Huber, Sahney, & Ford, 1969; Einhorn, 1971). This model takes the form

$$U = \prod_{n=1}^N x_n^{c_n} \quad (2)$$

where x_n is the same as for the additive model and c_n are parameters estimated using multiple regression and the log-transformed model

$$\log U = \sum_{n=1}^N c_n \log x_n \quad (3)$$

The conclusion was that the multiplicative model is roughly as accurate as the additive model, but there were significant variations identified. Other versions have been used, but they were found to be less predictive than the additive or conjunctive multiplicative model.

Since the additive models and the conjunctive multiplicative models are roughly equivalent, the user is free to choose between them on the basis of other factors. Additive models allow for direct client input for the parameters and are less sensitive to unsatisfactory x_n levels than multiplicative models. It sometimes may be the case that physical interpretations make a multiplicative model the preferred choice on a case-by-case basis.

Parameter determination can either be directly defined by the client or derived by a trained decision analysis professional. Only additive models may be defined by the client. Both additive and multiplicative models may use the method of derivation for determining parameters.

In the client explicated method, the client defines a relative satisfaction for utility values on each attribute and internal consistency is checked by the analyst. The client then ranks the attributes in order of importance with the most important attribute given a value of 1.0 and the remaining attributes are given a value between 0 and 1.0 based on their relative importance to the most important attribute. Internal consistency of the importance is checked and then the parameters may be used to determine utility. This method has the advantage of being easier for the decision-maker as well as the benefit of bringing the decision-maker into the process. The explicated parameter approach can also handle extreme nonlinear relationships.

To use the derived parameters method, the utility levels are determined first. If the values are nonlinear, then some of the additive methods of utility levels must be used. Once consistency of the utility scores is satisfied, the decision-maker should be provided with a set of alternatives that is similar to those being evaluated by the model. The decision-maker then provides his preference for each alternative on a 0 to 100 scale. This approach is the only one that adequately handles exponent parameters or when there are interaction terms in the additive model.

One example of a common utility function is the exponential utility function

$$u(x) = a + b^{-cx} \quad (4)$$

where $u(x)$ is the utility value, x is the attribute value, and a , b , and c are scaling constants. The constants a and b can be determined by setting the utility value of two consequences arbitrarily while the constant c can be found through use of lottery preferences. A lottery preference is when a decision-maker is given the choice between a

fixed consequence, x_3 , and a lottery between two other preferences, x_1 and x_2 , with each having a fifty percent chance of occurring. The value for x_3 at which the decision-maker is indifferent between the fixed consequence and the lottery is then found and by the rules of decision analysis the equation,

$$u(x_3) = 0.5 u(x_1) + 0.5 u(x_2) \quad (5)$$

must hold true. Substituting (1) into (2) and solving gives the value for the constant c (Keeney, 1982).

Gensure (2007) also elaborates on the use of utility theory. Intermediate values of attributes can be determined through the use of hypothetical lotteries that the decision-maker must choose between. These lotteries use different percentage chances of the best and worst outcomes occurring. An example would be a 70% chance of the best and a corresponding 30% chance of the worst outcomes occurring. When the decision-maker is indifferent to the lottery and the intermediate outcome being considered, then the outcome can be assigned a utility based on that lottery. This value is determined through the equation,

$$u_i = P(x_{1.0}) * u_{1.0} + P(x_{0.0}) * u_{0.0} \quad (6)$$

where $P(x)$ is the hypothetical probability of outcome x occurring, u_i is the utility of outcome i , and the subscripts 1.0 and 0.0 represent the best and worst cases, respectively. Equation (6) is more meaningful when the utility values are not scaled from 0.0 to 1.0; otherwise, the result will always be the probability of the best outcome occurring.

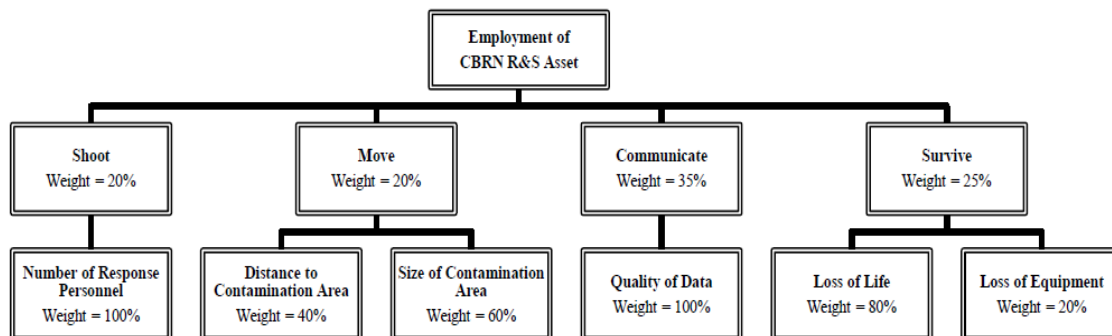
The expected utility of each option can then be calculated by multiplying the actual probability of an outcome occurring by its utility value and then summing for each

option. Whichever alternative has the highest value is then the preferred choice. This methodology only applies to a single-attribute utility function. In order to expand to more attributes, multi-attribute utility theory must be used. Gensure (2007) warns here that expanding beyond two attributes becomes increasingly complex.

Utility Theory Examples

A case study conducted on the use of Small Unmanned Aircraft Systems (SUAS) in the field for tactical Chemical, Biological, Radiological, and Nuclear (CBRN) Reconnaissance and Surveillance missions provides an example of implementing utility theory (Barnes, 2017). In conducting the case study, Barnes (2017) uses multi-criteria decision analysis to develop a decision aid for the employment of the SUAS.

First an objective hierarchy model was developed. This is seen below in Figure 2. The middle layer of this hierarchy is an example of how flexible decision analysis tools can be in defining objectives. In this case study, it represents how the decision will affect



a unit's ability to perform in these categories. Measures of effectiveness (MOE) are used to further breakdown the middle layer of categories into quantifiable units. Weights were assigned according to the author's preference.

Figure 2 - CBRN R&S Objective Hierarchy Decision Tree (Barnes, 2017)

Instead of setting the best alternatives score to be 100 and the worst score to 0 as some decision analysis methods do, Barnes (2017) establishes a threshold and objective for each MOE. This is seen in Figure 3. Setting a threshold and objective creates the potential where none of the alternatives are able to wholly fulfill an MOE. The values were determined by questioning SMEs.

MOE	Threshold	Objective
Number of Response Personnel	40	1
Distance to contamination area (time, s)	60	0
Area Covered (time, hr.)	8	0
Quality of Data	0	1
Loss of Life (USD)	\$400,000	0
Loss of Equipment (USD)	\$20,000	0

Figure 3 - MOE Thresholds and Objectives (Barnes, 2017)

The utility functions used were determined by the author on a case-by-case basis for each MOE with respect to the desirability of rate of return. Some of the MOEs used a direct return function represented by

$$y = x \quad (7)$$

others used a decreasing returns function represented by

$$y = 1 - (1 - x)^2 \quad (8)$$

and the rest used an increasing returns function represented by

$$y = x^2 \quad (9)$$

Where x is the input variable and y is the utility value.

The case study analyzed the use of three assets in two mutually exclusive scenarios. For each scenario, the assets were scored in terms of the MOEs of the decision

tree. Each alternative's total utility was then calculated using the model and could be compared to the other alternatives within the same scenario. The alternative with the highest utility score in a scenario would then be the recommended asset to use for the given scenario.

Next, a decision analytic approach based in MCDA develops a framework for evaluating Department of Defense (DoD) acquisition projects (Linkov et al., 2012). This approach allows for incorporation of the prevalent amounts of risk involved with DoD acquisitions and puts it in terms that are immediately relevant and familiar to a DoD project manager. Their framework is broken into two parts, one to analyze the likelihoods of risk realization and the other to calculate quantitative scores for the consequences of different failures to meet requirements. Combining the two parts provides a ranked list of alternatives, and an aggregate score can be generated for evaluation.

In the likelihood portion of the model, each alternative is broken down into its constituent critical technology elements (CTEs). These CTEs are given weights based on relative importance in terms of contribution to meeting requirements. Then each CTE is further broken down in terms of the likelihood that the CTE will be immature in its Technology Readiness Level (TRL), Integration Readiness Level (IRL), and Manufacturing Readiness Level (MRL). These three criteria are measured on a 1-9 scale using established measuring practices and assume predetermined cost, schedule, and performance parameters. The period that these criteria are estimated at can be chosen by the decision-maker, most likely at one of the major milestones of a program acquisition cycle such as Milestone A or B. Weights are given to these criteria to represent the

relative importance of their respective maturities to the functionality of the CTE. Finally, aggregation of the scoring can allow for comparison between CTEs or alternatives.

For the consequence model, the first two levels of the hierarchy remain the same as in the likelihood portion. The third level is composed of the differences between projected readiness levels and the required readiness levels (Δx_{RL}). The projected readiness level is determined through use of the likelihood assessment conducted in the first part. A fourth level is added to estimate the impact of immaturity to program cost, schedule, and performance. Aggregation of the scores by their weights is again done here all the way up to the alternative level.

Ranked lists can be created based on the scores for the likelihood and consequence. Additionally, multiplication of the likelihood and consequence scores produces an overall risk level for each alternative that can also be used to rank the alternatives. These scores can also be incorporated into the standard DoD risk reporting matrix to allow for a graphical representation of the performance of the alternatives.

SMARTS

Department of Defense acquisition decisions are of considerable complexity and, as such, simple heuristic methods of determining a best choice of action are not adequate (Gensure, 2007). Instead, decision-makers should use compensatory, structured decision strategy to analyze the problem and determine the best course of action. Compensatory strategies allow for trade-offs between different attributes. For example, one attribute's poor performance can be offset by exceptional performance in another area. The relative importance of each attribute influences how easily this can be accomplished.

Simple Multi-Attribute Rating Technique (SMART) is a relatively simple decision-making tool but still provides a marked improvement over non-compensatory, heuristics-based decision-making. Gensure (2007) describes an 8-step process for using SMART. Initial steps include identifying a decision-maker, the alternatives being considered, and the attributes that should be measured. Once the measurements are gathered, the lowest preferred measurement for each criterion is given a value of 0 and the most preferred measurement is given a value of 100. Intermediary values will take a value between 0 to 100 based on their relative distance between the two extremes. The decision-maker then determines the importance of each attribute by assigning weights to them. This is used in the equation,

$$S_i = \sum_{j=1}^n \omega_j s_{ij} = \omega_1 s_{i1} + \omega_2 s_{i2} + \dots + \omega_n s_{in} \quad (10)$$

where ω_j is the weight for property j and s_{ij} is the score of alternative i for property j . After completing the calculations for each alternative, sensitivity analysis should be conducted to determine how the results might change based on changes in the values and weights.

In order to compensate for situations where an attribute may be very important to a decision-maker, such as with cost or schedule, but the difference between the alternatives is small, the SMART with Swings (SMARTS) method adds a swing weighting system. The swing weight is determined by ranking the attributes from least to most preferred based on the difference between the least and most preferred values for each attribute. The least important attribute is then given a swing weight of 0 and the most important is given a swing weight of 100. Intermediate values are then assigned,

and the entire set is normalized. After generating these swing weights, the user can then return to Equation (10) and proceed as before.

Analytical Hierarchy Process

Similar to other decision analysis models, the AHP method assists the decision-maker in structuring the problem so that it can be measured and ranked based on the impacts of the parts on the system as a whole. AHP relies on the decision-maker's knowledge, experience, and objectives to set the priorities of the problem. It approaches this by testing the preference of alternatives for an attribute in a pairwise method (Saaty, 1982). The number of comparisons that must be made is related to the number of alternatives that are being compared through the relationship

$$\frac{n^2 - n}{2} \quad (11)$$

where n is the number of alternatives. AHP also has the benefit of being able to handle interdependence of elements in the system relatively easily. Primarily, it is well geared to handle additive interdependence or synergistic interdependence.

Additive interdependence occurs when each element contributes on its own, individually, but also contributes indirectly through overlapping or interacting with other elements. Total impact is easily obtained by determining the individual and overlapping portions and combining them together. It is possible to avoid using additive interdependence, however by giving a higher priority value to the element that is contributing to other elements.

Synergistic interdependence represents the adage, "The whole is greater than the sum of its parts." It occurs when the interaction of the elements is greater than the sum of

the elements. This interdependence occurs more often than additive interdependence. AHP addresses synergistic interdependence by having each criterion become an objective. Then all the other criteria are compared through the AHP process previously described to determine their contributions to the criterion in question. The result is a set of dependence weights that indicate the relative dependence of each criterion on all criteria. When synergistic interdependence occurs, it is important to include criteria that reveal the nature of the interaction. The overlapping element should be separated from its constituent parts. Difficulty in handling synergistic interdependence arises from the fuzziness of words.

While the preferences and judgements are subjective based on the decision-maker, their consistency is tested by the AHP process to ensure they are trustworthy. For example, if A is preferred to B by a factor of 2 and B is preferred to C by a factor of 3 then A should be preferred to C by a factor of 6 in order for the preferences to be consistent.

When developing a hierarchy for the AHP model, the main goal can be general in its conceptualization, such as “Good Choice for a Rocket Engine.” Further levels of the hierarchy will help bring to the forefront the relevant attributes for determining just what makes a “good choice.” It does not require substantial knowledge about the system or problem in order to structure the hierarchy either. Once the hierarchy and judgements have been determined, AHP uses a series of algebraic computations to generate an overall estimate of the relative priorities of alternative courses of action. This solution should feel correct to an experienced, well-informed decision-maker, or else they should repeat the process with adjustments to the hierarchy or judgements.

Finally, it is important to note the susceptibility of AHP to rank-reversal when alternatives are removed or new alternatives are added. Rank-reversal is not a problem that exists solely in AHP, but it has been the focus of criticism for this method (Wang & Luo, 2009). A suggested method for preventing this is to “set” all other existing relationships when comparing a new alternative to previously studied ones.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is able to handle problems with complex, and often unknown, relations between multiple inputs and multiple outputs (Cooper, Sieford, & Tone, 2000). The methodology focuses on evaluations of performance and is well suited to determining which propulsion system development choice should be made among COTS options. Many of its techniques are rooted in linear algebra and are very suited to use in programming or working within Excel. DEA evaluates the efficiency of alternatives. Efficiency is defined through the relationship,

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}} \quad (12)$$

An advantage of the DEA method is that it does not require the decision-maker, or user, to prescribe weights to the different elements of a decision analysis. DEA uses variable weights that are derived directly from the data. This has the added benefit of no longer requiring assumptions and personal judgements on the part of the decision-maker.

DEA makes use of an efficiency frontier, which describes the boundary of parameters for the best choices among alternatives, in comparison to a regression line, which can give you a relative measure of excellence or inferiority based on the deviation of a point from the regression line. Put another way, statistical regression approaches

measure a central tendency while DEA approaches determine a “best” performer and evaluate all other performances by deviations from the frontier line. This difference can lead to differences in results as well as in practical takeaways, such as in the case of where to gain improvements.

While DEA identifies the most efficient performers, it also provides insight into where improvements would need to be made for alternatives that fall below the efficiency frontier. Improvements can be realized in two different ways. The first is in purely technical inefficiency. This type of inefficiency is addressed by improving an input or output to a specified value. The second type of inefficiency is mix inefficiency. This inefficiency is fixed by adjusting the ratio of input to output.

There are several different models within DEA that provide different advantages in their approach to determining the efficiency frontier and improvements to inefficient alternatives. Broadly they are the CCR model (Charnes et al., 1978), the BCC model (Banker et al. 1984), the Additive model, and the Slacks-Based Measure of Efficiency (SBM) model. Within the CCR and BCC there exist two additional forms, the input-oriented and the output-oriented models. The input-oriented model attempts to minimize inputs while maintaining the given output levels. Meanwhile, the output-oriented model reverses that and attempts to maximize the outputs while maintaining the given input levels. The additive and SBM models avoid this need to decide between optimizing output or input by attempting to do both simultaneously. The additive model achieves this by comparing an alternative based on its direct distance from the efficient frontier and does not use the origin as a reference point. In doing so, it gains the benefit of becoming invariant to translation of the reference coordinate system; however, it loses the feature of

having a one-dimensional efficiency measurement value. If the one-dimensional efficiency measurement is important, the SBM model trades the property of translation invariance for it.

In addition to the efficiency frontier, the production possibility set represents the set of feasible criterion combinations for the problem. Clearly, many of the feasible combinations will not lie on the efficient frontier and will thus not be the optimal solution, but they nevertheless represent potential achievable combinations. By checking for dominated alternatives, which is identified by being inferior to any single other alternative in every measured respect, the number of combinations not on the efficiency frontier will be reduced.

Cooper et al. (2000) also define discretionary variables which can be varied at the command of management or some other decision-maker. Non-discretionary variables, however, may be outside the control of the decision-maker but still have an impact on the optimal decision. The non-discretionary portion of a problem is not optimized since it is unable to be controlled, but it is included in the constraints of the linear problem. It is in this constraints portion that the non-discretionary variables exert their influence upon the remainder of the problem.

Cost and Schedule Estimating

There are existing cost estimating relationships (CERs) for satellite development and manufacturing. CERs developed for larger satellites, which are usually weight-based, do not scale down for small satellites so new models that focus on SmallSats were developed by organizations in the industry. The Parametric Satellite Sizing Model used

by the U.S. Air Force Space and Missile Systems Center (SMC) in coordination with the Operationally Responsive Space Office (ORS) was developed by Air Force Cost Analysis Agency (AFCAA), the Small Satellite Cost Model (SSCM) was developed by The Aerospace Corporation, and the Demonstration Satellite Cost Model (DSCM) was developed by the National Reconnaissance Office (NRO) (Broder et al., 2010).

The SSCM takes traditional satellite CERs as its starting point but focuses on small satellites of <1,000 kg total mass, including fuel, for its database foundation. A wide range of missions are included as well, including civil, military, and educational. This creates a competing set of objectives as some missions will be more risk tolerant and others will have more management overhead. SSCM is able to generate estimates at the subsystem level split into recurring and non-recurring costs. Recurring costs represent costs attributed to manufacturing while non-recurring costs are attributed to the development of the system. Risk is incorporated through user understanding of the technical difficulties anticipated during development and the Foram Risk Assessment of System Cost Estimates (FRISK) from The Aerospace Corporation creates a cost distribution. In order to improve its estimation abilities compared to large-satellite cost models, SSCM allows for other parameters besides weight to be used to develop an estimate. Because there does not yet exist enough data to filter by mission type, careful review of the data must be performed to trim data points that do not fit trends so long as there is a valid reason for the removal. Unfortunately, SSCM found that extremely low mass satellites (<100 kg) did not follow the same trends as larger small satellites so now there are two sets of CERs: one for satellites between 100 kg and 1,000 kg, and one for micro satellites, defined as <100 kg.

The DSCM pursues a different focus from the SSCM; it identifies that programs pursuing new missions and prototype technologies do not follow the trends of satellites with established requirements and users. While recognizing that small satellites have been aggressively used in the realm of demonstration missions, the NRO Cost Analysis Improvement Group (CAIG) designed DSCM to include not only small satellites but also expand the scope to look at larger satellites that have an experimental mission. In addition to satellites less than 1,000 kg, the DSCM uses data from NRO programs up to 6,000 kg to create a parametric model. In addition to subsystem cost estimates, it also includes an estimating relationship for schedule, which is measured from authority to proceed to launch. The subsystem CERs use weight and sometimes a technical parameter related to the subsystem to generate its estimate. As an additional measure of appropriateness, the DSCM model was compared to the standard CERs used for larger satellites; it was discovered that as weight increases the savings of a high-risk posture demonstration program begin to be equal to an operational satellite. A final finding was that the majority of savings in demonstration satellite programs occurred in the systems engineering and integration portion of the budget.

AFCAA attempts to develop a model using only minimal concept-level inputs. It uses the DSCM CERs while also attempting to develop a sizing estimate based on mission parameters. By developing a sizing parametric estimation model, a mission that is in its conceptual stage can be sized and the sizing can then be applied to the DSCM CERs for a cost estimate. Data sources that were used to build the parametric model came from numerous organizations and academic texts.

Summary

In this chapter, a variety of different MCDM were reviewed. After discovering the different options available for decision analysis problems, a detailed review of promising methods for the research topic were explored. Highlighting the strengths and weaknesses of the methods as well as the basis for their application provide guidance in selecting methods for use in this research. Cost and schedule estimating methods and normalization techniques are other tools that are required, so reviews of additional articles covering these were performed.

III. Methodology

This chapter describes the application of the different decision analysis tools used and the metrics by which these tools will be evaluated. First, the selection of criterion to be used in measuring technical performance is described. Then the database used is presented, along with its limitations and assumptions. Then implementation of SMARTS from the generation of an objective hierarchy model to the weighting method is detailed. Next, a similar description of AHP is conducted. Finally, the additive DEA model, linear programming equations used, and reasons for input and output selection are given.

Criterion Selection

Though each model may develop weights and perform their analysis in different ways, they each need to use the same set of criteria when evaluating the alternatives. This provides a common basis for consideration. Selection of criteria also signal what is important in determining the goal of the analysis. In this case the goal is to select the best acquisition strategy for a CubeSat propulsion system. Cost, schedule, and performance are the standard trifecta used by project managers as their trade space in a project. Cost is measured in U.S. dollars and schedule in months. Performance requires further deconstruction to reach measurable criteria. Discussion with subject matter experts (SMEs) narrowed the performance criteria to the nominal thrust, specific impulse (I_{sp}), dry mass, and power required for the propulsion system. Additional criteria were also considered but not used in this sublevel. One of these criteria is volume of the propulsion system. It is desired that the propulsion system be smaller than 100mm x 100mm x 140mm. However, this is a binary requirement; there is no additional value gained from

being smaller than that. In a situation like this, the criteria would be best used as a pass/fail criteria. These are useful in evaluating whether an alternative is suitable for further consideration.

Database

The CubeSat project team has already conducted a trade study of different vendor offerings for propulsion systems. Appendix A lists all the data collected for each alternative considered. For this thesis, some of the original alternatives that were considered in the trade study were removed. Cognitive science has shown that going beyond nine elements overloads a person's working memory capacity (Mu and Rojas, 2017). This provides a pressing need to trim the original data set down to something manageable. For the AHP, a high number of alternatives creates an impractically large number of comparisons that need to be made. Even at 9 alternatives, the AHP will require the decision-maker to make over 225 individual preference judgements. The first alternatives removed were those that did not have existing data for the criteria selected. Next, alternatives that were dominated by other alternatives already present in the study were removed. Lastly, three of the alternatives were variant configurations of each other, representing a class, or family, of alternatives. The performances of the three alternatives were all similar, but different enough to avoid a strict dominance by any single one of them. A single representative was selected from the class. Selecting between them was determined based on a simple and quick analysis of their performance on the selected criteria.

Specifically, three alternatives were identified for the Micro Propulsion System family: the (New) Standard Micro Propulsion System (NSMPS), the Standard Micro Propulsion System (SMPS), and the EM Standard Micro Propulsion System (EMSMPS) alternatives. The SMPS was dominated by its successor variant, the NSMPS in every criteria except for cost, where the NSMPS was only slightly more expensive, so the SMPS was dropped for consideration. To decide between the NSMPS and EMSMPS, a count of the criteria that each alternative was better at, with no consideration to the magnitude of the difference, was conducted. The NSMPS was better on three criteria while the EMSMPS was better on two, so the EMSMPS was dropped from consideration.

The final list includes alternatives that may not be viable based on mission requirements, but they are still being considered in the analysis. Even though they do not meet requirements, such alternatives provide a broader understanding of what performance levels are capable of being achieved by current industry abilities. If a non-viable alternative is identified as being optimal in any of the models, the organization can consider asking the manufacturer to modify the identified alternative to meet requirements. If the manufacturer agrees, the analysis may be performed again to see how the modified product compares to other options.

Schedule data was not included in the trade study that was conducted. An assumption is made at this point that vendors will generally provide their product within a similar time frame. Review of some of the vendors product guides estimates an approximately 12-month lead time for product delivery (Cuero Aerospace, 2021). The unit will then need to be integrated into the system. A triangular probability distribution was used to provide uncertainty into the integration process. Nasa's CubeSat 101 (2017)

advises between 1-6 months of time for CubeSat design. It does not have an explicit duration for integration only, but the activities are similar enough to design development that the values for that were used. However, since these products do not need to be designed, only integrated, 2 months was selected as the most likely and 1 and 6 months were used as the minimum and maximum values.

The bespoke design alternative is a theoretical alternative and so it does not have any pre-existing performance values; instead they must be generated. It is assumed here that any purpose-built system will meet the performance mission requirements as part of the nature of a custom design. It is also assumed that the design team will not push to improve the design on a criterion once it has met the mission requirements. This leads to the use of the mission requirements as the bespoke design's performance specifications. However, mission requirements do not define all the criteria that have been selected for evaluation; I_{sp} must still be generated. I_{sp} is defined as total impulse divided by propellant weight. Total impulse is a mission requirement so that value is already defined and is used in the subsequent calculation. Propellant mass is not a mission requirement, but data on that parameter was collected for the trade study and a probability distribution for it is generated. Once again, a triangular distribution is utilized where the most likely value is the average of the different propellant masses in the trade study of Appendix A. Similarly, the minimum and maximum values match the highest and lowest values from the trade study.

NASA's CubeSat 101 (2017) again provides guidance for estimating the schedule. The same design schedule range of 1-6 months is used as with the COTS schedule estimate, but the triangular probability distribution uses a most likely value of 4

months instead of 2 to represent a higher degree of uncertainty associated with the task. Instead of only looking at the CubeSat design length, hardware fabrication and testing must also be included in the estimate. The estimated duration for this activity is 2-12 months. A triangular distribution with a most likely of 8, minimum of 2, and maximum of 12 is chosen to model this schedule uncertainty. The overall schedule duration for the two activities is an addition of the two probability distributions. This gives an estimate of 11 months as the mean value for schedule. The cost estimate uses the DSCM CER for propulsion to provide an estimate based on the mass of propellant used. Selection of the DSCM model was due to availability and appropriateness for the case study. Newer versions of the SSCM include more small satellite data, but the model is not publicly releasable. Older versions such as that published in the SME:SMAD by Wertz et al. (2018) do not include sufficient data on small satellites to be functional for the case study. The DSCM CERs shown in Appendix B are published in the journal by Broder et al. (2010) and the largest portion of its foundational data is from small satellite programs (<500 kg).

Simple Multi-Attribute Rating Technique with Swing Weights

SMART analysis typically covers the nine steps listed below (Olson, 1996).

1. Identify the decision-maker
2. Identify the issue
3. Identify the alternatives
4. Identify the criteria
5. Assign values for each criteria

6. Determine the weight of each of the criteria
7. Calculate a weighted average of the values assigned to each alternative
8. Make a provisional decision
9. Perform sensitivity analysis

For step 1, there were several potential decision-makers that could be selected. The decision-maker will shape many aspects of the analysis, from the goal to the weights, values, and criteria selected. Selection of a decision-maker should be done with the nature of the decision to be made in mind. An executive level decision should have an executive level decision-maker, while a routine task should select a low-level manager equivalent. Since this model's intent is to inform a subsystem-level decision for a project, the project manager of the CubeSat project was identified as the decision-maker.

Step 2 was determined by the selection of the thesis topic, which was the identification of an optimal acquisition strategy for a CubeSat propulsion system. This leads to step 3: identifying the alternatives. Staff on the project had previously conducted a trade study of propulsion systems from various commercial vendors, which is listed in Appendix A. An independent search was also conducted but found that the trade study captured the majority of products available. In addition to the commercial vendor alternatives, a bespoke (or custom) design by the project team was included as a viable alternative. The final identification step is to select criteria for evaluating the alternatives. The criteria selection section earlier in this chapter details the criteria selection process.

A key assumption is that the criteria selected are all mutually independent. Specifically, it is assumed that they are both preferentially independent and utility independent. This is a critical assumption to simplifying the MAUT model from an n -

attribute utility function to n single-attribute utility functions (Keeney & Raiffa, 1976). By leveraging this simplification, the SMARTS method may be used (Velazquez & Hector, 2013). These single-attribute utility functions can be then be assessed independently. While this assumption may not strictly hold to be true, Keeney and Raiffa (1976) explain that intentional use of nested multi-attribute functions can ease the restrictions necessary for these conditions to exist.

Once the framework of the problem has been assembled through the first four identification steps, the process can begin to assign scores. All the criteria selected are quantitatively measurable. However, the values cannot be directly used; they need to be normalized to a common measuring system, otherwise the difference in magnitudes will prevent comparison. For example, \$1,000,000 and a mass of 2 kg cannot be compared directly. In order to normalize values for each criteria, the best value is given a score of 1 while the worst value is given a score of 0. A linear approximation can be used for the value functions as long as the functions do not have a high degree of curvature (Edwards & Barron, 1994). Such curvature would indicate that for a set amount of a criterion it would have more or less value depending on where in the range it was added. A conservative rule of thumb proposed by Edwards and Barron (1994) considers the ratio of how desirable small improvements are at either end of the value function. If the desirability ratio is less than 2:1, then linear approximation is appropriate. For example, suppose a small reduction in power for the propulsion system is more desirable at the bottom of the function; as long as the same amount of power reduction is not twice as desirable to the decision-maker as when applied at the top of the function then the linear approximation may be used. If a linear approximation is not appropriate then, based on

decision-maker inputs, a different utility function that matches their preferences should be used. Barnes (2017) provides examples of two other functions he calls risk averse and risk taking.

The linear functions can be stated as follows. If the score of the criteria should increase as its value increases the function is,

$$y = x \quad (13)$$

Where x is the score of the alternative on the given criterion and y is the utility value. If, on the other hand, the score of the criteria should decrease as its value increases, then the function should be,

$$y = 1 - x \quad (14)$$

For a risk averse function, if the value increases as the score increases, it will exhibit increasing returns through the equation,

$$y = x^2 \quad (15)$$

If value decreases as the score increases then the risk averse function will be,

$$y = (1 - x)^2 \quad (16)$$

For a risk-taking function, if the value increases as the score increases, it will exhibit decreasing returns through the equation,

$$y = 1 - (1 - x)^2 \quad (17)$$

If value decreases as the score increases then the risk-taking function will be,

$$y = 1 - x^2 \quad (18)$$

In order to use these functions, the data needs to be translated. To achieve this, Barnes (2017) recommends that the range of values from worst to best needs to equal 1. To find any intermediate value the equation,

$$x = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (19)$$

will be used, where x_i is the original mass value of the alternative selected, x_{min} is the minimum mass among the alternatives, and x_{max} is the maximum mass among the alternatives.

Based on decision-maker preferences, schedule and dry mass should use a linear function. Because they exhibit higher utility for lower scores, Equation (14) is used to determine intermediate utility scores. Power, nominal thrust, I_{sp} , and cost should use a risk averse, or increasing returns function. Nominal thrust and I_{sp} exhibit increased utility for higher scores, so they will use Equation (15). Power and cost exhibit increased utility for lower scores, so they will use Equation (16).

Once the alternatives have been scored on the criteria, the next step is to determine the swing weights for the criteria (Gensure, 2007; Edwards & Barron, 1994). Swing weights ensure that only meaningful differences between alternatives are considered. They help the decision-maker to make evaluations not only on the preference of criteria but also on the range of values between alternatives for each criteria. Even if a criteria is identified as being very important by the decision-maker, if there is no meaningful difference between the alternatives on that criteria, it should not have a large impact on the decision. For example, even if schedule is a very important criterion for a

project, if all the alternatives have an estimated delivery that is similar, then the schedule criterion would not have a large swing weight due to the lack of meaningful difference among the alternatives.

This is done through direct elicitation from the decision-maker. A two-part process is used to determine the swing weights. First the decision-maker is asked to determine which swing is deemed the most important. To help conceptualize this, a scenario is posed to the decision-maker: "Imagine that you are required to purchase a propulsion system with the worst value for each attribute. Now, if you were allowed to improve one attribute from its worst value to its best value, which one attribute would you improve?" Repeated use of this process, while assuming the previously selected attributes are fixed at their worst values, determines a ranked order of the attributes. Next, the highest ranked attribute is given a weight of 100 and the lowest ranked attribute is given a weight of 0. To determine the weight of the intermediary attributes, the decision-maker must evaluate them on this scale from 0 to 100. The weights are then normalized by summing them, dividing each weight by the total, and multiplying by 100 so that they sum to 100, which is step 7.

Determining the preferred option is performed by summing the criteria scores by their swing weights for each alternative as shown by the equation,

$$S_i = \sum_{j=1}^n w_j s_{ij} = w_1 s_{i1} + w_2 s_{i2} + \dots + w_n s_{in} \quad (20)$$

where S_i is the total score for alternative i , w_j is the weight for criteria j , and s_{in} is the score of alternative i on criteria j . Whichever alternative has the highest score will be the most preferred. Because the data set used for this analysis could include non-viable

alternatives, the decision-makers should determine whether the most preferred alternative meets mission requirements. If it does, then they can accept it at that point. However, if it does not, they have two options they may pursue. The first option is to discard the alternative and examine the second most preferred alternative to determine whether it meets mission requirements. Alternatively, they could contact the vendor of the alternative and discuss the ramifications of altering the product to meet mission specifications. If the second option is selected, effectively a new alternative has been generated. If it does not clearly dominate the competition, the analysis should then be repeated.

An application of sensitivity analysis to this SMARTS method will allow for an exploration of possible weights independent of each other. Butler et al. (1997) recommend using randomly generated weights to fully explore a high-dimensional multi-criteria decision model. The random weights can be assigned randomly to the criteria, or the random weights can be applied in descending order from most important criteria to least. The latter method is useful if there is some confidence in at least the rank of the criteria if not in the exact values used. Further justification of a rank-order application can be seen in the development of the SMARTER method (Edwards & Barron, 1994). To apply the rank-order method, a set of $n-1$ random values on a uniform distribution (0,1) are generated, where n is there number of attributes. The weights are then defined through the set of equations,

$$k_n = 1 - r_{(n-1)}, \quad (21)$$

$$k_{n-1} = r_{(n-1)} - r_{n-2},$$

⋮

$$k_1 = r_{(1)} - 0$$

where r_n is a randomly generated number and k_n is a weight. In the n -dimensional solution space that defines which alternative is most preferred for any combination of criteria weights, ordering these weights from largest to smallest and then applying them to the criteria in order from most important to least will explore a constrained portion of the entire solution space.

Analytical Hierarchy Process

The AHP is a commonly used decision analysis tool. At a high level, it can be broken down into two distinct tasks: modelling the problem as a hierarchy and establishing priorities within that hierarchy. It allows for the integration of data with subjective judgements (Saaty, 1982). For best results, those subjective judgements should be from experts on the topic. While subjective judgements may initially cause concern, the method also provides for a way to perform a consistency check of the judgements. To develop the analytical hierarchy, the overall objective must first be identified. The objective in this research topic is to select a propulsion system. Subsequent levels contain the criteria considered important in making this selection. The criteria selection method previously discussed helps guide the creation of this part of the hierarchy. The first level of criteria was identified as the three primary aspects of a program manager's trade space: cost, schedule, and performance. Performance requires further decomposition into the measurable criteria mentioned earlier: dry mass, power, I_{sp} , and nominal thrust. At the bottom of the hierarchy resides the alternatives. Figure 4 shows this hierarchy. To prevent

unnecessary clutter in the hierarchy due to the high number of alternatives, they are not listed individually.

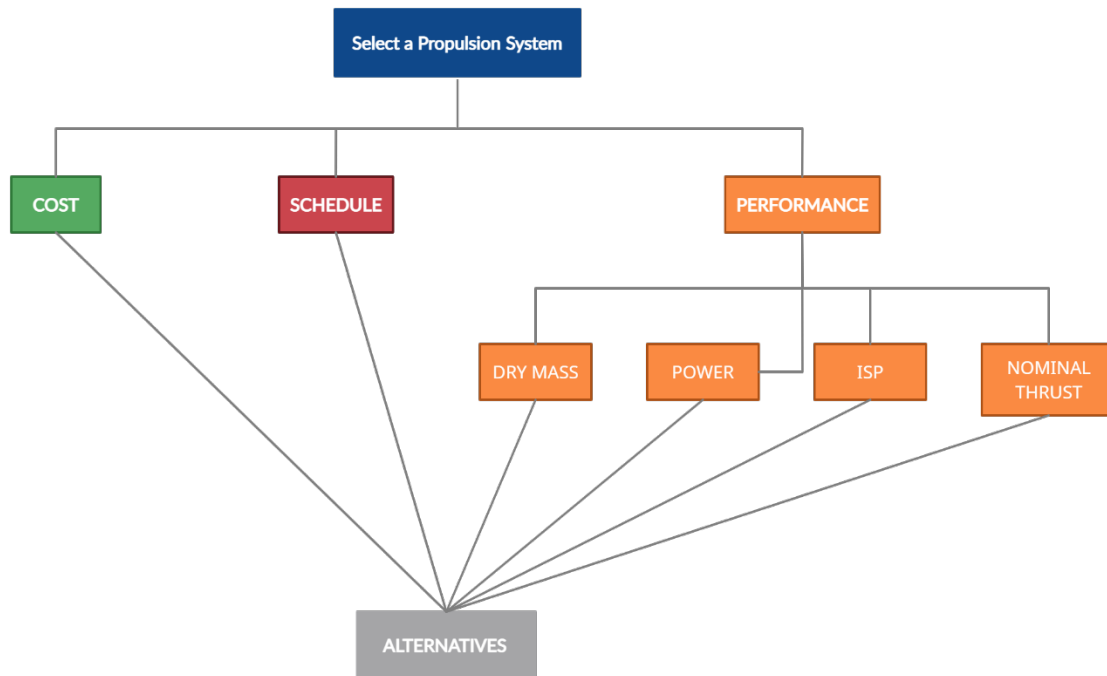


Figure 4 - Propulsion System Selection Hierarchy

The next step is to establish the preferences for the criteria and alternatives which gives it the distinctive trait of pairwise comparisons. The criteria must be compared with each other to determine relative preference; then alternatives are compared in pairs against a given criterion. To establish the relative preferences, the decision-maker is asked to score their intensity of preference for one of the two elements being compared.

For example, the decision-maker may prefer cost over schedule by a score of 4. Scoring uses the values 1-9, the definitions for which can be seen in Table 2.

Table 2 - Comparison Intensity Scale (Saaty, 1982)

Score	Intensity of Preference
1	Equal importance of both elements
3	Weak importance of one element over another
5	Strong importance of one element over another
7	Very Strong importance of one element over another
9	Extreme importance of one element over another
2,4,6,8	Intermediate values between two adjacent judgements

The standard way of tracking this data is through a comparison matrix - see Table 3 for an example. Scores indicate the strength of preference for the element in the row when compared with the column element. Every element is equal in preference to itself, so the diagonals of the comparison matrix are always equal to 1. When filling out the matrix, a dominated element receives the reciprocal of the score given to the more preferred one. For example, in Table 3 Lincoln is preferred over the Chevrolet by a score of 4; therefore, the Chevrolet receives a 1/4 score for its comparison to the Lincoln. These comparisons are done separately at every level: once for cost, schedule, and performance; then, again for the performance sub-criteria (i.e., dry mass, power, I_{sp} , and nominal thrust); and finally, for the alternatives based on their performance on the

different criteria. Table 3 provides an example of alternatives compared on a criterion and Table 4 shows a matrix of criteria compared on a higher-level objectives.

Table 3 - Example Alternative Comparison Matrix (Saaty, 1982)

<i>Comfort</i>	C	T	L
Chevrolet (C)	1	1/2	1/4
Thunderbird (T)	2	1	1/2
Lincoln (L)	4	2	1

Table 4 - Example Criteria Comparison Matrix

<i>Best Car</i>	C	Sp	Sf
Comfort (C)	1	1/4	1/7
Speed (Sp)	4	1	1/3
Safety (Sf)	7	3	1

Once the pairwise comparisons have been completed, they need to be combined to set the overall priorities; this combination process is called synthesis (Saaty, 1982). The first step in synthesis is to normalize each matrix. Each column of the matrix is totaled, then every entry in that column is divided by the total. The rows of the normalized matrix are then averaged to produce the vector priorities for that matrix. Then, an overall vector of priorities is obtained by multiplying each alternative's priority on a given criterion by the priority of that criterion and summing for all criteria, resulting in the following equations for the case study,

$$S_i = \sum_{j=1}^3 w_j s_{ij} \quad \text{for } i = 1, \dots, 9 \quad (22)$$

$$S_{i,perf} = \sum_{k=1}^4 w_k s_{ik} \text{ for } i = 1, \dots, 9 \quad (23)$$

where S_i is the total priority score for alternative i , w_j is the preference weight for criteria j , and s_{ij} is the priority score for alternative i on criteria j . Equation (22) is applied at the objectives level (cost, schedule, and performance), while Equation (23) is applied at the performance subcriteria level (dry mass, power, I_{sp} , and nominal thrust). Equation (23) is necessary because the decision-maker does not evaluate the alternatives directly on the performance objective ($s_{i,perf}$).

For example, if an alternative, A , was found to have a priority of 0.2 on criterion X , and criterion X was found to have a priority of .3 within its criteria level, then the priority of A derived from X would be $0.2 \times 0.3 = 0.06$. This same process would be repeated for A on the remaining criteria and the resultant values would be summed. Based on the structure of the hierarchy in Figure 4, the vector of priorities for the performance sub-criteria are multiplied by the value of the performance criteria in the higher-level vector of priorities. Using the previous example, if criterion X was a member of the sub-criteria for performance then the priority of performance, P , would need to be known. The priority of A derived from X would then equal $0.2 \times 0.3 \times P$. The largest number in the overall vector of priorities is the most preferred alternative. As with SMARTS, a review of the viability of the preferred option should then occur.

The AHP also possesses a means of checking the consistency of the judgements made in the pairwise comparison through a value called the consistency ratio (CR). To calculate the CR, first multiple the columns in a matrix by their relative priorities. The first column would be multiplied by the relative priority of the first row, the second

column by the second row, and so on. These values are then summed by row. Using Table 3 as an example if the relative priorities were Chevrolet at 0.13, Thunderbird at 0.21, and Lincoln at 0.66, then the matrix would look like Table 5.

Table 5 - Consistency Matrix Calculations (Saaty, 1982)

<i>Comfort</i>	C (.13)	T (.21)	L (.66)	Row Total
Chevrolet (C)	0.13	0.11	0.17	0.41
Thunderbird (T)	0.26	0.21	0.17	0.64
Lincoln (L)	0.52	0.84	0.66	2.02

Next the row totals that were obtained are divided by the priority values for that matrix. In Table 5 the row total for Chevrolet of 0.41 would be divided by 0.13, the Thunderbird 0.64 value would be divided by 0.21, and the Lincoln 2.02 value would be divided by 0.66. These new values are then averaged to find λ_{max} , which is the principal eigenvalue of the matrix. The eigenvalue is used to find the consistency index (CI) through the equation,

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (24)$$

where n is the dimension of the comparison matrix. CI is compared to the random value index (RI) which describes what the CI would be if random values were selected for the matrix. RI is a pre-determined value based on the dimension of the matrix, shown in Table 6.

Table 6 - Random Index Values (Saaty, 1982)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Finally, the CR is calculated by dividing the CI by RI,

$$CR = \frac{CI}{RI} \quad (25)$$

The CR should be 0.1 or less. When the CR rises above 0.1, the preferences should be re-evaluated (Saaty, 1982).

However, failure to meet the consistency check is not grounds for immediate rejection of the data. Examples of completely logical preferences that fail a consistency check can be constructed. Thus, an alternative way is needed to evaluate comparison matrices that fail the consistency check (Stanislov and Rosenbloom, 1999). Using the application of control charts (also known as Shewhart charts), which measure whether a process is under control, a rolling average of the CI values is computed and used to check for anomalous values among the CIs. For N comparison matrices, the rolling CI average, $CI_{a,i}$, is computed by the equation,

$$CI_{a,i} = \frac{CI_i + CI_{i+1} + CI_{i+2}}{3}; \quad i = 1, \dots, N - 2 \quad (26)$$

and has a range R_i of

$$\text{maximum}\{CI_i, CI_{i+1}, CI_{i+2}\} - \text{minimum}\{CI_i, CI_{i+1}, CI_{i+2}\} \quad (27)$$

The averages of averages are computed by the equations,

$$\underline{CI} = \sum \frac{CI_{a,i}}{N - 2} \quad (28)$$

$$\underline{R} = \sum \frac{R_i}{N - 2} \quad (29)$$

Control limits are constructed from these values with the equation,

$$\underline{CI} \pm 2.19\underline{R} \quad (30)$$

If a CI falls outside of these control limits, then the matrix is considered “out of control” and an inconsistent preference or mistake has likely occurred in its completion.

Sensitivity analysis of the solution is performed using a One-At-a-Time (OAT) approach which varies the criteria weights (priorities) individually by a specified percentage amount (Chen et al., 2010). For the case study, this sensitivity will be performed at the first criteria level which includes cost, schedule, and performance. There is no guidance on what constitutes an “acceptable” percentage change to use, so it is left to the preferences of the decision-maker to determine what level to test at. The reviewed literature used a 20% percent change in weights (Chen et al., 2010) and that value is used in this research’s sensitivity analysis. To determine what the new weight value should be, the equation below is used.

$$w_{j,new} = w_{j,old} + w_{j,old} * pc \quad (31)$$

where w_j is the weight of the j th criterion and pc is the percent change selected.

Additionally, the other weights must be adjusted to maintain the condition that they sum to 1. This is done through the equation,

$$w_{k,new} = (1 - w_{j,new}) \frac{w_{k,old}}{1 - w_{j,old}} \quad k \neq j, 1 \leq k \leq n \quad (32)$$

The vector of priorities is then computed as normal using the new weight vector and evaluated for any changes in the most preferred option. The weights are then set back to their original values and the process is repeated other criteria.

Data Envelopment Analysis

DEA determines a set of optimal weights for each alternative that is being considered. One major benefit of this is that the method does not require decision-makers to provide their preferences for criteria or alternatives. All that is required for DEA to work is the data set that is under consideration.

There are a number of different DEA models to select from depending on what sort of evaluation is desired. Some models attempt to minimize the inputs while keeping output levels constant; others attempt the reverse by keeping input levels at no more than the amount given while maximizing outputs. Models may also assume different returns to scale (RTS). Deciding among these options requires a review of the environment in which the analysis is being conducted.

First, the criteria need to be identified as inputs or outputs. A general rule of thumb to assist in identifying inputs from outputs is that inputs are values that should be minimized while outputs are values that should be maximized. Using this concept, the inputs of the problem are quickly identified as cost, schedule, dry mass, and power. This leaves I_{sp} and nominal thrust to function as the outputs of the problem.

Input-oriented models are better suited to operation and management problems (Cullinane et al., 2005). It is desirable for an organization to minimize the cost and schedule associated with purchasing or designing a propulsion subsystem, which provides the basis for an input-oriented approach. On the other hand, an output-oriented reason is that an organization would like to get the most output from a given cost and schedule budget. Considering that educational and research organizations usually have tight financial constraints, the input-oriented model is selected for implementation.

A selection of RTS is now needed to further identify which model should be utilized. Figure 5 helps to illustrate different RTS shapes. A constant return to scale (CRS) is shown in the top-left and reflects the situation where the output gained for a specified amount of input does not change, charting as a straight line in the graph. A variable return to scale (VRS) is in the top-right and shows the case where initially more output is gained for a specified amount as seen in the increased slope of the line. It levels off at CRS before finally there is a decreasing amount of output gained for a specified amount of input as seen in the lower slope of the line at the end. The remaining two shapes illustrate when there is no increasing return to scale and no decreasing return to scale, which removes the respective slope from the graphs.

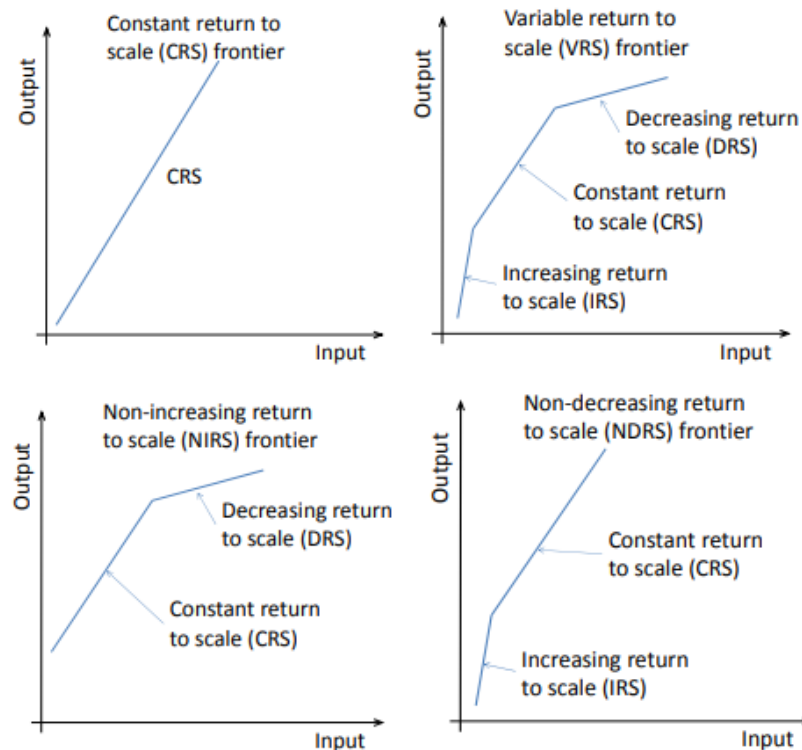


Figure 5 - Different RTS (Hui & Wan, 2013)

There is significant literature dedicated to RTS analysis (e.g., Seiford & Zhu, 1999; Cooper et al., 2000; Banker et al., 2004), but a practical concern for the case study will drive selection of the CRS option. Generally, CRS returns lower efficiency values than VRS, resulting in a smaller set of efficient alternatives (Cooper et al., 2000). To provide the best results, it is desired that the dataset follows the relationship,

$$n \geq \max\{m * s, 3(m + s)\} \quad (33)$$

where n is the number of alternatives, m is the number of inputs, and s is the number of outputs. This is due to the fact that degrees of freedom increase as alternatives increase but decrease as inputs and outputs increase. When this relationship is not held, DEA can still be applied but some of the value in the analysis is lost as discrimination among the efficient alternatives is reduced. Since the dataset used for the case study has 9 alternatives, 4 inputs, and 2 outputs, it does not meet this relationship constraint. The more stringent method can help to alleviate some of the loss in discrimination.

Now that the orientation and RTS have been determined, a model that operates under those conditions can be identified. The CCR-I method is a model that is both CRS and input-oriented, so it is selected for evaluating the dataset. Cooper et al. (2000) describe the implementation of the CCR-I model for n alternatives as follows. For a specific alternative, i , the fractional programming problem below must be solved,

$$\max \theta = \frac{\sum_{k=1}^s u_k y_{ki}}{\sum_{j=1}^m v_j x_{ji}} \quad (34)$$

$$\text{subject to} \quad \frac{\sum_{k=1}^s u_k y_{kl}}{\sum_{j=1}^m v_j x_{jl}} \leq 1 \quad (l = 1, \dots, n) \quad (35)$$

$$v_j, u_k \geq 0 \quad (36)$$

where θ is the efficiency value for alternative i , u_k is the output weight of output criterion k , y_{ki} is the value of alternative i on output criterion k , v_j input weight of input criterion j , and x_{ji} is the value of alternative i on input criterion j . Equation (35) provides a normalizing condition to the system, while Equation (36) ensures that the weights are strictly positive.

The fractional program is then converted to the following linear program which is still subject to Equation (36),

$$\max \theta = \sum_{k=1}^s u_k y_{ki} \quad (37)$$

$$\text{subject to} \quad \sum_{j=1}^m v_j x_{ji} = 1 \quad (38)$$

$$\sum_{k=1}^s u_k y_{kl} \leq \sum_{j=1}^m v_j x_{jl} \quad (l = 1, \dots, n) \quad (39)$$

This linear program can then be solved through linear solver tools, optimizing the weights for every alternative to determine the maximum efficiency it can achieve.

DEA solver software is widely available in free and premium forms. They perform the linear problem solving and return the efficiencies and other useful information such as the reference set for inefficient alternatives. This research used DEA Frontier Free (Zhu, n.d.) which operates in all versions of Microsoft Excel from version XP and onwards. Data was structured according to the format shown in Figure 6.

Note that DMUs stand for Decision Making Units and are synonymous with alternatives for this research. Once the data has been properly formatted, the software asks several prompts to determine which method will be performed. To use CCR-I, the selections should be “Envelopment Method,” “Input-Oriented,” and “CRS.”

	A	B	J	R	S	W	Z
1	DMU Name	Input Measure	Input Measure		Output Measure	Output Measure	
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17							
18							
19							
20							
21							
22							
23							
24							
25							

Figure 6 - DEAFrontier Free Data Format (Zhu, n.d.)

There are many methods of sensitivity analysis that can be conducted for DEA (Cooper et al., 2000). Options include simulation methods, algorithmic methods, and metric approaches. Simulation methods add or remove criteria and alternatives from the model and observe the effects. Algorithmic methods analyze the change of the inverse matrix that is used in solving simplex computer algorithms. Metric approaches compute a radii of stability based on distance from the efficient frontier. This research applies a simulation method, due to the ability to replicate the procedure without needing a DEA

expert to apply it. The simulation method used will sequentially remove the four input criteria one at a time and observe the changes in efficiency values that are calculated.

Composite Results

If the different methods do not agree on a preference ranking of the alternatives, then the results must be combined. A Borda counting method is used for the rank ordered methods (Borda, 1784). In this method, since there are nine total alternatives, the alternative ranked first for each of SMARTS and the AHP receives a score of 9, second most preferred will receive a score of 8, and so on. For DEA, the efficiency scores of the alternatives will be ranked in descending order from 1.0, with the alternatives that were identified as 1.0 receiving a score of 9. The next highest efficiency score would receive a score of $9-n$, where n is the number of alternatives that received a 1.0 efficiency. The best possible score an alternative could receive would be 27, which represents it being the most preferred alternative on SMARTS and the AHP as well as having an efficiency score of 1.0.

Summary

The techniques involved in using three different decision-making tools are described in this chapter. SMARTS uses a linear-additive utility weighting system to evaluate the total utility of an alternative on the selected criteria. Both the importance of the criteria and the range of values are necessary to determine the weights. The AHP uses pairwise comparisons to obtain the strength of preference between criteria and for alternatives on a given criterion. This is synthesized to provide a total vector of priorities. Additionally, the consistency of the judgements can be checked to provide increased

confidence. DEA determines a Pareto (or efficiency) frontier by optimizing each alternative with its own set of weights. Sensitivity analysis techniques for the different methods are also discussed.

IV. Analysis and Results

In this chapter the results of the three different decision analysis methods described in Chapter III are presented. Insight and characterization of the results are also provided which helps to describe the underlying reasons for a preference being valued higher than another. Additionally, sensitivity analysis is performed for each method to provide a measure of stability for the results.

SMARTS

To begin the SMARTS analysis, each alternative was scored against all five criteria (see Appendix C). Then, the swing weights were determined as shown in Table 7. It is important to keep in mind that swing weights measure both the importance of the criteria and the spread (i.e., range between worst to best) for each criteria. Thus, a criterion that is the most important may not outweigh the other criteria when spread is also considered. Dry mass provides an example; while it may be an important criterion for satellite design and CubeSat propulsion systems, based on the range of values it was determined to be the least important criterion for the case study.

It should be noted that the decision-maker responses for weights diverged from the planned methodology that was described in Chapter III; normalized weights were directly provided instead of setting the most important criterion weight to 100 and normalizing the other weights based on that scale. The methodology in Chapter III requires less abstraction than directly providing normalized weights because it asks the decision-maker to make direct comparisons without having to constantly ensure the sum of their weights add to 100. By not following the process, there is a possible loss in

accuracy for setting the weights. However, the ultimate goal is to capture the decision-maker's priorities for the criteria and in this respect the decision-maker setting the normalized weights still achieves that goal.

Table 7 – SMARTS Criteria Preferences

Attribute	Range	Rank	Weight
Dry Mass	500 g - 2610 g (2110 g)	6	0
Power	3.00 W - 60.00 W (57.00 W)	2	25
Nominal Thrust	.02 mN - 500 mN (499.98 mN)	3	20
ISP	40 s - 2100 s (2070 s)	5	5
Cost	\$50,000 - \$1,000,000 (\$950,000)	1	40
Schedule	11 mos. - 15 mos. (3 mos.)	4	10

Using the scores and weights, the total utility for each alternative is provided in Table 8. The results identify the Hydros-C as the best option among the group, followed closely by the BmP-220 and IFM Nano. There is a cluster of alternatives ranked 1-4 that are very close in utility score. One reason for this is that the most important technical criterion, power, has a cluster of alternatives in the upper performance range. On a range from 3.0 W to 60.0 W, only three alternatives are 20.0 W and above, while four of the alternatives are in a range of 10.0 – 12.0 W. This creates a situation where the criterion does not create a high degree of differentiation among the alternatives. High performance on power is not the only factor that matters though, IFM Nano ranked third in large part due to it being the cheapest alternative available. On the criteria that contributed 10% weight or more other than cost, it performed very poorly; however, cost was weighted so heavily it was able to overcome these shortcomings.

Table 8 – Total Utility Calculations

Thruster	Cost (40)	Schedule (10)	Dry Mass (0)	Power (25)	Nominal Thrust (20)	ISP (5)	Total Utility	Rank
(New)Standard Micro Propulsion System	0.587	0.000	0.829	0.709	0.040	0.000	42.02	5
C-POD	0.277	0.000	0.647	0.931	0.002	0.000	34.41	8
CuSP	0.709	0.000	0.910	0.739	0.002	0.000	46.89	4
Hydros-C	0.741	0.000	0.000	0.769	0.040	0.017	49.78	1
BIT-3	0.801	0.000	0.005	0.000	0.000	1.000	37.02	7
BGT-X5	0.000	0.000	0.526	0.492	1.000	0.008	32.35	9
BmP-220	0.543	0.000	1.000	1.000	0.000	0.312	48.28	2
IFM Nano	1.000	0.000	0.810	0.123	0.000	0.905	47.60	3
Custom Design	0.321	1.000	0.055	0.709	0.040	0.000	41.36	6

Looking at the Hydros-C, it performs well on both cost and power, which are the two most important criteria for the model. It has the worst dry mass value of the entire set, but that criterion was determined to be unimportant, so it does not have any effect on the total utility score of the alternative. Hydros-C does not otherwise have any exceptionally poor technical criteria values and should be evaluated on any pass/fail criteria that the organization has identified before selecting it. If it is determined to not be a viable alternative, the decision-maker would then look at the next best performer, the BmP-220. The evaluation would be repeated for this alternative, continuing to the next highest ranked alternative if the BmP-220 was deemed unsuitable.

For sensitivity analysis, random weights were generated and assigned in rank-order to the criteria; then the total utility was evaluated to discern any shifts. This was done five times. The complete results of the sensitivity iterations are provided in Table 9, and Appendix D provides a summary of the utility scoring for all the iterations. The weights column was applied to the criteria in descending preference order: cost, power, nominal thrust, schedule, I_{sp} , and dry mass. For three of the iterations, the most preferred alternative shifted from Hydros-C to a different alternative. In iterations one and two,

preference shifted from Hydros-C to the IFM Nano. This is due the increased weight on cost, while a reduced weight on power for those two iterations. For iterations three and four, Hydros-C returns to the top spot despite cost still being more heavily weighted; however, power also increased by 100% of its original weight, which IFM Nano performs poorly on when compared with Hydros-C. In the fifth iteration, preference shifted from Hydros-C to BmP-220. The weights for this iteration reduced price significantly, where Hydros-C had the advantage, and increased I_{sp} and dry mass weights, where BmP-220 held an advantage. Looking across all iterations, Hydros-C only shifted one rank for two of the iterations but did shift three ranks on the final iteration. In general, this points to stability, but the decision-maker should be careful when considering the importance of cost and power as they were seen to influence the rank order heavily.

Table 9 – Random Weighting Sensitivity Analysis Results

	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Thruster	Rank	Rank	Rank	Rank	Rank
(New)Standard Micro Propulsion System	7	6	5	5	6
C-POD	8	8	7	7	7
CuSP	3	3	3	3	3
Hydros-C	2	2	1	1	4
BIT-3	6	5	8	8	9
BGT-X5	9	9	9	9	8
BmP-220	4	4	2	2	1
IFM Nano	1	1	4	4	2
Custom Design	5	7	6	6	5

Analytical Hierarchy Process

Most of the data collection for the AHP takes the form of comparison matrices; Appendix E provides these comparison matrices for the case study with the preferences

of the decision-maker. These matrices undergo the normalization and synthesis described in Chapter III to produce the vector of priorities shown in Table 10. The global weights from the normalization process are shown in parenthesis under each criteria. IFM Nano is identified as the preferred choice based on these results.

Table 10 - Vector of Priorities

<i>Best Propulsion System</i>	Cost (0.62)	Schedule (0.14)	Dry Mass (0.01)	Power (0.14)	ISP (0.03)	Nominal Thrust (0.05)	Vector of Priorities	Rank
(New)Standard Micro Propulsion System	0.055	0.010	0.001	0.011	0.001	0.008	0.086	7
C-POD	0.017	0.010	0.001	0.032	0.001	0.004	0.064	8
CuSP	0.072	0.010	0.001	0.013	0.001	0.004	0.100	6
Hydros-C	0.087	0.010	0.001	0.015	0.003	0.008	0.124	3
BIT-3	0.115	0.010	0.001	0.002	0.012	0.002	0.142	2
BGT-X5	0.008	0.010	0.001	0.006	0.003	0.019	0.047	9
BmP-220	0.038	0.010	0.001	0.048	0.005	0.001	0.103	5
IFM Nano	0.205	0.010	0.001	0.004	0.009	0.001	0.229	1
Custom Design	0.026	0.059	0.001	0.010	0.001	0.008	0.104	4

Additionally, the consistency of the judgements made is important with the AHP process. The full list of eigenvalues, CI, and CR values for each comparison matrix are provided in Table 11. A serious issue with this data set is that in every non-trivial matrix (where there are more than a few complex judgements that must be made), the CRs rose above the recommended value of 0.10, which is indicated by the orange highlight on Table 11.

Table 11 - Eigenvalue, CI, CR Values

	Eig Max	CI	CR
<i>Best Propulsion System</i>	3.02	0.009	0.02
<i>Performance</i>	4.54	0.181	0.20
<i>Cost</i>	11.36	0.29	0.20
<i>Schedule</i>	9.00	0.00	0.00
<i>Dry Mass</i>	9.00	0.00	0.00
<i>Power</i>	11.01	0.25	0.17
<i>ISP</i>	10.49	0.19	0.13
<i>Thrust</i>	11.03	0.25	0.18

Ideally, the decision-maker and analyst would have a discussion on the values chosen and attempt to revise them. Time constraints and availability made this not feasible for the case study. The most likely candidate for the inconsistency can be identified by keeping in mind that inconsistency occurs when the logical relationships between preferences are not maintained (i.e., if A is twice as preferred as B and B is twice as preferred as C, then A should be four times as preferred as C). As a specific example, in the cost matrix (see Table 12), the Hydros-C alternative is preferred to the New Standard Micro Propulsion System (NSMPS) by a score of 5. However, both have an extreme preference (score of 9) when compared to the BGT-X5; to maintain the logical relationship between the Hydros-C and NSMPS, a score above 9 in preference strength would be needed. Scores above 9 do not exist for the scale, thus the inconsistency is introduced.

Table 12 - Cost Comparison Matrix

Cost	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro Propulsion System	1	7	1/4	1/5	1/7	9	3	1/7	7
C-POD	1/7	1	1/7	1/8	1/5	6	1/3	1/8	1/3
CuSP	4	7	1	1/2	1/4	9	5	1/7	5
Hydros-C	5	8	2	1	1/3	9	5	1/5	5
BIT-3	7	5	4	3	1	8	5	1/4	4
BGT-X5	1/9	1/6	1/9	1/9	1/8	1	1/8	1/9	1/7
BmP-220	1/3	3	1/5	1/5	1/5	8	1	1/5	5
IFM Nano	7	8	7	5	4	9	5	1	5
Custom Design	1/7	3	1/5	1/5	1/4	7	1/5	1/5	1

The Shewhart control method is used to evaluate the matrices since the consistency check failed. A distinction between trivial and non-trivial matrices is now made. Schedule and dry mass comparison matrices are considered trivial due to the extreme simplicity of their construction. The schedule matrix only has two scores to evaluate; the scores for the dry mass matrix do not matter because the decision-maker does not find any meaningful difference in the alternatives. As a result, these large matrices easily reach perfect consistency because of their simplicity. The remaining alternative comparison matrices are non-trivial because they involve many complex comparisons. Trivial comparison matrices are dropped from the analysis for this portion because they will unfairly bias the rolling average. For these matrices, $\underline{CI} = 0.24$ and $\underline{R} = 0.09$, which provides an upper control limit of 0.43 and a lower control limit of 0.05. None of the CIs fall outside of these limits, so the matrices are considered “in control” and remain valid.

Sensitivity analysis tested what influence an OAT 20% increase for cost, schedule, and performance would do to the vector of priorities. Table 13 shows the results for increasing the cost weight. Comparison with Table 10 shows that the cost

weight increased by 0.13 compared to the original value. The most preferred alternative remained unchanged with the new weighting, and the gap between it and the second most preferred alternative increased with the heavier weighting on cost. IFM Nano was the cheapest of the alternatives, so it is expected that its preference would continue to increase with further weighting on the cost criterion.

Table 13 - Cost Criterion Sensitivity

<i>COST Sensitivity</i>		Vector of	Rank
(New)Standard Micro		Priorities	
Weights Cost 0.75 Schedule 0.09 Performance 0.16	Propulsion System	0.087	6
	C-POD	0.052	8
	CuSP	0.105	4
	Hydros-C	0.129	3
	BIT-3	0.156	2
	BGT-X5	0.036	9
	BmP-220	0.089	5
	IFM Nano	0.262	1
	Custom Design	0.084	7

Table 14 and Table 15 provide similar sensitivity analysis results for schedule and performance. The schedule weight increased by 0.02 and the performance weight¹ increased by 0.05. In both analyses, the most preferred alternative remained the IFM Nano. The gap between IFM Nano and the second most preferred alternative remained stable for each of these criteria as well. This result shows that the most preferred alternative is stable within at least 20% of the preference scores. Other alternatives remained stable for the sensitivity analysis as well; three alternatives did not change rank at all, and the remaining alternatives shifted up or down by at most one rank.

¹ Performance weight was never directly shown in Table 9 since it is factored into the global weighting of the sub-criteria, but it can be shown that the original value was 0.24.

Table 14 - Schedule Criterion Sensitivity

		Vector of Priorities	Rank	
<i>Schedule Sensitivity</i>				
(New)Standard Micro				
Propulsion System		0.085	7	
Cost wt	0.60	C-POD	0.065	8
Sch wt	0.16	CuSP	0.099	6
Perf Wt	0.23	Hydros-C	0.123	3
		BIT-3	0.140	2
		BGT-X5	0.048	9
		BmP-220	0.102	5
		IFM Nano	0.224	1
		Custom Design	0.115	4

Table 15 - Performance Criterion Sensitivity

<i>Performance Sensitivity</i>		Vector of Priorities	Rank	
(New)Standard Micro				
Propulsion System		0.086	7	
Cost wt	0.58	C-POD	0.070	8
Sch wt	0.13	CuSP	0.098	6
Perf Wt	0.29	Hydros-C	0.124	3
		BIT-3	0.138	2
		BGT-X5	0.052	9
		BmP-220	0.111	4
		IFM Nano	0.219	1
		Custom Design	0.103	5

Data Envelopment Analysis

Using the DEA Frontier Free software, the alternatives are given an efficiency score from 0 to 1 as seen in Table 16. Alternatives with a score of 1.0 are efficient while the rest are considered inefficient. Because the condition in Equation (33) was not met, 55% of the alternatives were identified as efficient. It can be shown that other models besides CRS identify even more of the alternatives as efficient. Since DEA measures

whether an alternative is on the efficiency frontier or the distance an alternative is from it, differentiation among the options that are identified as efficient is not possible. The inefficient alternatives can be ranked based on how close to 1.0 they are, but the usefulness of such a ranking would be limited. Comparing the DEA efficiency results to the other two methods provides better context; the first and second most preferred alternatives in SMARTS and the AHP are identified as efficient.

Table 16 – DEA Efficiency Results

Inputs		Outputs
Cost (USD\$)		Nominal Thrust (mN)
Schedule (mos)		ISP (s)
Dry Mass (g)		
Power (W)		
DMU No.	DMU Name	Input-Oriented CRS Efficiency
1	(New)Standard Micro Propulsion System	0.72598
2	C-POD	0.21449
3	CuSP	0.24885
4	Hydros-C	1.00000
5	BIT-3	1.00000
6	BGT-X5	1.00000
7	BmP-220	1.00000
8	IFM Nano	1.00000
9	Custom Design	0.43837

Furthermore, the efficiency indicates the amount the input values would need to change for an inefficient alternative to become efficient. As an example, the CuSP alternative has an efficiency score of 0.24885. If all four input criteria were multiplied by 0.24885, the alternative would become technically efficient, which is also known as weak efficiency (Cooper et al., 2000). However, to become fully efficient, an alternative must also have mix efficiency which adjusts the proportions of the inputs. After reducing the inputs by the efficiency score, they are then reduced by their individual slack amount as shown in Table 17. The combination of multiplication by efficiency score and reduction

by slacks results in a final target value the input would need to reach to be identified as fully efficient, which is shown in Table 18. Continuing the CuSP example, after multiplying its inputs by 0.24885, the schedule and power would also need to be further reduced by 2.38 months and 1.14 W, respectively. It is possible for an alternative to have an efficiency score of 1.0 and still have slacks; however, this is not the case for the data set. Finally, fully efficient alternatives will have an input target that matches their actual input values.

Table 17 - DEA Input Slacks

DMU No.	DMU Name	<i>Input Slacks</i>			
		<i>Cost (USD\$)</i>	<i>Schedule (mos)</i>	<i>Dry Mass (g)</i>	<i>Power (W)</i>
1	(New)Standard Micro Propulsion System	0.00000	6.20105	0.00000	3.86744
2	C-POD	49999.03361	2.10500	179.74963	0.00000
3	CuSP	0.00000	2.38430	0.00000	1.13568
4	Hydros-C	0.00000	0.00000	0.00000	0.00000
5	BIT-3	0.00000	0.00000	0.00000	0.00000
6	BGT-X5	0.00000	0.00000	0.00000	0.00000
7	BmP-220	0.00000	0.00000	0.00000	0.00000
8	IFM Nano	0.00000	0.00000	0.00000	0.00000
9	Custom Design	0.00000	0.00000	442.10825	0.34941

Table 18 - DEA Input Targets

DMU No.	DMU Name	<i>Efficient Input Target</i>			
		<i>Cost (USD\$)</i>	<i>Schedule (mos)</i>	<i>Dry Mass (g)</i>	<i>Power (W)</i>
1	(New)Standard Micro Propulsion System	197466.98601	4.68868	625.07013	4.84434
2	C-POD	57246.98758	1.11238	87.07847	1.07246
3	CuSP	49769.64103	1.34842	171.70526	1.60165
4	Hydros-C	182000.00000	15.00000	2610.00000	10.00000
5	BIT-3	150000.00000	15.00000	2600.00000	60.00000
6	BGT-X5	1000000.00000	15.00000	1500.00000	20.00000
7	BmP-220	300000.00000	15.00000	500.00000	3.00000
8	IFM Nano	50000.00000	15.00000	900.00000	40.00000
9	Custom Design	197266.88103	4.82208	650.75027	4.91104

The sensitivity analysis that was performed by omitting a single input criteria and calculating efficiencies helps to give insight into the general validity of the solution. It is

seen in Appendix G that the solution set of efficient alternatives does not change significantly based on the input criteria. Hydros-C becomes inefficient if cost is not considered but is efficient when the other inputs are omitted. Similarly, BIT-3 becomes inefficient when schedule is omitted but is efficient otherwise. Because the solution set of efficient alternatives is stable, there is confidence in the results.

Combined Results

Following the methodology outline in Chapter III, Table 19 lists the total preference score for each alternative based on its ranking in the three methods. Hydros-C and IFM Nano tied for the most preferred composite score and BmP-220 was the third most preferred alternative. If the DEA Efficiency is removed from the scoring out of a desire to only use ranking methods, the top three preferences do not change.

Table 19 - Method Results Comparison

Thruster	SMARTS Rank	AHP Rank	DEA Efficiency	Total Preference Score
(New)Standard Micro Propulsion System	5	7	0.73	12.00
C-POD	8	8	0.21	5.00
CuSP	4	6	0.25	12.00
Hydros-C	1	3	1.00	25.00
BIT-3	7	2	1.00	20.00
BGT-X5	9	9	1.00	11.00
BmP-220	2	5	1.00	22.00
IFM Nano	3	1	1.00	25.00
Custom Design	6	4	0.44	13.00

Summary

In this chapter, the results of SMARTS, the AHP, and DEA are presented. SMARTS used a direct elicitation method to create a set of weights that are multiplied by

the normalized scores of the alternatives. The total utility scores showed that the Hydros-C was the most preferred alternative followed by the BmP-220 and IFM Nano.

Sensitivity showed that the most preferred alternative was tied to the weights of the cost and power criteria. The AHP used comparison matrices to create a vector of priorities which identified the IFM Nano as the most preferred alternative; the BIT-3 and Hydros-C were second and third most preferred, respectively. The comparison matrices did not pass the consistency check but were “in-control” from a process control standpoint. Sensitivity analysis conducted on this process showed stability within 20% of the calculated values. Lastly, the DEA model identified the Hydros-C, BIT-3, BGT-X5, BmP-220, and IFM Nano as efficient alternatives; however, it is unable to differentiate among the efficient alternatives to create a preference rank. Sensitivity analysis showed the procedure to be stable by sequentially removing the inputs to see if there was a shift in efficient alternatives.

The SMARTS provides the best method for selecting between a medium number of alternatives (approximately 5-15) by being easily scalable and using a familiar weight multiplied by score structure. Requisite knowledge for its use is limited to normalization techniques. The AHP uses pairwise comparisons to enable a decision-maker to make judgements in a manner that uses tangible comparisons rather than assigning weights but operates best when the number of alternatives in consideration is low. DEA is not suitable for identifying a single best alternative but excels at reviewing a large number of alternatives and producing a small solution set that has been identified as efficient in their combination of inputs and outputs.

V. Conclusions and Recommendations

This chapter summarizes the decision analysis objectives for selecting a propulsion system on a CubeSat project. Conclusions from the analysis presented in Chapter IV are also discussed and future research areas are recommended. The research goals stated in Chapter I are re-examined to determine whether the research accomplished its objectives. Additionally, the pros and cons of the three decision analysis tools are enumerated side-by-side for comparison and recommendations for future use of the models are given. Lastly, limitations of the findings and areas for future research are given.

Conclusions of Research

Several research questions were posited at the beginning of this document. They are now restated and considered in the context of the research.

“Which model is best suited to be used in selecting a propulsion system for a CubeSat education and research project?”

Selection of a best model is highly dependent on the environment surrounding the decision analysis problem. With the parameters set out for the case study, the SMARTS method provided the best ease of use while also retaining differentiation among the alternatives to allow for a rank ordering . The elicitation portion of the method did not require an overly demanding amount of consideration by the decision-maker but is still capable of making accurate predictions.

In contrast, if a single preferred alternative is desired, then the DEA method is the worst suited to handle the case study since it is only able to reduce the set of alternatives

by half. Even still, there are some very strong use cases for DEA that are made apparent by the case study. DEA may be well-suited as a first-pass method where a large number of alternatives are being considered. This allows the relationship for alternatives to inputs and outputs to be satisfied. Even if the method identifies multiple efficient alternatives, a method that allows for rank ordering such as SMARTS or AHP can then be employed.

The AHP also suffered from this decision environment but has its strengths as well. The relatively large number of alternatives under consideration translated into an unreasonable number of judgements from the decision-maker. With over 225 individual judgements to be made, if the decision-maker averaged a judgement every 30 seconds it would still take about 2 hours to complete the full set of judgements. Inconsistencies would require further time revising the preferences. Other factors that could affect the quality, such as decision fatigue, are potential concerns as well. Where the AHP excels is in the pairwise comparison elicitation method. Instead of asking the decision-maker to perform the mental calculus of abstracting the criteria into weights, very tangible comparisons between the alternatives are made. There is potential for a very powerful decision analysis process by combining DEA to filter the full range of alternatives into a smaller subset for use in the AHP. Lastly, if there is concern that the criteria or alternatives may change, then the AHP's susceptibility to rank reversal should be kept in mind when selecting a method.

“Will different decision analysis models identify the same alternative as the best choice?”

For the case study, SMARTS and the AHP did not closely agree, but DEA identified the most preferred alternative for both methods as efficient (see Table 19).

Comparing the AHP and SMARTS methods, there is potential concern for the performance metrics having a reduced significance in the AHP as a result of the hierarchical structure. Specifically, the combined weights of dry mass, power, I_{sp} , and nominal thrust in SMARTS equal 50%, whereas in the AHP their total weight is equal to 24%, which is the weight of the performance objective when compared to cost and schedule. Despite the same decision-maker providing these judgements there is a large difference between the weighting of the two methods. Much of the weight score that was lost by performance went to cost; the cost weight was 50% higher in the AHP than in SMARTS. Schedule kept a similar weight between the two methods. It is difficult to attribute any specific reason for the difference in weights between the two methods. It is possible having the weights directly provided for SMARTS caused them to be incorrect, or it is possible that the pairwise comparison method of the AHP elicited a set of preferences from the decision-maker that they were not consciously aware of. Just as comparison matrices can fail consistency checks but still be completely logical, the weights assigned for each method may also be completely logical to the decision-maker, yet still differ.

Even though cost was significantly more important in the AHP, it was the most important factor among both SMARTS and the AHP. Dry mass was determined to be an irrelevant criterion in this case study and received almost no weighting in either SMARTS or the AHP. The criterion was justifiably included in the analysis by discussion with SMEs; consideration should be given to whether dry mass actually does not contribute to the decision for this case and, if so, it should be dropped from consideration for any further analysis since it does not improve the selection methodology.

Significance of Research

This research has shown how decision analysis methods can be applied to a CubeSat project to provide quantitative support for analyzing a decision problem. By combining multiple methods, the weaknesses inherent in any one model are made up for by the others. With large data sets, DEA can help narrow the field of review to something manageable by other rank order preference models. It was also shown that the different models can elicit very different preferences even when the same decision-maker is providing the inputs. Using multiple models allows the decision-maker to better understand the factors that drive a given alternative to be preferred.

Implementing this methodology will arrange the decision-maker's preferences in an organized manner that reduces decision time and provides a consistent and repeatable methodology. Additionally, it will allow the decision-maker to select a single alternative for incorporation into their project. This methodology is auditable and defensible, while remaining flexible to revisions if preferences or requirements change.

Recommendations for Future Research

Future research is encouraged to investigate the effectiveness of a hybrid approach that has been postulated in this research such as DEA followed by the AHP or SMARTS. This research relied on a trade study that had already been conducted by the interested organization to generate its database. By beginning with a wider array of alternatives, an end-to-end process that filters down to a single selection can be created.

Cost was seen to be a very largely weighted criterion for both SMARTS and the AHP. By removing it from the criteria set for these methods, the analytical tools will be

able to better discern decision-maker values between the remaining criteria. Upon completing the SMARTS or AHP analysis the cost versus value can be plotted, creating an efficient frontier. This frontier will differ from the DEA frontier since it only has one input (cost), and all other criteria are reduced to a point value. Like DEA, this type of analysis will be unlikely to identify a single best alternative to select, but it can provide insight into which alternatives provide the best value for their price.

There is also another alternative that was not examined in this research. Organizations may sometimes negotiate with a vendor to modify an existing COTS product to better suit the mission needs. In this research, the response to these potential alternatives is to re-run the analysis tool with the new information as a separate alternative; however, a model relating the change of a criterion to the costs incurred for the change would be useful to organizations desiring to pursue a modified design. This data could provide the basis for a set of CERs that use the amount of change as a driving parameter. Analyzing the ratio of change to cost on a per vendor basis would reveal vendors that are more amenable when seeking modifications to a design. DEA also provides an additional avenue of research for modified alternatives. The target input values can be used to generate hypothetical alternatives for use in a rank ordered method such as SMARTS or the AHP, or they can be used as the starting point for negotiating modifications with a vendor.

Summary

Ultimately, all decision-making models reflect the judgements and preferences of the decision-maker who provided the inputs. Different decision-making tools employ

different methods for obtaining decision-maker preferences, and these methods in turn have a very tangible effect on the decisions. A decision-maker must understand how the decision-making environment influences these tools so that they can select the appropriate one to match their needs.

The research questions posited at the beginning have been answered. Consideration of the environment of the decision problem will guide an organization in selecting a single model for implementation but combining different models can help to highlight differences and stimulate critical thinking. Finally, many future research opportunities exist that can leverage this work as a starting point.

Appendix A – Propulsion Vendor Trade Study

Thruster	Vendor	Thruster Type	Propellants	Size	Dry Mass	Power	Nominal Thrust	Total Impulse	ISP	Delta V (10kg)	Mass of Propellant (kg)	Delta V (10kg satellite) (m/s)	Cost	Schedule
(New)Standard Micro Propulsion System	VACCO	Cold Gas	R236fa	100mmx100mmx100mm	861 g	12.00 W	100 mN	334 N-s	40 s	35 m/s	851 kg	35 m/s	\$272,000	
C-POD	VACCO	Cold Gas	R134a	98mmx94mmx101mm	1244 g	5.00 W	25 mN	186 N-s	40 s	19 m/s	0.474 kg	19 m/s	\$500,000	
CuSP	VACCO	Cold Gas	R134a / R-236fa	99mmx99mmx30mm	690 g	11.00 W	25 mN	69 N-s	40 s	7 m/s	0.176 kg	7 m/s	\$200,000	
Hydros-C	Tether Unlimited	Water Electrolyzed	Water	190mmx130mmx92mm	2610 g	10.00 W	100 mN	2100 N-s	310 s	98 m/s	0.691 kg	218 m/s	\$182,000	15 months
BIT-3	Busek	RF Ion Thruster	Iodine	180mmx102mmx88mm	2600 g	60.00 W	2 mN	23544 N-s	2100 s	2500 m/s	1.143 kg	2500 m/s	\$150,000	
BGT-X5	Busek	Green monopropellant	AF-M315E	100mmx100mmx100mm	1500 g	20.00 W	500 mN	565 N-s	225 s	100 m/s	0.256 kg	57 m/s	\$1,000,000	
Bmp-220	Busek	Micro-Pulsed Plasma	Teflon	82mmx76mmx80mm	500 g	3.00 W	0.02 mN	175 N-s	1190 s	17.5 m/s	0.015 kg	18 m/s	\$300,000	
IFM Nano	Emulsion	FEPP	Ionic Liquid	100mmx100mmx2.5mm	900 g	40.00 W	0.40 mN	5000 N-s	2000 s	506 m/s	0.255 kg	506 m/s	\$50,000	
Bespoke Design	-	-	-	-	2493 g	12.00 W	100 mN	330 N-s	40 s	-	547 kg	-	\$462,000	11 months

Appendix B – DSCM CERs and Schedule Parametric Relationship

Subsystem	CER / SER Form
SE / PM	$[\text{Cost (FY06\$K)}] = 0.26 [\text{Base (FY06\$K)}]^{1.03}$
I&T	$[\text{Cost (FY06\$K)}] = 33.0 [\text{S/C Dry Weight (lb)}]^{0.66}$ $\star 1.32^{[\text{Contract Includes Payload Integration}]}$ $\star 1.40^{[\text{Optical Payload}]} \star 1.70^{[\text{Propulsion}]}$
Structure	$[\text{Cost (FY06\$K)}] = 45.1 [\text{Subsystem Weight (lb)}]^{0.77}$ $\star 1.34^{[\text{Solar Array Mechanics}]}$
Thermal	$[\text{Cost (FY06\$K)}] = 62.7 [\text{Subsystem Weight (lb)}]^{0.70}$ $\star 1.63^{[\text{Optical Payload}]} + 144$
EPS	$[\text{Cost (FY06\$K)}] = 37.1 [\text{Subsystem Weight (lb)}]^{0.89}$ $\star 1.44^{[\text{Nickel-Hydrogen Battery}]}$
ADCS	$[\text{Cost (FY06\$K)}] = 288 [\text{Subsystem Weight (lb)}]^{0.59}$ $\star [\text{Number of Attitude Sensors}]^{0.23}$
Propulsion	$[\text{Cost (FY06\$K)}] = 398 [\text{Propellant Weight (lb)}]^{0.22}$ $\star [\text{Number of Thrusters}]^{0.37}$
TTC&DH	$[\text{Cost (FY06\$K)}] = 15.5 [\text{Subsystem Weight (lb)}]^{0.86}$ $\star [\text{Vehicle End of Life Power (W)}]^{0.41}$
Software	$[\text{Cost (FY06\$K)}] = 16.8 [\text{TT\&C Subsystem Weight (lb)}]^{1.18}$
Launch Support	$[\text{Cost (FY06\$K)}] = 82.3 [\text{Base (FY06\$K)}]^{0.22}$ $\star [\text{Number of Payloads}]^{0.51} \star 1.60^{[\text{Hydrazine Propellant}]}$
Optical Payload	$[\text{Cost (FY06\$K)}] = 760 [\text{Payload Weight (lb)}]^{0.69}$ $\star (\log[\text{Spectral Range (A)}])^{0.37} \star 0.28^{[\text{Cryostat}]}$
RF Payload	$[\text{Cost (FY06\$K)}] = 119 [\text{Payload Weight (lb)}]^{0.97}$ $\star [\text{Design Life (mo)}]^{0.28}$
Schedule	$[\text{Time to First Launch (mo)}] = 9.4 [\text{S/C Dry Weight (lb)}]^{0.14}$ $\star [\text{Design Life (mo)}]^{0.19} \star 1.13^{[\text{Optical Payload}]}$ $- 5.6^{[\text{Option on Extant Contract}]}$

Appendix C – SMARTS Scoring

Thrust	Cost	Score	Schedule	Score	Dry Mass	Score	Power	Score	Nominal Thrust	Score	ISP	Score
(New)Standard Micro Propulsion System	\$272,000	0.587	15 months	0.00	861 g	0.83	12.00 W	0.709	100 mN	0.040	40 s	0.000
C-POD	\$500,000	0.277	15 months	0.00	1244 g	0.65	5.00 W	0.931	25 mN	0.002	40 s	0.000
CusP	\$200,000	0.709	15 months	0.00	690 g	0.91	11.00 W	0.739	25 mN	0.002	40 s	0.000
Hydros-C	\$182,000	0.741	15 months	0.00	2610 g	0.00	10.00 W	0.769	100 mN	0.040	310 s	0.017
BIT-3	\$150,000	0.801	15 months	0.00	2600 g	0.00	60.00 W	0.000	2 mN	0.000	2100 s	1.000
BGT-X5	\$1,000,000	0.000	15 months	0.00	1500 g	0.53	20.00 W	0.492	500 mN	1.000	225 s	0.008
BmP-220	\$300,000	0.543	15 months	0.00	500 g	1.00	3.00 W	1.000	0.02 mN	0.000	1190 s	0.312
IFM Nano	\$50,000	1.000	15 months	0.00	900 g	0.81	40.00 W	0.123	0.40 mN	0.000	2000 s	0.905
Custom Design	\$462,000	0.321	11 months	1.00	2493 g	0.06	12.00 W	0.709	100 mN	0.040	40 s	0.000

Appendix D – SMARTS Sensitivity Iterations

The most preferred option for each iteration has been highlighted to identify it easily.

Thruster	Iteration 1			Iteration 2			Iteration 3			Iteration 4			Iteration 5		
	Total Utility	Rank	Weights	Total Utility	Rank	Weights	Total Utility	Rank	Weights	Total Utility	Rank	Weights	Total Utility	Rank	Weights
(New)Standard Micro Propulsion System	38.9	7	Cost 0.42	42.3	6	Cost 0.49	49.4	5	Cost 0.47	51.47	5	Cost 0.46	39.01	6	Cost 0.29
C-POD	29.1	8	Power 0.18	30.1	8	Power 0.17	41.0	7	Power 0.3	43.75	7	Power 0.33	34.11	7	Power 0.25
CuSP	44.0	3	Thrust 0.17	48.3	3	Thrust 0.16	55.5	3	Thrust 0.13	57.78	3	Thrust 0.1	42.91	3	Thrust 0.19
Hydros-C	45.8	2	Schedule 0.15	50.1	2	Schedule 0.12	58.5	1	Schedule 0.07	59.86	1	Schedule 0.06	41.63	4	Schedule 0.13
BIT-3	40.6	6	ISP 0.07	43.2	5	ISP 0.04	39.6	8	ISP 0.02	40.58	8	ISP 0.03	33.20	9	ISP 0.1
BGT-X5	26.4	9	Mass 0.01	24.9	9	Mass 0.01	27.8	9	Mass 0	26.99	9	Mass 0.01	33.65	8	Mass 0.04
Bmp-220	44.0	4		45.9	4		56.1	2		59.70	2		48.10	1	
IFM Nano	51.4	1		55.5	1		52.5	4		54.26	4		44.51	2	
Custom Design	42.0	5		40.5	7		43.9	6		44.67	6		40.80	5	

Appendix E – AHP Comparison Matrices

Primary Criteria

<i>Best Propulsion System</i>	C	S	P
Cost	1	4	3
Schedule	1/4	1	1/2
Performance	1/3	2	1

Performance Subcriteria

<i>Performance</i>	DM	P	ISP	NT
Dry Mass	1	1/7	1/7	1/7
Power	7	1	6	5
ISP	7	1/6	1	1/3
Nominal Thrust	7	1/5	3	1

Cost Preferences

<i>Cost</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro									
Propulsion System	1	7	1/4	1/5	1/7	9	3	1/7	7
C-POD	1/7	1	1/7	1/8	1/5	6	1/3	1/8	1/3
CuSP	4	7	1	1/2	1/4	9	5	1/7	5
Hydros-C	5	8	2	1	1/3	9	5	1/5	5
BIT-3	7	5	4	3	1	8	5	1/4	4
BGT-X5	1/9	1/6	1/9	1/9	1/8	1	1/8	1/9	1/7
BmP-220	1/3	3	1/5	1/5	1/5	8	1	1/5	5
IFM Nano	7	8	7	5	4	9	5	1	5
Custom Design	1/7	3	1/5	1/5	1/4	7	1/5	1/5	1

Schedule Preferences

<i>Schedule</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro									
Propulsion System	1	1	1	1	1	1	1	1	1/6
C-POD	1	1	1	1	1	1	1	1	1/6
CuSP	1	1	1	1	1	1	1	1	1/6
Hydros-C	1	1	1	1	1	1	1	1	1/6
BIT-3	1	1	1	1	1	1	1	1	1/6
BGT-X5	1	1	1	1	1	1	1	1	1/6
BmP-220	1	1	1	1	1	1	1	1	1/6
IFM Nano	1	1	1	1	1	1	1	1	1/6
Custom Design	6	6	6	6	6	6	6	6	1

Dry Mass Preferences

<i>Dry Mass</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro	1	1	1	1	1	1	1	1	1
C-POD	1	1	1	1	1	1	1	1	1
CuSP	1	1	1	1	1	1	1	1	1
Hydros-C	1	1	1	1	1	1	1	1	1
BIT-3	1	1	1	1	1	1	1	1	1
BGT-X5	1	1	1	1	1	1	1	1	1
BmP-220	1	1	1	1	1	1	1	1	1
IFM Nano	1	1	1	1	1	1	1	1	1
Custom Design	1	1	1	1	1	1	1	1	1

Power Preferences

<i>Power</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro									
Propulsion System	1	1/5	1/2	1/3	9	6	1/7	7	1
C-POD	5	1	5	5	9	7	1/3	8	5
CuSP	2	1/5	1	1/2	8	5	1/7	7	2
Hydros-C	3	1/5	2	1	7	5	1/5	6	3
BIT-3	1/9	1/9	1/8	1/7	1	1/7	1/9	1/6	1/8
BGT-X5	1/6	1/7	1/5	1/5	7	1	1/9	7	1/5
BmP-220	7	3	7	5	9	9	1	9	7
IFM Nano	1/7	1/8	1/7	1/6	6	1/7	1/9	1	1/5
Custom Design	1	1/5	1/2	1/3	8	5	1/7	5	1

ISP Preferences

<i>ISP</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard Micro									
Propulsion System	1	1	1	1/6	1/9	1/5	1/7	1/9	1
C-POD	1	1	1	1/6	1/9	1/5	1/7	1/9	1
CuSP	1	1	1	1/6	1/9	1/5	1/7	1/9	1
Hydros-C	6	6	6	1	1/7	4	1/5	1/7	5
BIT-3	9	9	9	7	1	8	6	3	9
BGT-X5	5	5	5	1/4	1/8	1	1/6	1/8	7
BmP-220	7	7	7	5	1/6	6	1	1/6	6
IFM Nano	9	9	9	7	1/3	8	6	1	9
Custom Design	1	1	1	1/5	1/9	1/7	1/6	1/9	1

Nominal Thrust Preferences

<i>Thrust</i>	NSMPS	C-POD	CuSP	Hydros-C	BIT-3	BGT-X5	BmP-220	IFM Nano	CD
(New)Standard	1	5	5	1	7	1/5	9	9	1
C-POD	1/5	1	1	1/5	6	1/8	8	8	1/5
CuSP	1/5	1	1	1/5	6	1/6	8	8	1/5
Hydros-C	1	5	5	1	7	1/5	9	9	1
BIT-3	1/7	1/6	1/6	1/7	1	1/8	7	7	1/7
BGT-X5	5	8	6	5	8	1	9	9	5
BmP-220	1/9	1/8	1/8	1/9	1/7	1/9	1	1/3	1/9
IFM Nano	1/9	1/8	1/8	1/9	1/7	1/9	3	1	1/9
Custom Design	1	5	5	1	7	1/5	9	9	1

Appendix F – DEA Sensitivity Analysis

Efficiency, slacks, and target values without cost as an input

DMU No.	DMU Name	Input-Oriented CRS Efficiency		Input Slacks			Efficient Input Target		
				Schedule (mos)	Dry Mass (g)	Power (W)	Schedule (mos)	Dry Mass (g)	Power (W)
1	(New)Standard Micro Propulsion System		0.34843	2.22648	0.00000	0.18118	3.00000	300.00000	4.00000
2	C-POD		0.21449	2.10500	179.74963	0.00000	1.11238	87.07847	1.07246
3	CuSP		0.12620	0.78063	0.00000	0.31575	1.11238	87.07847	1.07246
4	Hydros-C		0.46679	0.66161	806.98835	0.00000	6.34023	411.33202	4.66789
5	BIT-3		1.00000	0.00000	0.00000	0.00000	15.00000	2600.00000	60.00000
6	BGT-X5		1.00000	0.00000	0.00000	0.00000	15.00000	1500.00000	20.00000
7	BmP-220		1.00000	0.00000	0.00000	0.00000	15.00000	500.00000	3.00000
8	IFM Nano		1.00000	0.00000	0.00000	0.00000	15.00000	900.00000	40.00000
9	Custom Design		0.33333	0.66667	531.00000	0.00000	3.00000	300.00000	4.00000

Efficiency, slacks, and target values without schedule as an input

DMU No.	DMU Name	Input-Oriented CRS Efficiency	Input Slacks			Efficient Input Target		
			Cost	Dry Mass (g)	Power (W)	Cost	Dry Mass (g)	Power (W)
1	(New)Standard Micro Propulsion System	0.72598	0.00000	0.00000	3.86744	197466.98601	625.07013	4.84434
2	C-POD	0.21449	49999.03361	179.74963	0.00000	57246.98758	87.07847	1.07246
3	CuSP	0.24885	0.00000	0.00000	1.13568	49769.64103	171.70526	1.60165
4	Hydros-C	1.00000	0.00000	0.00000	0.00000	182000.00000	2610.00000	10.00000
5	BIT-3	0.64741	0.00000	703.85600	0.00000	97110.98648	979.40110	38.84439
6	BGT-X5	1.00000	0.00000	0.00000	0.00000	1000000.00000	1500.00000	20.00000
7	Bmp-220	1.00000	0.00000	0.00000	0.00000	300000.00000	500.00000	3.00000
8	IFM Nano	1.00000	0.00000	0.00000	0.00000	50000.00000	900.00000	40.00000
9	Custom Design	0.43621	0.00000	334.53012	0.00000	196674.69880	726.74699	5.10843

Efficiency, slacks, and target values without dry mass as an input

DMU No.	DMU Name	Input-Oriented CRS Efficiency	Input Slacks			Efficient Input Target		
			Cost	Schedule (mos)	Power (W)	Cost	Schedule (mos)	Power (W)
1	(New)Standard Micro Propulsion System	0.69440	0.00000	0.00000	0.62479	188876.06112	10.41596	7.70798
2	C-POD	0.21449	49999.03361	2.10500	0.00000	57246.98758	1.11238	1.07246
3	Cusp	0.22978	0.00000	0.00000	0.17921	45955.05618	3.44663	2.34831
4	Hydros-C	1.00000	0.00000	0.00000	0.00000	182000.00000	15.00000	10.00000
5	BIT-3	1.00000	0.00000	0.00000	0.00000	150000.00000	15.00000	60.00000
6	BGT-X5	1.00000	0.00000	0.00000	0.00000	1000000.00000	15.00000	20.00000
7	BmP-220	1.00000	0.00000	0.00000	0.00000	300000.00000	15.00000	3.00000
8	IFM Nano	1.00000	0.00000	0.00000	0.00000	50000.00000	15.00000	40.00000
9	Custom Design	0.43837	0.00000	0.00000	0.27795	197448.27586	4.70115	4.85057

Efficiency, slacks, and target values without power as an input

DMU No.	DMU Name	Input-Oriented CRS Efficiency	Input Slacks			Efficient Input Target		
			Cost	Schedule (mos)	Dry Mass (g)	Cost	Schedule (mos)	Dry Mass (g)
1	(New)Standard Micro Propulsion System	0.72598	0.00000	6.20105	0.00000	197466.98601	4.68868	625.07013
2	C-POD	0.10058	0.00000	0.37322	0.00000	50290.95942	1.13551	125.12391
3	CuSP	0.24885	0.00000	2.38430	0.00000	49769.64103	1.34842	171.70526
4	Hydros-C	1.00000	0.00000	0.00000	0.00000	182000.00000	15.00000	2610.00000
5	BIT-3	1.00000	0.00000	0.00000	0.00000	150000.00000	15.00000	2600.00000
6	BGT-X5	1.00000	0.00000	0.00000	0.00000	1000000.00000	15.00000	1500.00000
7	Bmp-220	1.00000	0.00000	0.00000	0.00000	300000.00000	15.00000	500.00000
8	IFM Nano	1.00000	0.00000	0.00000	0.00000	50000.00000	15.00000	900.00000
9	Custom Design	0.43837	0.00000	0.00000	437.98015	197448.27586	4.70115	627.47126

References

- Air Force Space Command, Range Safety User Requirements Manual Volume 3 – Launch Vehicles, Payloads, and Ground Support Systems Requirements. (2019). <https://static.e-publishing.af.mil/production/1/afspc/publication/afspcman91-710v3/afspcman91-710v3.pdf>
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, 30(9), 1078-1092.
- Banker, R. D., Cooper, W. W., Seiford, L. M., Thrall, R. M., & Zhu, J. (2004). Returns to scale in different DEA models. *European Journal of Operational Research*, 154(2), 345-362.
- Barnes, Brandon B. (2017) *Environmental Applications of Small Unmanned Aircraft Systems in Multi-Service Tactics, Techniques, and Procedures for Chemical, Biological, Radiological, and Nuclear Reconnaissance and Surveillance*. (Master's thesis, Air Force Institute of Technology, Dayton, United States). Retrieved from <http://scholar.afit.edu/etd/1661>.
- Borda, J. D. (1784). Mémoire sur les élections au scrutin. *Histoire de l'Academie Royale des Sciences pour 1781* (Paris, 1784).
- Broder, M., Mahr, E., Barkmeyer, D., Burgess, E., Alvarado, W., Toas, S., & Hogan, G. (2009). Review of three small-satellite cost models. In *AIAA SPACE 2009 conference & exposition* (p. 6689).
- Brown, Charles D. *Elements of Spacecraft Design*. AIAA. (2003).
- Butler, J., Jia, J., & Dyer, J. (1997). Simulation techniques for the sensitivity analysis of multi-criteria decision models. *European Journal of Operational Research*, 103(3), 531-546.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444.
- Chen, Y., Yu, J., & Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environmental modelling & software*, 25(12), 1582-1591.

- Cooper, William W. and Seiford, Lawrence M. and Kaoru, Tone. (2000). *Data Envelopment Analysis: A Comprehensive Text with Models*. Kluwer Academic Publishers.
- Cuero Aerospace. (2021). <http://www.cuaerospace.com/technology-products/compact-small-satellite-propulsion-unit-cubesats>
- Cullinane, K., Song, D. W., & Wang, T. (2005). The application of mathematical programming approaches to estimating container port production efficiency. *Journal of productivity analysis*, 24(1), 73-92.
- Dodgson, J. S. and Spackman, Michael and Pearman, Alan D. and Phillips, Lawrence. (2009). *Multi-Criteria Analysis: A Manual*. Crown.
- Edwards, W., & Barron, F. H. (1994). SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. *Organizational behavior and human decision processes*, 60(3), 306-325.
- Einhorn, H. J. (1971). Use of nonlinear, noncompensatory models as a function of task and amount of information. *Organizational behavior and human performance*, 6(1), 1-27.
- Gensure, J. R. (2007). Application of structured decision-making tools to defense acquisition. *Defense AR Journal*, 14(1), 261.
- Hui, S. C., & Wan, M. C. (2013, August). Study of hotel energy performance using data envelopment analysis. In 12. *International Conference on Sustainable Energy Technologies* (pp. 26-29).
- Huber, G. P. (1974). Multi-attribute utility models: A review of field and field-like studies. *Management science*, 20(10), 1393-1402.
- Huber, G. P., Sahney, V. K., & Ford, D. L. (1969). A study of subjective evaluation models. *Behavioral Science*, 14(6), 483-489.
- Karapetrovic, S., & Rosenbloom, E. S. (1999). A quality control approach to consistency paradoxes in AHP. *European Journal of Operational Research*, 119(3), 704-718.
- Keeney, R. L. (1982). Decision analysis: an overview. *Operations research*, 30(5), 803-838.

- Keeney, R. L., & Gregory, R. S. (2005). Selecting attributes to measure the achievement of objectives. *Operations Research*, 53(1), 1-11.
- Keeney, Ralph L. and Raiffa, Howard. (1976). *Decisions with Multiple Objectives: Preference and Value Tradeoffs*. John Wiley & Sons.
- Kessler, D. J., & Cour-Palais, B. G. (1978). Collision frequency of artificial satellites: The creation of a debris belt. *Journal of Geophysical Research: Space Physics*, 83(A6), 2637-2646.
- Konecny, G. (2004, July). Small satellites—A tool for Earth observation?. In *XXth ISPRS Congress, Commission* (Vol. 4, pp. 12-23).
- Lemmer, K. (2017). Propulsion for cubesats. *Acta Astronautica*, 134, 231-243.
- Linkov, I., Trump, B. D., Pabon, N., Collier, Z. A., Keisler, J. M., & Scriven, J. (2012). A decision analytic approach for Department of Defense acquisition risk management. *Military Operations Research*, 57-70.
- Mabrouk, Elizabeth. (August 7, 2017). What are SmallSats and CubeSats?. *National Aeronautics and Space Administration [NASA]*. <https://www.nasa.gov/content/what-are-smallsats-and-cubesats>
- Madden, J. M. (1963). *An application to job evaluation of a policy-capturing model for analyzing individual and group judgment* (Vol. 63, No. 15). Personnel Research Laboratory, Aerospace Medical Division, Air Force Systems Command.
- Mann, Adam. (January 17, 2020). Starlink: SpaceX's satellite internet project. <https://www.space.com/spacex-starlink-satellites.html>
- Mu, Enrique and Pereyra-Rojas, Milagros. (2017). *Practical Decision Making*. Springer International Publishing.
- National Aeronautics and Space Administration (NASA). (2017). *CubeSat 101: Basic Concepts and Processes for First-Time CubeSat Developers*. https://www.nasa.gov/sites/default/files/atoms/files/nasa_csli_cubesat_101_508.pdf
- Orbital Debris Program Office. (2019). *Orbital Debris Quarterly News, Vol 23, Issue 4*. NASA.

- Parnell, G. S., Small, C., Pohl, E., Goerger, S. R., Cilli, M., & Specking, E. (2020). Demonstrating set-based design techniques: an unmanned aerial vehicle case study. *The Journal of Defense Modeling and Simulation*, 17(4), 339-355.
- Saaty, Thomas L. (1982). *Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex World*. Wadsworth, Inc.
- Seiford, L. M., & Zhu, J. (1999). An investigation of returns to scale in data envelopment analysis. *Omega*, 27(1), 1-11.
- Straub, J. (2012, May). Cubesats: A low-cost, very high-return space technology. In *Proceedings of the 2012 Reinventing Space Conference*.
- Villela, T., Costa, C. A., Brandão, A. M., Bueno, F. T., & Leonardi, R. (2019). Towards the thousandth CubeSat: A statistical overview. *International Journal of Aerospace Engineering*, 2019.
- Wang, Y. M., & Luo, Y. (2009). On rank reversal in decision analysis. *Mathematical and Computer Modelling*, 49(5-6), 1221-1229.
- Wekerle, T., Pessoa Filho, J. B., Costa, L. E. V. L. D., & Trabasso, L. G. (2017). Status and trends of smallsats and their launch vehicles—An up-to-date review. *Journal of Aerospace Technology and Management*, 9(3), 269-286.
- Wertz, James R. and Everett, David F. and Puschell, Jeffrey J. (2018). *Space Mission Engineering: The New SMAD*. Microcosm Press.
- Zhu, Joe. DEA Frontier Free [Computer Software].
<http://www.deafrontier.net/deafree.html>

REPORT DOCUMENTATION PAGE					<i>Form Approved OMB No. 0704-0188</i>	
The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.						
PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.						
1. REPORT DATE (DD-MM-YYYY) 25-03-221		2. REPORT TYPE Master's Thesis			3. DATES COVERED (From - To) Sept 2019 - Mar 2021	
4. TITLE AND SUBTITLE Comparison of Decision Analysis Methods for CubeSat Propulsion System					5a. CONTRACT NUMBER	
					5b. GRANT NUMBER	
					5c. PROGRAM ELEMENT NUMBER	
					5d. PROJECT NUMBER	
6. AUTHOR(S) Pilcher, Jared L, Capt, USSF					5e. TASK NUMBER	
					5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way Wright-Patterson AFB OH 45433-7765					8. PERFORMING ORGANIZATION REPORT NUMBER AFIT-ENV-MS-21-M-256	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Intentionally Left Blank					10. SPONSOR/MONITOR'S ACRONYM(S) Intentionally Left Blank	
					11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Distribution Statement A. Approved for Public Release;Distribution Unlimited						
13. SUPPLEMENTARY NOTES This work is declared a work of the U.S. Government and is not subject to copyright protection in the United States.						
14. ABSTRACT Low Earth Orbit (LEO) is becoming an increasingly congested orbital regime. As a result, propulsion systems on CubeSats are becoming a more desirable feature to provide them with collision avoidance capabilities. To date, there have been very few CubeSat launches with a propulsion system on them. Due to the relatively high cost of a propulsion system compared to the budget of small educational organizations, a decision analysis model is needed so that these organizations can make the best decision between whether to purchase a Commercial-Off-The-Shelf (COTS) product or to develop one within the organization. This research applies three decision analysis methods: Simple Multi-Attribute Rating Technique with Swing weights (SMARTS), the Analytical Hierarchy Process (AHP), and Data Envelopment Analysis (DEA). A comparison of the strengths and weaknesses of these methods when applied to the propulsion system selection problem is then conducted.						
15. SUBJECT TERMS ^Decision Analysis, AHP, DEA, SMARTS, CubeSat						
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT UU	18. NUMBER OF PAGES 108	19a. NAME OF RESPONSIBLE PERSON Clay M. Koschnick, Lt Col AFIT/ENV	
a. REPORT U	b. ABSTRACT U	c. THIS PAGE U			19b. TELEPHONE NUMBER (Include area code) (312) 785-656 x4638 clay.koschnick@afit.edu	

Reset