DISSERTATION

MODELING FUZZY CRITERIA PREFERENCE TO EVALUATE TRADESPACE OF SYSTEM ALTERNATIVES

Submitted by

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ABSTRACT

MODELING FUZZY CRITERIA PREFERENCE TO EVALUATE TRADESPACE OF SYSTEM ALTERNATIVES

This dissertation explores techniques for evaluating system concepts using the point of diminishing marginal utility to determine a best value alternative with an optimal combination of risk, performance, reliability, and life cycle cost. The purpose of this research is to address the uncertainty of customer requirements and assess crisp and fuzzy design parameters to determine a best value system. At the time of this research, most commonly used decision analysis (DA) techniques use minimum and maximum values under a specific criterion to evaluate each alternative. These DA methods do not restrict scoring beyond the point of diminished marginal utility resulting in superfluous capabilities and overvalued system alternatives. Using these models, an alternative being evaluated could receive significantly higher scores when reported capabilities are greater than ideal customer requirements. This problem is pronounced whenever weights are applied to criteria where excessive capabilities are recorded. The techniques explored in this dissertation utilize fuzzy membership functions to restrict scoring for alternatives that provide excess capabilities beyond ideal customer requirements. This research investigates and presents DA techniques for evaluating system alternatives that determine an ideal compromise between risk, performance criteria, reliability and life cycle costs.

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I would like to thank my wife, Uraiphorn, for her unwavering support and encouragement towards pursuing a PhD. I would also like to thank my advisor, Dr. V. Chandrasekar, for his helpful guidance, patience, wisdom, and flexibility. Throughout this PhD journey, I got married, moved to the East Coast, had a baby, and lost my mother. Each of these major life events was challenging by itself and was certainly amplified in aggregation. Dr. Chandrasekar's sage advice and mentorship assisted me in balancing these major life milestones while continuing my PhD studies. I couldn't have completed this journey without his unwavering support. Additionally, I would like to thank my committee members for their schedule flexibility and sound recommendations for improving my research. I have incorporated each member's suggestions and believe it has significantly improved the quality of this paper.

DEDICATION

This work is dedicated to my son, Alexander, whom I hope to foster the love of continuous learning and discovery.

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1. INTRODUCTION

1.1 Motivation and Background

System analysis is difficult during early system design due to lack of test data from new, immature technologies and uncertain customer requirements. Since decisions made during conceptual design significantly influence all phases of development, researchers have focused on optimizing the decisions made during this critical phase. The United States (US) Government Accountability Office (GAO) recently reported that approximately 75 percent of a program's total Life Cycle Cost (LCC) is influenced by decisions made before a program is approved to start development. This GAO report also determined that several large acquisition programs have not provided a robust assessment of system options during the Analysis of Alternatives (AoA) [1]. Over the past few decades, acquisition professionals have focused on reducing system LCC while increasing reliability and performance. During this time, several authors have determined that concept designs heavily affect detailed designs [2]–[4] where approximately 80 percent of a system's total design and manufacturing cost is determined by the preferred conceptual design [5]. To address high military equipment costs, Gupta [6] reported that operation and support costs for a typical weapon system accounted for approximately 75 percent of total cost. Supporting Gupta's findings, Wilson [7] discovered that the cost of operating and supporting a product may exceed the initial purchase price of an item as much as ten times. While studying design for affordability, Noble and Tanchoco [8] demonstrated that the goal of designing the best product possible was often contrary to the goal of cost minimization. Dowlatshahi [9] established that the design of a product influences between 70 to 80 percent of a product's total Life Cycle Cost (LCC).

To address the imprecision and subjectivity of information during early system design, several researchers have turned to fuzzy sets to better represent this imprecise data [10]–[12]. To address varying degrees of customer preference during early system design, researchers have also used fuzzy sets to model ambiguous customer requirements [13]–[15]. There is inherent uncertainty in most decision making techniques. In *Fuzzy Set Theory and its Applications*, Zimmermann explored the various causes of uncertainty and categorized the various types as either stochastic uncertainty or fuzziness [16]. Stochastic uncertainty relates to uncertainty of occurrences and is best modeled using probability theory. Fuzzy uncertainty relates to imprecise and ambiguous system data or when information cannot be defined or described well due to limited knowledge or understanding. Fuzzy uncertainty represents vague or imprecise information and is best modeled as a membership function using fuzzy theory [17]. In *Decision-Making in a Fuzzy Environment*, Bellman and Zadeh [18] differentiated between randomness and fuzziness and argued the latter as a major source of imprecision in decision processes. They described the decision environment as fuzzy since goals and constraints are often fuzzy in nature. As an example, they described a fuzzy constraint as "x should be approximately in the range of 20-25" and a fuzzy goal as "x should be in the vicinity of $x2$". During the early stages of technology development, fuzzy methods better represent uncertainty stemming from a lack of empirical data available during concept development and preliminary design.

Along with uncertainty in decision making, mental mistakes and overexploited, shared resources can often lead to poor decisions. Since trade studies are typically led and evaluated by people, human error is often a factor. While studying the psychology of choice, Tversky and Kahneman [19] demonstrated that decision makers (DM), individuals with a high position within an organization with authority to make important decisions [20], easily anchor on certain values before evaluating all numerical data. While researching group decisions, Pennock [21] argued that government acquisition programs serve as a shared resource that disparate stakeholders often exploit to realize individual goals. In an effort to decrease human error in decision making, Smith et. al. [22] recommended that DMs increase their awareness of cognitive bias in order to make good, rational choices among alternatives. These abovementioned examples may explain why acquisition programs with high performance but high Life Cycle Costs (LCC) are still common in defense programs. Since anchoring and shared resources tend to bias DMs towards an overemphasis on technical performance, a decision control is necessary to reduce this natural human tendency.

The AH-24A “Apache” attack helicopter is an example of a system with high performance capabilities but poor reliability and high LCC. The Apache helicopter was introduced to the US Army in 1986. Although the AH-64 was considered the most advanced attack helicopter in the world at the time, the Apache helicopter suffered abysmal reliability and availability rates with operational readiness rates below the Army’s fully mission capable goal [23], [24]. The primary motivation behind this research is to study and develop a Decision Analysis (DA) technique that provides the best compromise between cost, reliability, and performance for selecting a best value system alternative.

1.2 Problem Statement

Best value acquisition decisions are difficult to make in system acquisition due to conflicting requirements. How does one design and build a reliable system with low life cycle costs while achieving high performance standards? According to a United States (US) General Accounting Office (GAO) report, Department of Defense (DOD) requirement setters aim for the most capability possible because they believe it may be several years before they get another opportunity for another weapon system. This belief creates willingness amongst DOD customers to accept cost increases and schedule delays that a commercial customer would otherwise not accept. [25] In 2010, the DOD conducted a Unmanned Aeiral Vehicle (UAV) reliability study and discovered that the services used lower quality parts in an attempt to keep costs down. Unfortunately, this approach resulted in lower availability and reliability with much higher maintenance hours than originally anticipated. [26] In an effort to expedite the acquisition process and incentivize better value alternatives, the US government created the Lowest Price Technically Acceptable (LPTA) source selection process. However, LPTA is only effective when DOD customers are sufficiently satisfied with threshold requirements. Whenever the DOD customer is willing to pay above threshold requirements and may benefit from a technologically superior solution, a tradeoff source selection between cost and performance factors is optimal [27]. This research explores fuzzy customer preference for evaluating system concepts to determine a best value alternative with an optimal combination of performance, reliability, and cost. Although the research initially focused on government applications, the techniques presented in paper can be successfully applied to any system engineering decision problem.

1.3 Research Objectives

This research introduces a new, innovative approach to optimize decisions at the point of diminished marginal utility. After conducting a comprehensive literature review, the lack of Decision Analysis (DA) research in ideal customer requirements became noticeably apparent. Although customer utility can be measured per requirement, most decision techniques do not optimize around this ideal value. Most decision techniques use maximum, minimum or mean aggregation techniques that often mask ideal customer value. The research presented in this dissertation addresses this customer utility void in the literature and presents techniques to solve this problem. As illustrated in Figure 1-1, customer utility increases steadily with additional performance until the point of diminished marginal utility where little customer utility is gained with increased performance. This research is focused on optimizing decisions at this "knee in the curve" where customer utility is ideal for a given performance criterion.

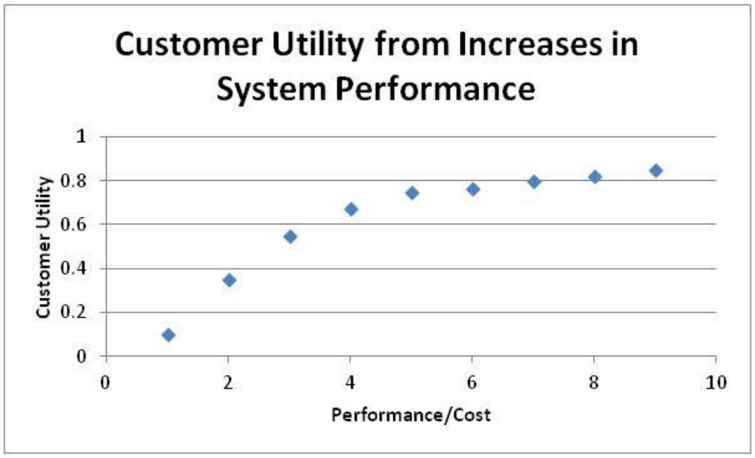

Figure 1-1: Customer Utility versus System Performance

The purpose of this research is to explore modeling fuzzy criteria preference to evaluate tradespace of system alternatives for determining the best value system. The primary research objective is to develop a straightforward technique for modeling customer criteria preference to select a best value alternative with an optimal mix of performance, reliability, and cost. Supporting research objectives include: evaluating customer preference on criteria weights and values; restricting decision scoring beyond point of diminished marginal utility; assessing ideal customer preference constraints on decision outcomes; determining an efficient method for handling mixed fuzzy and crisp information in decision data; and determining an effective way to incorporate risk in fuzzy criteria preference DA methods.

This research will significantly contribute to the educational literature by applying fuzzy customer preference and system data to decisions while saturating evaluation criteria at ideal customer requirements. Since Zadeh's revolutionary work in fuzzy numbers, much DA research has been conducted on applying fuzzy methods to various problems. However, most DA research focused on uncertainty associated with linguistic variables and little effort has been focused on other fuzzy applications. Chen's FTOPSIS approach was specifically created to incorporate linguistic variables in the decision process but hasn't been used to assess fuzzy design concepts. Although Bellman and Zadeh later introduced fuzzy goals to the DA community, little research has focused on incorporating fuzzy customer goals in DA problems. Additionally, little DA research has been conducted on constraining scores on alternatives that exceed ideal customer requirements.

1.4 Overview of Dissertation

This dissertation will present and evaluate three complimentary methods for modeling fuzzy criteria preference to evaluate the tradespace of system alternatives. An overview of system life cycle costs, fuzzy sets, Multiple Criteria Decision Analysis (MCDA) methods and other pertinent prior work will be discussed in Chapter 2. Techniques for conducting system evaluation during early system development will be reviewed in Chapter 3. Modeling system data and customer preference will be discussed in Chapters 4 and 5, respectively. Chapter 6 will introduce new Objective Criteria Saturation (OCS) MCDA techniques followed by a discussion of applying risk to OCS-MCDA in Chapter 7. Chapter 8 will demonstrate the effectiveness of the OCS-MCDA techniques through two case studies. To conclude, a summary and discussion of future work will be covered in Chapter 9.

2. PRIOR WORK AND BACKGROUND

2.1 System Life Cycle Analysis

System life cycle analysis is the assessment of system performance from a total life cycle perspective, from design to salvage. Life Cycle Costs (LCC) are total costs from initiation to disposal for both equipment and projects. [28] The primary goal of systems engineering is to reduce the risk associated with new systems or modifications to complex systems. The risk associated with system development is captured in the Figure 2-1. As indicated in the chart, 80 percent of total LCC has already been determined when only 20 percent of the actual costs have been accrued. [29] This figure highlights the importance of good information and sound analysis during early system decisions. Unfortunately, the lack of information available during early system development exacerbates this decision dilemma. Fortunately, this uncertainty can be modeled through fuzzy sets to model the imprecision and subjectivity during early system design.

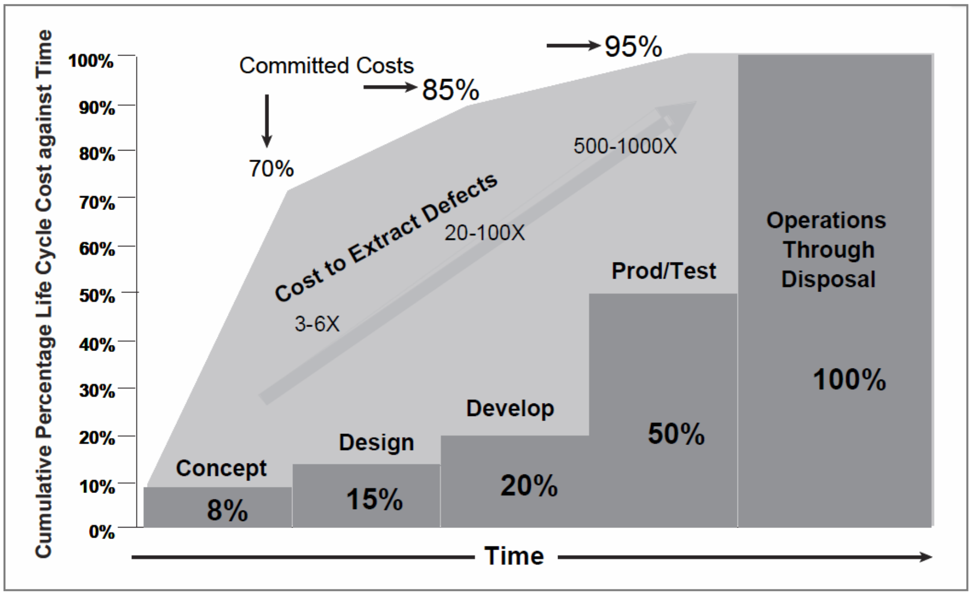

Figure 2-1: Committed Life Cycle Cost versus Time [30]

2.2 Fuzzy Sets

Zadeh [31] first introduced fuzzy set theory in 1965. Since Decision Makers (DM) often express preference in natural language, such as "poor" and "good", Zadeh utilized fuzzy sets to represent DM preference in linguistic terms. Building on Zadeh's research in fuzzy sets, several researchers have developed decision models capable of handling linguistic information [10], [32]–[34]. Expanding beyond linguistic uncertainty, Bellman and Zadeh [18] expanded fuzzy set theory to handle fuzziness of input information for decision making. Fuzzy input information covers two types: fuzzy requirements and fuzzy system data. In an effort to address the ambiguity of customer requirements, quite a few researchers have developed techniques that incorporate fuzzy numbers [13]–[15], [35]. To address the uncertainty of system data during early system design, Otto and Antonsson [11] created the Method of Imprecision (MOI) that leverages fuzzy numbers as well. While conducting their research, Otto and Antonsson observed that design descriptions are vague or imprecise during early system design. They noted that the design process at later stages of development reduced this imprecision until a final description became more precise. This research by Otto and Antonsson highlight the benefit of fuzzy methods early in technology development with a transition towards probability approaches as more precise information and test data become available.

A fuzzy set is comprised of two groups of variables. The first group of values are independent variables that are located along the x axis on the real number line $\mathbb{R}$. The second group of values are dependent variables that are located along the y axis. These dependent variables are called membership functions μ and represent the degree an independent variable x belongs in a set. Normal fuzzy sets have at least one $\mu(x) = 1$. The entire area of a fuzzy set on

$\mathbb{R}$ is called the support. The region of a fuzzy set where $\mu(x) = 1$ is called the core. The region of a fuzzy set where $\mu(x) \neq 1$ is called the boundary. [36]–[39]

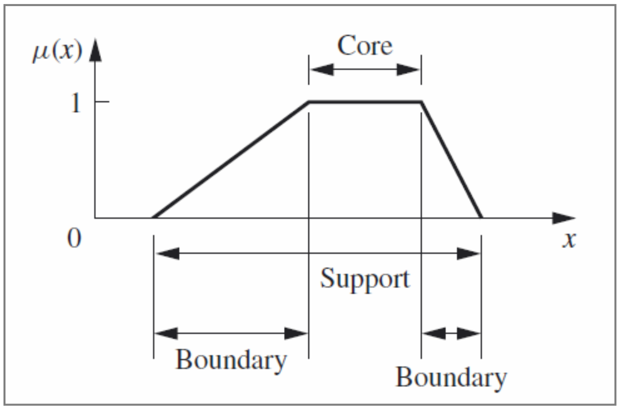

Figure 2-2: Core, Support, and Boundaries of a Fuzzy Set [39]

2.2.1 Multiple Meaning of Membership Functions. Fuzzy sets can be useful in modeling system criteria during Multiple Criteria Decision Analysis (MCDA). However, fuzzy membership functions can also have multiple meanings depending on the context. Fuzzy membership can represent a degree of uncertainty, preference, or similarity [36]. Fuzzy membership can also correspond to a random set or measurement viewpoint [40]. During early system development, imprecision and lack of information can be modeled as a degree of uncertainty using fuzzy sets. Conversely, ambiguous customer requirements can be modeled during early system design using fuzzy sets to model degrees of preference. The membership functions presented in this dissertation will represent either a degree of preference or uncertainty. The membership functions that represent degrees of uncertainty can be further separated into incomplete and unquantifiable information [41]. The following three meanings of membership functions will be used throughout this dissertation.

2.2.1.1 Fuzzy Preference. A membership function representing a degree of preference contains a set of more or less preferred objects or values. According to this viewpoint, the $\mu(x)$

of a decision variable represents the intensity of preference in favor of x. [36] Therefore, in the fuzzy preference view, fuzzy sets represent criteria or flexible constraints.[18] This perspective of fuzzy sets is useful for modeling fuzzy criteria preference that is often expressed as tradespace threshold and objective values.

2.2.1.2 Imprecise System Data. A membership function representing a degree of uncertainty with incomplete information contains a set of variables that have a possibility of containing a specific value. This concept of membership functions representing a degree of uncertainty was proposed by Zadeh when he introduced his possibility and approximate reasoning theories [42]. According to the fuzzy uncertainty viewpoint, $\mu(x)$ represents the possibility that a parameter has value x given limited information. This fuzzy uncertainty perspective also assumes the values encompassed by the support of the membership function (see Fig 2) are mutually exclusive where the membership degrees rank these values by their respective possibility. [39] This fuzzy uncertainty view is useful for modeling imprecise system data when limited information is known about the system, such as concept development or preliminary design.

2.2.1.3 Linguistic Data. A membership function representing a degree of uncertainty with unquantifiable information may consist of a set of linguistic data. Linguistic uncertainty is where words such as good, fair, and poor are used to describe a characteristic. Linguistic qualifiers, such as “very tall”, “around two meters”, or “approximately six feet” also result in unquantifiable information that can lead to uncertainty [33], [39]. Whenever linguistic qualifiers are used to describe a system criterion, this fuzzy linguistic uncertainty perspective is useful for modeling this unquantifiable information.

2.3 Multiple Criteria Decision Making (MCDA)

Multiple Criteria Decision Analysis (MCDA) methods, also called Multiple Criteria Decision Making (MCDM), have received much attention from researchers in evaluating, assessing and ranking alternatives across diverse industries [43]. Decision Makers (DM) are often faced with conflicting selection criteria where no solution can satisfy all criteria simultaneously. MCDA was established to evaluate conflicting criteria in decision making in an effort to select the best alternative. There are several MCDA techniques that attack different problems from diverse perspectives and methods. However, despite the various methods available, they all have certain aspects in common, such as the notion of alternatives and attributes [41]. MCDA can be largely classified into two categories: Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM) [16].

2.3.1 Multiple Objective Decision Making (MODM). Multiple objective decisions are problems where the decision space is continuous and the alternatives have not been predetermined. A typical example of a MODM method is mathematical programming problems with multiple objective functions. [41], [44]

2.3.2 Multiple Attribute Decision Making (MADM). Multiple attribute decisions are problems with discrete decision space where the alternatives have been predetermined [41], [44].

2.4 MCDA Methods Selected for Best Value Enhancement

The Weighted Sum Model (WSM), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy Technique for Order of Preference by Similarity to Ideal

Solution (FTOPSIS) are MADM methods that were selected as dissertation study candidates due to their wide use across various industries. [44]–[46]

2.4.1 Weighted Sum Model (WSM). The Weighted Sum Model (WSM) is the simplest and probably the most widely used method in decision making [45]. The WSM method applies the additive utility hypothesis to imply that the overall value of every alternative for a specific criterion is equivalent to the total sum [47]. Due to this additive utility assumption, WSM typically provides the most acceptable results using the same units and ranges across all criteria. However, since most problem solving problems include a wide range of units and ranges, WSM can also be applied to MCDA problems as long as the evaluation data is normalized [48], [49] and the decision objectives are not conflicting [50]. If a decision problem has both benefit and cost criteria that require determining both a minimum and a maximum for specific criteria, then the WSM will produce inaccurate results. Therefore, in MCDA problems with conflicting benefit and cost criteria, another decision tool should be used to ensure accurate results.

The steps for using the WSM method are as follows:

1. Populate the decision matrix D with data from each alternative A_i; where x_{ij} is the value for the *i*th alternative A_i with respect to the *j*th criterion C_j; and w_i represents the weight of the *j*th criterion C_j.

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{2-1}$$

$$w = [w_1, w_2, \dots, w_n]$$

2. Create a normalized decision matrix R from decision matrix D using Equation 2-2.

$$r_{ij} = \frac{x_{ij}}{Max_i(x_{ij})} \quad i = 1, 2 \ldots, m; \; j = 1, 2, \ldots, n \tag{2-2}$$

where r_{ij} is the normalized value of x_{ij}.

3. Calculate the weighted sum of matrix R using Equation 2-3.

$$A^*_{WSM\ (Score)} = \sum_{j=1}^{n} r_{ij} w_j, \; for \; i = 1, 2 \ldots, m \tag{2-3}$$

4. The alternative with the highest score represents the best alternative

2.4.2 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

To handle conflicting requirements, Hwang and Yoon [51] created the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to solve MCDA problems. Using TOPSIS, the best alternative should have the shortest distance from a Positive Ideal Solution (PIS) and the farthest distance from a Negative Ideal Solution (NIS). Expanding on Hwang and Yoon's initial technique, several researchers have applied TOPSIS to a wide range of applications [52]–[55]. To address the rank reversal phenomenon with TOPSIS, Garcia-Cascales and Lamata [56] recommended alterations to TOPSIS to prevent rank reversal.

The steps for Hwang and Yoon's TOPSIS are as follows:

1. Populate the decision matrix D using Equation 2-1.

2. Create a normalized decision matrix R from matrix D using Equation 2-4.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad i = 1, 2 \dots, m;\ j = 1, 2, \dots, n \tag{2-4}$$

where r_{ij} is the normalized value of x_{ij}.

3. Calculate the weighted normalized decision matrix V by multiplying the normalization values r_{ij} by the criterion weights w_j.

$$V = [v_{ij}]\, mxn \qquad i = 1, 2 \dots, m;\ j = 1, 2, \dots, n \tag{2-5}$$

where $v_{ij} = r_{ij}\ (\cdot)\ w_j$

4. Determine the Positive Ideal Solutions (PIS) v_j^+ and Negative Ideal Solutions (NIS) v_j^- using Equations 2-6 and 2-7.

$$PIS = \{v_{1,}^+ v_{2,}^+ \dots v_{j,}^+ \dots, v_{n,}^+\}; \tag{2-6}$$

$$NIS = \{v_{1,}^- v_{2,}^- \dots v_{j,}^- \dots, v_{n,}^-\} \tag{2-7}$$

where,

$$v_j^+ = \begin{cases} max(v_{j1}, v_{j2}, \dots, v_{jm});\ P_j\ is\ a\ benefit\ criterion \\ min(v_{j1}, v_{j2}, \dots, v_{jm});\ P_j\ is\ a\ cost\ criterion \end{cases}$$

$$v_j^- = \begin{cases} min(v_{j1}, v_{j2}, \dots, v_{jm});\ P_j\ is\ a\ benefit\ criterion \\ max(v_{j1}, v_{j2}, \dots, v_{jm});\ P_j\ is\ a\ cost\ criterion \end{cases}$$

5. Use Equations 2-8 and 2-9 to calculate the Euclidean distances d_i^+ and d_i^- of alternative A_i to PIS and NIS, respectively.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2},\ i = 1,2, \dots, m, \tag{2-8}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_J^-\right)^2}, i = 1,2, \dots, m. \quad (2\text{-}9)$$

6. Calculate the closeness coefficient CC_i. The closeness coefficient represents the distances of each alternative to v_j^+ and v_j^- and is calculated:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \dots, m. \quad (2\text{-}10)$$

7. The alternative with the highest CC_i represents the best alternative and is closest to PIS and farthest from NIS.

2.4.3 Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS). To address uncertainty in decision analysis, many researchers have combined fuzzy theory with TOPSIS. The concept of applying fuzzy numbers to TOPSIS was first suggested by Negi [57] and was revised by Triantaphyllou and Lin [45] who developed a fuzzy version of TOPSIS that calculated a fuzzy relative closeness for each alternative. Chen [58] applied TOPSIS to a fuzzy environment using triangular fuzzy numbers to replace the numeric linguistic scales for rating and weights. After Chen published his Fuzzy TOPSIS method for group decision making, several researchers published papers proposing extensions to his FTOPSIS with applications across multiple industries [35], [46], [59]–[61].

The steps to Chen's FTOPSIS are as follows:

1. Populate the decision matrix $\widetilde{D}$ with data from each alternative system A_i; where $\tilde{x}_{ij}$ is the value for the *i*th alternative A_i with respect to the *j*th criterion C_j; and w_i represents the weight of the *j*th criterion C_j.

$$\widetilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \dots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \dots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & \dots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{2-11}$$

$$w = [w_1, w_2, \dots, w_n]$$

2. Create a normalized decision matrix $\tilde{R}$ from decision matrix $\widetilde{D}$. First, perform a linear scale transformation to transform the various criteria scales into a comparable scale and obtain a normalized fuzzy decision matrix $\tilde{R}$.

$$\tilde{R} = [\tilde{r}_{ij}]\ mxn, \tag{2-12}$$

Next, perform a normalization calculation to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0,1]. Equation 2-13 calculates the set of benefit criteria $\tilde{B}$ and Equation 2-14 calculates the set of cost criteria $\tilde{C}$.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), j\ \in \tilde{B}, \tag{2-13}$$

$$c_j^+ = \max c_{ij}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) j\ \in \tilde{C}, \tag{2-14}$$

$$c_j^- = \min a_{ij}$$

3. Calculate the weighted normalized decision matrix $\tilde{V}$ by multiplying the normalization values $\tilde{r}_{ij}$ by the criterion weights w_j.

$$\tilde{V} = \left[\tilde{v}_{ij}\right] mxn \qquad i = 1, 2 \ldots, m; j = 1, 2, \ldots, n \tag{2-15}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \ (\cdot) \ w_j$

4. Define FPIS A^{+} and FNIS A^{-} using Equation 2-16 and 2-17, respectfully.

$$A^{+} = (\tilde{v}_1^{+}, \tilde{v}_2^{+}, \ldots, \tilde{v}_n^{+}), \tag{2-16}$$

$$A^{-} = (\tilde{v}_1^{-}, \tilde{v}_2^{-}, \ldots, \tilde{v}_n^{-}), \tag{2-17}$$

where,

$$\tilde{v}_{\mathrm{j}}^{+} = \begin{cases} \max\{\tilde{v}_{ij_3}\}, i = 1, 2, \ldots m;\ j = 1, 2, .. n;\ P_j\ is\ a\ benefit\ criterion \\ \min\{\tilde{v}_{ij_1}\}, i = 1, 2, \ldots m;\ j = 1, 2, .. n;\ P_j\ is\ a\ cost\ criterion \end{cases}$$

$$\tilde{v}_{\mathrm{j}}^{-} = \begin{cases} \min\{\tilde{v}_{ij_1}\}, i = 1, 2, \ldots m;\ j = 1, 2, .. n;\ P_j\ is\ a\ benefit\ criterion \\ \max\{\tilde{v}_{ij_3}\}, i = 1, 2, \ldots m;\ j = 1, 2, .. n;\ P_j\ is\ a\ cost\ criterion \end{cases}$$

5. Calculate the distance of each alternative from A^{+} and A^{-}.

$$d_i^{+} = \sum_{j=1}^{n} d_v \ \left(\tilde{v}_{ij,} \tilde{v}_j^{+}\right) \tag{2-18}$$

$$d_i^{-} = \sum_{j=1}^{n} d_v \ \left(\tilde{v}_{ij,} \tilde{v}_j^{-}\right) \tag{2-19}$$

where $d_v \left(\tilde{a}, \tilde{b}\right)$ is the distance measurement between two fuzzy numbers.

The distance between $\tilde{a}$ and $\tilde{b}$ can be calculated using the vertex method by:

$$d\left(\tilde{a},\ \tilde{b}\right) = \sqrt{\tfrac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{2-20}$$

6. Calculate the closeness coefficient CC_i. The closeness coefficient represents the distances to A^+ and A^- and is calculated:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \ldots, m. \tag{2-21}$$

7. The alternative with the highest CC_i represents the best alternative and is closest to A^+ and farthest from A^-.

3. SYSTEM EVALUATION DURING EARLY DEVELOPMENT

3.1 Measures of Effectiveness (MOE) and Measures of Performance (MOP)

Measures of Effectiveness (MOE) are a set of criteria that identify characteristics of a system response to its environment that are critical to its operational utility. MOEs are used to conduct an effectiveness analysis to determine whether or not a system concept is feasible and satisfies the operational objectives required to meet a projected need [62]. MOEs must be defined by a specified level of importance, as determined by the customer and the criticality of the functions the system will perform [63] and be independent of any particular solution [64].

Measures of Performance (MOP) are a set of criteria that characterize a physical or functional attribute relating to the execution of a process, function, activity or task. MOPs are used to assess quantity, quality, timeliness, and readiness of system performance characteristics. MOPs are determined by the following: selected standards; system boundaries; external interfaces, utilization environment, life cycle process requirements; design consideration, constraints, and verification criteria, and configuration control. [29] MOPs often become system performance requirements that result in achieving a critical threshold for the system MOEs [64]. For US DOD acquisition programs, MOPs are typically expressed as Key Performance Parameters (KPP) or Key System Attributes (KSA) that contain threshold and objective values [65].

The difference between MOEs and MOPs may be difficult for anyone not working with them consistently. The primary distinction between MOEs and MOPs is that they are formulated from different viewpoints. An MOE is expressed from the user viewpoint and refers to the effectiveness of a solution from mission or operational success. A MOP is expressed from the system viewpoint and represents actual performance which may only be indirectly related to user concerns. [64]

The United States (US) Department of Defense (DOD) mandates the use of MOEs and MOPs during large system acquisition. Although the military definitions of MOE and MOP are more combat focused than the aforementioned definitions, they still adhere to the same overall concept. According to the Defense Acquisition University (DAU) Defense Acquisition Guidebook (DAG), the definition of MOE is:

> The data used to measure the military effect (mission accomplishment) that comes from using the system in its expected environment. That environment includes the system under test and all interrelated systems, that is, the planned or expected environment in terms of weapons, sensors, command and control, and platforms, as appropriate, needed to accomplish an end-to-end mission in combat. [65]

The DAG definition of MOP is "system particular performance parameters such as speed, payload, range, time-on-station, frequency, or other distinctly quantifiable performance features". The DAG also states that several MOPs may be related to the achievement of a particular MOE [65]. By associating MOPs to MOEs, a system can be analyzed quantitatively to determine the degree it meets operational utility.

3.2 Concept of Operations (CONOPS) Evaluation

A Concept of Operations (CONOPS) for a system consists of a range of scenarios that represent the full scope of expected operational situations that the system may encounter. These scenarios must be based on extensive study of operational environments, discussions with experienced users, and a thorough understanding of past experiences and deficiencies of the current system [62]. Scenario thinking is an enduring concept that can be traced back to early philosophers such as Plato and Seneca[66]. Operational scenarios serve as a useful methodology for planning and decision making in complex and uncertain environments [29]. If a system if for a military user, there may be a requirement to develop several Operational Views (OV) for each CONOPS. The following are six common Operational Views (OV)[67]:

- High Level Operation Concept Graphic (OV-1)
- Operational Node Connectivity Description (OV-2)
- Operational Information Exchange Matrix (OV-3)
- Organizational Relationship Chart (OV-4)
- Operational Activity Model (OV-5)
- Operational Event/Trace Description (OV-6c)

Figure 3-1: Operational Views (OV)

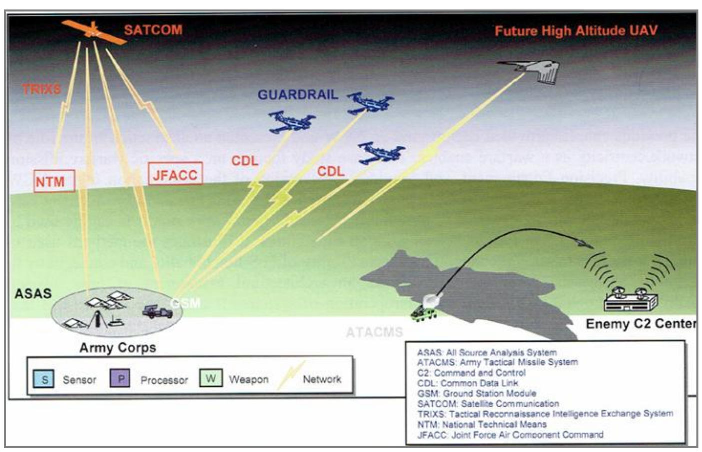

Figure 3-1-A: High-Level Operational Concept (OV-1) [67]

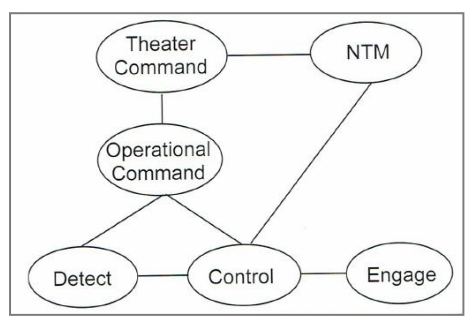

Figure 3-1-B: Node Connectivity (OV-2) [67]

Figure 3-1 (continued): Operational Views (OV)

Source OV-2 Node	Nodal Activity	Information Element	Receiving OV-2 Node
Theater Command	Issue Task Order and Guidance	Task Order and Guidance	Operational Command
Operational Command	Update Mission Plan	Collection Plan	Detect
	Update Mission Plan	Weapon Target Plan	Control
	Grant Permission to Fire	Permission to Fire	Control
Detect	Detect Target	Sensor Reports	Control
	Detect Environment	Sensor Reports	Control
Control	Nominate Target	Target Nomination	Operational Command
	Issue Fire Order	Fire Order	Engage
Engage	Execute Fire Order	Weapon Launch Report	Operational Command

Figure 3-1-C: Information Exchange Matrix (OV-3) [67]

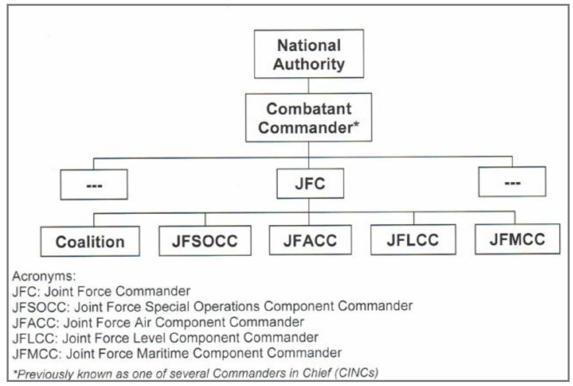

Figure 3-1-D: Command Relationships (OV-4) [67]

Detect	Control	Engage	Command
• Search • Detect target • Detect environment	• Identify target • Geolocate target • Nominate target • Issue fire order	• Execute fire order • Weapon fly out	• Update mission plan • Deconflict airspace • Grant permission to fire

Figure 3-1-E: Operational Activity Model (OV-5) [67]

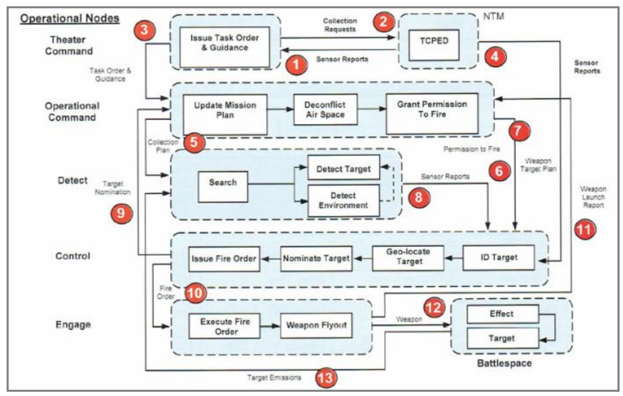

Figure 3-1-F: Event Trace Description (OV-6c) [67]

3.2.1 MOE Evaluation. During systems analysis, MOEs are used to ascertain how well a design alternative meets system goals. Typically, this assessment is accomplished through trade studies that are conducted to determine the best solution that can be realistically achieved with the available resources. The NASA Systems Engineering Handbook [64] proposes the following basic steps for analyzing alternative design solutions:

1. Determine system architectures / designs
2. Evaluate alternatives in terms of MOEs and system cost
3. Rank the alternatives according to appropriate selection criteria
4. Drop less promising alternatives and proceed to next level of abstraction, if necessary

3.2.2 System Performance Evaluation. Alternative system performance can be assessed using MOPs to evaluate how well a system meets performance requirements.

3.2.2.1 Mapping MOPs to MOEs. Since MOPs contribute to MOEs, MOPs can be used to quantitatively measure how well MOEs meet operational needs. By mapping MOPs to MOEs, quantitative Decision Analysis (DA) methods can be employed to evaluate system alternatives against evaluation criteria.

3.2.2.2 Using MCDA Methods to Evaluate System Alternatives. Multiple Criteria Decision Analysis (MCDA) methods are useful in assisting DMs evaluate system alternatives. Both Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM) methods can be employed to evaluate alternatives using both continuous and discrete methods. Since the decision space is continuous for MODM, these methods can be beneficial for conducting concept space exploration. An example of a MODM technique used for concept exploration is the Genetic Algorithm (GA), a technique that is based on Darwin's theory of evolution and survival of the fittest. The GA method enables the exploration of non-convex, multimodal, and displaced design spaces by searching the range through multiple points simultaneously. [68] Once the best alternative candidates are selected using MODM techniques, MADM can be used to evaluate alternatives using discrete MOPs. Some MADM techniques that are useful for this type of analysis are the aforementioned Weighted Sum Model (WSM), the Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solutions (FTOPSIS). The scope of this dissertation research is constrained to MADM techniques with a particular focus on WSM, TOPSIS, and FTOPSIS methods.

4. MODELING SYSTEM DATA

4.1 Crisp Data

Developers of mature systems with sufficient test and field data often provide crisp system performance data for potential customers. In fact, the majority of system data available is in a crisp format. According to naïve set theory [69], a crisp Set A can be defined as a collection of elements x out of a universal set X, where all elements in X have the same characteristics. The universal set X is a nonempty set containing all possible elements x. [70] For Multi Criteria Decision Analysis (MCDA), set operations can be useful for assessing alternative system characteristics for a single criterion.

4.1.1 Operations on Crisp Sets. Given two crisp sets A and B on the universal set X, the following operations can be applied to crisp sets[39].

Union $$A \cup B = \{x | x \in A \; or \; x \in B\} \tag{4-1}$$

Intersection $$A \cap B = \{x | x \in A \; or \; x \in B\} \tag{4-2}$$

Complement $$\overline{A} = \{x | x \notin A, x \in X\} \tag{4-3}$$

Difference $$A | B = \{x | x \in A \; or \; x \notin B\} \tag{4-4}$$

4.1.2 Properties of Crisp Sets. Given multiple sets on the universal set X, the following properties are significant because of the mathematical manipulation of sets and their similarity to fuzzy sets [39].

Commutativity
$$A \cup B = B \cup A$$
$$A \cap B = B \cap A. \tag{4-5}$$

Associativity

$$A \cup (B \cup C) = (A \cup B) \cup C$$
$$A \cap (B \cap C) = (A \cap B) \cap C. \tag{4-6}$$

Distributivity

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$$
$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C). \tag{4-7}$$

Idempotency

$$A \cup A = A$$
$$A \cap A = A. \tag{4-8}$$

Identity

$$\boldsymbol{A} \cup \emptyset = A$$
$$A \cap X = A$$
$$A \cap \emptyset = \emptyset$$
$$A \cup X = X. \tag{4-9}$$

Transivity

$$If\ A \subseteq B\ and\ B \subseteq C, then\ A \subseteq C. \tag{4-10}$$

Involution

$$\bar{\bar{A}} = A \tag{4-11}$$

De Morgan's Principles

$$\overline{A \cap B} = \bar{A} \cup \bar{B} \tag{4-12}$$

$$\overline{A \cup B} = \bar{A} \cap \bar{B}. \tag{4-13}$$

4.1.3 Types of Crisp Data. Unless developers incorporate fuzzy methods in their data collection, most data will be in a crisp format. Crisp data can be generally categorized in two forms: nominal and numeric.

4.1.3.1 Nominal Data. For decision making, nominal data represents values without any quantitative information. Nominal data may represent unstructured information that lacks the ability to be measured. Nominal data may also signify labels or descriptions, such as color or location names. In some circumstances, nominal data is applied to decision analysis to capture user preference. This preference could either be a mandatory or favoritism requirement. An example of a mandatory requirement would be the purchase of a specific colored jersey for a professional sports team. An example of a favoritism requirement would be the selection of a food entrée for a catered event.

4.1.3.2 Numerical Data. For decision making, numerical data represents values with quantitative information that can be measured and compared against other data. For most DA applications, numerical data is useful for measuring the degree parameters meets user preference.

4.2 Fuzzy Data

During early system development, most designs can best be represented with some level of imprecision or approximation [71]. According to Goguen [72] "Fuzziness is more than the exception in engineering design problems: usually there is no well-defined best solution or design." This quote by Goguen captures the reason for using fuzzy sets in early system design. For decision making during early system development, fuzzy sets are useful at capturing the approximations made during the early phases of engineering design. [71]

A fuzzy set contains elements that have varying degrees of membership in the set. This partial membership is what differentiates fuzzy sets from crisp sets where elements are either in or out of a defined set. For an element in a universe that contains fuzzy sets, the transition can be gradual. This gradual transition results in vague and ambiguous set boundaries where the membership function of fuzzy sets captures this uncertainty. [39] By relaxing boundaries conditions, fuzzy sets provide a useful means for modeling imprecise and ambiguous data that is often prevalent in early system design.

4.2.1 Operations on Fuzzy Sets Given sets $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ on the universal set X, the following operations can be applied to fuzzy sets[39].

Union $$\mu_{\tilde{A}\cup\tilde{B}}(x) = \mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}}(x). \tag{4-14}$$

Intersection $$\mu_{\tilde{A}\cap\tilde{B}}(x) = \mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x). \tag{4-15}$$

Complement $$\mu_{\bar{\tilde{A}}}(x) = 1 - \mu_{\tilde{A}}(x). \tag{4-16}$$

Unlike crisp sets, *Difference* operations are rarely applied on fuzzy sets and most fuzzy mathematics textbooks omit difference equations for fuzzy sets. A further discussion on different calculations is beyond the scope of this dissertation but additional information can be found at [73].

4.2.2 Properties of Fuzzy Sets. Fuzzy sets follow the same properties as crisp sets [39], [70]. Therefore, the properties given in Equations 4-5 through 4-13 are identical to those for fuzzy sets.

4.2.3 Types of Fuzzy Data Fuzzy data represents imprecise and ambiguous system data or when information cannot be defined or described well due to limited knowledge or understanding. Fuzzy data can be generally categorized in two forms: linguistic and imprecise.

4.2.3.1 Linguistic Data. During early system design and evaluation, engineers and DMs may use words such as good, fair, and poor to describe a characteristic or evaluate a system. Linguistic qualifiers, such as “very long”, “around ten meters”, or “approximately 15 feet” also result in unquantifiable information that can lead to uncertainty [33], [39]. Fuzzy sets are useful in modeling this ambiguous and ill defined information.

4.2.3.2 Imprecise Data. Despite high uncertainty during early system development, the design engineers of each alternative typically provide the best performance and reliability estimates [74]. By using the Method of Imprecision (MoI), designers can formally incorporate their judgment and experience using fuzzy sets. By applying MoI, designers can model their preference for a particular value or range [11]. Although cost estimates are often performed separate from design engineers, the cost estimates are often provided in a range from worst, most likely, to best case. These cost estimates, as well as MoI design estimates, can be modeled as a triangular membership function, where:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1, \\ \frac{x - a_1}{a_2 - a_1}, & a_1 \leq x \leq a_2, \\ \frac{a_3 - x}{a_3 - a_2}, & a_2 \leq x \leq a_3, \\ 0, & x > a_3. \end{cases} \tag{4-17}$$

MoI design estimates can also be modeled as a trapezoid membership function, where:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1, \\ \frac{x - a_1}{a_2 - a_1}, & a_1 \leq x \leq a_2, \\ 1, & a_2 \leq x \leq a_3, \\ \frac{a_4 - x}{a_4 - a_3}, & a_3 \leq x \leq a_4, \\ 0, & x > a_4. \end{cases} \tag{4-18}$$

4.3 Mixed Data (Crisp & Fuzzy)

Due to the inherent differences between crisp and fuzzy numbers, the existence of both types of data in a decision matrix may cause calculation errors. For example, the Euclidean distance calculations for TOPSIS are different from FTOPSIS. If both fuzzy and crisp data are used in either calculation, the analysis could produce undesirable results. Therefore, fuzzification or de-fuzzification should be performed in order to facilitate comparisons between fuzzy and crisp data. Unfortunately, there is no steadfast guidance on whether to perform fuzzification or de-fuzzification, although many DA techniques seem to prefer crisp transformation[43]. Perhaps a heuristic could be to decide a technique based on the higher occurrence of data type within a decision matrix. For example, if a higher percentage of crisp data is present in the data set, then de-fuzzification should be performed on all fuzzy data. Conversely, if more fuzzy data is present, then fuzzification should be performed on all crisp data. However, given the higher availability of crisp data, it may be assumed that de-fuzzification would be used more often. Perhaps this is why crisp transformations appear more frequently in the literature. This may change in the future, however, if fuzzy methods continue expanding in industry.

4.4 Transformations

In order to conduct effective decision analysis, fuzzy and crisp data should be transformed into a similar format. Fuzzification is the process of making a crisp number fuzzy and de-fuzzification, or crisp transformation, is the process of making a fuzzy number crisp.

4.4.1 Fuzzification. If crisp data is associated with imprecision, ambiguity, or vagueness, then the value can be represented by a fuzzy membership function. Under these circumstances, the uncertainty can be captured in the boundary portion of the fuzzy set. For example, hardware such as a digital voltmeter displays crisp data but is subject to experimental error. This experimental error can be modeled as a fuzzy membership function. Figure 4-1 depicts a range of errors for a voltage reading and its associated membership function represents that imprecision.[39]

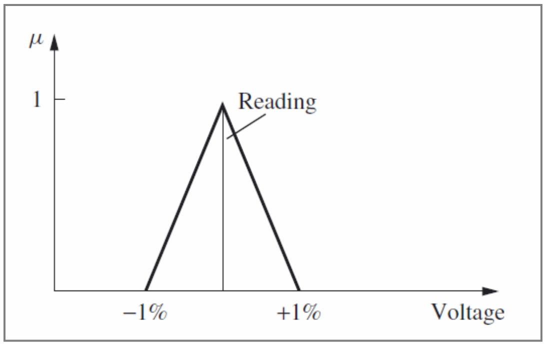

Figure 4-1: Membership function of crisp data with imprecision [39]

4.4.2 De-Fuzzification. There are many de-fuzzification techniques, each with advantages and disadvantages. The fuzzy sets in this dissertation are associated with normal triangular or trapezoidal fuzzy numbers. Therefore, the de-fuzzification techniques for non-normal fuzzy sets as well as techniques for different shaped fuzzy numbers were not included in this dissertation. Additional information about de-fuzzification techniques can be found at [39], [70], [75].

Fuzzy parameters derived from Method of Imprecision (MoI) usually conform to a normal fuzzy set where data with the highest design engineer confidence have a membership value of one. For symmetric triangular and trapezoidal membership functions, the maximum membership and mean maximum membership de-fuzzification techniques could be used to transform the fuzzy sets to crisp data, respectively. Equation 4-19 could be used for triangular membership functions and Equation 4-20 could be used for trapezoidal membership functions, where x^* is a defuzzified value for both equations. For Equation 4-20, a and b represent the peak of the trapezoidal membership function where $\mu_{\tilde{a}}(x) = 1$. If the membership function is asymmetrical with a noticeable skew, the graded mean integration technique [76] may be a better technique to capture the skewness in the data. The graded mean integration technique is a simple, straightforward de-fuzzification technique that is suitable for triangular and trapezoidal fuzzy sets. Since most MoI data is captured in triangular and trapezoidal fuzzy sets [11], the graded mean integration technique should be adequate for most calculations. To perform the graded mean integration technique for triangular membership functions, use Equation 4-21 and for trapezoidal membership functions, use Equation 4-22.

$$\mu_{\tilde{A}}(x^*) \geq \mu_{\tilde{A}}(x) \qquad \forall\, x \in X \tag{4-19}$$

$$x^* = \frac{a+b}{2} \tag{4-20}$$

$$P(\tilde{A}) = \frac{1}{6}\,(a_1 + 4a_2 + a_3) \tag{4-21}$$

$$P(\tilde{A}) = \frac{1}{6}\,(a_1 + 2a_2 + 2a_3 + a_4) \tag{4-22}$$

5. MODELING CUSTOMER PREFERENCE

Customer preference is often elicited through several methods. The three most common types of elicitation are collaborative, research, and experiments. Collaborative elicitation involves direct interaction with stakeholders to glean their experiences, expertise and judgment. Research involves methodically discovering and studying information from material or sources. Experiments include identifying previously unknown information through a controlled test. [77]

5.1 Customer Preference on Criteria Weights

Criteria weights are determined by requirements prioritization. This occurs after requirements are traced to ensure that requirements and designs at different levels are aligned to one another. After requirements are prioritized, they are often modeled to analyze, synthesize and refine customer elicitation results. During requirements modeling, different viewpoints are often employed for addressing the concerns of a particular stakeholder group. This process is similar to the Operational Viewpoints (OV) [67] that was discussed in section 3.2. Once all stakeholder issues have been addressed, the requirements are eventually verified and validated for further decision analysis. [77]

5.1.1 Requirement Prioritization Methods. Requirements prioritization is the act of ranking requirements to determine their relative importance to stakeholders. There are several factors that influence prioritization such as benefit, cost, risk, and dependencies of each requirement. All of these factors have to be addressed to adequately prioritize requirements. When conducting requirements prioritization, there are many techniques that can be used such as financial analysis, business cases, interviews, risk analysis, and workshops. [77] Requirement prioritization can also be performed through technical importance measurement using the Quality Functional Deployment (QFD) [68]. QFD is a method, developed by Yoji Akao, to transform the "voice of the customer" into engineering characteristics for a product [78]. In decision analysis, determination of criteria weights can sometimes be ad hoc [68], but it is preferred to link criteria weights to prioritized requirements that were elicited with one or more formalized techniques.

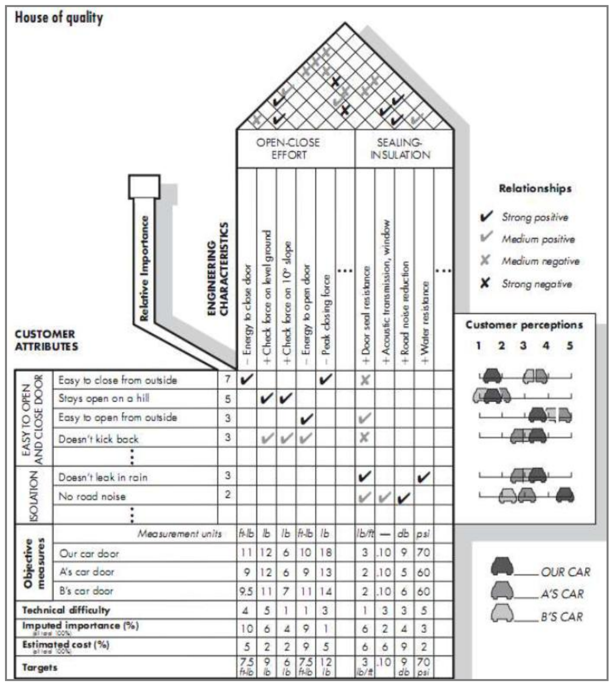

Figure 5-1: Quality Function Deployment [79]

5.1.2 Ranking Criteria Weights. Criteria weights play an important role for measuring overall preference of alternatives. There are several weighting methods available, each with advantages and disadvantages. Since the aim of the OCS-MCDA techniques is to reduce decision maker bias during system analysis, a rank sum weighting method [80] was used to rank criteria according to prioritized customer requirements. The rank sum method was selected because its ranking methodology and weight results reflect a prioritized list. To record criteria weights, the technique works best using a prioritized requirements list that was generated using standard business analysis processes. For government projects, any document that describes Key Performance Parameters (KPP) thresholds, objectives, and priorities should be sufficient. For most US government Request for Proposals (RFP), the solicitation document lists evaluation criteria in order of importance from most to least significant. Other sources of US government threshold, objective, and priorities include DODs Initial Capabilities Document (ICD), Capability Development Document (CDD) and the Department of Homeland Security's (DHS) Operational Requirements Document (ORD). Regardless of where criteria weights originate, the OCS-MCDA methods use the following weighting technique:

1. Rank criteria 1 through n to reflect customer priorities from most to least significant

2. Weight rank position using the rank sum method

$$w_j = \frac{n - r_j + 1}{\sum_{k=1}^{n} n - r_k + 1} \tag{5-1}$$

where r_j is the rank of the j^{th} criterion, j = 1, 2, …, n.

3. Ensure that all weights w_j sum up to one

$$\sum_{j=1}^{n} w_j = 1 \tag{5-2}$$

5.2 Customer Preference on Criteria Values

An important goal when conducting customer data elicitation is to determine the point of diminished marginal utility for each significant system criterion. Diminished marginal utility occurs when each additional unit provides less and less additional utility [81], [82]. For engineering applications, the point of diminished marginal utility is often referred to as the "knee in the curve" where the cost to increase a parameter is no longer worth the performance benefit [83]–[85]. Restricting diminished marginal utility is one of the objectives of this dissertation. The Objective Criteria Saturation (OCS) Multiple Criteria Decision Analysis (MCDA) techniques proposed in this research were created to constrain inflated scoring beyond the "knees in the curve".

5.2.1 Elicitation Methods. There are several elicitation techniques available to determine customer preference on criteria values. Some of these techniques include: benchmarking and market analysis; concept modeling; data mining; document analysis; focus groups; interface analysis; interviews and workshops. [77] After the customer elicitation data has been confirmed, verified and validated, it can be used with the OCS-MCDA decision techniques. The OCS techniques work best with validated customer preference data where the point of diminished marginal utility has already been identified and validated.

5.2.2 Modeling Validated User Needs. After user needs have been properly validated, they can be modeled using fuzzy sets. Since customers frequently explain their requirements in a vague and fuzzy manner, fuzzy sets are useful in modeling this uncertainty. Customer requirements are also frequently conflicting, such as low cost and high performance.

The US government applies threshold and objective criteria for its requirements, which can be modeled as a fuzzy set. By establishing objective and threshold requirements, the US government provides a trade space for developers to adjust conflicting capabilities to best meet government needs. Fuzzy sets provide a means for representing and dealing with flexible goals, in which the flexibility in the goals can be exploited to satisfy contradictory goals [86]. Previous researchers have advocated using triangular fuzzy numbers to model fuzzy customer requirements [13]–[15]. If cost and benefit criteria are aggregated, then the intersection of cost and benefit criteria should provide the maximum utility resulting in a triangular membership function (see Figure 5-2). However, if criteria are evaluated independently, then open shoulder Γ and L fuzzy sets better represent separate customer requirements, where the Γ membership function monotonically increases from the threshold value and the L membership function monotonically decreases from the threshold value.

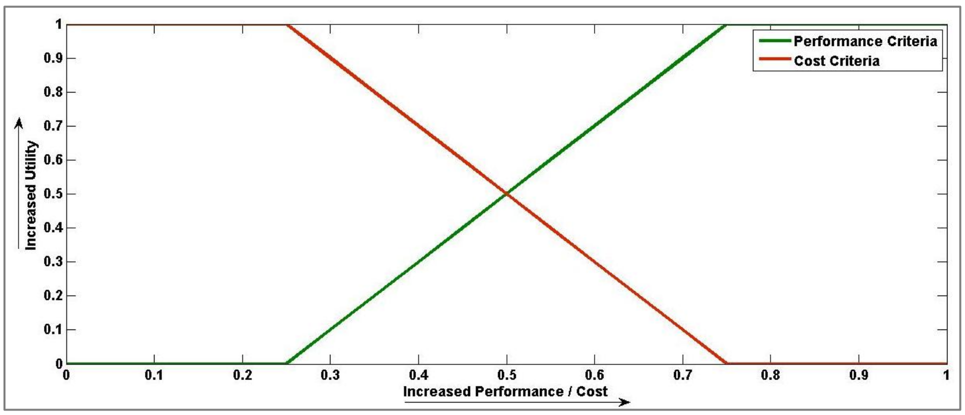

Figure 5-2: Relationship between Cost and Performance Criteria

According to the US Department of Defense (DOD), threshold criteria are mandatory minimum requirements and objective criteria are "applicable when a higher level of performance represents significant increase in operational utility". Conversely, "performance above the objective value does not justify additional expense" [87]. The US DOD's definition of objective criteria is essentially the point of diminished marginal utility, or the "knee in the curve". Figure 5-3 illustrates how objective criteria can be established at the point of diminished marginal utility. The aforementioned US DOD definitions explain why Γ and L fuzzy sets are preferred for modeling fuzzy customer requirements. As long as objective criteria is thoroughly researched and calculated, increased performance beyond objective requirements should gain marginal utility for the customer. For example, a crop dusting company has little utility for an aircraft that can fly extremely fast at high altitudes. However, this doesn't mean this particular customer doesn't have a preference for speed and altitude. Although some minimal requirements may be acceptable, this customer may prefer an aircraft that can perform at the required density altitude (e.g. Colorado on a hot summer day) at speeds that minimize transit times. Therefore, when conducting decision analysis using fuzzy requirements, Γ fuzzy sets should be applied to benefit criteria and L fuzzy sets should be applied to cost criteria.

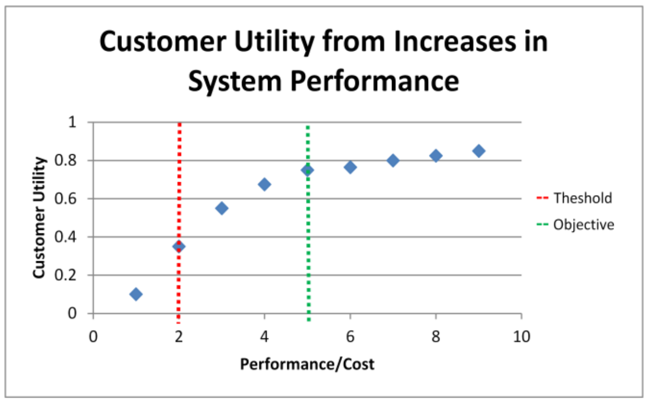

Figure 5-3: Customer Utility to define Objective Requirements

System requirements for the US government are often expressed as a Measures of Performance (MOP). MOPs are typically a quantitative measure of a system characteristic, such as velocity or scan rate. Each MOP should have a threshold value that states a minimum system requirement. Most MOPs also contain an objective value that represents an ideal requirement that is more demanding than the threshold value. MOP values may come from a requirement document or from Subject Matter Experts (SME). Regardless of how MOPS are established, the rationale for selecting threshold and objective values should be well documented [88]. In most US government documents, MOPs are expressed as Key Performance Parameters (KPP) or Key System Attributes (KSA). These KPP and KSAs usually contain threshold and objective values. The threshold and objective values from MOP, KPP, and KSAs provide a trade space that can be represented as a fuzzy set. If threshold criteria $C_{threshold}$ represents minimum requirements and objective criteria $C_{objective}$ represents maximum requirements, then cost criteria can be modeled as:

$$\mu_{\tilde{C}}(x) = \begin{cases} 1, & x \leq a \\ \frac{b-x}{b-a}, & a < x \leq b \\ 0, & x > b \end{cases} \tag{5-3}$$

where a represents $C_{objective}$ and b represents $C_{threshold}$.

Benefit criteria can be modeled as:

$$\mu_{\tilde{B}}(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & x > b \end{cases} \tag{5-4}$$

where a represents $C_{threshold}$ and b represents $C_{objective}$.

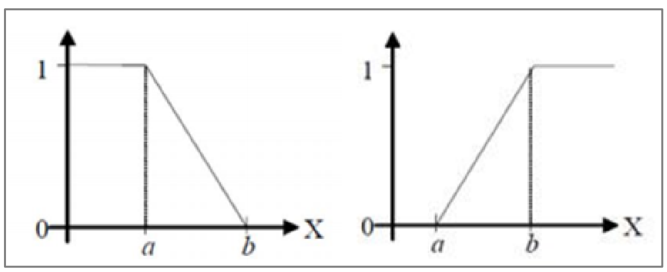

Figure 5-4: Cost (left) and Benefit (right) Criteria [39]

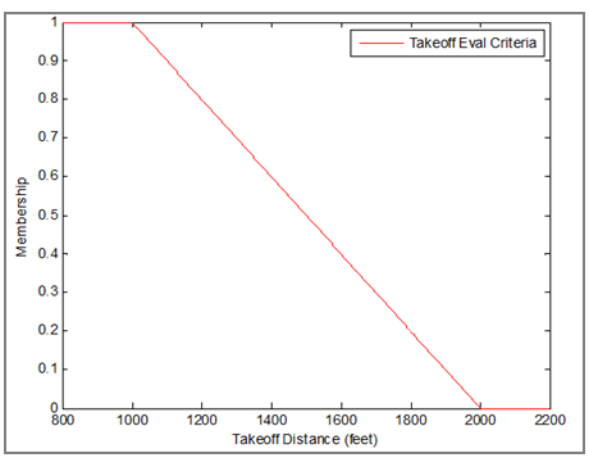

Figure 5-5: L Membership Function – Takeoff Distance Evaluation Criterion

Using criteria objectives as a maximum value should disincentive decision makers from anchoring their decisions based on excessive capabilities under a specific criterion. Currently, WPM and TOPSIS methods use minimum and maximum values under a specific criterion to evaluate each alternative. Using these current models, an alternative being evaluated could receive significantly higher scores when reported capabilities are greater than objective criteria. This problem is pronounced whenever weights are applied to criteria where excessive capability is recorded. Figure 5-3 represents cost and benefit criteria membership functions using $C_{threshold}$ and $C_{objective}$ for minimum and maximum values. The cost membership function, Equation 5-3 is on the left side of the figure and the benefit membership function, Equation 5-4 is on the right side. Figure 5-4 provides an example of a L (cost) membership function of an evaluation criterion using $C_{threshold}$ and $C_{objective}$ from DOD customer requirements. By saturating criteria at a maximum value of $C_{objective}$, the OCS-MCDA methods restrict bias scoring for alternatives that provide excess capabilities beyond ideal customer requirements.

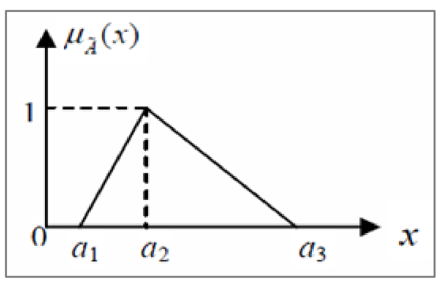

Figure 5-6: MoI Design Estimate as a Triangular membership Function[70]

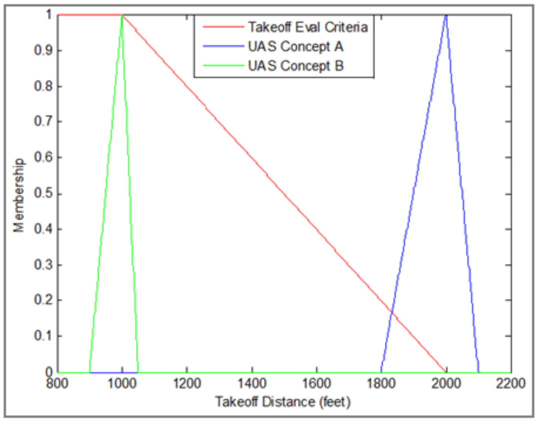

Figure 5-7: L Membership Function – Design Estimates and Takeoff Criteria

Membership functions are useful in measuring the degree a particular value belongs to a vaguely defined set. Since early system design is often subjective and imprecise, membership functions can be useful in determining how well a design meets requirements. Figure 5-5 demonstrates how a design estimate can be modeled using a triangular membership function. The example depicts higher certainty on greater performance over lower performance from a point estimate. Figure 5-6 illustrates how design estimates, represented as blue and green colored fuzzy triangular numbers, can be evaluated against a cost criterion, represented as a red colored L membership function. To determine the degree a value meets customer requirements, Equations 5-3 and 5-4 can be used for cost and benefit criteria, respectively. To determine the degree a value meets both a design estimate as well as customer requirements, a fourth membership function could be derived from Figure 5-6 by calculating the intersection of a design fuzzy set $\tilde{A}$ and the cost fuzzy set $\tilde{C}$ using Equation 5-5. For benefit criteria, Equation 5-6 can be used, where $\tilde{B}$ is a fuzzy set of benefit criteria.

$$\mu_{\tilde{A \cap C}}(x) = \min\,(\mu_{\tilde{A}}, \mu_{\tilde{C}}) \tag{5-5}$$

$$\mu_{\tilde{A \cap B}}(x) = \min\,(\mu_{\tilde{A}}, \mu_{\tilde{B}}) \tag{5-6}$$

Developers of mature systems with sufficient test and field data often provide crisp system performance data for potential customers. Displaying the system data as a membership function provides a visual and mathematical representation of the degree each alternative meets customer requirements. Figures 5-7 and 5-8 provide an example of a Γ (benefit) membership function and demonstrate how system data from each alternative can be modeled as a crisp membership function. Figure 5-7 displays system alternatives with various performance attributes and various degrees of membership. Figure 5-8 displays system alternatives with various performance attributes but the same degree of membership. Figure 5-8 visually depicts saturating criteria at a maximum value of $C_{objective}$. Since each alternative in Figure 5-8 exceeded objective requirements, each alternative is completely in the set and receives the same numeric value. By saturating excessive values through a membership function, the OCS-MCDA technique restricts bias scoring for alternatives that provide excess capabilities beyond ideal customer requirements.

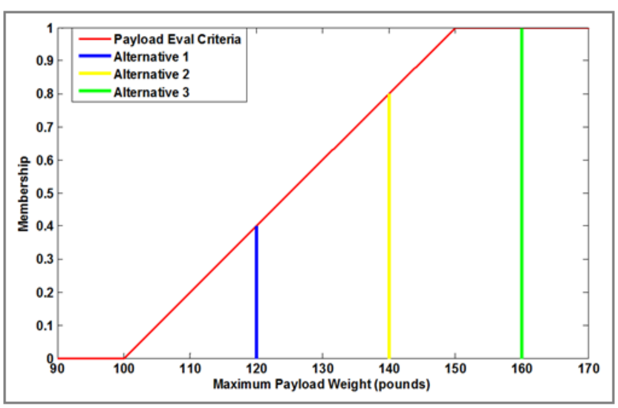

Figure 5-8: Membership Function – Within Trade Space

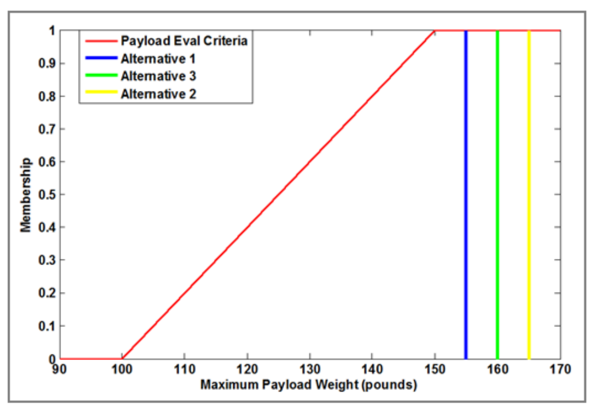

Figure 5-9: Membership Function – Exceeds Objective

5.2.2.1 Mandatory Requirements. Mandatory requirements are customer needs that a system must meet. For US DOD acquisitions, threshold criteria are considered mandatory minimum requirements. [87]

5.2.2.1.1 Screening Criteria with no Preference Limitation. For some criteria, only threshold requirements are provided. For these criteria, there is no determination of a point of diminished marginal utility. This may occur if a mandatory requirement is nominal, such as a mandatory color required for a professional sports team. In this situation, all alternatives that do not meet the mandatory requirement would be screened out for further consideration. Criteria without preference requirements may also occur if there is little to no diminished marginal utility with increased capability. Under these situations, the alternatives that meet threshold requirements would be evaluated by the degree each alternative meets the requirement. This is typically how alternatives are evaluated using traditional WSM and TOPSIS methods.

5.2.2.1.2 Screening Criteria with Preference Limitations. For the purpose of this Objective Criteria Saturation (OCS) research, preference limitation refers to the "knee in the curve" where diminished marginal utility is expected. For US DOD acquisitions, objective criteria can be considered a preference limitation since "performance above the objective value does not justify additional expense" [87]. Under these situations, the alternatives that meet threshold requirements should be evaluated using OCS-MCDA techniques to ensure that overinflated scoring does not occur.

5.2.2.2 Preference Requirements and Limitations. As defined above, preference limitation refers to the "knee in the curve" where diminished marginal utility is expected. For the purpose of this OCS research, preference requirements refer to customer desires that are not mandatory. Typically, preference requirements are nominal characteristics that may be nice to have, but not truly needed. For example, someone looking to purchase a new car may prefer a red car to a maroon car but is fine with either color. Other examples using the car buying analogy may include leather seats, heated steering wheel and autonomous parallel parking. Of course, determining what is required and what is not required is usually from the user viewpoint (e.g. some users may require autonomous parallel parking).

5.2.2.2.1 Preference Requirement without Mandatory Requirements. A preference requirement without a mandatory requirement usually occurs with optional capabilities. Depending on the importance of the capability, alternatives may receive a binary scoring (e.g. 1 or zero) depending on whether they meet the preference requirement. This may be useful if two alternatives are very close together in final ranking.

5.2.2.2.2 Preference Limitation with Mandatory Requirements. Mandatory requirements and preference limitations are often stated as threshold and objective requirements in US DOD acquisition documents [87]. These requirement conditions are ideal for OCS-MCDA techniques to ensure a best value decision with an optimal mix of performance, cost and reliability.

5.2.3 Overview of Objective Criteria Saturation (OCS) Multiple Criteria Decision Making (MCDA) Techniques. The OCS-MCDA methods are differentiated by which axis of the membership function the technique uses to perform calculations. One method is calculated on the Y-Axis of the membership function with the other two using the X-Axis for calculations. A brief explanation of the three techniques is provided below.

5.2.3.1 OCS-MCDA Methods (Y-Axis). The following technique utilizes the dependent variables on the Y-Axis of each membership function. By obtaining discrete preference information directly from each membership function, the technique provides an uncomplicated, straight forward technique.

5.2.3.1.1 Membership Function – Weighted Sum Model (MF-WSM). This decision analysis (DA) technique was created to provide an uncomplicated, best value Decision Maker (DM) tool that addresses the uncertainty of fuzzy requirements expressed as minimum and maximum values. The goal was also to reduce DM bias when faced with superfluous capabilities that may distract DMs and lead to anchoring on specific alternatives. The MF-WSM technique models fuzzy customer preference using fuzzy membership functions to determine user utility for a given design parameter. By leveraging both benefit and cost membership functions to determine user utility per criterion, the MF-WSM method can accurately handle conflicting requirements. By incorporating fuzzy numbers that have a maximum value of one, the MF-WSM method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements.

5.2.3.2 OCS-MCDA Methods (X-Axis). The following techniques utilize the independent variables on the X-Axis of the membership function. These techniques are modified versions of the Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solutions (FTOPSIS).

5.2.3.2.1 Objective Criteria Saturation – Technique for Order of Preference by Similarity to Ideal Solutions (OCS-TOPSIS). The OCS-TOPSIS method was created for evaluating mature concept designs with crisp design parameters using fuzzy customer requirements. In this technique, minimum and maximum customer requirements are used to establish the Negative Ideal Solution (NIS) and Positive Ideal Solution (PIS) in order to define and constrain the trade space. Since most conventional TOPSIS models use minimum and maximum values under a specific criterion to evaluate each alternative, a best value alternative may not be selected due to another alternative possessing excess capability in a heavily weighted criterion. This problem can become pronounced whenever evaluation criteria and priorities are published, such as in an

Request for Proposal (RFP). Since most government contracts require competitive selection, system providers may be compelled to focus on the highest weighted criteria while providing less focus to lower weighted criteria. This OCS-TOPSIS method addresses this problem by restricting preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements.

5.2.2.3.2.2 Objective Criteria Saturation – Fuzzy Technique for Order of Preference by Similarity to Ideal Solutions (OCS-FTOPSIS). The OCS-FTOPSIS method was created for evaluating immature concept designs with fuzzy design parameters using fuzzy customer requirements. In this technique, minimum and maximum customer requirements are used to establish the Fuzzy Negative Ideal Solution (FNIS) and Fuzzy Positive Ideal Solution (FPIS) in order to define and constrain the trade space. Instead of using linguistic variables to evaluate each criterion, like most FTOPSIS techniques, fuzzy design estimates are used to calculate Euclidean distances from FNIS and FPIS. Criteria weights are assigned according to a customer's prioritized requirements. Similar to the previous two techniques, the OCS-FTOPSIS method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements.

6. OBJECTIVE CRITERIA SATURATION (OCS) MULTIPLE CRITERIA DECISION MAKING (MCDA) TECHNIQUES

The Objective Criteria Saturation (OCS) Multiple Criteria Decision Making (MCDA) techniques were established to prevent inflated scoring from unnecessary capabilities and system overdevelopment. Under certain conditions using WSM and TOPSIS, an alternative meeting much fewer objective requirements than other alternatives can be selected as the best alternative. This sometimes occurs when the selected alternative possesses capabilities that exceed objective criteria in the highest weighted criteria despite lower capabilities for the remaining criteria. This problem can become pronounced whenever customer evaluation criteria and priority are published for prospective system providers, such as US government acquisition programs. Under these circumstances, systems providers may focus their efforts at exceeding objective requirements for heavily weighted criteria at the expense of lesser weighted criteria in hopes of winning a contract. Although this practice may produce a high performance system, it may also contribute to higher costs and poor reliability. The OCS-MCDA methods were created to solve this problem by saturating scores at ideal customer requirements in an effort to select a best value alternative with an optimal mix of performance, cost, and reliability.

The following OCS-MCDA methods were established from a practitioner's viewpoint with the intent of creating straightforward techniques that could easily transfer to field practice. Although the following methods are presently theoretical, they were created to serve as a basis for continuing empirical research and experimentation. Frey argued that "developments based on theory alone may prove to be ineffective in practice"[89]. While developing his axiomatic basis for statistics and decision making, Savage cautioned taking exaggerated stands regarding theoretical foundations and suggested a more balanced view of the interactions between foundations and professional practice[90]. The following DA methods were created as a foundation for future professional experimentation and practice.

There are three methods for applying Objective Criteria Saturation (OCS) in decision making. The three OCS-MCDA methods are either analyzed on the X or Y axis of membership functions. The OCS-TOPSIS and OCS-FTOPSIS procedures are analyzed on the X axis while the MF-WSM method is analyzed on the Y axis.

6.1 OCS-MCDA Methods (Y-Axis)

The following technique utilizes the dependent variables on the Y-Axis of each membership function. By obtaining discrete preference information directly from each membership function, the technique provides an uncomplicated, straight forward technique.

6.1.1 Membership Function – Weighted Sum Model (WSM). The procedure for conducting the MF-WSM is summarized as follows:

1. Populate the decision matrix D with performance, cost, and reliability data from each alternative system A_i; where x_{ij} is the system data of the *i*th alternative A_i with respect to the *j*th criterion C_j; and w_i represents the weight of the *j*th criterion C_j.

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{6-1}$$

$$w = [w_1, w_2, \dots, w_n]$$

2. Create a membership function matrix M from decision matrix D using Equation 6-2 for cost criteria and Equation 6-3 for benefit criteria, where a_{ij} represents the degree x_{ij} meets criteria C_j.

$$\mu_{\tilde{C}}(x) = \begin{cases} 1, & x \leq a \\ \frac{b-x}{b-a}, & a < x \leq b \\ 0, & x > b \end{cases} \tag{6-2}$$

where a represents $C_{objective}$ and b represents $C_{threshold}$.

Benefit criteria can be modeled as:

$$\mu_{\tilde{B}}(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & x > b \end{cases} \tag{6-3}$$

where a represents $C_{threshold}$ and b represents $C_{objective}$.

3. Calculate the weighted sum of matrix M using Equation 6-4.

$$A^*_{FM-WSM\ (Score)} = \sum_{j=1}^{n} a_{ij} w_j,\ for\ i = 1, 2 \ldots, m \tag{6-4}$$

4. The alternative with the highest score represents the best alternative.

6.2 OCS-MCDA Methods (X-Axis)

The following techniques utilize the independent variables on the X-Axis of the membership function. These techniques are modified versions of the Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solutions (FTOPSIS).

6.2.1 Objective Criteria Saturation – Technique for Order of Preference by Similarity to Ideal Solutions (OCS-TOPSIS). The procedure for conducting the OCS-TOPSIS is summarized as follows:

1. Populate the decision matrix D with performance, cost, and reliability data from each alternative system A_i; where x_{ij} is the system data of the *i*th alternative A_i with respect to the *j*th criterion C_j; $C_{Objective}$ represents the objective criteria of the *j*th criterion C_j; $C_{Threshold}$ represents the threshold criteria of the *j*th criterion C_j; and w_i represents the weight of the *j*th criterion C_j.

$$D = \begin{array}{c} \\ \boldsymbol{C_{Objective}} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \\ \boldsymbol{C_{Threshold}} \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \end{array} \\ \begin{bmatrix} \boldsymbol{C_{O1}} & \boldsymbol{C_{O2}} & \boldsymbol{C_{O3}} & \boldsymbol{C_{O4}} & \boldsymbol{C_{On}} \\ x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \\ \boldsymbol{C_{T1}} & \boldsymbol{C_{T2}} & \boldsymbol{C_{T3}} & \cdots & \boldsymbol{C_{Tn}} \end{bmatrix} \\ w = [w_1, w_2, \ldots, w_n] \end{array} \tag{6-5}$$

2. Create a constrained decision matrix S from decision matrix D using Equation 6-6 to saturate criteria values greater than $C_{objective}$.

$$s_{ij} = \begin{cases} C_{ojective}, & x_{ij} > C_{ojective} \\ x_{ij} & , otherwise \end{cases} \tag{6-6}$$

$$i = 1, 2 \dots, m; \ j = 1, 2, \dots, n$$

where s_{ij} is the constrained value of x_{ij}.

For S_j where a specified requirement of $C_{threshold}$ and $C_{ojective}$ is not stated in a government document, $s_{ij} = x_{ij}$.

3. Create a normalized decision matrix R from constrained matrix S using Equation 6-7.

$$r_{ij} = \frac{s_{ij}}{Max_i(s_{ij})} \qquad i = 1, 2 \dots, m; \ j = 1, 2, \dots, n \tag{6-7}$$

where r_{ij} is the normalized value of s_{ij}.

4. Calculate the weighted normalized decision matrix V by multiplying the normalization values r_{ij} by the criterion weights w_j that were based on the order of importance from a government solicitation document.

$$V = [v_{ij}]\, mxn \qquad i = 1, 2 \dots, m; \ j = 1, 2, \dots, n \tag{6-8}$$

where $v_{ij} = r_{ij} \, (\cdot) \, w_j$

5. Determine the Positive Ideal Solutions (PIS) v_j^+ and Negative Ideal Solutions (NIS) v_j^- using Equations 6-9 and 6-10.

$$PIS = \{v_{1,}^+ v_{2,}^+ \dots v_{j,}^+ \dots, v_{n,}^+\}; \tag{6-9}$$

$$NIS = \{v_{1,}^- v_{2,}^- \dots v_{j,}^- \dots, v_{n,}^-\} \tag{6-10}$$

where,

$$v_j^+ = \begin{cases} max(v_{j1}, v_{j2}, \ldots, v_{jm});\ P_j\ is\ a\ benefit\ criterion \\ min(v_{j1}, v_{j2}, \ldots, v_{jm});\ P_j\ is\ a\ cost\ criterion \end{cases}$$

$$v_j^- = \begin{cases} min(v_{j1}, v_{j2}, \ldots, v_{jm});\ P_j\ is\ a\ benefit\ criterion \\ max(v_{j1}, v_{j2}, \ldots, v_{jm});\ P_j\ is\ a\ cost\ criterion \end{cases}$$

6. Use Equations 6-11 and 6-12 to calculate the Euclidean distances d_i^+ and d_i^- of alternative A_i to PIS and NIS, respectively.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_J^+\right)^2},\ i = 1,2, \ldots, m, \tag{6-11}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_J^-\right)^2},\ i = 1,2, \ldots, m. \tag{6-12}$$

7. Calculate the closeness coefficient CC_i. The closeness coefficient represents the distances of each alternative to v_j^+ and v_j^- and is calculated:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-},\ i = 1, 2, \ldots, m. \tag{6-13}$$

8. The alternative with the highest CC_i represents the best alternative and is closest to v_j^+ and farthest from v_j^-.

6.2.2 Objective Criteria Saturation – Fuzzy Technique for Order of Preference by Similarity to Ideal Solutions (OCS-FTOPSIS). The procedure for conducting the OCS-FTOPSIS is summarized as follows:

1. Populate the decision matrix $\widetilde{D}$ with performance, cost, and reliability data from each alternative system A_i; where $\tilde{x}_{ij}$ is the system data of the *i*th alternative A_i with respect to the *j*th criterion C_j; $C_{Objective}$ represents the objective criteria of the *j*th criterion C_j; $C_{Threshold}$ represents the threshold criteria of the *j*th criterion C_j; and w_i represents the weight of the *j*th criterion C_j.

$$\widetilde{D} = \begin{array}{c} \\ \boldsymbol{C_{Objective}} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \\ \boldsymbol{C_{Threshold}} \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} \widetilde{\mathbf{C_{O_1}}} & \widetilde{\mathbf{C_{O_2}}} & \widetilde{\mathbf{C_{O_3}}} & \dots & \widetilde{\mathbf{C_{O_n}}} \\ \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \dots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \dots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & \dots & \tilde{x}_{mn} \\ \widetilde{\mathbf{C_{T_1}}} & \widetilde{\mathbf{C_{T_2}}} & \widetilde{\mathbf{C_{T_3}}} & \dots & \widetilde{\mathbf{C_{O_n}}} \end{bmatrix} \end{array} \tag{6-14}$$

$$w = [w_1, w_2, \dots, w_n]$$

2. Create a constrained decision matrix $\tilde{S}$ from decision matrix $\widetilde{D}$ using Equation 6-15 to saturate criteria values greater than $C_{objective}$. Equation (6-15) is used for strict adherence to threshold criteria and Equation 6-16 is used for partially meeting threshold requirements.

$$\tilde{s}_{ij} = \begin{cases} C_{objective}\ , & \forall\, x \in \tilde{x}_{ij} > C_{objective} \\ x \in \tilde{x}_{ij}\ , & otherwise \end{cases} \tag{6-15}$$

$$\tilde{s}_{ij} = \begin{cases} C_{objective}\ , & \forall\, x \in \tilde{x}_{ij} > C_{objective} \\ 0\ , & \forall\, x \in \tilde{x}_{ij} < C_{threshold} \\ x \in \tilde{x}_{ij}\ , & otherwise \end{cases} \tag{6-16}$$

$$i = 1, 2 \dots, m;\ j = 1, 2, \dots, n$$

where $\tilde{s}_{ij}$ is the constrained value of $\tilde{x}_{ij}$.

For S_j where $C_{threshold}$ and $C_{objective}$ is not stated in a customer requirements document, $\tilde{s}_{ij} = \tilde{x}_{ij}$.

3. Create a normalized decision matrix $\tilde{R}$ from constrained matrix $\tilde{S}$. First, perform a linear scale transformation to transform the various criteria scales into a comparable scale and obtain a normalized fuzzy decision matrix $\tilde{R}$.

$$\tilde{R} = [\tilde{r}_{ij}]\, mxn, \tag{6-17}$$

Next, perform a normalization calculation to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0,1]. Equation 6-18 calculates the set of benefit criteria $\tilde{B}$ and Equation 6-19 calculates the set of cost criteria $\tilde{C}$.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), j \in \tilde{B}, \tag{6-18}$$

$$c_j^+ = C_{objective}$$

$$\tilde{r}_{ij} = \left(\frac{c_j^-}{c_{ij}}, \frac{c_j^-}{b_{ij}}, \frac{c_j^-}{a_{ij}}\right) j \in \tilde{C}, \tag{6-19}$$

$$c_j^- = C_{threshold}$$

For C_j where a specified customer requirement of $C_{threshold}$ and $C_{objective}$ is not defined or stated in any document, the following normalization technique can be used where $c_j^+ = \max c_{ij}$ and $c_j^- = \min a_{ij}$.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), j \in \tilde{B}, \tilde{C} \tag{6-20}$$

$$c_j^+ = \max c_{ij}$$

4. Calculate the weighted normalized decision matrix $\tilde{V}$ by multiplying the normalization values $\tilde{r}_{ij}$ by the criterion weights w_j that were based on customer prioritized requirements.

$$\tilde{V} = \left[\tilde{v}_{ij}\right] mxn \qquad i = 1, 2 \dots, m; j = 1, 2, \dots, n \tag{6-21}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \, (\cdot) \, w_j$

5. Define FPIS and FNIS using Equation 6-22 and 6-23, respectfully.

$$\text{FPIS} = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+), \tag{6-22}$$

$$\text{FNIS} = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-), \tag{6-23}$$

where,

$$v_j^+ = \begin{cases} \max\{\tilde{v}_{ij_3}\}, i = 1, 2, \dots m;\ j = 1, 2, ..n;\ P_j\ is\ a\ benefit\ criterion \\ \min\{\tilde{v}_{ij_1}\}, i = 1, 2, \dots m;\ j = 1, 2, ..n;\ P_j\ is\ a\ cost\ criterion \end{cases}$$

$$v_j^- = \begin{cases} \min\{\tilde{v}_{ij_1}\}, i = 1, 2, \dots m;\ j = 1, 2, ..n;\ P_j\ is\ a\ benefit\ criterion \\ \max\{\tilde{v}_{ij_3}\}, i = 1, 2, \dots m;\ j = 1, 2, ..n;\ P_j\ is\ a\ cost\ criterion \end{cases}$$

6. Use Equations 6-24 and 6-25 to calculate the Euclidean distances d_i^+ and d_i^- of alternative A_i to PIS and NIS, respectively.

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_J^+\right)^2}, i = 1,2, \dots, m, \tag{6-24}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_J^-\right)^2}, i = 1,2, \dots, m. \tag{6-25}$$

where v_{ij} is the defuzzified value of $\tilde{v}_{ij}$.

To perform defuzzification on $\tilde{v}_{ij}$, the graded mean integration technique, Equation 6-26, is a simple, straightforward technique that is suitable for triangular fuzzy sets [76].

$$P(\tilde{V}) = \frac{1}{6}\left(\tilde{v}_{ij_1} + 4\tilde{v}_{ij_2} + \tilde{v}_{ij_3}\right) \tag{6-26}$$

7. Calculate the closeness coefficient CC_i. The closeness coefficient represents the distances to FPIS and FNIS and is calculated:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \dots, m. \tag{6-27}$$

8. The alternative with the highest CC_i represents the best alternative and is closest to FPIS and farthest from FNIS.

7. APPLYING RISK IN OBJECTIVE CRITERIA SATURATION (OCS) MULTIPLE CRITERIA DECISION MAKING (MCDA)

According to the International Council of Systems Engineering (INCOSE), “reducing the risk associated with new systems or modifications to complex systems continues to be a primary goal of the systems engineer” [91]. From a systems engineering perspective, risk can be viewed as a measure of uncertainty for meeting a goal, objective, or requirements pertaining to technical performance, cost and schedule [62]. From a project management perspective, risk can be viewed as an uncertain event or condition that could have a negative effect on one or more project objectives [92]. From a business analyst perspective, risk can be viewed as the possibility that a requirement cannot deliver the potential value or cannot be met at all [77]. Although these risk definitions may slightly differ, they all generally refer to the possibility of negative impacts on a project or system. Therefore, risk can certainly be viewed as a crucial factor that must be effectively addressed to successfully design and develop a system. As illustrated in Figure 2-1 in Chapter 2, approximately 80 percent of total Life Cycle Costs (LCC) has already been determined when only 20 percent of the actual costs have been accrued. This figure captures the risk associated with system development and highlights the importance of good information and sound analysis during early system decisions.[29]

7.1 Types of Risk

There are many ways to classify or categorize risk. Risks can be external, internal, technical, or unforeseeable. Risks can also be classified by where they originate in a project, such as schedule, cost, scope, or quality. Customer satisfaction and company resources can also be a source of risk.[93] The US Department of Defense (DOD) focuses on risks that affect project cost, schedule, and performance and groups these risks into three categories: business, programmatic, and technical. Business risks are non-technical risks that typically originate outside the program office. These risks typically come from stakeholders, regulations, market factors, weather and other external factors. Programmatic risks are also non-technical risks but fall within the control of the program management office. These risks area typically associated with program estimates, planning, execution, communications or contract structure. Technical risks prevent a system from performing as intended or from meeting performance expectations. These risks typically originate from requirements, technology, engineering, test, manufacturing, quality, logistics, system security, and training. Technical risks can also be internally or externally generated and may impact cost, schedule and/or performance. [94] Due to the breadth and impact of technical risks, these risks will be the primary focus for the OCS-MCDA methods in this dissertation.

7.1.1 Technology Risk. Technology risk must be accurately assessed during early system development since it has an impact on schedule, cost, and quality (see Figure 7-1). According to the US Government Accountability Office (GAO), "maturing new technology before it is included in a product is perhaps the most important determinant of the success of the eventual product" [95]. Since technology risk is considered to have the biggest impact on project success, technology maturity assessments were incorporated into the OCS-MCDA techniques.

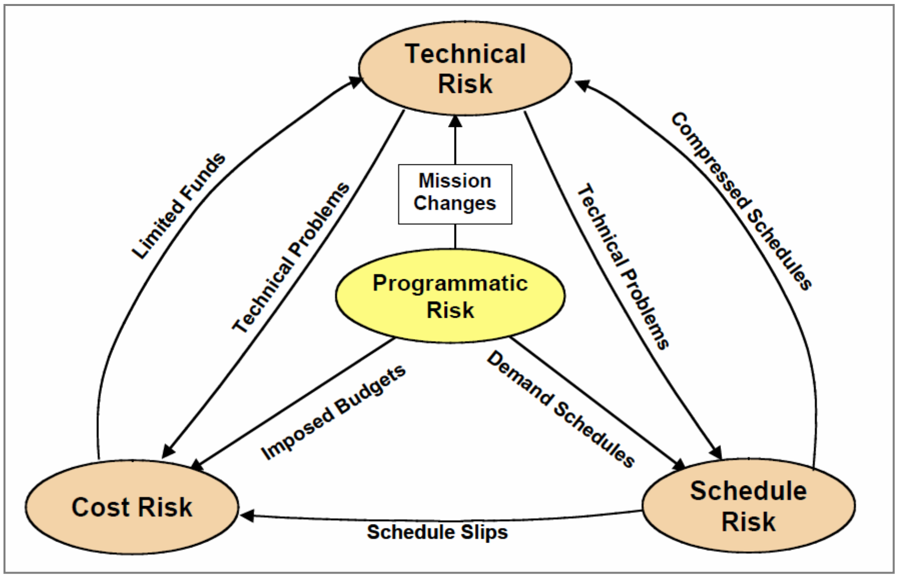

Figure 7-1: Typical Relationship among Risk Categories [91]

7.2 Risk Evaluation Methods

During system solution performance analysis, risks should be consistently identified and managed [96]. According to PMBOK, risks should be assessed by their probability of occurrence and impact [92]. In *Proactive Risk Management: Controlling Uncertainty in Product Development*, Smith and Merritt argue "The key to successful risk management is not managing the risk itself but rather the facts leading you to believe the risk will occur". The authors call these facts risk drivers [97]. According to the GAO, the biggest risk driver for a successful product is technology maturity [95]. Due to technology maturity having the largest impact on a system's outcome, technology risk will be the main risk focus in this dissertation.

7.2.1 Technology Evaluation Methods. The GAO has determined that the readiness of critical technologies at the start of system development affects the schedule and cost of developing a product [95], [98], [99]. In the US, a Technology Readiness Assessment (TRA) is required for large DOD acquisition programs prior to Milestone B [100], the review at the end of

Technology Maturation & Risk Reduction (TM&RR) phase of the acquisition life cycle [101]. The TRA identifies all critical technologies and verifies that all have been demonstrated in a relevant environment on the basis of an independent review [102], [103]. Since the GAO has already thoroughly researched the topic of Technology Readiness Assessments (TRA), their recommended use of Technology Readiness Levels (TRL) will be used throughout this dissertation. Additional information about TRA can be found in the *GAO Technology Readiness Assessment Guide* [103].

Table 7-1: Technology Readiness Levels (TRL) [102]

TRL	Definition	Description
1	Basic principles observed and reported.	Lowest level of technology readiness. Scientific research begins to be translated into applied research and development (R&D). Examples might include paper studies of a technology's basic properties.
2	Technology concept and/or application formulated.	Invention begins. Once basic principles are observed, practical applications can be invented. Applications are speculative, and there may be no proof or detailed analysis to support the assumptions. Examples are limited to analytic studies.
3	Analytical and experimental critical function and/or characteristic proof of concept.	Active R&D is initiated. This includes analytical studies and laboratory studies to physically validate the analytical predictions of separate elements of the technology. Examples include components that are not yet integrated or representative.
4	Component and/or breadboard validation in a laboratory environment.	Basic technological components are integrated to establish that they will work together. This is relatively "low fidelity" compared with the eventual system. Examples include integration of "ad hoc" hardware in the laboratory.
5	Component and/or breadboard validation in a relevant environment.	Fidelity of breadboard technology increases significantly. The basic technological components are integrated with reasonably realistic supporting elements so they can be tested in a simulated environment. Examples include "high-fidelity" laboratory integration of components.
6	System/subsystem model or prototype demonstration in a relevant environment.	Representative model or prototype system, which is well beyond that of TRL 5, is tested in a relevant environment. Represents a major step up in a technology's demonstrated readiness. Examples include testing a prototype in a high-fidelity laboratory environment or in a simulated operational environment.
7	System prototype demonstration in an operational environment.	Prototype near or at planned operational system. Represents a major step up from TRL 6 by requiring demonstration of an actual system prototype in an operational environment (e.g., in an air-craft, in a vehicle, or in space)
8	Actual system completed and qualified through test and demonstration.	Technology has been proven to work in its final form and under expected conditions. In almost all cases, this TRL represents the end of true system development. Examples include developmental test and evaluation (DT&E) of the system in its intended weapon system to deter-mine if it meets design specifications.
9	Actual system proven through successful mission operations.	Actual application of the technology in its final form and under mission conditions, such as those encountered in operational test and evaluation (OT&E). Examples include using the system under operational mission conditions.

7.2.1.1 Technology Readiness Levels (TRL). Technology Readiness Levels (TRL) are used to designate a technology maturation level through professional expert judgment. The TRL scale begins at TRL 1 where scientific research begins to be translated into applied research and development (R&D). As technology matures, it moves higher in the TRL scale until it reaches the highest TRL rating where a system is proven in actual mission operations. The TRL definitions and descriptions for TRL 1 through 9 are listed in Table 7-2. For assessing a system's technology maturity and overall technical risk, TRLs are suggested to be incorporated in the OCS-MCDA techniques presented in this dissertation.

7.2.1.1.1 TRL Transformation to Fuzzy Numbers. In some applications, there may be a need to convert Technical Readiness Levels (TRL) to fuzzy numbers. The "science and technology, systems engineering, and program management communities each views technology readiness through its own lenses, which can make for variable and subjective TRA results" [103]. Since the TRA is a subjective evaluation, there may be a level of uncertainty to the TRL rating. Therefore, if crisp data is associated with imprecision, ambiguity, or vagueness, then a crisp value can be represented by a fuzzy membership function. Under these circumstances, the uncertainty can be captured in the boundary portion of the fuzzy set. Figure 7-2 depicts an example of fuzzy representations of TRLs where uncertainty is captured on both sides of the rating. In the figure example, each TRL designation, except TRLs 1 and 9, depicts an uncertainty that the actual TRL could be one TRL higher or lower than the given rating.

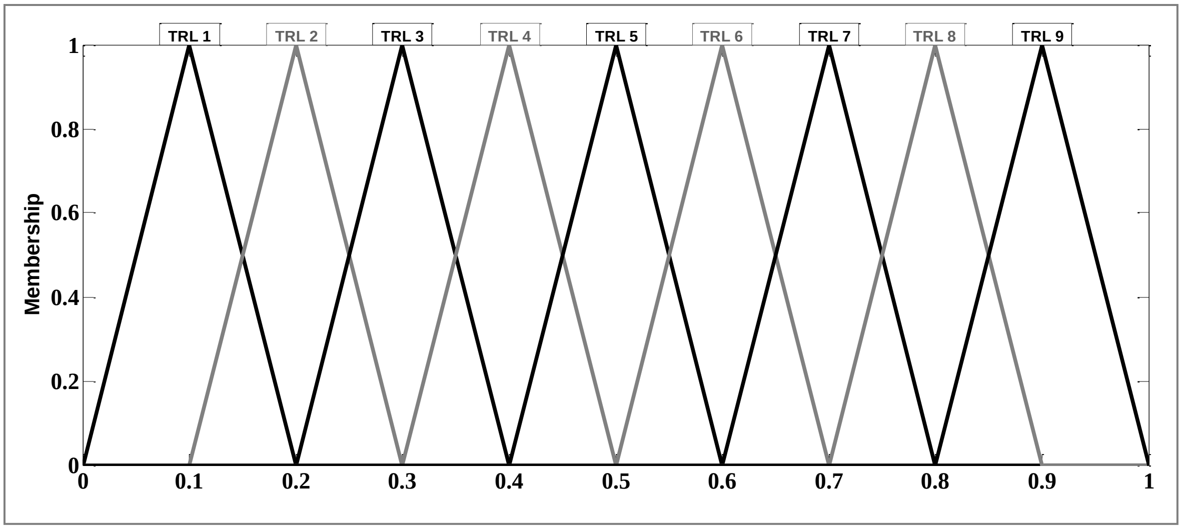

Figure 7-2: TRL Transformation to Fuzzy Numbers

8. APPLICATION OF OBJECTIVE CRITERIA SATURATION (OCS) MULTIPLE CRITERIA DECISION MAKING (MCDA)

8.1 Case Study #1 – Unmanned Aerial System (UAS)

The three OCS-MCDA techniques will be demonstrated using a United States Coast Guard (USCG) Unmanned Aerial System (UAS) development case study. The case study will apply the OCS methods to evaluate UAS design alternatives against performance, reliability and cost criteria.

Figure 8-1: Unmanned Aerial System (UAS) Alternatives
A1-Predator XP (top), A2-Shadow M2(middle), & A3-Hunter MQ5B (bottom) [104]–[106]

8.1.1 Scenario Background. In 2016, the United States elected Donald Trump as president. Throughout his campaign, Trump campaigned heavily on vastly improving border security. Although he mostly campaigned on building a physical wall, several of his advisors advocated for a virtual wall consisting of sensor systems [107]. Due to these recent political pressures for increased border security, the United States Coast Guard (USCG) may experience an increase in systems acquisitions during Trump's presidency. DHS Customs and Border Protection (CBP) already employs a network of manned and unmanned aircraft as well as tower mounted sensors [108]. The US Coast Guard (USCG), however, has only begun exploring the use of unmanned systems. [109]

As of 2016, the USCG began researching the use of UAS for land and cutter-based aviation capabilities. The USCG plans to augment is aviation fleet with cutter-based, low altitude small UAS and land-based, mid-altitude UAS. The small UAS will provide a tactical, on-demand capability while the medium UAS will provide a wide-area surveillance capability [109]. To demonstrate the utility of OCS-MCDA techniques, the focus of the study will be on medium UAS that can be used for USCG operations.

8.1.2 Data used in Study. To provide an example of the OCS-MCDA methods, all three techniques were applied to a set of requirements data that was derived from a US DOD Request for Proposals (RFP), for medium sized UAS [110]. The three alternative designs were from Predator, Pioneer/Shadow, and Hunter systems due to the availability of reliability and cost data. For performance data and procurement costs, information was used from Predator XP, Shadow RQ-7, and Hunter RQ5-B systems [111]–[115]. For reliability and operational costs, information was used from Predator MQ1, Pioneer RQ2, and Hunter RQ-5A systems [1], [116], [117]. Reliability and operational cost data from legacy systems was used due to the availability of several years of field data. It was assumed that the newer UAS would have similar reliability and operational costs to legacy UAS due to continuous improvement programs, government demands, and market competition. Since there was no significant separation between disposal costs among UAS alternatives, disposal costs were excluded from the analysis.

In order to demonstrate fuzzy system information using OCS-MCDA techniques, triangular fuzzy numbers were created based on collected UAS data with Method of Imprecision (MoI) applied to create a range of uncertainty. For this example, it was assumed that designers would use MoI to estimate higher uncertainty for decreased performance and increased cost associated with unknown USCG operating conditions and historical cost over runs.

To determine the criteria values for $C_{ojective}$ and $C_{threshold}$ alternatives, objective and threshold values were used from the UAS RFP for performance criteria 2 through 7. Risk was evaluated using Technology Readiness Level (TRL) assessments on each system alternative. Milestone B entrance criteria of TRL 6 [103] was used for $C_{threshold}$ with a maximum TRL of 9 for $C_{objective}$. For demonstration purposes, a TRL was assigned to each alternative based on when each UAS entered the market; the longer time in the UAS market resulted in a higher TRL rating. According to this measure, Alternatives 2, 1, and 3 were assigned TRLs 8, 7, and 6, respectively. For availability criteria 8 and reliability criteria 9, a minimum of 70 percent was used for $C_{threshold}$ with $C_{ojective}$ represented as a maximum of 100 percent. Since cost objectives were not stated in the UAS RFP, minimum and maximum costs under each criterion were used as $C_{ojective}$ and $C_{threshold}$, respectively.

The performance threshold and objective values from the UAS RFP are listed in Table 8-1. The evaluation criteria and normalized weights for the decision matrix are listed in Table 8-2 in rank order of importance. The criteria weights were calculated using the rank sum method using the UAS RFP's order of importance for evaluation criteria. Criterion 1 represents the total technology risk of the system and is given the top priority since it has the largest affect on the most criteria. Criteria 2 through 7 represent performance criteria. Criteria 8 through 10 represent reliability criteria and criteria 10 through 12 represent cost criteria, in $million. Criterion 7 is also a cost criterion where lower values are preferred to higher values, but measured in feet instead of dollars. Criterion 10 represents Operations and Maintenance (O&M) costs over a ten year period. In regards to the weights used for this case study, the government's strong preference of performance over cost and reliability is particularly noteworthy.

Table 8-1: UAS Performance Evaluation Criteria

Criteria		$C_{Threshold}$	$C_{Objective}$
C1=	Technical Readiness Level	6	
C2=	Maximum Payload Weight (pounds)	100	150
C3=	Maximum Endurance (hours)	8	10
C4=	Payload Power (kilowatts)	1	3
C5=	Maximum Cruise Airspeed (knots)	80	100
C6=	Maximum Altitude (thousand feet)	15	18
C7=	Take-off Distance (hundred feet)	20	10

Table 8-2: UAS Evaluation Criteria with Weights

Criteria		**Rank**	**Weight**	**Normalized**
C1=	Technology Readiness Level (TRL)	1	12	0.140
C2=	Maximum Payload Weight (pounds)	2	11	0.128
C3=	Maximum Endurance (hours)	3	10	0.116
C4=	Payload Power (Kilowatts)	4	9	0.105
C5=	Maximum Cruise Airspeed (knots)	5	8	0.093
C6=	Maximum Altitude (thousand feet)	6	7	0.081
C7=	Take-off Distance (hundred feet)	7	6	0.070
C8=	Availability	8	5	0.058
C9=	Reliability	8	5	0.058
C10=	Operations & Maintenance (O&M) Cost	8	5	0.058
C11=	Research & Development (R&D) Cost	9	4	0.047
C12=	Procurement Cost	9	4	0.047

Technology risk must be accurately assessed during early system development since it has an impact on schedule, cost, and quality. According to TRL definitions, TRL 6 represents a model or prototype system that has been tested in a relevant environment [102]. Since TRL 6 is required at the end of the TM&RR phase (Milestone B), TRL 6 was used to establish the threshold criterion for this UAS case study (see Table 8-1). The TRL definitions are listed in Table 7-1.

Two decision matrices were created to evaluate fuzzy and crisp data sets. Decision matrix D, shown in Table 8-3, was created after establishing risk, performance, reliability, and cost data for the three design alternatives along with objective and threshold criteria. Decision matrix D will be used for the MF-WSM and OCS-TOPSIS methods. The fuzzy decision matrix $\widetilde{D}$, shown in Table 8-4, was created using the same data as decision matrix D with the addition of MoI as explained above and expounded below in *section 8.1.2.1*. Fuzzy decision matrix $\widetilde{D}$ will be used with the OCS-FTOPSIS method.

Table 8-3: Decision Matrix D and Weights w_j of Three Alternative Systems

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
$C_{Objective}$	**9**	**150**	**10**	**3**	**100**	**18**	**10**	**1**	**1**	**167.3**	**50**	**16.25**
A1	7	325	35	4.8	120	25	20	0.93	0.89	345.7	209.9	67.5
A2	8	130	12	2	110	18	10	0.78	0.91	167.3	50	16.3
A3	6	258	20.8	3	109.1	17.9	9.9	0.97	0.81	387.5	138.2	30
$C_{Threshold}$	**6**	**100**	**8**	**1**	**80**	**15**	**20**	**0.70**	**0.70**	**387.5**	**209.9**	**67.5**
Weight	0.14	0.128	0.116	0.105	0.093	0.081	0.07	0.058	0.058	0.058	0.047	0.047

Table 8-4: Fuzzy Decision Matrix $\widetilde{D}$ and Weights of Three Design Alternatives

	C1	C2	C3	C4	C5	C6
$C_{Objective}$	(9, 9, 9)	(150, 150, 150)	(10, 10, 10)	(3, 3, 3)	(100, 100, 100)	(18, 18, 18)
A1	(6, 7, 8)	(293, 325, 341.25)	(32, 35, 36.75)	(4.3, 4.8, 5)	(108, 120, 126)	(22.5, 25, 26.25)
A2	(7, 8, 9)	(117, 130, 136.5)	(11, 12, 12.6)	(1.8, 2, 2.1)	(99, 110, 115.5)	(16.2, 18, 18.9)
A3	(5, 6, 7)	(234, 260, 273)	(19, 21, 22.05)	(2.7, 3, 3.2)	(99, 110, 115.5)	(16.2, 18, 18.9)
$C_{Threshold}$	(6, 6, 6)	(100, 100, 100)	(8, 8, 8)	(1, 1, 1)	(80, 80, 80)	(15, 15, 15)
Weight	0.14	0.128	0.116	0.105	0.093	0.081
	C7	**C8**	**C9**	**C10**	**C11**	**C12**
$C_{Objective}$	(10, 10, 10)	(1, 1, 1)	(1, 1, 1)	(158.9, 158.9, 158.9)	(47.5, 47.5, 47.5)	(15.4, 15.4, 15.4)
A1	(19, 20, 22)	(0.84, 0.93, 0.98)	(0.8, 0.89, 0.93)	(328.4, 345.7, 380.2)	(199.4, 209.9, 230.9)	(64.13, 67.5, 74.25)
A2	(9.5, 10, 11)	(0.70, 0.78, 0.82)	(0.82, 0.91, 0.96)	(158.9, 167.3, 184)	(47.5, 50, 55)	(15.44, 16.25, 17.88)
A3	(9.5, 10, 11)	(0.88, 0.98, 1)	(0.74, 0.82, 0.86)	(368.1, 387.5, 426.3)	(131.3, 138.2, 152)	(28.5, 30, 33)
$C_{Threshold}$	(20, 20, 20)	(0.7, 0.7, 0.7)	(0.7, 0.7, 0.7)	(426.3, 426.3, 426.3)	(230.9, 230.9, 230.9)	(74.3, 74.3, 74.3)
Weight	0.07	0.058	0.058	0.058	0.047	0.047

8.1.2.1 Asymmetrical Data. Since the Method of Imprecision (MoI) incorporates design engineer judgment, some design membership functions may exhibit a skew that captures a designer's uncertainty for upper or lower performance and cost estimates. To simplify and standardize the alternative design data, ten percent variance was used to model high designer uncertainty from UAS point estimates and five percent variance was used for lower uncertainty. The ten percent variance was applied to lower performance and higher costs from a point estimate. Five percent variance was applied to higher performance and lower costs.

8.1.3 OCS-MCDA Methods (Y-Axis). The MF-WSM is the only OCS technique that utilizes the dependent variables on the Y-Axis of each membership function. By obtaining discrete preference information directly from each membership function, the MF-WSM technique provides the most uncomplicated, straight forward approach of the three OCS-MCDA techniques.

8.1.3.1 MF-WSM Applications to Case Study #1. The MF-WSM technique models fuzzy customer preference using fuzzy membership functions to determine user utility for a given design parameter. The MF-WSM method leverages both benefit and cost membership functions to determine user utility per criterion that enables the accurate calculation of conflicting requirements. By incorporating fuzzy numbers that have a maximum value of one, the MF-WSM method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements. This MF-WSM approach will be demonstrated using the UAS case study described above.

8.1.3.1.1 Initial Conditions. The decision matrix *D*, represented in Table 8-3, was used for this MF-WSM application to case study #1. The three alternatives being evaluated are listed in the table along with their crisp system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

8.1.3.1.2 Case Study #1 Results. The results of the MF-WSM analysis are shown in Tables 8-5 through 8-7. As stated above, the decision matrix *D* and weights *w* used for the analysis are displayed in Table 8-3. Table 8-5 shows the transformed membership function matrix *M* and Table 8-6 displays the weighted membership function matrix *V*. Table 8-7 displays the results of the analysis. As indicated in bold font in Table 8-7, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-1 and 8-2.

Table 8-5: Transformed Membership Function Matrix M

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
$C_{Objective}$	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
A1	0.33	1	1	1	1	1	0	0.72	0.56	0.19	0	0
A2	0.67	0.6	1	.5	1	1	1	0.12	0.64	1	1	1
A3	0	1	1	0.99	1	0.95	1	0.87	0.25	0	0.45	0.73
$C_{Threshold}$	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Weight	0.14	0.128	0.116	0.105	0.093	0.081	0.07	0.058	0.058	0.058	0.047	0.047

Table 8-6: Weighted Membership Function Matrix V

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
A1	0.047	0.128	0.116	0.105	0.093	0.081	0	0.042	0.033	0.011	0	0
A2	0.093	0.077	0.116	0.052	0.093	0.081	0.07	0.007	0.037	0.058	0.047	0.047
A3	0	0.128	0.116	0.103	0.093	0.077	0.07	0.05	0.015	0	0.021	0.034
Weight	0.14	0.128	0.116	0.105	0.093	0.081	0.07	0.058	0.058	0.058	0.047	0.047

Table 8-7: MF-WSM Results & Comparison to TOPSIS

	LCC	**MF-WSM**		**TOPSIS**	
	($mil)	Total	Rank	CC_i	Rank
A1	343.2	0.65523	3	**0.627027**	**1**
A2	**91.3**	**0.77791**	**1**	0.379463	3
A3	227.6	0.70769	2	0.506052	2

8.1.3.1.3 Discussion / Comparison to TOPSIS. In order to evaluate the effectiveness of the MF-WSM method, the results of the study were compared against standard TOPSIS results. At the conclusion of the UAS trade study, the results highlighted the benefit of MF-WSM over conventional TOPSIS. Since standard WSM cannot accurately calculate data with conflicting requirements, it was excluded from this comparison. As Table 8-7 indicates, the MF-WSM results were completely different than conventional TOPSIS. As demonstrated in the table, the MF-WSM technique completely changed the ranking order by constraining the decision matrix through the use of membership functions. While conventional TOPSIS ranked alternative 1 the highest, the MF-WSM technique ranked alternative 1 the lowest and selected alternative 2 as the best value for meeting government requirements. This difference in outcome highlights the benefit of saturating objective requirements while constraining the decision matrix using threshold and objective requirements.

A visual comparison of the alternative system characteristics supports the conclusion of the MF-WSM analysis. Figure 8-2 depicts the performance and cost characteristics of each alternative. As can be seen in the figure, Alternative 1 provided excess capabilities beyond customer objectives at approximately three times the cost of Alternative 2. Alternative 1 also failed to meet the objective requirement for the Takeoff (T/O) distance criterion. For this criterion, both Alternatives 2 and 3 performed better than Alterative 1. Although Alternative 3 met or exceeded all performance objectives, Alternative 3 also had the highest technology risk, lowest reliability, and the highest O&M costs. Alternative 2 was the lowest cost alternative but did not meet objective requirements for power or payload weight. However, Alternative 2 met or exceeded all remaining performance criteria and had the best reliability and lowest Life Cycle Cost (LCC). By possessing the lowest technology risk and highest reliability at less than half the total cost of either alternative, Alternative 2 provided the best value choice in regards to risk, reliability, performance, and cost. This figure highlights the benefits of MF-WSM over conventional TOPSIS for determining best value from conflicting requirements. Since Alternative 1 had excess performance requirements, it was scored higher using conventional TOPSIS techniques. By saturating alternative criteria scores at objective requirements, the MF-WSM technique provided equal scoring for alternative capabilities that met or exceeded objective requirements. Since MF-WSM prevented inflated scoring from excess capabilities, the technique provided a ranked list of alternatives that was more aligned with customer stated requirements.

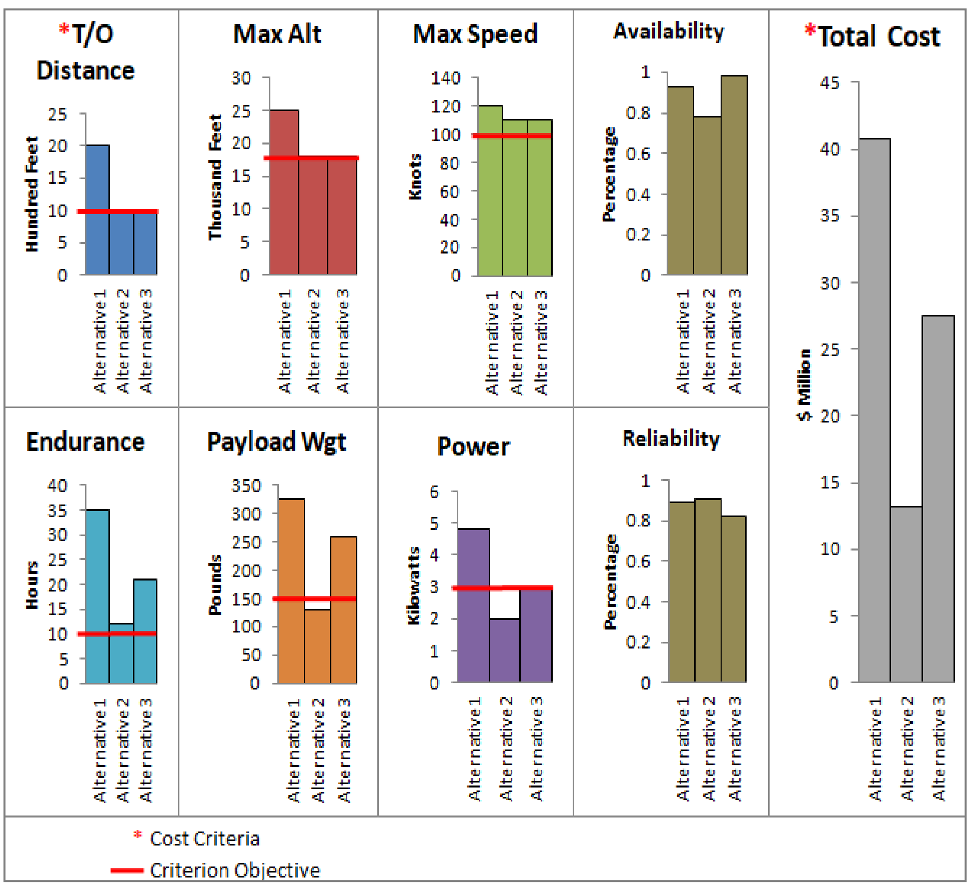

Figure 8-2: Alternative Comparison – Performance, Availability, Reliability & Cost

Unfortunately, all models have limitations and levels of inaccuracy. The MF-WSM method will only perform as well as the data provided. Different data often produces different results. For example, the MF-WSM method assumed that the government accurately stated its objective requirements and ranking of evaluation criteria. If the government was uncertain or misinterpreted its requirements or prioritization, the results of MF-WSM may not align with government expectations.

8.1.4 OCS-MCDA Methods (X-Axis). The OCS-TOPSIS and OCS-FTOPSIS techniques utilize the independent variables on the X-Axis of the membership function. Since these techniques are modified versions of TOPSIS and FTOPSIS, all calculations are performed on the real number line $\mathbb{R}$ of the membership function.

8.1.4.1 OCS-TOPSIS Applications to Case Study #1. The OCS-TOPSIS method incorporates minimum and maximum customer requirements to establish the Negative Ideal Solution (NIS) and Positive Ideal Solution (PIS) in order to define and constrain the trade space. By constraining the trade space, OCS-TOPSIS restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements. This OCS-TOPSIS approach will be demonstrated using the UAS case study described above.

8.1.4.1.1 Initial Conditions. The decision matrix *D,* represented in Table 8-3, was used for this OCS-TOPSIS application to case study #1. The three alternatives being evaluated are listed in the table along with their crisp system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

According to TOPSIS definitions, cost criteria are defined as criteria where a minimum value is preferred over a maximum value. Benefit criteria is defined as criteria where a maximum value is preferred over a minimum value [51]. While preparing TOPSIS calculations, each criterion must be classified as either benefit or cost. This step is addressed in step 5 of the OCS-TOPSIS method, listed in section 6.2.1. Using TOPSIS terminology, criteria 7, 10, 11 and 12 are classified as cost criteria with the remaining classified as benefit criteria. Examples of cost criteria are demonstrated in Table 8-3 and Tables 8-8 through 8-10 where $C_{threshold}$ values are larger than $C_{objective}$. Since the remaining criteria are classified as benefit criteria, $C_{objective}$ values are higher than $C_{threshold}$. After normalizing the constrained decision matrix S, all alternatives that meet or exceed $C_{objective}$ for benefit criteria will equal 1. For cost criteria, the worst performing alternatives will equal 1 (see Table 8-9).

To limit the rank reversal phenomenon in OCS-TOPSIS, a modified version of Garcia-Cascales and Lamata's solution to the rank reversal problem was implemented. Rank reversal is an incident that can occur when the relative rank of alternatives becomes inverted when the original decision set is altered. Garcia and Lamata's solution to rank reversal was to select a different normalization method and introduce fictitious alternatives that represent the best and worst solution [56]. Although prior research concluded that the vector normalization technique worked best for TOPSIS [118], Garcia-Cascales and Lamata's demonstrated how this normalization technique could lead to rank reversal. Therefore, the aforementioned authors' normalization technique was implemented in OCS-TOPSIS since it had an error rate less than one percent compared to the vector method [119], [120]. To implement the second rank reversal prevention measure, the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ were implemented into the decision set to represent PIS and NIS, respectively. To determine the criteria values for

$C_{ojective}$ and $C_{threshold}$ alternatives, objective and threshold values were used from the UAS RFP for performance criteria 2 through 7. For availability criteria 8 and reliability criteria 9, a minimum alternative criteria value of 70 percent was used for $C_{threshold}$ with $C_{ojective}$ represented as a maximum of 100 percent. Since cost objectives were not stated in the UAS RFP, minimum and maximum costs under each criterion were used as $C_{ojective}$ and $C_{threshold}$, respectively. By incorporating the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ in the decision set, rank reversal was successfully mitigated while also constraining the decision matrix to a fuzzy customer requirement set of PIS and NIS.

8.1.4.1.2 Case Study #1 Results. The results of the case study are shown in Tables 8-8 through 8-12. As stated above, the decision matrix *D* and weights *w* used for the analysis are displayed in Table 8-3. Table 8-8 shows the constrained decision matrix *S* using Equation 6-6. Since the RFP did not specify threshold or objective requirements for availability, reliability, procurement or O&M cost criteria, these criteria did not change in the constrained decision matrix. Table 8-9 displays the normalized decision matrix *R* using Equation 6-7 and Table 8-10 shows the weighted normalized decision matrix *V* using Equation 6-8. The Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS) are listed in Table 8-11 and the results of the OCS-TOPSIS analysis is shown in Table 8-12. As indicated in bold font in Table 8-12, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-1 and 8-2.

Table 8-8: Constrained Decision Matrix S

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
$C_{Objective}$	**9**	**150**	**10**	**3**	**100**	**18**	**10**	**1**	**1**	**167.3**	**50**	**16.3**
A1	7	150	10	3	100	18	20	0.93	0.89	345.7	209.9	67.5
A2	8	130	10	2	100	18	10	0.78	0.91	167.3	50	16.3
A3	6	150	10	3	100	18	10	0.98	0.82	387.5	138.2	30
$C_{Threshold}$	**6**	**100**	**8**	**1**	**80**	**15**	**20**	**0.75**	**0.75**	**387.5**	**209.9**	**67.5**

Table 8-9: Normalized Decision Matrix R

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
$C_{Objective}$	**1**	**1**	**1**	**1**	**1**	**1**	**0.5**	**1**	**1**	**0.43**	**0.24**	**0.24**
A1	0.78	1	1	1	1	1	1	0.93	0.89	0.89	1	1
A2	0.9	0.87	1	0.67	1	1	0.5	0.78	0.91	0.43	0.24	0.24
A3	0.67	1	1	1	1	1	0.5	0.98	0.82	1	0.66	0.44
$C_{Threshold}$	**0.67**	**0.67**	**0.8**	**0.33**	**0.8**	**0.83**	**1**	**0.7**	**0.7**	**1**	**1**	**1**

Table 8-10: Weighted Normalized Decision Matrix V

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
$C_{Objective}$	**0.14**	**0.128**	**0.116**	**0.105**	**0.093**	**0.081**	**0.035**	**0.058**	**0.058**	**0.025**	**0.011**	**0.011**
A1	0.109	0.128	0.116	0.105	0.093	0.081	0.07	0.054	0.052	0.052	0.047	0.047
A2	0.124	0.111	0.116	0.07	0.093	0.081	0.035	0.045	0.053	0.025	0.011	0.011
A3	0.093	0.128	0.116	0.105	0.093	0.081	0.035	0.057	0.048	0.058	0.031	0.021
$C_{Threshold}$	**0.093**	**0.085**	**0.093**	**0.035**	**0.074**	**0.068**	**0.07**	**0.041**	**0.041**	**0.058**	**0.047**	**0.047**

Table 8-11: $\boldsymbol{v_j^+}, \boldsymbol{v_j^-}$ - Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS)

v_j^+	0.14	0.128	0.116	0.105	0.093	0.081	0.035	0.058	0.058	0.025	0.011	0.011
v_j^-	0.093	0.085	0.093	0.035	0.074	0.068	0.07	0.041	0.041	0.058	0.047	0.047

Table 8-12: OCS-TOPSIS and Conventional TOPSIS

	OCS-TOPSIS				**Conventional TOPSIS**			
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
A1	0.073855	0.091307	0.552832	3	**0.059044**	**0.099263**	**0.627027**	**1**
A2	**0.044035**	**0.094262**	**0.681592**	**1**	0.099249	0.060691	0.379463	3
A3	0.061947	0.10103	0.619903	2	0.063356	0.064908	0.506052	2

8.1.4.1.3 Discussion / Comparison to Standard TOPSIS. In order to evaluate the effectiveness of the OCS-TOPSIS method, the results of the study were compared against standard TOPSIS results. At the conclusion of the UAS trade study, the results highlighted the benefit of OCS-TOPSIS over conventional TOPSIS. As Table 8-12 indicates, the OCS-TOPSIS results were completely different than the conventional TOPSIS method. As demonstrated in the table, the OCS-TOPSIS technique completely changed the ranking order by constraining the decision matrix. While conventional TOPSIS ranked alternative 1 the highest, the OCS-TOPSIS technique ranked alternative 1 the lowest and selected alternative 2 as the best value for meeting customer requirements. This difference in TOPSIS outcome highlights the benefit of saturating objective requirements while constraining the decision matrix using threshold and objective requirements as NIS and PIS, respectively.

A visual comparison of the alternative system characteristics supports the conclusion of the OCS-TOPSIS analysis. As demonstrated in MF-WSM example, Figure 8-2 highlights the benefits of OCS-TOPSIS over conventional TOPSIS for determining best value. Since Alternative 1 had excess performance requirements, it was scored higher using conventional TOPSIS techniques. By saturating alternative criterion scores at objective requirements, the OCS-TOPSIS technique provided equal scoring for alternative capabilities that met or exceeded objective requirements. Since OCS-TOPSIS prevented inflated scoring from excess capabilities, the technique provided a ranked list of alternatives that was more aligned with customer stated requirements.

The results in Figure 8-3 and Table 8-12 highlight the benefit of saturating scores at ideal customer requirements through OCS-TOPSIS. As illustrated in Figure 8-3, there is a distinct difference between the constrained OCS-TOPSIS technique (left graphic) and the unconstrained, TOPSIS technique (right graphic). By not constraining the decision space, the excess capabilities of Alternative 1 greatly expanded the Euclidean distances of PIS and NIS. As a result, Alternative 1 is pulled farther from NIS while pushing Alternatives 2 farther from PIS. Due to these unconstrained capabilities, Alternative 1 received the best score using conventional TOPSIS. By applying the OCS-TOPSIS technique, Alternative 1's excessive capabilities are constrained resulting in Euclidean distances from PIS and NIS that are more reflective of customer defined value. As shown in Figure 8-3, the Euclidean distances from PIS and NIS are adjusted to the constrained decision space after applying OCS-TOPSIS. This difference in

TOPSIS outcome highlights the benefit of saturating customer requirements while constraining the decision matrix using threshold and objective requirements as NIS and PIS, respectively.

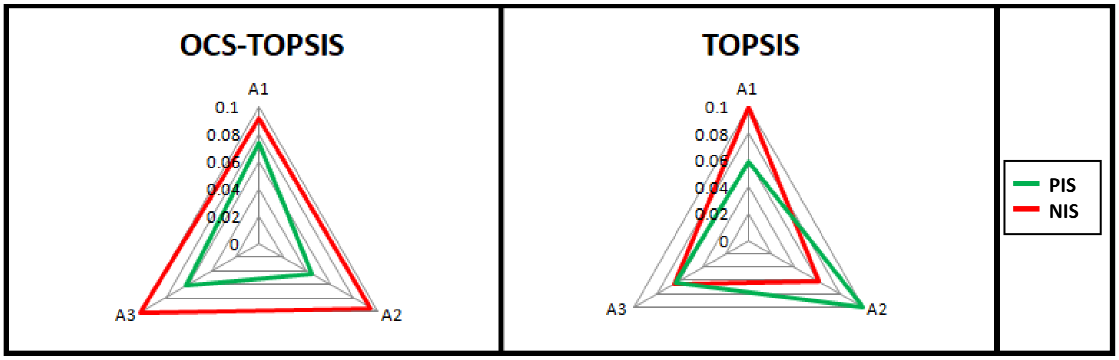

Figure 8-3: TOPSIS Technique Comparison – Alternative Distance to PIS/NIS

Unfortunately, all models have limitations and levels of inaccuracy. The OCS-TOPSIS method will only perform as well as the data provided. Different data often produces different results. For example, the OCS-TOPSIS method assumed that the government accurately stated its objective requirements and ranking of evaluation criteria. If the government was uncertain or misinterpreted its requirements or prioritization, the results of OCS-TOPSIS may not align with government expectations. If the government shifted its priorities, a change in weights may have changed the ranked outcome. Additionally, one of the biggest limitations of any TOPSIS technique is the problem of rank reversal. By incorporating the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ as well as an alternate normalization technique in OCS-TOPSIS, the risk of rank reversal was mitigated to an acceptable level.

8.1.4.2 OCS-FTOPSIS Applications to Case Study #1. In the OCS-FTOPSIS method, minimum and maximum customer requirements are used to establish the Fuzzy Negative Ideal Solution (FNIS) and Fuzzy Positive Ideal Solution (FPIS) in order to define and constrain the trade space. Instead of using linguistic variables to evaluate each criterion, like most FTOPSIS techniques, fuzzy design estimates are used to calculate Euclidean distances from FNIS and

FPIS. Similar to the previous two techniques, the OCS-FTOPSIS method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements. This OCS-FTOPSIS approach will be demonstrated using the UAS case study described above.

8.1.4.2.1 Initial Conditions. The decision matrix $\widetilde{D}$, represented in Table 8-3, was used for this OCS-FTOPSIS application to case study #1. The three alternatives being evaluated are listed in the table along with their fuzzy system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

Similar to TOPSIS definitions, FTOPSIS cost criteria are defined as criteria where a minimum value is preferred over a maximum value. Benefit criteria is defined as criteria where a maximum value is preferred over a minimum value. While preparing FTOPSIS calculations, each criterion must be classified as either benefit or cost. This step is addressed in step 5 of the OCS-FTOPSIS method, listed in section 6.2.2. Using FTOPSIS definitions, criteria 7, 10, 11, and 12 are classified as cost criteria. This is demonstrated in Table 8-3 and Tables 8-13 through 8-15 where $C_{threshold}$ values are larger than $C_{objective}$. Since the remaining criteria are classified as benefit criteria, $C_{objective}$ values are higher than $C_{threshold}$. After normalizing the constrained fuzzy decision matrix $\tilde{S}$, all alternatives that met or exceeded $C_{objective}$ will equal 1. For cost criteria, the worst performing alternatives will equal 1 or have the highest numerical value (see Table 8-14).

The rank reversal phenomenon was mitigated using a modified version of Garcia-Cascales and Lamata's TOPSIS solution, similar to OCS-TOPSIS. In order to minimize the risk of rank reversal in OCS-FTOPSIS, the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ were implemented into the decision set to represent FPIS and FNIS, respectively. By incorporating the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ in the decision set, rank reversal was successfully mitigated while also constraining the decision matrix to a fuzzy customer requirement set of FPIS and FNIS.

8.1.4.2.2 Case Study #1 Results. The results of the UAS case study are shown in Tables 8-13 through 8-17. As stated above, the decision matrix $\widetilde{D}$ and weights *w* used for the analysis are displayed in Table 8-3. Table 8-13 shows the fuzzy constrained decision matrix $\tilde{S}$ using Equation 6-16 to demonstrate calculating a fuzzy set that partly meets threshold criteria. Since the RFP did not specify threshold or objective requirements for availability, reliability, or cost criteria, these criteria did not change in the constrained decision matrix. Table 8-14 displays the fuzzy normalized decision matrix $\tilde{R}$ using Equation 6-17 and Table 8-15 shows the fuzzy weighted normalized decision matrix $\tilde{V}$ using Equation 6-21. The Fuzzy Positive Ideal Solutions (FPIS) and Fuzzy Negative Ideal Solutions (FNIS) are indicated in Table 8-16 using Equations 6-22 and 6-23, respectively. The results of the OCS-FTOPSIS analysis along with conventional FTOPSIS distance calculations are shown in Table 8-17. The conventional FTOPSIS calculation is a straight fuzzy calculation, without Subject Matter Expert (SME) input or constraints, using the same UAS alternative and requirements data as the other two techniques. For the initial FTOPSIS comparison in this section, the focus is on evaluating the calculation outcomes for both FTOPSIS and OCS-FTOPSIS methods using the same, standardized data. FTOPSIS analysis using SME data will be analyzed in the subsequent section. As indicated in bold font in Table 8-17, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-1 and 8-2.

Table 8-13: Constrained Fuzzy Decision Matrix $\tilde{S}$ and Weights of Three Design Alternatives

	C1	C2	C3	C4	C5	C6
$C_{Objective}$	(9, 9, 9)	(150, 150, 150)	(10, 10, 10)	(3, 3, 3)	(100, 100, 100)	(18, 18, 18)
A1	(6, 7, 8)	(150, 150, 150)	(10, 10, 10)	(3, 3, 3)	(100, 100, 100)	(18, 18, 18)
A2	(7, 8, 9)	(117, 130, 136.5)	(10, 10, 10)	(1.8, 2, 2.1)	(99, 100, 100)	(16.2, 18, 18)
A3	(6, 6, 7)	(150, 150, 150)	(10, 10, 10)	(2.7, 3, 3)	(99, 100, 100)	(16.2, 18, 18)
$C_{Threshold}$	(6, 6, 6)	(100, 100, 100)	(8, 8, 8)	(1, 1, 1)	(80, 80, 80)	(15, 15, 15)
Weight	0.14	0.128	0.116	0.105	0.093	0.081
	C7	**C8**	**C9**	**C10**	**C11**	**C12**
$C_{Objective}$	(10, 10, 10)	(1, 1, 1)	(1, 1, 1)	(15.89, 15.89, 15.89)	(47.5, 47.5, 47.5)	(74.25, 74.25, 74.25)
A1	(19, 20, 20)	(0.84, 0.93, 0.98)	(0.8, 0.89, 0.93)	(32.84, 34.57, 38.02)	(199.41, 209.9, 230.89)	(64.13, 67.5, 74.25)
A2	(10, 10, 11)	(0.70, 0.78, 0.82)	(0.82, 0.91, 0.96)	(15.89, 16.73, 18.4)	(47.5, 50, 55)	(15.44, 16.25, 17.88)
A3	(10, 10, 11)	(0.88, 0.98, 1)	(0.74, 0.82, 0.86)	(36.81, 38.75, 42.63)	(131.29, 138.2, 152.02)	(28.5, 30, 33)
$C_{Threshold}$	(20, 20, 20)	(0.7, 0.7, 0.7)	(0.74, 0.74, 0.74)	(42.63, 42.63, 42.63)	(230.89, 230.89, 230.89)	(15.44, 15.44, 15.44)
Weight	0.07	0.058	0.058	0.058	0.047	0.047

Table 8-14: Fuzzy Normalized Decision Matrix $\tilde{R}$

	C1	C2	C3	C4	C5	C6
$C_{Objective}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
A1	(0.67, 0.78, 0.89)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
A2	(0.78, 0.89, 1)	(0.78, 0.87, 0.91)	(1, 1, 1)	(0.6, 0.67, 0.7)	(0.99, 1, 1)	(0.9, 1, 1)
A3	(0.67, 0.67, 0.78)	(1, 1, 1)	(1, 1, 1)	(0.9, 1, 1)	(0.99, 1, 1)	(0.9, 1, 1)
$C_{Threshold}$	(0.67, 0.67, 0.67)	(0.67, 0.67, 0.67)	(0.8, 0.8, 0.8)	(0.33, 0.33, 0.33)	(0.8, 0.8, 0.8)	(0.83, 0.83, 0.83)
	C7	**C8**	**C9**	**C10**	**C11**	**C12**
$C_{Objective}$	(0.5, 0.5, 0.5)	(1, 1, 1)	(1, 1, 1)	(0.37, 0.37, 0.37)	(0.21, 0.21, 0.21)	(0.21, 0.21, 0.21)
A1	(0.95, 1, 1)	(0.84, 0.93, 0.98)	(0.8, 0.89, 0.94)	(0.77, 0.81, 0.82)	(0.86, 0.91, 1)	(0.86, 0.91, 1)
A2	(0.5, 0.5, 0.55)	(0.7, 0.78, 0.82)	(0.82, 0.91, 0.96)	(0.37, 0.39, 0.43)	(0.21, 0.22, 0.24)	(0.21, 0.22, 0.24)
A3	(0.5, 0.5, 0.55)	(0.89, 0.98,	(0.74, 0.82, 0.86)	(0.86, 0.91, 1)	(0.57, 0.6, 0.7)	(0.38, 0.4, 0.44)
$C_{Threshold}$	(1, 1, 1)	(0.7, 0.7, 0.7)	(0.7, 0.7, 0.7)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)

Table 8-15: Fuzzy Weighted Normalized Decision Matrix $\tilde{V}$

	C1	C2	C3	C4	C5	C6
$C_{Objective}$	(0.14, 0.14, 0.14)	(0.13, 0.13, 0.13)	(0.12, 0.12, 0.12)	(0.1, 0.1, 0.1)	(0.09, 0.09, 0.09)	(0.08,0.08, 0.08)
A1	(0.09, 0.11, 0.12)	(0.13, 0.13, 0.13)	(0.12, 0.12, 0.12)	(0.1, 0.1, 0.1)	(0.09, 0.09, 0.09)	(0.08,0.08, 0.08)
A2	(0.11, 0.12, 0.14)	(0.1, 0.11, 0.12)	(0.12, 0.12, 0.12)	(0.06, 0.07, 0.07)	(0.09, 0.09, 0.09)	(0.07, 0.08, 0.08)
A3	(0.09, 0.09, 0.11)	(0.13, 0.13, 0.13)	(0.12, 0.12, 0.12)	(0.09, 0.1, 0.1)	(0.09, 0.09, 0.09)	(0.07, 0.08, 0.08)
$C_{Threshold}$	(0.09, 0.09, 0.09)	(0.09, 0.09, 0.09)	(0.09, 0.09, 0.09)	(0.04, 0.04, 0.04)	(0.07, 0.07, 0.07)	(0.07, 0.07, 0.07)
	C7	**C8**	**C9**	**C10**	**C11**	**C12**
$C_{Objective}$	(0.04, 0.04, 0.04)	(0.06, 0.06, 0.06)	(0.06, 0.06, 0.06)	(0.02, 0.02, 0.02)	(0.01, 0.01, 0.01)	(0.01, 0.01, 0.01)
A1	(0.07, 0.07, 0.07)	(0.05, 0.05, 0.06)	(0.05, 0.05, 0.05)	(0.05, 0.05, 0.05)	(0.04, 0.04, 0.05)	(0.04, 0.04, 0.05)
A2	(0.04, 0.04, 0.04)	(0.05, 0.05, 0.05)	(0.05, 0.05, 0.06)	(0.02, 0.02, 0.03)	(0.01, 0.01, 0.01)	(0.01, 0.01, 0.01)
A3	(0.04, 0.04, 0.04)	(0.05, 0.06, 0.06)	(0.04, 0.05, 0.05)	(0.05, 0.05, 0.06)	(0.03, 0.03, 0.03)	(0.2, 0.2, 0.2)
$C_{Threshold}$	(0.07, 0.07, 0.07)	(0.4, 0.4, 0.4)	(0.4, 0.4, 0.4)	(0.06, 0.06, 0.06)	(0.05, 0.05, 0.05)	(0.05, 0.05, 0.05)

Table 8-16: v_j^+, v_j^- - Fuzzy Positive Ideal Solutions (FPIS) and Fuzzy Negative Ideal Solutions (FNIS)

	C1	C2	C3	C4	C5	C6
v_j^+	0.14	0.128	0.116	0.105	0.093	0.081
v_j^-	0.093	0.085	0.093	0.035	0.074	0.068
	C7	**C8**	**C9**	**C10**	**C11**	**C12**
v_j^+	0.035	0.058	0.058	0.022	0.01	0.01
v_j^-	0.07	0.041	0.041	0.058	0.047	0.047

Table 8-17: FTOPSIS Technique Comparison - Alternative Distance to FPIS/FNIS

	Max LCC	**OCS-FTOPSIS**				**FTOPSIS (no SME data)**			
	($mil)	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
A1	343.2	0.062227	0.091753	0.595711	3	**11.20936**	**0.792368**	**0.066021**	**1**
A2	91.3	**0.04507**	**0.088334**	**0.662154**	**1**	11.302353	0.699109	0.058252	2
A3	227.6	0.059027	0.094284	0.614984	2	11.312016	0.689409	0.057444	3

8.1.4.2.3 Discussion / Comparison to Standard FTOPSIS (no SME data). In order to evaluate the effectiveness of the OCS-FTOPSIS method, the results of the study were compared against standard FTOPSIS results without SME input. At the conclusion of the UAS trade study, the results highlighted the benefit of the OCS-FTOPSIS method over the unconstrained, conventional FTOPSIS calculations. The results of the UAS case study using OCS-FTOPSIS and FTOPSIS methods is shown in Table 8-17 along with maximum Life Cycle Costs (LCC).

The results in Table 8-17 highlight the benefit of saturating scores at ideal customer requirements through OCS-FTOPSIS. This difference in FTOPSIS outcome highlights the benefit of saturating customer requirements while constraining the decision matrix using threshold and objective requirements as FNIS and FPIS, respectively.

A visual comparison of the alternative system characteristics supports the conclusion of the OCS-FTOPSIS and FTOPSIS analysis. As demonstrated in the MF-WSM and OCS-TOPSIS examples, Figure 8-2 highlights the benefits of OCS-FTOPSIS for determining best value. Since Alternative 1 had excess performance requirements, it was scored higher using an unconstrained, direct calculation technique. By saturating alternative criterion scores at objective requirements, the OCS-FTOPSIS technique provided equal scoring for alternative capabilities that met or exceeded objective requirements. Since OCS-FTOPSIS prevented inflated scoring from excess capabilities, the technique provided a ranked list of alternatives that was more aligned with the government stated requirements.

Unfortunately, all models have limitations and levels of inaccuracy. Despite attempts to reduce uncertainty with the OCS-FTOPSIS method, the model will only perform as well as the data provided. Different data often produces different results. For example, the OCS-FTOPSIS technique assumed that customer requirements were accurately described and prioritized, albeit not precise. If a customer was unsure or misinterpreted its requirements or prioritization, the results of the OCS-FTOPSIS may not have aligned with customer expectations. If a customer shifted his or her priorities, a change in weights may have changed the ranked outcome. Additionally, one of the biggest limitations of the TOPSIS and FTOPSIS technique is the problem of rank reversal. By incorporating rank reversal prevention measures, the OCS-FTOPSIS method mitigated this risk to an acceptable level.

8.1.4.2.4 Discussion / Comparison to Standard FTOPSIS (SME data). In order to evaluate the reasonableness of the OCS-FTOPSIS results, expert opinion was elicited using the conventional FTOPSIS method. Since a US DOD UAS example was used for the analysis, three volunteers were selected with 89 years of combined government experience, 75 years of aviation experience, and 27 years of acquisition experience. The SMEs were provided with the same UAS alternative and requirements data that was used in the UAS case study, except for no system TRL data. The SMEs were instructed to rate the importance of each criterion using the linguistic variables in Table 8-18 followed by rating each UAS alternative against each criterion using the linguistic variables in Table 8-19. The results of the SME criteria ratings are in Table 8-20 and their UAS alternative ratings are in Table 8-21.

Table 8-18: Linguistic Variable – Criterion Weights

Very Low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium Low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium High (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1)
Very High (VH)	(0.9, 1, 1)

Table 8-19: Linguistic Variables – Ratings

Very Poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium Poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium Good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very Good (VG)	(9, 10, 10)

Table 8-20: Decision Maker(DM) Ratings – Criteria

	DM1	**DM2**	**DM3**
C1	ML	VH	VH
C2	MH	H	VH
C3	MH	H	H
C4	M	VH	H
C5	ML	VH	MH
C6	VH	VH	M
C7	H	H	H
C8	MH	H	H
C9	M	MH	MH
C10	L	MH	L
C11	MH	MH	ML

Table 8-21: Decision Maker(DM) Ratings – Alternatives against Criteria

Criteria	**Alternatives**	**Decision Makers**			**Criteria**	**Alternatives**	**Decision Makers**		
		DM1	**DM2**	**DM3**			**DM1**	**DM2**	**DM3**
C1	A1	VG	VG	VG	**C7**	A1	G	VG	G
	A2	G	G	F		A2	VG	F	F
	A3	G	VG	VG		A3	G	VG	VG
C2	A1	VG	VG	VG	**C8**	A1	G	VG	G
	A2	G	VG	MG		A2	VG	VG	G
	A3	VG	VG	G		A3	MG	G	MG
C3	A1	VG	VG	VG	**C9**	A1	MG	G	F
	A2	G	F	F		A2	G	VG	VG
	A3	G	VG	G		A3	F	G	F
C4	A1	G	VG	VG	**C10**	A1	MP	F	F
	A2	G	VG	G		A2	G	VG	VG
	A3	G	VG	G		A3	F	G	MG
C5	A1	VG	F	VG	**C11**	A1	MP	F	P
	A2	G	G	F		A2	G	VG	VG
	A3	G	G	F		A3	F	G	G
C6	A1	F	P	P					
	A2	G	VG	VG					
	A3	G	VG	VG					

The results of the UAS trade study using OCS-FTOPSIS and SME elicited FTOPSIS methods are shown in Table 8-22. Also included in the analysis is a straight fuzzy calculation of FTOPSIS, without SME input or constraints, using the same UAS alternative and requirements data as the other two techniques. The result of this calculation is also in Table 8-22. Figure 8-4 graphically displays the Euclidian distances from FPIS and FNIS for all UAS alternatives using the three different FTOPSIS techniques. As indicated in bold font in Table 8-22, Alternative 3 was calculated to have best value according to government stated requirements that were reflected in Tables 8-1 and 8-2. This change is rank position between Alternatives 1 and 2 was caused by the omission of the TRL criteria. Since the TRL criterion was the highest weighted in the previous examples, the change in criteria weighting resulted in a rank reversal.

Table 8-22: FTOPSIS Technique Comparison (Without Risk) - Alternative Distance to FPIS/FNIS

	OCS-FTOPSIS				**FTOPSIS (SME data)**				**FTOPSIS (no SME data)**			
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
A1	0.073991	0.105107	0.586871	3	5.9212249	7.059757	0.5438539	3	**49.78181**	**54.39187**	**0.522127**	**1**
A2	0.049183	0.104194	0.679333	2	5.9265121	7.438754	0.5565736	2	46.38494	49.401903	0.515748	3
A3	**0.045824**	**0.116677**	**0.718008**	**1**	**5.721862**	**7.587347**	**0.570083**	**1**	48.750333	52.502197	0.518527	2

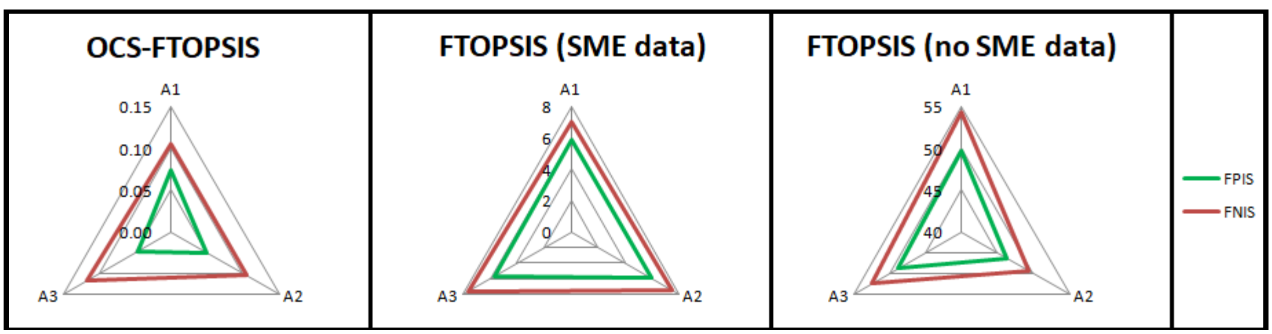

Figure 8-4: FTOPSIS Technique Comparison – Alternative Distance to FPIS/FNIS

An evaluation of the Euclidean distances between FTOPSIS methods in Figure 8-4 provides insight into the results of each technique. The group FTOPSIS technique (middle graphic) presented results relatively consistent with OCS-FTOPSIS (left graphic). Using the group decision FTOPSIS technique, the SMEs also selected Alternative 3 as the best value. Conversely, the FTOPSIS method without SME input (right graphic) diverged from the other two results and was more consistent with the conventional TOPSIS results evaluated in section 8.1.4.1.3. Since the SME results using FTOPSIS matched the OCS-FTOPSIS results, the SME analysis reinforced the alternative ranking provided by OCS-FTOPSIS.

8.1.5 Comparison of MF-WSM, OCS-TOPSIS, & OCS-FTOPSIS Results. Since each OCS-MCDA method uses different calculations, there will be some variation in OCS output data. For the OCS-TOPSIS and OCS-FTOPSIS methods, fuzzy Euclidean distance calculations will vary from crisp Euclidean distance calculations due to the spread and skew of the fuzzy membership functions in OCS-FTOPSIS. Figure 8-7 displays the total aggregated Euclidean distance calculations for OCS-TOPSIS and OCS-FTOPSIS methods for each UAS alternative. These distance calculations used symmetric fuzzy data for the OCS-FTOPSIS calculations, as opposed to the asymmetrical calculations used in the previous case study. Although the variation between OCS-TOPSIS and OCS-FTOPSIS calculations is slight, future practitioners should be aware of this disparity to ensure consistent results. This variation is particularly noteworthy whenever the top alternative candidates are very close in final ranking. Caution should also be applied to the MF-WSM method. The OCS-TOPSIS and OCS-FTOPSIS methods both perform distance calculations from a single point to two ideal points. The MF-WSM method only performs one calculation based on a single point. This difference in calculation creates variation in output results where future practitioners should exercise caution whenever final rankings are close.

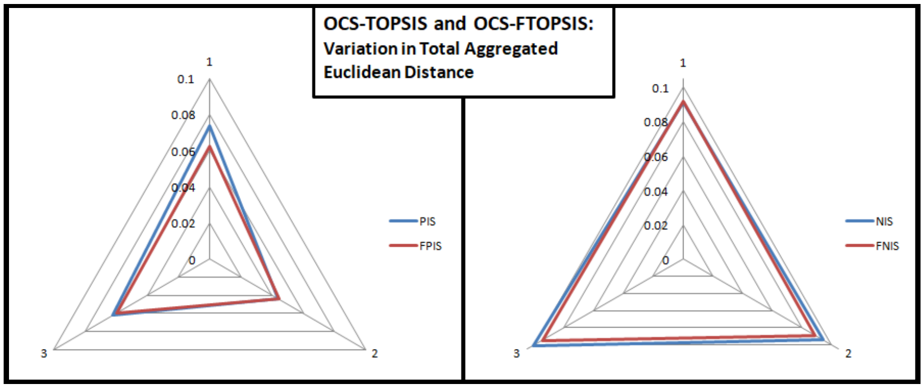

Figure 8-5: Variation in Total Aggregated Euclidean Distance

A sensitivity analysis was conducted to determine if OCS-MCDA results were sensitive to moderate changes in the weighting of TRL risk. Although the importance of risk was emphasized in the UAS RFP used in the case study, the RFP did not specifically quantify the importance of risk over performance, reliability, and cost. Since OCS-MCDA techniques use customer order of importance to rank criteria weights, the sensitivity analysis did not focus on performance, reliability, and cost criteria because the importance of these criteria were specified in the RFP. Due to these reasons, TRL risk was the primary focus for the sensitivity analysis.

At the conclusion of the sensitivity analysis, the OCS-MCDA methods proved fairly robust against moderate changes to the weighting of TRL risk. To conduct the sensitivity analysis, the TRL weight was changed three times: less than the performance criteria; less than performance and reliability criteria, and less than all criteria. All three OCS methods did not experience rank reversal until TRL risk was weighted last. When TRL risk was weighted less than all other criteria, all three OCS-MCDA methods experienced a rank reversal where Alternative 3 became the best candidate. This result is consistent with SME study where TRL risk was completely removed from the analysis and Alternative 3 was selected as the best candidate for both OCS-FTOPSIS and the SME FTOPSIS.

To ensure confidence in results, a Decision Analysis tool should be reliable and valid. Reliability means that results from a technique are stable and consistent. Validity relates to sound evidence to demonstrate that the test interpretation matches its proposed use. [121] Methods for evaluating the validity of a model are to compare the results to actual decision results, expert opinion, or another model [122]. As demonstrated in the UAS case study, the result of each OCS-MCDA method was consistent with all OCS methods. When compared against expert opinion, the OCS-FTOPSIS results were the same as the Subject Matter Experts (SME). In fact, all the results from the OCS-MCDA techniques were the same after removing the risk criterion and recalculating weights (see Table 8-23). The UAS case study provided a means to demonstrate the reliability and validity of the OCS-MCDA methods through model comparisons and expert onion. In the subsequent case study, a larger data set will be explored where OCS results can be compared against a different acquisition decision.

Table 8-23: OCS-MCDA Technique Comparison (Without Risk)

	OCS-FTOPSIS				**OCS-TOPSIS**				**MF-WSM**	
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank	Total	Rank
A_1	0.073991	0.105107	0.586871	3	0.0647651	0.1139858	0.6376797	3	0.70742	3
A_2	0.049183	0.104194	0.679333	2	0.052156	0.0976668	0.6518822	2	0.79595	2
A_3	**0.045824**	**0.116677**	**0.718008**	**1**	**0.041044**	**0.124396**	**0.751911**	**1**	**0.82245**	**1**

8.2 Case Study #2 – Space Launch Systems

The three Objective Criteria Saturation (OCS) Multiple Criteria Decision Analysis (MCDA) techniques will be demonstrated using a United States Air Force (USAF) rocket acquisition case study. The case study will apply the OCS-MCDA methods to evaluate rocket alternatives against primary and sub criteria. This second case study was conducted to further test the reliability of the OCS methods.

Figure 8-6: Rocket Alternatives
A1-Atlas II (left), A2-Delta II (middle), A3-Ariane 4 (right) [123]–[125]

8.2.1 Scenario Background. The US Air Force (USAF) began the Evolved Expendable Launch Vehicle (EELV) program in 1995 to develop a new generation of launch vehicles to provide affordable access to space for government satellites [126]. Program requirements for the EELV program include reliability, accuracy, and standard interface [127]. In October 2017, the USAF released a Request for Proposal (RFP) to leverage commercial launch solutions for placing a payload in geosynchronous (GEO) orbit. Prior to releasing the RFP, the USAF acquisition strategy began with technology maturation to raise the technology readiness level and increase the knowledge base for the entire U.S. rocket propulsion industrial base. [128]

This case study will focus on evaluating the risk, performance, reliability, and cost of three commercial rocket manufacturers. Since the RFP requires mature and currently operational systems, Technology Readiness Levels (TRL) will not be used in this case study. Alternatively, overall risk assessments will be used in accordance with the EELV RFP [128]. In addition to the risk assessment, other qualitative assessments will be used in this case study to demonstrate the use of fuzzy linguistic variables.

8.2.2 Data used in Study. To provide an second example of the OCS-MCDA methods, all three techniques were applied to a set of requirements data that was derived from a USAF Request for Proposals (RFP) for rocket acquisitions [128]. The three alternative systems were from Atlas, Delta, and Ariane rocket families [129]–[131]. The Atlas, Delta, and Ariane rockets were selected because they are currently the only rockets that are capable of reaching GEO orbit. Although Space X recently tested a rocket that can reach GEO, the rocket has not reached TRL 9 at the time of this dissertation and will not be considered in the analysis [128], [132]. In order to ensure data consistency for evaluation purposes, historical performance, reliability, and cost information was used from *Space Mission Analysis and Design, 3rd Ed.* [133].

To determine the criteria values for $C_{ojective}$ and $C_{threshold}$ alternatives, objective and threshold values were used from the EELV RFP for performance criteria 1 through 4 along with their respective sub criteria. For reliability criterion 5, a minimum of 75 percent was used for $C_{threshold}$ with $C_{ojective}$ represented as a maximum of 100 percent. Criteria 6 through 9 represent qualitative ratings on each rocket manufacturer pertaining to technical approach, risk, past performance relevancy and past performance competency. Since a cost objective was not stated in the EELV RFP, minimum and maximum costs were used as $C_{ojective}$ and $C_{threshold}$, respectively.

The performance threshold and objective values from the EELV RFP are listed in Table 8-24. The evaluation criteria and normalized weights for the decision matrix are listed in Table 8-25 in rank order of importance. The criteria weights were calculated using the rank sum method using the EELV RFP's order of importance for evaluation criteria. Criterion 1 represents orbital accuracy to GEO orbit and criteria 2 and 3 represent rocket loads and dynamics. Criterion 4 represents the total payload mass that a rocket is capable of transporting to GEO transfer orbit. Criteria 1 through 3 are given the top priority with criterion 4 given the second highest priority. Criteria 1 through 4 represent performance criteria. Criterion 5 represents reliability by displaying the percentage of successful launches per rocket manufacturer. Criteria 6 through 9 represent qualitative risk assessments from four different viewpoints using linguistic variables that were derived from the EELV RFP. Criterion 10 represents the total cost of the rocket system, in $million. In regards to OCS-MCDA definitions of cost and benefit criteria described in Chapter 2, criteria 1 through 3 and 10 are considered cost criteria where lower values are preferred to higher values. Criteria 4 through 9 are considered benefit criteria where higher values are preferred to lower values.

Table 8-24: Performance Evaluation Criteria

Criteria		$C_{Threshold}$	$C_{Objective}$
C1=	**Orbital Accuracy to GEO Transfer Orbit**		
C1A =	Apogee (kilometers)	350	50
C1B =	Perigee (kilometers)	2	0.5
C1C =	Inclination (degrees)	0.5	0.05
C2=	**Loads & Dynamics - Load Factors (g's)**		
C2A =	Axial Load - Steady State	3	1
C2B =	Axial Load – Dynamic	3	1
C2C =	Lateral Load – Dynamic	5	1
C3=	**Loads & Dynamics - Fundamental Frequency (Hz)**		
C3A =	Axial Fundamental Frequency	50	10
C3B =	Lateral Fundamental Frequency	50	10
C4=	**Payload Mass to Geo Transfer Orbit (pounds)**	1250	2500

Table 8-25: Launch System Evaluation Criteria with Weights

Criteria		Rank	Weight	Normalized
C1=	**Orbital Accuracy to GEO Transfer Orbit**	**1**	**10**	**0.12**
C1A =	Apogee (km)			0.04
C1B =	Perigee (km)			0.04
C1C =	Inclination (deg)			0.04
C2=	**Loads & Dynamics - Load Factors (g's)**	**1**	**10**	**0.12**
C2A =	Axial Load - Steady State			0.04
C2B =	Axial Load – Dynamic			0.04
C2C =	Lateral Load – Dynamic			0.04
C3=	**Loads & Dynamics - Fundamental Frequency (Hz)**	**1**	**10**	**0.12**
C3A =	Axial Fundamental Frequency			0.06
C3B =	Lateral Fundamental Frequency			0.06
C4=	**Payload Mass to GEO Transfer Orbit**	**2**	**9**	**0.108**
C5=	**Launch Reliability**	**3**	**8**	**0.096**
C6=	**Technical Rating**	**3**	**8**	**0.096**
C7=	**Technical Risk Rating**	**3**	**8**	**0.096**
C8=	**Past Performance Relevancy**	**4**	**7**	**0.084**
C9=	**Past Performance Confidence Assessment**	**4**	**7**	**0.084**
C10=	**Launch Vehicle Cost**	**5**	**6**	**0.072**

Four qualitative assessments were employed to assess risk from various viewpoints. These qualitative assessments focused on the manufacturer’s technical approach, overall risk, past performance relevancy, and past performance competency. The rating and description for each qualitative assessment are listed in Tables 8-26 though 8-29. Due to the unavailability of the actual proposal, all rocket alternatives were rated as acceptable for the technical approach rating. For the technical risk rating, alternative 2 was rated as moderate risk with the other two alternatives rated as high risk. Alternative 1 was rated as high risk due to the rocket’s use of Russian RD-180 rocket engines and the United States turbulent relationship with Russia [134], [135]. Alternative 3 was rated as high risk since it is a foreign manufacturer with European manufacturing standards and a different system of measurement. Since Alternatives 1 and 2 have had ongoing launch services with EELV, they were both rated as “very relevant” for the past performance relevancy rating. Alternative 3 was rated as “relevant” since it has government launch experience in Europe but doesn’t have sufficient launch history with the USAF. For the past performance competency rating, Alternative 2 was rated the highest with “substantial confidence" because it had the longest work history with the USAF along with the highest reliability. Alternative 1 received the second highest rating with "satisfactory confidence" due to a shorter work history than Alternative 2 coupled with the worst reliability rating of the three alternatives. Alternative 3 received a "neutral confidence" since the company does not have a relevant performance record with the EELV program.

This rocket case study provides an opportunity to demonstrate the use of fuzzy linguistic variables. The linguistic ratings in Tables 8-26 through 8-29 were all converted to fuzzy triangular numbers using the membership functions displayed in Figure 8-7. The color rating used in Table 8-26 are displayed in the figure along with the linguistic ratings for Tables 8-27 and 8-28. Although the linguistic ratings for Table 8-29 are not specified in the figure, the colors represented by blue through red can represent the linguistic ratings in Table 8-29 for "substantial confidence" through "no confidence", respectively. By conducting this fuzzy transformation, the uncertainties of the linguistic variables in each table were captured mathematically for further analysis and comparison.

Table 8-26: Technical Ratings[128]

Color	Adjectival Rating	Description
Blue	Outstanding	Proposal indicates an exceptional approach and understanding of the requirements and contains multiple strengths.
Purple	Good	Proposal indicates a thorough approach and understanding of the requirements and contains at least one strength.
Green	Acceptable	Proposal indicates an adequate approach and understanding of the requirements.
Yellow	Marginal	Proposal has not demonstrated an adequate approach and understanding of the requirements.
Red	Unacceptable	Proposal does not meet requirements of the solicitation and, thus, contains one or more deficiencies and is unawardable.

Table 8-27: Technical Risk Ratings[128]

Rating	Description
Low	Proposal may contain weakness (es) which have little potential to cause disruption of schedule, increased cost or degradation of performance. Normal contractor effort and normal Government monitoring will likely be able to overcome any difficulties.
Moderate	Proposal contains a significant weakness or combination of weaknesses which may potentially cause disruption of schedule or degradation of performance. Special contractor emphasis and close Government monitoring will likely be able to overcome difficulties.
High	Proposal contains a significant weakness or combination of weaknesses which is likely to cause significant disruption of schedule or degradation of performance. Is unlikely to overcome any difficulties, even with special contractor emphasis and close Government monitoring.
Unacceptable	Proposal contains a material failure or a combination of significant weaknesses that increases the risk of unsuccessful performance to an unacceptable level.

Table 8-28: Past Performance Relevancy Ratings[128]

Rating	Description
VERY RELEVANT	A past or ongoing mission that involved launch services for an EELV mission for either a single payload or multi-mission payload involving essentially the same scope, magnitude and complexity as the evaluated mission.
RELEVANT	A Government mission for launch services for either a single payload or multi-mission payload involving similar scope, magnitude and complexity as the evaluated mission.
SOMEWHAT RELEVANT	A Government or commercial mission for launch services for either a single payload or multi-mission payload involving some of the scope, magnitude and complexity as the evaluated mission.
NOT RELEVANT	A Government or commercial mission for launch services for either a single payload or multi-mission payload involving little or none of the scope, magnitude and complexity as the evaluated mission.

Table 8-29: Past Performance Confidence Assessment Rating[128]

Rating	Description
SUBSTANTIAL CONFIDENCE	Based on the offeror's recent/relevant performance record, the Government has a high expectation that the offeror will successfully perform the required effort.
SATISFACTORY CONFIDENCE	Based on the offeror's recent/relevant performance record, the Government has reasonable expectation that the offeror will successfully perform the required effort.
NEUTRAL CONFIDENCE	No recent/relevant performance record is available or the offeror's performance record is so sparse that no meaningful confidence assessment rating can be reasonably assigned. The offeror may not be evaluated favorably or unfavorably
LIMITED CONFIDENCE	Based on the offeror's recent/relevant performance record, the Government has a low expectation that the offeror will successfully perform the required effort.
NO CONFIDENCE	Based on the offeror's recent/relevant performance record, the Government has no expectation that the offeror will be able to successfully perform the required effort.

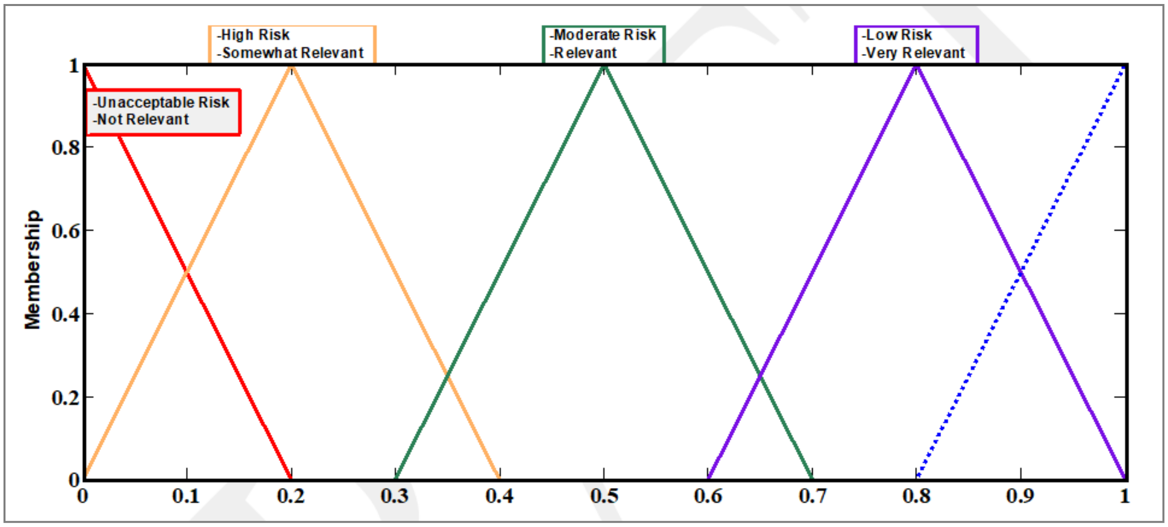

Figure 8-7: Linguistic Fuzzy Numbers

Two decision matrices were created to evaluate fuzzy and crisp data sets. Decision matrix D, shown in Table 8-30, was created after establishing risk, performance, reliability, and cost data for the three design alternatives along with objective and threshold criteria. For criteria 6 though 9, the fuzzy linguistic variables were transformed to crisp numbers using Equation 4-19. Decision matrix D will be used for the MF-WSM and OCS-TOPSIS methods. The fuzzy decision matrix $\widetilde{D}$, shown in Table 8-31, was created using the same data as decision matrix D with the addition of MoI and fuzzy linguistic variables. Fuzzy decision matrix $\widetilde{D}$ will be used with the OCS-FTOPSIS method. In order to demonstrate fuzzy system information using OCS-MCDA techniques, triangular fuzzy numbers were created based on collected rocket data with Method of Imprecision (MoI) applied to create a range of uncertainty. The MoI technique used in the case study will be expounded below in ***section 8.2.4.2***.

Table 8-30: Decision Matrix D and Weights w_j of Three Alternative Systems

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6	C7	C8	C9	C10
$C_{Objective}$	100	0.50	0.05	1	1	1	10	10	2000	1	1.00	1.00	1.000	1.000	52.50
A1	82	1.7	0.01	1.3	1.5	1	15	10	2810	0.92	0.5	0.2	0.8	0.8	85.0
A2	337	0.25	0.12	2.4	1	2.5	35	15	1840	0.95	0.5	0.5	0.8	1	52.5
A3	102	0.91	0.03	1.5	1.5	5	18	10	2050	0.94	0.5	0.2	0.5	0.5	57.5
$C_{Threshold}$	400	2	0.15	5	5	5	50	25	1000	0.75	0.00	0.00	0.00	0.00	85.00
Weight	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.06	0.108	0.096	0.096	0.096	0.084	0.084	0.072

Table 8-31: Fuzzy Decision Matrix $\widetilde{D}$ and Weights of Three Design Alternatives

	C1A	**C1B**	**C1C**	**C2A**	**C2B**
$C_{Objective}$	(100, 100, 100)	(0.5, 0.5, 0.5)	(0.05, 0.05, 0.05)	(1, 1, 1)	(1, 1, 1)
A1	(77.9, 82, 86.1)	(1.6, 1.7, 1.8)	(0, 0.01, 0.01)	(1.2, 1.3, 1.4)	(1.4, 1.5, 1.6)
A2	(320.2, 337, 353.8)	(0.2, 0.25, 0.27)	(0.1, 0.12, 0.13)	(2.3, 2.4, 2.5)	(1, 1, 1.1)
A3	(96.9, 102, 107.1)	(0.9, 0.91, 0.95)	(0, 0.03, 0.03)	(1.4, 1.5, 1.6)	(1.4, 1.5, 1.6)
$C_{Threshold}$	(400, 400, 400)	(2, 2, 2)	(0.15, 0.15, 0.15)	(5, 5, 5)	(5, 5, 5)
	C2C	**C3A**	**C3B**	**C4**	**C5**
$C_{Objective}$	(1, 1, 1)	(10, 10, 10)	(10, 10, 10)	(2000, 2000, 2000)	(1, 1, 1)
A1	(1, 1, 1.1)	(14.3, 15, 15.8)	(9.5, 10, 10.5)	(2670, 2810, 2951)	(0.87, 0.92, 0.96)
A2	(2.4, 2.5, 2.6)	(33.3, 35, 36.8)	(14.3, 15, 15.8)	(1748, 1840, 1932)	(0.9, 0.95, 1)
A3	(4.8, 5, 5.25)	17.1, 18, 18.9)	(9.5, 10, 10.5)	(1948, 2050, 2153)	(0.89, 0.94, 0.99)
$C_{Threshold}$	(5, 5, 5)	(50, 50, 50)	(25, 25, 25)	(1000, 1000, 1000)	(0.75, 0.75, 0.75)
	C6	**C7**	**C8**	**C9**	**C10**
$C_{Objective}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(49.9, 52.5, 57.8)
A1	(0, 0.2, 0.4)	(0, 0.2, 0.4)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(80.8, 85, 93.5)
A2	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.6, 0.8, 1)	(0.8, 1, 1)	(49.9, 52.5, 57.8)
A3	(0, 0.2, 0.4)	(0, 0.2, 0.4)	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(54.6, 57.5, 63.3)
$C_{Threshold}$	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(80.8, 85, 93.5)

8.2.2.1 Symmetrical Data. Since the previous case study used asymmetrical data, this case study will use symmetrical data for Method of Imprecision (MoI) estimates. To simplify and standardize the alternative design data, five percent variance was used to model designer uncertainty from a point estimate across all but criteria 6 through 9. For these criteria, fuzzy linguistic variables were used that were derived from the membership functions displayed in Figure 8-7.

8.2.3 OCS-MCDA Methods (Y-Axis). The MF-WSM is the only OCS-MCDA technique that utilizes the dependent variables on the Y-Axis of each membership function. By obtaining discrete preference information directly from each membership function, the MF-WSM technique provides the most uncomplicated, straight forward approach of the three OCS techniques.

8.2.3.1 MF-WSM Applications to Case Study #2. The MF-WSM technique models fuzzy customer preference using fuzzy membership functions to determine user utility for a given design parameter. The MF-WSM method leverages both benefit and cost membership functions to determine user utility per criterion that enables the accurate calculation of conflicting requirements. By incorporating fuzzy numbers that have a maximum value of one, the MF-WSM method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements. This MF-WSM approach will be demonstrated using the rocket case study described above.

8.2.3.1.1 Initial Conditions. The decision matrix *D*, represented in Table 8-30, was used for this MF-WSM application to case study #2. The three alternatives being evaluated are listed in the table along with their crisp system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

8.2.3.1.2 Case Study #2 Results. The results of the MF-WSM analysis are shown in Tables 8-32 through 8-34. As stated above, the decision matrix *D* and weights *w* used for the analysis are displayed in Table 8-30. Table 8-32 shows the transformed membership function matrix *M* and Table 8-33 displays the weighted membership function matrix *V*. Table 8-34 displays the results of the analysis. As indicated in bold font in Table 8-32, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-24 and 8-25.

Table 8-32: Transformed Membership Function Matrix M

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6	C7	C8	C9	C10
$C_{Objective}$	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
A1	1	0.2	1	0.93	0.88	1	0.88	1	1	0.66	0.5	0.2	0.8	0.8	0
A2	0.21	1	0.3	0.65	1	0.63	0.38	0.67	0.84	0.8	0.5	0.5	0.8	1	1
A3	0.99	0.73	1	0.88	0.88	0	0.8	1	1	0.76	0.5	0.2	0.5	0.5	0.85
$C_{Threshold}$	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Weight	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.06	0.108	0.096	0.096	0.096	0.084	0.084	0.072

Table 8-33: Weighted Membership Function Matrix V

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6	C7	C8	C9	C10
A1	0.04	0.008	0.04	0.037	0.035	0.04	0.053	0.06	0.108	0.064	0.048	0.019	0.067	0.067	0
A2	0.008	0.04	0.012	0.026	0.04	0.025	0.023	0.04	0.091	0.077	0.048	0.048	0.067	0.084	0.072
A3	0.04	0.029	0.04	0.035	0.035	0	0.048	0.06	0.108	0.073	0.048	0.019	0.042	0.042	0.061
Weight	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.06	0.108	0.096	0.096	0.096	0.084	0.084	0.072

Table 8-34: MF-WSM Results & Comparison to TOPSIS

	Cost		**MF-WSM**		**TOPSIS**	
	$ Mil	**R**	Total	Rank	CC_i	Rank
A1	85	0.92	0.6886	2	**0.552444**	**1**
A2	52.5	0.95	**0.70343**	**1**	0.528294	2
A3	57.5	0.94	0.68223	3	0.415944	3

8.2.3.1.3 Discussion / Comparison to TOPSIS. In order to evaluate the effectiveness of the MF-WSM method, the results of the study were compared against standard TOPSIS results. As Table 8-34 indicates, the MF-WSM results were different than conventional TOPSIS. Since standard WSM cannot accurately calculate data with conflicting requirements, it was excluded from this comparison. Although both techniques selected Alternative 3 last, the MF-WSM and standard TOPSIS selected different Alternatives as the best value candidate. As demonstrated in Table 8-34, the MF-WSM technique changed the ranking order by constraining the decision matrix through the use of membership functions. While TOPSIS ranked alternative 1 the highest, the MF-WSM technique ranked alternative 2 as the best value for meeting government requirements. This difference in decision outcome highlights the affect that saturating objective requirements has on a decision outcome. By constraining values at ideal customer requirements, the MF-WSM method selected the alternative with the highest reliability and lowest cost with a compromise of acceptable performance standards. To evaluate the consistency of this MF-WSM outcome, the case study #2 results will be compared to the other OCS-MCDA techniques.

8.2.4 OCS-MCDA Methods (X-Axis). The OCS-TOPSIS and OCS-FTOPSIS techniques utilize the independent variables on the X-Axis of the membership function. Since these techniques are modified versions of TOPSIS and FTOPSIS, all calculations are performed on the real number line $\mathbb{R}$ of the membership function.

8.2.4.1 OCS-TOPSIS Applications to Case Study #2. The OCS-TOPSIS method incorporates minimum and maximum customer requirements to establish the Negative Ideal Solution (NIS) and Positive Ideal Solution (PIS) in order to define and constrain the trade space. By constraining the trade space, OCS-TOPSIS restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements resulting in a ranked list of alternatives that is more aligned with customer stated requirements. This OCS-TOPSIS approach will be demonstrated using the rocket case study described above.

8.2.4.1.1 Initial Conditions. The decision matrix *D*, represented in Table 8-30, was used for this OCS-TOPSIS application to case study #2. The three alternatives being evaluated are listed in the table along with their crisp system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

According to TOPSIS definitions, cost criteria are defined as criteria where a minimum value is preferred over a maximum value. Benefit criteria is defined as criteria where a maximum value is preferred over a minimum value [51]. While preparing TOPSIS calculations, each criterion must be classified as either benefit or cost. This step is addressed in step 5 of the OCS-TOPSIS method, listed in section 6.2.1. Using TOPSIS terminology, criteria 1 through 3 and 10 are classified as cost criteria with the remaining classified as benefit criteria. As noted in Table 8-30 and Tables 8-35 through 8-37, the $C_{threshold}$ values for criteria 1 through 3 and 10 are larger than the criteria $C_{objective}$ values. Since the remaining criteria are classified as benefit criteria, the other criteria $C_{objective}$ values are higher than $C_{threshold}$. After normalizing the constrained decision matrix S, all alternatives that meet or exceed $C_{objective}$ for benefit criteria will equal 1. For cost criteria, the worst performing alternatives will equal 1 or have the highest numerical value (see Table 8-36).

To limit the rank reversal phenomenon in OCS-TOPSIS, a modified version of Garcia-Cascales and Lamata's solution to the rank reversal problem was implemented. Rank reversal and prevention measures were discussed in section 8.1.4.1. As in the previous case study, the alternative normalization technique and the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ were implemented into the decision set to represent PIS and NIS, respectively. To determine the criteria values for $C_{ojective}$ and $C_{threshold}$ alternatives, objective and threshold values were used from the rocket RFP for performance criteria 1 through 4, including all sub criteria. Since cost objectives were not stated in the UAS RFP, minimum and maximum costs under the cost criterion were used as $C_{ojective}$ and $C_{threshold}$, respectively. By incorporating the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ in the decision set, rank reversal was successfully mitigated while also constraining the decision matrix to a fuzzy customer requirement set of PIS and NIS.

8.2.4.1.2 Case Study #2 Results. The results of the rocket case study are shown in Tables 8-35 through 8-39. As stated above, the decision matrix *D* and weights *w* used for the analysis are displayed in Table 8-30. Table 8-35 shows the constrained decision matrix *S* using Equation 6-6. Since the RFP did not specify threshold or objective requirements for cost criterion 10, this criterion did not change in the constrained decision matrix. Table 8-36 displays the normalized decision matrix *R* using Equation 6-7 and Table 8-37 shows the weighted normalized decision matrix *V* using Equation 6-8. The Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS) are listed in Table 8-38 and the results of the OCS-TOPSIS analysis is shown in Table 8-39. As indicated in bold font in Table 8-39, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-24 and 8-25.

Table 8-35: Constrained Decision Matrix S

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6	C7	C8	C9	C10
$C_{Objective}$	**100**	**1**	**0.05**	**1**	**1**	**1**	**10**	**10**	**2000**	**1**	**1**	**1**	**1**	**1**	**52.5**
A1	100	1.7	0.05	1.3	1.5	1	15	10	2000	0.916	0.5	0.2	0.8	0.8	85
A2	337	0.5	0.12	2.4	1	2.5	35	15	1840	0.95	0.5	0.5	0.8	1	52.5
A3	102	0.91	0.05	1.5	1.5	5	18	10	2000	0.939	0.5	0.2	0.5	0.5	57.5
$C_{Threshold}$	**400**	**2**	**0.15**	**5**	**5**	**5**	**50**	**25**	**1000**	**0.75**	**0**	**0**	**0**	**0**	**85**

Table 8-36: Normalized Decision Matrix R

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6	C7	C8	C9	C10
$C_{Objective}$	**0.25**	**0.25**	**0.333**	**0.2**	**0.2**	**0.2**	**0.2**	**0.4**	**1**	**1**	**1**	**1**	**1**	**1**	**0.618**
A1	0.25	0.85	0.333	0.26	0.3	0.2	0.3	0.4	1	0.916	0.5	0.2	0.8	0.8	1
A2	0.843	0.25	0.8	0.48	0.2	0.5	0.7	0.6	0.92	0.95	0.5	0.5	0.8	1	0.618
A3	0.255	0.455	0.333	0.3	0.3	1	0.36	0.4	1	0.939	0.5	0.2	0.5	0.5	0.676
$C_{Threshold}$	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0.5**	**0.75**	**0**	**0**	**0**	**0**	**1**

Table 8-37: Weighted Normalized Decision Matrix V

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	C3B	C4	C5	C6		C7	C8	C9
$C_{Objective}$	**0.010**	**0.01**	**0.013**	**0.008**	**0.008**	**0.008**	**0.012**	**0.024**	**0.108**	**0.096**	**0.096**	**0.096**	**0.084**	**0.084**	**0.045**
A1	0.010	0.034	0.013	0.010	0.012	0.008	0.018	0.024	0.108	0.088	0.048	0.019	0.067	0.067	0.072
A2	0.034	0.01	0.032	0.019	0.008	0.020	0.042	0.036	0.100	0.092	0.048	0.048	0.067	0.084	0.045
A3	0.010	0.018	0.013	0.012	0.012	0.040	0.022	0.024	0.108	0.091	0.048	0.019	0.042	0.042	0.049
$C_{Threshold}$	**0.040**	**0.040**	**0.040**	**0.040**	**0.040**	**0.040**	**0.060**	**0.060**	**0.054**	**0.072**	**0**	**0**	**0**	**0**	**0.072**

Table 8-38: $\boldsymbol{v_j^+}, \boldsymbol{v_j^-}$ - Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS)

v_j^+	**0.010**	**0.010**	**0.013**	**0.008**	**0.008**	**0.008**	**0.012**	**0.024**	**0.108**	**0.096**	**0.096**	**0.096**	**0.084**	**0.084**	**0.045**
v_j^-	**0.040**	**0.040**	**0.040**	**0.040**	**0.040**	**0.040**	**0.060**	**0.060**	**0.054**	**0.072**	**0.000**	**0.000**	**0.000**	**0.000**	**0.072**

Table 8-39: OCS-TOPSIS and Conventional TOPSIS Results

	Cost		**OCS-TOPSIS**				**Conventional TOPSIS**			
	$ Mil	**R**	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
A1	85	0.92	0.101517	0.149816	0.596086	2	**0.060486**	**0.074662**	**0.552444**	**1**
A2	52.5	0.95	**0.085262**	**0.152677**	**0.641666**	**1**	0.064262	0.071971	0.528294	2
A3	57.5	0.94	0.114466	0.128582	0.52904	3	0.073913	0.052638	0.415944	3

8.2.4.1.3 Discussion / Comparison to Standard TOPSIS. In order to evaluate the effectiveness of the OCS-TOPSIS method, the results of the study were compared against standard TOPSIS results. As Table 8-39 indicates, the OCS-TOPSIS results were different than the conventional TOPSIS method. As demonstrated in the table, the OCS-TOPSIS technique changed the ranking order by constraining the decision matrix. While conventional TOPSIS ranked alternative 1 the highest, the OCS-TOPSIS technique ranked alternative 2 as the best value for meeting customer requirements. Since these OCS-TOPSIS results were consistent with the MF-WSM results, the similarities and differences between OCS-TOPSIS and TOPSIS were the same as the MF-WSM technique. These consistent results between OCS-TOPSIS and MF-WSM methods reinforce the reliability and validity of both techniques.

8.2.4.2 OCS-FTOPSIS Applications to Case Study #2. In the OCS-FTOPSIS method, minimum and maximum customer requirements are used to establish the Fuzzy Negative Ideal Solution (FNIS) and Fuzzy Positive Ideal Solution (FPIS) in order to define and constrain the trade space. Instead of using linguistic variables to evaluate each criterion, like most FTOPSIS techniques, fuzzy design estimates are used to calculate Euclidean distances from FNIS and FPIS. Similar to the previous two techniques, the OCS-FTOPSIS method also restricts preferential scoring for alternatives that provide excess capabilities beyond ideal customer requirements. This OCS-FTOPSIS approach will be demonstrated using the rocket case study described above.

8.2.4.2.1 Initial Conditions. The decision matrix $\widetilde{D}$, represented in Table 8-31, was used for this OCS-FTOPSIS application to case study #2. The three alternatives being evaluated are listed in the table along with their fuzzy system criteria and weights. The fuzzy preference criteria $C_{threshold}$ and $C_{objective}$ are also listed in the decision matrix.

Similar to TOPSIS definitions, FTOPSIS cost criteria are defined as criteria where a minimum value is preferred over a maximum value. Benefit criteria is defined as criteria where a maximum value is preferred over a minimum value. While preparing FTOPSIS calculations, each criterion must be classified as either benefit or cost. This step is addressed in step 5 of the OCS-FTOPSIS method, listed in section 6.2.2. Using FTOPSIS definitions, criteria 1 through 3 and 10 are classified as cost criteria. As noted in Table 8-31 and Tables 8-40 through 8-42, the $C_{threshold}$ values for criteria 1 through 3 and 10 are larger than criteria $C_{objective}$ values. Since the remaining criteria are classified as benefit criteria, the other criteria $C_{objective}$ values are higher than $C_{threshold}$. After normalizing the constrained fuzzy decision matrix $\tilde{S}$, all alternatives that meet or exceed $C_{objective}$ will equal 1. For cost criteria, the worst performing alternatives will equal 1 or have the highest numerical value (see Table 8-41).

The rank reversal phenomenon was mitigated using a modified version of Garcia-Cascales and Lamata's TOPSIS solution, similar to OCS-TOPSIS. In order to minimize the risk of rank reversal in OCS-FTOPSIS, the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ were implemented into the decision set to represent FPIS and FNIS, respectively. By incorporating the fictitious alternatives of $C_{ojective}$ and $C_{threshold}$ in the decision set, rank reversal was successfully mitigated while also constraining the decision matrix to a fuzzy customer requirement set of FPIS and FNIS.

8.2.4.2.2 Case Study #2 Results. The results of the rocket case study are shown in Tables 8-40 through 8-44. As stated above, the decision matrix *D* and weights *w* used for the analysis are displayed in Table 8-31. Table 8-40 shows the fuzzy constrained decision matrix $\tilde{S}$ using Equation 6-15 to demonstrate calculating a fuzzy set that completely meets threshold criteria. Since the RFP did not specify threshold or objective requirements for cost criterion 9, this criterion did not change in the constrained decision matrix. Table 8-41 displays the fuzzy normalized decision matrix $\tilde{R}$ using Equation 6-17 and Table 8-42 shows the fuzzy weighted normalized decision matrix $\tilde{V}$ using Equation 6-21. The Fuzzy Positive Ideal Solutions (FPIS) and Fuzzy Negative Ideal Solutions (FNIS) are indicated in Table 8-43 using Equations 6-22 and 6-23, respectively. The results of the OCS-FTOPSIS analysis along with conventional FTOPSIS distance calculations are shown in Table 8-44. The conventional FTOPSIS calculations used in this case study are straight fuzzy calculations, without Subject Matter Expert (SME) input or constraints, using the same rocket alternative and requirements data as the other two techniques. As indicated in bold font in Table 8-44, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-24 and 8-25.

Table 8-40: Constrained Fuzzy Decision Matrix $\tilde{\boldsymbol{S}}$ and Weights of Three Design Alternatives

	C1A	**C1B**	**C1C**	**C2A**	**C2B**
$C_{Objective}$	(50, 50, 50)	(0.5, 0.5, 0.5)	(0.05, 0.05, 0.05)	(1, 1, 1)	(1, 1, 1)
A1	(77.9, 82, 86.1)	(1.6, 1.7, 1.8)	(0.05, 0.05, 0.05)	(1.2, 1.3, 1.4)	(1.4, 1.5, 1.6)
A2	(320.2, 337, 353.8)	(0.5, 0.5, 0.5)	(0.1, 0.12, 0.13)	(2.3, 2.4, 2.5)	(1, 1, 1.1)
A3	(96.9, 102, 107.1)	(0.9, 0.91, 0.95)	(0.05, 0.05, 0.05)	(1.4, 1.5, 1.6)	(1.4, 1.5, 1.6)
$C_{Threshold}$	(400, 400, 400)	(2, 2, 2)	(0.15, 0.15, 0.15)	(5, 5, 5)	(5, 5, 5)
	C2C	**C3A**	**C3B**	**C4**	**C5**
$C_{Objective}$	(1, 1, 1)	(10, 10, 10)	(10, 10, 10)	(2000, 2000, 2000)	(1, 1, 1)
A1	(1, 1, 1.1)	(14.3, 15, 15.8)	(10, 10, 10.5)	(2000, 2000, 2000)	(0.87, 0.916, 0.962)
A2	(2.4, 2.5, 2.6)	(33.3, 35, 36.8)	(14.3, 15, 15.8)	(1748, 1840, 1932)	(0.903, 0.95, 0.998)
A3	(4.8, 5, 5)	17.1, 18, 18.9)	(10, 10, 10.5)	(1948, 2000, 2000)	(0.892, 0.939, 0.986)
$C_{Threshold}$	(5, 5, 5)	(50, 50, 50)	(25, 25, 25)	(1000, 1000, 1000)	(0, 0, 0)
	C6	**C7**	**C8**	**C9**	**C10**
$C_{Objective}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(49.9, 52.5, 57.8)
A1	(0.3, 0.5, 0.7)	(0, 0.2, 0.4)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(80.8, 85, 93.5)
A2	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.6, 0.8, 1)	(0.8, 1, 1)	(49.9, 52.5, 57.8)
A3	(0.3, 0.5, 0.7)	(0, 0.2, 0.4)	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(54.6, 57.5, 63.3)
$C_{Threshold}$	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(80.8, 85, 93.5)

Table 8-41: Fuzzy Normalized Decision Matrix $\tilde{R}$

	C1A	**C1B**	**C1C**	**C2A**	**C2B**
$C_{Objective}$	(0.25,0.25, 0.25)	(0.2,0.2, 0.2)	(0.07, 0.07, 0.07)	(0.4, 0.4, 0.4)	(0.5, 0.5, 0.5)
A1	(0.25,0.25, 0.25)	(0.32, 0.34, 0.36)	(0.07, 0.07, 0.07)	(0.49, 0.52, 0.55)	(0.71, 0.75, 0.79)
A2	(0.8, 0.84, 0,89)	(0.2,0.2, 0.2)	(0.76, 0.8, 0.84)	(0.91, 0.96, 1)	(0.5, 0.5, 0.53)
A3	(0.25,0.25, 0.27)	(0.2,0.2, 0.2)	(0.19, 0.2, 0.21)	(0.57, 0.6, 0.63)	(0.71, 0.75, 0.79)
$C_{Threshold}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
	C2C	**C3A**	**C3B**	**C4**	**C5**
$C_{Objective}$	(0.2, 0.2, 0.2)	(0.29, 0.29, 0.29)	(0.5, 0.5, 0.5)	(1, 1, 1)	(1, 1, 1)
A1	(0.2, 0.2, 0.2)	(0.41, 0.43, 0.45)	(0.5, 0.5, 0.53)	(1, 1, 1)	(0.87, 0.92, 0.96)
A2	(0.48, 0.5, 0.53)	(0.95, 1, 1)	(0.71, 0.75, 0.79)	(0.7, 0.74, 0.77)	(0.9, 0.95, 1)
A3	(0.95, 1, 1)	(0.49, 0.51, 0.54)	(0.5, 0.5, 0.53)	(0.78, 0.82, 0.86)	(0.89, 0.94, 0.99)
$C_{Threshold}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(0.6, 0.6, 0.6)	(0, 0, 0)
	C6	**C7**	**C8**	**C9**	**C10**
$C_{Objective}$	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(0.56, 0.59, 0.62)
A1	(0.3, 0.5, 0.7)	(0, 0.2, 0.4)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(0.91, 0.95, 1)
A2	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.6, 0.8, 1)	(0.8, 1, 1)	(0.56, 0.59, 0.62)
A3	(0.3, 0.5, 0.7)	(0, 0.2, 0.4)	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.61, 0.65, 0.68)
$C_{Threshold}$	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0.91, 0.95, 1)

Table 8-42: Fuzzy Weighted Normalized Decision Matrix $\widetilde{V}$

	C1A	C1B	C1C	C2A	C2B
$C_{Objective}$	(0.01, 0.01, 0.01)	(0.008, 0.008, 0.008)	(0.03, 0.03, 0.03)	(0.016, 0.016, 0.016)	(0.03, 0.03, 0.03)
A1	(0.01, 0.01, 0.01)	(0.013, 0.014, 0.014)	(0.03, 0.03, 0.03)	(0.02, 0.021, 0.022)	(0.043, 0.045, 0.047)
A2	(0.032, 0.034, 0.036)	(0.008, 0.008, 0.008)	(0.031 0.032, 0.034)	(0.037, 0.039, 0.04)	(0.03, 0.03, 0.032)
A3	(0.01, 0.01, 0.011)	(0.008, 0.008, 0.008)	(0.008, 0.008, 0.008)	(0.23, 0.24, 0.25)	(0.043, 0.045, 0.047)
$C_{Threshold}$	(0.04, 0.04, 0.04)	(0.04, 0.04, 0.04)	(0.04, 0.04, 0.04)	(0.045, 0.045, 0.045	(0.06, 0.06, 0.06)
	C2C	**C3A**	**C3B**	**C4**	**C5**
$C_{Objective}$	(0.012, 0.012, 0.012)	(0.017, 0.017, 0.017)	(0.03, 0.03, 0.03)	(0.108, 0.108, 0.108)	(0.108, 0.108, 0.108)
A1	(0.012, 0.012, 0.012)	(0.025, 0.026, 0.027)	(0.03, 0.03, 0.032)	(0.108, 0.108, 0.108)	(0.094, 0.099, 0.104)
A2	(0.029, 0.03, 0.032)	(0.057, 0.06, 0.06)	(0.043, 0.045, 0.047)	(0.076, 0.08, 0.084)	(0.098, 0.103, 0.108)
A3	(0.057, 0.06, 0.06)	(0.029, 0.031, 0.033)	(0.03, 0.03, 0.032)	(0.094, 0.089, 0.093)	(0.097, 0.102, 0.107)
$C_{Threshold}$	(0.06, 0.06, 0.06)	(0.06, 0.06, 0.06)	(0.06, 0.06, 0.06)	(0.065, 0.065, 0.065)	(0, 0, 0)
	C6	**C7**	**C8**	**C9**	**C10**
$C_{Objective}$	(0.108, 0.108, 0.108)	(0.108, 0.108, 0.108)	(0.108, 0.108, 0.108)	(0.108, 0.108, 0.108)	(0.04, 0.043, 0.045)
A1	(0.033, 0.054, 0.076)	(0, 0.022, 0.043)	(0.065, 0.087, 0.108)	(0.065, 0.087, 0.108)	(0.065, 0.069, 0.072)
A2	(0.033, 0.054, 0.076)	(0.033, 0.054, 0.076)	(0.065, 0.087, 0.108)	(0.087, 0.108, 0.108)	(0.04, 0.043, 0.045)
A3	(0.033, 0.054, 0.076)	(0, 0.022, 0.043)	(0.033, 0.054, 0.076)	(0.033, 0.054, 0.076)	(0.044, 0.047, 0.049)
$C_{Threshold}$	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0.065, 0.069, 0.076)	(0.065, 0.069, 0.072)

Table 8-43: v_j^+, v_j^- - Fuzzy Positive Ideal Solutions (FPIS) and Fuzzy Negative Ideal Solutions (FNIS)

	C1A	C1B	C1C	C2A	C2B	C2C	C3A	
v_j^+	0.01	0.008	0.003	0.016	0.03	0.012	0.017	
v_j^-	0.04	0.04	0.04	0.04	0.06	0.06	0.06	
	C3B	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
v_j^+	0.03	0.108	0.108	0.108	0.108	0.108	0.108	0.4
v_j^-	0.06	0.065	0.000	0.000	0.000	0.000	0.076	0.072

Table 8-44: FTOPSIS Technique Comparison - Alternative Distance to FPIS/FNIS

	Cost		OCS-FTOPSIS				FTOPSIS (no SME data)			
	$ Mil	**R**	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
A_1	85	0.92	0.1125	0.1955	0.6347	2	**14.2323**	**0.7637**	**0.0509**	**1**
A_2	52.5	0.95	**0.1073**	**0.1982**	**0.6487**	**1**	14.2822	0.7070	0.0472	2
A_3	57.5	0.94	0.1400	0.1615	0.5357	3	14.3816	0.6161	0.0411	3

8.2.4.2.3 Discussion / Comparison to Standard FTOPSIS (no SME data). In order to evaluate the effectiveness of the OCS-FTOPSIS method, the results of the study were compared against standard FTOPSIS results without SME input. The results of the rocket case study using OCS-FTOPSIS and FTOPSIS methods are shown in Table 8-44. As indicated in bold font in the table, Alternative 2 was calculated to have best value according to government stated requirements that were reflected in Tables 8-24 and 8-25. The standard FTOPSIS method without SME data selected Alternative 1 as the best candidate. This difference in FTOPSIS outcome further reinforces the benefit of saturating customer requirements while constraining the decision matrix using threshold and objective requirements as FNIS and FPIS, respectively. By saturating values at ideal customer requirements, the OCS-FTOPSIS approach selected the alternative with the highest reliability and lowest cost with a compromise of acceptable performance standards.

8.2.5 Comparison of MF-WSM, OCS-TOPSIS, & OCS-FTOPSIS Results. At the conclusion of Case Study #2, all OCS-MCDA techniques obtained the same ranking of alternatives. Table 8-45 summarizes the results of each OCS method. As can be seen in the table, all OCS-MCDA techniques achieved similar outcomes. The results of the second case study reinforce the reliability and consistency of the OCS methods.

Table 8-45: OCS-MCDA Technique Comparison

	OCS-FTOPSIS				**OCS-TOPSIS**				**MF-WSM**	
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank	Total	Rank
A1	0.1125	0.1955	0.6347	2	0.101517	0.149816	0.596086	2	0.6886	2
A2	**0.1073**	**0.1982**	**0.6487**	**1**	**0.085262**	**0.152677**	**0.641666**	**1**	**0.70343**	**1**
A3	0.1400	0.1615	0.5357	3	0.114466	0.128582	0.52904	3	0.68223	3

A sensitivity analysis was conducted to determine if OCS-MCDA results were sensitive to moderate changes in the criteria weighting. After conducting the sensitivity analysis, the OCS methods proved fairly robust against moderate changes to criteria weighting. Since OCS-MCDA techniques use customer order of importance to rank criteria weights, the sensitivity analysis focused on rank intensity instead of rank order. For example, Table 8-46 displays the revised criteria weights used for the sensitivity analysis with the changed parameters indicated in red. For the criteria weights used in the case study, the ranking used numbers 1 through 6 in sequential order. For the criteria weights used in the sensitivity analysis, the rank number was changed to 5 after the performance criteria since rank 1 was used repeatedly. This change in ranking increased the emphasis for performance criteria and deemphasized the remaining criteria. After changing the rank intensity, only the MF-WSM method experienced a rank reversal where Alternative 1 became the best candidate. Both the OCS-TOPSIS and OCS-FTOPSIS alternatives did not experience a rank reversal and maintained Alternative 2 as the best alternative.

Table 8-46: Revised Launch System Evaluation Criteria with Weights

Criteria		Rank	Weight	Normalized
C1=	**Orbital Accuracy to GEO Transfer Orbit**	**1**	**10**	**0.152**
C1A =	Apogee (km)			0.051
C1B =	Perigee (km)			0.051
C1C =	Inclination (deg)			0.051
C2=	**Loads & Dynamics - Load Factors (g's)**	**1**	**10**	**0.152**
C2A =	Axial Load - Steady State			0.051
C2B =	Axial Load – Dynamic			0.051
C2C =	Lateral Load – Dynamic			0.051
C3=	**Loads & Dynamics - Fundamental Frequency (Hz)**	**1**	**10**	**0.152**
C3A =	Axial Fundamental Frequency			0.076
C3B =	Lateral Fundamental Frequency			0.076
C4=	**Payload Mass to GEO Transfer Orbit**	**2**	**9**	**0.136**
C5=	**Launch Reliability**	**5**	**6**	**0.091**
C6=	**Technical Rating**	**6**	**5**	**0.076**
C7=	**Technical Risk Rating**	**6**	**5**	**0.076**
C8=	**Past Performance Relevancy**	**7**	**4**	**0.061**
C9=	**Past Performance Confidence Assessment**	**7**	**4**	**0.061**
C10=	**Launch Vehicle Cost**	**8**	**3**	**0.045**

At the conclusion of both case studies, the OCS-MCDA techniques demonstrated consistent reliability and validity. The OCS results were compared against each other as well as the WSM, TOPSIS, and FTOPSIS methods. Throughout both case studies, the OCS-MCDA methods produced consistent results where the best value alternative was selected. In all cases, the OCS techniques provided a rank order of alternatives that provided the best compromise between risk, performance, reliability and cost. The OCS-MCDA methods even reached the same conclusion as subject matter experts who conducted independent system evaluations. The prior UAS case study provided a means to demonstrate the reliability and validity of the OCS methods through model comparisons and expert onion. The following rocket case study reinforced those results by providing continued consistent results amongst the OCS techniques.

9. CONCLUSION AND FUTURE WORK

9.1 Summary

This research introduced an original, pioneering approach to optimize decisions at the point of diminished marginal utility. Prior to this study, there was a lack of Decision Analysis (DA) research in ideal customer requirements. The research presented in this dissertation addressed this void in the literature and presented techniques to solve this problem. In addition to this dissertation, portions of this research were published and presented at the 2017 Annual Reliability and Maintainability Symposium (RAMS) and the 12th Annual IEEE Systems Conference [136], [137].

The purpose of this research was to explore modeling fuzzy criteria preference to evaluate tradespace of system alternatives for determining a best value system. The primary research objective was to develop a straightforward technique for modeling customer criteria preference to select a best value alternative with an optimal mix of performance, reliability, and cost. The goal was also to prevent decision maker bias when faced with superfluous capabilities that may distract decision makers (DM) and lead to anchoring on specific alternatives. The Objective Criteria Saturation (OCS) Multiple Criteria Decision Analysis (MCDA) techniques presented in this paper restrict decision scoring beyond diminished marginal utility by applying preference constraints. This research contributes to the educational literature by applying fuzzy customer preference and fuzzy system data to MCDA while saturating evaluation criteria at ideal customer requirements.

This research focused on exploring three OCS-MCDA techniques: The Weighted Sum Model (WSM), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS). Since most conventional WSM and TOPSIS models use minimum and maximum values under a specific criterion to evaluate each alternative, a best value alternative may not be selected due to another alternative possessing excess capability in a heavily weighted criterion. This problem can become pronounced whenever evaluation criteria and priorities are published, such as government systems acquisition. Under these circumstances, system providers may be compelled to focus on the highest weighted criteria while providing less focus to lower weighted criteria. The OCS-MCDA techniques presented in this paper addressed this problem by restricting preferential scoring for alternatives that provided excess capabilities beyond ideal customer requirements. By restricting scoring beyond diminished marginal utility, the OCS-MCDA methods produced a ranked list of alternatives that was more aligned with customer stated requirements.

9.2 Future Work

The potential applications for Objective Criteria Saturation (OCS) Multiple Criteria Decision Analysis (MCDA) techniques are numerous. Since decision makers (DM) often prefer to employ more than one decision analysis technique, an OCS-MCDA method could be implemented as a best value baseline to compare against other decision techniques. Another application may be to make quick acquisition decisions when there is not enough time to go through a more time consuming decision technique. Other applications of OCS-MCDA techniques may include data mining or machine learning where best fit data needs to be extracted from large data sets using a defined range. Regardless of the application, the OCS decision methods offer a viable technique for selecting best value alternatives with an optimal mix of performance, cost, and reliability.

Further research is suggested in objective criteria saturation. New research can focus on applying Objective Criteria Saturation (OCS) techniques to other decision analysis methods beyond those covered in this dissertation. Additionally, further empirical studies are recommended to further test and evaluate the OCS-MCDA techniques against other decision analysis methods.

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