UNIVERSITY OF TURKISH AERONAUTICAL ASSOCIATION
INSTITUTE OF SCIENCE AND TECHNOLOGY

A COMPARATIVE ANALYSIS OF MULTI-CRITERIA DECISION MAKING (MCDM) AND DATA ENVELOPMENT ANALYSIS (DEA) METHODS IN LAUNCH VEHICLE SELECTION FOR A GEOSTATIONARY COMMUNICATION SATELLITE

MASTER THESIS

Taha TETİK

Institute of Science and Technology

Master of Science in Engineering Management

AUGUST 2016

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Taha TETİK

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LIST OF ABBREVIATIONS

AHP	:	Analytic Hierarchy Process
AI	:	Artificial Intelligence
ANP	:	Analytic Network Process
CBR	:	Case-Based Reasoning
CRS (CCR)	:	Constant Return to Scale
DEA	:	Data Envelopment Analysis
DEMATEL	:	Decision-Making Trial and Evaluation Laboratory
DM	:	Decision Maker
DMU	:	Decision Making Unit
ELECTRE	:	Elimination and Choice Expressing Reality
ELV	:	Expendable Launch Vehicle
GA	:	Genetic Algorithm
GSO	:	Geo Synchronous/Stationary Orbit
GTO	:	Geostationary Transfer Orbit
LP	:	Linear Programming
MADM	:	Multiple Attribute Decision Making
MAUT	:	Multi-Attribute Utility Theory
MCDA	:	Multi-Criteria Decision Analysis
MCDM	:	Multi Criteria Decision Making
MODM	:	Multiple Objective Decision Making
PROMETHEE	:	Preference Ranking Organization Method for Enrichment Evaluation
RLV	:	Reusable Launch Vehicle
SMART	:	Simple Multi-Attribute Rating Technique
TOPSIS	:	Technique for Order Performance by Similarity to Ideal Solution
VIKOR	:	Multi criteria Optimization and Compromise Solution
VRS (BCC)	:	Variable Return to Scale

ABSTRACT

A COMPARATIVE ANALYSIS OF MULTI-CRITERIA DECISION MAKING (MCDM) AND DATA ENVELOPMENT ANALYSIS (DEA) METHODS IN LAUNCH VEHICLE SELECTION FOR A GEOSTATIONARY COMMUNICATION SATELLITE

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In space business, Launch Vehicle selection for a satellite is a crucial managerial and technical decision making problem taking into consideration of various qualitative and quantitative factors involved into a multidimensional decision. The aim of this thesis is to analyze several Geostationary Transfer Orbit (GTO) launch vehicle alternatives available in the commercial market to boost a geostationary communication satellite into desired orbit under a MCDM (Multi-Criteria Decision Making) scheme in the presence of both qualitative and quantitative constituents. To this end, the conventional MCDM methods, including AHP, ELECTRE, PROMETHEE together with DEA (Data Envelopment Analysis) as a discrete non-parametric linear programming based methodology and Fuzzy DEA are utilized. In this study, five launch vehicle alternatives among commercially available options are examined under a composed criteria hierarchy. The outcomes of the hereinabove mentioned MCDM methods were compared and eventually the best alternative is found out.

Keywords: Launch vehicle, Satellite, Geostationary satellite, MCDM, AHP, ELECTRE, PROMETHEE, DEA, Fuzzy DEA.

ÖZET

YERE EŞ ZAMANLI HABERLEŞME UYDUSU İÇİN FIRLATICI SEÇİMİNDE ÇOK KRİTERLİ KARAR VERME (ÇKKV) VE VERİ ZARFLAMA ANALİZ (VZA) METOTLARININ KARŞILAŞTIRMALI ANALİZİ

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Uzay alanında, bir uydu için fırlatma aracı seçimi çok boyutlu muhtelif nitel ve nicel faktörlerin bulunduğu, kritik bir idari ve teknik karar verme problemidir. Bu tezin amacı, söz konusu nitel ve nicel unsurların varlığında, ÇKKV (Çok Kriterli Karar Verme) mimarisi çerçevesinde, istenilen yörüngeye bir yere eş zamanlı iletişim uydusunu fırlatmak için kullanılan ve piyasada ticari olarak var olan Yere Eş Zamanlı Transfer Yörünge (YTY) fırlatma araçları alternatiflerini analiz etmektir. Bu amaçla geleneksel ÇKKV metotları olan AHP, ELECTRE, PROMETHEE ilave olarak parametrik olmayan doğrusal programlama tabanlı bir metodoloji olarak VZA (Veri Zarflama Analiz) yönetimi ve bulanık VZA kullanılmıştır. Bu çalışmada, ticari olarak mevcut bulunan seçenekler arasından beş fırlatma aracı alternatifi, bileşik kriterler hiyerarşisi altında incelenmiştir. Bahsedilen ÇKKV yöntemlerinin sonuçları karşılaştırılmış ve nihayetinde en iyi alternatif bulunmuştur.

Anahtar Kelimeler: Fırlatma Aracı, Uydu, Yere Eş Zamanlı Uydu, ÇKKV, AHP, ELECTRE, PROMETHEE, VZA, Bulanık VZA

CHAPTER ONE

INTRODUCTION

1.1 Background

The satellite is a high-tech product which is launched to deep space and travels encircling a body in universe. As an example to natural satellite will be Earth and Moon. There are different types of satellites in orbit such as; astronomical satellites, atmospheric studies satellite, communications satellites, navigation satellites, reconnaissance satellites, remote sensing satellites, space exploration satellites and weather satellites, etc.

The communication satellites are utilized to receive radio signals from earth station and re-transmit amplified signals to wide geography within the coverage area to the end users. The communications satellites are used for television and radio broadcasting, telephone, internet, and data applications. The geostationary satellite is placed in space at an altitude of approximately 36.000 kilometers over Earth.

In order to boost a satellite to space, launcher carrier rockets are used to place the satellite into desired orbit in accordance with its mission requirements.

The determination of the launch vehicle is a significant decision making undertaking for the commercial satellite operators. The commercial satellite operators consider variety of factors while determining the launch vehicle for placing their satellites into desired orbit such as vehicle's flight heritage, reliability rate, launcher performance, cost, availability, suitability, schedule flexibility, government regulations and program management aspects. Following to award of the project, the satellite and its selected launch vehicle manufacturing proceed in synchronization and the completion of the project takes around 3 years. Since the selection of the launch vehicle impacts the satellite performance and service life in space, it is becoming challenging task for the satellite operators.

A medium size geostationary satellite project is costed around 200 to 300 million USD contingent on the missions onboard including launch, insurance and ground segment hardware. Depending upon the selected launch vehicle, launch price can vary from 20% to 40% of the total cost of a satellite project. Therefore, the launcher should be as cost effective as possible while also being credible and evidently must be compatible with the mission's specific performance requirement needs simultaneously.

The majority of commercial satellite operators takes advantage of multiple types of launchers to blast off their satellites into orbit while revealing themselves not to engage in a single launch vehicle. In the contrary, they would rather keep options available. They appraise potential alternatives by making technical, financial, contractual, programmatic, and sometimes even international recurring trend trade-offs. In this perspective, the launch vehicle selection arises to be a Multi-Criteria Decision Making (MCDM) problem.

Multi-Criteria Decision Analysis (MCDA) is one of the swiftly growing domain in various disciplines in order to reconcile multiple and usually conflicting objectives. MCDA is becoming an extensive research area, with growing specialized journals, as well as increasing number of real-world implementations to support decision-making process. MCDA methods furnish methods and techniques for attaining a compromised solution.

The research area of MCDA is emerged to provide resolution assistance for complicated decision situations. The fundamental objective of the MCDA is to furnish a set of decision analysis methods in order to distinguish, collate and appraise alternatives logically in accordance with their diverseness, generally under contradictory criteria arising from financial, strategical, social and surrounding considerations. In the frame of MCDA process, a decision maker evaluates alternatives or options with regard to defined criterions, determine weight of criteria and eventually selects the most favorable choice among the available set of options (Darehmiraki & Behdani, 2013).

A decision-making methodology entails a series of course of actions, which can be summarized as follows; (i) identifying nature of the problem, (ii) formulating the hierarchy and preferences, (iii) appraising the alternatives and (iv) determining the foremost option (Tzeng & Huang, 2011).

In the MCDM framework, the outranking or foremost alternative selection is attained by evaluating each alternative with its performance on individually determined criteria. The main principal of MCDM is to help people either to select the best choice among the available options or to generate compromised solution or to prompt form of preferential ranking.

While making a decision for supplier selection process, it has been pointed out that most of time the supplier evaluation methods practiced in industry are depended upon simple weighted scoring which includes excessive subjectivity and the inconsistent determination of weights (Wu & Blackhurst, 2009), (Narasimhan, Talluri, & Mendez, 2001).

In most of the businesses, the appropriate evaluation and selection of suppliers is vital for the long term success of the entities. The process of supplier selection is in relation with miscellaneous criteria, including quality, timely delivery performance, cost, reliability, and so forth where it is often difficult satisfy all the criteria at the same time. When we contemplate a circumstance in which one vendor could provide required merchandises in cheap rates however generally fails to deliver on schedule. Conversely, another vendor could supply high-quality commodities but the performances of delivery and costs are not admissible. Under these conditions, it becomes evident that the supplier selection is affiliated to the MCDM problem in which the companies require to determine the priorities for selecting the most appropriate supplier based on their preferences, market needs and dynamic condition of the their business (Agarwal, Sahai, Mishra, Bag, & Singh, 2011).

The launch vehicle selection could be considered as supplier selection for the satellite operators and the satellite manufacturers. In the literature, the problem of structural supplier selection is essentially regarded as a MCDM problem (Chai, Liu, & Ngai, 2013).

In the frame of thesis, the launcher selection problem for a geostationary satellite is managed under a MCDM scheme in the midst of qualitative and quantitative constituents.

1.2 Problem Definition

The launch vehicle selection for a satellite project is a crucial managerial and technical decision making problem taking into consideration of various factors involved into a multidimensional decision, which affects success and durability of satellite operators. The selection of the launch vehicle is quite complicated process since there are several trade-offs between several technical, programmatic and financial matters. Both spacecraft and launch vehicle manufacturing is quite complicated process. There is limited number of satellite and launcher manufacturers in the world to be able to meet technical specifications.

Since the selection of the launch vehicle impacts on the satellite performance and service life in space, it is becoming challenging task for the satellite operators. If the selected launch vehicle could not bring the satellite to a required altitude, then the mission of the satellite would be reduced. In this case, the expected revenue of the satellite owner company would be affected seriously. The selection of a launch vehicle according to the size of the satellite and mission directly affects the operational life of the satellite in its orbit. In case of improper selection of the launch vehicle in terms of performance/price perspective, the cost of a satellite project increase dramatically.

In the frame of this thesis, the best launch vehicle alternative is determined to lift off a geostationary communication satellite into required orbit.

1.3 Objectives

The aim of this thesis is to analyze several Geostationary Transfer Orbit (GTO) launch vehicle alternatives available in the commercial market to boost a geostationary communication satellite into desired orbit under a MCDM scheme in the presence of various factors. To this end the conventional MCDM methods including AHP, ELECTRE, PROMETHEE together with Data Envelopment Analysis (DEA) as a discrete linear programming based methodology and Fuzzy DEA are utilized. The aspiration of the study is to resolve the launcher selection problem in space business systematically under MCDM proposition without subjectivity and the inconsistency in the decision making process.

Five launch vehicle alternatives among commercially available options are examined and a criteria hierarchy is considered in this study. The outcomes of the aforementioned MCDM methods are analyzed and the best alternative is determined.

In the frame of this study, commercial geostationary communication satellites and available related launch vehicles are considered. The mentioned group of satellites excludes the Low-Earth Orbit (LEO) satellites, fully governmental satellite projects with classified payloads and satellites carrying scientific missions.

1.4 Scope and Research Methodology

Several GTO launch vehicle alternatives to boost a geostationary communication satellite into desired orbit are analyzed under a MCDM scheme.

The utilized scheme involves the implementation of conventional MCDM methods including AHP, ELECTRE and PROMETHEE together with DEA as a non-parametric linear programming-based methodology with fuzzy logic. The following methods were implemented in this study;

i. AHP

ii. ELECTRE
   a. Electre Superior
   b. Electre Inferior
   c. Electre Combined

iii. Promethee
   a. Positive Flow
   b. Negative Flow
   c. Net Flow

iv. DEA
   a. DEA with Super Efficiency Methods
   b. Input-Oriented CCR and BCC
   c. Output-Oriented CCR and BCC

   with Performance Matrix, Normalized Performance Matrix and Abbreviated Norm. Performance Matrix

v. Fuzzy DEA
   a. DEA Super Efficiency Methods
   b. Input Oriented CCR
   c. Output Oriented CCR

   With Performance Matrix, Normalized Performance Matrix and Abbreviated Norm. Performance Matrix

   for α =0.60, α =0.80, α =1 and λ=0.60

The outcomes of the different methods were compared and the best alternative is found out by utilizing a criteria set, which is established by the experts. This hierarchy is presented in detail in Chapter 5.

1.5 Organization of The Study

The thesis is organized into eight chapters. Chapter 1 gives a preview of the thesis topic under consideration. Chapter 2 gives the literature review on conventional MCDM methods, DEA, fuzzy MCDM Methods and fuzzy DEA. Chapter 3 gives background information of the conventional MCMD methods, including AHP, ELECTRE, PROMETHEE and DEA along with their theory. Each method is summarized step by step approach to facilitate the implementation of the methods to a given problem. The concept and several methods in the literature for utilization of the DEA as a MCDM tool is also addressed. The overview of the fuzzy logic and Fuzzy DEA Methods are explained as well in Chapter 3. Chapter 4 presents synopsis of a geostationary communication satellite and the launch vehicles which are being used to boost the satellite into space and summarize the general characteristic of the available launch vehicles available in the market. Chapter 5 introduces the framework of the problem of launch vehicle selection with the explanation of several criteria considered in the study. Chapter 6 gets into the application of the methodologies to rank the alternatives. Chapter 7 presents, analyze and discuss the results obtained from the utilized MCDM methods. Eventually, Chapter 8 exhibits conclusions in the frame of this study and recommendations for future work.

CHAPTER TWO

LITERATURE REVIEW

This chapter presents a literature review on MCDM Methods, DEA, Fuzzy MCDM methods and Fuzzy DEA.

2.1 Literature Review of the Decision Making Problems in Space Business

The literature review on the decision making problems in space business revealed that, only a few studies dealt with space related problems.

Frank (1995) aimed to choose safety improvement strategies for NASA flight vehicles, launch vehicles and ground search facilities by considering cost, schedule, technical feasibility, etc (Frank, 1995). He investigated different decision making approaches like intuition, cost/ benefit ratio, expected impact and AHP. decision making approaches are intuition, cost/benefit ratio, expected impact, and Analytic Hierarchy Process decision making approaches are intuition, cost/benefit ratio, expected impact, and Analytic Hierarchy Process

In another study conducted for NASA, Tavana (2004) evaluated the alternative mission architectures for the human exploration of Mars (Tavana, 2004). Tavana evaluated three alternative scenarios by considering different phases of a mission like departure, Mars transfer, Mars arrival, etc.

Different from above problems, Kahriman et al. (2015) selected a communication satellite manufacturer for a satellite system operator using AHP and TOPSIS by considering a set of factors like cost, payload capacity, ground segment infrastructure, etc (Kahriman, Öztokatlı, & Daş, 2015).

According to the above presented literature survey, literature on space related decision making problems is very limited. The aim of this thesis is to study on such a problem which aims to select a launch vehicle for a geostationary communication satellite.

2.2 Literature Review on Conventional MCDM Methods

MCDM method facilitates to identify the best alternatives under various criteria where the best choice is determined by analyzing the distinct scope for the criteria, weights of the criteria and selection of the most favorable choice (Aruldoss, Lakshmi, & Venkatesan, 2013).

In MCDM process, available set of alternatives, criteria and their associated weights are represented as in the following form;

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{11} \end{bmatrix} \end{array} \qquad \textbf{(Equation 2.1)}$$

$$W = \begin{bmatrix} w_{m1} & w_{m1} & \cdots & w_{m1} \end{bmatrix} \qquad \textbf{(Equation 2.2)}$$

where $A_1, A_2, \ldots, A_m$ are the alternatives or options under evaluation, $C_1, C_2, \ldots, C_n$ are defined criteria for the given problem and a_{ij} is the performance score of i^{th} alternative with respect to the j^{th} criterion, and w_j is the preference weight of j^{th} criterion (Chen, 2014).

MCDA has accompanied incredible amount of utilization over the last several decades where its role in distinctive application areas has intensified significantly as new methods develop and as old methods enhance. (Velasquez & Hester, 2013)

Hwang and Yoon (1981) mentioned that MCDM problems are classified into two principal categories as Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) considering various intentions and distinctive types of data (Hwang & Yoon, 1981).

MADM is utilized for the purpose of evaluations among available limited alternatives under predefined criteria with distinct preference ratings; whereas the MODM is particularly suitable for design and planning purposes. The objective is to achieve the optimum or desired targets by considering the assorted interactions within the given constraints (Tzeng & Huang, 2011).

Numerous methods have been advanced to deal with the MCDM problems in supplier selection, such as Analytic Hierarchy Process (AHP), Artificial Intelligence (AI), Analytic Network Process (ANP), Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), Multi criteria Optimization and Compromise Solution (VIKOR), Simple Multi Attribute Rating Technique (SMART), Decision-Making Trial and Evaluation Laboratory (DEMATEL), DEA (Data Envelopment Analysis), Neural Networks (NN), Genetic Algorithm (GA), Case-Based Reasoning (CBR), Fuzzy Set Theory (FST) and their hybrids.

Velasquez and Hester (2013) published a literature review of common MCDM methods which examining the pros and cons of the related methods with their relative strengths and weaknesses. In that study, the analysis of MCDM methods provides a clear guide for how MCDM methods should be used in particular situations. (Velasquez & Hester, 2013)

William Ho et al (2010) studied on the MCDM methods proposed for supplier appraisal. The associated articles are gathered and analyzed from the international journals between 2000 and 2008. For supplier selection problem, numerous MCDM approaches such as AHP, ANP, SMART, GA, CBR, DEA, Fuzzy Set Theory, Mathematical Programming and their hybrids have been offered. (Ho, Xu, & Dey, 2010)

Likewise, Agarwal et al (2011) reviewed various MCDM methodologies studied in the academic literature from 2000 to 2011 on the supplier evaluation and selection process over sixty-eight research articles (Agarwal, Sahai, Mishra, Bag, & Singh, 2011).

Chai et al (2013) published a literature review of decision making techniques for supplier evaluation from the perspective of decision problems, decision environments, decision-makers and decision approaches by considering 123 articles published between 2008 and 2012 (Chai, Liu, & Ngai, 2013).

MCDM is a methodological process whose main objective is to support decision makers with a sophisticated recommendation among available limited alternatives (also called as candidates, objects, solutions or actions), while being appraised from various standpoints, called criteria (also called as objectives, features or attributes).

Based upon the principle behind the MCDM methods, Chai et al (2013) classified them into four classes; (i) multi-attribute utility methods such as AHP and ANP, (2) outranking methods such as ELECTRE and PROMETHEE, (iii) compromise methods such as TOPSIS and VIKOR and (iv) other MCDM techniques such as SMART and DEMATEL (Chai, Liu, & Ngai, 2013).

Ishizaka & Nemery (2013) mentioned about different ways of nominating most suitable MCDM methods to handle specific given problems depending on the input information which are the data and parameters of the method and the outcomes as given in Table 2-1 and Table 2-2 (Ishizaka & Nemery, 2013). In that tables, several MCDA ranking and sorting methods are listed in terms of required amount of input information in descending order. In Table 2-1 and Table 2-2, the inputs and outputs of each methods are presented.

Table 2.1: Necessary inputs for MCDM ranking or choice methods (Ishizaka & Nemery, 2013)

	Inputs	Effort input	MCDA method	Output
Ranking/choice problem	utility function	Very HIGH	**MAUT**	Complete ranking with scores
	pairwise comparisons on a ratio scale and interdependencies		**ANP**	Complete ranking with scores
	pairwise comparisons on an interval scale		**MACBETH**	Complete ranking with scores
	pairwise comparisons on a ratio scale		**AHP**	Complete ranking with scores
	indifference, preference and veto thresholds		**ELECTRE**	Partial and complete ranking (pairwise outranking degrees)
	indifference and preference thresholds		**PROMETHEE**	Partial and complete ranking (pairwise preference degrees and scores)
	ideal option and constraints		**Goal programming**	Feasible solution with deviation score
	ideal and anti-ideal option		**TOPSIS**	Complete ranking with closeness score
	no subjective inputs required	Very LOW	**DEA**	Partial ranking with effectiveness score

Table 2.2: Necessary inputs comparison of MCDM sorting methods (Ishizaka & Nemery, 2013).

	Inputs	Effort Input	MCDA method	Output
Sorting method	utility function	HIGH	UTADIS	Classification with scoring
	pairwise comparisons on a ratio scale	↑	AHPSort	Classification with scoring
	indifference, preference and veto thresholds	↓	ELECTRE-TRI	Classification with pairwise outranking degrees
	indifference and preference thresholds	LOW	FLOWSORT	Classification with pairwise outranking degrees and scores

In this study AHP, ELECTRE and PROMETHEE are selected among the set of conventional MCDM methods. In addition to these methods, DEA is also employed by considering its strength as a discrete non-parametric linear programming based methodology. DEA is preferred due to its marvelous feature of not requiring subjective evaluation during application of the method in despite of other MCDM methods. In addition, fuzzy DEA is employed and the results of fuzzy DEA is compared with DEA and AHP, ELECTRE and PROMETHEE.

2.3 Literature Review on DEA

DEA was proposed by Charnes, Cooper and Rhodes (CCR) in 1978. They illustrated how a fractional objective function can be changed into a Linear Programming (LP) format. By this achievement, decision-making units (DMUs) are appraised under multiple inputs and multiple outputs, despite the fact that the production function is not known.

The DEA solves an LP for each DMU and the weights assigned to each linear aggregation are the results of the corresponding LP. The weights are determined in such way that to present the specific DMU is as positive as possible, under the constraint that no other DMU, given the same weights, is more than 100% efficient (Apolloni, 2007). Consequently, a Pareto frontier is achieved, determined by specific

DMUs on the boundary line of input–output variable space (Adler, Friedman, & Sinuany-Stern, 2002).

The CCR model appraises both scale and technical efficiencies via the optimal ratio form. The enclosing in CCR is described as constant returns to scale which corresponds to a grow in inputs effect in a proportional gain in outputs. Following to that, Banker et al (1984) further proposed the BCC model to approximate the technical efficiency of decision making units with reference to the efficient frontier which also determines whether a DMU is operating in increasing, decreasing or constant returns to scale (Toloo & Nalchigar, A new integrated DEA model for finding most BCC-efficient DMU, 2009). Therefore, CCR models are specialized form of BCC models.

The essential characteristics of DEA are pointed out as; (i) multiple inputs and outputs are analyzed without pre-determined weights, (ii) relative efficiency is measured based upon the perceived data without necessarily having knowledge on the production role and (iii) preferences of decision maker can be included into DEA models (Darehmiraki & Behdani, 2013).

The basic mathematical model of a constant returns-to-scale (CRS) or also called CCR model proposed by Charnes et al. (1978) is given as follows where outputs; $y_{rk}, r = 1, 2, ..., s$ and inputs; $x_{ik}, i = 1, 2, ..., m$, u_r is coefficient or weight assigned by DEA to output r, v_i is coefficient or weight assigned by DEA to input i. The objective is maximizing efficiency measure of DMU's.

$$\theta = h_k = \max_{u_r, v_i} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad \textbf{(Equation 2.3)}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \text{ for } j = 1, 2, \ldots, n \qquad \textbf{(Equation 2.4)}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \text{ for } j = 1, 2, \ldots, n \qquad \textbf{(Equation 2.5)}$$

$$u_r, v_i \geq 0 \qquad \textbf{(Equation 2.6)}$$

In order to achieve better discrimination among alternative scores, several techniques have been proposed since the basic DEA model could not achieve full discrimination among alternatives where several alternatives may get score of equal to 1 or %100 which corresponds to an efficient unit (Sarkis, 2000). To improve the discrimination ability of DEA, several researchers proposed improved DEA models.

Adler et al (2002) classified these improved DEA methods in the literature into six categories. These are; (i) cross-efficiency method where the units are self and peer evaluated, (ii) super-efficiency method, ranks through the exclusion of the unit being evaluated, (iii) benchmarking method, in which a unit is highly ranked if it is chosen as a useful target for many other units, (iv) multivariate statistical techniques, (v) outranking inefficient units through proportional measures of inefficiency, (vi) combination of MCDM methodologies with the DEA approach (Adler, Friedman, & Sinuany-Stern, 2002).

Conceptually, DEA methodology assigns the weights that are most favorable to individual DMU under consideration by computing the ratio of the accumulated output to the accumulated input (Liu, 2008).

Actually, there are occasions where each component must be retained at a minimum level for the production mechanism. In order deal with this aspect, Thompson et al (1986) and Thompson et al (1990) proposed the Assurance Region (AR) concept where the weight constraint is imposed to avoid the evaluated DMUs from overlooking or depending on excessively on any criterion in evaluation (Liu, 2008).

In order to deal with the vagueness in information and the fundamental fuzziness of human judgment and preference, Fuzzy DEA methods are proposed to realistically represent real-world problems compare with the conventional DEA models (Yang, Chiu, Tzeng, & Yeh, 2008).

2.4 Literature Review on Fuzzy DEA

Evaluation of the performance of DMUs by conventional DEA models necessitates crisp input/output data. Nonetheless, in most of the real life problems, the available information in a MCDM process is usually imprecise, vague or uncertain and the pre-defined criteria are not certainly independent (Yang, Chiu, Tzeng, & Yeh, 2008).

In order to deal with the vagueness of available information and the fuzziness of human preferences and judgments, fuzzy set theory was proposed by Zadeh in 1965 and a decision making method in a fuzzy environment was developed by Bellman and Zadeh in 1970 (Yang, Chiu, Tzeng, & Yeh, 2008).

Despite the fact that DEA is mainly proposed for efficiency measurement, some restraints exist which need to be taken into account in its applications. One of the important restrictions is the sensitivity of the DEA in terms of the data under evaluation. For instance, since DEA is a methodology concentrated on boundaries or frontiers, inaccuracy in data measurement might lead significant issues (Lertworasirikula, Fanga, Joines, & Nuttle, 2003). Therefore, in order to apply DEA successfully, quantification of both the inputs and outputs should be performed accurately. Nevertheless, in some situations, inputs and outputs are unstable and complicated. It could be difficult to measure the input and output data accurately. Furthermore, the data that is being used could be qualitative, which could be expressed linguistically. For instance, “new/old” equipment and “good/bad” service. To quantify vague and imprecise data in real world problems, fuzzy set theory has been suggested by the researchers as an alternative approach (Zimmermann H. , Fuzzy Set Theory and Its Application, 1996).

The DEA models, which use fuzzy data are called fuzzy DEA models. These models are suitable to represent real-world problems compare with the standard DEA models. Fuzzy set theory also permits linguistic data to be utilized straightly within the DEA model and Fuzzy DEA models take the form of fuzzy linear programming models (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

Because coefficients in the fuzzy CCR model are consisted of fuzzy numbers, a standard LP solver can’t resolve the fuzzy CCR models as though a crisp CCR model (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

When the papers published on fuzzy DEA are investigated, five distinct approaches are encountered. These are; (i) tolerance approach, (ii) possibility approach (iii) α-level based approach (iv)fuzzy ranking approach and (v) defuzzification approach.

The defuzzification approach was introduced by Lertworasirikul (2001) where the fuzzy inputs and the fuzzy outputs are first defuzzified into crisp values and then by taking into account these crisp values, the derived crisp model can be solved by an LP solver (Lertworasirikul S. , Fuzzy Data Envelopment Analysis for Supply Chain Modeling and Analysis, 2001).

The defuzzification method is adopted with the center of gravity method in (Juan, 2009) study. The defuzzification approach is mentioned also in (Rebai, 2009) and (Nojehdehi, Abianeh, & Valami, 2012) articles.

In the article of Angiz et all (2012), the defuzzification approach is quoted as one of the model in assessing DMUs in Fuzzy DEA where the four traditional approaches are classified as the (i) fuzzy ranking approach as (ii) defuzzification approach, (iii) tolerance approach and (iv) α-cut based approach (Angiz, Emrouznejad, & Mustafa, 2012).

Nedeljkovic and Drenova (2012) measured the efficiency of the post offices using fuzzy DEA. They advocated that defuzzification approach is one of the method in the literature (Nedeljkovic & Drenova, 2012).

Khodabakhshi and Aryavash (2014) ranked DMUs with fuzzy data using DEA. They employed defuzzification method to transform the obtained fuzzy score into a crisp score. Then DMUs are ranked according to their crisp scores (Khodabakhshi & Aryavash, 2014).

As also discussed in Emrouznejad et al (2014)'s study, fuzzy DEA is a growing field as shown in Figure 2-1 and a lot has to be done on fuzzy DEA.

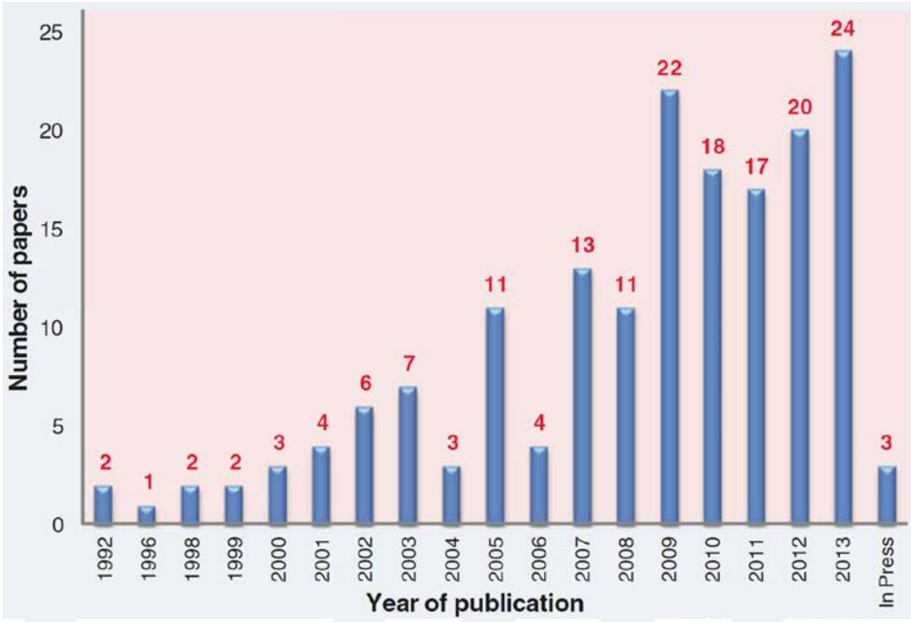


Figure 2.1: The fuzzy DEA development history (1992–2013) (Emrouznejad, Tavana, & Hatami-Marbini, The State of the Art in Fuzzy Data Envelopment Analysis, 2014).

As discussed in this chapter, various decision-making approaches have been proposed to tackle the supplier selection problem. There are plenty of applications exist on supplier selection topic. The Conventional MCDM tools such as AHP, ANP, TOPSIS, DEMATEL, VIKOR, ELECTRE, PROMETHEE, SMART have been widely utilized. DEA method is being originally utilized as efficiency analysis. DEA utilization as MCDM is relatively rare compare with the other MCDM methods. Fuzzy application of DEA is also relatively limited.

CHAPTER THREE

BACKGROUND INFORMATION OF THE MCDM METHODS EMPLOYED IN THE THESIS

In the past decade MCDM gets attraction by the scholars and decision makers since they will often try to achieve multiple and most of the times conflicting objectives. The principal objective of MCDM is to support decision-makers in their decision making process as justification of a given decision with respect to the presumed hierarchy of criteria.

As explained in previous chapters, several methods have been proposed to tackle with the MCDA problems. In this thesis; AHP, ELECTRE, PROMETHEE and DEA is used as MCDA tools and their results are compared for the launch vehicle selection problem. In this chapter, theory of each employed methods are elucidated.

3.1 AHP

AHP was developed by Saaty (1977, 1980) which is a distinctively beneficial method when the decision-maker is incapable of constructing a utility function in other respect MAUT (Multi-Attribute Utility Theory) is recommended (Ishizaka & Nemery, 2013).

AHP is a productive and convincing tool to deal with complicated decision-making problem and assist the decision maker to assign priorities in order to achieve the best decision. AHP also incorporates a beneficial method for examining the consistency of the decision maker’s evaluations, therefore lessening the predilection in the decision making process.

The AHP produces a weight for each evaluation criterion based on the decision maker's pairwise comparisons of the defined criteria. The criterion obtains the weight according to their importance. As a next step, for a given criterion, the AHP assigns a rating to each alternative in accordance with pairwise comparisons of the alternatives. The alternatives acquire scores according to their performance on that criterion. Finally, the AHP cooperating the weights of criteria and the scores of options, thus settling an overall score for each alternative, and a resulting ranking.

The AHP is an efficient tool since the scores and thus the final ranking, are achieved based on the pairwise relative assessments of both the criteria and the alternatives pre-defined by the decision makers. The decision maker's practical experience guides the computations of the AHP and thus the AHP is considered as a method, which considers the assessments of both qualitative and quantitative factors.

The implementation of AHP is summarized in the following steps by an assumption of there are m evaluation criteria and n alternatives (options) are available ((Ishizaka & Nemery, 2013), (Lee, Chen, & Kang, 2009),):

Step 1. Structuring Problem in a Hierarchical Form

The problem is disintegrated into a hierarchy of objective, criteria, sub-criteria and options/alternatives as shown in Figure 3-1.

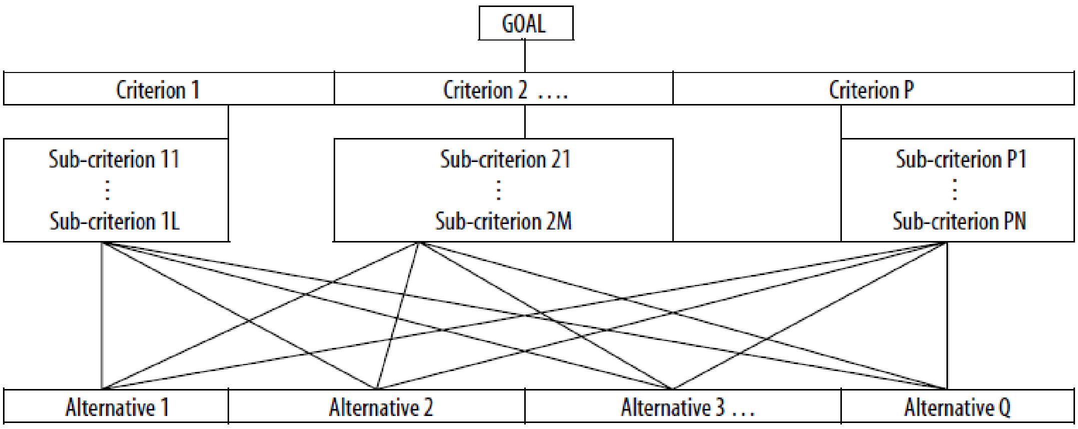


Figure 3.1: Hierarchical form of a MCDM problem.

Step 2. Computing the Vector of Criteria Weights

To determine the weights for the pre-defined criteria, the AHP composes a pairwise comparison matrix, called matrix A that is a $m \times m$ matrix where m is the number of criteria. Each element a_{jk} of the matrix A stands for the significance of the j^{th} criterion in relation to the k^{th} criterion.

$$A = \begin{array}{l} \\ criterion\_1 \\ criterion\_2 \\ \vdots \\ \vdots \\ criterion\_m \end{array} \begin{array}{c} criterion\_1 \quad \cdots\cdots\cdots\cdots \quad criterion\_\mathrm{m} \\ \begin{bmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} = 1/a_{12} & 1 & a_{23} & \cdots & a_{2m} \\ a_{31} = 1/a_{13} & \cdots & 1 & \cdots & \vdots \\ \vdots & \vdots & \vdots & 1 & \vdots \\ a_{m1} = 1/a_{1m} & \cdots & \cdots & \cdots & 1 \end{bmatrix} \end{array} \quad \textbf{(Equation 3.1)}$$

The a_{jk} and a_{kj} fulfill the following restriction;

$$a_{jk} a_{kj} = 1 \quad j,k = 1,2,...,m \qquad \textbf{(Equation 3.2)}$$

And for all j:

$$a_{jj} = 1 \quad j = 1,2,...,m \qquad \textbf{(Equation 3.3)}$$

The pairwise comparison matrix is established in accordance with a numerical scale from 1 to 9, as shown in Table 3-1: Saaty's Rating Scale.

Table 3.1: Saaty's rating scale.

Intensity of importance	Definition for weight values	Explanation
1	Equal importance	Two factors contribute
3	Somewhat more important	Experience and judgement slightly favor
5	Much more important	Experience and judgement strongly favor one over
7	Very much more important (Very Strong)	Experience and judgement very strongly favor one over the other. Its
9	Absolutely more important.	The evidence favoring one over the other is of
2,4,6,8	Intermediate values	When compromise is needed

Several methods are proposed to calculate priority vector from the comparison matrix such as eigenvalue method, approximate method and the geometric mean method (Ishizaka & Nemery, 2013). Saaty proposed approximate methods to obtain priority vector. The additive normalization method derives priorities by summing up the columns in matrix A and averaging obtained values in rows (Srdjevic, 2005).

Following to creation of the matrix A, the normalized pairwise comparison matrix A_{norm} is built by column normalization, for instance each element $\overline{a}_{jk}$ of the matrix A_{norm} is calculated as;

$$\overline{a}_{jk} = \frac{a_{jk}}{\sum_{l=1}^{m} a_{lk}} \quad j,k = 1,2,...,m \qquad \textbf{(Equation 3.4)}$$

The above equation is valid for benefit type criteria (bigger-the-better). For the cost type criteria (smaller-the-better) the following equation is used to normalize by linear scale transformation sum method (Stanujkic, Dorđevic, & Dorđevic, 2013):

$$\overline{a}_{jk} = \frac{\frac{1}{a_{jk}}}{\sum_{l=1}^{m} \frac{1}{a_{lk}}} \quad j,k = 1,2,...,m \qquad \textbf{(Equation 3.5)}$$

Lastly, the vector of criteria weight called w is built by averaging the entries on each row of A_{norm};

$$w_j = \frac{\sum_{l=1}^{m} \overline{a}_{jl}}{m} \quad j = 1,2,...,m \qquad \textbf{(Equation 3.6)}$$

Step 3. Computing the Matrix of Alternative Scores

In this step, alternatives score S ($n \times m$) matrix is generated by first building $B^{(j)}$ ($n \times n$) pairwise comparison matrix where $j = 1,2,\ldots,m$ for each of the m criteria and n alternatives(options).

The elements of $B^{(j)}$ matrix conform the following condition:

$$b_{ih}^{(j)} \bullet b_{hi}^{(j)} = 1 \quad \textbf{(Equation 3.7)}$$

and for all i;

$$b_{ii}^{(j)} = 1 \quad \textbf{(Equation 3.8)}$$

Several methods are proposed to obtain score matrix. Millet and Saaty (2000) give guidance on the utilization of different normalization method (Ishizaka & Nemery, 2013). Lee et al (2009) utilized column normalization in their study. In this study the same additive normalization method is employed to calculate the score matrix since the problem is a closed system which no alternative will be added or removed. In the additive method, following to generation of $B^{(j)}$ matrix, the AHP carries out the similar procedure described as matrix A to matrix $B^{(j)}$. The each elements of the $B^{(j)}$ matrix is normalized by column sum. Then the elements on each row are averaged and consequently the $S^{(j)}$ score vectors are obtained.

The $S^{(j)}$ score vector includes the grades of the alternatives under evaluation with respect to the j^{th} criterion.

Finally, the score matrix of S is achieved as follows where the j^{th} column of S matrix corresponds to $S^{(j)}$;

$$S = [\mathrm{s}^{(1)}, \mathrm{s}^{(2)} \cdots \mathrm{s}^{(m)}] \quad \textbf{(Equation 3.9)}$$

Step 4. Ranking of the Alternatives

Following to the w (criteria weight vector) and the S (score matrix) generation, a global scores vector v is computed as follows;

$$v = S \bullet w \quad \textbf{(Equation 3.10)}$$

The i^{th} entry v_i of v demonstrates the overall grade assigned to the i^{th} alternative. Then as a final step for the ranking of the alternatives is attained by grading the overall scores in lessening order.

Step 5. Consistency Check

Once the global score vector is generated, a consistency check need be performed to discern possible inconsistencies in the entries. During several sequential pairwise comparisons, there might be contradiction in them. The reasons for these prospective contradictions could be due to lack of sufficient information, vaguely defined problems, doubtful information or lack of attentiveness during appraisal process. AHP permits up to a 10% inconsistency compared to the average inconsistency of 500 randomly filled matrices (Ishizaka & Nemery, 2013).

The consistency check method is leaned upon the calculation of an appropriate consistency index. The Consistency Index (CI) is acquired by the following formulation;

$$CI = \frac{\frac{A \bullet w}{w} - m}{m - 1} \qquad \textbf{(Equation 3.11)}$$

Ideally, the target is to have $CI = 0$, however small values of inconsistency may be tolerated, if the following conditions is satisfied (Saaty, 1980);

$$\frac{CI}{RI} < 0.1 \qquad \textbf{(Equation 3.12)}$$

The inconsistencies are endurable and a reliable consequence is achieved by the AHP technique. The RI is representing the Random Index when the elements of matrix A are entirely random.

The values of RI for small scale problems where m ≤ 10 are shown in Table 3-2.

Table 3.2: Values of the random index (RI).

m (size of matrix)	2	3	4	5	6	7	8	9	10
RI (Random Index)	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

3.2 Electre

Roy (1968) and Benayoun et al. (1966) initially utilized the thought of outranking relations to introduce the ELECTRE method. Since then various ELECTRE models have been developed and proposed by the scholars based on the nature of the problem (Tzeng & Huang, 2011).

The key characteristic and benefit of the ELECTRE methods is the compensation between criteria and any normalization process is avoided, which deforms the original data (Ishizaka & Nemery, 2013).

The basic concept of the ELECTRE method is to handle outranking relations by utilizing pairwise comparisons among alternatives with respect to each one of the criteria separately (Triantaphyllou, Shu, Sanchez, & Ray, 1998).

The implementation of the ELECTRE method is elucidated in the following steps (Benayoun, 1966) (Triantaphyllou, Shu, Sanchez, & Ray, 1998) (Pang, 2011), (Stanujkic, Dorđevic, & Dorđevic, 2013):

Step 1. Normalizing the Decision Matrix

The evaluation of each alternative is transformed into the decision matrix by utilizing the following formulation;

$$x_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{M} a_{ij}^2}}$$ **(Equation 3.13)**

The normalized matrix X is established as follows;

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1N} \\ x_{21} & x_{22} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ x_{M1} & x_{M2} & x_{M3} & \cdots & x_{MN} \end{bmatrix}$$ **(Equation 3.14)**

In the normalized matrix definition,

M = number of options or alternatives and

N = number of predefined criteria

x_{ij} = the preference degree of the i^{th} alternative in terms of the j^{th} criterion.

The Equation 3.12 is valid for benefit type criteria (bigger the better). For the cost type criteria (smaller-the-better) the following equation is used to normalize:

$$x_{ij} = \frac{\frac{1}{a_{ij}}}{\sqrt{\sum_{i=1}^{M}\left(\frac{1}{a_{ij}}\right)^2}}$$ **(Equation 3.15)**

Step 2. Weighting the Normalized Decision Matrix

The weighted matrix denoted as Y is computed by multiplication of the X normalized decision matrix and its related weights ascribed to the criteria as follows:

$$Y = XW$$ **(Equation 3.16)**

where:

$$Y = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \cdots & y_{1N} \\ y_{21} & y_{22} & y_{22} & \cdots & y_{2N} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ y_{M1} & y_{M2} & y_{M3} & \cdots & y_{MN} \end{bmatrix}$$ **(Equation 3.17)**

$$Y = \begin{bmatrix} w_1 x_{11} & w_2 x_{12} & w_3 x_{13} & \cdots & w_N x_{1N} \\ w_1 x_{21} & w_2 x_{22} & w_3 x_{22} & \cdots & w_N x_{2N} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ w_1 x_{M1} & w_2 x_{M2} & w_3 x_{M3} & \cdots & w_N x_{MN} \end{bmatrix}$$ **(Equation 3.18)**

and

$$W = \begin{bmatrix} w_1 & 0 & 0 & \cdots & 0 \\ 0 & w_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & w_M \end{bmatrix}$$ **(Equation 3.19)**

and also

$$\sum_{i=1}^{N} w_i = 1$$ **(Equation 3.20)**

Step 3. Determination of the Concordance and Discordance Sets

The concordance set C_{kl} of two options A_k and A_l, where $k,\ l \geq 1$, is defined as the set of all criteria for which A_k is preferred to A_l which is given as follows:

$$C_{kl} = \{j,\ such\ that:\ y_{kj} \geq y_{lj}\},\ for\ j = 1,\ 2,\ 3,\ ...,\ N \qquad \textbf{(Equation 3.21)}$$

The discordance set is type of complementary subset of concordance set and it is illustrated as follows:

$$D_{kl} = \left\{j,\ such\ that:\ y_{kj} < y_{lj}\right\},\ for\ j = 1,\ 2,\ 3,\ ...,\ N. \qquad \textbf{(Equation 3.22)}$$

Step 4. Construction of the Concordance and Discordance Matrices

The comparative value of the entries in the concordance matrix C is computed by the concordance index. The concordance index c_{kl} is the sum of the weights affiliated with the criteria included in the concordance set and shown as follows:

$$c_{kl} = \sum_{j \in c_{kl}} w_j \text{ for j=1,2,3 …, N} \qquad \textbf{(Equation 3.23)}$$

The concordance index signifies the relative importance of alternative A_k with respect to alternative A_l, where $0 \leq c_{kl} \leq 1$. Hence, the concordance matrix C is described as follows:

$$C = \begin{bmatrix} - & c_{12} & c_{13} & \cdots & c_{1M} \\ c_{21} & - & c_{23} & \cdots & c_{2M} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ldots & \vdots \\ c_{M1} & c_{M2} & c_{M3} & \cdots & - \end{bmatrix} \qquad \textbf{(Equation 3.24)}$$

The discordance matrix D demonstrates the extent of alternative A_k is worse than alternative A_l. The elements d_{kl} of the discordance matrix are described as follows:

$$d_{kl} = \frac{\max\limits_{j \in D_{kl}} \left| y_{kj} - y_{lj} \right|}{\max\limits_{j} \left| y_{kj} - y_{lj} \right|} \qquad \textbf{(Equation 3.25)}$$

The discordance matrix is determined as follows:

$$D = \begin{bmatrix} - & d_{12} & d_{13} & \cdots & d_{1M} \\ d_{21} & - & d_{23} & \cdots & d_{2M} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ldots & \vdots \\ d_{M1} & d_{M2} & d_{M3} & \cdots & - \end{bmatrix} \qquad \textbf{(Equation 3.26)}$$

Step 5. Determination of the Concordance and Discordance Dominance Matrices

The concordance dominance matrix is comprised through a threshold value for the concordance index. For instance, if the concordance index c_{kl} is more than a specific threshold value $\underline{c}$, A_k dominates A_l where it is described as follows;

$$c_{kl} \geq \underline{c} \qquad \textbf{(Equation 3.27)}$$

The threshold value $\underline{c}$ is computed as the average concordance index with the following formulation;

$$\underline{c} = \frac{1}{M(\mathrm{M}-1)} x \sum_{\substack{k=1 \\ and\_k \neq l}}^{M} \sum_{\substack{l=1 \\ and\_l \neq k}}^{M} c_{kl} \qquad \textbf{(Equation 3.28)}$$

The concordance dominance matrix, called matrix F , is determined based on the threshold value as follows:

$$f_{kl} = 1,\ if\ c_{kl} \geq \underline{c} \qquad \textbf{(Equation 3.29)}$$

$$f_{kl} = 0,\ if\ c_{kl} \leq \underline{c} \qquad \textbf{(Equation 3.30)}$$

Likewise, the discordance dominance matrix, called matrix G , is defined by a threshold value $\underline{d}$, where $\underline{d}$ is defined as follows:

$$\underline{d} = \frac{1}{M(\mathrm{M}-1)} x \sum_{\substack{k=1 \\ and\_k \neq l}}^{M} \sum_{\substack{l=1 \\ and\_l \neq k}}^{M} d_{kl} \qquad \textbf{(Equation 3.31)}$$

$$g_{kl} = 1, \ if \ d_{kl} \geq \underline{d}$$ **(Equation 3.32)**

$$g_{kl} = 0, \ if \ d_{kl} \leq \underline{d}$$ **(Equation 3.33)**

Step 6a. Calculation of the Net Superior and Inferior Value

The net superior value c_k is determined as summation of the number of competitive superiority for all alternatives, and the bigger value, is the better. The c_k is computed as follows:

$$c_k = \sum_{l=1}^{N} c_{(k,l)} - \sum_{l=1}^{N} c_{(l,k)}$$ **(Equation 3.34)**

On the other side, the net inferior value d_k is determined as the number of inferiority ranking of the alternatives, and the smaller is better. The d_k is computed as follows:

$$d_k = \sum_{l=1}^{N} d_{(k,l)} - \sum_{l=1}^{N} d_{(k,l)}$$ **(Equation 3.35)**

Step 7a. Ranking According to Net Superior and Inferior Values

The alternatives are ranked in accordance with the net superior values as per the concordance. The option whose net superior value is the greatest is ranked as the prominent. Similarly, the alternatives are ranked according to net inferior values as per the discordance. Alternative whose net inferior value is the lowest is ranked as the highest and the final ranking is determined by the combination of concordant and discordant rankings (Pang, 2011).

Instead of Step 6a and 7a, the following steps can be utilized to settle the aggregate dominance matrix to eliminate the less favorable alternatives (Benayoun, 1966) (Triantaphyllou, Shu, Sanchez, & Ray, 1998):

Step 6b. Determination of the Aggregate Dominance Matrix

The entries of the aggregate dominance matrix E are computed as follows:

$$e_{kl} = f_{kl} \times g_{kl}$$ **(Equation 3.36)**

Step 7b. Elimination of the Less Favorable Alternatives

By using the E aggregate dominance matrix, partial preference ordering of the options can be acquired. If $e_{kl} = 1$, then A_k is preferred to A_l under the concordance and discordance criteria.

Step 8. Ranking the Alternatives

According to the concordance of alternatives, ranking is achieved by ordering the net superior values c_k in decreasing order; alternative whose net superior value is the maximum is ranked as the best. On the other hand, based on the discordance, alternatives are sorted according to the net inferior values d_k in increasing order. The final decision is determined by the combination of concordant and discordant rankings.

3.3 PROMETHEE

The PROMETHEE I is utilized generally to obtain partial ranking among alternatives and PROMETHEE II aspires for complete ranking, which were developed by J.P. Brans in 1982.

The implementation of PROMETHEE requires decision maker's assessment on the relative importance of the criteria and determination of the preference function, which is being utilized when comparing the options with respect to each distinct criterion.

The PROMETHEE algorithm is outlined as follows (Brans et al., 1986; Geldermann et al., 2000) (Figueira, Greco, & Ehrgott, 2005):

Step 1. Generate Data Matrix

Let a MCDM problem is represented as follows:

$$Max\left\{ f_1(\mathrm{a}_i), f_2(\mathrm{a}_i), \ldots\ldots f_j(\mathrm{a}_i) \ldots\ldots f_n(\mathrm{a}_i) \mid \mathrm{a}_i \in A \right\} \quad \textbf{(Equation 3.37)}$$

where $A = \{a_i \mid i = 1, 2, \ldots, m\}$ is set of available alternatives and $f = \{ f_j \mid j = 1, 2, \ldots, n\}$ is set of defined criteria; $f_j(a_i)$ describes performance of a_i with respect to the j^{th} criterion.

The MCDM problem is demonstrated by a decision matrix $(m\ x\ n)$ whose elements signify the assessments or the appraise of the options a_i according to the criterion f_j.

The weights vector, which is a quantification of the comparative significance of each criterion, is specified with $W = \{w_1, \ldots, w_n\}$. The higher the weight means the more important the criterion. The weights can be considered as normed weights given as follows:

$$\sum_{j=1}^{n} w_j = 1 \qquad \textbf{(Equation 3.38)}$$

Step 2. Define Preference Function P(d)

The preference function Pj expresses the difference between the assessments, which are scores of the options a_i and a_k with respect to a certain criterion into a preference extent varying from 0 to 1.

The value of the preference degree is computed for each pair of options and for each criterion. $f_j(a_i)$ is the value of a given criterion j for a decision a_i. The $dj(a_i, a_k)$ is noted as the distinction of a criterion j for the decisions a_i and a_k.

$$P_j(\mathrm{a}_i, a_k) = \mathrm{G}_j\left[d_j(\mathrm{a}_i, \mathrm{a}_k)\right] \qquad \textbf{(Equation 3.39)}$$

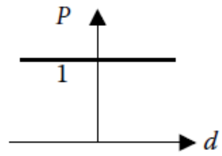
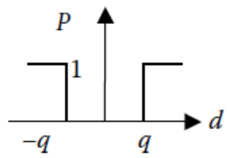
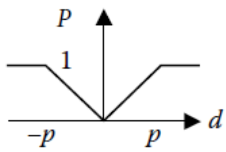
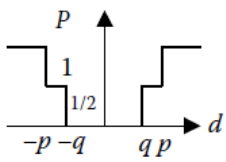
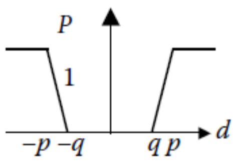
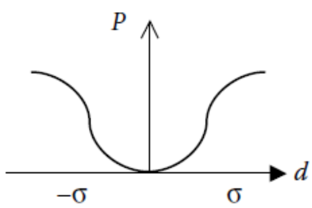
$$d_j(\mathrm{a}_i, \mathrm{a}_k) = \left[f_j(\mathrm{a}_i) - f_j(\mathrm{a}_k)\right] \qquad \textbf{(Equation 3.40)}$$

$$0 \leq P_j(\mathrm{a}_i, \mathrm{a}_k) \leq 1 \qquad \textbf{(Equation 3.41)}$$

$P_j(a_i, a_k)$ is the value of the preference degree of a criterion j for two decisions a_i and a_k. In order to facilitate the selection of a specific preference function, six types of functions were proposed by (Brans & Vincke, 1985).

The six possible types of conventional criteria in PROMETHEE methods is summarized in (Tzeng & Huang, 2011) by reference source of (Brans, Mareschal, & Vincke, 1984) as given in Table 3-3.

Table 3.3: Types of preference functions (Brans, Mareschal, & Vincke, 1984).

Types of Criteria	Analytical Definition	Shape	Parameter
Type I: Usual criterion	$P(d)=\begin{cases}0, & d=0;\\ 1, & \lvert d\rvert>0.\end{cases}$		*NA*
Type II: Quasi-criterion	$P(d)=\begin{cases}0, & \lvert d\rvert\le q;\\ 1, & \text{otherwise.}\end{cases}$		q
Type III: V-sharp criterion	$P(d)=\begin{cases}\frac{\lvert d\rvert}{p}, & \lvert d\rvert\le p;\\ 1, & \lvert d\rvert>0.\end{cases}$		p
Type IV: Level-criterion	$P(d)=\begin{cases}0, & \lvert d\rvert\le q;\\ 1/2, & q<\lvert d\rvert\le p;\\ 1, & \text{otherwise.}\end{cases}$		q, p
Type V: Linear criterion	$P(d)=\begin{cases}0, & \lvert d\rvert\le q;\\ \frac{\lvert d\rvert-q}{p-q}, & q<\lvert d\rvert\le p;\\ 1, & \text{otherwise.}\end{cases}$		q, p
Type VI: Gaussian criterion	$P(d)=1-\exp\left\{-\frac{d^2}{2\sigma^2}\right\}$		σ

Step 3. Generate the Associate Preference Functions

Based on the nominated preference function; the associated preference functions $P(a_1,a_2)$, $P(a_2,a_1)$, $P(a_1,a_3)$, *etc.* are generated between alternatives by the following equation;

$$P_j(a_i,a_k)=\begin{cases}0, f_j(a_i)\le f_j(a_k)\\ p_j[f_j(a_i)-f_j(a_k)], f_j(a_i)>f_j(a_k)\end{cases} \quad \textbf{(Equation 3.42)}$$

which means if a_i is better than a_k than $P_j(a_i,a_k)>0$, otherwise $P_j(a_i,a_k)=0$.

The interrelations of the associated preference functions are described in Figure 3-2.

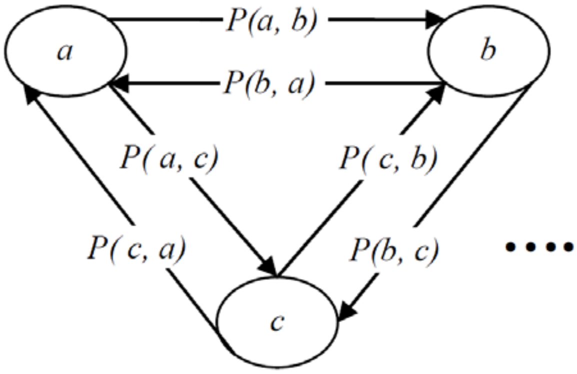


Figure 3.2: Diagrammatic representation of the preference functions.

Step 4. Calculate the Index of Preferences (IP)

Following to definition of the general criterion type, it is required to determine the value of function preference of action a_i in relation to action a_k for each criterion, and calculate the "Index of Preferences (IP)" or "Aggregated Preference Indices (or Indicators)" of action a_i in relation to action a_k. Each pair of actions is in set $A=\{a_i \mid i=1,2,\ldots,m\}$, alternative solutions.

$$\begin{cases} \pi(\mathrm{a}_i,\mathrm{a}_k)=\sum_{j=1}^{n}[w_j \times P_j(\mathrm{a}_i,a_k)] \\ \pi(\mathrm{a}_k,\mathrm{a}_i)=\sum_{j=1}^{n}[w_j \times P_j(\mathrm{a}_k,a_i)] \end{cases} \quad \textbf{(Equation 3.43)}$$

$\pi(\mathrm{a}_i,\mathrm{a}_k)$ is indicating degree of a_i is preferred to a_k over all the criteria and $\pi(\mathrm{a}_k,\mathrm{a}_i)$ indicates how a_k is preferred to a_i. The following conditions are satisfied for all $(\mathrm{a}_i,\mathrm{a}_k)\in A$

$$\begin{cases} \pi(\mathrm{a}_i,\mathrm{a}_i)=0 \\ 0\le \pi(\mathrm{a}_i,\mathrm{a}_k)\le 1 \\ 0\le \pi(\mathrm{a}_k,\mathrm{a}_i)\le 1 \\ 0\le \pi(\mathrm{a}_i,\mathrm{a}_k)+\pi(\mathrm{a}_k,\mathrm{a}_i)\le 1 \end{cases} \quad \textbf{(Equation 3.44)}$$

The following inference is clearly obtained;

$\{\pi(a_i, a_k) \approx 0$, *implies a weak preference of* a_i *over* a_k

$\{\pi(a_i, a_k) \approx 1$, *implies a strong preference of* a_i *over* a_k

Once the $\pi(a_i, a_k)$ and $\pi(a_k, a_i)$ are obtained for each pair of options of set A, a complete appraised outranking graph, comprising two arcs between each pair of nodes, is achieved as seen Figure 3-3.

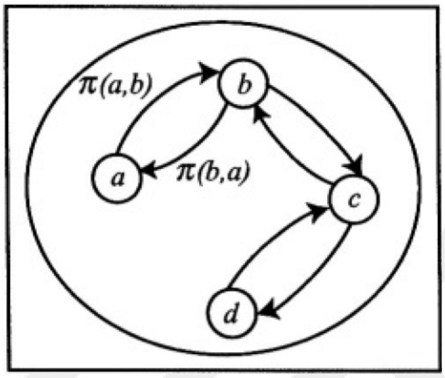


Figure 3-3: Diagrammatic representation of valued outranking graph.

Step 5. Calculate Positive and Negative Outranking Flows for Alternatives

The ranking is achieved by computing the outranking flows. For each plausible decision a_i, the positive outranking flow (leaving flow) represented by $\phi^{+}(a)$ and the negative outranking flow (entering flow) represented by $\phi^{-}(a)$ are calculated.

Each alternative is a_i facing $(m-1)$ other alternatives in A. The outranking flows are computed as follows:

$$\begin{cases} \phi^{+}(a_i) = \dfrac{1}{m-1} \displaystyle\sum_{\substack{i=1 \\ i \neq k}}^{m} \pi(a_i, a_k) \\ \phi^{-}(a_i) = \dfrac{1}{m-1} \displaystyle\sum_{\substack{i=1 \\ i \neq k}}^{m} \pi(a_k, a_i) \end{cases}$$ **(Equation 3.45)**

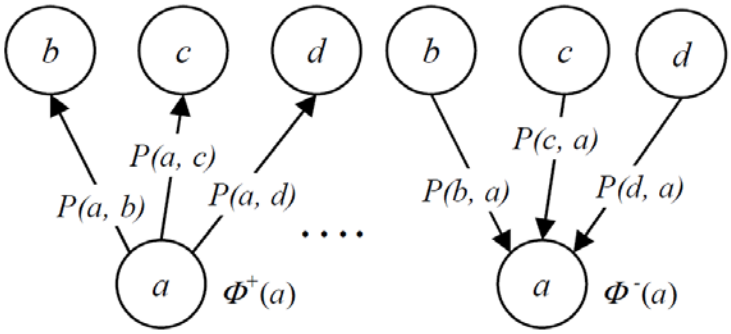


Figure 3.4: Positive and Negative Outranking Flows for Alternative a.

Step 6. PROMETHEE 1: Partial Ranking

Partial rankings are determined by PROMETHEE 1, which establishes the outranking relation between various alternatives.

The Preference $\left(P^{I}\right)$, Indifference $\left(I^{I}\right)$, Incomparability $\left(R^{I}\right)$ are defined as a result of the PROMETHEE 1;

$a_i P^I a_k$; the preference of the alternative a_i over a_k; if the one of the following condition is fulfilled;

$$\begin{cases} i.\phi^{+}(\mathrm{a}_i) > \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) < \phi^{-}(\mathrm{a}_k), \mathrm{or} \\ ii.\phi^{+}(\mathrm{a}_i) > \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) = \phi^{-}(\mathrm{a}_k), \mathrm{or} \\ iii.\phi^{+}(\mathrm{a}_i) = \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) < \phi^{-}(\mathrm{a}_k) \end{cases} \qquad \textbf{(Equation 3.46)}$$

$a_i I^I a_k$; the indifference between alternatives a_i and a_k; if the following condition is fulfilled;

$$\left\{ i.\phi^{+}(\mathrm{a}_i) = \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) = \phi^{-}(\mathrm{a}_k) \right. \qquad \textbf{(Equation 3.47)}$$

$a_i R^I a_k$; the incomparability of the two alternatives a_i and a_k; if the one of the following condition is fulfilled (inconsistency case);

$$\begin{cases} i.\phi^{+}(\mathrm{a}_i) > \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) > \phi^{-}(\mathrm{a}_k), \mathrm{or} \\ ii.\phi^{+}(\mathrm{a}_i) < \phi^{+}(\mathrm{a}_k) and \phi^{-}(\mathrm{a}_i) < \phi^{-}(\mathrm{a}_k) \end{cases} \qquad \textbf{(Equation 3.48)}$$

Step 7 PROMETHEE II: Complete Ranking

The PROMETHEE II method gets into process, which completes the entire ranking procedure, instituting outranking relation for all alternatives under a hierarchy from best to worst.

The net outranking flow is described with the following equation.

$$\phi(\mathrm{a}_i) = \phi^{+}(\mathrm{a}_i) - \phi^{-}(\mathrm{a}_i) \qquad \textbf{(Equation 3.49)}$$

The higher the net flow means the better is the alternative. Based upon the computed whole outranking flow; the following decisions are derived;

$a_i P^{II} a_k$; if $\phi(\mathrm{a}_i) > \phi(\mathrm{a}_k)$ → The alternative a is preferable to b

$a_i I^{II} a_k$; if $\phi(\mathrm{a}_i) = \phi(\mathrm{a}_k)$ →The alternative a is indifferent to b

By implementing the PROMETHEE II concept, all alternatives can be comparable. Nevertheless, the derived information might be more controversial since some information might get lost by considering the difference of the positive and negative outranking flows while calculating the net ranking.

The following properties hold in the PROMETHEE II notion:

$$\begin{cases} -1 \le \phi(\mathrm{a}_i) \le 1 \\ \sum_{i=1}^{m} \phi(\mathrm{a}_i) = 0 \end{cases} \qquad \textbf{(Equation 3.50)}$$

When $\phi(\mathrm{a}_i) > 0$, a_i is more outranking all the alternatives on all the criteria, when $\phi(\mathrm{a}_i) < 0$, a_i is more outranked.

3.4 Data Envelopment Analysis (DEA)

Charnes et al. (Charnes, Coope, & Rhodes, 1978) introduced DEA as an innovative data oriented mathematical approach to evaluate multiple relative efficiency measurements of a set of peer DMUs.

DEA evaluates the relative efficiency of DMUs with multiple inputs and multiple outputs. Linear programming is the underlying methodology that makes DEA remarkably powerful compared with alternative productivity management tools (Sherman & Zhu, 2006).

DEA determines the efficiency of each DMU relative to a frontier set by all DMUs. DEA computes an efficiency score for each DMU. If a DMU is entirely efficient, it has an efficiency score of 1 or %100 in percentage, otherwise the efficiency of the DMU could be improved. DEA evaluates how much input should be reduced or how much output should be increased to become more efficient for a given DMU by defining target values for input and output (Ishizaka & Nemery, 2013).

Performance evaluation of a DMU is a main objective of the DEA to find weaknesses and then accordingly to implement the required improvements.

3.4.1 DEA Mathematical Model

The following section provides mathematical formulation of DEA. In the model, the following representation is used;

j = *number of DMU being compared in the DEA*

DMU_j = *service unit number* j

θ = *efficiency rating of the service unit being evaluated by DEA*

y_{rj} = *amount of output r used by service unit j*

x_{ij} = *amount of input i used by service unit j*

i = *number of inputs used by the DMUs*

r = *number of outputs generated by the DMUs*

u_r = *coefficient or weight assigned by DEA to output* r

v_i = *coefficient or weight assigned by DEA to input* i

$$\text{Maximize } \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \ldots + u_s y_{ro}}{v_1 x_{1o} + v_2 x_{2o} + \ldots v_m x_{mo}} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad \textbf{(Equation 3.51)}$$

(Maximize the efficiency rating θ for service unit o)

The objective of the above model is to maximize the efficiency rating. It is subject to the constraints when the calculated u and v coefficients is implemented to all other DMUs being compared. Moreover, the model guarantees that there will be no DMU gets more than 1 or 100% in percentage efficiency as follows (Sherman & Zhu, 2006);

$$SU1 \quad \frac{u_1 y_{11} + u_2 y_{21} + ... + u_r y_{r1}}{v_1 x_{11} + v_2 x_{21} + ... v_m x_{m1}} = \frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}} \leq 1 \qquad \textbf{(Equation 3.52)}$$

$$SU2 \quad \frac{u_1 y_{12} + u_2 y_{22} + ... + u_r y_{r2}}{v_1 x_{12} + v_2 x_{22} + ... v_m x_{m2}} = \frac{\sum_{r=1}^{s} u_r y_{r2}}{\sum_{i=1}^{m} v_i x_{i2}} \leq 1 \qquad \textbf{(Equation 3.53)}$$

….

$$\mathrm{SU}_o \quad \frac{u_1 y_{1o} + u_2 y_{2o} + ... + u_r y_{ro}}{v_1 x_{1o} + v_2 x_{2o} + ... v_m x_{mo}} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \leq 1 \qquad \textbf{(Equation 3.54)}$$

….

$$\mathrm{SU}_j \quad \frac{u_1 y_{1j} + u_2 y_{2j} + ... + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + ... v_m x_{mj}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad \textbf{(Equation 3.55)}$$

$$u_1, u_2, ..., u_s \ \geq \ 0 \text{ and } \mathrm{v}_1, \mathrm{v}_2, ..., \mathrm{v}_m \ \geq \ 0 \qquad \textbf{(Equation 3.56)}$$

If the θ for the DMU under evaluation is less than 1 or 100% in percentage, then that unit is identified as inefficient. For such DMUs it is considered that there is a capability for that DMU to yield the same level of outputs with less inputs. The theoretical details of DEA is deliberated in Cooper et all (2000) and Zhu (2003) (Sherman & Zhu, 2006).

DEA diverges from an easy efficiency ratio since it handles multiple inputs and outputs which yields consequential information on efficiency potential improvements. Furthermore, it works without a priori information of the value of the outputs and inputs.

In order to solve DEA model with a linear programming software, the fractional objective functions are reformulated as follows;

$$\mathit{Maximize}\ \theta = u_1 y_{1o} + u_2 y_{2o} + ... + u_r y_{ro} \ \left(= \sum_{r=1}^{s} u_r y_{ro}\right) \qquad \textbf{(Equation 3.57)}$$

Subject to the constraints;

$$v_1x_{1o} + v_2x_{2o} + ...v_mx_{mo} = \sum_{i=1}^{m} v_ix_{io} = 1 \quad \textbf{(Equation 3.58)}$$

$$u_1y_{1j} + u_2y_{2j} + ... + u_ry_{rj}(\sum_{r=1}^{s} u_ry_{rj}) \leq v_1x_{1j} + v_2x_{2j} + ...v_mx_{mj}(\sum_{i=1}^{m} v_ix_{ij}) \quad \textbf{(Equation 3.59)}$$

$$u_1, u_2, ..., u_s \ \geq \ 0 \text{ , } \mathrm{v}_1, \mathrm{v}_2, ..., \mathrm{v}_m \ \geq \ 0 \quad \textbf{(Equation 3.60)}$$

Based on the above expression, the DEA model is actually calculated as;

$$Maximize \sum_{r=1}^{s} u_ry_{ro} \quad \textbf{(Equation 3.61)}$$

Subject to the constraints;

$$\sum_{i=1}^{m} v_ix_{io} = 1 \quad \textbf{(Equation 3.62)}$$

$$\sum_{r=1}^{s} u_ry_{rj} - \sum_{i=1}^{m} v_ix_{ij} \leq 0 \text{ , j=1,2,...n} \quad \textbf{(Equation 3.63)}$$

$$u_s \text{ , } \ \mathrm{v}_i \geq \ 0 \quad \textbf{(Equation 3.64)}$$

The above model is known as "*Multiplier Mode*l" where u_r and v_i symbolize output and input weights respectively (Sherman & Zhu, 2006).

In order to solve the above model with a linear programming package, the dual form of the model is needed as follows;

$$Min \ \theta \quad \textbf{(Equation 3.65)}$$

Subject to the constraints;

$$\sum_{j=1}^{n} \lambda_jx_{ij} \leq \theta x_{io} \quad \text{i=1,2,...m} \quad \textbf{(Equation 3.66)}$$

$$\sum_{j=1}^{n} \lambda_jy_{rj} \geq y_{ro} \quad \text{r=1,2,...s} \quad \textbf{(Equation 3.67)}$$

$$\lambda_j \geq \ 0 \qquad \text{j=1,2,...n} \quad \textbf{(Equation 3.68)}$$

The above model is referred as the "*Envelopment Model*". In the model, the y represents the dual variables and the $\lambda(lambda)$ values represent the weights. The dual model is trying to find the efficiency, $minimize\ \theta$, subject to the constraint that the weighted sum of the inputs of the other DMU is less than or equal to the inputs of the DMU being evaluated and the weighted sum of the outputs of the other DMUs is greater than or equal to the service unit being evaluated (Sherman & Zhu, 2006).

3.4.2 Types of DEA Models

There are two basic DEA models; (i) Constant Returns-to-Scale (CRS) or CCR model and (ii) Variable Returns-to-Scale (VRS) or BCC model. The BCC model is an extension of the CCR model which the efficient frontiers or reference set is described by a convex curve passing through all efficient DMUs (Hatami-Marbini, Emrouznejad, & Tavana, 2011). Hereinafter constant returns-to-scale mode is referred as CCR and variable returns-to-scale model is referred as BCC.

In Figure 3-5, the envelopment surface of CCR and BCC models are depicted. The CCR model supposes that an increase in input value would result in a proportional increase in output values. On the other hand, the BCC model was introduced for cases where an increase in input values does not affect the output values proportionally by Banker et al (1984).

Later, (Andersen & Petersen, 1993) introduced a reduced version of CCE model which improves ranking ability of DEA. This version is referred as RCCR or super-efficiency. In the RCCR model, the DMU under evaluation is eliminated from the constraint set hence the DMU can obtain an efficiency score of greater than 1, which provides a method for ranking efficient and inefficient units. (Yılmaz & Yurdusev, 2011).

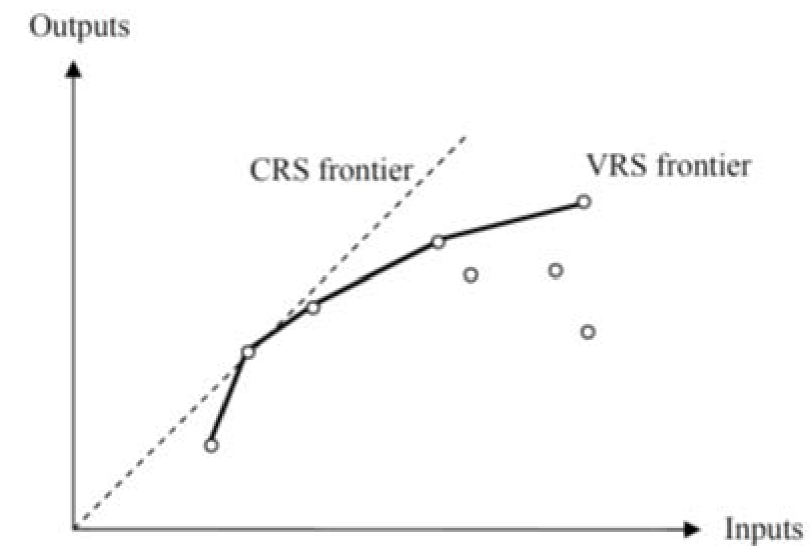


Figure 3.5: CCR (CRS) and BCC (VRS) envelopment surfaces (Yılmaz & Yurdusev, 2011).

In Figure 3-6, a BCC output-oriented DEA problem with outputs of Y and Z, and an input of X is illustrated. The line of $L1L2$ represents the technical efficient frontier. The points of $P1, P2, and\ P3$ on the line are theoretically efficient DMUs (Hatami-Marbini, Emrouznejad, & Tavana, 2011).

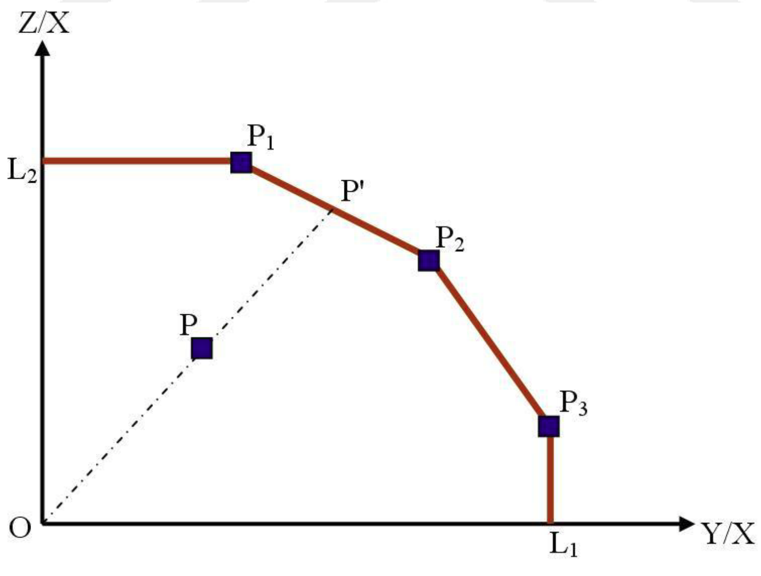


Figure 3.6: Representation of BCC output-oriented DEA model (Hatami-Marbini, Emrouznejad, & Tavana, 2011).

The mathematical model of the CCR and BCR are summarized as follows in Table 3-4. The BCC model includes supplemental constant variable, c_k, to allow variable returns-to-scale (Adler, Friedman, & Sinuany-Stern, 2002).

Table 3.4: CCR and BCR mathematical models summary.

Outputs; $y_{rk}, r = 1, 2, \ldots, s$ Inputs; $x_{ik}, i = 1, 2, \ldots, m$	
CCR Model (Charnes et al., 1978)	BCR Model (Banker et al., 1984)
Original form;	Original form;
the efficiency measure for DMU k; $h_k = \max_{u_r, v_i} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$	the efficiency measure for DMU k; $h_k = \max_{u_r, v_i} \frac{\sum_{r=1}^{s} u_r y_{rk} + c_k}{\sum_{i=1}^{m} v_i x_{ik}}$
$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$ for $j = 1, 2, \ldots, n$	$\frac{\sum_{r=1}^{s} u_r y_{rj} + c_k}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$ for $j = 1, 2, \ldots, n$
$u_r, v_i \geq 0$	$u_r, v_i \geq 0$
Linear programming form;	Linear programming form;
$h_k = \max \sum_{r=1}^{s} u_r y_{rk}$	$h_k = \max \sum_{r=1}^{s} u_r y_{rk} + c_k$
Subject to the; $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0$ for $j = 1, 2, \ldots, n$ $\sum_{i=1}^{m} v_i x_{ij} = 1$, $u_r \geq 0$ for $r = 1, 2, \ldots, s$ $v_i \geq 0$ for $i = 1, 2, \ldots, m$	Subject to the; $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - c_k \geq 0$ for $j = 1, 2, \ldots, n$ $\sum_{i=1}^{m} v_i x_{ij} = 1$, $u_r \geq 0$ for $r = 1, 2, \ldots, s$ $v_i \geq 0$ for $i = 1, 2, \ldots, m$

A DEA model could be formulated as an input-oriented or an output-oriented type. In the input oriented model, DEA decreases input for a given level of output. This shows how much a DMU can reduce its input for a given level of output. In the output oriented model, DEA increases output as much as possible for a given level of input; which means that, it signifies how much a DMU can raise its output for a given level of input (Ishizaka & Nemery, 2013).

An input oriented DEA for both CCR and BCC models having m input variables $(x_1, x_2, ..., x_m)$, s output variables $(y_1, y_2, ..., y_m)$ and n decision making units $(j = 1, 2, ..., n)$ is presented in Table 3-5. The only difference between the CCR and BCC models is the inclusion of the convexity constraints of $\sum_{j=1}^{n} \lambda_j = 1,$ in the BCC model (Emrouznejad, Tavana, & Hatami-Marbini, The State of the Art in Fuzzy Data Envelopment Analysis, 2014).

Table 3.5: An input oriented DEA model (Emrouznejad, Tavana, & Hatami-Marbini, The State of the Art in Fuzzy Data Envelopment Analysis, 2014).

Input; $(x_1, x_2, ..., x_m)$ Output; $(y_1, y_2, ..., y_m)$ DMUs; $(j = 1, 2, ..., n)$	
A basic CCR model	A basic BCC model
$\min \theta_p$	$\min \theta_p$
Subject to the; $\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_p x_{ip}, \quad \forall \mathrm{i}$ $\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp}, \quad \forall \mathrm{r}$ $\lambda_j \ge 0, \quad \forall j$	Subject to the; $\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_p x_{ip}, \quad \forall \mathrm{i}$ $\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp}, \quad \forall \mathrm{r}$ $\sum_{j=1}^{n} \lambda_j = 1, \ \lambda_j \ge 0, \quad \forall j$

The CCR model is interpreted as the target DMU is being compared with combination of other DMUs. The purpose of the CCR model is to decide on a vector of weights such that the efficiency of the target DMU compared to other DMUs is maximized, on the condition that no other DMUs or linear combination of other DMUs could achieve the same output levels with smaller amount of any input. In similar manner, the Dual CCR (DCCR) model is interpreted as the target DMU is efficient if no linear combination of other DMUs can yield the same or higher output levels using less of all inputs (Lertworasirikul S. , 2002).

3.5 Utilization of the DEA as MCDM Tool

The main purpose of the DEA is to determine efficient and inefficient DMUs and to estimate the efficient frontier with a proposition how to improve inputs and/or outputs of inefficient units in order to escalate them to the efficient frontier. Thus outranking of the DMUs is not main objective of the DEA.

The relationship between DEA and MCDM is being established by designating the maximizing criteria as outputs and the minimizing criteria as inputs (Yılmaz & Yurdusev, 2011).

Notwithstanding the fact that DEA is an advantageous tool for efficiency measurement, there are some inadequacies related with the method when it is intended to utilize as a MDCM method. In the literature, DEA is criticized for its low discriminating ability and its unrealistic weights distribution. The issue of low discriminating ability takes place when the number of DMUs is not large enough compared to the total number of inputs and outputs (Moheb-Alizadeh, Rasouli, & Tavakkoli-Moghaddam, 2011). When this situation occurs, the results of the classic DEA models classify several DMUs as efficient. In the unrealistic weight distribution case, some DMUs may have very large weights in a single output and some others may have very small weights in a single input. These DMUs would also be identified as efficient while these extreme weights are practically unreasonable or undesirable (Moheb-Alizadeh, Rasouli, & Tavakkoli-Moghaddam, 2011).

In the literature, existing studies trying to improve the discriminating capability of DEA for ranking could be categorized into six groups; (i) cross-efficiency model proposed by (Sexton, Silkman, & Hogan, 1986) (ii) super-efficiency model suggested by (Andersen & Petersen, 1993) (iii) benchmarking model developed by (Torgersen et al.,1996) (iv) ranking of inefficient DMUs on the basis of their proportional inefficiencies (v) techniques of multivariate statistics combined with DEA and (vi) combination of multi-criteria decision technique with DEA (Adler, Friedman, & Sinuany-Stern, 2002).

The cross-efficiency method was initially proposed by Sexton et al. (1986), instituting ranking in DEA. The cross-efficiency method basically computes the efficiency score of each DMU n times, utilizing the optimum weights estimated by the n linear programs. The all of the DEA cross-efficiency scores are outlined in a cross-efficiency matrix format as given below (Adler, Friedman, & Sinuany-Stern, 2002);

$$h_{kj} = \max_{u_r, v_i} \frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}}, \; k = 1, 2, \ldots, n, \; j = 1, 2, \ldots, n \qquad \textbf{(Equation 3.69)}$$

In this formulization, h_{kj} represents the score of unit j in the DEA by the weights of unit k. Note that all the entries in the matrix are between 0 and 1, $0 \le h_{kj} \le 1$, and the diagonal elements h_{kk} represent the standard DEA efficiency score. For the efficient units $h_{kk} = 1$ and for inefficient units $h_{kk} < 1$.

Finally, the cross-efficiency method utilizes the outcomes of the cross-efficiency matrix h_{kj} in order to rank the units.

h_k is defined as the cross efficiency average score given to unit k;

$$\overline{h_k} = \sum_{j=1}^{n} \frac{h_{kj}}{n} \qquad \textbf{(Equation 3.70)}$$

The super-efficiency method enables to achieve an efficiency score greater than 1 for an extreme efficient unit k by eliminating the k^{th} constraint in the formulation, as shown below (Adler, Friedman, & Sinuany-Stern, 2002);

$$h_k = \max \sum_{r=1}^{s} u_r y_{rk} \qquad \textbf{(Equation 3.71)}$$

Subject to the;

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \ge 0 \text{ for } j = 1, 2, \ldots, n, \; j \ne k \qquad \textbf{(Equation 3.72)}$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1, \quad \textbf{(Equation 3.73)}$$

$$u_r \geq \varepsilon \text{ for } r = 1, 2, \ldots, s \quad \textbf{(Equation 3.74)}$$

$$v_i \geq \varepsilon \text{ for } i = 1, 2, \ldots, m \quad \textbf{(Equation 3.75)}$$

The dual form of the super-efficient model, calculates the distance between the Pareto frontier and the unit itself which is evaluated without unit k, i.e. for $J = \{ j = 1, 2, \ldots n, j \neq k \}$.

The dual of the super-efficient model is given as follows (Adler, Friedman, & Sinuany-Stern, 2002);

$$Min \;\; f_k \quad \textbf{(Equation 3.76)}$$

Subject to the;

$$\sum_{j \in J} L_{kj} x_{ij} \leq f_k x_{ik} \text{ for } i = 1, 2, \ldots, m \quad \textbf{(Equation 3.77)}$$

$$\sum_{j \in J} L_{kj} y_{rj} \leq y_{rk} \text{ for } r = 1, 2, \ldots, s \quad \textbf{(Equation 3.78)}$$

$$L_{kj} \geq 0 \text{ for } j = 1, 2, \ldots, n \quad \textbf{(Equation 3.79)}$$

The benchmarking method is used to completely ranks efficient DMUs in DEA by evaluating the importance of efficient units as a benchmark for inefficient units. The benchmarking is assessed in a two stage procedure. In the first stage, the additive model is used to analyze the value of the slacks. The efficient units set represented by V have slack values of zero. In the second stage a benchmark measure ρ_k^r showing the total accumulated possible increase in output r is calculated. Then the average value of ρ_k is computed in order to rank all efficient DMUs entirely.

The multivariate statistical method is presented as an alternative approach in the literature incorporating utilization of statistical techniques in relationship with DEA to accomplish a full ranking. The main intention of this methodology is to converge the DEA method and the classical statistical approaches.

The concept of ranking inefficient units proposed to rank inefficient units utilizing a Measure of Inefficiency Dominance (MID) (Adler, Friedman, & Sinuany-

Stern, 2002). By using the MID index, the method only ranks the inefficient DMUs with respect to their mean proportionate inefficiency in all inputs and outputs. Nevertheless, similar to the benchmarking approach which only ranks the efficient units, the MID index method only ranks the inefficient units which cannot grant entire ranking.

In the frame of launch vehicle selection problem, super-efficiency method is utilized to overcome the shortcomings of classical DEA.

3.6 Overview of the Fuzzy Set Theory

Fuzzy set theory was proposed by Lofti A. Zadeh in 1965 to deal with the vagueness in information and the essential fuzziness of human judgment/preference (Zadeh L. , Fuzzy sets, 1965). Since then, he theory of fuzzy sets has progressed in several disciplines such as in artificial intelligence, expert systems, control engineering, computer science, medicine, decision theory, operations research, management science, robotics and pattern recognition, etc.

Researchers working in the field of decision making also utilized the concept of fuzzy sets since the attainable information in the process of MCDM is generally imprecise, uncertain, or vague and the defined criteria are not necessarily independent (Yang, Chiu, Tzeng, & Yeh, 2008).

The membership functions are utilized to delineate the fuzzy sets. The fuzzy sets depict the level of any member x of X that have the partial membership to set A. The membership degree of an unit belongs to a set is defined by the value between 0 and 1. If an element x really belongs to set $A, \mu_A(x)=1$, otherwise $\mu_A(x)=0$. The higher membership value μ means, the belongingness of an element x to a set *A* is greater (Zimmermann H. , Fuzzy Set Theory, 2010) A tilde is put above a symbol if it represents a fuzzy set.

Linguistic variables are variables whose values are words or sentences in a natural or artificial language (Zadeh L. , The concept of a linguistic variable and its application to approximate reasoning, 1975). Linguistic descriptions, such as expressing skill degrees for an expert, can be best coded in fuzzy terms by using linguistic variables (Daş & Göçken, 2014). Thus, in this study linguistic variables are used to evaluate the launch vehicles with respect to the established criteria set.

A linguistic variable is characterized by a quintuple representation $(x, T(x), U, G, \tilde{M})$ in which

1. x represents the variable,
2. $T(x)$ indicates the set of linguistic values of x.
3. Each of these values is a fuzzy variable, symbolized generally by X and extending over a domain of U, which is related with the base variable u
4. G is a syntactical rule for generating the name, X, of values of x.
5. M is a semantical rule to associate with each X and its meaning.
6. $\tilde{M}(x)$ is a fuzzy subset of U (Kahraman, Demirel, Demirel, & Ates, 2008)·

The linguistic variables to represent 'age' is illustrated in Figure 3-7 (Zadeh L. , 1973).

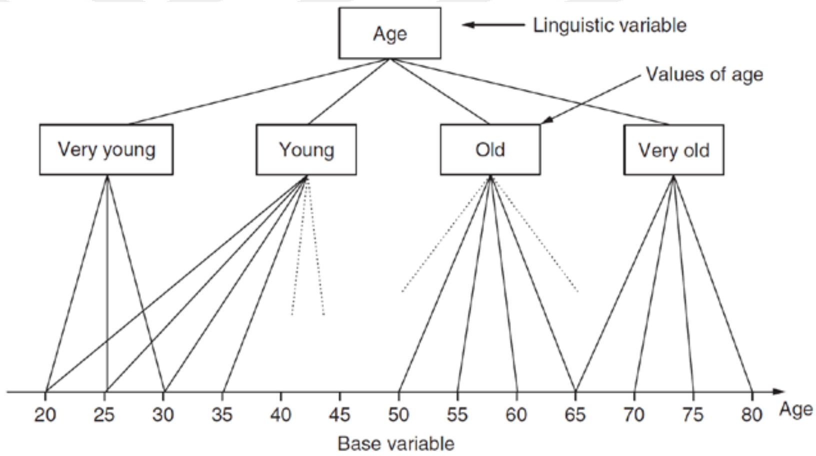


Figure 3.7: Linguistic variable for age ((Zadeh L. , 1973), (Zimmermann H. , Fuzzy Set Theory, 2010)).

Linguistic variables could be represented by triangular or trapezoidal fuzzy numbers.

3.6.1 Trapezoidal Fuzzy Numbers

A trapezoidal number $\tilde{a}$ is represented by $[a_1, a_2, a_3, a_4]$, and has the membership function $\mu_{\tilde{a}}(a)$ as given below;

$$\mu_{\tilde{a}}(a) = \begin{cases} 0, & a \leq a_1 \\ 1 - \left(\dfrac{a - a_2}{a_1 - a_2} \right)^2, & a_1 \leq a \leq a_2 \\ 1, & a_2 \leq a \leq a_3 \\ 1 - \left(\dfrac{a - a_3}{a_4 - a_3} \right)^2, & a_3 \leq a \leq a_4 \\ 0, & otherwise \end{cases}$$ **(Equation 3.80)**

The geometric demonstration and membership function of a trapezoidal number is illustrated in Figure 3-8.

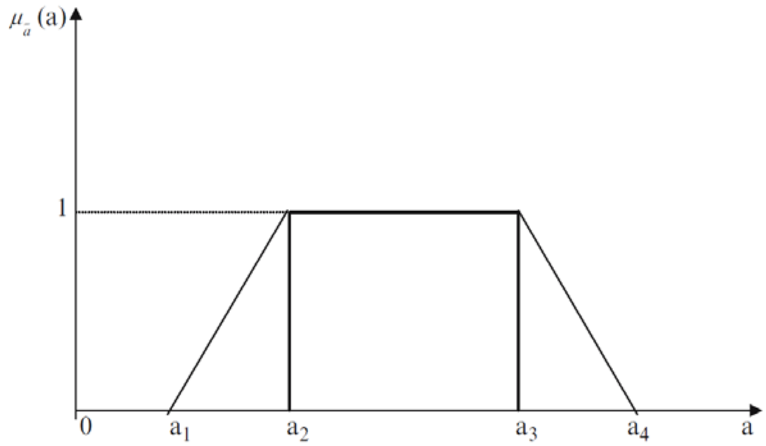


Figure 3.8: Membership function of a trapezoidal number.

3.6.2 Triangular Fuzzy Numbers

A triangular fuzzy number is represented by $(l,\ m,\ u)$. The membership function of a triangular fuzzy number is denoted as follows:

$$\mu_A(x) = \begin{Bmatrix} \frac{(x-l)}{(m-l)}, l \le x \le m \\ \frac{(u-x)}{(u-m)}, m \le x \le u \\ 0, otherwise \end{Bmatrix}$$ **(Equation 3.81)**

where,

1. m is the most plausible value of a fuzzy number in set A,
2. l is the lower bound,
3. u is the upper bound.

3.7 Fuzzy DEA Methods

The classical DEA methods generally consider precise measurement of inputs and outputs, which are expressed in crisp values. Nevertheless, in real life problems, the perceived values of the input and output data are occasionally vague or inaccurate inherent in the information. To deal with such decision situations, different version of fuzzy methods has been proposed by the researchers to handle this ambiguity and impreciseness in DEA model.

Bellman and Zadeh (1970) and Zimmermann (1978) introduced the fuzzy sets into the MCDM field. With this advancement, new methods are emerged to take care of issues that had been unattainable and irresoluble with classical MCDM techniques.

The DEA models having fuzzy input and/or fuzzy output data are called “fuzzy DEA" models. Fuzzy DEA models represent real life problems more realistically compare to the classical DEA models. Fuzzy DEA models could be solved with fuzzy linear programming method.

The primal and its dual fuzzy input-oriented CCR models is formulated in Table 3-6 where $\tilde{x}_{ij}$ is the fuzzy input i consumed by $DMU-j$ and $\tilde{y}_{rj}$ is the fuzzy output r produced by $DMU-j$, v_i and u_r are the input and output weights assigned to the i^{th} input and r^{th} output in Dual CCR Model (Emrouznejad, Tavana, & Hatami-Marbini, The State of the Art in Fuzzy Data Envelopment Analysis, 2014).

Table 3.6: Fuzzy primal and dual CCR model (input oriented).

Input; $(\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m)$ Output; $(\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_m)$ DMUs; $(j = 1, 2, ..., n)$	
Fuzzy Primal CCR model	Fuzzy Dual CCR Model
$\min \theta_p$	$\max w_p = \sum_{r=1}^{s} u_r \tilde{y}_{rp}$
Subject to the; $\sum_{j=1}^{n} \lambda_j \tilde{x}_{ij} \leq \theta_p \tilde{x}_{ip}, \quad \forall \mathrm{i}$ $\sum_{j=1}^{n} \lambda_j \tilde{y}_{rj} \geq \tilde{y}_{rp}, \quad \forall \mathrm{r}$ $\lambda_j \geq 0, \quad \forall j$	Subject to the; $\sum_{i=1}^{m} v_i \tilde{x}_{ip} = 1,$ $\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{rj} \leq 0, \quad \forall j$ $u_r, v_i \geq 0, \quad \forall r, i$

In order to establish fuzzy BCC model, the constraint $\sum_{j=1}^{n} \lambda_j = 1,$ is incorporated into the CCR model as shown in Table 3-7 (Emrouznejad, Tavana, & Hatami-Marbini, The State of the Art in Fuzzy Data Envelopment Analysis, 2014).

Table 3.7: Fuzzy primal and dual BCC model (input oriented).

Input; $(\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m)$ Output; $(\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_m)$ DMUs; $(j = 1, 2, ..., n)$	
Fuzzy Primal BCC model	Fuzzy Dual BCC Model
$\min \theta_p$	$\max w_p = \sum_{r=1}^{s} u_r \tilde{y}_{rp} + u_0$
Subject to the; $\sum_{j=1}^{n} \lambda_j \tilde{x}_{ij} \leq \theta_p \tilde{x}_{ip}, \quad \forall \mathrm{i}$ $\sum_{j=1}^{n} \lambda_j \tilde{y}_{rj} \geq \tilde{y}_{rp}, \quad \forall \mathrm{r}$ $\sum_{j=1}^{n} \lambda_j = 1,$ $\lambda_j \geq 0, \quad \forall j$	Subject to the; $\sum_{i=1}^{m} v_i \tilde{x}_{ip} = 1,$ $\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} + u_0 \leq 0, \quad \forall j$ $u_r, v_i \geq 0, \quad \forall r, i$

The fuzzy DEA models cannot be solved by a standard linear programming method like a crisp DEA model since coefficients of the fuzzy DEA model are fuzzy sets. Thus, different methods are proposed to solve these models. These are; (i) tolerance approach, (ii) possibility approach (iii) α-level based approach (iv) fuzzy ranking approach and (v) defuzzification approach (Hatami-Marbini, Emrouznejad, & Tavana, 2011) (Angiz, Emrouznejad, & Mustafa, 2012).

Each of aforementioned proposed fuzzy DEA approaches to solve the fuzzy models has both benefits and inadequacies. For instances, the tolerance approach fuzzifies the inequality or equality signs however it does not handle fuzzy coefficients directly (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

The defuzzification approach is straightforward. However, the uncertainty in inputs and outputs is not thoroughlytaken into account (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

The α-level based approach comes up with fuzzy efficiency thus requires the ranking of fuzzy efficiency sets (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

The fuzzy ranking approach provides fuzzy efficiency for an evaluated DMU at a specified level in which Guo and Tanaka (2001) compare fuzzy efficiencies using only one number at a given level in their study where the possible range off fuzzy efficiency is ignored at that level (Lertworasirikula, Fanga, Joines, & Nuttle, 2003).

In this study, defuzzification method is utilized to solve fuzzy DEA models. The defuzzification approach was developed by (Lertworasirikul S. , 2002). While applying this method first the fuzzy inputs and the fuzzy outputs are first defuzzified into crisp values. Then utilizing these crisp values, obtained crisp model is solved by an LP solver.

For the defuzzification, five frequently employed defuzzification methods are utilized as listed below (Lertworasirikul S. , 2002);

1. center of area (COA) method,
2. max-min method,
3. max-max method,
4. mean of maxima (MOM) method and
5. α-cut method.

In the frame of thesis study, α-cut method is utilized as a defuzzification method. The α-cut method is noted as inclusion of the decision maker's confidence over his/her preference or the judgements (Prakash, 2003). Using this approach, ambiguity in decision maker's knowledge could be incorporated into the model using the optimism index (λ) which expresses the decision maker's attitude on the matter under consideration.

The α-cut values are between 0 to 1. If the α-cut is 1, then the decision-maker is highly confident about the assessment on a phenomenon. Then, in the fuzzy performance set, the outcome is being a single value having the membership of 1. In this case, no the further steps are needed. However, when the α- cut value is less than 1, this means that the decision-maker is evidently uncertain about the decision. When the α-cut value is zero, this indicates the highest level of uncertainty (Prakash, 2003).

The α -cut results in an interval set of values from a fuzzy number. For instance, an $\alpha = 0.5$ will yield a set $\alpha_{0.5}$ = [0.3, 0.4, 0.5, 0.6, 0.7]. The operation is illustrated below in Figure 3-9.

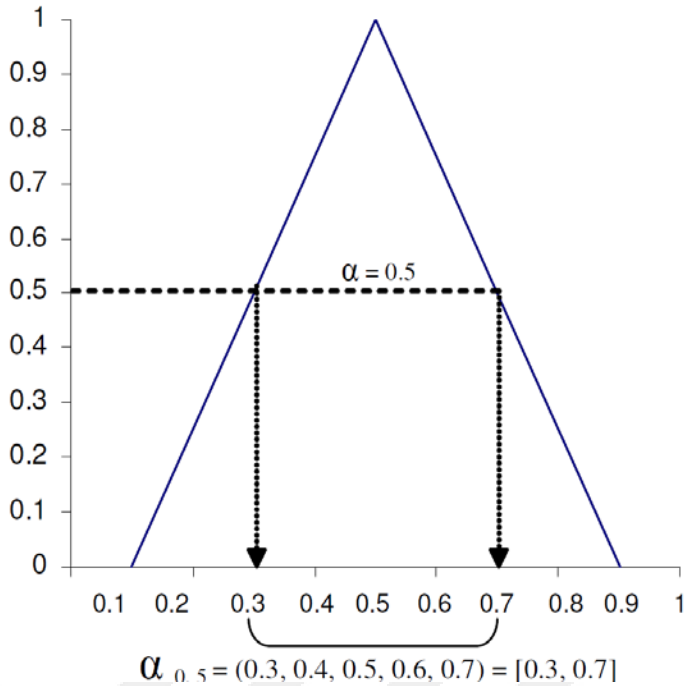


Figure 3.9: Alpha cut representation of a triangular fuzzy number (Prakash, 2003).

The crisp performance matrix is acquired by utilizing the optimum index (λ) and the α value. The following formulation for the defuzzification of a triangular fuzzy number is employed by Hsu & Nian, (1997) and Liou & Wang, (1992) and also quoted and utilized by (Özbek, 2014).

$$
\begin{aligned}
& a_{ij}^{\alpha} = [\lambda . L_{ij}^{\alpha} + (1-\lambda). U_{ij}^{\alpha}] \\
& where, \\
& L_{ij}^{\alpha} = (M_{ij} - L_{ij}).\alpha + L_{ij} \\
& U_{ij}^{\alpha} = U_{ij} - (U_{ij} - M_{ij}).\alpha \\
& \lambda = [0,1] \\
& \alpha = [0,1]
\end{aligned}
\qquad \textbf{(Equation 3.82)}
$$

CHAPTER FOUR

OVERVIEW OF GEOSTATIONARY COMMUNICATION SATELLITES AND LAUNCH VEHICLES

This chapter presents synopsis of the geostationary communication satellite fundamentals and the launch vehicles which are being utilized to boost the satellites into space. A summary of the general characteristic of available launch vehicles available in the market is also included.

4.1 Geostationary Communication Satellites

The world's first artificial satellite was launched in 1957 by the Soviet Union. The satellite, which is called Sputnik-I, revealed a new era for practical utilization of the outer space. Following to the launch of Sputnik-I, in 1958, United States' Explorer-I satellite was launched successfully. Even though these satellites were essentially not intended for communication purpose, it is demonstrated that an artificial satellite is technically and economically feasible.

The utilization of satellites in orbits is now a well-integrated as part of current the world's telecommunications network. The evolution of the technology in space field along with introduction of more powerful launchers in the market have render the satellites suitable for various objective including television broadcasting, national communications and mobile services.

The communication satellite system is essentially divided into two major parts, which are designated as the earth or ground section and the space segment. The space segment consists of the satellite itself, while the earth portion includes the satellite control station and the transmission control stations.

The satellite control station sustains the satellite in desired orbital positon. It maintains control of the satellite health status, orbital control with attitude maneuvers to retain required mission and configures the communication payload system.

The communication subsystem of the satellite system works as a radio system with a repeater relay implanted on the satellite. The signals are broadcasted on a carrier frequency from earth uplink center received by the satellite antenna system, amplified, shifted in frequency to desired downlink frequency range and transmitted back to the earth.

The communication satellite transmits and receives signals mainly in the microwave frequencies band in 3 - 30 GHz range. In these frequency ranges, the parabolic reflector antennas are used. The parabolic antennas concentrate the radio signals in a small cone, therefore it is possible to broadcast to large areas in the earth. The illuminated part is called the coverage area or footprint, and most of the transmitted power from the satellite is concentrated in this area (Guteberg, 1994).

4.2 A Brief Historical Review of Satellite

The utilization of the geostationary orbit for communication satellites was suggested by the English physicist Arthur C Clark who was born 1917. He published an article, in 1945, on “Extra-Terrestrial Relays” in the Wireless World Magazine. In the article a satellite broadcasting system for television was delineated. At that time there was an ongoing discussion on distribution of television signals. The existing technology was not mature enough for the establishment of reliable satellites.

The space era initiated in 1957 with the launching of the first artificial satellite called Sputnik-I. The first trans-Atlantic telephone cable was also stretched in the same year. In the subsequent years, several satellites were launched for both scientific purposes and also for specific applications.

The first telecommunication satellites were launched in the early 1960s. The satellite called Courier was launched in 1960, the Telstar-I and -II satellites in 1962 and 1963 and Relay-I and -II satellites in 1962 and 1964 respectively. They were all placed into low earth orbits where the altitude varying between 1000 and 8000 km. Telstar-I satellite was transmitted television signals directly from America to England and France as a novelty.

In 1963, the first geostationary orbit satellite called Syncom-II was launched. The launch of first geostationary satellite was a significant break- through for satellite communication in commercial business.

In 1965, the first commercial geostationary satellite, Early Bird, was placed in a position over the Atlantic Ocean (Guteberg, 1994).

4.3 Utilization of the Communication Satellites

The main objective of a communication satellite is simply to receive radio signals from earth station and re-transmit amplified signals to wide geography within the coverage area.

One of the most prominent application of satellite communication is television broadcasting and data transmission. In order to initiate satellite communication, significant investment is required in earth stations with large size antennas along with related data and radio frequency processing equipment.

The rapid development in the satellite technology and the use of more powerful launch vehicles has led to the utilization of satellite systems in more restricted areas (Guteberg, 1994).

Satellite communications now establish an indispensable part of our new world. Since its introduction in 1965, satellite communications have prompted abundance of global or regional telecommunication services. The satellite communications have enabled a global and automatically-switched telephone network to be devised. Although, since 1956, submarine cables commenced to connect the continents with available telephony circuits, reliable communication links for television, telephone and data transmission is only accommodated by the satellite communications which is being provided against any terrestrial obstacles. The specific characteristics of a satellite communication can be summarized as follows;

1. multiple access capability, for instance, point-to-point, point-to-multipoint or multipoint-to-multipoint connectivity, in particular for business or private communications networks or rural communications.
2. distribution capability for instance, point-to-multipoint transmission including TV program broadcasting and other video and multimedia applications, data distribution (e.g. for business services, wideband internet services, etc.) and flexibility for changes in traffic and in network architecture and also ease of operation and putting into service (Handbook on Satellite Communication).

4.4 Launch Vehicles and Alternatives

In the 1950s, the first launch systems were developed by government agencies to boost satellites into orbits for satellite communication and surveillance systems into Low-Earth orbits which have approximately 150-200 km altitude above the atmosphere. The initial version of most of the launchers were derived from the intercontinental ballistic missiles at that time.

In the 1960s, the development of powerful rockets is advanced by the space exploration programs associated with flights to the Moon and planets which are more capable of inserting higher masses into the geostationary orbit, called as the Geo Synchronous/Stationary Orbit (GSO) which has 35786 km altitude above the atmosphere.

In the 1970s, the extensive utilization of GSO communication satellites commenced and has continued progressively to the present time.

Currently various kind of launchers in several classes are available for different mission such as inter- planetary, surveillance, meteorological, scientific, etc.

The essential requirements for the selection of a launch system are; (i) lift capability to the desired orbit, (ii) availability of the launch vehicle following to satellite construction phase and (iii) cost of the services. In the past, the alternatives have been quite limited and negotiations have usually been coordinated with government agencies. Nowadays, a new era has advanced in which variety of launch vehicles are available commercially by involving private corporations and government organizations. The launch industry is growing rapidly and new performance capabilities and services are faithfully being promoted (Handbook on Satellite Communication).

In order to reach the geostationary orbit, the satellite must be accelerated to 3.075 km/s at an altitude of approximately 36000 km with zero inclination. The operation of launching satellite is comprised of multistage capability of a launch vehicle.

The launch vehicles are fundamentally divided into two groups as (i) Expandable Launch Vehicles (ELVs) and (ii) Reusable Launch Vehicles (RLVs).

ELVs are intended for one-time utilization which typically segregated from their payload, and take apart during atmospheric reentry. An ELV is composed of one or more rocket stages. After each stage has completed its mission, it is jettisoned from the vehicle and return back to Earth (Jain & Trost, 2013). The components of the ELV are not designed to reuse after recovery.

RLVs are designed is such a way that some stages to be recuperated and utilized again for succeeding launches such as the Space Shuttle which was only a Partly Reusable Launch Vehicle (Jain & Trost, 2013).

In the following Table 4-1, Geostationary Transfer Orbit (GTO) launch vehicle alternatives available in the market are summarized with their brief technical prominent characteristics.

Table 4.1: Launch vehicles summary.

Vehicle	Delta IV Medium+ (5,4)	Atlas V 401	Atlas V 501	Falcon 9 v.1.1	Zenit 3SL	Soyuz 2	Proton M	Ariane 5 ECA	Soyuz 2	Long March 3B	H-IIA	PSLV XL
Country/Region	USA	USA	USA	USA	Multinational	Russia	Russia	Europe	Europe	China	Japan	India
2013 Total Launches	2	5	1	2	1	5	10	4	2	3	1	1
Launch Reliability (2013)	2/2 100%	5/5 100%	1/1 100%	2/2 100%	0/1 0%	5/5 100%	9/10 90%	4/4 100%	2/2	3/3 100%	1/1 100%	1/1 100%
Launch Reliability (Last 10 Years)	4/4 100%	18/18 100%	5/5 100%	2/2 100%	23/25 92%	17/19 89%	69/77 90%	38/39 97%	6/6 100%	21/21 100%	20/21 95%	2/2 100%
Year of First Launch	2009	2002	2010	2013	1999	2004	2001	2002	2011	1996	2001	2012
Active Launch Sites	CCAFS, VAFB	CCAFS, VAFB	CCAFS, VAFB	CCAFS, VAFB	Odyssey Pacific Ocean Platform	Baikonur, Plesetsk	Baikonur	Kourou	Kourou	Xichang	Tanegashima	Satish Dhawan
LEO kg (lbs)	13,774 (30,365)	9,797 (21,598)	8,123 (17,908)	13,150 (28,991)	--	4,850 (10,692)	23,000 (50,706)	21,000 (46,297)	4,850 (10,692)	--	10,000 (23,046)	1,800 (3,968)
GTO kg (lbs)	7,434 (16,389)	4,750 (10,470)	3,775 (8,320)	4,850 (10,692)	6,160 (13,580)	1,700 (3,800)	6,920 (15,256)	9,500 (20,944)	3,250 (7,165)	5,100 (11,244)	6,000 (13,228)	1,140 (2,513)

(Federal Aviation Agency-FAA, 2013)

CHAPTER FIVE

LAUNCH VEHICLE SELECTION PROBLEM

The selection of the launch vehicle is a significant decision for the commercial satellite operators. The commercial satellite operators consider variety of factors while determining the launch vehicle for placing their satellites into desired orbit such as vehicle’s flight heritage, reliability rate, launcher performance, cost, availability, suitability, schedule flexibility, government regulations and program management aspects. These factors are considered in order to establish the criteria hierarchy presented in the following section.

In this study, commercially available selected launch vehicle alternatives (presented CHAPTER 4) re ranked for a geostationary communication satellite and the outcomes are compared by using different well known MCDM methods and DEA techniques.

It is acknowledged that the ranking result might differentiate for conventional MCDM methods if the weights of the criteria will be changed depending upon the ultimate objectives and priorities of decision maker authority. This is quite conceivable since the main objective of a satellite that would be launched could vary. The aim of such a mission could be expanding the market opportunities, replacing the existing satellite in the shortest time period, protection orbital slot frequency right or a joint venture project of different operators. In each different case, the weights of the considered criteria might change. For instance, if placing the satellite in shortest time is required, criteria related to the schedule, availability and reliability would have the highest priority. Whereas performance related criteria would become more dominant, if the target is to expand the market opportunities without urgent need.

On the other hand, DEA come into prominence as a non-parametric linear programming based mathematical method. In DEA implementation, the weighing of criteria is not required due to the nature of the methodology. Only input and outputs are determined and their numerical values are supplied to the mathematical model. In this study, various variants of DEA method are implemented to check the consistency of the outcomes relative to the conventional MCDM methods.

5.1 Collecting Data

In the frame of this study, five launch vehicle alternatives called A1, A2, …, A5 are evaluated.

Each alternative is appraised based on the established criteria set by four senior experts working in the satellite and launch systems engineering department. These experts have been working in the industry for at least 10 years.

Data for criteria such as cost, reliability etc., is obtained from related sources and the launcher authorities Other criteria which requires expert evaluation is s collected in two formats as crisp and fuzzy.

The crisp data is obtained using the Saaty’s Rating Scale from 1 to 9 as given in Table 5-1.

Table 5.1: Saaty’s rating scale.

Intensity of importance	Definition for weight values	Definition for performance values	Explanation
1	Equal importance	Very Bad (Very Less)	Two factors contribute equally to the objective
3	Somewhat more important	Bad (Less)	Experience and judgement slightly
5	Much more important	Fair	Experience and judgement strongly
7	Very much more important (Very Strong)	Good (Much)	Experience and judgement very strongly favour one over the
9	Absolutely more important.	Very Good (Very Much)	The evidence favoring one over the other is of
2,4,6,8	Intermediate values		When compromise is needed

To obtain fuzzy data linguistic variables are utilized. Four linguistic variables namely Very Good (VG), Good (G), Fair (F) and Bad (B) are used by the experts. Depending on the criteria, equivalent linguistic variables Very Much (VM), Much (M), Fair and Less (L) are also used. These linguistic variables and their corresponding membership functions which are firstly used by Prakash (2003) are presented in Table 5-2.

Table 5.2: Linguistic variables and membership functions.

Linguistic Variable	Fuzzy TFN
Bad (B)	(1, 3, 5)
Fair	(3, 5, 7)
Good	(5, 7, 9)
Very Good	(7, 9, 11)

The schematic demonstration of the membership functions of the utilized linguistic variables are given in Figure 5-1.

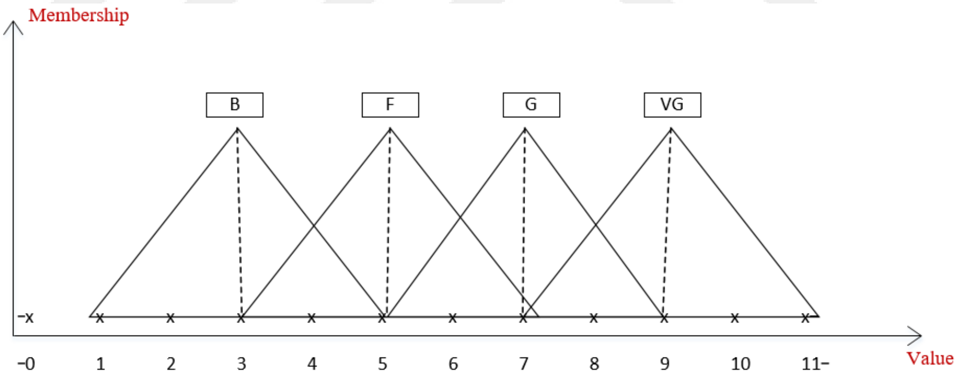


Figure 5.1: Membership function of the linguistic variables.

5.2 Criteria Hierarchy

In the frame of this study, the following criteria are utilized to evaluate the launch vehicle alternatives;

1. Flight Heritage (FH)
   a. Number of Total Launch (FH1)
   b. Number of Last Consecutive Successful Launch (FH2)
2. Reliability Rate (R)

3. Cost (M$ per launch) (C)
4. Launcher Performance (LP)
5. Availability and Schedule (AS)
   a. Number of Launches per Year (AS1)
   b. Solidity to External Factors (AS2)
6. Government Regulations (GR)
7. Programmatic Factors (PF)
   a. Access to Information and Work in Progress (PF1)
   b. Schedule Control and Failure Management (PF2)

The presented criteria set consist of the 7 main and 6 sub criteria. The criteria of “Number of Total Launch” and “Number of Last Consecutive Successful Launch” under the “Flight Heritage” criteria, “Reliability Rate”, “Cost” per launch, “Launcher Performance”, “Number of Launches per Year” sub criteria under the “Availability and Schedule” criteria are based on the objective data. Rest of the criteria are categorized as subjective. Data for subjective criteria is obtained from experts by considering the satellite projects’ vital facet.

5.2.1 Flight Heritage

Flight Heritage refers to the extensive records of historical launch data back to the earliest launch vehicles inherited from the past. Under the repercussion of high demand in the space industry, most of the launcher rockets have been evolved from the national ballistic missile programs to the space launch vehicles.

While evaluating the flight heritage criteria data for “Number of Total Launch” and “Number of Last Consecutive Successful Launch” sub criteria are being obtained from the historical data sourced by the launch vehicle statistics as of end of 2015 (Kyle, 2015).

Number of Total Launch corresponds to the accumulative number of flights since the maiden flight of the same configuration of a given launch vehicle.

Number of Last Consecutive Successful Launch points out the most recent total number of back to back successful launches of a launch vehicle configuration under consideration.

5.2.2 Reliability Rate

The reliability of a launch vehicle is state of having moderate risk of technical failure based upon historical events of prior mission success (Federal Aviation Agency-FAA, 2001). The reliability of launcher is one of the most important factors that should be considered in appraising a launch vehicle

The launcher credibility is a critical fact since a reliable launch vehicle would strengthen the prospect that payloads will reach designed orbit properly. In the case of a novel satellite undertaking, a launch vehicle failure could significantly affect the existence of the company in the market.

If a satellite operator could not replace its old satellite in timely manner, the existing broadcasting on the satellite mi be interrupted. This situation would affect the reputation of the company in the market and affect the potential revenues. Therefore, satellite operators are disposed to place great prominence on flight provability of the launch vehicle. For a satellite operator, a launch vehicle is assumed to be provable, if it has an affirmative record of launch success. In addition to the credibility factor, other essential factors while selecting launch vehicle for flying payloads would be viability and risk free proneness (Federal Aviation Agency-FAA, 2001).

In order to calculate the reliability rate of the launch vehicle alternatives, the numbers of successful launches, failures and partial failures have been evaluated based on the launch vehicle statistics for 2015 (Kyle, 2015).

5.2.3 Cost

The cost of a launcher rocket is another significant factor in launch vehicle selection problem. The launcher price constitutes roughly 20 to 40 percent of a total cost of satellite project including insurance cost. Therefore, the cost of launcher is a major consideration in the course of selection process. If the price of a launch service is found to be attractive compared to other alternatives, then it quickly gains popularity in the market. Most of time a notable increase in launch vehicle prices would have an influence on satellite operators' rate of growth or replacement of satellites, which could potentially shoot them out of business (Federal Aviation Agency-FAA, 2001).

In this study, the price of the rockets for launching an approximately 5-ton class geostationary communication satellite is utilized. (Space Exploration Technologies Corp, 2014; Futron, 2002; Jain & Trost, 2013).

5.2.4 Launcher Performance

The launch vehicle's performance is also a prominent factor in launcher selection.

Performance of a launcher rocket consists of its lifting capability of a certain mass to a desired altitude above the Earth and its capability to place in its payloads into the right orbit (Federal Aviation Agency-FAA, 2001).

The launcher is a major design driver factor for a satellite as well. The launcher prompts the configuration of the satellite since it determines;

(i) the available volume for accommodating the stowed configuration with the shape and size of the interface between the satellite and the launcher,

(ii) the launch loads and the resulting stiffness and strength requirements that will define almost all the structural elements design requirements,

(iii) the allowable satellite launch mass and the location of the satellite center of mass (Aguirre, 2013).

The satellite operators are interested in the boost capability of a launch vehicle which corresponds competence of the vehicle to raise certain amount of mass to space. Most of the customers of a launcher seek high capacity vehicle since recently ordered satellites are getting progressively heavier. In addition to that it is desired to rise up a satellite to a high altitude close to the designated orbit in order to get longer orbital maneuver life of the satellite.

5.2.5 Availability and Schedule

With increasing market trends, it becomes important to select a launcher rocket whose accessibility is consistent with satellite operator's preferred launch schedule. In the ideal case, the satellite should have launched as soon as its manufacturing and testing on ground are completed. It should be launched in a timely manner in order to start the commercial activities as quick as possible.

Since the available launch opportunity in a year is limited depending upon the selected launcher, it becomes important to have some flexibility on assignment of the launch slot. In addition to that, it is also expected by the customer to keep the given slot firmly without getting impacted from other disturbances.

In this perspective, this criterion is related with the possible number of launches per year and robustness of the launcher authority to protect the assigned launch slot.

During the evaluation, “Number of Launches per Year” and “Solidity to External Factor” criteria are considered as a sub criterion of “Availability and Schedule”.

Number of Launches per year is considered as a sub-criterion under the “Availability and Schedule” criteria. The launch vehicle providers should provide extended number of launch opportunities throughout a year. The possible number of launches depends on the manufacturing capacity of the production plant and the number of payload that can be processed in their launch complex facilities each year. For instance, in a launch complex, it could take a couple of weeks to integrate a satellite whereas in another launch complex this could take months due to the specific processes.

Solidity to external factors is another sub-criterion under the “Availability and Schedule” criteria. There is a certain amount of launcher authority in the world. Most of them are related with national agencies and governments. Therefore, in some occasions, the priority of a launch might be given to a government related project. By considering this fact, the satellite operators certainly expect the launcher authorities to keep their launch manifest firmly without being affected from outside sources.

5.2.6 Government Regulations

Government export regulations and technology exchange provisions are becoming a major consideration for satellite operators’ during the launcher selection.

For instance, before a United States based launcher authority trade the technical information with another satellite client outside US, a license for marketing must be obtained from the State Department. Then the launcher authority has to secure additional government license, known as Technical Assistance Agreement

(Federal Aviation Agency-FAA, 2001). The process of obtaining these licenses usually takes months.

There are other issues for the Chinese launcher authority inline the sanctions applied by the United States government. In general, Chinese rockets are commercially available in the market. However, in the recent years, the United States government regulations imply some restrictions to the launch of U.S. manufactured satellite by a Chinese Launcher (Federal Aviation Agency-FAA, 2001). The sanctions are also applied to any satellite manufactured by other international satellite manufacturers with employing U.S. based hardware onboard. These restrictions seriously diminish the number of commercial satellite launches by Chinese Launcher, despite the fact that it is still available in the market.

5.2.7 Programmatic Factors

When running the project, customer relations instituted with a launch service provider is a critical factor. Since it takes several years to complete a satellite project, the program management aspect becomes an important factor for satellite operators. Thus, professionalism on the program management throughout the project duration should considered as a decision criterion.

During the evaluation, “Access to Information and Work in Progress” and “Schedule Control and Failure Management” criteria considered as a sub criterion of “Programmatic Factors”.

Access to Information and Work in Progress criterion is related with the amount of technical information that a customer could reach throughout the project. Since manufacturing of a launch vehicle is a strategical capability for a nation, launcher authorities share limited technical information with the commercial customer in the frame of the project. Depending on the willingness of a customer to access such technical information, this becomes an important factor.

Customer relations on “access to information and work in progress” refer to the culture of a business on how it communicates and interacts with various parties in the project. For any business, it is necessary to cultivate high quality customer relations to attract customers and to keep a loyal base of customers. It is essential to establish a pleasure relation during both procurement and project execution stages of launch vehicle program.

It is also important for the satellite companies to develop solid and long-term relations with launch providers. Since working with the same provider repetitively can grant a satellite owner the advantages of bulk buying.

Depending upon the launcher authority’s facility access and security rules, the customer and its representatives afford to access to the work being performed under the project. The aim is to observe the quality and progress of the Contractor’s performance during the project.

Schedule Control and Failure Management is another sub-criterion under the “Programmatic Factors” criteria. When launching a satellite, several organizations are involved to the project for different processes such as for satellite manufacturing, launcher manufacturing and launch and transfer orbit operations of the satellite. Thus, schedule control of a project becomes more important when there are several parties involved to the project and various activities are linked to each other.

It is also important to organize and control resources, protocols and procedures to achieve such a mission critical specific goals in launching expensive assets. Failure Management is a due diligence in case of malfunctions of the hardware or ground systems to recover and maintain the progress of launches without losing so much time.

In summary; this study utilizes a decision making scheme, consisting of the 7 main evaluation criteria as defined above, in order to select a launch vehicle for a roughly 5 ton sized geostationary communication satellite. The selection is made among the five commonly utilized launchers as shown in Figure 5-2.

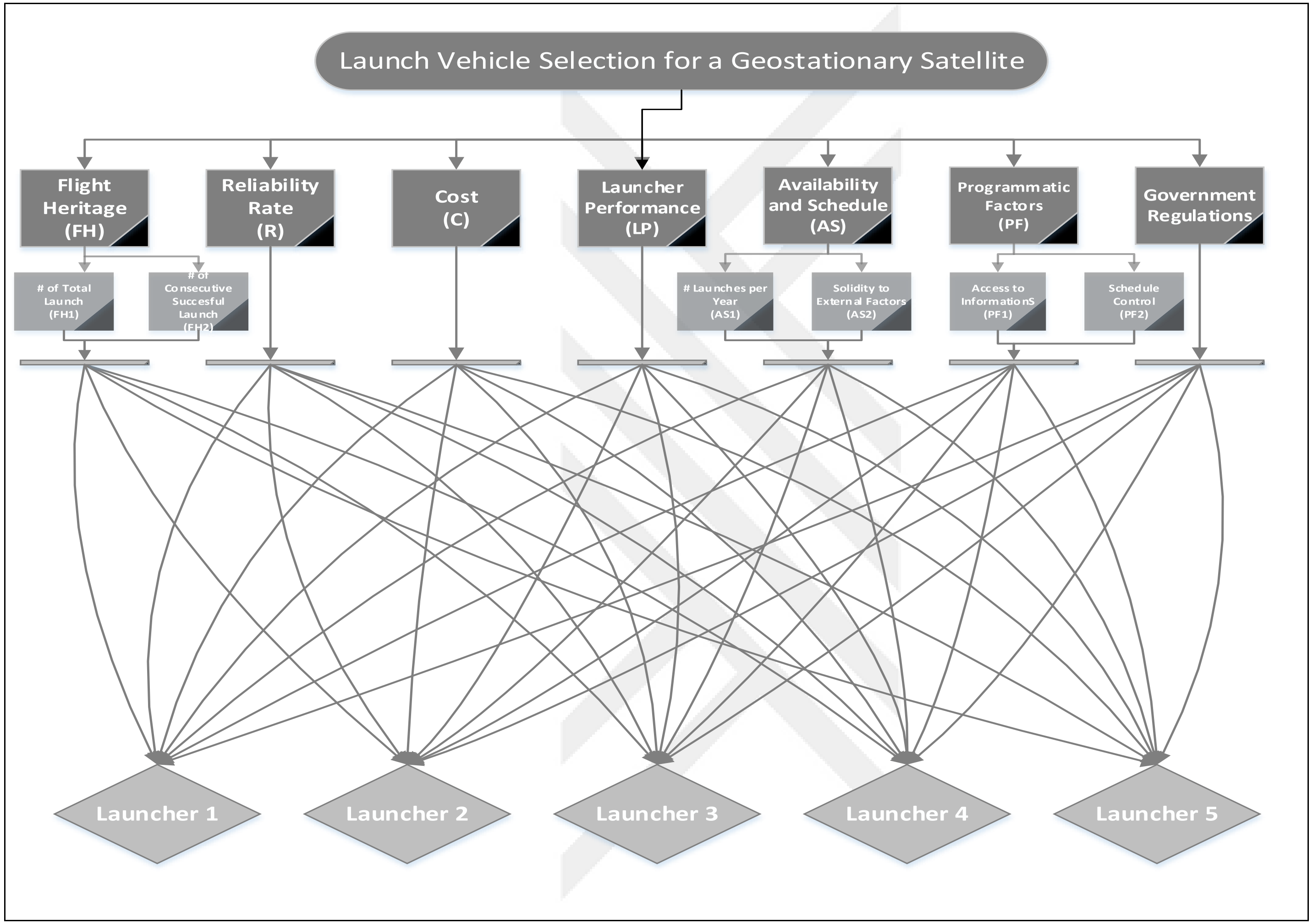


Figure 5.2: Decomposition of the launch vehicle selection problem.

CHAPTER SIX

IMPLEMENTATION OF MCDM METHODS AND DEA FOR LAUCNH VEHICLE SELECTION PROBLEM

In this chapter, the conventional MCDM methods including AHP, ELECTRE, PROMETHEE and variants of DEA are implemented on launch vehicle selection problem. Launch vehicle selection is a decision making problem considering qualitative and quantitative factors. Five launch vehicle alternatives (they are denoted as A1, A2, …, A5 in the applications of the methods) among the commercially available options are considered using the criteria set described in CHAPTER 5.

The flow diagram of the current study is supplied in Figure 6-1.

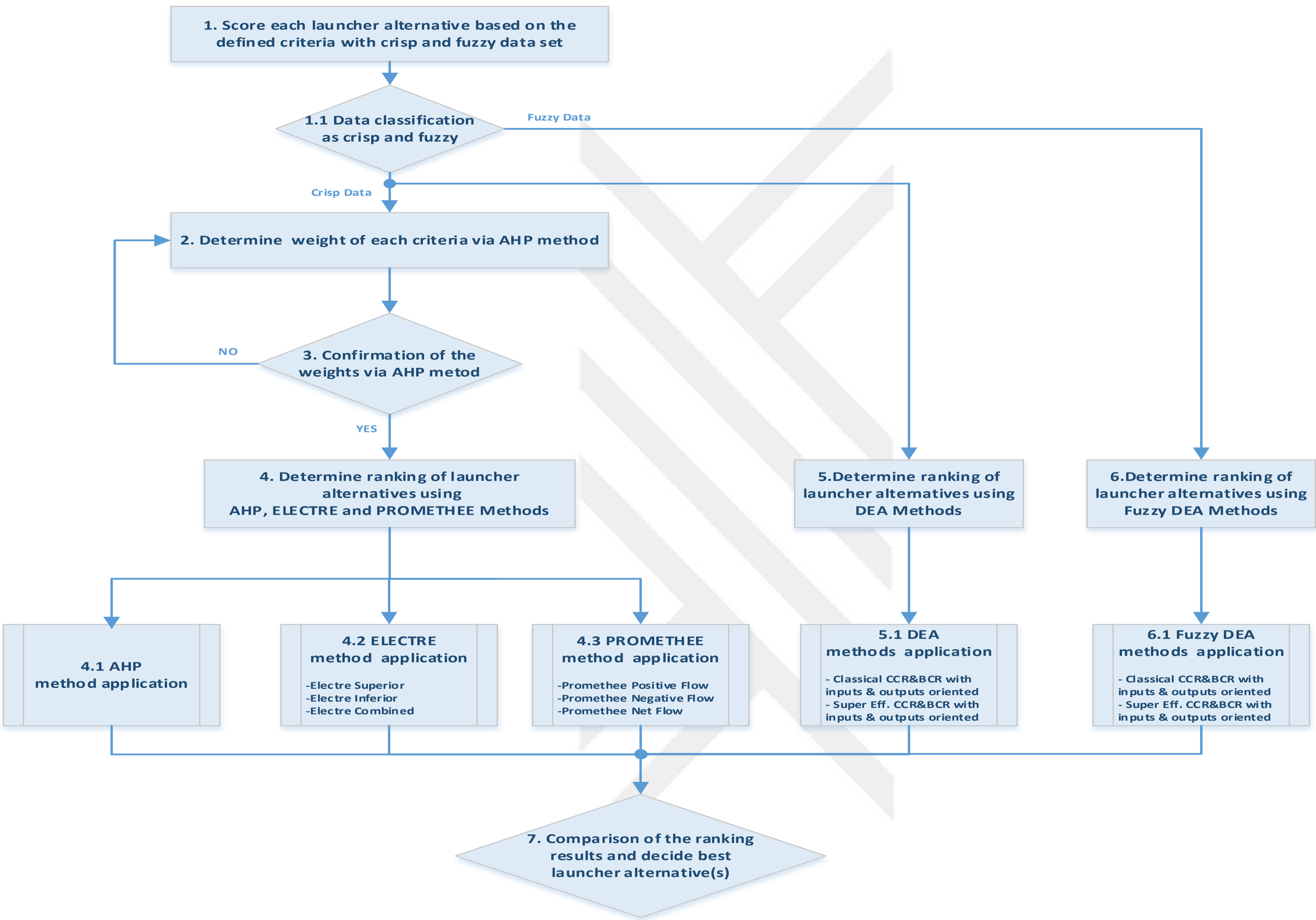


Figure 6.1: Flow chart of the current study.

First, each alternative is evaluated based on the defined criteria set by senior satellite and launch systems engineering experts. The evaluations are made both using crisp and fuzzy data. If the information on hand is tangible such as catalog specification, this data is taken into account directly as crisp data. If the evaluations are based on experts' experience and judgments, this data is collected in two formats both crisp and fuzzy. Fuzzy data is obtained using linguistic variables such as, Very Good (VG), Good (G), Fair (F), Bad (B) for the criteria of "Availability and Schedule" and "Programmatic Factors". To evaluate the "Government Regulations" criteria, Very Much (VM), Much (M), Fair and Less (L) are used. Based on these evaluations, two performance data matrixes are prepared with crisp and fuzzy data.

Then, the weights of each criterion (for the conventional MCDM methods) are defined by the pairwise comparisons offered by the AHP method. After obtaining the weights of each criteria and the evaluations for each alternative; AHP, ELECTRE and PROMETHEE methods are implemented. In addition to conventional MCDM tools, several versions of DEA methods are utilized with crisp and fuzzy data. By using MCDM methods and DEA, ranking of launcher alternatives based on the expert evaluations are obtained. At the end of the process, above mentioned methods are compared and the best alternative is determined for the decision makers. These steps of the flow chart are explained in the following sections.

6.1 Scoring Each Alternative Based on the Defined Criteria

After establishing the criteria set, each launcher alternative is evaluated by senior experts working in this industry for long time with crisp and fuzzy data. To obtain crisp data from experts, Saaty's nine-point scale is used. As for the fuzzy data, linguistic variables which are first used by (Prakash, 2003) are employed (in Table 5-2).

The Saaty's Rating Scale is presented in Table 6-1 and is used for subjective evaluations. Cost and Government Regulations criteria are the cost type (smaller-the-better) criteria; while the rest are the benefit type (bigger-the-better).

Table 6.1: Saaty's rating scale.

Intensity of importance	Definition for weight values	Explanation
1	Equal importance	Two factors contribute equally to the objective
3	Somewhat more important	Experience and judgement slightly
5	Much more important	Experience and judgement strongly
7	Very much more important (Very Strong)	Experience and judgement very strongly favor one over the other.
9	Absolutely more important.	The evidence favoring one over the other is of
2,4,6,8	Intermediate values	When compromise is needed

The membership function of the utilized triangular fuzzy numbers in Table 5-2 that are employed in the grading of the alternatives in this study is given in Figure 6-2.

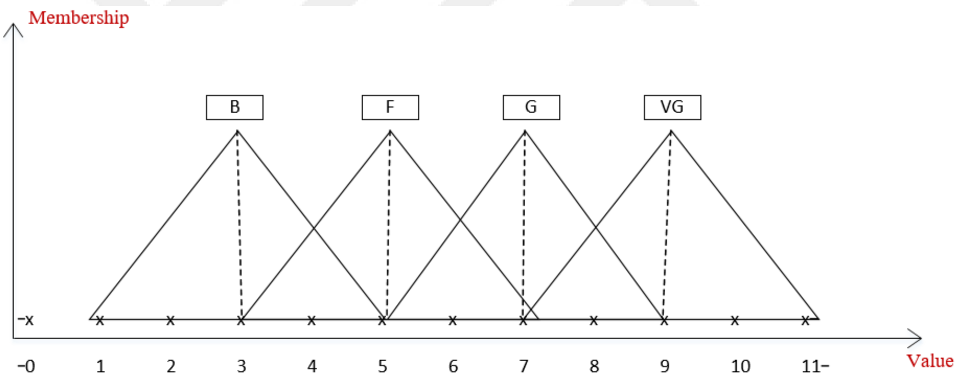


Figure 6.2: Membership function of the TFN in the model.

The score matrixes obtained with crisp and linguistic data are provided in Table 6-2 and Table 6-3 respectively.

Table 6.2: Score data matrix with crisp data.

	FH1	FH2	R	C	LP	AS1	AS2	GR	PF1	PF2
A1	53	52	0.981	$131.00	6.50	10	7	1	9	7
A2	46	32	0.957	$69.23	5.50	6	3	3	1	2
A3	14	1	0.929	$61.20	4.85	12	7	5	7	7
A4	86	4	0.895	$110.15	6.65	12	1	7	3	3
A5	29	23	0.966	$115.00	5.70	8	2	2	3	2

Table 6.3: Score data matrix with crisp and linguistic data.

	FH1	FH2	R	C	LP	AS1	AS2	GR	PF1	PF2
A1	53	52	0.981	$131.00	6.50	10	G	L	VG	G
A2	46	32	0.957	$69.23	5.50	6	B	F	B	B
A3	14	1	0.929	$61.20	4.85	12	G	F	G	G
A4	86	4	0.895	$110.15	6.65	12	B	M	B	B
A5	29	23	0.966	$115.00	5.70	8	B	L	B	B

Where,

FH: Flight Heritage

FH1: Number of Total Launch

FH2: Number of Last Consecutive Successful Launch

R: Reliability Rate

C: Cost (M$ per launch)

LP: Launcher Performance

AS: Availability and Schedule

AS1: Number of Launches per Year

AS2: Solidity to External Factors

GR: Government Regulations

PF: Programmatic Factors

PF1: Access to Information and Work in Progress

PF2: Schedule Control and Failure Management

andA1, A2, A3, A4, A5 are the alternative launch vehicles available in the commercial market.

6.2 Determining Weight of Each Criteria via AHP Method

As described in Chapter 3.1, the weights of the criteria are obtained by using pairwise comparisons using the Saaty’s rating scale based on the consensus of the experts. The pairwise comparison matrix A that is built for 7 main criteria are given in Table 6-4.

Table 6.4: Pairwise comparison matrix A.

	FH	R	C	LP	AS	GR	PF
FH	1	1	2	3	4	8	7
R	1,000	1	2	4	5	9	8
C	0,500	0,500	1	1	3	7	6
LP	0,333	0,250	1,000	1	3	7	6
AS	0,250	0,200	0,333	0,333	1	4	3
GR	0,125	0,111	0,143	0,143	0,250	1	0,333
PF	0,143	0,125	0,167	0,167	0,333	3,000	1

It should be noted that pairwise comparisons are done from the perspective of a communication satellite operator. Different evaluations can be made depending upon the objectives of different satellite programs. For instance, if an operator needs a satellite urgently, then the decision maker should be more prioritizing “Availability and Schedule” type criteria.

In Table 6-5, normalized matrix Anorm is presented which is derived from matrix A by column normalization:

Table 6.5: Normalized matrix A_{norm}.

	FH	R	C	LP	AS	GR	PF
FH	0,298	0,314	0,301	0,311	0,241	0,205	0,223
R	0,298	0,314	0,301	0,415	0,302	0,231	0,255
C	0,149	0,157	0,151	0,104	0,181	0,179	0,191
LP	0,099	0,078	0,151	0,104	0,181	0,179	0,191
AS	0,075	0,063	0,050	0,035	0,060	0,103	0,096
GR	0,037	0,035	0,022	0,015	0,015	0,026	0,011
PF	0,043	0,039	0,025	0,017	0,020	0,077	0,032

In Table 6-6, weight vector w_m of the criteria set is obtained by row normalization of A_{norm}.

Table 6.6: Main-criteria weight vector w_m.

FH	0,271
R	0,302
C	0,159
LP	0,141
AS	0,069
GR	0,023
PF	0,036

The local and global shared weights of 6 sub-criteria are shown in Table 6-7. The local weights of the sub-criteria are evaluated by the experts and judged equally important. The sub-criteria weights are weighed by the priority of their parent criterion to obtain their global weights (Saaty T. L., 2008).

Table 6.7: The local and global weights of main and sub criteria.

Main Criteria	FH		AS		PF	
Weight	0,271		0,069		0,036	
Sub-Criteria	FH1	FH2	AS1	AS2	PF1	PF2
Local Weight	0,5	0,5	0,5	0,5	0,5	0,5
Global Weight	0,135	0,135	0,034	0,034	0,018	0,018

6.3 Confirmation of the Weights via AHP Method

Following the step of obtaining weight vector w, a consistency check is needed to discern possible inconsistencies in the entries (Previously described in step 5 of Chapter 3.1). In order to obtain a consistency ratio (CR), the following calculations are done as shown in Table 6-8:

Table 6.8: Criteria weights consistency check via AHP.

	w	A.w	A.w/w
FH	0,271	2,023	7,476
R	0,302	2,291	7,580
C	0,159	1,169	7,356
LP	0,141	1,048	7,456
AS	0,069	0,496	7,229
GR	0,023	0,162	7,105
PF	0,036	0,254	7,021
Average of A.w/w ((λmax)			7,317

Consistency index (CI) for a 7-dimensional weight vector is computed by the following equation:

$$CI = \frac{\lambda_{\max} - m}{m-1} = \frac{7.317-7}{7-1} = 0.053 \qquad \textbf{(Equation 6.1)}$$

Random Index (RI) is 1.32 for m=7, where m is the size of the weight vector (see Table 3-2). Then, consistency ratio is computed by the following equation:

$$CR = \frac{CI}{RI} = \frac{0.053}{1.32} = 0.03919 = 3.919\% \qquad \textbf{(Equation 6.2)}$$

Since CR is less than 0.1, it could be concluded that, inconsistencies in the pairwise comparisons are tolerable and the obtained weights of criteria are valid.

6.4 Implementation of MCDM Methods using Crisp Data

In this section, the MCDM methods including AHP, ELECTRE, PROMETHEE and various variants of DEA are implemented for the launch vehicle selection problem. While implementing these methods, only crisp evaluations are utilized.

6.4.1 Implementation of AHP

Once the vector of weights is obtained, AHP is used to rank the alternative launch vehicles. Column normalization is applied to obtain the normalized score matrix S_{norm} (the score matrix S is presented previously in Table 6-2). The normalized score matrix S_{norm} is supplied in Table 6-9;

Table 6.9: Normalized score data matrix, S_{norm}.

	FH		R	C	LP	AS		GR	PF	
	FH1	FH2				AS1	AS2		PF1	PF2
A1	0,2325	0,4643	0,2076	0,1358	0,2226	0,2083	0,3500	0,4595	0,3913	0,3333
A2	0,2018	0,2857	0,2023	0,2571	0,1884	0,1250	0,1500	0,1532	0,0435	0,0952
A3	0,0614	0,0089	0,1964	0,2908	0,1661	0,2500	0,3500	0,0919	0,3043	0,3333
A4	0,3772	0,0357	0,1894	0,1616	0,2277	0,2500	0,0500	0,0656	0,1304	0,1429
A5	0,1272	0,2054	0,2043	0,1547	0,1952	0,1667	0,1000	0,2298	0,1304	0,0952

During normalization, scores of Cost (C) and government regulations (GR) criteria are transformed to the benefit type (maximum is preferable).

The global normalized scores matrix v that is obtained by multiplying S_{norm} and W is given in Table 6-10.

Table 6.10: Global scores and ranking via AHP.

Alternative #	*v (Global score)*	*Ranking*
A1	0,2527	1
A2	0,2099	2
A3	0,1727	5
A4	0,1875	3
A5	0,1772	4

The following alternative ranking is obtained by listing the global normalized scores in decreasing order:

A1 $\Rightarrow$ A2 $\Rightarrow$ A4 $\Rightarrow$ A3 $\Rightarrow$ A5

6.4.2 Implementation of ELECTRE

ELECTRE I method is also applied to rank the launcher alternatives as set out in Section 3.2.

Step 1. Normalizing the Decision Matrix

Normalization is applied to the score matrix *S* given in Table 6-2 as explained in Section 3.2. The obtained normalized decision matrix for ELECTRE is provided in Table 6-11.

Table 6.11: Normalized decision matrix for electre-I.

	FH		R	C	LP	AS		GR	PF	
	FH1	FH2				AS1	AS2		PF1	PF2
A1	0,459	0,795	0,464	0,290	0,495	0,453	0,661	0,839	0,737	0,653
A2	0,398	0,489	0,452	0,549	0,418	0,272	0,283	0,280	0,082	0,187
A3	0,121	0,015	0,439	0,621	0,369	0,543	0,661	0,168	0,573	0,653
A4	0,744	0,061	0,423	0,345	0,506	0,543	0,094	0,120	0,246	0,280
A5	0,251	0,352	0,456	0,331	0,434	0,362	0,189	0,419	0,246	0,187

Step 2. Weighting the Normalized Decision Matrix

The weighted matrix is built by multiplying the normalized decision matrix in Table 6-11 with the normalized weights given in Table 6-6. The obtained matrix is presented in Table 6-12.

Table 6.12: Weighted normalized decision matrix for electre-I.

	FH		R	C	LP	AS		GR	PF	
	FH1	FH2				AS1	AS2		PF1	PF2
A1	0,062	0,108	0,140	0,046	0,070	0,016	0,023	0,019	0,013	0,012
A2	0,054	0,066	0,137	0,087	0,059	0,009	0,010	0,006	0,001	0,003
A3	0,016	0,002	0,133	0,099	0,052	0,019	0,023	0,004	0,010	0,012
A4	0,101	0,008	0,128	0,055	0,071	0,019	0,003	0,003	0,004	0,005
A5	0,034	0,048	0,138	0,053	0,061	0,012	0,006	0,010	0,004	0,003

Step 3. Determination of the Concordance and Discordance Sets

Using the criteria assignment; FH1:1a, FH2:1b, R:2, C:3, LP:4, AS1:5a, AS2:5b, GR:6, PF1:7a, PF2:7b; concordance and discordance sets are determined according to values obtained in Table 6-12. The concordance set is given in Table 6-13.

Table 6.13: Electre-I concordance set.

C12	1a,1b,2,4,5a,5b,6,7a,7b	C21	3	C31	3,5a	C41	1a,3,4,5a	C51	3
C13	1a,1b,2,4,5b,6,7a,7b	C23	1a,1b,2,4,6	C32	3,5a,5b,7a,7b	C42	1a,4,5a,7a,7b	C52	2,4,5a,6,7a
C14	1b,2,5b,6,7a,7b	C24	1b,2,3,5b,6	C34	2,3,5a,5b,6,7a,7b	C43	1a,1b,4	C53	1a,1b,2,4,6
C15	1a,1b,2,4,5a,5b,6,7a,7b	C25	1a,1b,3,5b,6,7b	C35	3,5a,5b,7a,7b	C45	1a,3,4,5a,5b,7a,7b	C54	1b,2,5b,6

The discordance set is given in Table 6-14.

Table 6.14: Electre-I discordance set.

D21	1a,1b,2,4,5a,5b,6,7a,7b	D12	3	D13	3,5a	D14	1a,3,4,5a	D15	3
D31	1a,1b,2,4,5b,6,7a,7b	D32	1a,1b,2,4,6	D23	3,5a,5b,7a,7b	D24	1a,4,5a,7a,7b	D25	2,4,5a,6,7a
D41	1b,2,5b,6,7a,7b	D42	1b,2,3,5b,6	D43	2,3,5a,5b,6,7a,7b	D34	1a,1b,4	D35	1a,1b,2,4,6
D51	1a,1b,2,4,5a,5b,6,7a,7b	D52	1a,1b,3,5b,6,7b	D53	3,5a,5b,7a,7b	D54	1a,3,4,5a,5b,7a,7b	D45	1b,2,5b,6

Step 4. Construction of the Concordance and Discordance Matrices

The concordance matrix C is computed by using the concordance index which is the sum of the weights affiliated with the criteria included in the concordance set. The concordance matrix C is given in Table 6-15.

Table 6.15: Electre-I concordance matrix C.

	A1	A2	A3	A4	A5
A1	-	0,841	0,807	0,531	0,841
A2	0,159	-	0,736	0,654	0,505
A3	0,337	0,264	-	0,589	0,264
A4	0,469	0,346	0,411	-	0,540
A5	0,159	0,518	0,736	0,495	-

The discordance matrix D is formed by the discordance index, which is the sum of the weights affiliated with the criteria included in the discordance set. The Discordance Matrix D is given in Table 6-16.

Table 6.16: Electre-I discordance matrix D.

	A1	A1	A1	A1	A1
A1	-	0,994	0,498	0,389	0,107
A2	1,000	-	0,202	0,808	0,092
A3	1,000	1,000	-	1,000	0,986
A4	1,000	1,000	0,520	-	0,589
A5	1,000	1,000	1,000	1,000	-

Step 5. Calculation of the Net Superior and Inferior Value

Using the concordance and discordance matrices, the net superior and inferior values obtained. The net superior and inferior values are given in Table 6-17.

Table 6.17: Electre-I net superior and inferior values.

	Net Superior	Net Inferior
A1	1,896	-2,012
A2	0,084	-1,892
A3	-1,238	1,765
A4	-0,502	-0,087
A5	-0,241	2,226

Step 6. Ranking the alternatives

Ranking by considering the net superior values are accomplished by sequencing alternatives in decreasing order in terms of net superior value. On the other hand, ranking by considering net inferior values is accomplished by sorting net inferior values in increasing order. The ranking orders obtained by ELECTRE-I net superior and net inferior values are demonstrated in Table 6-18.

Table 6.18: Rankings of electre-i net superior and inferior values.

	Superior Ranking	Inferior Ranking
A1	1	1
A2	2	2
A3	5	4
A4	4	3
A5	3	5

Based on the obtained results, A1 is ranked as the first alternative since its grading is the best for both in concordant and discordant comparisons. Although, full ranking is not possible (since ranks are different for superiority and inferiority), an overall ranking can be constituted by combining rankings of net superior and inferior values as given in Table 6-19.

Table 6.19: Rankings of electre-i combined values.

	Electre-I Combined (Net Superior-Net Inferior)	Electre-I Combined Ranking
A1	3,908	1
A2	1,976	2
A3	-3,003	5
A4	-0,415	3
A5	-2,467	4

According to the ELECTRE-I combined value by merging net superior and inferior values, the following ranking is achieved:

A1 $\Rightarrow$ A2 $\Rightarrow$ A4 $\Rightarrow$ A5 $\Rightarrow$ A3

6.4.3 Implementation of PROMETHEE

PROMETHEE method is also applied to rank the launcher alternatives as described in Section 3.3.

Step 1. Generate Data Matrix

The score matrix for the alternatives that is supplied in Table 6-2 is used.

Step 2. Define Preference Function P(d)

As a general approach, Type III criterion is utilized for the criteria which are based on statistical values and Type I is used for the ones that are not depend on statistical data. In order to obtain a linear change between 0 and 1, the difference between maximum and minimum score of the related alternative is selected as *p* value, which is a necessary value for Type III criterion function shown in Table 3-3.

In a nutshell, Type III is used for FH1, FH2, R, C, LP and AS1 criteria whereas Type I is used for GR, PF1 and PF2 criteria.

Step 3. Generate the Associate Preference Functions

The preference matrices are calculated based on the criteria functions defined in step 2. These matrices for each criterion are as follows:

Flight Heritage

For the "Number of Total Launch (FH1)" criteria, Type III is used and *p* value is 72. Preference matrix for this criteria is provided in Table 6-20.

Table 6.20: Preference matrix for FH1.

FH1	A1	A2	A3	A4	A5
A1	0	0,097	0,542	0	0,333
A2	0	0	0,444	0	0,236
A3	0	0	0	0	0
A4	0,458	0,556	1,000	0	0,792
A5	0	0	0,208	0	0

Type III is used for the "Number of Last Consecutive Successful Launch (FH2)" criteria and the *p* value is 51. Preference matrix for this criteria is provided in Table 6-21.

Table 6.21: FH2 preference matrix for promethee implementation.

FH2	A1	A2	A3	A4	A5
A1	0	0,392	1,000	0,941	0,569
A2	0	0	0,608	0,549	0,176
A3	0	0	0	0	0
A4	0	0	0,059	0	0
A5	0	0	0,431	0,373	0

Reliability Rate

For Reliability Rate (R), Type III is used and *p* value is 0.09. Reliability Rate (R) criteria preference matrix is given in Table 6-22.

Table 6.22: R preference matrix for promethee implementation.

R	A1	A2	A3	A4	A5
A1	0	0,287	0,613	1,000	0,182
A2	0	0	0,326	0,713	0
A3	0	0	0	0,387	0
A4	0	0	0	0	0
A5	0	0,105	0,431	0,818	0

Cost

Type III is used for Cost (C) and *p* value is 69.8 M$. Cost (C) criteria preference matrix is provided in Table 6-23.

Table 6.23: C preference matrix for promethee implementation.

C	A1	A2	A3	A4	A5
A1	0,000	0	0	0	0
A2	0,885	0,000	0	0,586	0,656
A3	1,000	0,115	0,000	0,701	0,771
A4	0,299	0	0	0,000	0,069
A5	0,229	0	0	0	0,000

Launcher Performance

Type III is used for Launcher Performance (LP) and *n* value is 1.80. Launcher Performance (LP) criteria preference matrix is provided in Table 6-24.

Table 6.24: LP preference matrix for promethee implementation.

LP	A1	A2	A3	A4	A5
A1	0	0,556	0,917	0	0,444
A2	0	0	0,361	0	0
A3	0	0	0	0	0
A4	0,083	0,639	1,000	0	0,528
A5	0	0,111	0,472	0	0

Availability and Schedule

Type III is used for the Number of Launches per Year (AS1) and *p* value is 6. Number of Launches per Year (AS1) criteria preference matrix is provided in Table 6-25.

Table 6.25: AS1 preference matrix for promethee implementation.

AS1	A1	A2	A3	A4	A5
A1	0	0,667	0	0	0,333
A2	0	0	0	0	0
A3	0,333	1,000	0	0	0,667
A4	0,333	1,000	0	0	0,667
A5	0	0,333	0	0	0

Type I is used for Solidity to External Factors (AS2). Solidity to External Factors (AS2) criteria preference matrix is provided in Table 6-26.

Table 6.26: AS2 preference matrix for promethee implementation.

AS2	A1	A2	A3	A4	A5
A1	0	1	0	1	1
A2	0	0	0	1	1
A3	0	1	0	1	1
A4	0	0	0	0	0
A5	0	0	0	1	0

Government Regulations

Type I is used for Government Regulations (GR). Government Regulations (GR) criteria preference matrix is provided in Table 6-27.

Table 6.27: GR preference matrix for promethee implementation.

GR	A1	A2	A3	A4	A5
A1	0	1	1	1	1
A2	0	0	1	1	0
A3	0	0	0	1	0
A4	0	0	0	0	0
A5	0	1	1	1	0

Programmatic Factors

Type I is used for Access to Information and Work in Progress (PF1) and its preference matrix is provided in Table 6-28.

Table 6.28: PF1 preference matrix for promethee implementation.

PF1	A1	A2	A3	A4	A5
A1	0	1	1	1	1
A2	0	0	0	0	0
A3	0	1	0	1	1
A4	0	1	0	0	0
A5	0	1	0	0	0

Type I is used for Schedule Control and Failure Management (PF2). Schedule Control and Failure Management (PF2) criteria preference matrix is provided in Table 6-29.

Table 6.29: PF2 preference matrix for promethee implementation.

PF2	A1	A2	A3	A4	A5
A1	0	1	0	1	1
A2	0	0	0	0	0
A3	0	1	0	1	1
A4	0	1	0	0	1
A5	0	0	0	0	0

Step 4. Calculate the Index of Preferences (IP)

After obtaining the individual preference matrices for each criterion, the "Index of Preferences (IP)" or "Aggregated Preference Indices (or Indicators)" matrix is generated. The aggregated preference matrix is provided in Table 6-30.

Table 6.30: Aggregated preference matrix for promethee implementation

	A1	**A2**	**A3**	**A4**	**A5**
A1	0	0,3473	0,5636	0,5229	0,3443
A2	0,1406	0	0,3145	0,4402	0,1944
A3	0,1703	0,1231	0	0,3218	0,2159
A4	0,1326	0,2355	0,2838	0	0,2333
A5	0,0364	0,0997	0,3059	0,3548	0

Step 5. Calculate Positive and Negative Outranking Flows for Alternatives

The positive and negative priorities and outranking flows are calculated by using the data generated at Step 4. The positive and negative priorities are provided in Table 6-31.

Table 6.31: Positive and negative priorities for promethee implementation.

	A1	**A2**	**A3**	**A4**	**A5**
$\phi^{+}(a)$	1,7781	1,0896	0,8312	0,8853	0,7969
$\phi^{-}(a)$	0,4800	0,8055	1,4678	1,6397	0,9879

Step 6. PROMETHEE 1: Partial Ranking

The positive and negative flows show some differences in the order of preference, which is summarized in Table 6-32.

Table 6.32: Promethee-I partial ranking results.

	A1	A2	A3	A4	A5
Positive Flow	1	2	4	3	5
Negative Flow	1	2	4	5	3

According to Positive Flow values, the following ranking is obtained in decreasing order:

Positive Flow

A1 ⇨ A2 ⇨ A4 ⇨ A3 ⇨ A5

In accordance with the Negative Flow values the following ranking is achieved in decreasing order:

Negative Flow

A1 ⇨ A2 ⇨ A5 ⇨ A3 ⇨ A4

Since positive and negative flows show differences, there are couples of incomparability. The incomparable alternatives obtained via Promethee I are as follows:

A3 and A4

A3 and A5

A4 and A5

The first two alternatives are ranked the same in both cases.

Step 7 PROMETHEE II: Complete Ranking

Since there are incomparable alternatives, Promethee II method is also applied to obtain a full ranking of all alternatives.

A complete ranking could be calculated by using data in Table 6-32. The total score of each alternative and the complete ranking is given in below:

The Promethee-II full raking results are summarized in the Table 6-33.

Table 6.33: Promethee-II full ranking results.

A1	A2	A3	A4	A5
1,2981	0,2840	-0,6366	-0,7545	-0,1910

According to the Promethee-II, the following ranking is obtained:

A1 ⇨ A2 ⇨ A5 ⇨ A3 ⇨ A4

6.5 Implementation of DEA Methods

In this chapter, two versions of DEA namely CCR and BCC models are utilized to find the best efficiency score for each alternative. Both input- and output-oriented DEA versions are tested to make fair comparison.

Low discriminating power of the classical DEA methods are realized when more than one DMU is identified as efficient. This situation occurs when number of DMUs is not large enough in comparison with the total number of inputs and outputs.

The rule of thumb for DEA method to calculate number of potential efficient units is as follows;

$$(number\ of\ \ outputs\ \times\ number\ of\ \ inputs)\ =\ number\ of\ \ potentially\ efficient\ units$$

Hence lessening the dimensionality of the given problem will ensure less units being efficient and consequently more knowledge acquired (Hussain & Jones, 2010).

In this study, since the number of outputs is 8 and inputs is 2, it is expected to have 16 efficient units. Therefore, in order to improve the discrimination capability of DEA, so called the abbreviated matrix is composed by combining the sub criteria in to a single criterion. By this way, the number of potential efficient units is decreased.

To overcome the mentioned issues in the classical DEA models and to use DEA as a MCDM technique, several methods are proposed in the literature as discussed in Section 3.5. Among these methods, super-efficiency ranking technique is utilized in addition to the classical DEA models as described in section 3.5

In order to use DEA as a MCDM tool, the criteria to be maximized are accepted as outputs and the criteria to be minimized are accepted as inputs in the DEA model.

The commercial DEA software manufacturers adapted their products to the ranking methods available in the literature. Seven software packages, which are currently available, are listed in Table 6-34 (Adler, Friedman, & Sinuany-Stern, 2002).

Table 6.34: DEA software packages and their ranking capabilities (Adler, Friedman, & Sinuany-Stern, 2002).

	Super-efficiency	Cross-efficiency	Benchmark (simple count)	Statistics
DEAP[a]	–	–	×	–
DEA-Solver-Pro[b]	–	–	–	–
EMS[c]	×	–	×	–
Frontier[d]	–	×	–	–
IDEAS[e]	–	–	–	–
On Front[f]	–	–	×	–
Warwick[g]	×	–	–	–

[a] http://www.une.edu.au/febl/EconStud/emet/deap.htm.
[b] See http://www.saitech-inc.com.
[c] EMS is free to the academic community and available from Holger Scheel at http://www.wiso.uni-dortmund.de/lsfg/or/scheel/ems.
[d] See http://www.banxia.com.
[e] See http://www.ideas2000.com.
[f] See http://www.emq.com.
[g] Contact e.thanassoulis@aston.ac.uk.

Among the commercial DEA software (see Table 6-34), Frontier Analyst software which is also mentioned in the article of (Adler, Friedman, & Sinuany-Stern, 2002) is utilized to make necessary calculations in this thesis.

Although normalization of the score matrix is not required for the DEA implementation, both original score matrix and the normalized score matrix is utilized in the calculations.

The results of classical CCR and BCC utilizing the score data matrix that is provided in Table 6-2 are presented in Table 6-35. According to this table, except alternative 5, all the alternatives seem to be efficient. As it is expected, the standard DEA models couldn't discriminate the alternatives since the number of DMUs is not large enough compared to the total number of inputs and outputs.

Table 6.35: DEA CCR/BCC models summary.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100,00%	100,00%	100,00%	100,00%
	A2	100,00%	100,00%	100,00%	100,00%
	A3	100,00%	100,00%	100,00%	100,00%
	A4	100,00%	100,00%	100,00%	100,00%
	A5	91,10%	91,60%	91,10%	99,10%

To distinguish the real efficient alternatives, the super-efficiency ranking technique is utilized by using the score data matrix given in Table 6-2. The ranking obtained by super-efficiency ranking technique is presented in Table 6-36. As it can be seen from the table, the super-efficiency ranking technique is able to discriminate and rank the alternatives. According to the CCR model (both input and output oriented) A1 ranks first. However, BCC model (both input and output oriented) still could not make discrimination between the alternatives. For example, in the output oriented BCC model, A1, A2 and A3 have the same rank.

Table 6-36: DEA super-efficiency ranking summary.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	2	1	2
	A2	3	4	3	2
	A3	2	2	2	2
	A4	4	2	4	4
	A5	5	5	5	5
Scores	A1	628.30%	1000.00%	628.30%	1000.00%
	A2	157.40%	157.70%	157.40%	1000.00%
	A3	241.50%	1000.00%	241.50%	1000.00%
	A4	123.60%	1000.00%	123.60%	169.80%
	A5	91.10%	91.60%	91.10%	99.10%

The results of classical CCR and BCC model for input and output oriented combinations by using the normalized score data matrix given in Table 6-9 is summarized in the following Table 6-37. The results of the super-efficiency ranking technique by using the normalized score data matrix are given in Table 6-38. DEA, that used the original score matrix and the normalized matrix, gave identical values.

Table 6.37: DEA CCR/BCC models summary with normalized matrix.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100,00%	100,00%	100,00%	100,00%
	A2	100,00%	100,00%	100,00%	100,00%
	A3	100,00%	100,00%	100,00%	100,00%
	A4	100,00%	100,00%	100,00%	100,00%
	A5	91,10%	91,60%	91,10%	99,10%

Table 6.38: DEA super-Eff. ranking summary with normalized matrix.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	2	1	2
	A2	3	4	3	2
	A3	2	2	2	2
	A4	4	2	4	4
	A5	5	5	5	5
Scores	A1	628.30%	1000.00%	628.30%	1000.00%
	A2	157.40%	157.70%	157.40%	1000.00%
	A3	241.50%	1000.00%	241.50%	1000.00%
	A4	123.60%	1000.00%	123.60%	169.80%
	A5	91.10%	91.60%	91.10%	99.10%

In order to reduce the dimensionality of the problem without violating the architecture of the problem structure, the sub criteria are combined underneath their respective main criteria and the resultant performance matrix is called abbreviated normalize performance matrix (in Table 6-39). The abbreviated normalized performance matrix contains 7 criteria (the sub-criteria are combined in one criteria) whereas the original performance matrix consists of 7 criteria and 6 sub-criteria.

Table 6.39: Abbreviated normalized performance matrix.

	FH	R	C	LP	AS	GR	PF
A1	0,348	0,208	0,269	0,223	0,279	0,056	0,362
A2	0,244	0,202	0,142	0,188	0,138	0,167	0,069
A3	0,035	0,196	0,126	0,166	0,300	0,278	0,319
A4	0,206	0,189	0,226	0,228	0,150	0,389	0,137
A5	0,166	0,204	0,236	0,195	0,133	0,111	0,113

The results of classical CCR and BCC models using the abbreviated normalized performance matrix (given in Table 6-39) were summarized in Table 6-40. Following to utilization of the abbreviated matrix, there occurred a slight improvement on the discrimination ability of the classical CCR model. Compared to the previous results, CCR model discriminated more alternatives this time whereas BCC models discrimination ability did not improve at all.

Table 6.40: DEA CCR/BCC models summary with abbrev. norm. matrix.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100.00%	100.00%	100.00%	100.00%
	A2	100.00%	100.00%	100.00%	100.00%
	A3	100.00%	100.00%	100.00%	100.00%
	A4	76.00%	100.00%	76.00%	100.00%
	A5	91.10%	91.60%	91.10%	99.10%

The abbreviated normalized matrix is also used by the super-efficiency ranking technique. The results of the DEA super-efficiency ranking technique with the original score matrix and the abbreviated normalized matrix gave identical values (see Table 6-41).

Table 6.41: DEA Super-Eff. ranking summary with abbrev. norm. data.

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	2	1	2
	A2	3	4	3	2
	A3	2	2	2	2
	A4	5	2	5	4
	A5	4	5	4	5
Scores	A1	614.40%	1000.00%	614.40%	1000.00%
	A2	155.00%	155.50%	155.00%	1000.00%
	A3	230.00%	1000.00%	230.00%	1000.00%
	A4	76.00%	1000.00%	76.00%	107.90%
	A5	91.10%	91.60%	91.10%	99.10%

6.6 Implementation of Fuzzy DEA Methods

Fuzzy DEA has also applied to the launch vehicle selection problem. Similar to the crisp models, fuzzy versions of CCR and BCC models and super-efficiency ranking technique were tested. For each model, both input- and output-oriented versions are considered.

As previously explained in Chapter 3.7, the fuzzy data is defuzzified by employing the α-cut method. Then, the resulting crisp model is solved by Frontier software. While applying the α-cut method to address potential ambiguities in expert knowledge, three different level of α levels are utilized (0.6, 0.8 and 1). As for the optimism index λ, 0.6 is selected to address the decision maker's attitude on the evaluation of the alternatives.

6.6.1 α-cut Method Implementation Using Fuzzy Data with α=0.60

The score matrix presented in Table 6-3 is transformed to a matrix having crisp values as presented in Table 6-42. To transform the fuzzy values to crisp values, α value of 0.6 is used.

For the defuzzification of a triangular fuzzy number, Eq. 6.3 is employed.

$$
\begin{aligned}
& a_{ij}^{\alpha} = [\lambda . L_{ij}^{\alpha} + (1-\lambda) . U_{ij}^{\alpha}] \\
& where, \\
& L_{ij}^{\alpha} = (M_{ij} - L_{ij}) . \alpha + L_{ij} \\
& U_{ij}^{\alpha} = U_{ij} - (U_{ij} - M_{ij}) . \alpha \\
& \lambda = [0,1] \\
& \alpha = [0,1]
\end{aligned}
\quad \textbf{(Equation 6.3)}
$$

Table 6.42: Transformed norm. data matrix (α=0.6).

Normalized Performance Matrix

α (conf.lvl) =0.60

λ (opt.indx) =0.60

	FH1	FH2	R	C	LP	AS1	AS2	GR	PF1	PF2
A1	0.232	0.464	0.208	0.269	0.223	0.208	0.308	0.128	0.365	0.308
A2	0.202	0.286	0.202	0.142	0.188	0.125	0.128	0.218	0.117	0.128
A3	0.061	0.009	0.196	0.126	0.166	0.250	0.308	0.218	0.283	0.308
A4	0.377	0.036	0.189	0.226	0.228	0.250	0.128	0.308	0.117	0.128
A5	0.127	0.205	0.204	0.236	0.195	0.167	0.128	0.128	0.117	0.128

The results of fuzzy CCR and BCC models utilizing the normalized score data matrix (given in Table 6-42) are outlined in Table 6-43. The results obtained by using the super-efficiency ranking technique are also given in Table 6-44.

Table 6.43: Fuzzy DEA CCR/BCC models summary with norm. matrix (α=0.6).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100.00%	100.00%	100.00%	100.00%
	A2	100.00%	100.00%	100.00%	100.00%
	A3	100.00%	100.00%	100.00%	100.00%
	A4	100.00%	100.00%	100.00%	100.00%
	A5	100.00%	100.00%	100.00%	100.00%

Compared to the CCR and BCC models using crisp data and models using fuzzy data still could not discriminate the alternatives. Alternatives 1 to 4 are still seem to be efficient. Thus, in this problem, the use of fuzzy data did not improve the discrimination ability of the CCR and BCC models.

Table 6.44: Fuzzy DEA Super-Eff. ranking summary with norm. matrix (α=0.6).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	2	1	4
	A2	3	4	3	3
	A3	2	2	2	2
	A4	4	2	4	5
	A5	5	5	5	2
Scores	A1	285.90%	1000.00%	285.90%	311.30%
	A2	157.40%	157.70%	157.40%	466.10%
	A3	237.30%	1000.00%	237.30%	1000.00%
	A4	126.50%	1000.00%	126.50%	169.80%
	A5	106.40%	107.50%	106.40%	1000.00%

6.6.2 α-cut Method Implementation Using Fuzzy Data with α=0.80

For the α value of 0.8, the normalized performance matrix that is obtained is given in Table 6-45.

Table 6.45: Transformed norm. data matrix (α=0.8).

Normalized Performance Matrix
α (conf.lvl) =0.80
λ (opt.indx) =0.60

	FH1	FH2	R	C	LP	AS1	AS2	GR	PF1	PF2
A1	0.232	0.464	0.208	0.269	0.223	0.208	0.306	0.129	0.363	0.306
A2	0.202	0.286	0.202	0.142	0.188	0.125	0.129	0.218	0.119	0.129
A3	0.061	0.009	0.196	0.126	0.166	0.250	0.306	0.218	0.281	0.306
A4	0.377	0.036	0.189	0.226	0.228	0.250	0.129	0.306	0.119	0.129
A5	0.127	0.205	0.204	0.236	0.195	0.167	0.129	0.129	0.119	0.129

The results of the CCR and BCC models using fuzzy data are outlined in Table 6-46. The results of the super-efficiency ranking technique using the same transformed normalized score data matrix are given in Table 6-47. With the super-efficiency method, full ranking is obtained.

Table 6.46: Fuzzy DEA CCR/BCC models summary with norm. matrix (α=0.8).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100.00%	100.00%	100.00%	100.00%
	A2	100.00%	100.00%	100.00%	100.00%
	A3	100.00%	100.00%	100.00%	100.00%
	A4	100.00%	100.00%	100.00%	100.00%
	A5	100,00%	100,00%	100,00%	100,00%

Table 6-47: Fuzzy DEA super-eff. ranking summary with norm. matrix (α=0.8).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	1	1	1
	A2	3	3	3	3
	A3	2	2	2	2
	A4	4	4	5	5
	A5	5	5	4	4
Scores	A1	282.10%	282.10%	250.70%	250.70%
	A2	157.40%	157.40%	155.00%	155.00%
	A3	237.10%	237.10%	231.40%	231.40%
	A4	126.80%	126.80%	81.70%	81.70%
	A5	106.30%	106.30%	106.30%	106.30%

6.6.3 α-cut Method Implementation Using Fuzzy Data with α=1

When the α value is selected as 1, although the normalized performance matrix is changed as given in Table 6-48, the ranking obtained by using the BCC and CCR models (see Table 6-49) and the super efficiency technique (see Table 6-50) did not change.

Table 6.48: Norm. Data matrix with crisp and linguistic data (α=1).

Normalized Performance Matrix

α (conf.lvl) =1,00

λ (opt.indx) =0,60

	FH1	FH2	R	C	LP	AS1	AS2	GR	PF1	PF2
A1	0.232	0.464	0.208	0.269	0.223	0.208	0.304	0.130	0.360	0.313
A2	0.202	0.286	0.202	0.142	0.188	0.125	0.130	0.217	0.120	0.127
A3	0.061	0.009	0.196	0.126	0.166	0.250	0.304	0.217	0.280	0.306
A4	0.377	0.036	0.189	0.226	0.228	0.250	0.130	0.304	0.120	0.127
A5	0.127	0.205	0.204	0.236	0.195	0.167	0.130	0.130	0.120	0.127

Table 6.49: Fuzzy DEA CCR/BCC models summary with norm. matrix (α=1).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Scores	A1	100,00%	100,00%	100,00%	100,00%
	A2	100,00%	100,00%	100,00%	100,00%
	A3	100,00%	100,00%	100,00%	100,00%
	A4	100,00%	100,00%	100,00%	100,00%
	A5	100,00%	100,00%	100,00%	100,00%

Table 6.50: Fuzzy DEA super-eff. ranking summary with norm. matrix (α=1).

		Input Oriented		Output Oriented	
		CCR	BCC	CCR	BCC
Ranking	A1	1	2	1	4
	A2	3	4	3	3
	A3	2	2	2	2
	A4	4	2	4	5
	A5	5	5	5	2
Scores	A1	278.50%	1000.00%	278.50%	300.00%
	A2	157.40%	157.70%	157.40%	466.10%
	A3	236.90%	1000.00%	236.90%	1000.00%
	A4	127.00%	1000.00%	127.00%	169.80%
	A5	106.20%	107.30%	106.20%	1000.00%

CHAPTER SEVEN

COMPARISON OF MCDM METHODS APPLICATION RESULTS

This chapter presents an evaluation and comparison of the results of MCDM methods and DEA implemented on the launch vehicle selection problem.

As a summary of the methods utilized in this study; initially the conventional MCDM methods including AHP, ELECTRE and PROMETHEE were applied. The weights of the criterion were obtained by utilizing pairwise comparisons.

Following to the implementation of the conventional MCDM methods, various models of DEA were implemented on the same problem. The classical CCR and BCC models of the DEA were utilized to obtain the best efficiency score of each alternative. Each model was run with input- and output-oriented type version. In addition to the classical DEA models, the super-efficiency ranking technique is utilized to overcome the low discriminating power of the classical methods. By the implementation of the super-efficiency ranking technique, a better ranking was obtained.

Moreover, the DEA model was run with the original score matrix and the normalized matrix. However, a difference in rankings did not observed

In order to lessen the dimensionality of the problem without impacting the architecture of the problem structure, the sub criteria are combined underneath of their main criteria and an abbreviated normalize performance matrix is established. The abbreviated normalized performance matrix consists of 7 criteria (the sub-criteria are combined in one criteria) whereas the original performance matrix consists of 7 criteria and 6 sub-criteria. The results of showed that there is a slight improvement on the discrimination ability of the classical CCR model.

Finally, Fuzzy DEA was implemented for ranking of the alternatives. Similar to the classical DEA application, first CCR model, BCC model and super-efficiency ranking technique are employed to find the best efficiency score of each alternative with fuzzy data set. Each model was run both for the input- and output-oriented version. In the frame of the fuzzy DEA application, the defuzzification was utilized by employing the α-cut method. In the α-cut method, three different levels of α was used as 0.6, 0.8 and 1. As for the optimism index λ, 0.6 was taken into account to address the decision-maker's attitude on the evaluation of the alternatives.

The results of the conventional MCDM methods; AHP, ELECTRE and PROMETHEE is given in the Table 7-1. As seen from table, by applying various versions of the AHP, ELECTRE and PROMETHEE a consistent ranking is obtained since all methods ranked the same alternative as the best.

As for the DEA application, the results obtained by using the CCR method and the super efficiency technique are given in the Table 7-2. Compared to the classical DEA method, a better ranking is obtained because of the high discriminating ability of the the super-efficiency ranking technique, When the different versions of the super efficiency technique are compared, it could be seen that the results are consistent. The same alternative is ranked as the best alternative in all cases.

The ranking obtained by using the fuzzy DEA for different α-cut levels are given in the Table 7-3. It is observed that, various α-cut levels give the same ranking, which indicates that DEA algorithm is pretty robust to the different α-cut levels. Also for the normalized performance matrix and the abbreviated normalized performance matrix, a consistent ranking is observed.

Table 7.1: AHP, promethee and electre methods results summary.

		Conventional MCDM Methods						
		AHP	Electre Superior	Electre Inferior	Electre Combined	Promethee Positive Flow	Promethee Negative Flow	Promethee Net Flow
Ranking	A1	1	1	1	1	1	1	1
	A2	2	2	2	2	2	2	2
	A3	5	5	4	5	4	4	4
	A4	3	4	3	3	3	5	5
	A5	4	3	5	4	5	3	3
	A2	0,210	0,084	-1,892	1,976	1,090	0,806	0,284
	A3	0,173	-1,238	1,765	-3,003	0,831	1,468	-0,637
	A4	0,188	-0,502	-0,087	-0,415	0,885	1,640	-0,754
	A5	0,177	-0,241	2,226	-2,467	0,797	0,988	-0,191

Table 7.2: DEA super efficiency methods results summary.

		DEA					
		Performance Matrix		Normalized Performance Matrix		Abbreviated Norm. Performance Matrix	
		Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency
		Input Oriented	Output Oriented	Input Oriented	Output Oriented	Input Oriented	Output Oriented
		CCR	CCR	CCR	CCR	CCR	CCR
Ranking	A1	1	1	1	1	1	1
	A2	3	3	3	3	3	3
	A3	2	2	2	2	2	2
	A4	4	4	4	4	5	5
	A5	5	5	5	5	4	4
Scores	A1	628,30%	628,30%	628,30%	628,30%	614,40%	614,40%
	A2	157,40%	157,40%	157,40%	157,40%	155,00%	155,00%
	A3	241,50%	241,50%	241,50%	241,50%	230,00%	230,00%
	A4	123,60%	123,60%	123,60%	123,60%	76,00%	76,00%
	A5	91,10%	91,10%	91,10%	91,10%	91,10%	91,10%

Table 7.3: Fuzzy DEA super efficiency methods results summary.

		Fuzzy DEA				Fuzzy DEA				Fuzzy DEA			
		α =0,60		λ =0,60		α =0,80		λ =0,60		α =1,00		λ =0,60	
		Normalized Performance Matrix		Abbreviated Norm. Performance Matrix		Normalized Performance Matrix		Abbreviated Norm. Performance Matrix		Normalized Performance Matrix		Abbreviated Norm. Performance Matrix	
		Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency	Super Efficiency
		Input Oriented	Output Oriented	Input Oriented	Output Oriented	Input Oriented	Output Oriented	Input Oriented	Output Oriented	Input Oriented	Output Oriented	Input Oriented	Output Oriented
		CCR	CCR	CCR	CCR	CCR	CCR	CCR	CCR	CCR	CCR	CCR	CCR
Ranking	A1	1	1	1	1	1	1	1	1	1	1	1	1
	A2	3	3	3	3	3	3	3	3	3	3	3	3
	A3	2	2	2	2	2	2	2	2	2	2	2	2
	A4	4	4	5	5	4	4	5	5	4	4	5	5
	A5	5	5	4	4	5	5	4	4	5	5	4	4
Scores	A1	285.90%	285.90%	253.70%	253.70%	282.10%	282.10%	250.70%	250.70%	278.50%	278.50%	251.90%	251.90%
	A2	157.40%	157.40%	155.00%	155.00%	157.40%	157.40%	155.00%	155.00%	157.40%	157.40%	155.00%	155.00%
	A3	237.30%	237.30%	231.30%	231.30%	237.10%	237.10%	231.40%	231.40%	236.90%	236.90%	231.40%	231.40%
	A4	126.50%	126.50%	81.50%	81.50%	126.80%	126.80%	81.70%	81.70%	127.00%	127.00%	81.90%	81.90%
	A5	106.40%	106.40%	106.40%	106.40%	106.30%	106.30%	106.30%	106.30%	106.20%	106.20%	106.20%	106.20%

It is apparently observed that, the same alternative A1 is identified as the best in all implemented methods. It shows that the results of the AHP, ELECTRE, PROMETHEE, DEA with super-efficiency ranking technique and Fuzzy DEA with super-efficiency ranking technique determined the best alternative as A1. However, the rank of the other alternatives changed depending upon the applied method. For instance, alternative A4 is ranked 4^{th} and 5^{th} depending on the method applied. On the other side, the same ranking of the all alternatives are achieved for (input and output oriented) CCR models with super-efficiency ranking technique.

CHAPTER EIGHT

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In space business, launch vehicle selection for a satellite is a crucial technical and managerial decision making problem with multiple dimensions. Therefore, selection of a proper launcher is a critical decision making problem for a satellite operator. In this study, this problem is solved by considering five launch vehicle alternatives that could boost a geostationary communication satellite into desired orbit. To solve the problem by using MCDM techniques and DEA, a criteria set - established by the experts of the field is used.

The implemented MCDM methods include the conventional method such as AHP, ELECTRE, PROMETHEE and DEA which is a non-parametric linear programming based methodology. The results obtained with different methods are compared with each other and it is observed that the same alternative A1 is ranked first in all cases.

In the conventional MCDM methods, such as AHP, ELECTRE, PROMETHEE; the weights are appointed intuitively and arbitrarily without extensively considering entire aspects of the criteria prior to the evaluation. Thus, the resultant ranking of alternatives may not provide an appropriate solution. Nevertheless, in the case of DEA, a priori weighing of the criteria or an interaction of decision-maker is not required since it is a non-parametric method.

As a matter of fact, the weights of evaluation criterion often contingent upon business precedence and strategies of a satellite operator. It is acknowledged that the results could differentiate for AHP, ELECTRE and PROMETHEE methods, because of the changing weights of the criteria depending upon the ultimate objectives and priorities of decision maker authority. On one hand this is quite conceivable since the main aim of a satellite to be launched may be varied as discussed before.

Notwithstanding the conventional MCDM methods, DEA is rather prominent as an alternative methodology for decision making analysis. Because, the inputs and outputs are processed without postulated information about production function and weights.

Despite the fact that DEA is an advantageous method for evaluating the efficiency, it has some inadequacies when it is used as a MCDM tool. These inadequacies are low discerning strength and impractical weights distribution. The conventional classical DEA models only determine subsets of efficient and inefficient units and does not furnish complete ranking of them, since most of the time it fails to differentiate among units. Therefore, several techniques were proposed in the literature to overcome the identified shortcomings. In the frame of this thesis, super efficiency technique is employed to obtain more appropriate results.

In spite of several conventional MCDM methodologies attainable, the implementation of DEA as a non-parametric alternative MCDM method provides reasonable and comparable results.

The ranking dispositions are not entirely the same for each implemented method, however alternative A1 is the best followed by A2 or A3. Thus, the implemented methods in this study can certainly assist the decision maker during the launch vehicle selection problem efficiently. In addition to that, the comparison of several methods served as a consistency check for the launch vehicle selection problem.

It is also noticed the Fuzzy DEA with different α-cut levels also generated the same ranking compared to the crisp DEA. The ranking did not change when normalized and abbreviated normalized performance matrix are used.

Whatever the technique is used in MCDA, the decision maker may obtain additional information by conducting a sensitivity analysis in order to be sure about the consequence of the different methods.

As proposed in Friedman and Sinuany-Stern (1998), an alternative possible productive concept would be invoked assorted ranking procedures and afterwards to determine an average or median rank based upon the outcomes of the models employed in the study (L. & Sinuany-Stern, 1998).

The techniques discussed here were chosen due to their popularity in literature and practical usage; however, there are many other techniques available. As for the future directions; it is encouraged to search for additional techniques to supplement those mentioned methods implemented in this study. Each decision problem has certain features that will be more effectively handled by using a particular MCDA technique Therefore it is important to not only understand the problem, but also details of the methods available as well as their limitations.

It would be also worthwhile to study on DEA to improve the discriminatory power of it as a MCDM tool. Likewise, it would be valuable to compare different fuzzy approaches to assess the performance of the DEA method when the problem at hand includes vague and imprecise data.

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