

Enhancing the Systems Decision Process with Flexibility Analysis for Optimal Unmanned Aircraft System Selection

by

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United States Military Academy, 1998

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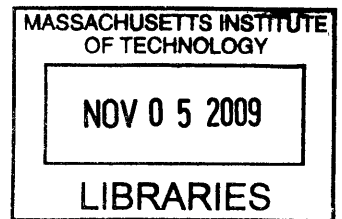
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Chris H. Bachmann

Submitted to the Engineering Systems Division
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ABSTRACT

Systems Engineers often conduct decision analysis in order to provide decision makers with a quantifiable means to make decisions. However, the field of Systems Engineering is often criticized for focusing on processes and requirements instead of the actual system. As a result, it limits the decision maker's ability to understand the system's properties and behaviors. This research enhances an existing decision methodology in order to maintain holistic thinking and provide decision makers with measureable information that result in better decisions.

This thesis explores commercial, off the shelf systems in order to provide a potential solution to a backpackable, lethal unmanned aircraft system (UAS). It first employs the Systems Decision Process which is a widely applicable decision method that focuses on system function and requirements in order to select an optimal solution. The System Decision Process utilizes the additive value model. The additive value model is a universally accepted quantitative approach for evaluating a candidate solution space in order to determine a best solution. This research then applies Flexibility Analysis in order to enhance the System Decision Process.

Flexibility Analysis is a three step process developed by the researcher. The first step involves decomposing and modeling the UAS as a system of systems. The next step introduces the Requirements Flexibility Graph as a structured technique which incorporates stakeholder levels of acceptability along with the engineers' stochastic estimates of a system's changeability with respect to constraints. The final step replaces preference weighting in the additive value model with potential value. Potential value is a quantifiable measure of a system's flexibility. It supplies decision makers with information about a system's inherent value and allows them to allocate resources to those system attributes that provide the most value return. Finally, a realized value score informs the decision maker of the resulting value of changing the system from the status quo to a future state.

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As an active duty officer in the Army, I am required to acknowledge that the views expressed in this thesis are mine and do not reflect the official policy or position of the United States Army, the Department of Defense, or the United States Government.




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Assignment

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1 Introduction

Systems Engineers often conduct decision analysis in order to provide decision makers with a quantifiable basis on which to make decisions. However, the field of Systems Engineering is often criticized for being too focused on processes and requirements instead of the systems or the outcomes [72]. There exist numerous methods for conducting decision analysis. This research will utilize the Systems Decision Process and Classical Decision Analysis. It will then integrate Flexibility Analysis in order to keep focus on the system as a whole and to quantify potential value inherent in each candidate solution. Furthermore, integrating Flexibility Analysis provides stakeholders and decision makers a more complete understanding of system properties, and it shows how these properties can influence decision making. Ultimately, this thesis aims to improve decision making.

This chapter describes the Systems Decision Process, where it fits into the System Life Cycle, and an overview of Flexibility Analysis. Additionally, it provides a definition of flexibility as used in this thesis, shows how this thesis fits into the framework of Engineering Systems, and describes the motivation behind the research.

1.1 The Systems Decision Process

The Systems Decision Process (SDP) is a methodology created and taught by the Department of Systems Engineering at the United States Military Academy (USMA) located at West Point, New York. Throughout the life cycle of a system, decisions about the system must be made. The Department of Systems Engineering at West Point utilizes the SDP as a structured method for problem solving and making recommendations to decision makers. There are also numerous other decision processes with similar objectives such as: Athey's Systematic Systems Approach, the Military Decision Making Process (MDMP), Dobber and McConnell's Complex, Large-scale, Integrated, Open Systems (CLIOS), and Ross's Multi-Attribute Tradespace Exploration with Concurrent Design (MATE-CON). This thesis uses SDP because it is readily available and utilizes common quantitative methods such as the additive value model. Classical Decision Analysis or CDA is the term this work uses to describe the quantitative method within SDP to produce a best solution. It is described as classical because the mathematical construction behind the quantitative process in SDP is the same as that set forth by Ralph L. Keeney and Howard Raiffa in their work "Decisions with Multiple Objectives: Preference and Value Tradeoffs." Keeney and Raiffa published their work in 1976, and it is the basis for much of the work in decision analysis past and present.

The SDP has four major phases: (1) Problem Definition; (2) Solution Design; (3) Decision Making; and (4) Solution Implementation. Each phase decomposes into three steps. For example, the problem definition phase consists of stakeholder analysis, functional analysis, and value modeling. The solution design phase includes idea generation, alternative generation, and solution enhancement. Decision making is a quantitative phase which involves solution scoring, sensitivity analysis, and value-focused thinking. Finally, the solution implementation phase includes planning for action, execution, and assessment and control. The Department of Systems Engineering (DSE) outlines the following advantages in utilizing the SDP [65].

- "The SDP encapsulates the dynamic flow of systems engineering activities and the evolution of the system state, starting with the current status (what is) and ending with a system that successfully delivers value to system stakeholders (what should be)."
- "It has a core focus on the needs and objectives of stakeholders and decision makers concerned with the value being delivered by the system."

- “It has four major phases organized into a logical progression (problem definition, solution design, decision making, and solution implementation) that embrace systems thinking and apply proven systems engineering approaches, yet are highly iterative.”
- “It explicitly considers the environment (its factors and interacting systems) that systems operate in as critical to systems decision making, and thus highlights a requirement for multidisciplinary systems engineering teams.”
- “It emphasizes value creation (value modeling, solution enhancements, and value-focused thinking) in addition to evaluation (scoring and sensitivity analysis) of alternatives.”

The SDP is used throughout the System Life Cycle. Its role in the System Life Cycle is explained in the next section.

This work focuses on three of the four phases of the SDP. The solution implementation phase is equally as important as the problem definition, solution design, and decision making phases; however, solution implementation is outside the scope of this work. Figure 1-1 below depicts the SDP.

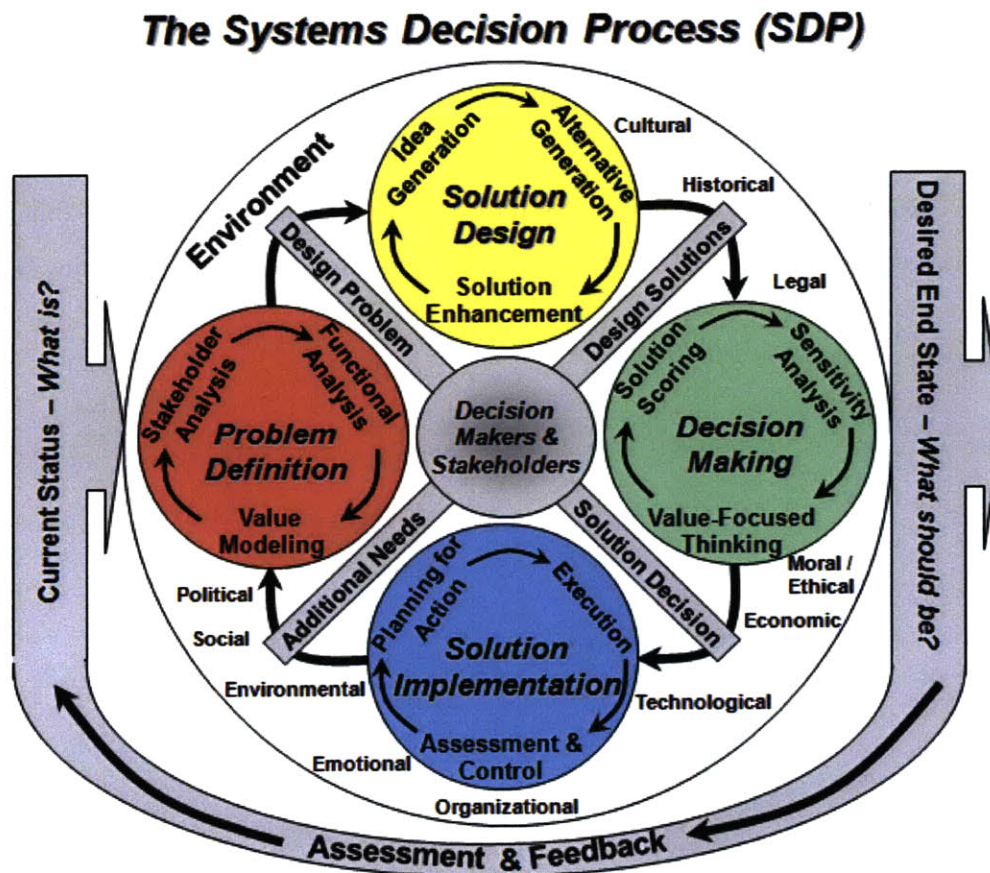


Figure 1-1: Department of Systems Engineering SDP [65]

As Figure 1-1 shows, the SDP is an iterative process. The figure further illustrates that decision makers and stakeholders are the heart of the process. Since their input drives the process, systems engineers should carefully capture their needs and requirements.

1.1.1 When to Use the Systems Design Process

The SDP provides a general framework for problem-solving. Throughout the System Life Cycle, decision makers must continually make choices. The SDP provides the system engineer a structured analytical method to decide among alternatives to make the best recommendation to the decision maker. It is very general and grounded on solid principles; therefore, it is useful in situations where no systems engineers are available [65]. Additionally, depending on the decision application, practitioners of SDP can tailor or omit parts of the process as required. As a result of these characteristics, it is useful in many different situations. The general nature and sound foundations of the SDP make it an excellent candidate to use in an academic work attempting to improve the overall decision making process. Equally important to the SDP is an understanding of the System Life Cycle.

1.2 SDP in the System Life Cycle

It is imperative to describe how the SDP fits into the System Life Cycle (SLC) framework. The International Council on Systems Engineering (INCOSE) states that every man-made system has a life cycle [34]. There are many variants of the SLC as the figure below illustrates.

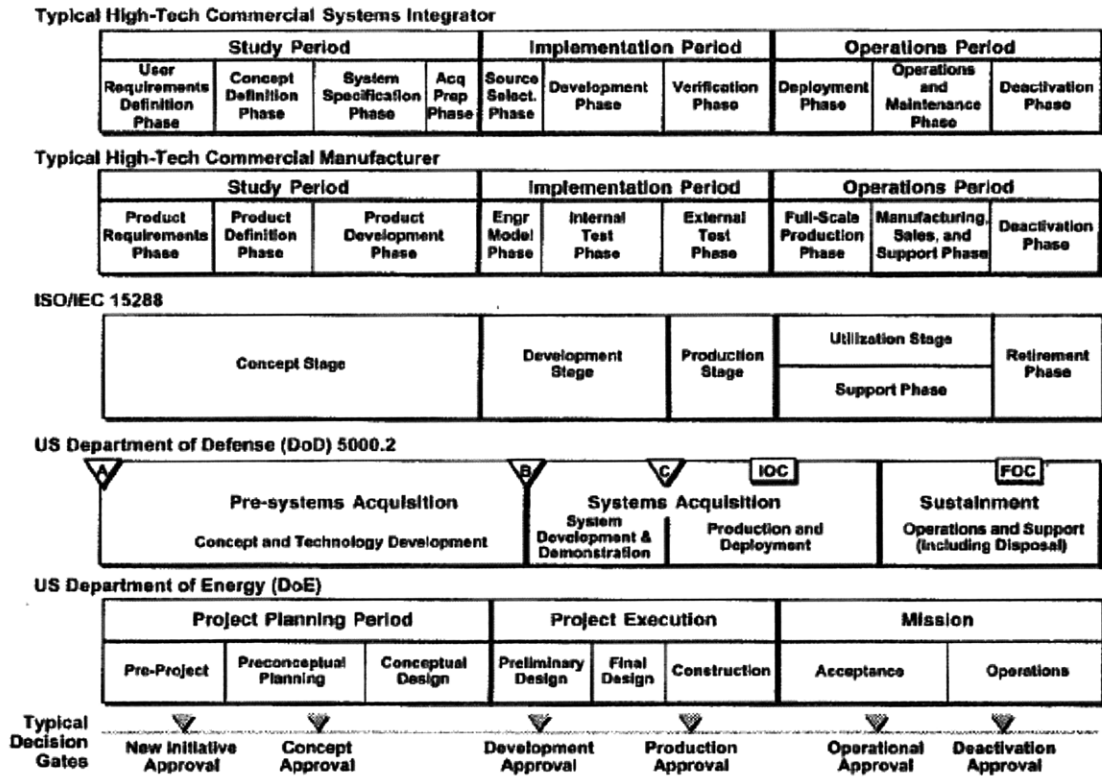


Figure 1-2: System Life Cycles [34]

The SLCs in Figure 1-2 capture the same evolution of a system but with varying degrees of detail. The SLCs in Figure 1-2 are linear presentations; however, more common representations are the Waterfall and Spiral models as Figures 1-3 & 1-4 depict.

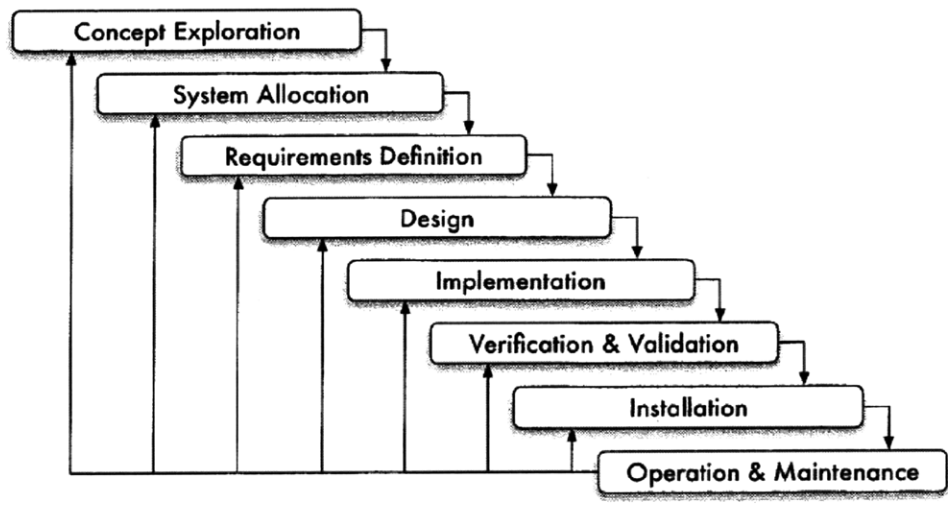


Figure 1-3: Waterfall System Life Cycle [65]

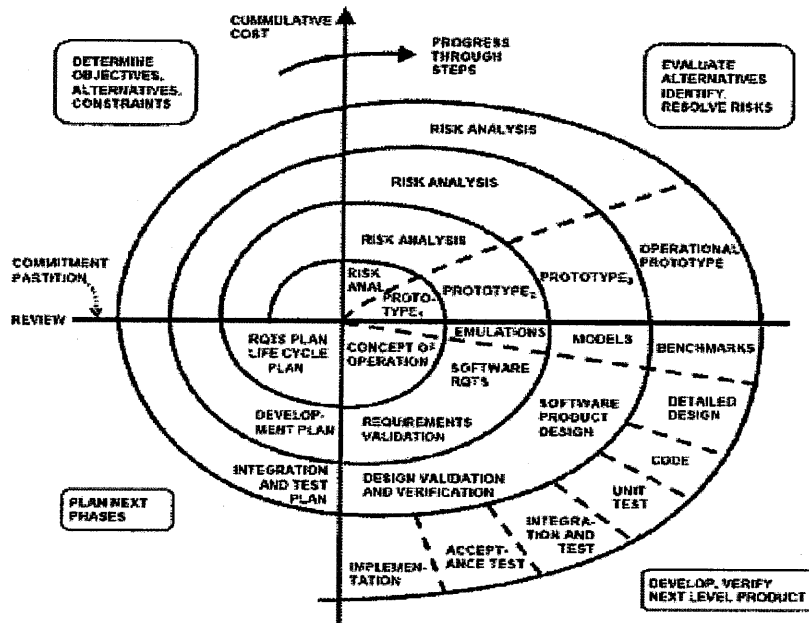


Figure 1-4: Spiral System Life Cycle [65]

The Waterfall and Spiral models visually capture the iterative nature of the systems process. However, the Spiral model formalizes the iterative nature of systems to a greater extent because it is centered around an origin. The method employed depends on the organization or the individual. For example, the Operational Assessment and Training Team for small unmanned aircraft systems at Natick Soldier Systems Center, an Army research lab, uses the Spiral method. Whereas, Netgains Network Solutions, who specialize in designing websites, uses the Waterfall method. Because there are numerous different methods, each organization determines which is best for them and may use more than one method to achieve their goals.

It is not important in this research to focus on any one cycle or how it is depicted. The important aspect is at the bottom of Figure 1-2 labeled “Typical Decision Gates.” This shows where the SDP integrates into the SLC. Additionally, it highlights the multiple points throughout the SLC that require a formal decision process. A formalized decision process prevents ad hoc decisions that can result in unintended consequences or unplanned budget expenditures later in the cycle.

LIFE CYCLE STAGES	PURPOSE	DECISION GATES
CONCEPT	Identify stakeholders' needs Explore concepts Propose viable solutions	Decision Options - Execute next stage - Continue this stage - Go to a preceding stage - Hold project activity - Terminate project
DEVELOPMENT	Refine system requirements Create solution description Build system Verify and validate system	
PRODUCTION	Produce systems Inspect and test [verify]	
UTILIZATION	Operate system to satisfy users' needs	
SUPPORT	Provide sustained system capability	
RETIREMENT	Store, archive, or dispose of the system	

Figure 1-5: Decision Gates within the System Life Cycle [34]

The figure above illustrates the core stages of any SLC and the purpose for that stage. The far right column further demonstrates that a structured decision process is important throughout the SLC. The DSE at West Point views the SDP as a bridge between each stage of the SLC. Each bridge does not require the complete SDP. As explained earlier, the SDP has the benefit of being tailored to fit each bridge. Figure 1-6 below demonstrates the bridge concept.

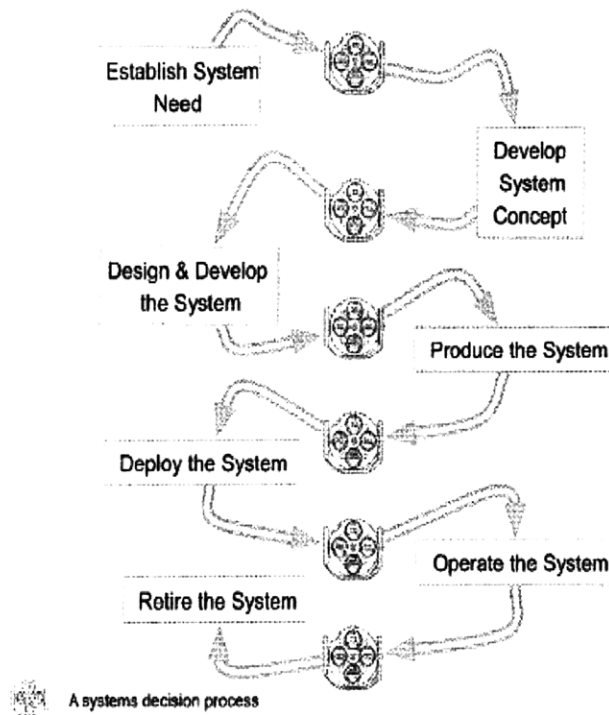


Figure 1-6: Systems Decision Process as a bridge in SLC [65]

All physical systems have a life cycle [34]. This section showed the various structured life cycle models organizations use. There are numerous methods, and they differ in detail, but all capture the same core components. This section also explained where a decision making process fits into the overall structure of the SLC. More specifically, it illustrated how the SDP serves as a bridge between the SLC's core stages. The SDP allows the system engineer to recommend whether the system should progress to the next life cycle stage [65]. This thesis will utilize the SDP in order to choose a best solution for a backpackable, lethal unmanned aircraft system (UAS). The solution the SDP selects as the best solution would then be past to the Design and Development stage of the life cycle. Chapter 4 of this work focuses on using the SDP to make a decision between the Concept Development and Design and Development stages of the SLC. The researcher will then attempt to improve the decision making process and the final solution by analyzing flexibility within the UASs. Before describing the method to improve the decision process, the researcher will first define important concepts and terms such as who are stakeholders and decision makers, and what Engineering Systems and flexibility entail.

1.3 Stakeholders and Decision Makers

Important aspects of the decision making process are the stakeholders and decision makers. These two groups are essential to making good decisions. Requirements, needs, and desires of a system come straight from the stakeholders. They have an important role in ensuring that the intended purpose of a system is conveyed. Stakeholders permeate both the SLC and SDP. Buede (2000) illustrates this point with the following definition:

- “**Stakeholder.** Owner and/or bill payer, developer, producer or manufacturer, tester, deployer, trainer, operator, user, victim, maintainer, sustainer, product improver, and decommissioner” [12].

There is a direct link between stakeholders and each stage of the SLC. Figure 1-7 maps each stakeholder to a stage in the DoD SLCs.

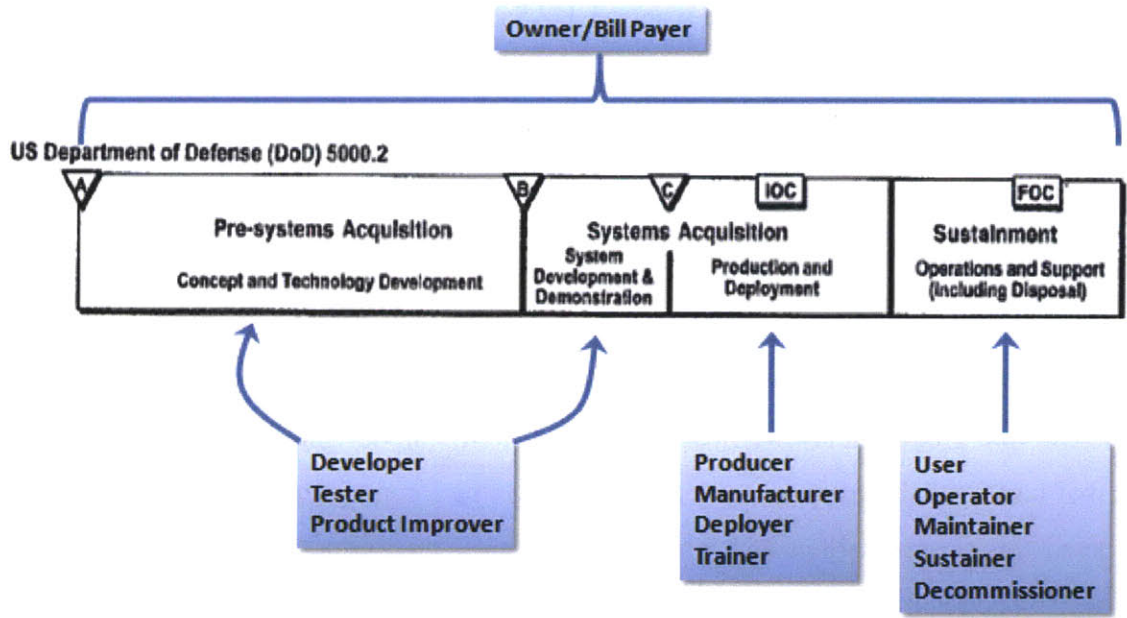


Figure 1-7: Stakeholders mapped to DOD System Life Cycle

It is easy to identify the different stakeholders in the small, UAS studied in this research. The owner and bill payer is the United States Department of Defense (DoD). The developer, producer/manufacturer, tester, and product improver are the different civilian corporation involved in producing UASs for the DoD. The deployer is the military acquisition corps. The trainer, operator, user, maintainer, sustainer are the Soldiers and Marines. Finally, the decommissioner is the DoD. The definition also includes the victim; however, the victim plays a passive role as a stakeholder with the lethal UAS. The active stakeholders do develop requirements and needs based off of effects upon intended and unintended victims.

Like the stakeholders, the decision makers also have an important role in the SLC and SDP. As the name implies, decision makers are responsible for making choices at each decision gate described above in the SLC. The system engineer uses the SDP at the decision gates in order to make the best recommendation to the decision maker. In addition to decisions at decision gates, the decision makers must also choose the final solution that is used to solve the problem of concern. Since stakeholders and decision makers cooperate during both SLC and the SDP, the researcher uses them interchangeably, unless otherwise stated, for the remainder of this paper. The reader should now understand who the stakeholders and decision makers are, and their role in the SLC and the SDP. In order to determine the requirements for the UAS, the

researcher surveyed stakeholders relevant to UASs. The next section identifies the relevant stakeholders of the backpackable, lethal UAS.

1.3.1 Relevant UAS Stakeholders

As Section 1.3 described, it is important to involve the relevant stakeholders in the design and decision process. Therefore, the researcher sought out those stakeholders that are important to the backpackable, lethal UAS. The researcher attempted to involve each stakeholder from Section 1.3 and was successful with most.

The first group interviewed was the user. The researcher gathered information from four peers that had firsthand experience with small UASs in a combat environment. The researcher considered this the most important group because they represent “where the rubber meets the road” idea. The feedback gathered was very insightful and useful in developing this work.

The United States Soldier Systems Center in Natick, Massachusetts was another stakeholder that proved to be very cooperative. This lab serves as the trainer and tester for small military UASs. Natick provided the researcher hands on experience with small UASs. Additionally, they provided information on the tasks of training UAS operators and testing different UA systems.

The Unmanned Aircraft Systems Development Division at Fort Benning, Georgia is the developer stakeholder. They are responsible for developing system requirements. They are co-located with the United States Infantry School which has primary ownership of the backpackable, lethal UAS. The researcher corresponded with them numerous times via phone and email in order to capture system requirements. These requirements are currently under development and are continually changing. However, the information they provided was very useful in constructing this work.

The United States Army Unmanned Aircraft Systems Operation Branch at Redstone Arsenal, Alabama is the primary acquisition component of UASs for the Army. Therefore, they represent the deployer stakeholder. They served as a great source for contact information of other stakeholders. For example, they provided the contact information for the UAS developer at Fort Benning along with points of contact at different producers and manufactures.

The final groups of stakeholders that the researcher attempted to include with varying degrees of success were the producers and manufactures. Many were very cooperative with

supplying system specific data; however, others, due to proprietary issues, could not participate or only participate in a limited capacity. Therefore, the system specific data in this research comes from a variety of sources. The researcher gathered as much data from the makers as possible. Internet searches and extrapolation filled in any missing information.

This section and Section 1.3 provide the reader a complete explanation of stakeholders. It should now be clear who they are both in general and in the context of this research. The next section provides the reader the foundations of Engineering Systems and defines important terms used in this research.

1.4 Engineering Systems and Flexibility Defined

Two key terms used throughout this thesis are Engineering Systems and flexibility. It is important to provide the reader their definitions. This section will provide complete definitions and explanations for the context in which this paper uses them.

1.4.1 Engineering Systems

Engineering Systems is defined as:

“A field of study taking an integrative holistic view of large-scale, complex, technologically-enabled systems with significant enterprise level interactions and socio-technical interfaces” [72].

The phrase “holistic view” is a key aspect of Engineering Systems. As mentioned before Systems Engineering focuses on process, requirements, and functions. This difference of looking at the system as a whole versus components or functions supports Rhodes and Hastings assertion that Systems Engineering is a field within Engineering Systems. Additionally, there are three other fields that underlie Engineering Systems. Operations Research and systems analysis, Engineering Management, and Technology and Policy are all elements that comprise Engineering Systems [35]. Figure 1-8 illustrates Engineering Systems’ four pillars or subfields.

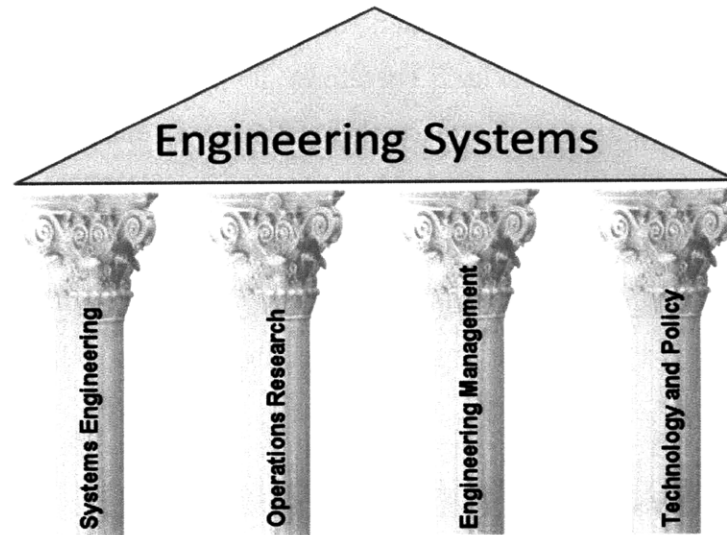


Figure 1-8: Four pillars of Engineering Systems [35]

The four subfields above provide the framework for Engineering Systems. Engineering Systems is interested in systems that exhibit the following characteristics: (list found in [35])

- Technologically Enabled
- Large Scale and Complex (large number of interconnections and components)
- Dynamic, Involving Multiple Time Scales and Uncertainty
- Social and Natural Interactions with Technology
- May have Emergent Properties

Examples of these systems are: (list found in [35])

- Military Aircraft Production and Maintenance Systems
- Commercial and Military Satellite Constellations
- Megacity Surface Transportation Systems
- The Worldwide Air Transportation and Air Traffic Control System
- The Worldwide Web and the Underlying Internet
- Automobile Production
- Consumer Supply Logistics Networks

The key discriminator between Engineering Systems and any other system is the existence of an engineering component at its core. Because it is important that the system has an engineering system at its core the following systems are of no interest to Engineering Systems: (list found in [54])

- Human Central Nervous System
- German Political System
- U.S. Federal Reserve
- Integrated Circuit Devices

The system this research uses is a backpackable unmanned aircraft system (UAS). The UASs of interest are those with a potential military application. They are technologically enabled, complex, dynamic, and they have social-technical considerations.

Engineering Systems incorporates both traditional engineering properties with non-traditional properties. Traditional engineering properties are function, performance, and cost. The non-traditional properties unique to Engineering Systems are called “ilities” [54]. Examples of “ilities” are:

- Flexibility
- Scalability
- Durability
- Sustainability
- Reliability
- Recyclability
- Maintainability
- Quality

The inclusion of both traditional and non-traditional properties makes the Engineering Systems field a very comprehensive method for system design and evaluation. The reader

should now have a firm understanding of what Engineering Systems is and what it encompasses. The next step is to define the framework in which this work uses flexibility.

1.4.2 Flexibility

The last section defined Engineering Systems and part of that definition included “ilities.” The core theme in this work is flexibility; therefore, it is crucial to define for the reader the context in which the researcher uses the term flexibility. There are numerous definitions of flexibility. While most of the definitions have a common theme, they each vary to some degree. The following list provides the reader with a range of the different definitions of flexibility.

- “Flexibility—simply stated as the ability of a manufacturing system to cope with changes” [33].
- “The ability to change or react with little penalty in time, effort, cost, or performance” [83].
- “Ability of a system to adapt to changes in environmental conditions and in process requirements” [88].

The last definition given is that of the Engineering Systems Division at the Massachusetts Institute of Technology (MIT):

- “The property of a system that is capable of undergoing classes of changes with relative ease” [18].

In addition to specific definitions, there are many types of flexibility. (Browne 1984) lists the following eight [10]:

- Machine flexibility
- Product flexibility
- Process flexibility
- Operation flexibility
- Routing flexibility
- Volume flexibility
- Expansion flexibility

- Production flexibility

This work focuses on the flexibility in a UAS. Within the UAS, one could choose to concentrate effort on any one of the eight flexible areas listed above. This research specifically targets finding flexibility in the machine. The UAS's subsystems represent the machine.

Similarly, (Gupta 1993) addresses levels of flexibility. In the context of manufacturing he describes four levels [32]:

- Machine level
- Cell level
- Plant level
- Corporate level

The UAS can be decomposed into comparable levels. The UAS represents the plant level, the major subsystems the cell level, and the flexible attributes represent the machine level. Section 5.2 explains these levels in greater detail. Section 5.6 describes how elucidating the flexibility in a system provides the stakeholders, who represent the corporate level, with increased information and knowledge. This information and knowledge permits them flexibility in their decision making.

As stated before, flexibility's definition varies as does its type and level, but each definition reflects that flexibility is directly linked to change. However, this change in flexibility is difficult to measure [32]. Furthermore, not having a good flexibility measure makes it difficult to compare the flexibility of different candidates within a solution space [6]. Most references quantifying flexibility are encountered in the area of manufacturing. Consequently, without a way to measure flexibility, decision makers often overlook its value [61]. The idea of quantifying flexibility is one of the focal points of this research. Once the value of flexibility is captured, it can be presented to decision makers in order to improve decision making. This paper uses the term flexibility with this idea of measuring change. Therefore, flexibility is defined as:

- ***Flexibility***: The ability of a system to change in order to derive potential value.

Unless otherwise stated, this is the researcher's intended meaning of flexibility when used in this thesis. Within the definition for flexibility is the term value. It is also important to define for the reader the meaning of value as used in this paper:

- “*Value*: That quality of a thing which makes it more or less desirable or useful” [86].

In order to close the loop on the definition of value and flexibility, the “quality of the thing” which gives the value is the changeability. A final term that this work needs to define for the reader is resource. Throughout this paper, reference is made to resources being utilized in order to influence change or take advantage of flexibility. Resources in the context of this work can mean: time, effort, experience, or budget.

In summary, there are many different definitions of flexibility; however, they all have the core idea of change. Lacking the ability to quantify a system's flexibility causes decision makers to overlook potential best solutions. A key element of this thesis is to develop a method for capturing the value gained from the changes in systems. The analyst can then use this measured value increase to determine the flexibility of individual systems. This information gives decision makers the option to allocate resources to previously non-optimal solutions. As a result, due to a system's inherent flexibility, it becomes the optimal choice after resource allocation. With a working definition of flexibility, the researcher can now describe how Flexibility Analysis improves the decision making process.

1.5 Flexibility Analysis: Improving the Decision Making Process

Section 1.2 demonstrated the importance of decision making throughout the life cycle of a system. The choices decision makers make about a system significantly impact the system's scope, schedule, and cost. These three factors are often referred to as the “Iron Triangle” [20]. This research focuses on influencing the decision making process prior to the implementation of a final solution. A good decision making process should result in reducing the tension of the Iron Triangle and providing a better final solution.

When attempting to identify potential solutions to a problem, the SDP eliminates potential solutions because they fall outside of the established constraints. SDP eliminates potential best solutions because they are not considered “feasible” due to a constraint. Flexibility Analysis does not eliminate all solutions that fall outside of a specific constraint. It retains more

solutions and provides the stakeholder the ability or opportunity to leverage resources to that attribute in order to bring it within required constraints. In addition to eliminating potential best solutions, current decision making methods heavily depend upon stakeholder preferences [73]. Depending on human preference yields an undesired bias and error. Keeney, Raiffa, and de Neufville, leaders in the decision analysis field, consider this error a major concern [73]. As Section 1.5.1 will show, Flexibility Analysis eliminates this error.

The UAS will serve as the system this research uses to test whether the proposed improvements to the SDP provide the decision maker more complete information resulting in a better final solution. The current problem statement, which is defined in Section 1.6, is to identify potential solutions to a backpackable, lethal UAS. Therefore, this thesis first uses the SDP to produce a best solution. It then uses Flexibility Analysis (FA) to find potential value inherent in each candidate solution which results in a better final solution. Finally, the researcher integrates the two methods to produce a better decision making process.

1.5.1 Major Differences between Flexibility Analysis and the Systems Decision Process that uses Classical Decision Analysis

As stated previously, Flexibility Analysis is an attempt to improve the decision making process. As detailed in earlier sections, the decision making process this work will attempt to improve is the SDP using CDA. The first major difference between FA and SDP is how they determine and construct the system hierarchy. In Figure 1-9, below the fundamental objective, the UAS, in the value hierarchy, the SDP lays out required functions the system must perform and can include value added attributes such as safety and efficiency. FA focuses on major subsystems instead of functions. FA's hierarchical construction by major subsystems prevents systems engineers from becoming too focused on processes and requirements and keeps the system as the focal point. This focus on the process and requirement is a major concern of Rhodes and Hastings found in the introduction of this thesis. Changing hierarchical construction from function centered to system centered eliminates this concern found in Rhodes and Hastings' work. Additionally, it allows the decision analyst to visually show which subsystem within the overall system has the most flexibility.

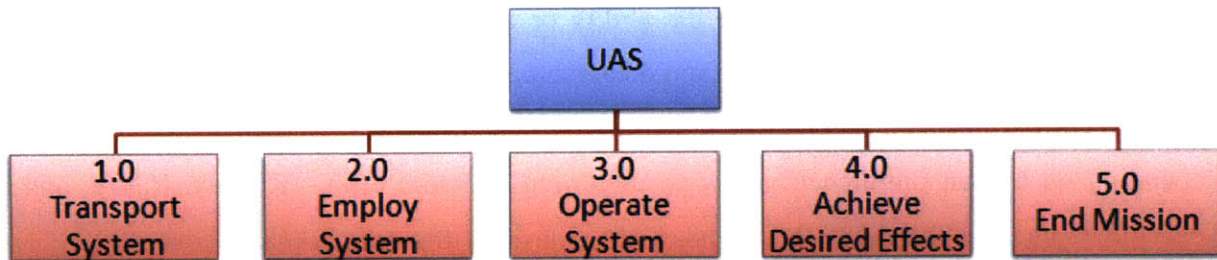


Figure 1-9: Functional Analysis of a UAS

As Figure 1-9 shows above, the focus is on the functions or process the system must perform. The functions of the system are very important, but this does not allow the systems engineer to visually see the interfaces within the system. Initially, the systems engineer needs to understand the system of systems and how they interface. Once they understand the system as a whole, they can provide the decision makers with a more complete analysis. They can better convey where the most flexibility in the system is and where resources, whether monetary or nonmonetary, can be leveraged in order to meet system requirements. Figure 1-10 illustrates a hierarchy where the level after the fundamental objective, in this example the UAS, is the major subsystems.

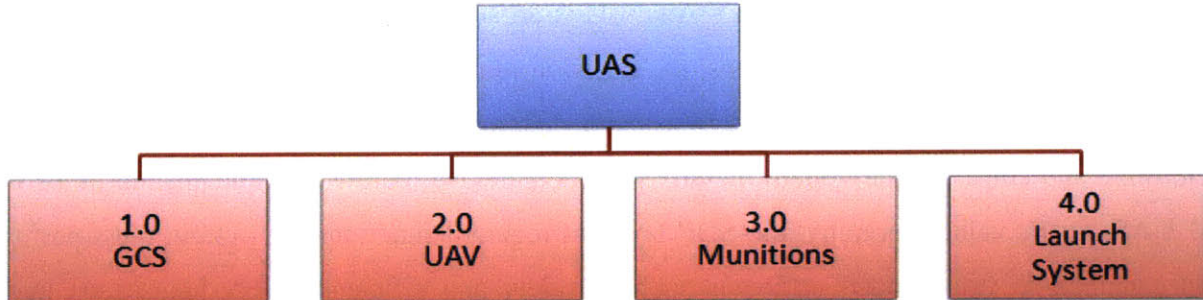


Figure 1-10: Major Subsystems of a UAS

Each subsequent level in the FA and SDP hierarchies has minor differences. Later chapters will cover these differences in greater detail. Of importance is that the FA hierarchy, unlike the SDP hierarchy, captures the major subsystems and keeps the system as the focal point.

The next major difference between FA and SDP is the determination of the feasible solution space. Too often, decision methodologies early in the decision process reduce the solution space to one or two candidates [73]. In the same way, the SDP determines the possible solution space by identifying feasibility constraints during the Problem Definition phase of the decision process. The systems engineer takes stakeholder requirements or needs and establishes

a discrete, static constraint that serve as a screening filters. The screening filters evaluate potential solutions on a pass or fail basis only; therefore, the candidate system passes the filter or it does not [65].

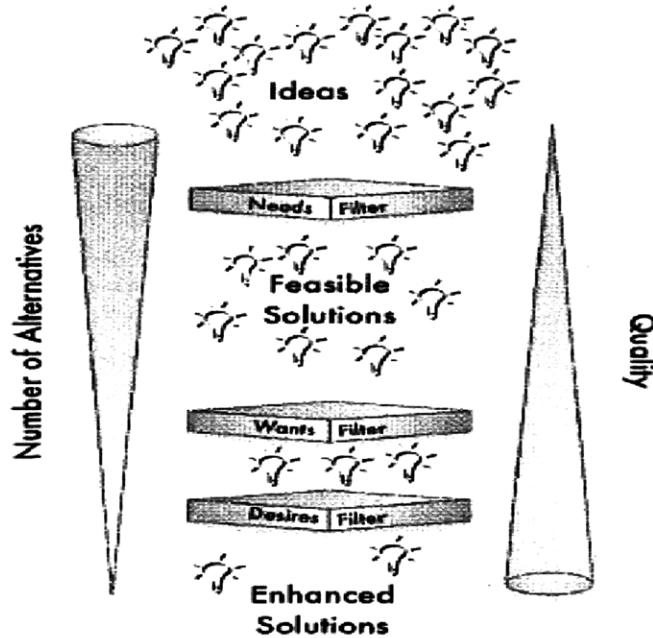


Figure 1-11: SDP Feasibility Screening [65]

Figure 1-11 implies that as one reduces the solution space with a discrete constraint the quality of the remaining solutions increases. The researcher will show this is not always true. Furthermore, the thesis will demonstrate screening filters do not always increase quality because they eliminate potential best solutions. The SDP does not provide a structured method to modify or delete the constraint. In contrast, FA presents a heuristic for defining the feasible solution space thereby preventing the elimination of potential best solutions early in the decision process. A detailed explanation of the heuristic is in Chapter 5.

The final major difference is how the quantitative model scores each candidate solution in the solution space. The SDP requires stakeholders and/or decision makers to determine and rank functions or more specifically performance measures. The systems engineer transforms this ranking into a global weight that represents one-half of the mathematical formula in CDA. The mathematics of CDA is covered in Chapter 4. FA attempts to remove the human biasing parameter out of the equation. When calculating flexibility, one is interested in the value gained from changing the status quo and not preference within the status quo [61]. Instead of a preference weight accounting for one-half of the equation, this weight is replaced by a value

difference weight. This value change represents which subsystems within the system have the most flexibility. Additionally, this is where decision makers can use resources to influence the most change in the system.

The following provides a concise list of the three major differences between the SDP and Flexibility Analysis:

1. Hierarchical structure of SDP is centered on function where as FA is centered on the system.
2. SDP has discrete, static constraints to determine the feasible solution space. FA uses a heuristic to prevent the elimination of potential best solutions.
3. SDP relies heavily on human preference or bias. FA relies on potential value in the system.

Using FA provides the decision makers a more holistic view of the solution space. It will evaluate the problem from a system perspective, eliminate some human bias, and take advantage of the flexibility in the system. Additionally, it addresses the social-technical aspect because it empowers decision makers and allows them to decide the best place to allocate budget and or resources. However, the researcher does not propose that SDP and CDA be eliminated as an evaluation method but incorporated into or used in conjunction with FA. Now that the reader has an understanding of where this work can improve the decision process and relevant terms, the researcher will formulate the thesis problem.

1.6 Problem Statement

There exists a capability gap in the utilization of UASs in the military. The military has UASs that range in size from those that the dismounted soldier can carry into battle to UASs that are the size of small commuter planes. Throughout this range of systems only those too large for the dismounted soldier provide lethality. The military is actively conducting research on arming backpackable UASs that the dismounted soldier can employ in the close fight. Due to the urgency of the requirement as a result of the War on Terror, the military acquisition system is searching for commercial off the shelf systems that have the potential to be armed. This is only a temporary solution until a system can be designed, developed, tested, and fielded that meets mission requirements. It is this urgent need that provides the problem of interest for this research.

Problem Statement: Evaluate commercial off the shelf (COTS) systems in order to provide potential solutions to a backpackable, lethal UAS for the company level and below. (See Appendix B for military organization chart)

This problem statement is the nexus for improving the decision making process. The current SDP using CDA results in a potential non-optimal solution. The researcher will show that using the Flexibility Analysis methodology results in better final solutions than the SDP alone. As a result, this research answers the following question:

Does Flexibility Analysis coupled with the SDP result in a better final solution?

This thesis does not assert that the solution determined as “best” in this research is the actual best answer to the problem stated above. The answer is simply the best solution of the candidates evaluated. The solution space for small UASs is too large to include all possible candidates into this research. Therefore, the importance gained from this work is an improved method of decision making. The next section describes the researcher’s motivation for this research.

1.7 Motivation

The idea for this thesis came from LTC Michael J. Kwinn Jr., PhD. LTC Kwinn is the Director of the Systems Engineering and Operations Research Programs in the Department of Systems Engineering at USMA. The original idea was to evaluate UASs for potential lethal use in small unit operations. Through conversations with peers, the researcher found that infantry units, company level down to squad level, have a real need for this capability. This capability of a backpackable, lethal UAS has significant relevance in current military operations. There are two scenarios that capture the need for a system of this type. The first and most important scenario the researcher’s peers agreed upon was in urban combat. The following scenario provides the reader a visualization of a situation where a soldier could employ a lethal UAS:

An infantry company is conducting a direct assault operation on a hostile section of a city where terrorist are known to operate. The city consists of narrow roads with numerous connecting alleyways. As the infantry company begins to enter the sector, it takes small arms fire from two dismounted personnel in an alley two city blocks up the narrow road. Due to the channeling nature of the city road, advancing to neutralize the targets causes undesirable risk to the soldiers. The organic weapons available to the unit leader are not accurate enough to be effective without numerous trials which could lead to unwanted collateral damage. His non-organic fire support is similarly not accurate enough and due to

its explosive power, is not allowable in this situation. Finally, the leader's close air support assets have the required precision, but due to explosive power and cost are not authorized. If the unit had a backpackable, lethal UAS, it could launch the vehicle and using a video feed and GPS coordinates from the UAS in conjunction with a map, acquire the targets in the alley. Once the targets are acquired and identified, the UAS could be flown into them. The UAS provides the accuracy and limited explosive power required for this scenario.

The second scenario where a dismounted soldier could benefit from a lethal UAS is in a mountainous environment.

Missions in Afghanistan often require foot soldiers to climb steep and rocky terrain. The majority of these missions are reconnaissance missions searching out weapons caches and insurgents. It is common knowledge within the military that the person who controls the high ground has an advantage in battle. U.S. soldiers conducting missions in the Afghan mountains find themselves at a disadvantage because the insurgents typically control the high ground. Instead of scaling a mountain, which puts soldiers in great danger, they could employ a lethal UAS. While the UAS neutralizes the target, the soldiers could remain a safe distance away.

These scenarios represent two key uses of a lethal UAS, but there are many other situations where their employment would benefit the soldier. This work no longer focuses exclusively on UASs. The core idea remains the same; however, this work now focuses on the method for evaluating systems, and the system of interest is the small UAS with potential lethality. There are three primary motivations for this research and each is explained in detail below.

1.7.1 Helping the War Fighter

As an Army officer, the researcher's first and most important motivation should always be centered on helping the war fighter. So as not to confuse the reader that has little or no experience with the military, I provide the following definition of a war fighter.

- ***War Fighter:*** Any soldier or officer whose everyday mission is to train or conduct military operations. War Fighters are found in Brigade Combat Teams (BCT) or units that directly support BCTs. They are either conducting military operations in locations like Afghanistan or Iraq or training for military operations at their permanent Stateside or European based locations.

Since this work focuses more on the method for evaluating systems and not specifically on finding the best system, it loses some significance for the war fighter. However, the hope is

that an improved decision process will benefit the war fighter indirectly. Additionally, it may highlight which aspects of the UASs have the most flexibility. Consequently, this flexibility analysis may result in a better final solution for the backpackable UAS.

1.7.2 Integrating Engineering Systems and Systems Engineering

Engineering Systems and Systems Engineering are two fields that people often confuse as being one in the same. Engineering Systems views systems more holistically than Systems Engineering. (Rhodes and Hastings 2004) assert that the evolution of Systems Engineering within Engineering Systems enriches engineering [72]. This work wants to reinforce the idea of gaining benefit from integrating both Engineering Systems and Systems Engineering. It attempts to demonstrate that Systems Engineering fits within the framework of Engineering Systems.

Integrating the two fields is important to the researcher because while he is working toward a Master of Science in Engineering Systems, he will be teaching in the Systems Engineering field. Teaching Systems Engineering students to place Systems Engineering within the strategic framework of Engineering Systems will enable them to view the SLC holistically rather than as discrete decision points. Similarly, it will keep focus on systems rather than functions. Finally, after studying the SDP, the researcher saw the potential to improve the SDP. Section 1.5.1 describes those areas of potential improvement.

1.7.3 Draper Laboratory and Decision Making

The researcher is also a Fellow at Charles Stark Draper Laboratory and wants to assist the lab in their current decision making process. In Section 1.5, the researcher describes Flexibility Analysis as a method to improve the decision making process. A key feature of FA is viewing the objective system by its major subsystems instead of functions. Once the decision analyst identifies the subsystems with the most flexibility, he presents this to the decision makers. They then determine whether allocating resources to that subsystem is warranted. It is this point where Draper Lab enters the decision process.

The system of interest in this thesis is the UAS. If the decision analyst determines the most flexible subsystem in the UAS is the ground control station, he presents this information to the decision maker. The decision maker then decides to allocate resources to improving the ground control station. As a result, Draper, who has expertise in micro-electro-mechanical systems (MEMS) and software development, receives a development contract. If the decision

maker were only considering functions as in the SDP, Draper may not have received a contract. Similarly, Draper can use the method outlined in this work for internal projects. For example, during their work on the Wide Area Surveillance Projectile (WASP) project, which is a potential solution to the UAS problem, Draper can use FA to evaluate the subsystems of WASP that have the most potential for change or improvement. With this information, they can better direct lab resources.

Flexibility analysis benefits Draper in two ways. First, FA keeps the initial focus on systems and not functions. Clients award Draper contracts to develop or improve systems not functions. If decision makers look at functions only, they will not see the potential for subsystem improvement, and therefore, do not seek out Draper. Finally, FA enables Draper to meet project requirements more efficiently by devoting finite resources to those project aspects with the most flexibility or potential for improvement. In conclusion, whether helping the war fighter or integrating Engineering Systems and Systems Engineering, the overall motivation is to improve decision making.

1.8 Thesis Structure

This work is organized into seven chapters. Chapter 2 provides a detailed overview of unmanned aerial vehicles, their role in military operations, and the associated difficulties in reducing their size. The chapter provides a significant amount of information on the difficulties associated with reducing UAS size with the intent to show the difficulty in engineering complex systems, so the reader can develop an appreciation for the importance of an improved decision making process.

Chapter 3 provides the reader with different methodologies for decision making. The purpose is two-fold. First, it gives the reader a list of alternatives to compare and critique the method presented in this thesis. The researcher does not want to give the impression that his method is best for every situation, but rather his work attempts to improve upon existing methods. Secondly, it demonstrates that the researcher considered other methods of analysis besides the one introduced in this work.

Chapter 4 uses the SDP and CDA in order to determine the best solution for a backpackable, lethal UAS. It begins the SDP in the Problem Definition stage and runs through the Decision Making stage. During the Decision Making stage, the researcher performs a

complete quantitative analysis of the candidate solutions using CDA. The researcher presents the resulting best solution to include sensitivity analysis.

In Chapter 5, the researcher employs the complete methodology for Flexibility Analysis that is outlined in Section 1.5. As in Chapter 4, he executes a complete quantitative analysis in order to produce a solution with the most potential value. The chapter also links potential value to current value to determine realized value.

Chapter 6 is a comparative analysis of the SDP and FA methodologies and results. The researcher describes how FA can be used as a stand-alone method or can be combined with SDP in order to produce an optimal solution. The chapter will also discuss limitations of using FA as a stand-alone method.

Chapter 7 concludes the thesis by reviewing the problem and summarizing the approach and results. Additionally, it addresses potential future work extending from this research. Finally, the chapter ends with the researcher's conclusions. Figure 1-12 provides the reader a visual structure of this work.

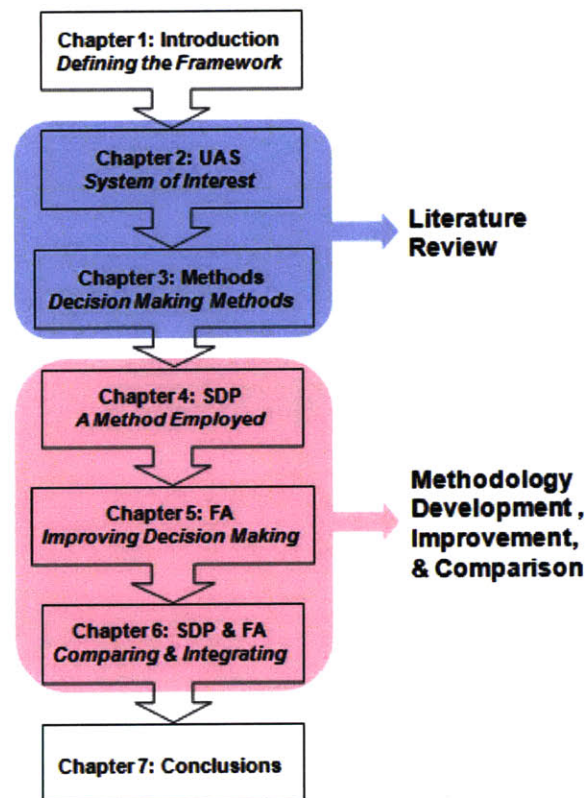


Figure 1-12: Thesis Structure

1.9 Summary

In this chapter, the researcher makes a case for the need to improve the decision making process. He provides the key areas where this research will improve decision making. In order to provide the reader an understanding of the problem, he describes the SDP which is the decision making method the work attempts to improve. Similarly, he describes the SLC, and how the SDP fits into the overall life cycle. Additionally, the chapter describes Engineering Systems and provides definitions for the important terms of stakeholder, flexibility, value, and resources. This chapter also outlines Flexibility Analysis and provides the keys aspects which result in an improved decision making methodology. Finally, the chapter provides the problem statement and the question this work attempts to answer. It concludes with the researcher's motivation for the work and the structure of the thesis. The next chapter describes the history and complexity of Unmanned Aircraft Systems which are utilized in the remainder of this work.

2 Unmanned Aircraft Systems

As Chapter 1 described, an engineered system must be present in order to be of interest to Engineering Systems. The engineered system this thesis uses is the unmanned aircraft system (UAS). The UAS embodies the five characteristics of engineering systems outlined by (Hastings 2004) in Section 1.4.1. These characteristics: are technologically enabled, complex, dynamic, social and natural interactions, and exhibiting emergent properties. Additionally, the UAS is an excellent system to demonstrate the benefits the SDP and the improvements FA offers to decision making.

This chapter provides a brief history of UASs and describes the different types of UASs along with their military applications. It then explains in rigorous detail the difficulties associated with small UASs, which are the focus of this work. The intent is to fully illustrate the difficulties engineers face when designing small UASs. The researcher believes that it is important for the reader to gain an appreciation of these difficulties because it underscores the vital need for an effective decision process that can evaluate the potential value inherent in each candidate solution, and not just the best solution based on existing parameters and decision maker preferences.

2.1 Types of UASs

There are four basic types of UASs: fixed wing, rotary wing, vertical take-off and landing (VTOL), and lighter than air (LTA). Although, fixed wing UASs are most common within the military and are the focus of this work, the military does employ or is developing each of the other types.

2.2 History of UASs

The Wright Brother's flight at Kitty Hawk, North Carolina began man's journey into human flight. However, unmanned aircraft flight dates back farther than the famous 1903 Wright Brother's accomplishment [38]. As is often seen in history, military conflict accelerates the need for new technology. World War I served as the impetus for developing both manned and unmanned aircraft [57]. However, successful application of UASs did not occur during World War I. It was not until January 1918 that the United States Army awarded a contract to Charles Kettering to develop an unmanned aerial vehicle capable of delivering a 180 pound warhead [84]. The vehicle Kettering developed was nicknamed the "Kettering Bug" and is considered the first UAS [60].



Figure 2-1: The Kettering Bug UAS [45]

UAS development gained inertia again in the 1930s. The Naval Research Laboratory developed a radio-controlled aircraft called the TDR-1 that could carry a 2,000 pound bomb [57]. The military placed its first order for two-hundred TDR-1s during World War II in March 1942, but it was not successfully used in combat until September 1944 [57].



Figure 2-2: The TDR-1 UAS [76]

The Allies were not alone in the development of UASs. It is well documented that Germany is responsible for the creation of many innovative and advanced military technologies. The Germans' first successes with UASs occurred a year prior to the Allies. The most notable of these was the sinking of the Italian battleship Roma in September of 1943, and the sinking of the British troop ship, Rohna, in November of 1943, which killed over 1,000 American, British, and Australian military personnel [57].

Development of UAS technology continued after World War II. In 1964, the United States Air Force in conjunction with Ryan Aeronautical Company fielded the Lighting Bug which was the first photo-reconnaissance UAS [43]. The Lighting Bug proved valuable to the United States' mission in Vietnam by finding surface-to-air missile sites and providing bomb damage assessment. By the end of the Vietnam War, it had flown 3,435 operational sorties [85]. Its success in Vietnam demonstrated to other countries the value of UASs. Consequently, the Israelis requested the Lighting Bug in order to assist their destruction of Arab air defense systems along the Suez Canal [13]. However, after Vietnam the United States' military budget was downsized and by 1979 all military UAS programs were eventually terminated [38].

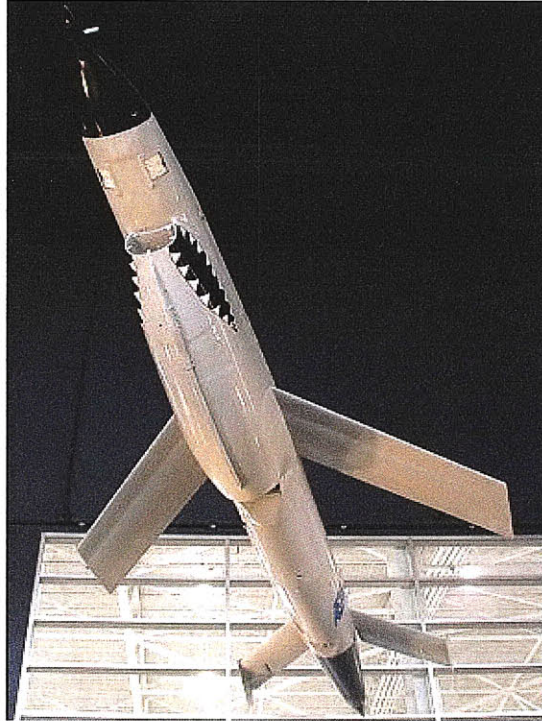


Figure 2-3: The Lightning Bug UAS [48]

In 1985, the Navy once again initiated military development of a UAS [43]. The Navy called this system Pioneer. The Pioneer flew 330 missions and over 1,000 hours in support of Army and Marine ground forces during Operations Desert Shield and Desert Storm [43]. The success of Pioneer in Desert Shield and Desert Storm renewed interest in the military application of UASs. The Pioneer continued to be the mainstay of the United States military after Desert Storm through 1995 while development of other systems progressed. The Pioneer flew in support of military operations over Bosnia, Haiti, and Somalia, and Operation Iraqi Freedom [43].



Figure 2-4: The Pioneer UAS [66]

The next leap in UAS technology occurred in 1995. The now highly recognizable Predator was used in support of military operations over the Balkans. It flew over 600 missions and 4,000 hours in support of Balkan operations [67]. Some credit the Predator with significantly influencing the conflict in the Balkans and bringing about the Dayton Peace Accord in December of 1995 [43]. Unlike now, the Predator was only a reconnaissance platform. The Predator continues to be a widely used asset of the military and has undergone significant changes and improvements. The Predator is addressed in further detail in Section 2.5 of this chapter.

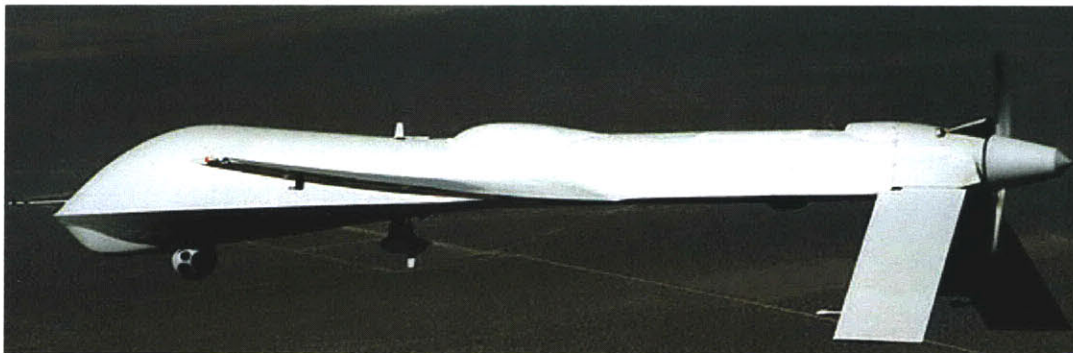


Figure 2-5: The Predator UAS [67]

It was during this same time in 1995 that the momentum for man portable or backpackable UASs emerged. In an interview with CBS's "60 Minutes" TV show, Admiral Owens of the Joint Chiefs of Staff, showed the national TV audience a model of MIT Lincoln Laboratory's micro UAS and stated the military planned to develop this technology so every soldier could carry one in his backpack [57]. From this declaration the race to develop a functional, backpackable UAS for the military began. The wars in Afghanistan and Iraq would both add to the urgency of this capability and validate their need. Thirteen years after "60 Minutes" aired Admiral Owens' interview, the capability has been realized; however, it still requires considerable improvement to fully meet the needs of the military. Additionally, advancing the technology in order to weaponize the backpackable UAS has just recently permeated military thinking. At the time this work was written, developing and validating lethal, backpackable UASs were at the forefront of military developmental programs.

2.3 Current Military UASs

The Unmanned Aircraft Systems Roadmap 2005-2030 (UAS Roadmap 2005), published by the Office of the Secretary of Defense, provides a complete list of the UASs currently operating within the military. At the time of this thesis, 10 different fixed winged UASs were in wide spread use in support of the Global War on Terror (GWOT) compared to just one, Pioneer, during Desert Shield and Desert Storm. Table 2-1 below depicts these systems and their users.

System	User	System	User
Dragon Eye	Marines	FPASS	Air Force
Global Hawk	Air Force	Hunter	Army
Pioneer	Navy/Marines	Predator	Air Force
Pointer	SOCOM	Raven	Army
Shadow	Army	Silver Fox	Navy

Table 2-1: Current UASs used in the GWOT [81]

The UASs listed in Table 2-1 vary in size from the Global Hawk, the largest, to the Raven, the smallest. Figures 2-6 and 2-7 illustrate the difference in dimensions between the Global Hawk and the Raven UASs.



Figure 2-6: Global Hawk UAS [81]



Figure 2-7: The Raven UAS [77]

2.3.1 UAS Classes

Due to the significant difference in size and capability of the UASs listed above in Table 2-1, the military categorizes each system according to classes or tiers. The classes and tiers do not match exactly among the services. For example, the Marine Corps uses a tier system comprised of three tiers [75], whereas the Army's consist of four classes. The difference in categorizing is mainly due to each service having dissimilar systems and different operational requirements. The classes described in this work are those outlined by the Army for the Future Combat System (FCS). The characteristic and capability requirements outlined below are current as of 2005. As described previously, the idea of arming Army UASs, especially Class I UASs is a new concept, hence lethality is not listed as a capability requirement for any class below.

Class I UASs are those located at the platoon level. (See Appendix B for military organization chart) Class I UASs are those of interest in this research. Table 2-2 provides a summary of their expected characteristics and capabilities.

characteristics:	<ol style="list-style-type: none"> 1) man-packable and allows visibility over one major terrain feature 2) does not require an airfield for launch and recovery 3) provides very coarse targeting for area munitions 4) a primary purpose of providing enhanced situational awareness in day and night conditions to include limited communications relay capability
capabilities:	<ol style="list-style-type: none"> 1) capable of a threshold 50 minutes times on station at an area of interest (AI) of 8 km and an objective 90 minutes times on station at an area of interest (AI) of 16 km 2) operated through the FCS battle command system 3) provides targeting information from an altitude of 500 feet above ground level at a slant range of 500 meters 4) has loiter capability in winds up to 20 knots

Table 2-2: Class I UAS Characteristics and Capabilities [1]

Class II UASs are located at the company level. Table 2-3 provides a summary of their expected characteristics and capabilities.

characteristics:	<ol style="list-style-type: none"> 1) mounted on ground vehicles organic to the unit 2) does not require an airfield for launch and recovery 3) provides persistent staring capability by hovering and perching to allow prolonged loitering times 4) performs target acquisition and designation 5) conducts RSTA operations under canopy, in open, rolling, complex and urban terrain
capabilities:	<ol style="list-style-type: none"> 1) will be capable of a threshold 2 hours time on station at an area of interest (AI) of 16 km and an objective 5 hours time on station at an area of interest (AI) of 32 km 2) will require one soldier no more than 5 minutes to launch 3) will require a threshold of two soldiers and an objective of one soldier to remount the launcher from the recovery area 4) provides targeting information during day, night and adverse weather conditions from an altitude of 1000 feet above ground level to recognize a man within a threshold of 25 meters and an objective of 10 meters and locate, identify, and designate a target at a slant range of 3 km 5) has loiter capability in winds up to 20 knots

Table 2-3: Class II UAS Characteristics and Capabilities [1]

Class III UASs are located at the battalion level. Table 2-4 provides a summary of their expected characteristics and capabilities.

characteristics:	<ol style="list-style-type: none"> 1) mounted on its own ground vehicle 2) does not require an airfield for launch and recovery 3) detects mines and chemical, biological, radiological, and nuclear agents 4) conducts meteorological surveys 5) performs target acquisition and designation 6) conducts RSTA operations with emphasis on targeting
capabilities:	<ol style="list-style-type: none"> 1) will be capable of a threshold 6 hours time on station and an objective 10 hours time on station at an area of interest (AI) of 40 km 2) will require two soldiers to move to the launch site and back to its carrier 3) performs target acquisition and designation in adverse weather conditions from an altitude of 2000 feet above ground level to recognize a man within a threshold of 25 meters and an objective of 10 meters 4) has the capability to launch, recover and operate in crosswinds of 20-30 knots and in precipitation up to 1 inch per hour

Table 2-4: Class III UAS Characteristics and Capabilities [1]

Class IV UAS are located at the brigade level. Table 2-5 provides a summary of their expected characteristics and capabilities.

characteristics:	<ol style="list-style-type: none"> 1) may require an unimproved airfield for launch and recovery 2) must be capable of persistent staring (72 hours) 3) must provide robust, long endurance communications relay across the depth of the 75 km combat radius 4) provides wide area search to cue other sensors 5) detects mines and chemical, biological, radiological, and nuclear agents 6) will assist other manned systems in performing reconnaissance and close combat with ground forces missions throughout the spectrum of Army operations 7) conducts RSTA operations
capabilities:	<ol style="list-style-type: none"> 1) will be capable conducting 72 hours continuous operations at a threshold area of interest (AI) of 75 km and an objective area of interest (AI) of 150 km 2) performs target acquisition and designation in adverse weather conditions to recognize a man within a threshold of 25 meters and an objective of 10 meters. This sensor is capable of supporting concurrent Air to Ground missile engagements of 2 or more targets. This UAV is capable of range finding to 16 km and designation for anti-Tank Guided Missiles to 16 km 3) has the capability to launch, recover and operate in crosswinds of 20-30 knots and in precipitation up to 1 inch per hour

Table 2-5: Class IV UAS Characteristics and Capabilities [1]

Comparing the organizational chart in Appendix B to the four classes, the reader sees that the Army does not have a class of UAS for units above the brigade level. The Army has no organic division level or above UAS capabilities. For these requirements, the Army relies on strategic assets that are under Air Force control such as the Predator and Global Hawk.

2.4 UAS Missions

The preceding sections provided the framework for UASs within the military. The size and capability of the different UASs varied considerably. However, their mission categories do not change appreciably across the diverse range of systems. The Army Field Manual Interim (FMI) 3-04.155 lists the following mission categories for all UASs [27]:

- Reconnaissance
- Surveillance
- Security
- Manned-Unmanned Teaming
- Communications Relay

Similarly, the UAS Roadmap 2005, lists reconnaissance as the number one priority of each service for all Classes of UASs. The GWOT and specifically the Iraq and Afghanistan wars have drastically increased the demand for the unmanned missions listed above. The total number of flight hours by UASs in Iraq and Afghanistan has surpassed 500,000, [5], and the demand continues to grow at an exponential rate. For example, excluding the flight hours flown by the Raven, the number of flight hours in 2007 was 258,000 compared to 165,000 in 2006 [5]. Colonel Bob Quackenbush, deputy director of Army Aviation, stated that the Raven, which is transported by dismounted soldiers, individually accounted for 300,000 flight hours [5]. Colonel Quackenbush's statement demonstrates the importance of backpackable UASs to the current GWOT.

2.4.1 Why UASs?

There are three primary reasons for the high demand of UASs. Dr. James G. Roche, former Secretary of the Air Force, best explains the first reason with the following: "They

(UASs) offer expanding opportunities for new and unique capabilities, and they offer an invaluable advantage, the ability to perform necessary missions without putting war fighters into harm's way" [38]. American sensitivity to military casualties has steadily increased since the Vietnam War. As a result, military and government officials have worked tirelessly to develop technologies that can reduce the American service member's exposure to danger. The UAS is a crucial instrument in accomplishing this goal.

The second major reason for the increased demand for UAS missions is because conventional manned aviation assets cannot provide the same number of flight hours. Manned aviation assets are a more finite asset than their unmanned counterpart, especially compared to the Class I UASs used at the platoon level. During the researcher's deployments to Afghanistan and Iraq, the requests for aviation assets far exceeded the unit's ability to support them. By integrating UASs into companies and platoons, this gap can be significantly filled.

The UAS Roadmap 2005 describes the third reason for using UASs as the "Dull" factor [81]. Military missions can last for many hours at a time, which stresses pilots under normal conditions. Include the pressure of a combat environment and this stress can increase significantly. However, UASs can maintain the highest levels of alertness nearly indefinitely. By considering these three reasons alone, one can sufficiently explain the value of unmanned aviation assets.

2.5 UAS Capability Gap

As described in the previous section, the primary mission of the UAS is reconnaissance. However, the military has given considerable effort to arming UASs. The Predator UAS was the first UAS platform in modern time to be successfully armed. Predator-A is the reconnaissance version and Predator-B is the armed version. In February 2001, a Predator-B launched and hit a target tank with a Hellfire missile [31]. In November of the following year, the United States used the Predator-B to successfully engage and killed six al-Qaida members in Yemen making it the first combat strike mission of a UAS since World War II [31]. The Predator-B remained the only lethal UAS in the military's inventory until late 2007. The Air Force improved the Predator-B's capabilities and renamed it the Reaper. Figure 2-8 below shows a Reaper UAS carrying a Hellfire missile and a laser-guided bomb.



Figure 2-8: The Reaper (Predator-B) UAS [71]

The wars in Afghanistan and Iraq would accelerate the development of other weaponized UASs. The Army, who was most affected by the Afghanistan and Iraq wars, desired a lethal UAS of their own because of the limited availability of the armed Predator. The Army experimented with arming the Hunter UAS. On September 1, 2007, the Army successfully dropped a laser-guided bomb from a Hunter UAS in Iraq and killed two men emplacing a roadside bomb [63].



Figure 2-9: The Hunter UAS [40]

The value an armed UAS provides the war fighter is immeasurable. (UAS Roadmap 2005) best summarizes this with the following: “The ability to operate in high threat environments without putting war fighters at risk is not only safer, but potentially quicker and more effective than current manned systems” [81]. An example of this value occurred during the invasion of Iraq in April 2003. A Predator was sent to Baghdad in order to destroy an antenna

system used by “Baghdad Bob,” a proliferator of propaganda for Saddam Hussein. The Predator destroyed the antenna without harming a Fox News antenna less than 150 meters away [38]. Using the Predator to destroy the antenna represents a precision strike in a high threat environment without endangering a pilot.

Currently, only the Predator and Hunter UASs have successfully been armed. The Predator is a strategic asset controlled by the Air Force, and the Hunter is a brigade level asset for the Army. While they represent an important capability with proven success, they are not an asset the company or platoon can depend on for fire support. Due to their level of control and limited numbers, companies and platoons will rarely have them as dedicated resources. More often these platforms will be in general support and on call to many units in a specific area of operation. The delay encountered due to this type of support may often result in fire support arriving too late to be used against the identified target. Similarly, because the requesting unit is not directly in control of the UAS, more time is lost trying to direct the operator of the UAS to the proper target.

Additionally, like other types of indirect fire and close air support (CAS) assets, the effects from the weapons these systems deliver may be too destructive or too expensive to make them feasible options. For example, indirect fires from artillery and mortars are considered danger close when used on targets within 600 meters of friendly forces. In today’s conflicts, distances within 600 meters are the norm and not the exception. When using munitions dropped from CAS assets, danger close can be much farther than 600 meters. In addition, a single Hellfire missile fired from a Predator can cost more than \$50,000. As a result of the timeliness of support, the destructive power of the weapons, and their cost, a gap exists between the munitions the current lethal UAS provides and the munitions needed by the platoon and company size units.

The Battle of Fallujah in November of 2004 proved the need for a backpackable, lethal UAS. Numerous indirect fire rounds were fired within 200 meters of friendly units [15]. Because it was an urban environment, the surrounding buildings provided cover during the danger close missions. However, this also resulted in increased amounts of collateral damage. These danger close calls for fire were often “walked-in” to the target [15]. Walking indirect fires into a target involves dropping rounds closer and closer to the intended target with each successive round until the target is destroyed. This expends unnecessary rounds and again

increases collateral damage. Additionally, support from CAS and Predators proved to be unsuccessful due to time delays associated with not having organic control [15]. Finally, indirect fires and CAS were ineffective against targets of opportunity [15]. Targets of opportunity are not targets of the primary mission but when neutralized, positively support the mission. Generally, these targets only present themselves for brief periods of time. The battle of Fallujah is only one of many examples that occur on a daily basis in the GWOT where a backpackable, lethal UAS is needed.

2.6 Difficulties in Bridging the Gap

Developing a lethal, backpackable UAS is a technically difficult problem. In order to begin considering a UAS small enough to stow in a backpack, the following three advances in technology were needed: small engines, small radio receivers and transmitters, and small actuators [57]. As is obvious, in order to successfully fly a small UAS, every aircraft component must be reduced in size. Only recently has technology advanced in order to make small UASs possible. The most important advancement came with micro-electro-mechanical systems (MEMS). MEMS devices are comparable in size to microprocessor chips; however, they function like mechanical machines and are often times coupled with electronic devices [39]. MEMS technology is the only way to shrink aircraft components down to a size that are useable in small UASs [2]. While reducing the size of the components on board the aircraft is a major obstacle to successfully developing backpackable UASs, others persist. Aerodynamics, weight of materials, and system integration also contribute to the difficulty of development. Arming small UASs adds an additional level of complexity that is currently the focus of significant research and the underlying problem in this work.

2.6.1 Vehicle Considerations

The UAS is composed of several different parts. The center piece of the UAS is the aircraft or vehicle. As the previous section described, vehicle development presents the biggest obstacle to successfully creating a backpackable UAS. Developing small UASs is very difficult because it requires “high degrees of system integration with unprecedented levels of multifunctionality, component integration, payload integration, and minimization of interfaces among functional elements” [4]. As a result, the remainder of this chapter will explain in detail

the difficulties associated with reducing unmanned aircraft (UA) down to a size a dismounted soldier can carry on his back.

2.6.1.1 Aerodynamics

The aerodynamics of the UA are important because they ultimately determine the flight characteristics and stability of the platform. Having a stable vehicle platform is critical to sensor operation, controllability, and weapon delivery accuracy. Three aerodynamic factors significantly affect whether a small aircraft can enter and maintain stable flight: Reynolds Number, Lift-to-Drag Ratio, and Aspect Ratio.

2.6.1.1.1 Reynolds Number

Reynolds number, R_e , is a critical aerodynamic element that becomes more difficult to overcome as it decreases. It takes into account air density, airspeed, wing chord, and the air's viscosity. In Equation 2.1 below, ρ , is air density, V is velocity, c is wing chord length, and μ is viscosity. Wing chord length is the distance from the leading edge of the airfoil to the trailing edge along the center line.

$$R_e = \frac{\rho V c}{\mu} \quad (2.1)$$

The Reynolds number is directly proportional to an aircraft's size and speed [39]. As a result, the smaller the aircraft is and the slower it flies, results in a smaller Reynolds number. Figure 2-10 illustrates the Reynolds numbers associated with different flying masses.

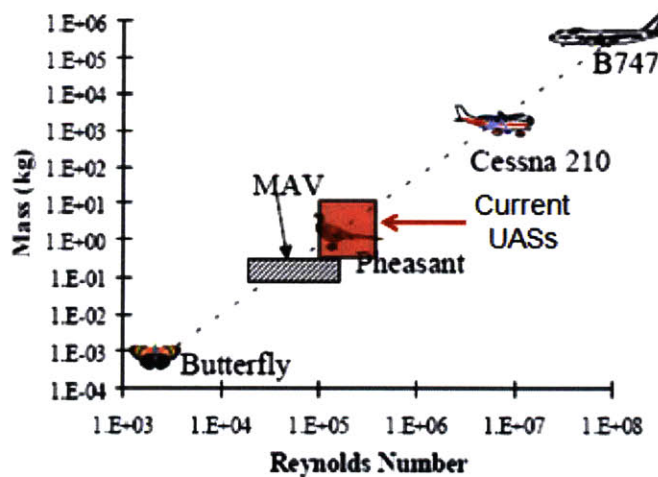


Figure 2-10: Reynolds Number vs. Mass [57]

The figure above has a boxed area labeled MAV. MAV stands for micro air vehicle. MAV is the ultimate sizing goal of a backpackable, lethal UAS. Currently, small military UASs typically have a Reynolds number between 200,000 and 500,000 [74]. The red box in Figure 2-10 highlights the approximate region of the current military small UASs.

The Reynolds number is very important to airfoil performance. Historic airfoil technology is efficient above Reynolds numbers of 200,000; however, performance quickly degrades below a Reynolds number of 100,000 [56]. The red area in Figure 2-11 below illustrates the exponential decrease in the lift-to-drag ratio at Reynolds numbers below 100,000.

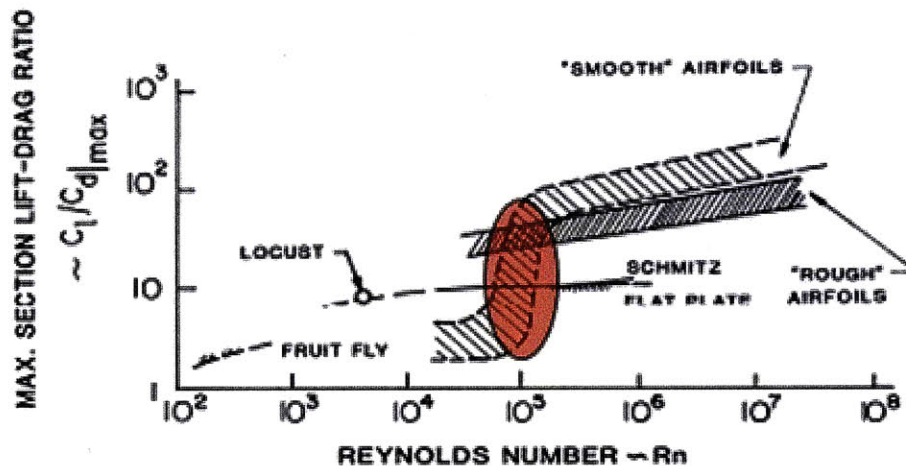


Figure 2-11: Reynolds' Number Effect on Lift-to-Drag Ratio [56]

Conventional jets have lift-to-drag ratios of approximately 15, and sail-planes can have ratios as large as 30 to 50 [19]. These aircraft have high Reynolds numbers. However, small UASs, with low Reynolds numbers, typically have lift-to-drag ratios 3 to 4 times smaller than conventional aircraft [52].

Ultimately, Reynolds numbers do more than just reduce the lift-to-drag ratio. Due to the lower lift-to-drag ratios, it increases the propulsion power required to maintain flight [52]. Similarly, at low Reynolds numbers, propellers are not as efficient [52]. As a result, new airfoil design is vital to diminishing the effects of the Reynolds number. Significant research has and is currently being performed in order to develop airfoils that provide better lift-to-drag ratios at low Reynolds numbers.

2.6.1.1.2 Lift-to-Drag Ratio

The lift-to-drag ratio is defined as follows:

$$\frac{L}{D} = \frac{C_L \frac{1}{2} \rho S V^2}{C_D \frac{1}{2} \rho S V^2} = \frac{C_L}{C_D} \quad (2.2)$$

Where C_L is the coefficient of lift, C_D is the coefficient of drag, ρ is air density, S is airfoil area, and V is velocity. The lift-to-drag ratio is important in determining the propulsive power required for flight. It is a measure of aerodynamic efficiency [56]. Wing area and velocity directly affect the lift-to-drag ratio. As a result, when the angle of attack and airspeed are the same, a wing with an area of 200 square feet provides twice as much lift as a wing with an area of 100 square feet [24]. Similarly, lift changes with the square of the velocity [24]. Therefore, an airfoil with a velocity of 200 miles per hour is producing four times as much lift as the same airfoil with a velocity of 100 miles per hour.

The two examples above explain why small UASs are difficult to design. They have small wing areas and generally operate at low airspeeds; therefore, they are unable to produce high lift numbers. Additionally, they have low Reynolds numbers which increases the amount of drag they experience. As a result, their lift-to-drag ratios are lower, representing a lower aerodynamic efficiency. Designing small UASs requires engineers to make tradeoffs between the size of the vehicle and its performance. As technology and vehicle design advances, the tradeoffs become less significant.

2.6.1.1.3 Aspect Ratio

Aspect ratio is the wing span divided by the chord length. Chord length was used in calculating the Reynolds number as well. It can also be expressed as the square of the wing span divided by the surface area of the wing.

$$AR = \frac{b}{c} = \frac{b^2}{S} \quad (2.3)$$

In Equation 2.3, AR is aspect ratio, b is wing span, c is chord length, and S is surface area of the wing. For small UASs this relationship leads to a desired aspect ratio of one or near one [29]. Aspect ratios one or less have the advantage of creating both linear and nonlinear lift that larger aircraft do not create [55]. However, UASs with small aspect ratios result in an overall degradation of aerodynamic performance. As the aspect ratio is reduced, the drag increases which reduces the lift-to-drag ratio [57]. Without better wing design, the only way to reduce drag is to increase the aspect ratio by increasing the wing span and decreasing the chord length.

However, this decreases the packability of the UAS and could potentially lead to increases in vehicle weight in order to support the longer wing span. Once again, this demonstrates that tradeoffs must be made when designing backpackable UASs. As the previous three sections illustrate, there is a direct relationship among Reynolds number, lift-to-drag ratio, and aspect ratio. Changing vehicle design parameters in order to increase performance of one of these vehicle characteristics directly affects the aerodynamic performance of the other two.

2.6.1.2 Size and Weight Limitations

Size and weight of the UAS are major considerations when developing a backpackable, lethal UAS. The previous sections demonstrated that reducing the size of the air vehicle significantly affects its aerodynamic characteristics. As a result, the payload weight the UAS can carry is considerably reduced. The sensors, processors, data links, and control systems account for the majority of the allowable payload. Consequently, this leaves very little payload weight for munitions. Without sufficient explosive power, the system is ineffective as a weapon. Figure 2-12 below depicts several UASs with their wing span versus their payload capacity. The area labeled MAV in the figure is the ultimate goal for size, but these have very little payload capacities.

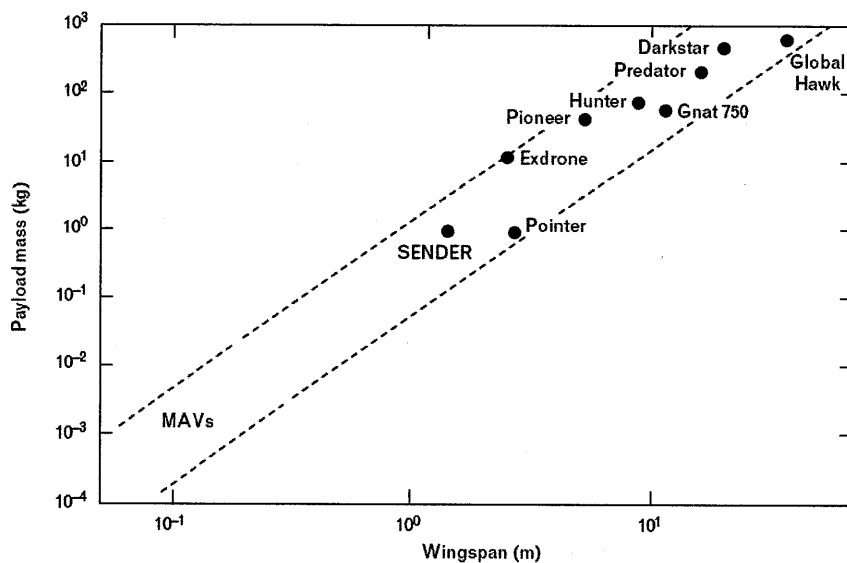


Figure 2-12: Current UAS Wing Span vs. Payload Capacity [19]

In order to solve this problem, further advancement in technology must occur. Current methods to address the problem are to make payloads multifunctional and modular [81]. Creating multifunctional components is now becoming widespread in the commercial sector.

For example, Figure 2-13 depicts the Tiny Guidance Engine (TGE) developed by Continental Controls and Design. The TGE combines a Global Positioning System (GPS) with inertial navigation, control data, control actuator commands, and serial communication [78]. It is highly beneficial to develop components that can perform multiple functions because this eliminates the need for separate components and reduces the payload's weight.

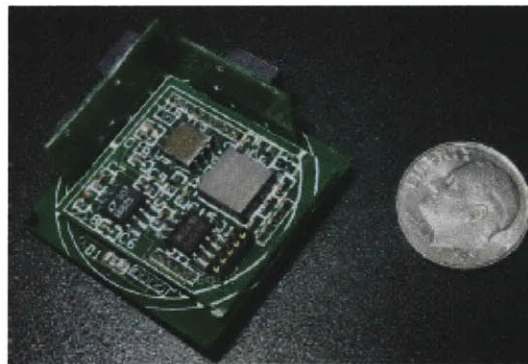


Figure 2-13: Tiny Guidance Engine [78]

An additional method that does not require advancements in technology is trading battery weight for payload weight. The payload weight is at its maximum when battery weight is at zero and vice versa [16]. However, trading battery weight for payload weight reduces endurance time, so this tradeoff must be balanced.

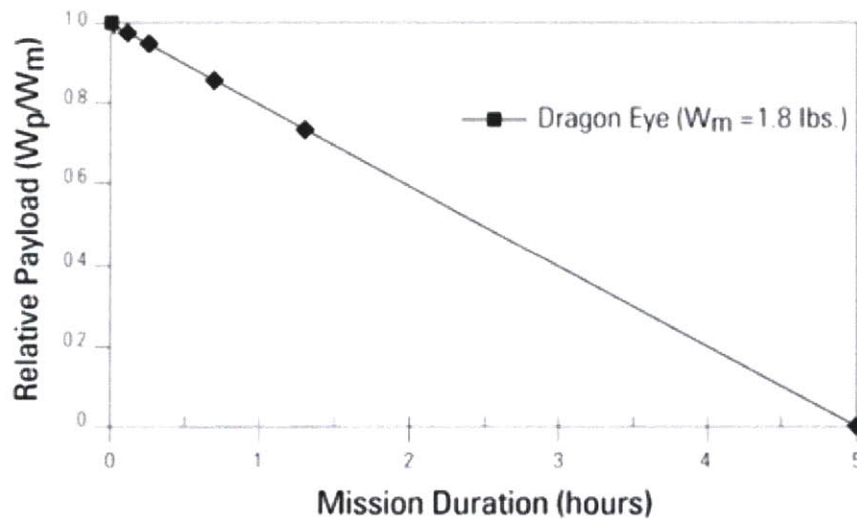


Figure 2-14: Endurance vs. Payload [16]

Figure 2-14 shows the relationship between battery weight and payload weight for the Dragon Eye UAS. The Dragon Eye is a UAS that will be included in the potential solution space later in this work. Because the stakeholders surveyed in Chapter 1 only require the endurance

time of a backpackable, lethal UAS to be less than one hour, it allows the Dragon Eye to trade battery weight for munitions weight. Finally, weight reductions in other components, due to advancements in technology or better engineering, will increase the available munitions payload weight.

2.6.1.3 Propulsion

Propulsion includes both the motor and the power source to run the motor. Propulsion is considered a significant challenge and accounts for a majority of the weight budget for small UASs [19]. Propulsion typically accounts for at least 30% of the UAVs weight and in many systems even more so.

Weight Budgets for 20-Minute Flight

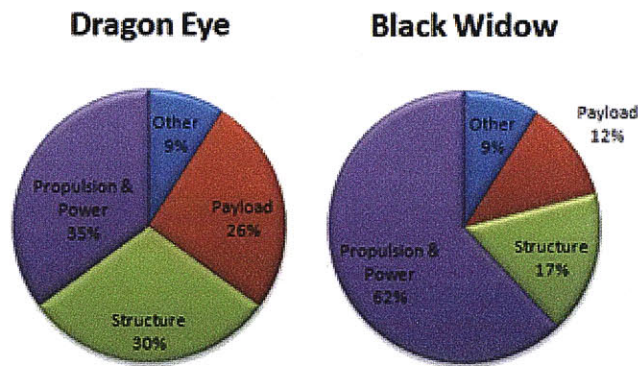


Figure 2-15: Dragon Eye and Black Widow Weight Allocations [16]

Like the Dragon Eye, the Black Widow UASs in Figure 2-15 is also a potential solution that is used later in this work. The propulsion and power (the purple area) account for 35% of the Dragon Eye’s weight and 62% of the Black Widow’s weight.

Depending on the manufacturer, UASs can use both combustion and electric motors. Small motor performance is measured using specific fuel consumption and specific power [81]. Specific fuel consumption is a measure of efficiency and specific power is a measure of performance. Small combustion motors generally produce more specific power but are less efficient than electric motors [57]. Also, electric motors are more reliable, do not use consumable fuel, and have a lower acoustic signature [19]. Consequently, they are the preferred choice for small UASs. Figure 2-16 depicts a variety of small UAS electric motors next to a six inch ruler.

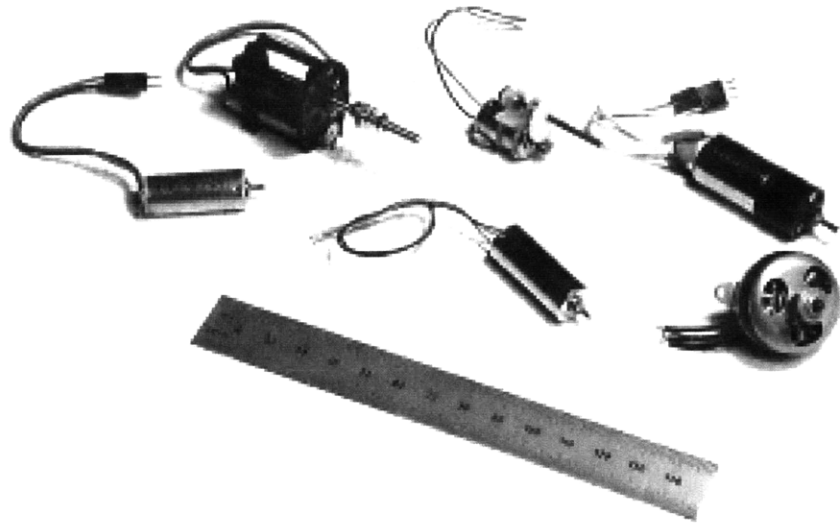


Figure 2-16: Small UAS Electric Motors [57]

2.6.1.4 **Power Sources**

There are three potential power sources for UASs: combustion fuels, batteries, and fuel cells. Each has advantages and disadvantages for small UAS applications, and each are addressed in further detail in the sections that follow.

2.6.1.4.1 **Batteries**

Prior to the 1970s, battery technology was not advanced enough to be a viable source of power for UASs. Due to progress in battery technology, they are now the power source of choice for small UAS designers. The first batteries used in small UASs were composed of nickel cadmium and nickel metal hydride with specific power levels between 20 and 50 watt hours per kilogram ($W \cdot h/kg$) [57]. However, further battery research led to lithium-ion being the new choice in battery chemistry. Lithium-ion batteries have specific power levels that are between 150 and 200 $W \cdot h/kg$ [57]. This is a 400 percent increase in specific power.

Batteries have a much lower specific energy than combustible fuels, which requires an increase in the amount of batteries to produce the same power [57], and an increase in the amount of batteries increases the total weight. Research continues in order to develop new chemistries that increase specific power levels above those of current lithium-ion. As the specific power levels increase, it will reduce the weight UASs must carry to power themselves.

2.6.1.4.2 Combustible Fuel

For many large UASs, combustible fuel is the preferred power source. Combustible fuel has very high specific power levels compared to other power sources. Its specific power can be 100 times higher than lithium-ion batteries [57]. However, there are numerous drawbacks to using combustible fuels for small UASs. As described previously, they are not as reliable as and produce higher acoustic signatures than batteries. Also, they increase logistical footprints because the fuel for UASs does not meet battlefield requirements defined by DoD regulations [81]. Therefore, additional fuel sources must be supplied to units in the field possessing UASs. Additionally, since the UASs of interest will be carried in the backpack of a dismounted soldier, it has the potential to cause a hazardous material injury. For these reasons, combustible fuel is not a feasible option for backpackable UASs.

2.6.1.4.3 Fuel Cells

Fuel cells are a potentially unique solution as a power source for UASs. Fuel cells have become more common due to their use in automobiles as a way to reduce gasoline consumption, increase fuel mileage, and reduce harmful emissions. They represent a power source that is nearly equal to combustion fuels for specific power levels with less weight than batteries [81]. However, due to size and weight restrictions, current fuel cell technology is not mature enough to consider it a feasible choice as a power source for small UASs.

2.6.1.5 Reliability

The reliability of UASs is ever increasing. Reliability is very important in both large and small UASs. Large UASs must be reliable because they present similar dangers to ground personnel and property as manned aircraft when they crash. Similarly, small UASs must be reliable because when they fail soldiers are put in harm's way to recover them. One of the Infantry officers the researcher interviewed as a user stakeholder explained that each time his company's Raven UAS went down; he was forced to send his soldiers to recover it.

The United States Soldier Systems Center in Natick, Massachusetts which was the trainer and tester stakeholder provided two reasons small UASs primarily fail. The first was lack of experience by users. Part of Natick Laboratories mission is to train military personnel who will be the primary trainers in their units. However, due to finite resources, they are unable to provide training to every potential trainer. Many users do not end up receiving the required

amount of training to be a successful operator of the system. The second cause of failure was due to loss of data link, which the personnel at Natick Laboratories felt was the most common reason for failure. (UAS Roadmap 2005) similarly stated this as a major concern. The urban battlefield the military currently faces is very “hostile” to wireless data communication resulting in the failure of many UASs while in flight [81]. The reason for this is most military UASs operate with one frequency. Even the newest UASs only offer slightly more. As a result, frequency interference can occur and communication with the UAS is lost. New methods of communicating between the ground control station and the vehicle are currently being researched.

2.6.2 Arming Considerations

Successful employment of small UASs to conduct reconnaissance and security missions has led the military to begin research into determining the possibility and feasibility of arming them. Arming UASs significantly increases their complexity. As a result, designers must consider many new factors during development. Additionally, many of the previously addressed difficulties associated with small air vehicle design are exacerbated. Designers must consider not just the size and weight of the weapons and their associated effectiveness against the intended target, but they must also determine how the size and weight of the weapons will affect the flight characteristics of the vehicle. Additional, factors the designers will now face are targeting methods and weapon accuracy and safety.

2.6.2.1 Weapon Size and Weight

Section 2.6.1.2 described the size and weight limitations of small UAS payloads. The majority of the available payload was consumed by systems required to make the vehicle function properly while in flight. Very little payload weight was available to add explosive material to the vehicle. As a result, this prevented the small UAS from being a viable weapon system. There are two methods to overcome this problem. The first is better engineering and advances in vehicle design. As aerodynamic performance increases, multifunctional components evolve, and propulsion advances, available payload weight will be freed up to incorporate more explosive material. The second method to solve this dilemma is advances in weapons technology. The Air Force is actively sponsoring research into lightweight, high energy explosives that are suitable for use in small UASs [39]. Advances in weapons technology

combined with improvements in vehicle design will ultimately lead to smaller and smaller lethal UASs.

2.6.2.2 Targeting Method

The targeting method for small UASs is a major concern of the military. (UAS Roadmap 2007) states that reliable targeting is the primary concern when arming UASs [82]. Through interviews with stakeholders, the researcher determined that visual-based targeting is the preferred method. Visual-based targeting improves both weapons effectiveness and safety. It increases effectiveness because the operator sees the target all the way until impact. Visual-based technology for small UASs currently exists and has been validated by Procerus Technologies. Integrating their OnPoint™ targeting algorithm into their test UASs has achieved three meters of accuracy [62]. Additionally visual-based targeting increases safety because the operator sees the intended target as opposed to targeting based on believed GPS coordinates.

2.6.2.3 Weapon Effectiveness

Weapon effectiveness is a major concern when arming small UASs. Because small UASs will not be capable of carrying large amounts of explosive material, their effectiveness will depend on impact proximity to the target. Again, through interviews with stakeholders, the researcher found that the desired explosive power was comparable to that of an Army hand grenade. The Army's hand grenade has 6.5 ounces of explosive material, a kill radius of five meters, and an effective radius of 15 meters [25]. Consequently, if targets can be hit reliably to within three meters, as the OnPoint™ technology allows, then sufficient effectiveness can be obtained with minimal weapons payload.

2.6.2.4 Weapon Safety

Weapons safety is a paramount concern of the military. (UAS Roadmap 2005) gives the absence of a pilot controlled master arming switch and electromagnetic interference (EMI) as the primary safety considerations for UAS weaponization [81]. Manned aircraft rely on the pilot to activate an arming switch in order to employ weapons. However, unmanned systems do not have an onboard pilot to safe and arm the aircraft. As a result, UAS designers must develop an independent path in order to safe and arm the UAS. Additionally, they must find ways to shield the weapon from EMI.

2.7 Summary

The history of UASs predates that of their manned counterpart. However, manned flight has evolved at a much faster rate. While manned aircraft continued development between wars, unmanned aircraft only experienced high levels of interest and development during wars. This pattern slowly began to change in 1985 when the Navy began its Pioneer program. The current wars in Afghanistan and Iraq have significantly increased the demand for UAS technologies and brought about systems that rival and surpass their manned equivalent in some performance measures. Additionally, these wars have proven the need for UASs that the dismounted soldier can carry on his back into battle.

Designers face many challenges in trying to miniaturize systems in order to meet the dismounted soldier's requirements. The aerodynamics of small aircraft are significantly different than that of conventional aircraft. Prior to 1995, engineers had conducted little research into the flight characteristics of airfoils with Reynolds numbers below 200,000. Research in this area has exploded and considerable data now exists to assist designers of small UASs. Additionally, advances in component technology, mainly due to MEMS, has bridged many barriers that prevented progress in reducing the size of UASs. Finally, propulsion technologies continue to further evolve, breaching design barriers that previously prevented successful application of small UASs.

The primary mission UASs have traditionally performed is reconnaissance. However, the successful arming of the Predator caused military leadership to consider arming smaller backpackable UASs. However, arming small UASs further complicated the already difficult problem of designing functional systems.

The military is turning toward commercial technologies in order to solve the challenges encountered by designers. (UAS Roadmap 2005) specifically identifies commercial, off the shelf (COTS) technologies as the answer to the small UAS problem. Commercial solutions are advantageous because they “avoid using defense development dollars, which provides the opportunity for other developments, and offers the concept of ‘consumable logistics’” [81]. Consumable logistics is not buying into long sustainable systems, as the military traditionally does, but buying the newest and best technologies every few years.

With this in mind, the UASs that comprise the potential solution space in Chapters 4 and 5 are a collection of COTS systems. A few of them were specifically designed for the military,

but they utilized COTS components in their development. The decision making methodology developed in Chapter 5 is an ideal way to evaluate COTS systems for their potential to be used in military applications because the method determines a system's flexibility with respect to military specific attributes. In the next chapter, the author presents several currently used decision making methods.

3 Decision Making Methods

At this point in the work, the reader should have an understanding of the researcher's purpose and goal, along with an appreciation of the complexity involved in engineering a backpackable, lethal UAS. Before the researcher presents the SDP and FA methods for selecting an optimal UAS, it is important to describe other methods of decision analysis available. The methods presented are not complete processes like the SDP, but rather evaluation techniques. An evaluation technique is at the core of every decision process. By presenting different methods, it provides the reader a spectrum of the different approaches they can use to compare to those presented in this research.

3.1 Biased versus Unbiased Analysis

Decision making techniques fit into one of two categories: biased or unbiased. As the researcher described in Chapter 1, one improvement FA makes to the SDP is the removal of stakeholder preference. Using preference in decision making is biased analysis. The researcher found that the majority of methods were a form of biased analysis.

Many techniques use weighting methods in order to rank order the importance level of every system attribute. Examples of these are swing, ratio, fuzzy preference relations, and entropy weightings. Of these four, only entropy is unbiased. Similarly, of the matrix style

techniques described below, only the Pugh Method is unbiased, and only if the attributes are defined quantitatively and not qualitatively.

Lastly, there are numerous optimization methods available such as linear, integer, and nonlinear programming, as well as multidisciplinary design optimization. Each of these is an unbiased method. This work only presents linear programming as an unbiased method because it is the most widely used technique. The researcher also presents linear physical programming in order to illustrate a biased optimization method.

3.2 Decision Matrices

Decision matrices are a popular technique for determining which candidate in a solution space is optimal. Pugh (1991) considers matrices the best way to structure an evaluation procedure [70]. One of the most widely accepted and practiced techniques using matrices is the additive value model. Numerous books dedicated to decision making use the additive value model as the quantitative foundation for calculating the best solution. Examples of these are: *Decision with Multiple Objectives* by Ralph Keeney and Howard Raiffa, *Strategic Decision Making* by Craig Kirkwood, and *The Engineering Design of Systems* by Dennis Buede. Additionally, the additive value model is the method the SDP uses and is described in detail in Chapter 4. Methods that are described in this chapter and do not use the additive value model are the Pugh and Quality Function Deployment methods. Critical to the additive value model is the weighting of each system attributes' importance levels.

3.2.1 Attribute Weighting Techniques

There were numerous approaches in the literature for eliciting an attribute's weight. Four of these methods (swing, ratio, entropy, and uniform fuzzy relations) are explained in the following sections. The SDP uses swing weighting; therefore, it is covered in detail in Chapter 4. The remaining three have varying degrees of mathematical rigor.

3.2.1.1 Ratio

Determining ratio weights requires little mathematical rigor and is highly dependent on preference. As a result, it is highly biased and the ratios can vary significantly between individuals. The process begins at the bottom of a hierarchy tree. Each attribute at the bottom of the tree is ranked ordered by its level of importance with respect to its immediate objective.

After rank ordering, each attribute is then assigned a weight. For example, the least important attribute is assigned a weight of 10 and each higher ranked attribute is given a greater weight in multiples of 10, depending on how much more important it is deemed by the decision maker [8]. This process is performed on each level of the hierarchy. Figure 3-1 illustrates a system hierarchy depicting this process.

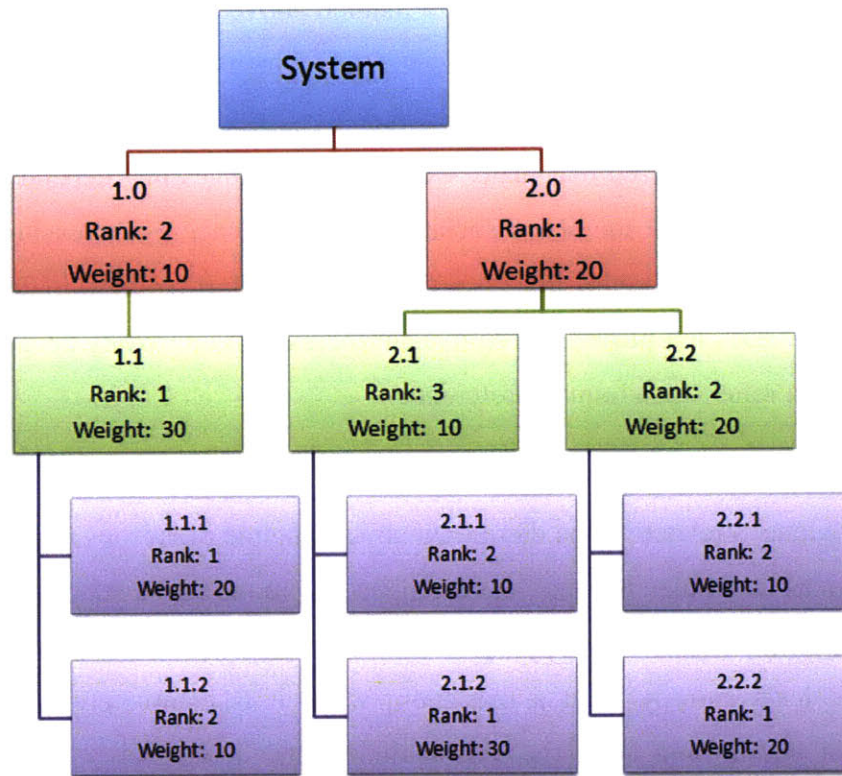


Figure 3-1: Ratio Weighting

A preference weight can now be determined for each objective at each level of the hierarchy. For example, the weight for Objective 1.0 is 0.5, and the weight for Objective 2.0 is 1.0. Additionally, when choosing among predefined alternatives, the ratio weights can be converted to utility values [14]. For each alternative, the utility values are summed to produce the alternative most desired by the decision maker. The best solution heavily depends on how the decision maker ranks and weights the objectives. Consequently, results can vary greatly among decision makers.

3.2.1.2 *Fuzzy Majority*

A rigorous approach to determining biased weights is the Fuzzy Majority Method using fuzzy preference relations. The Fuzzy Majority Method is a mathematically intensive technique

that rank orders a decision maker's preferences with an ordered vector and permutation functions. Additionally, it requires the use of quadratic programming and Lagrangian functions in order to determine the weight parameter in the additive value model. However, this method completely depends upon the decision maker's subjective preferences [49]. The complex mathematics required in order to calculate the weight parameter is more rigorous, but it experiences the same vulnerabilities as the ratio method above. If the reader desires a more in-depth description of the mathematics of the Fuzzy Majority Method see the paper by (Ma, Zhang, and et.al 2001).

The researcher discovered that many weighting techniques that depend upon preference attempt to negate the impact of the bias associated with preference by increasing the complexity of the mathematics. Ultimately, this increases the time and effort required to determine the best choice. However, it does not provide an equivalent increase in optimality because regardless of the rigor involved, it relies upon human preference.

3.2.1.3 *Entropy*

This technique is related to the thermodynamic principle of entropy. In thermodynamics, entropy increases as molecules become less arranged and move into a state of equilibrium with their surrounding environment. For example, as the ice on a frozen pond melts, its entropy is increasing. The ice's entropy is at a maximum when it is completely melted and the ice molecules are in equilibrium with the surrounding water molecules. Similarly, if all the candidate solutions have an equivalent or near equivalent value for a specific attribute, that attribute is at maximum entropy [9]. These attributes with maximum entropy are not important to the decision maker because they provide no differentiation among the candidate solution space. In contrast, those attributes that exhibit low entropy are very important because they offer the decision maker a means to discriminate among candidate solutions.

The significance of entropy weights is that they rely upon the characteristics of the different candidate solution attributes and not assigned preference weights. Entropy allows systems to demonstrate their true value with respect to their solution space, as opposed to a decision maker injecting bias which influences how a system is evaluated. In a sense, it allows systems to speak instead of a decision maker speaking for them. For further details on calculating entropy weights see (Borer and Mavris 2005) [9].

3.2.2 Pugh Method

The Pugh method is an unbiased, matrix centered decision approach. It is unbiased because it avoids the drawback associated with the use of preference weights [58]. Stuart Pugh, the inventor of the Pugh method, describes his process as “controlled convergence” [69]. The method provides a structured process for reducing a candidate solution space until it converges on one remaining solution.

The Pugh method has two phases. The first phase involves a stepwise process in order to determine a best solution. The best solution that emerges from phase one then proceeds to phase two for further engineering. Depending upon which source used, the number of steps vary. For instances, in *Total Design* by Stuart Pugh [70] there are 15 steps, but in *Creating Innovative Products Using Total Design* [68] by Stuart Pugh but edited by Don Clausing and Ron Andrade there are 11 steps. The researcher summarizes those found in the latter with the 10 steps below:

1. Populate a candidate solution space to include a sketch of its form.
2. Create a concept comparison and evaluation matrix.
3. Incorporate the concept sketches into the matrix to allow pattern emergence.
4. Ensure that comparison metrics are valid for every concept.
5. Determine the criteria used for evaluating the concepts.
6. Select a datum to compare all other concepts.
7. In the matrix use (+) to mean better than, (-) to mean worse than, and (S) for the same as the datum.
8. Check for concepts that exhibit exceptional strengths. Remove these strengths and rerun the matrix.
9. If strong concepts do not emerge from steps 7 and 8, replace the datum and repeat steps 7 and 8.
10. If a strong concept emerges, replace the datum with it and repeat steps 7 and 8 to ensure strength of concept.

In order to identify which concepts emerge as the strongest solutions, the number of (+), (-), and (S) are summed for each concept. However, these scores should not be treated as absolute but only serve as guidance in selection [69]. Consequently, this is a drawback of the

Pugh method because the scores generated provide no information on how selection criteria relate to each other [59]. For an example of a Pugh matrix used for car horn selection see Appendix C.

3.2.3 Quality Function Deployment

Quality Function Deployment (QFD) is a popular method used in engineering design. The method has wide application and can be found in Lean Six Sigma courses, with a business improvement perspective, as well as NASA’s system engineering “Toolbox” manual. The matrix that is developed using QFD is called the “House of Quality” [64]. It is called this because the matrix resembles a house. Figure 3-2 illustrates the different components of the House of Quality (HoQ).

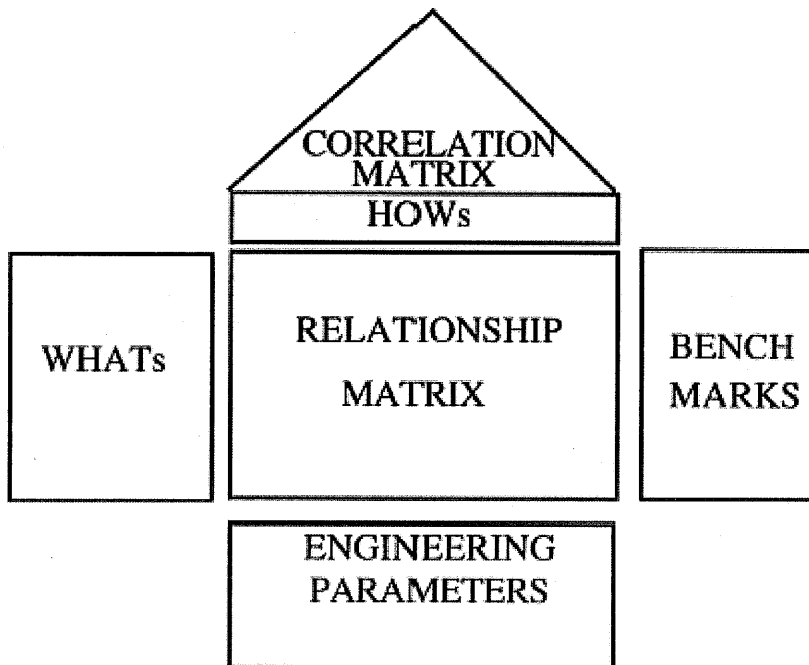


Figure 3-2: House of Quality [30]

The main purpose of the QFD is to translate the stakeholder’s requirements into engineering language [7]. There are two approaches to filling in the HoQ. NASA’s system engineering manual directly fills in the HoQ with numerical values, whereas most other sources the researcher reviewed used a method of symbols that correlated directly to values. The researcher found that the HoQs that used symbols were visually more informative because discerning patterns or trends with symbols was easier than with numerical values. Regardless of

the approach employed, the values are the same. For example, in the relationship part of the matrix, 1 represents a weak, 3 a medium, and 9 a strong relationship between the WHATs and HOWs in the HoQ, where the HOWs are customer requirements and the WHATs are quantifiable solutions to the requirements. In place of these numbers, the following symbols are used:

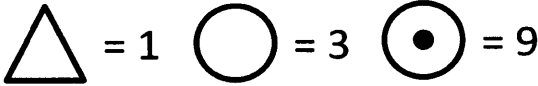


Figure 3-3: HoQ Numeric Equivalent Symbols [7]

A similar convention is used for the correlation part of the matrix which is often called the roof. Here the correlation between the HOWs is determined. The HOWs are evaluated based on strong and weak positive correlation or strong and weak negative correlation. The following symbols identify the different types of correlation:

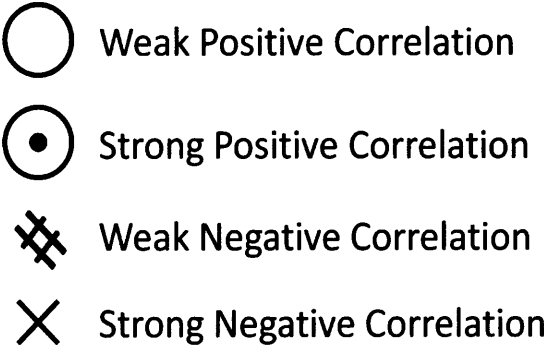


Figure 3-4: HoQ Correlation Symbols [7]

The QFD is a biased method because it requires decision makers to subjectively weight the importance of each requirement in the WHATs of the HoQ. Using an equation similar to the additive value model, the subjective weights and relationship values are aggregated in order to produce scores that determine which HOW is the most important to achieving the stakeholder’s WHATs [30]. The goal of QFD and the HoQ is to serve as a transfer function between the stakeholders’ requirements and quantifiable engineering design measures [7]. Additionally, it determines the technical risk associated with designing the system. Appendix D provides an example of a completed HoQ for a Tunable Infrared Signature Missile Target.

3.3 Optimization Techniques

Decision makers rely on many different optimization techniques in order to determine a best solution. The term optimization may cause some confusion because the methods described in Section 3.2 are approaches for determining an optimal solution as well. However, they are not typically considered optimization techniques. Optimization methods generally refer to mathematical programming; the most recognized being linear programming. Other popular variants are non-linear and integer programming with the latter being a form of linear programming. Additionally, goal, compromise, and linear physical programming (LPP) combine aspects of optimization and more traditional decision making methods. The following sections will describe linear programming because it is so ubiquitous and LPP because it combines optimization with stakeholder preferences.

3.3.1 Linear Programming

Linear Programming (LP) has an ever-present application in academia, industry, and government. Every organization has finite resources and needs to maximize the use of these resources in order to be successful and efficient. Because LP takes advantage of linear relationships, it is able to produce an optimal mix of finite resources. Every LP model has an objective function constructed of decision variables that are subject to constraints. These constraints define the finite resources. In order to use LP as an optimization tool, the following three conditions must be satisfied [50]:

1. The objective function must be a linear function of system outputs.
2. System outputs are nonnegative, linear combinations of system inputs.
3. All or part of the system inputs are subject to constraints.

Once these three conditions are satisfied, the LP model can then be solved in order to produce an optimal solution. Many methods have been developed in order to search the feasible region for the optimal solution; however, the Simplex method is the most widely used [87]. Figure 3-5 illustrates the Simplex method in two dimensions.

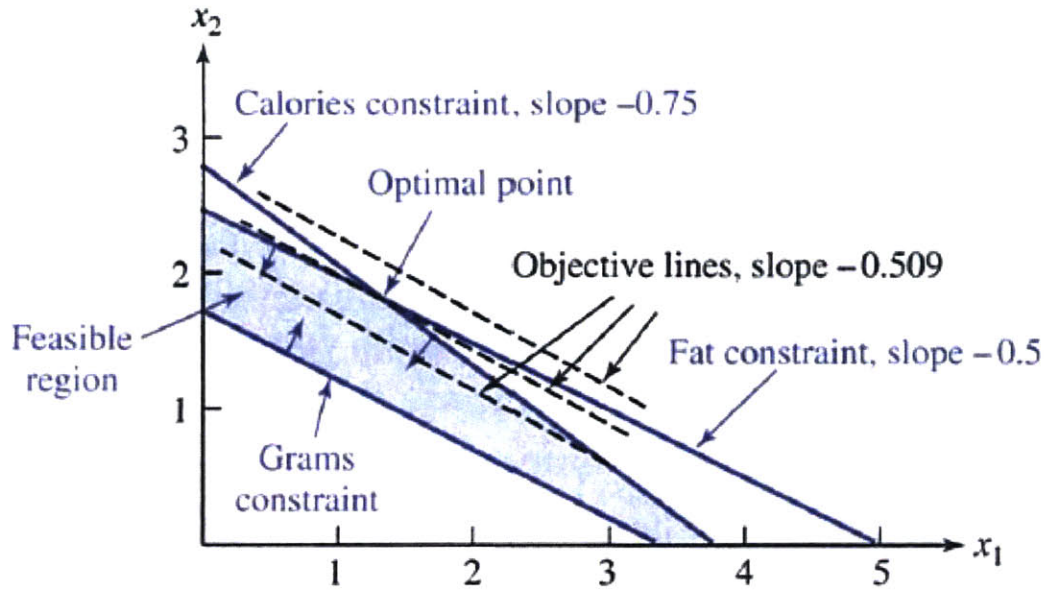


Figure 3-5: Simplex Method [87]

The straight blue lines are system constraints that define the blue shaded feasible region. The optimal point is where the decision variables are at their greatest with respect to the objective function's maximum attainable output subject to the imposed constraints. LP models can be applied to both maximization and minimization problems. LP is an unbiased method for determining an optimal solution; however, if stakeholder preference is required, LPP can be applied.

3.3.2 Linear Physical Programming

The premise of LPP is that it eliminates the requirement for decision makers to specify the subjective weights found in decision matrix methods. It eliminates this with class functions. Instead of the stakeholder specifying meaningless preference weights, they express their preferences using one of four class functions. The four class functions are 1S, 2S, 3S, and 4S which represent smaller is better, larger is better, value is better, and range is better respectively [58]. Figure 3-6 depicts the four class functions.

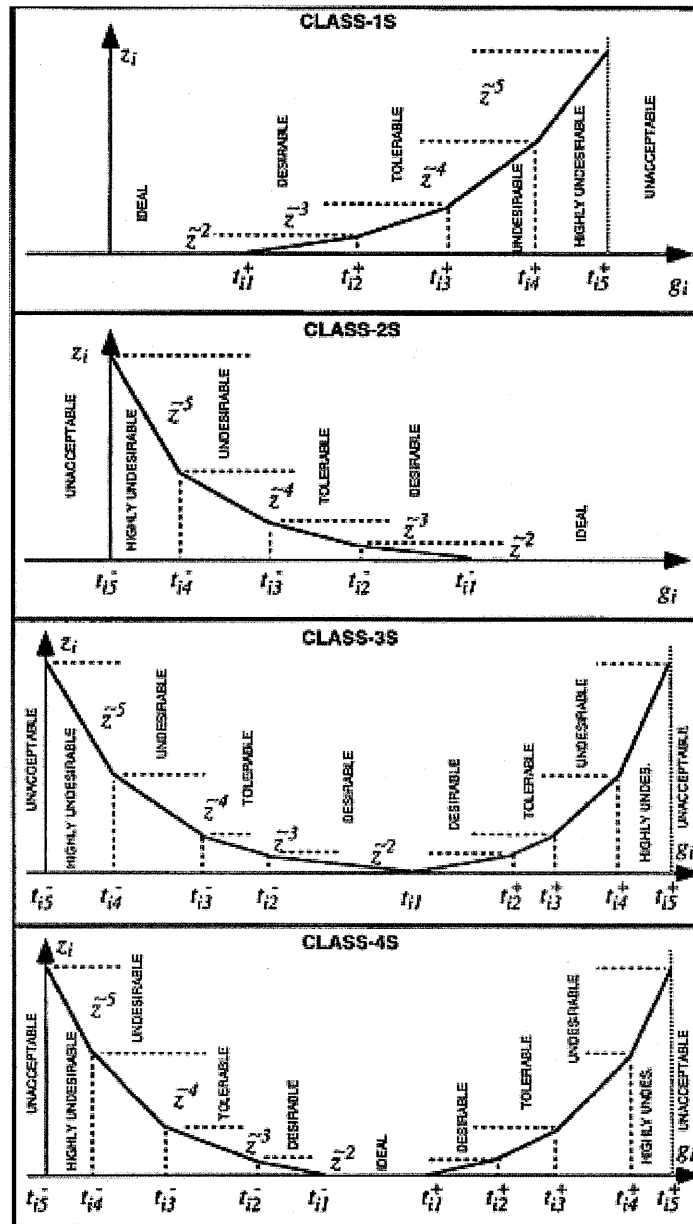


Figure 3-6: LPP Class Functions [53]

The stakeholders must define the bounds of the preference ranges depicted in Figure 3-6. (Mullur and et.al 2003) describes this as the “most significant advantage” of LPP because exact preference weights need not be specified [58].

After the preference ranges are converted into class functions, the LPP weight algorithm is used to calculate the weights used in scoring each concept. The total score is a summation of the preference function values for every system attribute. The complete process involves the following four steps and is described in complete detail in (Messac and et.al 1996) [53]:

1. The decision maker classifies each attribute according to one of the class functions.
2. The decision maker determines the ranges in each class function specified.
3. The LPP algorithm is used to generate weights for concept scoring.
4. The following linear programming equation is used to calculate the total scores:

$$\min_i J^i = \sum_{p=1}^P \sum_{s=2}^5 (\omega_{ps}^- d_{ps}^{i-} + \omega_{ps}^+ d_{ps}^{i+}) \quad 3.1$$

where J^i represents the total score of the i -th concept, P represents the number of attributes defining the selection, ω_{ps}^- and ω_{ps}^+ are the incremental weights for the p -th attribute, and d_{ps}^{i-} and d_{ps}^{i+} are the deviations of the p -th attribute value of the i -th concept. As the equation shows, the goal is to find the candidate solution with the minimum score.

3.4 Summary

The goal of this chapter was to present to the reader a survey of different techniques that are utilized in decision analysis. The techniques are categorized into biased and unbiased methods. The biased techniques involve injecting stakeholder preference into the decision quantitative models, whereas the unbiased methods do not. As the following chapter will demonstrate, the SDP is a biased method that requires preference weighting in order to arrive at an optimal solution. The researcher views preference weighting as a suboptimal approach beset with potential errors; therefore, he presents the unbiased method of FA to eliminate the errors associated with preference weighting.

In addition to the explanation provided on bias versus unbiased techniques, the researcher also presented different approaches to decision analysis. The approaches are grouped into matrix and optimization methods. For the matrix style decision methods, the researcher describes different techniques conducted in order to calculate the weights used with the additive value model. The additive value model is the quantitative model used by both the SDP in Chapter 4 and FA in Chapter 5. Additionally, other commonly used matrix methods like the Pugh and QFDs are explained. Finally, the researcher addresses the optimization method of mathematical programming and presents the two examples of LP and LPP. The former method represents an unbiased approach and the latter a biased approach. The remaining chapters in this work provide

an in-depth analysis of selecting a COTS backpackable, lethal UAS using the SDP and FA decision methods.

4 Decision Analysis Using the Systems Decision Process

In Chapter 1 the researcher presented the problem of evaluating commercial UASs in order to find a potential solution to a backpackable, lethal UAS. Next, Chapter 2 explained both the military application of UASs and the difficulties associated with engineering them. Then, Chapter 3 described different methods available to evaluate the solution space in order to find an optimal solution. This chapter evaluates the solution space using the Systems Decision Process (SDP). As described in Chapter 1, the researcher chose the SDP because it is readily available, generally applicable, and based on proven quantitative principles.

The SDP consists of four major phases, each of which is comprised of several steps. These major phases are: Problem Definition, Solution Design, Decision Making, and Solution Implementation. This chapter discusses in detail, the first three phases of the SDP. At the conclusion of the chapter, an optimal solution is presented to the backpackable UAS problem.

4.1 Problem Definition

The first step in the SDP is the Problem Definition phase. A structured method is important to defining the problem because it ensures the correct problem is addressed [65]. Consequently, the Problem Definition phase consists of Stakeholder Analysis, Functional Analysis, and Value Modeling. At the conclusion of the Problem Definition phase, the decision

maker has a refined problem statement approved by the decision maker, a set of screening criteria the candidate solutions must meet, and qualitative and quantitative value models.

4.1.1 Stakeholder Analysis

The first step to defining the problem is to conduct stakeholder analysis. Section 1.3.1 defined the relevant stakeholders for this work. Stakeholder analysis is a critical step because it lays the foundation for the remainder of the process. During this phase, the stakeholders define for the decision analyst their requirements and desires. There are three common methods of performing stakeholder analysis. The analyst can elicit and collect system requirements through surveys, focus group meetings, and/or conducting interviews [65]. (Ulrich and Eppinger 2004) use a five step process to ensure stakeholder needs are captured [80]:

1. Gather raw data from stakeholders.
2. Interpret the raw data in terms of stakeholder needs.
3. Establish the relative importance of the needs.
4. Organize the needs into a hierarchy.
5. Reflect on the results.

Following Ulrich and Eppinger's first step for the backpackable UAS problem, the researcher interviewed a wide range of stakeholders in order to gather UAS data. The stakeholders interviewed included users, developers, producers and manufactures, deployers, trainers, and testers. Such a wide range of stakeholders were interviewed in order to ensure all UAS requirements were defined.

The user was the first group interviewed. The researcher interviewed four peers with combat and UAS experience. This group consisted of two Infantry officers, one Special Forces officer, and one Armor officer (an Armor officer is typically found in units with M1 Abrams tanks). It was a general consensus among this group that they thought Intelligence, Surveillance, and Reconnaissance (ISR) were the most important function of UASs. However, each one felt a lethal UAS that the dismounted soldier can carry, would be a valuable capability.

The deployer was the next group interviewed. The Army's Unmanned Aircraft Systems Operations Branch (AUAS-OB) at Redstone Arsenal, Alabama is the primary acquisition

component for UASs in the Army. This office provided general requirements being considered for a lethal UAS. Section 4.2.1.1 lists these requirements.

The researcher next interviewed a developer. The Unmanned Aircraft Systems Development Division (UASDD) at Fort Benning, Georgia has the responsibility for developing the Infantry’s requirements for the backpackable UAS. Their requirements closely match those of the deployer. Section 4.2.1.1 compares developer and deployer requirements.

The Soldier System Center in Natick, Massachusetts is the trainer and tester stakeholder. They were very helpful in providing data and information on current UASs, but they are not responsible for generating requirements. Their purpose is to ensure currently fielded UASs meet established requirements. As a result, these interviews did not produce any requirements.

The producers and manufactures were the last stakeholders the researcher interviewed. Similar to the Soldier System Center, they are not responsible for generating requirements. The producers and manufactures take established requirements and then attempt to design a system that meets the requirements. The next section discusses the requirements collected from these interviews.

4.1.1.1 *Defining Requirements*

Once the analyst completes interviewing the relevant stakeholders, the data is compiled and interpreted. This represents step two of Ulrich and Eppinger’s process. Table 4-1 illustrates the information collected from the stakeholders.

Requirements and Desires											
Stakeholder	Weight	Dimensions	Endurance	Range	Blast Radius	# Operators	Delivery	Day/Night	Infrared	Non-LOS	GPS
Army Officers	< 20 lbs	MOLLE	> 20 min	> 5 km	> 3 m	1	Visual	Yes	Yes	Yes	Yes
AUAS-OB	< 25 lbs	MOLLE	> 15 min	≥ 10 km	Not Specified	≤ 2	Visual	Yes	Yes	Yes	Yes
UASDD	≤ 10 lbs	MOLLE	> 5 min	≥ 2 km	≥ 10 m	1	Visual	Yes	Yes	Yes	Yes

Table 4-1: Stakeholder Requirements and Desires

Immediately obvious is that the stakeholders do not agree on every requirement. The stakeholders differ on the required weight, endurance, range, blast radius, and number of operators required. Consequently, the researcher conducts the analysis and determines what the UAS must do according to the prime stakeholder—the decision maker. Additionally, he must extrapolate latent or hidden requirements not specifically given by the stakeholders to ensure critical needs are not overlooked [80].

Requirements for a backpackable, lethal UAS are still being developed; therefore, they routinely change. However, through additional interviews, the researcher was able to determine values that the stakeholders did agree upon. He also determined a Technology Readiness Level (TRL) of 6 or greater was required. This was a hidden requirement not directly mentioned by the stakeholders. The Army acquisition system is currently searching for commercial, off the shelf (COTS) UASs that can provide lethality. As a result, candidate solutions with a TRL below six are not far enough along in their development. To clarify, the National Aeronautics and Space Administration (NASA) considers a system TRL 6 when a system model has been demonstrated in a relevant environment [51].

Step three in Ulrich and Eppinger's process involves determining the importance of each requirement. Determining the importance levels allows the analyst to establish system constraints. These constraints are used during feasibility screening to reduce the candidate solution space. Section 4.2.1 of this work describes feasibility screening. The requirements that are the most important to the backpackable UAS are weight, range, dimensions, and TRL. The other values in Table 4-1 are requirements with some elasticity or desires that do not constrain the system. Before accomplishing step 4 of Ulrich and Eppinger's process, a system boundary must be established and functional analysis performed.

4.1.2 Defining the System Boundary

Establishing a system boundary is an important step before functional analysis. It is critical because the system boundary isolates the elements that are included in the system from those that are not [65]. Defining the system boundary allows the analyst to focus his attention on evaluating only those elements that characterize the system. Figure 4-1 puts the backpackable, lethal UAS into context with other fire support capabilities.

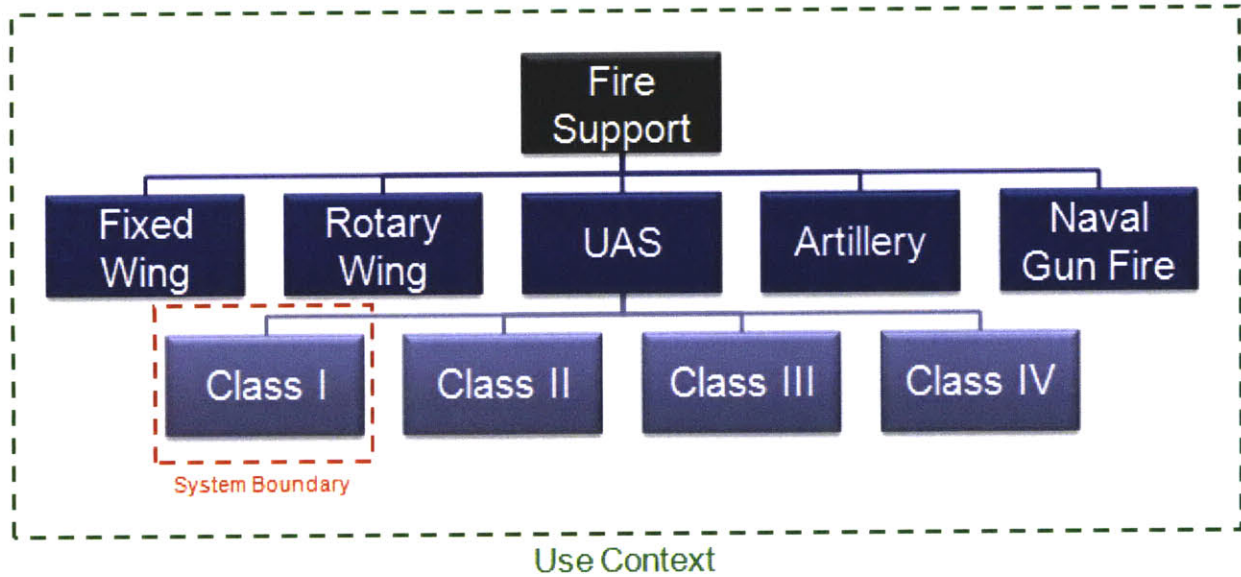


Figure 4-1: Use Context of Lethal UAS

Within Figure 4-1, Class I UASs have a system boundary around it. The system boundary needs to be decomposed in further detail in order to precisely define the elements of interest for the problem presented in this work. (Ulrich and Eppinger 2006) recommend using a classification tree in order to better describe the solution space [80].

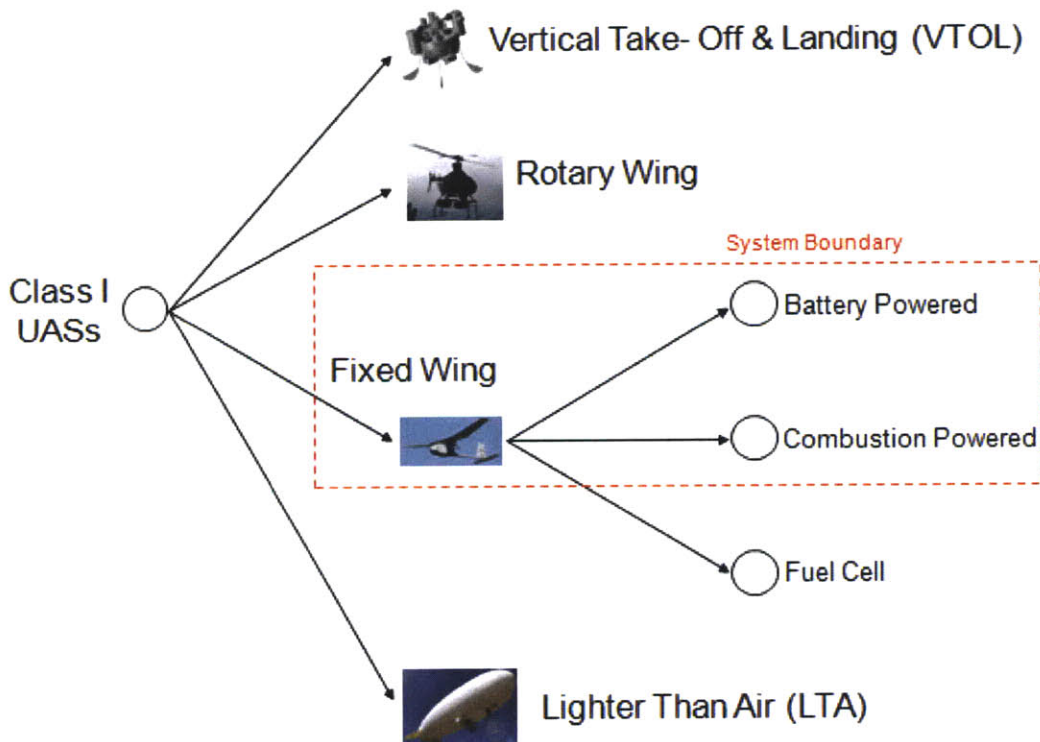


Figure 4-2: UAS Classification Tree

Figure 4-2 shows the reader the different types of UASs. Additionally, the system boundary illustrates that the researcher only considers fixed winged UASs that operate on battery or combustion power into the solution space. Figure 4-3 provides the final system boundary.

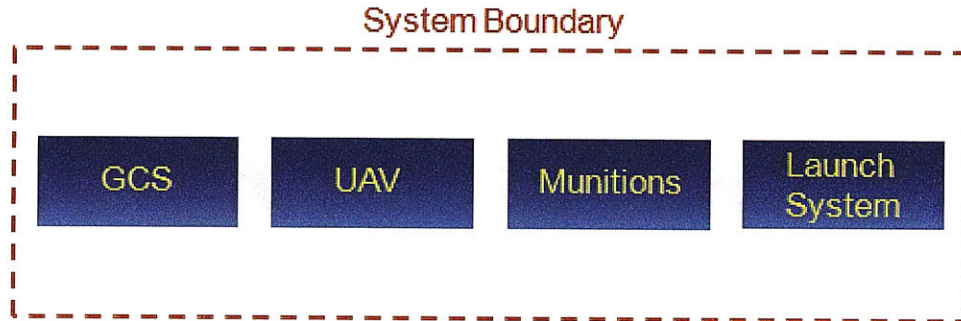


Figure 4-3: UAS System Boundary

The elements of the UAS that this work evaluates are the GCS, the unmanned aerial vehicle (UAV), the munitions, and the launch system. All other elements are external to this boundary. The system boundary seems intuitive, but it is important to define the exact system boundary because it is common for people to use UAS and UAV interchangeably. (Air Force Magazine 2006) describes the reason for this confusion:

For decades, certain kinds of remotely piloted aircraft have been called “unmanned aerial vehicles,” or UAVs. Well, that is now officially old-think. The Defense Department has begun encouraging use of the new term, “Unmanned Aircraft System,” or UAS, to denote those systems formerly known as UAVs. You may well ask, why? The Pentagon reasons that most mentions of a UAV were actually references to an entire system, comprising not only a flying aircraft but also ground control stations, satellite links, communications, and so forth. Hence the new, officially approved term, “UAS” [36].

The Air Force Magazine illustrates two important points. First, as mentioned above, UAS and UAV are commonly confused. Without physically defining the elements that compose our system, someone can easily believe evaluating the UAV is the same as evaluating the UAS. Secondly, the quote includes satellite links and communications as part of the UAS. This work does not include these elements. For this reason, defining the exact elements of interest with a system boundary is imperative. Now that the system boundary is clear, the next step in defining the problem is functional analysis.

4.1.3 Functional Analysis

Functional analysis identifies all the functions a system must be able to perform. When applying the SDP, it is imperative decision analysts determine these functions because if a function is missed then the system will not perform as required [65]. During functional analysis, the system's objectives and evaluation measures must also be defined. The functions, objectives, and evaluations measures are all used to create the functional hierarchy. Organizing the stakeholders' needs into a hierarchy is step four of Ulrich and Eppinger's process.

4.1.3.1 Functions

The decision analyst uses the information gathered during stakeholder interviews in order to determine the functions for a system. The stakeholder may directly state functions, but similar to requirements, there may be hidden functions. As described in Chapter 1, the SDP is an iterative process; therefore, the first cut at the functions is usually not the final solution. After a few iterations, the researcher identified five functions for the UAS. The functions are the first level in our functional hierarchy.

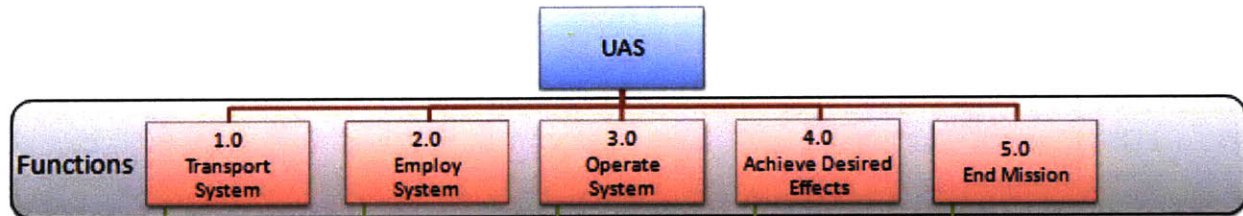


Figure 4-4: UAS Functions

The functions shown within Figure 4-4 serve as a pathway that describes the UAS. For example, the dismounted soldier must transport it and then employ it. Once it is employed, the UAS must operate and then, while operating, achieve the desired effects of the user. Finally, the UAS must have a mission end state. Within each function, there can be one or more sub-functions that further describe the system. When the system is completely functionally defined, the analyst then develops objectives for each function or sub-function at the bottom of the hierarchy.

4.1.3.2 Objectives

Objectives are the next level in the functional hierarchy. They describe what the evaluation measures must do. In other words, they indicate the preferred direction of movement for the evaluation measures [47]. For example, objectives are described with terms like maximize and minimize. Developing objectives required the most iteration for the researcher because as stakeholder requirements evolved, they affected the objectives. For example, during initial interviews, it was not clear whether the UAV would be used to drop munitions or whether the munitions would be incorporated into the UAV. The stakeholders themselves were still working through this issue. As the requirements matured, the stakeholders decided the most feasible option was to incorporate the munitions into the UAV. As a result, the objective to recover the UAV no longer applied. Other changes also occurred as a result of requirement evolution. Figure 4-5 illustrates the finalized objectives associated with each function.

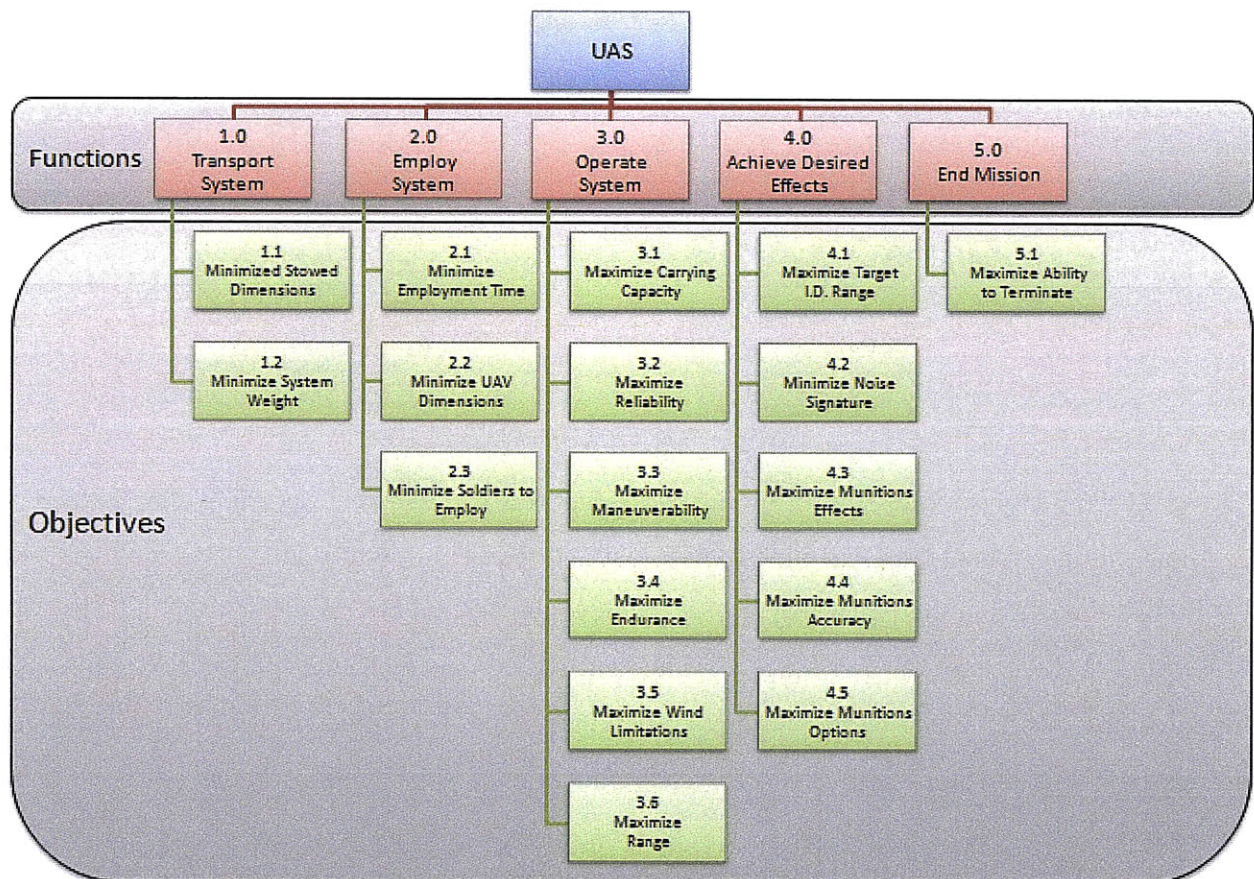


Figure 4-5: UAS Objectives and Functions

4.1.3.3 *Evaluation Measures*

Each of the objectives presented in Figure 4-5 has one or more measurable attributes. To clarify, the following terms are interchangeable with evaluation measures: measure of effectiveness (MOE), attribute, performance measure, value measure, and metric [47]. The evaluation measures allow the measurement of the objectives, which in turn quantifies each candidate in the solution space. There are four types of measures: direct-natural; direct-constructed; proxy-natural; and proxy-constructed. The table below provides an example of each measure when considering a person’s economic well-being.

Type of Measure	<i>Direct</i>	<i>Proxy</i>
<i>Natural</i>	Income in Dollars	GDP: Gross Domestic Product
<i>Constructed</i>	NPV: Net Present Value	House Size

Table 4-2: Measures for Economic Well-being

As direct implies, this type of attribute directly measures the attainment of an objective [47]. In contrast, a proxy attribute reflects the degree to which an objective is satisfied, but it does not directly measure it [44]. A natural scale is one that is familiar and openly accepted [47]. For example, inches, meters, and dollars all constitute natural scales. The opposite of a natural scale is then a constructed scale. A constructed scale is one that the analyst develops in order to measure the attainment of an objective [47]. An example of a constructed scale occurs with objective 3.2--Maximize Reliability. Typically, reliability is measured by the mean time to failure (MTTF) of a system/component. However, because this information was not available, the researcher constructed a scale based on whether a UAS has a gas, electric, rocket motor, or no motor. He assigned a number to each type of motor from zero to three. If a UAS did not have a motor, it was assigned the number three. A three represents the most reliable motor and zero represents the least reliable motor. Consequently, the value associated with three is higher than the value associated with zero. (See Appendix F for the reliability value function.) As the reader may surmise, we want as many of our evaluation measures to be direct-natural measures as possible because proxy and constructed measures result in a loss of accuracy. Moreover, a proxy-constructed measure is the least precise type of measurement scale. Using the convention described above, the researcher determined the value measures depicted below for each objective.

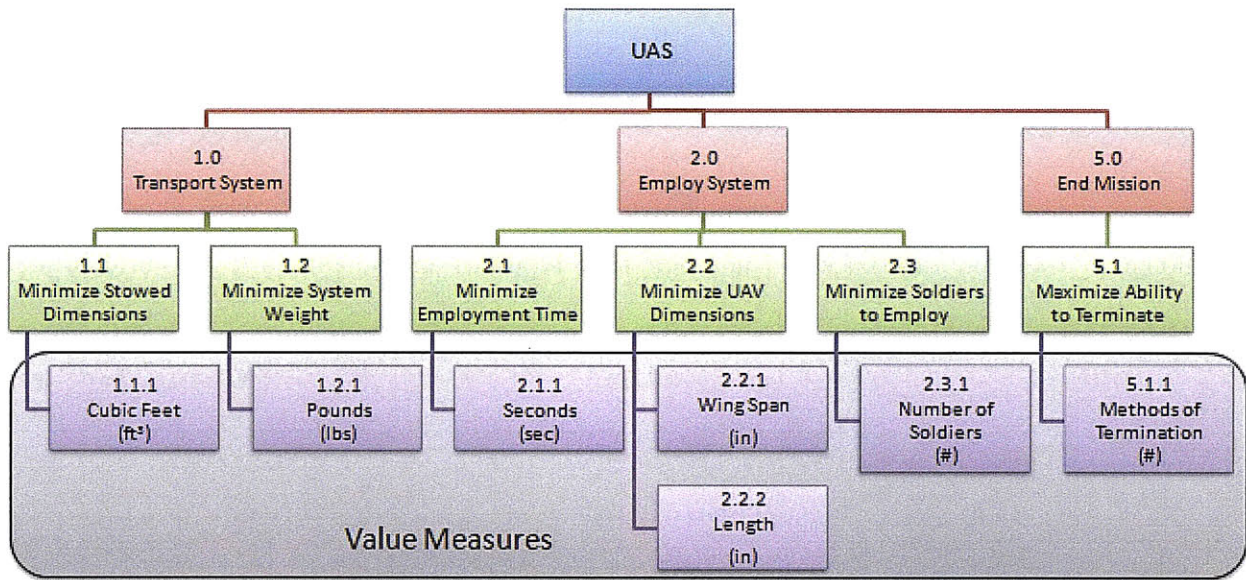


Figure 4-6: Functions 1.0, 2.0, and 3.0 Value Measures

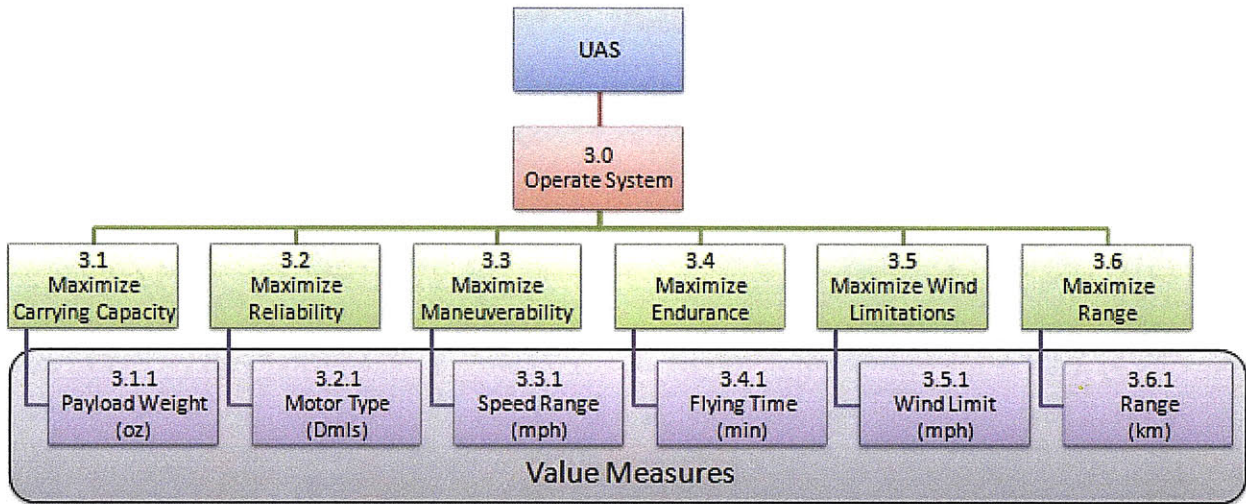


Figure 4-7: Function 3.0 Value Measures

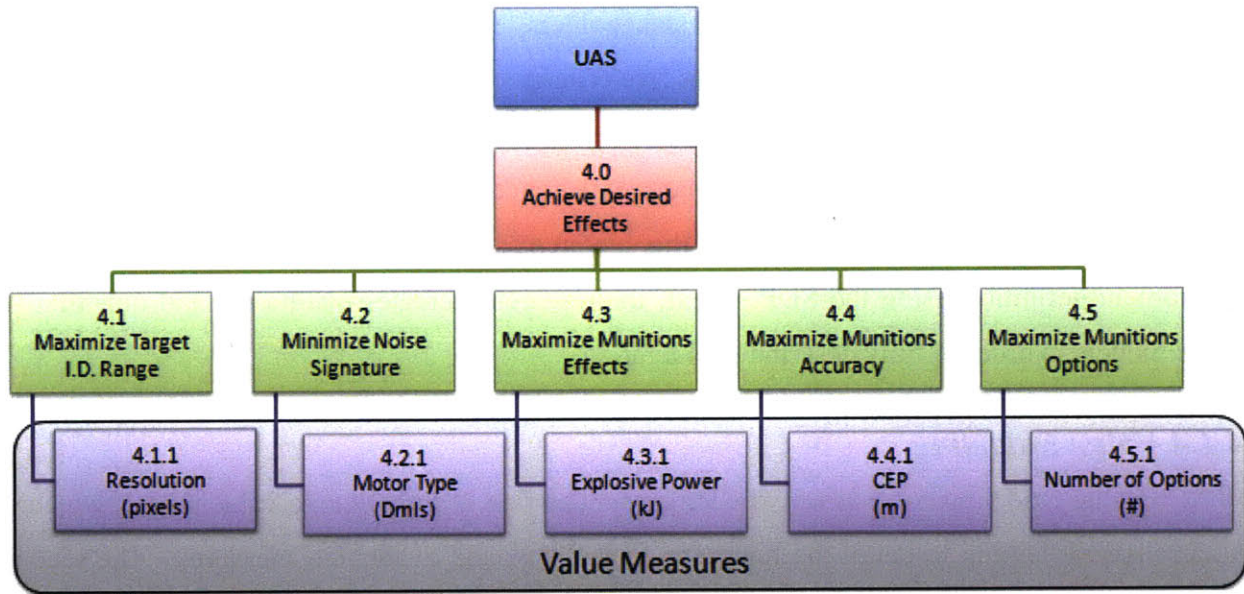


Figure 4-8: Function 4.0 Value Measures

Due to the number of value measures, the functional hierarchy is broken up into separate figures. The three figures above compose the complete functional hierarchy for the UAS. After constructing the hierarchy, the analyst must check its quality. Checking the quality of the hierarchy is also the last step in Ulrich and Eppinger’s process; however, they call it “reflecting on the results.” In order to check the quality, (Keeney and Raiffa 1976) describe five desirable properties the hierarchy should have [44]:

1. **Complete:** The hierarchy is sufficient at indicating the degree to which the overall objective is met. It is considered complete when the lowest-level objectives satisfy all stakeholder concerns.
2. **Operational:** The hierarchy must be meaningful to the decision maker. It must use terminology the decision maker can understand.
3. **Decomposable:** The hierarchy can be quantified. The value measures are a critical element in determining decomposability.
4. **Non-redundant:** The final set of attributes should prevent double-counting. For example, including the weight of the UAS and the weight of individual components is redundant.
5. **Minimal:** The hierarchy should be as small as possible while still describing the complete system.

After a few iterations with the stakeholders, the researcher checked the hierarchy depicted above against Keeney and Raiffa's five criteria. However, the hierarchy presented does not represent the only possible functional hierarchy. (Keeney and Raiffa 1976) point out that no hierarchy is unique; therefore, those with more experience using the SDP or working with UASs may construct a different hierarchy. Still, this hierarchy is sufficient to demonstrate the process of problem definition using the SDP. Next, the researcher creates qualitative and quantitative value models in order to fully describe the hierarchy.

4.1.4 Value Modeling

Value modeling consists of two elements. The first is a qualitative value model, which is a narrative explaining in detail the functions, objectives, and evaluation measures. The second element is a quantitative value model, which permits the scoring of the candidate solutions in order to resolve which candidate best achieves the stakeholder's goals.

4.1.4.1 Qualitative Value Model

The qualitative value model begins by listing the major goals the analyst identified during stakeholder analysis and concludes with a complete description of the hierarchy. Through stakeholder interviews, the researcher identified the major goals below:

- The UAS must be easily transported by a single dismounted soldier.
- The UAS should carry as much payload as possible.
- The UAS must be able to travel at least two kilometers.
- The UAS must be able to differentiate targets from surrounding terrain, day or night.
- The UAS should be able to incapacitate one or more people within close proximity.

This is not an exhaustive list of all goals, but it represents the primary goals of the stakeholders. The analyst then uses these major goals to create a fundamental objective for the UAS. The resulting fundamental objective is the problem statement:

Problem Statement: Evaluate commercial, off the shelf systems in order to provide potential solutions to a backpackable, lethal unmanned aircraft system for the company level and below.

After the goals and fundamental objective are identified, the analyst next defines each objective and value measure in the functional hierarchy.

Objective 1.1 → *Minimize Stowed Dimensions*: This includes the stowed dimensions of the entire UAS, which includes GCS, UAV, munitions, and launch system.

Measure 1.1.1 → *Cubic Feet (ft³)*: The stowed dimensions of each candidate solution are determined in cubic feet. The dimensions are directly measured. This is a direct-natural scale where less is better.

Objective 1.2 → *Minimize System Weight*: This includes the weight of the entire UAS.

Measure 1.2.1 → *Pounds (lbs)*: The weight of each candidate solution is weighed in pounds. The weight is directly measured. This is a direct-natural scale where less is better.

Objective 2.1 → *Minimize Employment Time*: This is the amount of time it requires the operator/s to setup and launch the UAS.

Measure 2.1.1 → *Seconds (s)*: Each candidate solution has an expected time it takes to employ the system. This time is based off trained operator/s employing the system. Exact times were not given by the makers. The makers gave the times in whole minute increments. The time to employ is directly measured. This is a direct-natural scale where less is better.

Objective 2.2 → *Minimize UAV Dimensions*: This objective is different than Objective 1.1 because it evaluates only the dimensions of the UAV when it is configured for employment. This is an important consideration because the larger the UAV is, the more difficult it becomes to launch. Additionally, the larger the UAV is, the easier it is to identify in flight. The dimensions are broken down into two components: wing span and length.

Measure 2.2.1 → *Wing Span (in)*: The wing span of each UAS is measured in inches (in). The wing span is directly measured. This is a direct-natural scale where less is better.

Measure 2.2.2 → *Length (in)*: The length is the distance from the nose of the UAV to the tail or body length. The length of each UAS is measured in inches. The length is directly measured. This is a direct-natural scale where less is better.

Objective 2.3 → *Minimize Soldiers to Employ*: This objective is the maximum number of soldiers required to launch and operate the UAS. For example, most UASs only require one operator while in flight; however, some need two during launch. If a candidate solution requires two soldiers to launch, but only one to operate it once in flight, the researcher considers the system needing two soldiers to employ.

Measure 2.3.1 → *Number of Soldiers (#)*: The number of soldiers required to employ the UASs are given by the makers. The number of soldiers required is directly measured. This is a direct-natural scale where less is better.

Objective 3.1 → *Maximize Carrying Capacity*: In order to be effective, the UAV needs to be able to carry as much payload as possible. The payload includes all systems required on the UAV such as a camera and GPS, along with available payload weight for the munitions.

Measure 3.1.1 → *Payload Weight (oz)*: The payload weight is measured in ounces (oz). The available payload weight of the UAS is given by the makers. The available payload weight is directly measured. This is a direct-natural scale where more is better.

Objective 3.2 → *Maximize Reliability*: Determining the reliability of the different candidate UAS is difficult. Reliability is usually given as MTTF, but the makers do not have this information or did not give it for their particular system. Therefore, in order to determine the reliability of each candidate solution, the type of motor it has is used. Reliability is not included in the candidate scoring step because the remaining solution space, after feasibility screening, only has UASs with electric motors.

Measure 3.2.1 → *Motor Type (Dmls)*: There are four types of motors to consider in the solutions space: gas, electric, rocket, and no motor. Having no motor is considered the most reliable followed by rocket, electric, and gas. Motor type does not directly measure reliability; therefore, it is a proxy measure, and it is dimensionless (Dmls). Additionally, the researcher constructs the value associated with each type of motor, so this is a proxy-constructed scale where more is better.

Objective 3.3 → *Maximize Maneuverability*: Maneuverability of the UAS is difficult to measure. The difference in each UASs maximum and minimum speed is used to determine maneuverability. In general, the larger the difference between these speeds will result in better maneuverability because speed can be traded for other flight parameters. If the range between the maximum and minimum speed is very small, it does not allow for sufficient tradeoff.

Measure 3.3.1 → *Speed Range (mph)*: The speed range is measured in miles per hour. The difference in each candidate solutions' maximum and minimum speeds is directly measured; however, it does not directly measure maneuverability. Speed range is a proxy-natural scale for measuring maneuverability where more is better.

Objective 3.4 → *Maximize Endurance*: Endurance is the amount of time the UAV can remain airborne.

Measure 3.4.1 → *Flying Time (min)*: Flying time is measured in minutes. The flying time of each UAS is directly measured. This is a direct-natural scale where more is better.

Objective 3.5 → *Maximize Wind Limitations*: Wind limitation is the maximum winds in which a UAV can effectively operate.

Measure 3.5.1 → *Wind Limit (mph)*: Wind limit is measured in miles per hour. The maximum wind speed a UAV can effectively operate is directly measured. This is a direct-natural scale where more is better.

Objective 3.6 → *Maximize Range*: Range is the distance that the UAV can travel while in flight.

Measure 3.6.1 → *Range (km)*: Range is measured in kilometers. Range is directly measured. This is a direct-natural scale where more is better.

Objective 4.1 → *Maximize Target I.D. Range*: Target I.D. range is the distance at which the UAV operator can identify the intended target. Target identification is directly correlated to the resolution of the camera. The higher the resolution of the camera, the better the image.

Measure 4.1.1 → *Resolution (pixels)*: Resolution is measured in average pixels. The camera resolution is reported in horizontal and vertical pixels. For example, the BATCAM has 640 horizontal pixels and 480 vertical pixels. An average of the horizontal and vertical pixels is calculated. Using this method, the BATCAM's resolution is 560 pixels. The pixels are directly measured, but pixels are not a natural measure. This is a direct-constructed scale where more is better.

Objective 4.2 → *Minimize Noise Signature*: The amount of noise that the UAV creates directly relates to its signature. The UAS makers did not report the noise level of their systems. As a result, the researcher uses the type of motor the UAV had in order to determine its noise signature. Noise signature is not used in the scoring of candidate solutions because after feasibility screening, there were only electric powered UASs remaining.

Measure 4.2.1 → *Motor Type (Dmls)*: There are four types of motors to consider in the solutions space: gas, electric, rocket, and no motor. Having no motor has the lowest noise signature followed by electric, gas and rocket. Motor type does not directly measure noise signature; therefore, it is a proxy measure, and it is dimensionless (Dmls). Additionally, the researcher constructs the value associated with each type of motor, so this is a proxy-constructed scale where more value is better.

Objective 4.3 → *Maximize Munitions Effects*: Munitions effects are the actual destruction or neutralization of a target.

Measure 4.3.1 → *Explosive Power (kJ)*: Explosive power is measure in kilojoules. The researcher uses Composition B as the explosive material for this research. Composition B is the same material used in fragmentary grenades, and the Army labels this material as a bursting material. Composition B has a Relative Effectiveness (RE) factor of 1.35. Trinitrotoluene (TNT) is the base line material for calculating RE--its RE factor is 1.0

[26]. Explosive power is not directly measured. This is a proxy-natural scale where more is better.

Objective 4.4 → *Maximize Munitions Accuracy*: Munitions accuracy is how close the UAV with a munition hits relative to the intended target. This is critical with a backpackable UAS because of the limited size of the munitions it carries. Also, it is important in reducing collateral damage. The Army requires the UAV to fly into the intended target using its camera. Therefore, the accuracy of the UAV is directly related to the resolution of the onboard camera. As a result, this objective is not included in the candidate scoring step in order to prevent counting resolution values twice.

Measure 4.4.1 → *Circular Error Probable (CEP) (m)*: CEP is measured in meters. The Department of Defense Dictionary of Military and Associated Terms defines CEP as “an indicator of the delivery accuracy of a weapon system . . . it is the radius of a circle within which half of a missile’s projectiles are expected to fall” [42]. CEP is directly measured. This is a direct-natural scale where less is better.

Objective 4.5 → *Maximize Munitions Options*: The Army wants to make the UAS flexible enough to adjust to different mission scenarios. Therefore, the more munitions options the candidate UAV can carry, the more adaptable it will be to accomplish the specific mission. This objective is not included in the candidate scoring step because the stakeholders have not identified what munitions options they desire.

Measure 4.5.1 → *Number of Options (#)*: The number of options is directly measured. The researcher assigns values for each number of options. Therefore, this is a direct-constructed scale where more is better.

Objective 5.1 → *Maximize Ability to Terminate*: The stakeholders did not want the UAV to be recoverable due to safety considerations. As a result, the UAV is terminal once it is launched. If the UAV is not used against the target for any reason, it must have other means to terminate itself in order to prevent the risk of unexploded ordinance. This objective is not included in the scoring step because the remaining candidates, after feasibility screening, have the same methods of termination.

Measure 5.1.1 → *Methods of Termination (#)*: The number of methods to terminate is directly measured. The researcher assigns values for each number of options. Therefore, this is a direct-constructed scale where more is better.

This completes the qualitative model for the UAS using the SDP. As is evident in Section 4.1.4.1, the qualitative model defines the visually depicted functional hierarchy. Again, the researcher emphasizes that the functional hierarchy and qualitative model described above are not the only solutions. The reader may see alternative ways to depict and describe the functional hierarchy. However, the intent is only to create a creditable model, so the researcher

can illustrate the SDP. After defining the qualitative model, the next step is to develop and define a quantitative model.

4.1.4.2 *Quantitative Value Model*

The quantitative value model determines how well stakeholder requirements are met. As the qualitative model showed, there are tradeoffs that occur among the different evaluation measures. Some of the evaluation measures provide more value as they increase and others give more value as they decrease. A method that gives a way to quantify conflicting tradeoffs is Multiple Objective Decision Analysis (MODA) [65]. Chapter 3 demonstrated many mathematical techniques that can be used with MODA. As described in Chapter 1, the SDP uses Classical Decision Analysis (CDA). CDA has the following mathematical construction [65]:

$$v(x) = \sum_{i=1}^n w_i v_i(x_i) \tag{4.1}$$

where $v(x)$ is the value of the candidate solution, $i = 1$ to n for the number of MOEs, w_i is the swing weight for the i^{th} MOE, $v_i(x_i)$ is the single dimensional value of the i^{th} MOE, and x_i is the raw score of the candidate solution of the i^{th} MOE.

One of the advantages of this model is if value measures are dependent, they are combined into one measure reducing the number of calculations and preventing double counting of similar metrics [65]. As Equation 4.1 illustrates, the quantitative value model has two sub-components: value functions and swing weights. These two components are the basis for determining the overall attainment of stakeholder requirements. The following sections describe how to create value functions and calculate swing weights.

4.1.4.2.1 *Value Functions*

The evaluation measures have many different units. Trying to compare evaluation measures with different units is unadvisable because changing the magnitude of the units could greatly affect the final results. For example, the stakeholders of the UAS are concerned with its stowed dimensions. This work uses cubic feet as the units for stowed dimensions; however, the dimensions could just as easily be calculated in cubic inches or even cubic meters or centimeters. As is evident, changing the units can greatly change the numerical value associated with stowed dimensions, and this could result in a different final solution. A value function prevents errors

caused by changing units because all units are converted to a standard unit [65]. The x-axis of the function is the specific unit of the value measure and the y-axis is the standard unit. In this thesis the y-axis is a value from 0 to 1, but it can have any range of values the analyst desires. Figure 4-9 provides an example of the value function for stowed dimensions.

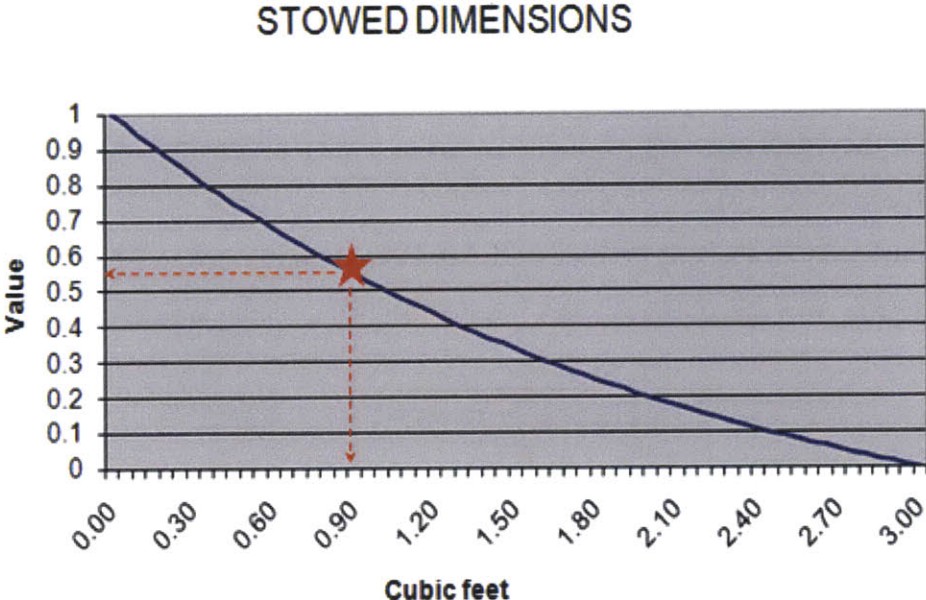


Figure 4-9: Value Function of Stowed Dimensions

Using this value function, a numerical value can be determined for any UAS in the solution space without concerning ourselves with the units associated with the dimensions. For example, the Dragon Eye, depicted by the red star above, has stowed dimensions of 0.91 cubic feet. This corresponds to a value of 0.54 on the y-axis. Whether the units are cubic feet or cubic centimeters, the y-axis value for the Dragon Eye will not change.

The function in the figure above is always decreasing. All the value functions in this work will be monotonic. If a value function is not monotonic, it indicates that one or more objectives are combined [12]. A value function can be discrete or continuous and generally takes on one of four shapes: decreasing returns to scale (RTS), linear RTS, increasing RTS, or S-shaped. Figure 4-10 illustrates the different types of value functions.

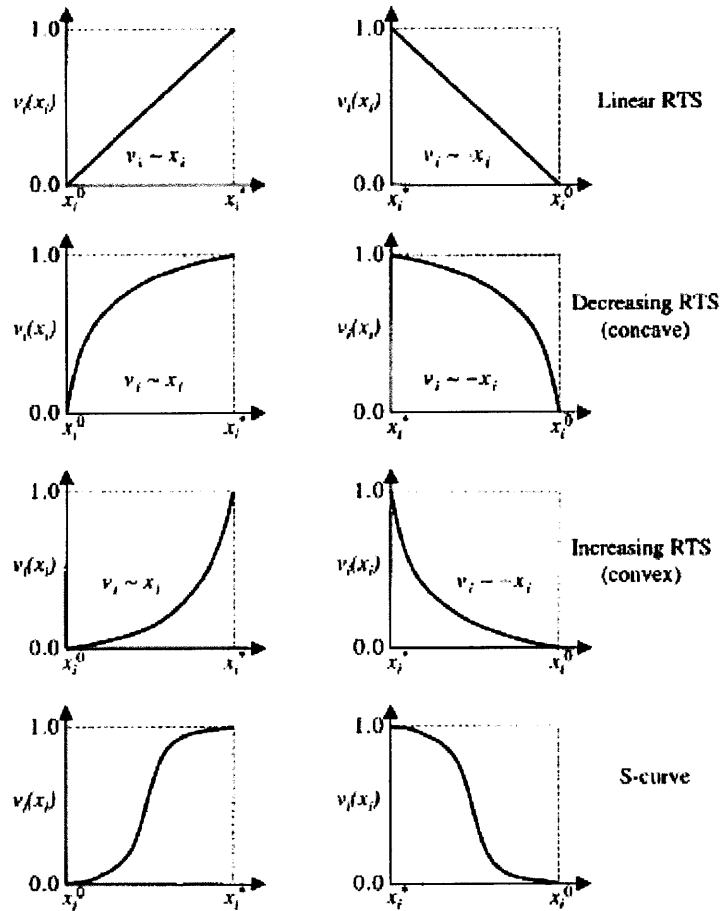


Figure 4-10: Common Value Functions [12]

Kirkwood (1997) describes two procedures for constructing value functions: exponential and piecewise linear. The researcher uses both procedures to develop the value functions in this work. This work uses predominately exponential value functions for the evaluation measures because they produce a more exact calculation of value. The exponential value functions depend on the evaluation measure and a constant signified by ρ (rho). In order to calculate ρ , the analyst only needs to determine a midvalue. Kirkwood (1997) defines the midvalue as “the score such that the difference in value between the lowest score in the range and the midvalue is the same as the difference in value between the midvalue and the highest score” [47]. The value functions become more linear as the value of ρ increases. Should the reader be interested in a detailed explanation of how to calculate ρ see (Kirkwood 1997).

There are two types of exponential value functions: increasing and decreasing. To create an increasing value function (Kirkwood 1997) uses the following equation [47]:

$$v(x) = \begin{cases} \frac{1 - \exp[-(x - \text{Low})/\rho]}{1 - \exp[-(\text{High} - \text{Low})/\rho]}, & \rho \neq \text{Infinity} \\ \frac{x - \text{Low}}{\text{High} - \text{Low}}, & \text{otherwise} \end{cases} \quad (4.2)$$

where $v(x)$ is the single dimension value, x is the evaluation measure, Low is the lowest x of interest, High is the highest x of interest, and ρ is the exponential constant. For a decreasing value function, Equation 4.3 is used [47].

$$v(x) = \begin{cases} \frac{1 - \exp[-(\text{High} - x)/\rho]}{1 - \exp[-(\text{High} - \text{Low})/\rho]}, & \rho \neq \text{Infinity} \\ \frac{\text{High} - x}{\text{High} - \text{Low}}, & \text{otherwise} \end{cases} \quad (4.3)$$

The piecewise linear procedure is only necessary when value measures do not have countable units. An example of an evaluation measure that uses a piecewise linear function is the reliability of the UAS. As previously described in Section 4.1.3.3, motor type was used to determine system reliability. There are no units associated with each type of motor; therefore, using the equations for determining an exponential function is impossible. The piecewise linear procedure first assigns a value to each of the four types of motors based on the motor type reliability, and then straight lines are drawn between these points in order to construct a function. Figure 4-11 illustrates an example of a piecewise linear value function for system reliability using motor type.

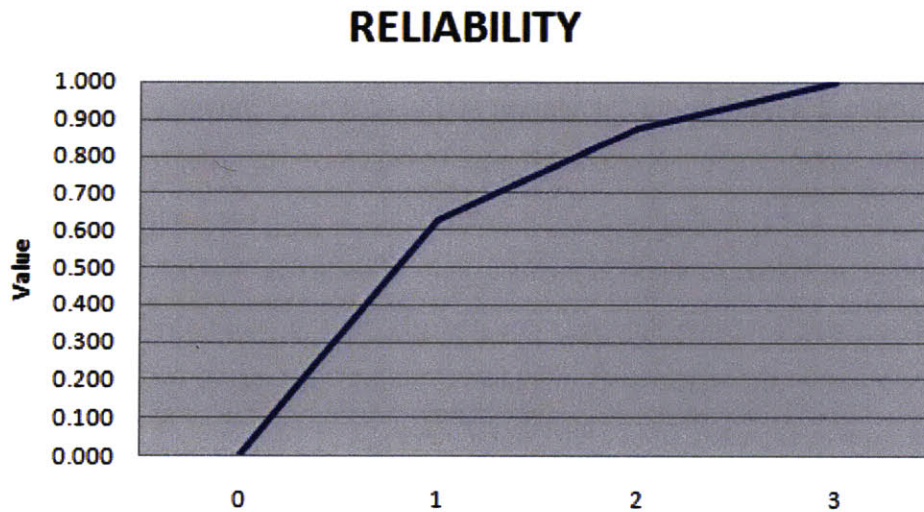


Figure 4-11: Piecewise Linear Value Function of Reliability

The piecewise linear functions are less rigorous because they require subjective assignment of value. For this reason, these types of measures are discouraged in systems decision making. As a result, the researcher minimizes their use in this work.

4.1.4.2.2 Weighting the Value Model

After creating the value functions, the analyst must then determine a swing weight for each evaluation measure. Calculating swing weights is an iterative process the analyst must perform with the stakeholders in order to determine which evaluation measures are the most important. Through the stakeholder interviews, the analyst determines an initial importance level of each metric. He then presents this to the decision maker to ensure that the decision maker agrees with his assessment. This process repeats until the decision maker agrees with the assigned weights. The SDP uses the following matrix in order to determine weights for each measure.

		Level of Importance of the Value Measure		
		Very Important	Important	Less Important
Variation in Measure Range	High	A	B ₂	C ₃
	Medium	B ₁	C ₂	D ₂
	Low	C ₁	D ₁	E

- A > all other cells
- B₁ > C₁, C₂, D₁, D₂, E
- B₂ > C₂, C₃, D₁, D₂, E
- C₁ > D₁, E
- C₂ > D₁, D₂, E
- C₃ > D₂, E
- D₁ > E
- D₂ > E

Table 4-3: Swing Weight Matrix [65]

As the table shows, the most important value measures with the most variation in their possible measurement range are in the top left of the matrix. Those that are the least important and have the smallest variation in their measurement range are in the lower right. The evaluation measures in A through E can have any weighting range. This work uses the range of 1 to 100.

As described previously in this chapter, the researcher interviewed relevant stakeholders in order to determine their preferences for each evaluation measure developed for the UAS. These preferences are combined with the matrix above to produce the following swing weights.

		Level of importance of the value measure					
		High	Medium	Low			
Variation in measure range	High	1.2.1 System Weight	100	1.1.1 Stowed Dimensions	50	3.4.1 Endurance	20
		3.6.1 Range	95	2.2.1 Wing Span	45		
		2.1.1 Time to Employ	85	2.2.2 Length	45		
		3.3.1 Maneuverability	75				
	Medium	4.1.1 Camera Resolution	69			4.3.1 Explosive Power	15
		3.5.1 Wind Limit	65				
	Low	3.1.1 Payload Weight	60	2.3.1 # of Soldiers	35		

Table 4-4: UAS Swing Weight Matrix

The weights depicted above are then normalized in order to prevent one evaluation measure from inappropriately dominating. The following equation is used to calculate the normalized global weight for each measure:

$$w_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (4.4)$$

where w_i is the weighted preference of the i^{th} stakeholder, f_i is the preference assigned to the i^{th} value measure, and $n = 1$ to n for the number of value measures [65]. Using this equation resulted in the following global weights:

Value Measure	Swing Weight	Global Weight
1.1.1 Stowed Dimensions	50	0.07
1.2.1 System Weight	100	0.13
2.1.1 Time to Employ	85	0.11
2.2.1 Wing Span	45	0.06
2.2.2 Length	45	0.06
2.3.1 # of Soldiers	35	0.05
3.1.1 Payload Weight	60	0.08
3.3.1 Speed Range (Maneuverability)	75	0.10
3.4.1 Endurance	20	0.03
3.5.1 Wind Limit	65	0.09
3.6.1 Range	95	0.13
4.1.1 Camera Resolution	69	0.09
4.3.1 Explosive Power	15	0.02
Total =	759	1.00

Table 4-5: Global Weights for UAS Evaluation Measures

As the table shows, system weight and range still have the highest values as in the swing weight matrix; however, they no longer dominate the other evaluation measures. Calculating the global weights completes the Problem Definition phase of the SDP.

4.2 Solution Design

Having completed the Problem Definition phase, the next phase of the SDP is the Solution Design phase. At this point in the SDP, the UAS problem is fully defined; therefore, the analyst must gather candidates that are potential solutions. The group of potential candidates is called the candidate solution space. The steps required to define the problem in previous sections provide the analyst with important tools and information that allow him to generate ideas and alternatives that satisfy stakeholder requirements.

During the Problem Definition phase, the SDP defined the system boundary for the UAS of interest in this thesis. By defining a system boundary, it focuses the analyst's search for appropriate candidate solutions. The system boundary defined in Section 4.1.2 focuses the analyst's search to Class I, fixed-winged UASs that are gas or battery powered. By simply defining the system boundary, it significantly reduces the potential solution space from several hundred to less than a hundred.

The next step in defining the problem was Functional Analysis. Functional Analysis produced a functional hierarchy. The functional hierarchy further reduces the solution space because not all remaining UASs can perform the functions depicted in the hierarchy. Additionally, the functional hierarchy enables the analyst to search for alternatives. Kirkwood (1997) contends that a hierarchy helps decision makers to more fully understand the considerations critical to evaluating potential solutions [47]. For example, the WASP and Sonobuoy Precision Aerial Delivery (SPAD) UASs represent alternative solutions to the backpackable UAS. Using the functional hierarchy, the researcher determined that both the WASP and SPAD are viable solutions. These UASs are considered alternatives to the solution space because the WASP is tube launched and the SPAD is air dropped, which are very different than the methods of delivery for other UASs included in the candidate solution space. Using the system boundary and the functional hierarchy creates an effective initial candidate solution space; however, a more rigorous method is required in order to generate the final candidate solution space that is scored.

4.2.1 Feasibility Screening

The SDP uses feasibility screening to produce the final candidate solution space. As described in Section 4.1.1, in stakeholder interviews during the Problem Definition Phase, the analyst determines their requirements and desires. Through iteration with the stakeholders, some of the system requirements become constraints. These constraints that are developed in the Problem Definition Phase are now used in the Solution Design Phase and serve as the filters the SDP uses to produce the final candidate solution space. Figure 4-12 is presented again here to illustrate the filtering process the SDP utilizes.

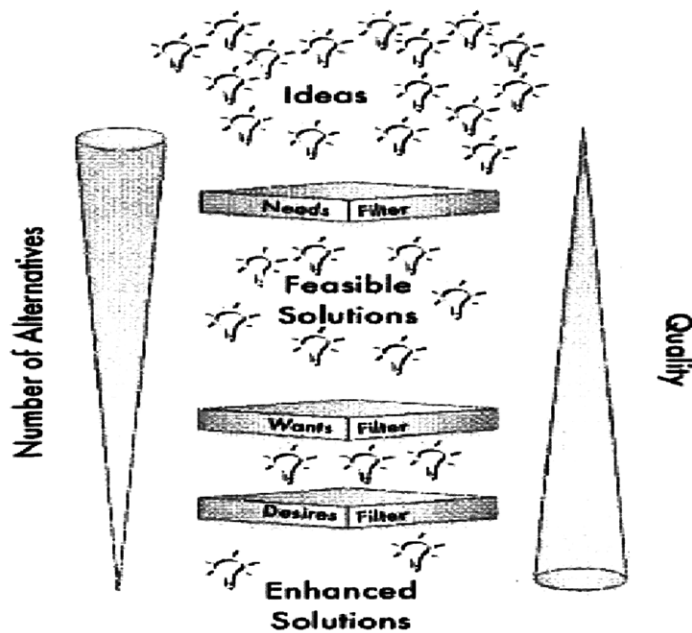


Figure 4-12: SDP Feasibility Screening [65]

As the figure depicts, solutions either pass through the filter or they do not. Additionally, it shows that as the number of solutions decrease, the quality of the remaining candidates increase. The two “Enhanced Solutions” remaining in the figure are the only two that proceed to the scoring step of the SDP.

As described in Section 4.1.1.1, the analyst determined that the stakeholder’s four most important requirements were weight, range, stow dimensions, and TRL. Table 4-6 shows the requirements that constrain the UASs.

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level
Limit	≤ 15 lbs	≥ 2 km	≤ 2.3 ft ³	≥ 6

Table 4-6: UAS constraints

Total weight for the system, to include ground control station (GCS), must be 15 pounds or less, and it must have a range of at least two kilometers. Endurance is not a constraint because the stakeholders were more concerned with the range the UAS can travel than how long it could remain airborne. Equally important to weight is the UAS dimensions. Because a dismounted soldier has to carry the system, it must fit within the current Army’s Modular Lightweight Load-carrying Equipment (MOLLE) backpack. The current MOLLE has inner dimensions of 2.3 cubic feet [46]. Finally, the last requirement the UAS must meet, although it was not specifically voiced by the stakeholders, is a TRL 6.

Even though this work began with 15 UASs in its initial solution space, using the constraints in Table 4-6 to filter the solution space reduces it to three candidates.

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level	Overall Assessment
Limit	≤ 15 lbs	≥ 2 km	≤ 2.3 ft ³	≥ 6	
SYSTEM					
BATCAM	6.00	10	0.10	9	Go
Black Widow	15.18	1.8	0.05	9	No Go
Desert Hawk	16.50	15	2.37	9	No Go
CCLR	10.00	3	0.10	3	No Go
Dragon Eye	12.20	5	0.91	9	Go
Javelin	65.00	1.6	3.17	9	No Go
Locust	6.25	5	0.13	9	Go
Orbiter	24.33	15	6.00	9	No Go
Pointer	31.60	5	3.17	9	No Go
Puma	31.70	10	3.17	7	No Go
Raven	11.20	10	2.85	9	No Go
ScanEagle	47.90	20	10.00	9	No Go
Skylite B	23.22	10	10.00	9	No Go
SPAD	31.20	2	0.39	6	No Go
WASP	18.74	48	0.24	6	No Go

Table 4-7: UAS Feasibility Screening

As the table shows, most of the candidates failed to pass through one or more filters. After filtering, only the BATCAM, Dragon Eye, and Locust UASs remain in the final solution space. These are the only three candidates that the SDP evaluates during the Decision Making phase.

The researcher deviates from the SDP at this point in order to increase the final number of UASs that are scored. Upon completing the Decision Making phase, it was discovered that these three candidates did not adequately illustrate the solution scoring or sensitivity analysis steps. Consequently, the researcher feels it is important to increase the number of candidates in order to better illustrate these steps. Table 4-8 depicts the new constraints used.

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level
Limit	≤ 15 lbs	≥ 2 km	≤ 3 ft ³	≥ 6

Table 4-8: Modified UAS Constraints

As the table shows, the stowed dimensions are increased from 2.3 to 3 cubic feet. Three cubic feet is larger than the current MOLLE, but the UAS added to the solution space does not change the final result and only serves to aid the researcher in describing the solution scoring and sensitivity analysis steps. The researcher does not increase any other constraints because other than the Close Combat Lethal Reconnaissance (CCLR) UAS, the Raven UAS only fails one constraint. Adding the Raven UAS to the solution space allows the researcher to illustrate specific solution scoring and sensitivity analysis results that were not possible without it. Additionally, it requires the smallest change in the constraints. Using the new constraints to screen the candidate solution space produces the following results:

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level	Overall Assessment
Limit	≤ 15 lbs	≥ 2 km	≤ 3 ft ³	≥ 6	
SYSTEM					
BATCAM	6.00	10	0.10	9	Go
Black Widow	15.18	1.8	0.05	9	No Go
Desert Hawk	16.50	15	2.37	9	No Go
CCLR	10.00	3	0.10	3	No Go
Dragon Eye	12.20	5	0.91	9	Go
Javelin	65.00	1.6	3.17	9	No Go
Locust	6.25	5	0.13	9	Go
Orbiter	24.33	15	6.00	9	No Go
Pointer	31.60	5	3.17	9	No Go
Puma	31.70	10	3.17	7	No Go
Raven	11.20	10	2.85	9	Go
ScanEagle	47.90	20	10.00	9	No Go
Skylite B	23.22	10	10.00	9	No Go
SPAD	31.20	2	0.39	6	No Go
WASP	18.74	48	0.24	6	No Go

Table 4-9: New Candidate Solution Space

The candidate solution space now includes the BATCAM, Dragon Eye, Locust, and Raven. These four UASs are evaluated during the next phase of the SDP.

4.3 Decision Making

During this phase of the SDP the remaining UASs from feasibility screening are evaluated using a scoring methodology. There are three pieces of data required to score each UAS: raw score, value score, and global weight. Using this data and Equation 4.1 from Section 4.1.4.2 generates a numerical value which is used to determine the best solution of the four remaining UASs.

4.3.1 Raw Scores

The raw score is the actual numerical value of a specific evaluation measure for the UASs. Raw scores are the data that the analyst compiles for each UAS in the solution space prior to feasibility screening. See Appendix E for an example of a table with a list of the raw scores for the 15 UASs used in this thesis. The raw scores for the four UASs remaining after feasibility screening are given in Table 4-10.

Objectives→	1.0 Transport System		2.0 Employ System				3.0 Operate System				4.0 Achieve Effects		
Candidate Solutions	1.1.1 Stowed Dimensions (ft ²)	1.2.1 System Weight (lbs)	2.1.1 Time to Employ (min)	2.2.1 Wing Span (in)	2.2.2 Length (in)	2.3.1 # of Soldiers (#)	3.1.1 Payload Weight (oz)	3.3.1 Speed Range (mph)	3.4.1 Endurance (min)	3.5.1 Wind Limit (mph)	3.6.1 Range (km)	4.1.1 Camera Resolution (pixels)	4.3.1 Explosive Strength (kilojoules)
BATCAM	0.10	6.00	5	21	21	1	0.83	27	80	27	10	560	86.57
Dragon Eye	0.91	12.20	5	45	36	1	7.30	23	60	20	5	631	759.65
Locust	0.13	6.25	5	18	10	1	0.50	19	45	30	5	499	52.03
Raven	2.85	11.20	5	55	36	2	8.00	41	90	20	10	1792	832.50

Table 4-10: UAS Raw Scores

4.3.2 Value Scores

The raw scores in the table above are then converted into value scores using the value functions described in Section 4.1.4.2.1. Appendix F gives the SDP value functions used in this work. Table 4-11 shows the value scores that result.

Objectives→	1.0 Transport System		2.0 Employ System				3.0 Operate System				4.0 Achieve Effects		
Candidate Solutions	1.1.1 Stowed Dimensions (ft ³)	1.2.1 System Weight (lbs)	2.1.1 Time to Employ (min)	2.2.1 Wing Span (in)	2.2.2 Length (in)	2.3.1 # of Soldiers (#)	3.1.1 Payload Weight (oz)	3.3.1 Speed Range (mph)	3.4.1 Endurance (min)	3.5.1 Wind Limit (mph)	3.6.1 Range (km)	4.1.1 Camera Resolution (pixels)	4.3.1 Explosive Strength (kilojoules)
BATCAM	0.9400	0.6898	0.2651	0.5463	0.4849	1.0000	0.0187	0.4382	0.9911	0.7019	0.7977	0.1141	0.0226
Dragon Eye	0.5427	0.4154	0.2651	0.2647	0.2654	1.0000	0.2114	0.3604	0.9535	0.5088	0.5084	0.1473	0.2094
Locust	0.9254	0.6776	0.2651	0.5963	0.7167	1.0000	0.0111	0.2875	0.8898	0.7772	0.5084	0.0863	0.0135
Raven	0.0239	0.4560	0.2651	0.1921	0.2654	0.5137	0.2383	0.7546	1.0000	0.5088	0.7977	0.8400	0.2308

Table 4-11: UAS Value Scores

As the researcher explained in the qualitative value model, some objectives are not included in the scoring step. As a result, their associated evaluation measures are not in the tables above. The value scores in the table are one half of the final scores.

4.3.3 Solution Scoring

Once the analyst has the value score for each metric of each UAS, he can then combine this value score with the global weights to calculate a final value score. Figure 4-13 illustrates the different parts of Equation 4.1.

$$v(x) = \sum_{i=1}^n w_i v_i(x_i)$$

Figure 4-13: Scoring Equation

Table 4-12 shows the total value scores for the four UAS remaining in our solution space.

Candidate Solutions	Candidate Score
BATCAM	0.5314
Dragon Eye	0.3999
Locust	0.4949
Raven	0.4862

Table 4-12: Total Value Score

As the table depicts, the BATCAM has the most value with respect to the evaluation measures. Therefore, this is the best solution for the backpackable UAS using the SDP. A stacked bar chart is provided below so the reader can see how much each evaluation measure contributes to the total value for each candidate solution.

SDP FINAL VALUE SCORES

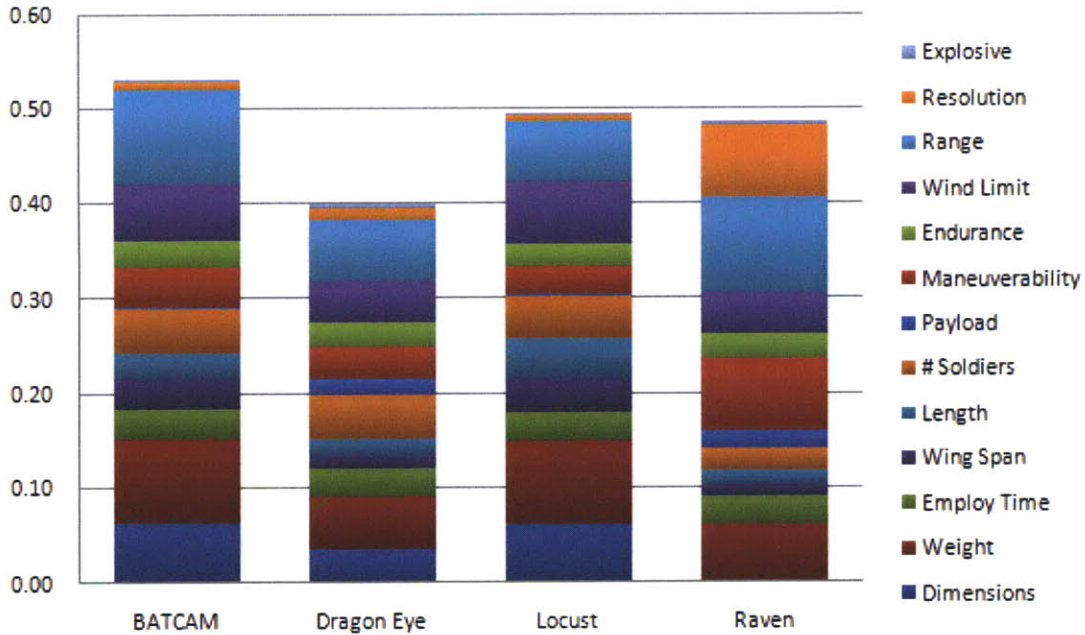


Figure 4-14: Stacked Bar Chart of Final Value Scores

As the stacked bar chart shows, the Raven receives very little value from its dimensions compared to the other UASs. Conversely, it gains a lot of value from the resolution of its camera. As explained above, increasing the stowed dimensions to include the Raven UAS allows the researcher to better describe the results and their differences in the Decision Making phase.

4.3.4 Sensitivity Analysis

Once the analyst calculates the total value scores and determines the optimal solution, he must conduct sensitivity analysis. Because half of Equation 4.1 is dependent on stakeholder preference, the analyst must ensure that changes in their preferences do not significantly affect the final solution. Systems Engineers consider the solution insensitive if crossover does not occur within 10% of a given preference weight [65]. Crossover is when one solution's total value becomes larger than a previously higher valued solution due to a change in a global weight. For example, the Raven UAS has a higher total value when the global weight for system weight is 0.05; however, when the global weight changes to 0.10, the Locust UAS has a higher total value.

In order to test the sensitivity of the BATCAM, the researcher varied the global weight of the system weight evaluation measure. The original global weight for system weight is 0.13 or 13%. This weight is varied between 0% and 25%. Table 4-13 provides the results of the sensitivity tests.

SDP Sensitivity Analysis Results							
<i>System Weight Varied</i>							
	Base Case	0	0.05	0.1	0.15	0.2	0.25
BATCAM	0.5314	0.5074	0.5165	0.5256	0.5347	0.5438	0.5530
Dragon Eye	0.3999	0.3975	0.3984	0.3993	0.4002	0.4011	0.4020
Locust	0.4949	0.4672	0.4777	0.4882	0.4988	0.5093	0.5198
Raven	0.4862	0.4908	0.4891	0.4873	0.4856	0.4839	0.4821

Table 4-13: Sensitivity Analysis Results

Table 4-13 illustrates that the BATCAM is not sensitive to changes in the global weight for the system weight evaluation measure. However, as stated above, the Raven is sensitive to a change in the global weight. The figure shows that the crossover occurs between the Raven and Locust UASs when the global weight is 10%.

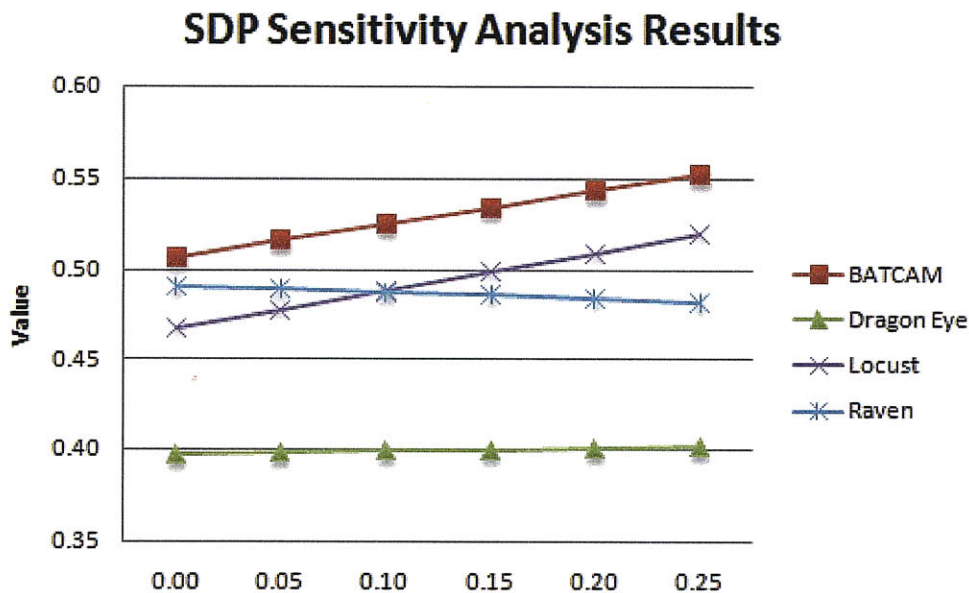


Figure 4-15: SDP Sensitivity Analysis Results

Including the Raven into the final solution space allows the researcher to demonstrate the concept of crossover. After assessing the sensitivity of the final solution, the analyst can now present the results, make a recommendation, and elicit a decision from the decision maker.

4.3.5 Solution Decision

Performing the sensitivity analysis above is done to confirm the robustness of the final solution. The analyst now presents to the decision maker that the BATCAM is the best solution to the backpackable, lethal UAS. It is now the decision maker's responsibility to accept or reject the solution. The decision maker can also decide to accept the final solution but with changes. For example, he may accept the BATCAM but require the maker to improve the available payload weight for munitions. If this change results in significant changes to other aspects of BATCAM, then it may require the analyst to re-score the candidate solution space to ensure the changes do not affect the final outcome. Once the decision maker is satisfied with the final solution, this solution is carried forward to the Solution Implementation phase of the SDP.

4.4 Solution Implementation

Solution Implementation is the last phase of the SDP. In order for the solution to be successfully implemented, the Problem Definition, Solution Design, and Decision Making phases must be performed correctly [65]. The Solution Implementation has three steps: 1. planning for action, 2. execution, and 3. assessment and control. This thesis focuses only on the first three phases of the SDP. As a result, Solution Implementation is not conducted and is only mentioned here in order to provide the reader an understanding of what it is and where it fits into the SDP.

4.5 Summary

In this Chapter the researcher followed the SDP to determine the best solution to the backpackable UAS problem. The SDP has four major phases: 1. Problem Definition, 2. Solution Design, 3. Decision Making, and Solution Implementation. Solution Implementation is presented but not performed because it is outside the scope of this work.

Section 4.1 describes the process of stakeholder analysis in order to define system requirements. Also, a system boundary is presented in order to precisely identify for the reader which aspects of the UASs this work focuses on in order to solve the backpackable UAS problem. Additionally, the researcher performs functional analysis and develops qualitative and quantitative value models. Finally, value functions are presented along with weighting of stakeholder preferences.

Section 4.2 begins by describing how the SDP creates the initial candidate solution space. It then explains how feasibility screening reduces the initial solution space using constraints as filters in order to generate a final solution space. The section concludes with the researcher deviating from the SDP in order to add the Raven UAS back into the final solution space. By adding an additional UAS, the researcher is better able to illustrate the mechanics of following section.

Section 4.3 describes the Decision Making phase of the SDP. Within this section, the researcher performs solution scoring in order to produce an optimal solution from the remaining solution space. The solution is checked for sensitivity and then presented to the decision maker. Finally, the chapter ends with a brief explanation of Solution Implementation.

5 Decisions with Flexibility Analysis

The previous chapter employed the complete Systems Decision Process using Classical Decision Analysis (CDA) to determine a best solution. In Chapter 1, the researcher stated the intent of this work was to improve this process and decision making. Section 1.5.1 described the three areas where Flexibility Analysis (FA) would improve the SDP. These improvements are a better hierarchical representation that keeps focus on the whole system, an improved feasibility screening method, and the reduction of human bias. This chapter expands on these three improvements. The chapter works within a similar framework used in Chapter 4. The purpose for mirroring Chapter 4 is so the reader can devote their attention to the improvements developed in this work and not become bogged down in trying to understand differing methodologies. As a result, some material in this Chapter may be repetitive; however, the researcher tries to keep this to a minimum and makes reference to it when it occurs.

5.1 Stakeholders and Decision Makers

The stakeholders and decision makers remain the same as those described in Section 4.1.1. They are still at the heart of the process, and they still provide the requirements of the objective system. However, FA has two areas where the interactions with the decision makers differ. The first difference is during the feasibility screening step. As stated earlier, an improvement of FA over SDP is how potential solutions are screened. SDP through stakeholder

analysis determines static, discrete constraints that each candidate solution either passes or fails. Through an iterative process with the stakeholders, FA determines a range in which the candidate solutions may fall. The exact method is discussed in greater detail in Section 5.4. The second difference involves the FA analyst. The analyst uses information about the potential value, inherent in the candidate solutions, to provide the stakeholders more complete information about them. For example, the analyst can inform the stakeholder which subsystem offers the most flexibility across the system of systems. Additionally, the analyst can present the stakeholder with the candidate solutions that have the most potential value and the realized value that results. Section 5.3.3.2 describes how to calculate potential, and Section 5.5.2 describes how to calculate realized values.

5.1.1 Engineer Involvement

A stakeholder that FA involves more in decision making than the SDP is the engineer. The engineer performs two important functions in FA. The first is during the feasibility screening step. In order to determine a range of values in which candidate solutions may fall, the engineer must work closely with other stakeholders during requirements development. The stakeholder provides the static, discrete constraint and the engineer provides an estimate of acceptable variations from that constraint. This variation is then used to determine a range of values for feasibility screening. Section 5.4.2 provides an example of stakeholder and engineer interaction in order to determine the feasible solution space. The second function requires engineers to provide subsystem estimates. The engineer must provide the analyst with estimates of how much each subsystem is able to change. Some subsystems may have little or no ability to change, while others can do so significantly. The FA analyst uses the engineer's estimates to calculate the potential value in each candidate solution. Engineers are critical to measuring flexibility in systems since they have the most expertise about the systems; therefore, the decision analyst must assimilate this knowledge into the decision process. After conducting stakeholder analysis, the FA analyst must then define the system of systems.

5.2 Defining the System of Systems

This section represents one of the three key improvements FA makes to the SDP. This section mirrors Section 4.1.3. As the reader may notice, the researcher does not define the system boundary. The system boundary has not changed between the SDP and FA; therefore,

the reader can assume the same boundary applies. In Section 4.1.3 the decision analyst conducted functional analysis with information gathered from stakeholders. FA does not focus on function or process, but maintains the whole system as the focal point. Dettmer (2006) states “a holistic or whole system approach is considerably better,” for the complex systems encountered today [22]. In order to maintain holistic thinking, the analyst must decompose the system of systems into its major subsystems, flexible attributes, and measures of flexibility.

5.2.1 Major Subsystems

In the SDP, the fundamental objective is composed of the functions the system must perform. The method for determining system functions is covered in Section 4.1.3.1. However, as outlined in Chapter 1, this is one of the drawbacks of the SDP and Systems Engineering. By focusing on function and process, it loses visibility on system properties. In order to maintain visibility, the hierarchical structure must show major subsystems of the objective system. Figure 5-1 shows the major subsystems of the UAS.

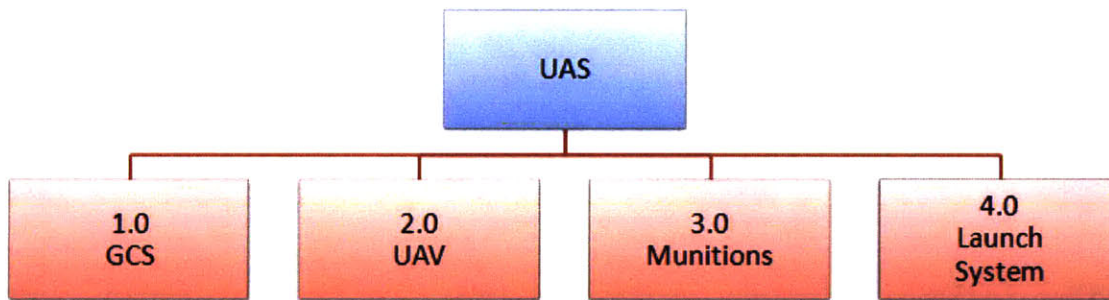


Figure 5-1: Major Subsystems of the UAS

Representing the structure in this form maintains system focus. Additionally, it allows the analyst to evaluate each subsystem to find flexibility. Defining the system by functions, as the SDP does, provides little insight into potential value to be gained from flexibility. Furthermore, one can isolate the proportion each metric accounts for the whole. In order to clarify the statement of isolating proportions the researcher presents the following example. Each candidate system weighs a specific amount, and each subsystem accounts for a certain proportion of the total weight. If one subsystem is disproportionate to all other subsystems, this indicates a potential point of flexibility. As a result, this should assist decision makers in allocating resources for system improvements.

Moreover, studying Figure 5-1 shows that the UAS is composed of very different subsystems. It would be difficult to find one organization with expertise in each of these areas. Consequently, this is another benefit of FA hierarchy representation. The decision maker can easily identify subsystems and search for specific organizations that have expertise in ground control stations (GCS), unmanned aerial vehicles (UAVs), munitions, and launch systems. Conversely, the SDP's functions of "Employ System" or "Operate System" tell the decision maker very little. Thus, system properties are not readily apparent with the SDP hierarchy. After defining the major subsystems, FA then decomposes the major subsystems into flexible attributes.

5.2.2 Flexible Attributes

Flexible attributes are similar to major subsystems in that they decompose subsystems into smaller parts as subsystems did to the objective system. In reality, they are the subsystems of the subsystems. Figure 5-2 illustrates the flexible attributes of the UAS.

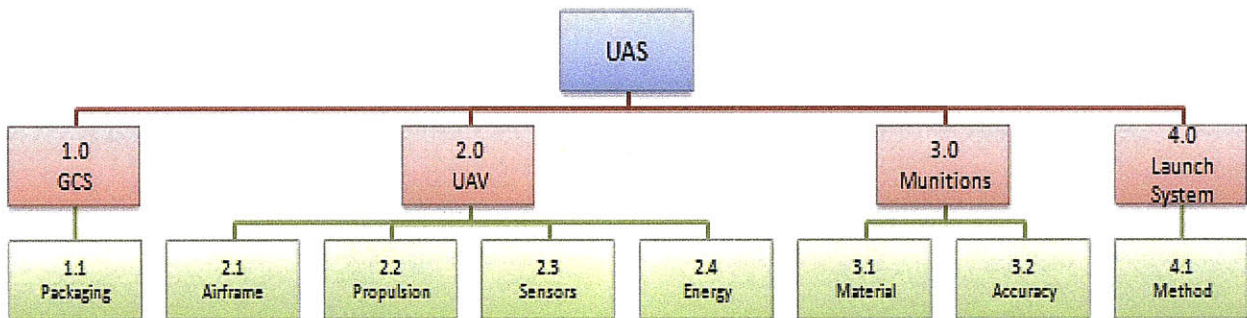


Figure 5-2: Flexible Attributes of the UAS

FA's flexible attributes mirror the objectives found in the SDP hierarchy. However, objectives only describe whether the stakeholders want a measure of effectiveness to be minimized or maximized. Additionally, objectives tend to be aggregated. (Section 4.1.3.2 defined the objectives of the UAS.) For example, objective 1.2 was "Minimize System Weight." Aggregated into this objective are the major subsystems of the GCS, UAV, and Launch System. Additionally, Objective 1.2 includes the flexible attributes of Packaging, Airframe, Propulsion, Sensors, Energy, Material, and Launch System. Conversely, FA's use of major subsystems and then flexible attributes decomposes the system into separate, analyzable pieces. As a result, the analyst can evaluate every aspect of the system for flexibility. This further illustrates how systems engineering loses focus on the system as a whole. Thus, using only the SDP limits the

decision maker’s ability to understand system properties and behaviors. The SDP lacks the ability to account for flexibility and measure its value. Once the flexible attributes are defined, each of these has one or more measures of flexibility.

5.2.3 Measures of Flexibility

The final level in FA’s hierarchical structure is similar to the SDP’s hierarchical structure. As described in Section 4.1.3.3, Measures of Effectiveness or MOEs are a way to quantify the achievement of an objective. Measures of Flexibility or MOFs quantify those aspects of the flexible attributes and major subsystems that are flexible. Many of the MOFs and MOEs are the same; however, because FA decomposes the hierarchy by major subsystem, some of the MOFs below are not found in the functional hierarchy depicted in Chapter 4. Figure 5-3 shows the complete FA hierarchy with MOFs.

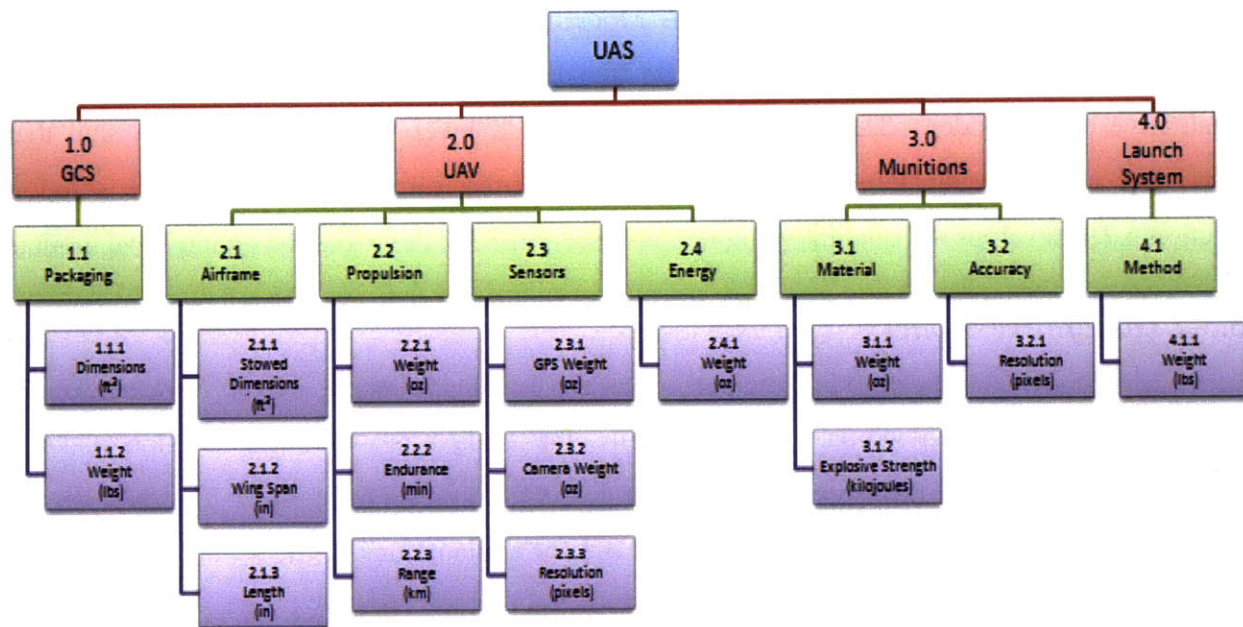


Figure 5-3: Complete FA hierarchy with Measures of Flexibility

As the reader may notice, many of the MOFs measure the same quantity. For example the most ubiquitous MOF is weight. This represents a significant difference between MOEs and MOFs. Decision analysis discourages repetitive MOEs because it biases the results and skews them toward the recurring metric [44]. This is not a concern in FA because this actually helps locate the metric with the most flexibility across the entire system. For example, in the UAS, it can easily be observed that weight is an important metric in each major subsystem.

These measures of flexibility serve as important value measures. The potential value inherent in each of the UASs is calculated directly using the MOFs in Figure 5-3. The method for calculating the potential value is described in Section 5.3.2.2. Finally, the researcher does not want to imply that Figure 5-3 is the approved solution for the UAS hierarchy. It is likely that others, especially experts in designing UASs, can create a more complete hierarchy. The intended purpose is to provide a working example to prove the validity of FA. The next step in the FA method is to create both a qualitative and quantitative model.

5.3 Systems Modeling

As is the case when using the Systems Decision Process, the FA method develops both qualitative and quantitative models. The SDP referred to this as Value Modeling. (See Section 4.1.4 for the complete SDP value models.) Once again, FA wants to maintain systems thinking; therefore, FA refers to this step as Systems Modeling. Now that the FA hierarchy has been developed and constructed, it is important to translate the hierarchy into words to produce a qualitative value model. The analyst must define each level within the hierarchy and then develops a mathematical model in order to quantify the value of each candidate solution. Section 5.3.1 develops the qualitative model, and Section 5.3.2 describes the quantitative model.

5.3.1 Qualitative Model

As described in Section 5.3, the purpose of the qualitative model is to convert the visually presented hierarchy into words. By doing this, the analyst provides the decision maker a complete explanation of the system. The reader may want to refer to Figure 5-3 throughout this section for the FA hierarchy and to Section 4.1.3.3 for explanations of the scaling terms proxy, direct, constructed, and natural used below.

Major Subsystem 1.0 → *Ground Control Station (GCS)*: The GCS is the interface between the UAV and the operator. The GCS provides the operator real-time information about the UAV's airspeed, altitude, and location. Additionally, the GCS incorporates a viewer display so the operator can view what the UAV is viewing. Finally, the GCS allows the operator to preprogram flight information as well as program in-flight changes for the UAV.

Flexible Attribute 1.1 → *Packaging*: Packaging is the structure that houses the GCS. Included in this are any external antennas or cables required to operate the GCS.

Measure 1.1.1 → *Dimensions*: The dimensions for packaging are measured in cubic feet. The dimensions are directly measured. This is a direct-natural scale where less is better.

Measure 1.1.2 → *Weight*: The weight for packaging is measured in pounds. The weight is directly measured. This is a direct-natural scale where less is better.

Major Subsystem 2.0 → *Unmanned Aerial Vehicle (UAV)*: The UAV is the fundamental part of the UAS. Every other system is built around it. It also represents the most technically demanding aspect of the UAS. The reader should refer to Chapter 2 for a full appreciation of the technical difficulties in designing small UAVs.

Flexible Attribute 2.1 → *Airframe*: The airframe includes all lift producing surfaces of the UAV. It does not include any of the internal components.

Measure 2.1.1 → *Stowed Dimensions*: The dimensions are measured in cubic feet. The dimensions are directly measured. This is a direct-natural scale where less is better.

Measure 2.1.2 → *Wing Span*: The wing span is measured in inches. The wing span is directly measured. This is a direct-natural scale where less is better.

Measure 2.1.3 → *Length*: The length of the UAV is measured in inches. The length is directly measured. This is a direct-natural scale where less is better.

Flexible Attribute 2.2 → *Propulsion*: Propulsion includes the motor, whether gas, electric, or rocket driven, and the associated hardware. The associated hardware could include propellers, speed regulators, wiring, and other devices. It does not include the energy that powers the motor.

Measure 2.2.1 → *Weight*: The weight of the motor is measured in ounces. The weight is directly measured. This is a direct-natural scale where less is better.

Measure 2.2.2 → *Endurance*: The endurance of the motor is measured in minutes. The endurance is directly measured. This is a direct-natural scale where more is better.

Measure 2.2.3 → *Range*: The range of the motor is measured in kilometers. The range is measured in-directly through the distance the UAV can travel. Therefore, range is a proxy scale. Kilometer is a natural scale. The range is a proxy-natural scale where more is better.

Flexible Attribute 2.3 → *Sensors*: Sensors are any device on the UAV that collects or measures conditions in the environment or within the UAV. Examples of sensors are the

GPS and camera. The sensors include all associated wiring and adaptors required for them to operate.

Measure 2.3.1 → *GPS Weight*: The GPS weight is measured in ounces. The weight is directly measured. This is a direct-natural scale where less is better.

Measure 2.3.2 → *Camera Weight*: The camera weight is measured in ounces. The weight is directly measured. This is a direct-natural scale where less is better.

Measure 2.3.3 → *Resolution*: Resolution is measured in pixels. The pixels are measured directly. Resolution is given by the manufacturer in horizontal and vertical pixels. There was no correlation between camera weight and number of pixels within the sample space. Therefore the analysis uses the average number of total pixels. Pixels are not a natural scale; therefore, this is a direct-constructed scale where more is better.

Flexible Attribute 2.4 → *Energy*: Energy is any fuel source the UAV requires to operate. The sample space only includes gas and electric energy sources.

Measure 2.4.1 → *Weight*: The weight of energy is measured in ounces. The weight is measured directly. This is a direct-natural scale where less is better.

Major Subsystem 3.0 → *Munitions*: Munitions are a unique aspect of small UAVs. The munitions include the explosive materials and all components required to detonate them. Equipping backpackable UAVs with lethality has only recently become possible. The reader should review Section 2.6.2 in order to understand the characteristics and issues associated with arming UASs.

Flexible Attribute 3.1 → *Material*: Material is the explosive substance/composite that gives the UAS its lethality. The researcher uses Composition B as the material for this research. Composition B is the same material used in fragmentary grenades, and the Army labels this material as a bursting charge. Composition B has a Relative Effectiveness (RE) factor of 1.35. Trinitrotoluene (TNT) is the base line material for calculating RE—TNT's RE factor is 1.0 [26].

Measure 3.1.1 → *Weight*: The weight of material is measured in ounces. The weight is measured directly. This is a direct-natural scale where less is better.

Measure 3.1.2 → *Explosive Strength*: Explosive Strength is measured in kilojoules. It is not measured directly. This is a proxy-natural scale where more is better.

Flexible Attribute 3.2 → *Accuracy*: Accuracy is how close the UAV hits to its intended target. This is often called Circular Error Probable or CEP. The Department of Defense Dictionary of Military and Associated Terms defines CEP as “an indicator of the delivery

accuracy of a weapon system . . . it is the radius of a circle within which half of a missile's projectiles are expected to fall" [42]. The Army requires the UAV to fly into the intended target using its camera. Therefore, the accuracy of the UAV is directly related to the resolution of the onboard camera.

Measure 3.2.1 → *Resolution*: Resolution is measured in pixels. The pixels are measured directly. Pixels are not a natural scale; therefore, this is a direct-constructed scale where more is better. This is the same as Measure 2.3.3. As a result, this is not included into the quantitative model because it counts twice the effects of one MOF.

Major Subsystem 4.0 → *Launch System*: The launch system is the device or method the operator uses to get the UAV airborne.

Flexible Attribute 4.1 → *Method*: Examples of different launch methods are bungees, catapults, gun tubes, air drop, and the operator's hand.

Measure 4.1.1 → *Weight*: The weight of the launch system is measured in pounds. The weight is directly measured. This is a direct-natural scale.

This completes the qualitative model for the UAS using the FA methodology. As is evident in Section 5.3.1, the qualitative model defines the visually depicted FA hierarchy, but defines it differently than the SDP's qualitative model. The SDP decomposed the system by function and objective. As a result, holistic system thinking was lost. This section demonstrates that by decomposing the fundamental system by major subsystem and flexible attributes, decision makers and analysts remain focused on the whole system and its properties. Again, the researcher wants to affirm that the hierarchy and qualitative models described above are not the only solutions. The reader may see different and more effective ways to depict and describe the models. However, the intent is to create a creditable model that allows the researcher to develop and analyze the FA methodology. After defining the qualitative model, the next step is to develop and define a quantitative model.

5.3.2 Quantitative Systems Model

In the last section, the researcher defined the qualitative model. A qualitative model cannot provide the decision maker with a best solution. Therefore, a quantitative model is needed in order to mathematically show which candidate in our solution space is the best. Section 4.1.4.2 defined the mathematical model the SDP uses. As the researcher stated in Section 1.1, the SDP uses the additive value model which this work calls CDA. The CDA model

consists of two parts: a value function and a normalized stakeholder preference weight. The reader should reference Equation 4.1 in order to familiarize themselves with the CDA model, if they have not read Chapter 4.

FA uses a similar mathematical construction as CDA. However, in order to remove human bias and account for system flexibility, FA replaces the normalized stakeholder preference weight. This is an important difference in using FA. Half of the value calculated using CDA comes directly from a preference weight. It is important to replace preference because one stakeholder will always dominate the process, skewing results. Economist Kenneth Arrow won the Noble Prize in part because he demonstrated that no method exists which prevents a dominate stakeholder from emerging [3]. Accordingly, FA replaces this preference with the change in value associated with system flexibility. The researcher labels the change in value derived from system flexibility as potential value. In the same way that potential energy is stored energy within an object, potential value is stored value within a system. The following sections will describe FA value functions and how to calculate potential value.

5.3.2.1 Flexibility Analysis Value Functions

Many of the value functions CDA uses are the same functions FA uses. However, because FA defines and decomposes the system differently, it does require a few new value functions. For example, the SDP only used total system weight in its analysis. Because FA looks for flexibility within the system, it requires a component weight value function. The FA component function has an exponential shape, whereas the SDP weight function is more linear. Figures 5-4 and 5-5 illustrate the FA component weight value function and the SDP UAS weight value function respectfully. See Appendix F for the FA value functions.

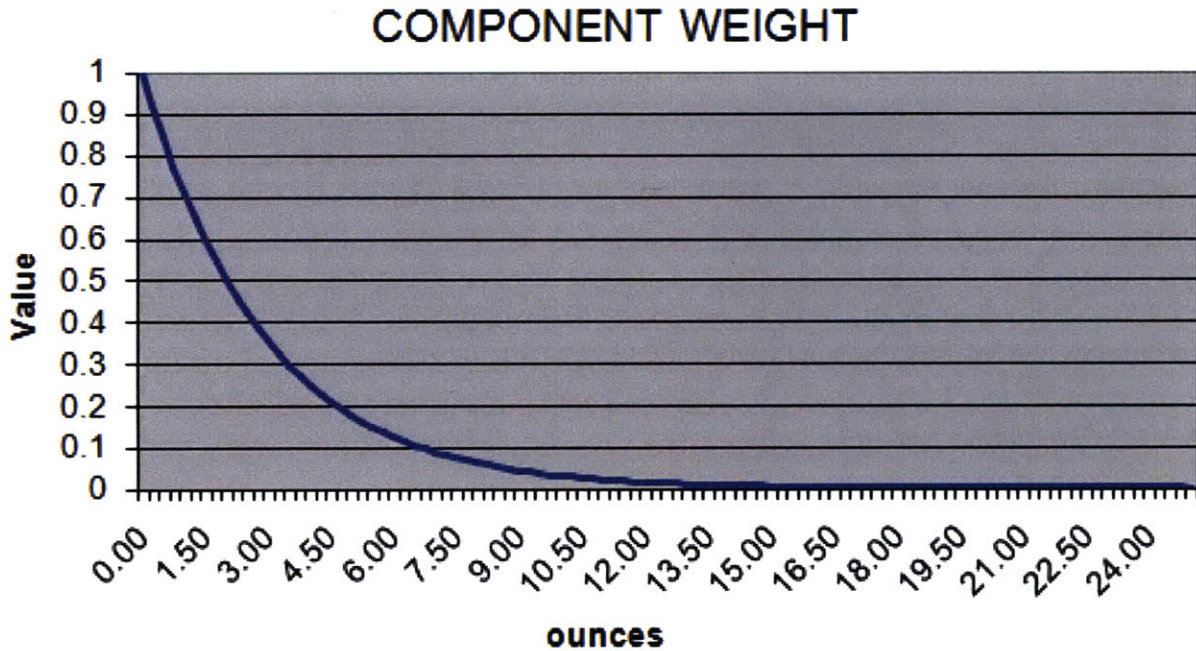


Figure 5-4: FA Component Weight Function

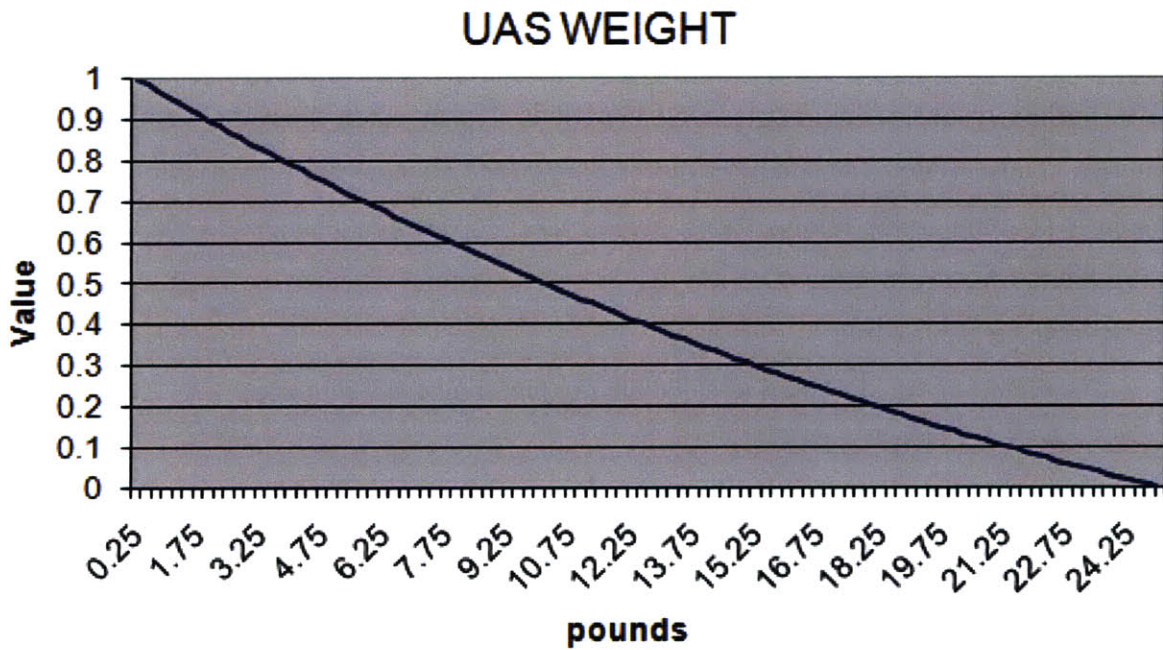


Figure 5-5: SDP UAS Weight Function

The functions have significantly different shapes even though the x-axes both end at 25. The units are different, but this does not affect the function's shape. The midvalue is the reason one function is exponential in shape and the other is nearly linear. The midvalue for component weight is much further to the left within the component weight range than that of the UAS's

weight range. For complete explanations of midvalue and how the researcher derived the value functions see Section 4.1.4.2.1. It is important to note that the mathematical method to determine the value functions for FA and the SDP are exactly the same. Therefore, the researcher does not repeat the explanation of how to create them. He only emphasizes that due to how each method decomposes the system, one set of value functions will not suffice. Even though FA and the SDP use the same method to create value functions, they use very different techniques to construct the other half of the mathematical model.

5.3.2.2 Calculating Potential Value

In order to remove latent errors caused by human preference, the researcher replaces the normalized stakeholder preference weight with potential value. Thus, this results in two benefits which improve decision making. The first benefit is potential value eliminates preference, which is an important source of error in decision analysis. Field and de Neufville (1988) show that small changes in normalized weight indices, like preference weights, can significantly alter results causing meaningless rankings for decision makers [28]. Similarly, (Ross 2003), who advocates the use of preference, acknowledges that preference can cause significant errors and lead to useless results [73]. The second benefit is it provides a measure of inherent system flexibility. Those systems which offer more value due to changes are more flexible. Evaluating a system's potential value allows the decision maker to quantify changes to the system before making them. As a result, the decision maker can determine whether the resources required to make the change are feasible.

The equation the SDP used to calculate the preference weights was:

$$w_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (5.1)$$

where w_i is the weighted preference of the i^{th} stakeholder, f_i is the preference assigned to the i^{th} value measure, and $n = 1$ to n for the number of value measures [65]. FA replaces this parameter with the flexibility measure δ_i . The resulting equation to calculate δ_i is:

$$\delta_i = v_i(x_i^*) - v_i(x_i) \quad (5.2)$$

where δ_i is the potential value measure of the i^{th} MOF, $v_i(x_i^*)$ is the new single dimensional value of the i^{th} MOF due to changing the system, $v_i(x_i)$ is the original single dimensional value of the i^{th} MOF before changing the system, and x_i is the raw score of the candidate solution for the i^{th} MOF.

In order to determine the new single dimensional value, the analyst must involve the engineers. As described in Section 5.1.1, the analyst works closely with the design engineers to determine the amount of feasible change available in each candidate solution. The analyst takes the estimates the engineers provide and calculates the potential value inherent in each flexible attribute. The following paragraphs describe this process for the reader.

The design engineers determine the candidate solutions can change by 50%. The decision analyst takes this estimate and applies it to the solution space. There are 16 different functions for the UAS using FA, and Figures 5-6 and 5-7 serve as two examples of these. Figure 5-6 illustrates an example of a monotonically decreasing (less is better) function, and Figure 5-7 represents a monotonically increasing (more is better) function. For an explanation of monotonicity see Section 4.1.4.2.1.

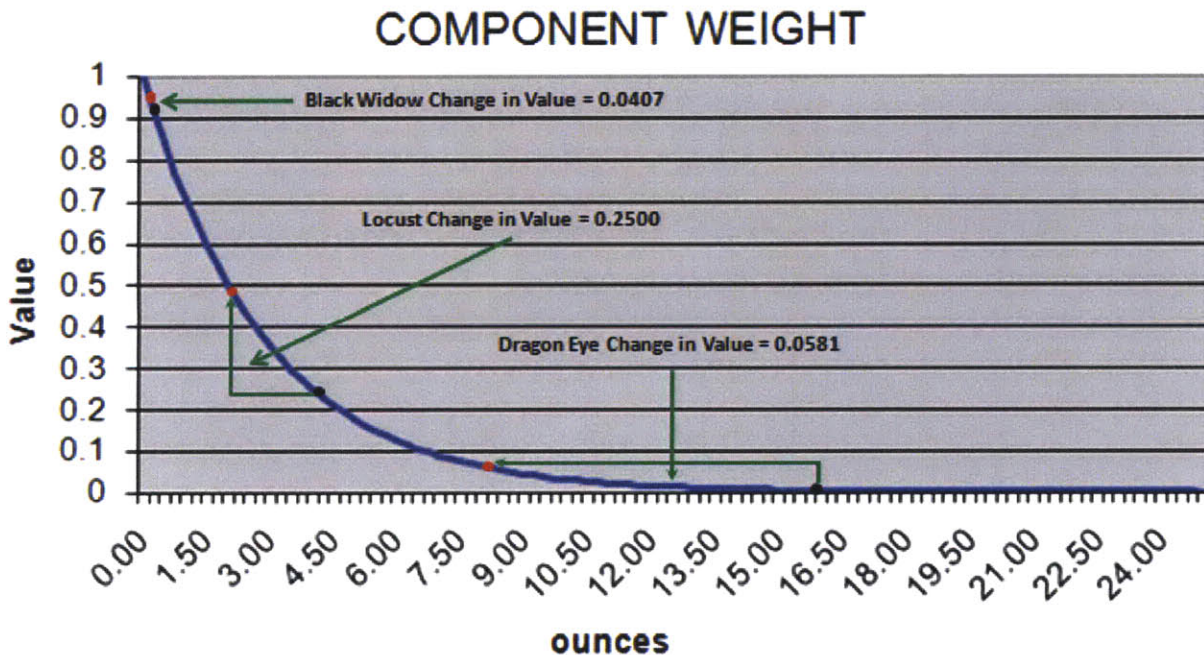


Figure 5-6: Calculating Potential Value Using a Monotonically Decreasing Function

The three candidate solutions were chosen in order to illustrate the process for calculating potential value: the Black Widow (top left), the Locust (middle), and the Dragon Eye (bottom right). The flexible attribute this function depicts is propulsion weight. The black dot represents the original value of each candidate. The red dot indicates the new value after change. The Locust exhibits significantly more potential value than both the Black Widow and the Dragon Eye. The Black Widow begins very high up the value curve because its original value was very high which means its motor weight is very low. Reducing its motor weight of 0.25 ounces by 50% does not result in significant movement along the curve. Conversely, reducing the Dragon Eye motor weight by 50% does result in significant movement. However, the Locust, whose movement is between that of the Black Widow and the Dragon Eye, results in the most gain in value. The Locust has the most potential value due to the shape of the curve and its location on the curve. Therefore, the Locust has the most potential value available with respect to the flexible attribute of propulsion weight. In the context of this work, it is the most flexible. Table 5-1 provides the above results in tabular form.

Candidate Solution	New Value	Original Value	Change in Value
Black Widow	0.9574	0.9167	0.0407
Dragon Eye	0.0617	0.0037	0.0581
Locust	0.4987	0.2486	0.2500

Table 5-1: Candidate Solution Values and Results

The previous paragraph illustrated a monotonically decreasing function. Here the researcher presents a monotonically increasing function.

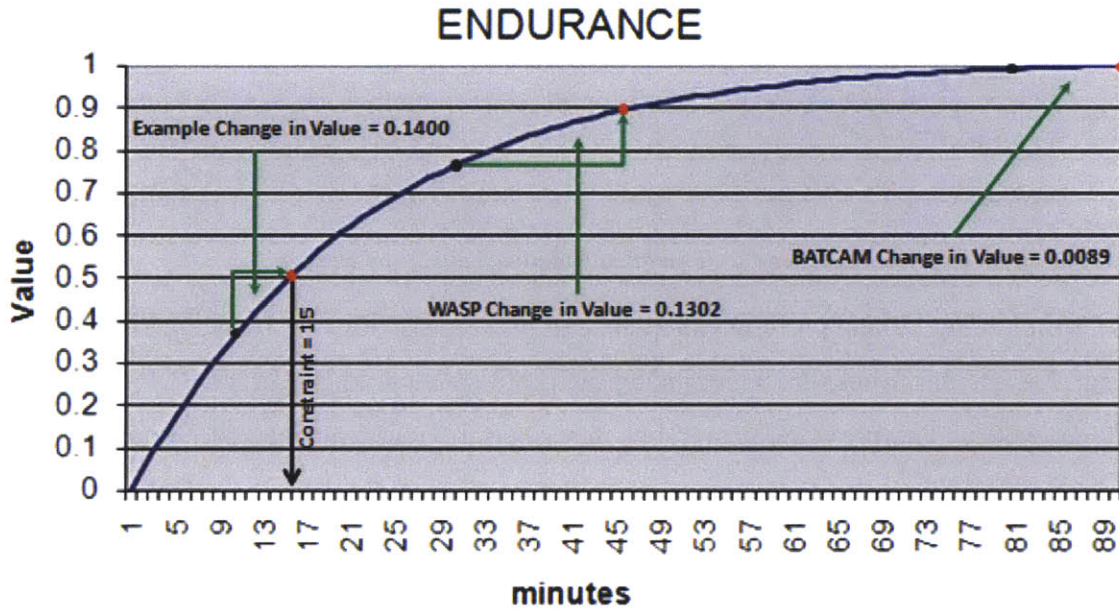


Figure 5-7: Calculating Potential Value Using a Monotonically Increasing Function

Again, the three candidate solutions were selected in order to illustrate the process for calculating potential value: BATCAM (top right), WASP (middle), and an Example candidate (left). The reader should notice this figure has a constraint line. The relevant stakeholders determined that they wanted the minimum flight endurance to be 15 minutes. Consequently, the researcher added the Example candidate in order to show a candidate that originally did not meet the constraint. Increasing endurance by 50% and then using the same procedure as before, one sees that the Example candidate has the most potential value, closely followed by the WASP. Unfortunately, the Example solution would have not been considered using the SDP because it fell outside the constraint. The Example solution’s movement along the curve is the least of the three, but due to its location on the curve, it results in the most value gain. Another point to note is a candidate solution cannot have a single dimensional value score greater than 1.0. For example, the BATCAM has an initial endurance of 80 minutes. When this is increased by 50%, the endurance is 120 minutes. However, the value function does not exceed 90 minutes because the stakeholders determined that there is no added value past 90 minutes. The BATCAM’s original single dimensional value is .9911, and its new single dimensional value is 1.0 because once the candidate solution reaches 1.0 it stops gaining value. Therefore, a candidate solution cannot have a single flexible attribute that skews the overall results. Table 5-2 gives the candidate solutions values and results in tabular form.

Candidate Solution	New Value	Original Value	Change in Value
BATCAM	1.0	0.9911	0.0089
Example	0.4936	0.3536	0.1400
WASP	0.8898	0.7596	0.1302

Table 5-2: Candidate Solution Values and Results

Eliminating human preference in decision making is critical to reducing errors in decision making. FA accomplishes this by replacing the preference parameter in the SDP with a potential value parameter. The previous paragraphs described the mathematical differences in these two parameters. Additionally, they demonstrate the procedure FA uses to calculate the potential value from both a decreasing and increasing single dimensional value function. The analyst calculates the potential value of the remaining flexible attributes using the same process. Now that the reader understands how FA eliminates errors caused by preference, the next step is to show the process FA uses to determine the candidate solution space.

5.4 Creating the Solution Space

The intent of this work is to improve the decision making process. Chapter 1 outlined the three areas to be improved. Section 5.2 explained the first improvement, and the last section described the second improvement this work makes to the decision making process. This section explains the third and final improvement. A major disadvantage the researcher cites with the SDP is the method it uses to determine the feasible solution space. As Sections 1.5.1 and 4.2.1 show in greater detail, the SDP uses static, discrete constraints in order to reduce the solution space to only one or two potential candidates. Using this method can result in the best solution being eliminated before the scoring step, which produces a sub-optimal solution. Ross (2003) agrees that the solution space should not be limited in the early phases of design. Ross (2003) states: “The designers of a system need to be able to freely explore the possible solution space to find those solutions that may not be readily apparent and are not simply a rehash of an old idea in order to save effort” [73].

Furthermore, (Ross 2003) explains that MIT professors McManus and Warmkessel taught this as a shortcoming of typical design processes and similarly believe it results in sub-optimal designs [73]. As the researcher shows later in this chapter, the best solution using FA is different than the typical UAS; therefore, it is not initially apparent as a possible solution.

The FA method for idea and alternative generation is essentially the same as the SDP's method (see Section 4.2.1 for the SDP method) with one major difference. As opposed to a static, discrete constraint, FA allows a constraint range. The analyst determines the constraint range by working closely with both engineers and stakeholders. Through this interaction, a range constraint is produced that the engineers determine is feasible and the stakeholders agree is allowable. The following section describes how to construct the range constraint.

5.4.1 Requirements Flexibility Graphic

The first step in creating the constraint range is surveying the stakeholders. The analyst must determine, through stakeholders, what the absolute limit a system can have for each requirement that constrains it. As Section 4.2.1 described, system weight, range, stow dimensions, and technology readiness level constrain the UAS. Next, the analyst must work with engineers to extrapolate the estimated changes that are feasible within the constraining requirement. This information is then aggregated and used to construct a Requirements Flexibility Graphic (RFG). The idea for a RFG came from the linear physical programming's class functions. For a description of linear physical programming and its class functions see Section 3.3.2. For a complete explanation see the paper by Professor Messac et al. [53]. The following paragraphs provide an example of constructing a RFG for UAS weight.

As explained above, the first step is to find out what the stakeholders determine is the absolute limit the UAS can weigh. Through conversions and surveys with the stakeholders outlined in Section 1.3.1, the researcher found that 25 pounds was the limit the UASs could weigh. This is not the desired weight the stakeholders wanted, but the weight above which the stakeholders would not accept. The next step of working with engineers to extrapolate change estimates proved to be difficult. Engineers were often unavailable or due to proprietary issues UAS makers would not release this data. Therefore, engineering data used in this work are estimates of the researcher. This is not a critical issue; for once again, it is the method and process that are important to this research. Finally, once the analyst aggregates the data from the stakeholders and engineers, he constructs the Requirements Flexibility Graphic. Figure 5-8 depicts the RFG for UAS weight.

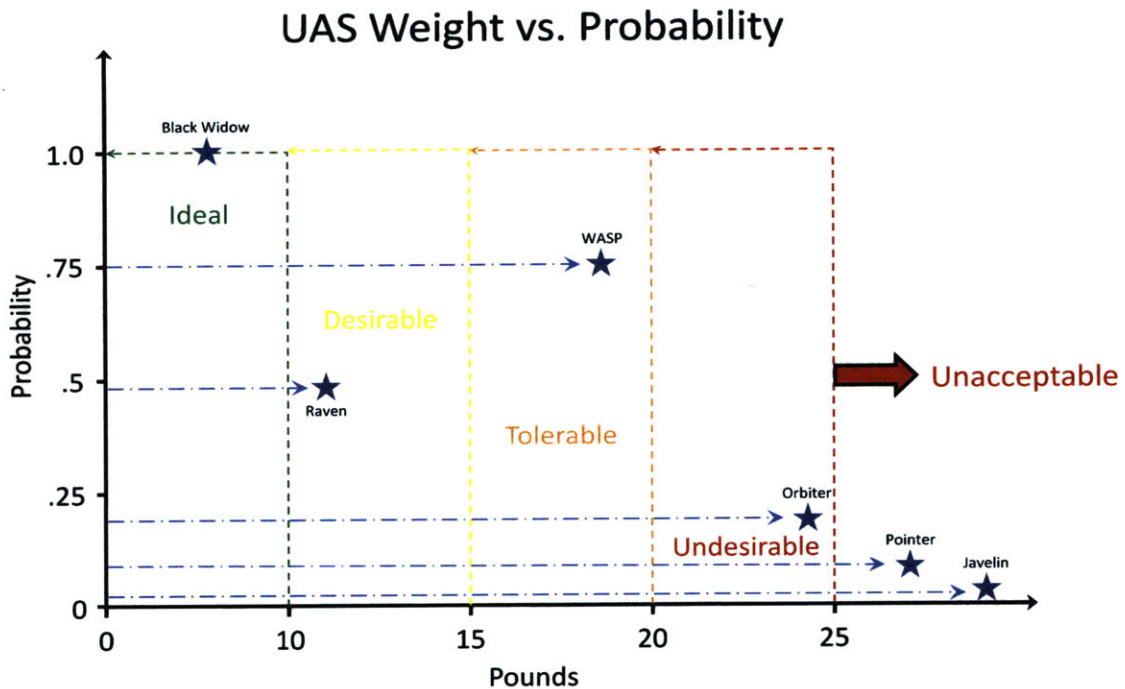


Figure 5-8: Requirements Flexibility Graphic for UAS Weight

The RFG provides a significant amount of information. As stated before, the stakeholders decided that the UAS weight limit was 25 pounds or less. Therefore, systems heavier than 25 pounds are considered unacceptable as the RFG depicts. Also, through stakeholder interviews, the researcher determined that a system 10 pounds or less was the most preferred. As a result, the values 10 and less are considered ideal, and the RFG depicts this range with a green boundary and the word “Ideal.” Through further iteration, Desirable, Tolerable, and Undesirable ranges are extrapolated. The RFG depicts these with yellow, orange, and red boundaries, respectfully. Also important to highlight is the y-axis. For those systems with weights 10 pounds and less, there is a 100% probability that they meet the requirement. Any system with a weight greater than 10 pounds will have less than a 100% probability. The probabilities are the engineers’ estimates of how certain they are that the system will be able to be changed to meet the Ideal weight requirement. For example, engineers for the WASP, which weighs 18.74 pounds, are 75% certain that they can reduce their UAS weight to fall within the Ideal range. Whereas Orbiter’s engineers estimate only a 20% probability they can reduce its current 24.33 pounds into the Ideal range. Only five candidates in the solution space are on the RFG in order to reduce clutter. Normally, the analyst would put the entire solution space on the RFG.

Another point to emphasize is that Figure 5-8 does not show correlation between the range a candidate solution falls in and the associated probability. For example, the Raven UAS falls in the Desirable range, but it only has a probability of 49% of falling into the Ideal range. Whereas, the WASP UAS is in the Tolerable range but has a probability of 75%. This illustrates that the WASP engineers estimate it has a greater ability to change than the Raven. A greater ability to change indicates more flexibility. There are numerous reasons this may occur. Through conversations with Natick Labs (see Section 1.3.1 for Natick Labs), the researcher found that the specific reason for the Raven situation is the result of a weight reduction initiative for the Pointer UAS. Therefore, it has already undergone significant change, which makes further change less probable. It is possible that the range will correlate to the probabilities in some situations, but it is not the case in this research.

The following provides a heuristic for creating the RFG and determining the feasible candidate solution space:

1. Determine stakeholder's system requirements—to include absolute limits.
2. Collect engineers' estimates on system changeability.
3. Create RFGs for each system requirement.
4. Determine the decision maker's cutoff probabilities for each range.
5. Finalize candidate solution space.

The previous paragraphs explained numbers one through three of the heuristic which is the method for creating the RFG. However, four and five of the heuristic were not explained. After the analyst completes the first three steps of the heuristic, he then works with the decision makers to determine their cutoff probabilities. For example, the decision maker may decide that candidates in the Undesirable range of the RFG must have a probability (certainty of changeability) greater than 75%. Additionally, the decision maker may require the Tolerable range to have a probability greater than 65%. This gives the analyst the last information he needs to finalize the candidate solution space in step five. The finalized solution space includes only the candidates the analyst will evaluate through solution scoring. The following section shows the creation of the UAS candidate solution space.

5.4.2 FA's Candidate Solution Space

Section 4.2 described the SDP's creation of the UAS candidate solution space. In order to create that solution space, the stakeholders determined the following static, discrete constraints:

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level
Limit	≤ 15 lbs	≥ 2 km	≤ 2.3 ft ³	≥ 6

Table 5-3: UAS Constraints Using the SDP

Table 5-3 depicts the stakeholders' four requirements that constrain the UAS. As described in Section 4.2.1, the UAS is to weigh 15 pounds or less, have a range greater than or equal to two kilometers, be packable in the Army's Modular Lightweight Load-carrying Equipment (MOLLE), and have a TRL of six or greater. Using only these constraints, the SDP reduced the solution space from 15 to only three candidates: BATCAM, Dragon Eye, and Locust.

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level	Overall Assessment
Limit	≤ 15 lbs	≥ 2 km	≤ 2.3 ft ³	≥ 6	
SYSTEM					
BATCAM	6.00	10	0.10	9	Go
Black Widow	15.18	1.8	0.05	9	No Go
Desert Hawk	16.50	15	2.37	9	No Go
CCLR	10.00	3	0.10	3	No Go
Dragon Eye	12.20	5	0.91	9	Go
Javelin	65.00	1.6	3.17	9	No Go
Locust	6.25	5	0.13	9	Go
Orbiter	24.33	15	6.00	9	No Go
Pointer	31.60	5	3.17	9	No Go
Puma	31.70	10	3.17	7	No Go
Raven	11.20	10	2.85	9	No Go
ScanEagle	47.90	20	10.00	9	No Go
Skylite B	23.22	10	10.00	9	No Go
SPAD	31.20	2	0.39	6	No Go
WASP	18.74	48	0.24	6	No Go

Table 5-4: SDP Candidate Solution Space

Consequently, the SDP eliminated potential best solutions. Using the heuristic described in the last section, results in relaxing the rigid constraints in Table 5-3. As a result, the new screening criteria are:

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level
Limit	≤ 25 lbs	≥ 1 km	≤ 3.3 ft ³	≥ 6

Table 5-5: New Constraints Using FA Heuristic

As the reader notices, TRL has not changed in Table 5-5. TRL represents a requirement outside the internal changeability of the UASs. Therefore, the FA heuristic is not applicable to this constraint. Evaluating the 15 UASs using the FA method, results in seven candidate solutions remaining. Table 5-6 below depicts the new candidate solution space.

Constraint	Weight Criteria	Range	MOLLE Packable	TR Level	Overall Assessment
Limit	≤ 25 lbs	≥ 1 km	≤ 3.3 ft ³	≥ 6	
SYSTEM					
BATCAM	6.00	10	0.10	9	Go
Black Widow	15.18	1.8	0.05	9	Go
Desert Hawk	16.50	15	2.37	9	Go
CCLR	10.00	3	0.10	3	No Go
Dragon Eye	12.20	5	0.91	9	Go
Javelin	65.00	1.6	3.17	9	No Go
Locust	6.25	5	0.13	9	Go
Orbiter	24.33	15	6.00	9	No Go
Pointer	31.60	5	3.17	9	No Go
Puma	31.70	10	3.17	7	No Go
Raven	11.20	10	2.85	9	Go
ScanEagle	47.90	20	10.00	9	No Go
Skylite B	23.22	10	10.00	9	No Go
SPAD	31.20	2	0.39	6	No Go
WASP	18.74	48	0.24	6	Go

Table 5-6: FA Candidate Solution Space

The new solution space consists of the previous candidate solutions--BATCAM, Dragon Eye, and Locust, with four new candidates--Black Widow, Desert Hawk, Raven, and WASP. Because FA redefines how to screen the solution space, the systems close to the rigid constraints are no longer eliminated. For example, Black Widow is only 0.2 kilometers from the range requirement of two kilometers.

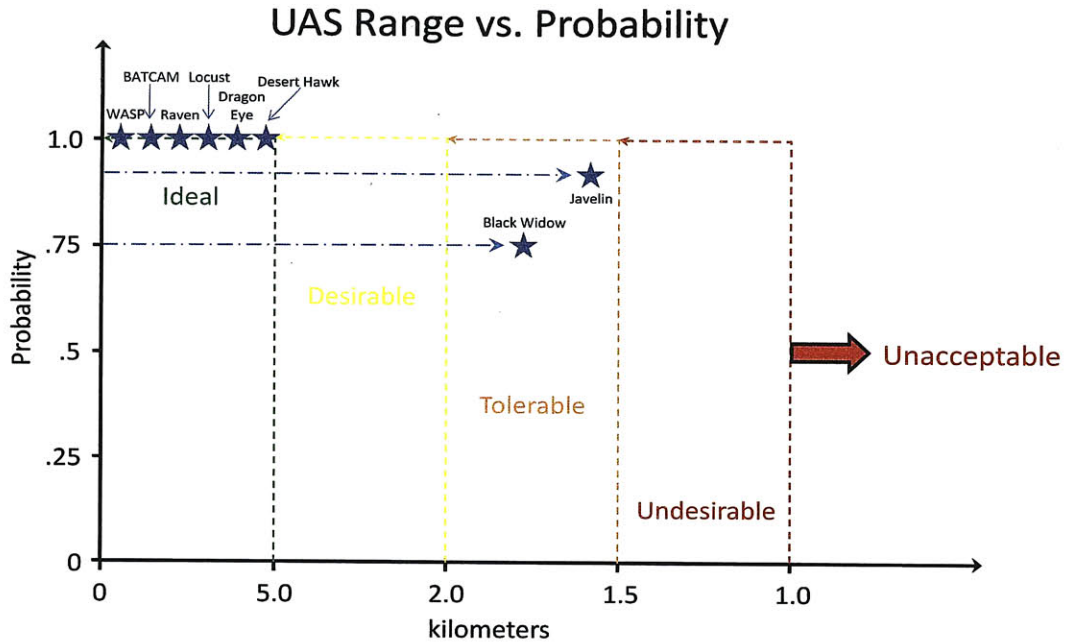


Figure 5-9: RFG of UAS Range

As Figure 5-9 depicts, by expanding the value range to a minimum of 1.0 kilometer and incorporating a high level of certainty, 0.75, that the range of the Black Widow can be extended beyond 2.0 kilometers, excludes it from elimination. The figure also shows the other six solutions that currently fall in the Ideal range, and therefore, lie on the 100% probability line. Additionally, it includes the Javelin UAS. The Javelin is included to highlight that even though it falls in the same range boundary as the Black Widow and has a higher certainty level, it is not included in the solution space because it fails on the system weight RFG. Figure 5-8 shows the Javelin has almost zero probability of falling within the desired weight range. Similarly, using the FA heuristic for UAS dimensions, the Desert Hawk and Raven are now allowed to be included in the solution space.

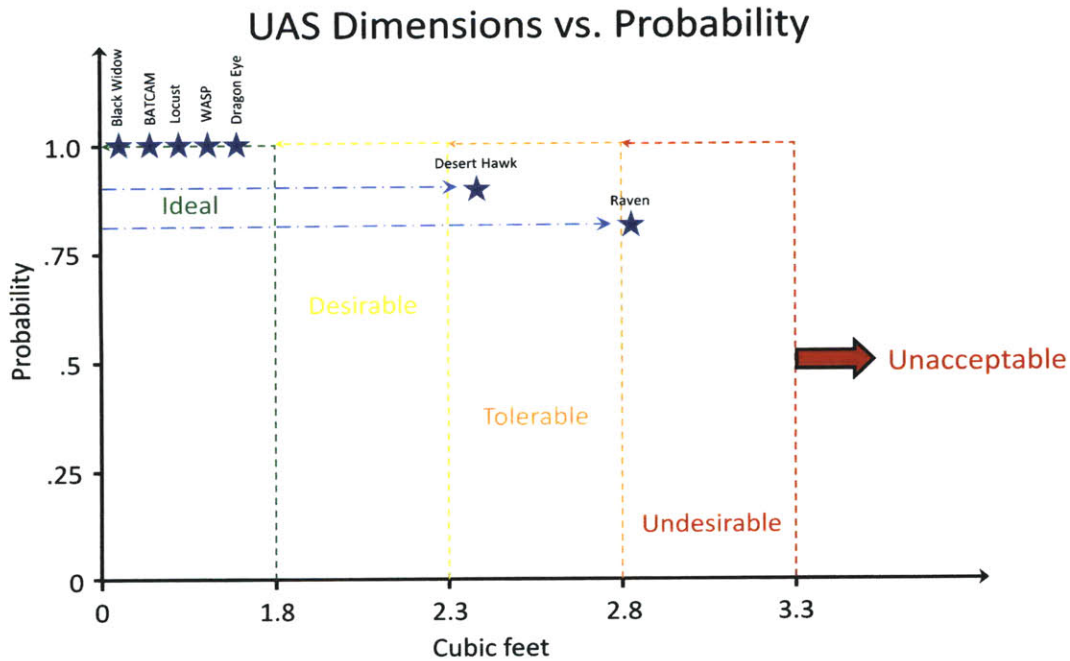


Figure 5-10: RFG for UAS Dimensions

In conclusion, the RFG serves two purposes. It provides a method to filter the solution space without using a static, discrete constraint. The graphic does indicate values that the stakeholders find undesirable and unacceptable; however, if a solution is in one of these range boundaries, and the engineers estimate with high certainty that it can fall into the Ideal or Desirable range, it is not eliminated. This leads to the second purpose the RFG serves. The RFG gives the analyst the ability to present decision makers with the option to keep candidate solutions outside the Ideal range based off their estimated changeability. The decision makers determine the acceptable level of certainty for each boundary. Using the FA method, system attributes replace static constraints, which the SDP uses to create the feasible solution space. Focusing on decision metrics and not constraints reduces the risk of eliminating potential best solutions [73]. The heuristic described in this section leads to the final solution space. Each candidate in this solution space will be evaluated to determine which candidate is the most flexible and optimal. The researcher has now described each FA improvement to the SDP. The remainder of this chapter will utilize these improvements to determine a best solution, and it will summarize how FA gives decision makers more information to make better choices.

5.5 Scoring the Candidate Solution Space

Section 5.3.2 described the method FA uses to calculate potential value, and Section 5.4 outlined how to create the candidate solution space. The final step is to score each candidate in the solution space. This section calculates each solution's potential value as well as its realized value. From these, the researcher will show which solution is the most flexible.

5.5.1 Potential Value Scores

The first score calculated is the potential value of each candidate in the remaining solution space. The feasible solution space includes the following candidate UASs:

Candidate Solutions
BATCAM
Black Widow
Desert Hawk
Dragon Eye
Locust
Raven
WASP

Figure 5-11: FA Candidate Solution Space

Using the method described in Section 5.3.2, along with a 50% change across the 14 MOFs, results in the following potential values:

Major Subsystem	1.0 GCS			2.0 UAV								3.0 Munitions		
Flexible Attributes	1.1 Packaging		2.1 Airframe			2.2 Propulsion			2.3 Sensors		2.4 Energy	3.1 Material		
Candidate Solutions	1.1.1 Stowed Dimensions (ft ³)	1.2.1 System Weight (lbs)	2.1.1 Stowed Dimensions (ft ³)	2.1.2 Wing Span (in)	2.1.3 Length (in)	2.2.1 Weight (oz)	2.2.2 Endurance (min)	2.2.3 Range (km)	2.3.1 GPS Weight (oz)	2.3.2 Camera Weight (oz)	2.3.3 Resolution (pixels)	2.4.1 Weight (oz)	3.1.1 Weight (oz)	3.1.2 Explosive Strength (kilojoules)
BATCAM	0.3342	0.1202	0.0297	0.1945	0.2196	0.2488	0.0201	0.1191	0.0880	0.1694	0.1363	0.2114	0.0098	0.0114
Black Widow	0.1915	0.3092	0.0142	0.0753	0.0860	0.0407	0.1302	0.1281	0.0423	0.0103	0.1179	0.0573	0.0102	0.0118
Desert Hawk	0.3257	0.2332	0.3257	0.2593	0.2758	0.1869	0.0129	0.0614	0.2283	0.2084	0.1589	0.2324	0.0868	0.0749
Dragon Eye	0.2048	0.1900	0.2048	0.2581	0.2758	0.0581	0.0465	0.1762	0.2283	0.2084	0.1589	0.1841	0.1569	0.1147
Locust	0.1869	0.1319	0.0368	0.1772	0.1317	0.2500	0.0821	0.1762	0.1342	0.0764	0.1179	0.2594	0.0057	0.0068
Raven	0.3334	0.1758	0.3338	0.2590	0.2758	0.2392	0.0129	0.1191	0.2283	0.2483	0.7900	0.2324	0.1836	0.1276
WASP	0.2550	0.2332	0.0675	0.2598	0.2104	0.0713	0.1302	0.0002	0.2366	0.0534	0.3728	0.1629	0.9935	0.3437

Table 5-7: MOFs Potential Value Scores

It is important to note that there are only 14 MOFs as opposed to 16 depicted on Figure 5-3 in Section 5.2.3. As described in the qualitative value model in Section 5.3.1, the Flexible Attribute 3.2-Accuracy, is not included in the quantitative value model. It is not included in the

calculations because as the qualitative model points out, its measure of resolution is the same measure as that under Flexible Attribute 2.3, Sensors. Additionally, the researcher does not include the major subsystem 4.0, Launch System, because the remaining candidates in the solution space have negligible launch system weights. Some may argue that the WASP launch system is not negligible since it is canon fired. However, because the dismantled soldier does not carry the launch system, the researcher assumes it to be zero. Furthermore, if this system were reduced enough to be fired from a mortar tube, the mortar system is already an organic capability of the dismantled infantry unit. Therefore, it again adds no additional weight.

In order to glean useful insights about potential value, the UASs' original value scores and their potential value scores must be compared. For example, Figure 5-12 compares the candidates' original GCS stowed dimensions value with their potential GCS stowed dimensions value.

Candidate Solutions	Original Value	Change in Rank	Potential Value
	x		x^*
	1.1.1 Stowed Dimensions (ft³)		1.1.1 Stowed Dimensions (ft³)
BATCAM	0.0125	7 → 1	0.3342
Black Widow	0.5770	2 → 6	0.1915
Desert Hawk	0.1132	5 → 3	0.3257
Dragon Eye	0.5427	3 → 5	0.2048
Locust	0.5885	1 → 7	0.1869
Raven	0.0341	6 → 2	0.3334
WASP	0.4021	4 → 4	0.2550

Figure 5-12: GCS Stowed Dimensions' Original Value vs. Potential Value

As Figure 5-12 shows, the rank order of the values is reversed. The Locust, which had the highest original value, now has the lowest potential value. Similarly, the BATCAM, which had the lowest original value, now has the highest potential value. This seems relatively intuitive. The Locust's GCS has the smallest dimensions and the BATCAM's GCS has the largest dimensions; therefore, when their dimensions are reduced by 50%, the BATCAM's overall GCS dimensions change more than the Locust's, and this produces a greater change in value. The BATCAM's larger change in value is a direct result of the shape of the value function.

STOWED DIMENSIONS

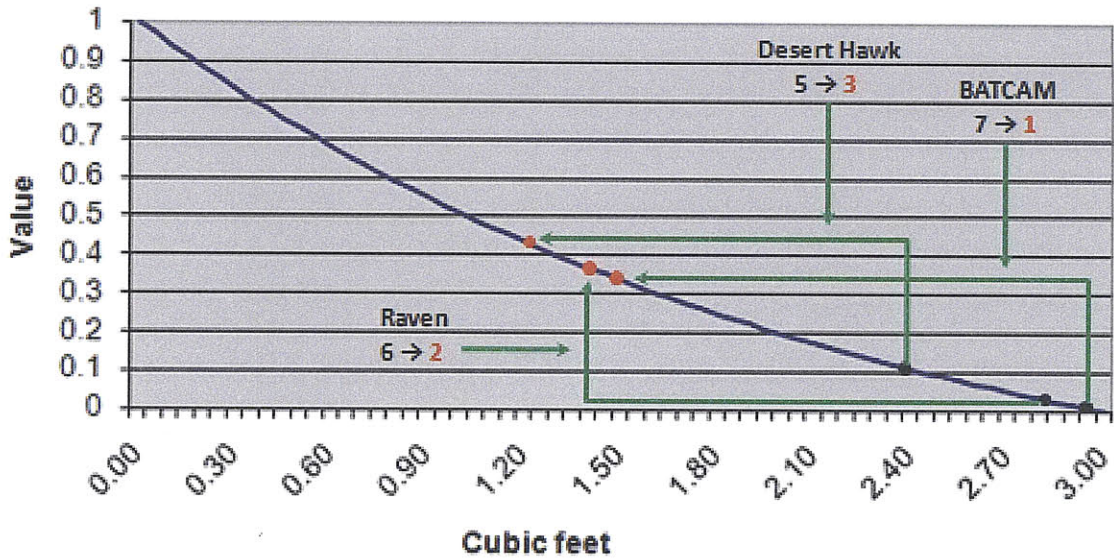


Figure 5-13: Stowed Dimensions Value Function

The stowed dimensions' value function is nearly linear. As a result, movement along the curve produces very similar changes in value. Put another way, the greater the change in a GCS's real dimensions yields a greater change in value. This is not the situation across all MOFs.

A MOF that illustrates a non-linear change is the UASs' propulsion weights. If the candidates' propulsion weight original values are compared with their potential values, a very different result occurs than that seen with stowed dimensions. Figure 5-16 shows the candidate solutions' change in rank with respect to a 50% change in their propulsion weight.

Candidate Solutions	Original Value	Change in Rank	Potential Value
	x		x*
	2.2.1 Weight (oz)		2.2.1 Weight (oz)
BATCAM	0.2858	2 → 2	0.2488
Black Widow	0.9167	1 → 7	0.0407
Desert Hawk	0.0617	5 → 4	0.1869
Dragon Eye	0.0037	7 → 6	0.0581
Locust	0.2486	3 → 1	0.2500
Raven	0.1565	4 → 3	0.2392
WASP	0.0058	6 → 5	0.0713

Figure 5-14: Propulsion Weight's Original Value vs. Potential Value

Here, the rank order is not simply an inversion. As with the GCS, the system with the highest original value does have the lowest potential value. However, the remaining systems do not follow this pattern. For example, the BATCAM's original value rank is two, and its potential value rank is two. Additionally, the Locust jumps in rank from three to one. Again, the reason for these results is directly due to the UAS's value function.

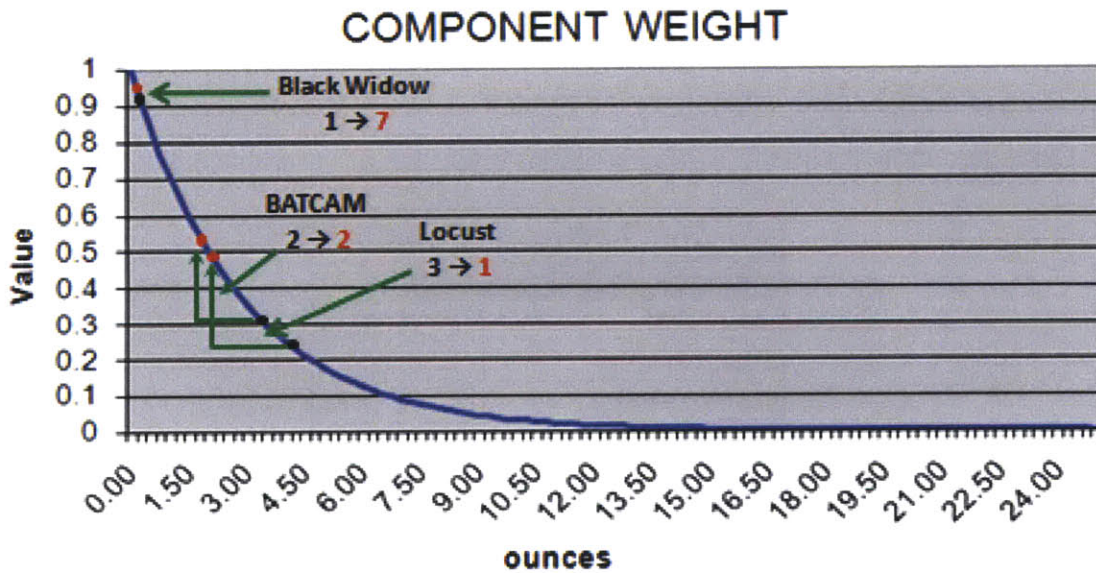


Figure 5-15: Component Weight Value Function

The value function for component weights is more exponential. Consequently, the overall change in rank between the original and potential values is not as intuitive. By looking at Figure 5-17, it should be evident that the shape of the value functions and where the UAS lies on

it are critical for calculating potential value. GCS dimensions and propulsion weight are only two of the 14 MOFs. Each value function has its own unique shape; therefore, the resulting potential value for each MOF is different. Yet, some MOFs use the same value function. For example, Propulsion weight (2.2.1), GPS weight (2.3.1), and Camera weight (2.3.2) all use the component weight value function. However, each candidate solution has different raw values for each of these components. Thus, each has a different resulting potential value. Only when the value function is the same and the candidate solutions have the same raw value will two candidates have the same potential value. The ultimate goal is to determine which UAS has the most potential value across the entire system of systems.

Consequently, the last step in calculating the candidate solution’s potential value is to sum the potential value of each MOF. The following formula is used to calculate the total potential value of each candidate solution:

$$\delta(x) = \sum_{i=1}^n v_i(x_i^*) - v_i(x_i) \quad (5.3)$$

where δ_i is the potential value measure of the i^{th} MOF, $i = 1$ to n for the number of MOFs, $v_i(x_i^*)$ is the new single dimensional value of the i^{th} MOF due to changing the system, $v_i(x_i)$ is the original single dimensional value of the i^{th} MOF before changing the system, and x_i is the raw score of the candidate solution for the i^{th} MOF.

Using Equation 5-3, the following potential values result for each candidate solution.

Candidate Solutions	Potential Value
<i>BATCAM</i>	1.9014
<i>Black Widow</i>	1.2249
<i>Desert Hawk</i>	2.6575
<i>Dragon Eye</i>	2.4657
<i>Locust</i>	1.7732
<i>Raven</i>	2.9162
<i>WASP</i>	2.6073

Table 5-8: Potential Value Scores of the Candidate Solutions

Table 5-8 shows the Raven has the highest potential value followed by the Desert Hawk, and then the WASP. Each of these UASs was eliminated before the scoring step with the SDP. However, using the FA methodology, the candidates are not removed and represent those

solutions with the most flexibility. In order to better illustrate the results, a stacked bar chart is given.

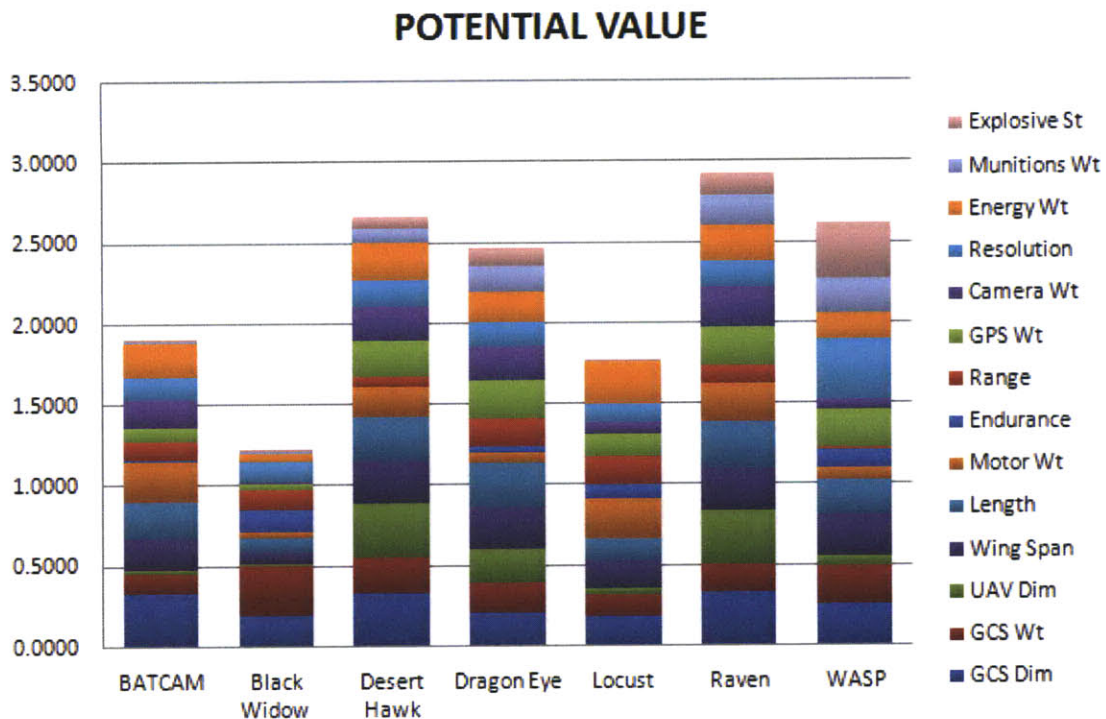


Figure 5-16: Stacked Bar Chart of Potential Value Scores

The stacked bar chart shows how much each MOF contributes to the total potential value for each candidate solution. The potential value provides the decision maker a clear understanding of which UAS returns the most value when changed. Extending this to the definition of flexibility used in this work, the UAS with the most potential value is the system with the most flexibility. Still, knowing which system has the most flexibility is only half the information the decision maker needs in order to make a decision.

5.5.2 Realized Value Scores

At this point in the FA decision process, the decision maker knows which UAS has the most flexibility. Nevertheless, he cannot make a decision based only on which UAS is the most flexible. Just because a system is the most flexible does not mean it is the best solution. The potential value gives no indication of the difficulty required to attain that value. For example, a UAS may be very flexible, but the resources required to take advantage of that flexibility may not be feasible. Consequently, a way must be provided in order to measure how feasible the

potential value is to obtain. The following equation combines the potential value and the feasibility of acquiring that value:

$$r(x) = \sum_{i=1}^n \delta_i v_i(x_i) \quad (5.4)$$

where $r(x)$ is the realized value of the candidate solution, $i = 1$ to n for the number of MOFs, δ_i is the potential value for the i^{th} MOF, $v_i(x_i)$ is the single dimensional value of the i^{th} MOF, and x_i is the raw score of the candidate solution of the i^{th} MOF. Using this equation produces the following realized values for each candidate solution:

Candidate Solutions	Realized Value
<i>BATCAM</i>	0.8078
<i>Black Widow</i>	0.6168
<i>Desert Hawk</i>	0.5620
<i>Dragon Eye</i>	0.8111
<i>Locust</i>	0.8981
<i>Raven</i>	0.7615
<i>WASP</i>	1.0924

Table 5-9: Realized Value of Candidate Solutions

Table 5-9 shows the WASP has the most realized value followed by the Locust. The SDP eliminated both of these solutions during the screening process. By using the FA method, two potential best solutions for the UAS problem are retained.

The researcher uses the term Realized Value because Equation 5.4 considers where the candidate solution currently is and how much flexibility is inherent in the system. As a result, the score the equation gives is a realized value from changing the system from the status quo to a future state. Stated differently, the realized value tells the decision maker that if resources are allocated equally, the solution with the highest realized value gives the most value return from the allocated resources. For example, the Desert Hawk has the second highest potential value, but its original total value is the lowest of the UASs. Consequently, when both parameters are considered, the Desert Hawk has the lowest realized value. In other words, the Desert Hawk did not originally offer much value for the decision maker; therefore, its potential value is not

sufficient to make it an optimal choice. Figure 5-17 shows the original value of each UAS before the potential value is evaluated.

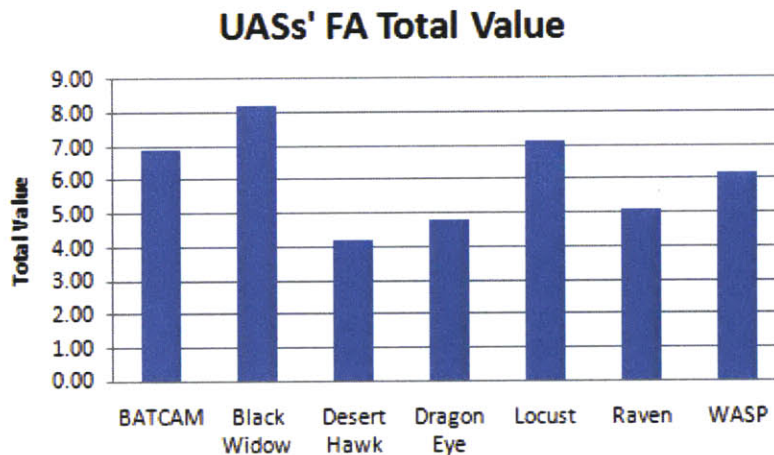


Figure 5-17: Original Total Value of Each UAS

Table 5-10 shows the potential and realized value of each candidate solution.

Candidate Solutions	Potential Value	Realized Value
BATCAM	1.9014	0.8078
Black Widow	1.2249	0.6168
Desert Hawk	2.6575	0.5620
Dragon Eye	2.4657	0.8111
Locust	1.7732	0.8981
Raven	2.9162	0.7615
WASP	2.6073	1.0924

Table 5-10: Potential and Realized Values

By comparing Figure 5-17 and Table 5-10, the reader sees the WASP's original total value is the fourth best, and its potential value is third best. However, once FA considers both parameters, the WASP has the most realized value. Combining this information provides the decision maker with a complete picture of the candidate solutions. He or she can then decide whether to allocate resources toward the WASP. By allocating resources to the WASP, the decision maker knows that it will result in the best final solution. It is important to emphasize that using FA the WASP is the best solution within the solution space used in this research. Figure 5-18 is a stacked bar chart that illustrates the realized value of each candidate solution and how much each MOF contributes to the total realized value.

REALIZED VALUE

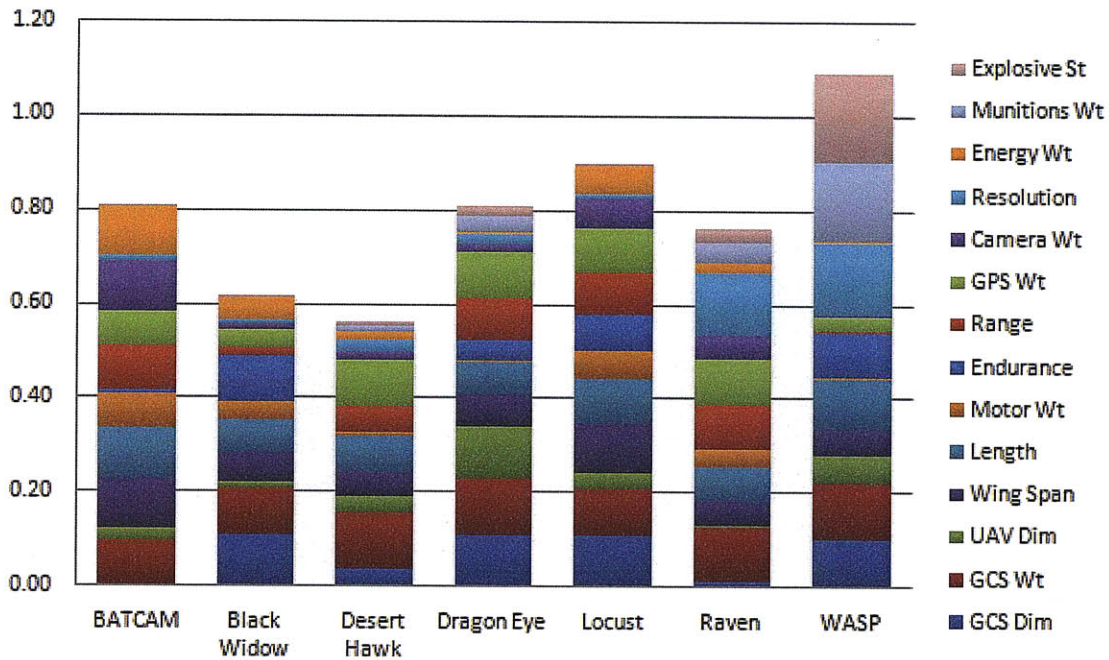


Figure 5-18: Stacked Bar Chart of the UASs' Realized Value

The researcher has demonstrated the complete FA process and produced a best solution to the UAS problem. The final step to certify this process is to conduct sensitivity analysis. If the method is not sensitive, then the researcher has successfully improved the decision process and validated a proven method to quantified flexibility inherent in engineering systems.

5.5.3 Sensitivity Analysis

The FA process determined the best solution to the UAS problem was the WASP UAS. It is important to ensure the solution FA produces is not sensitive to change. In order to certify FA, robustness must be checked. Robustness of FA can be validated through conducting sensitivity analysis. Section 4.3.4 checked the sensitivity of the global weight assigned to the system weight by plus and minus 13%. Similarly, the researcher varies the percentage the MOFs are changed by plus and minus 15%. If there is no crossover within 10%, then systems engineers consider the solution not sensitive to change [65]. Table 5-9 provides the values for each system at each level of variation, and Figure 5-21 illustrates the results reported in the table.

FA Sensitivity Analysis Results							
<i>Percentage UASs are Changed</i>							
	Base Case	0.35	0.40	0.45	0.55	0.60	0.65
BATCAM	0.8078	1.0746	0.9837	0.8949	0.7225	0.6387	0.5564
Black Widow	0.6168	0.8030	0.7407	0.6786	0.5552	0.4937	0.4323
Desert Hawk	0.5620	0.7765	0.7015	0.6301	0.4968	0.4343	0.3743
Dragon Eye	0.8111	1.0840	0.9901	0.8992	0.7233	0.6375	0.5536
Locust	0.8981	1.1876	1.0894	0.9930	0.8046	0.7124	0.6213
Raven	0.7615	0.9951	0.9138	0.8360	0.6898	0.6208	0.5542
WASP	1.0924	1.4022	1.2998	1.1949	0.9922	0.8940	0.7978

Table 5-11: FA Sensitivity Analysis Results

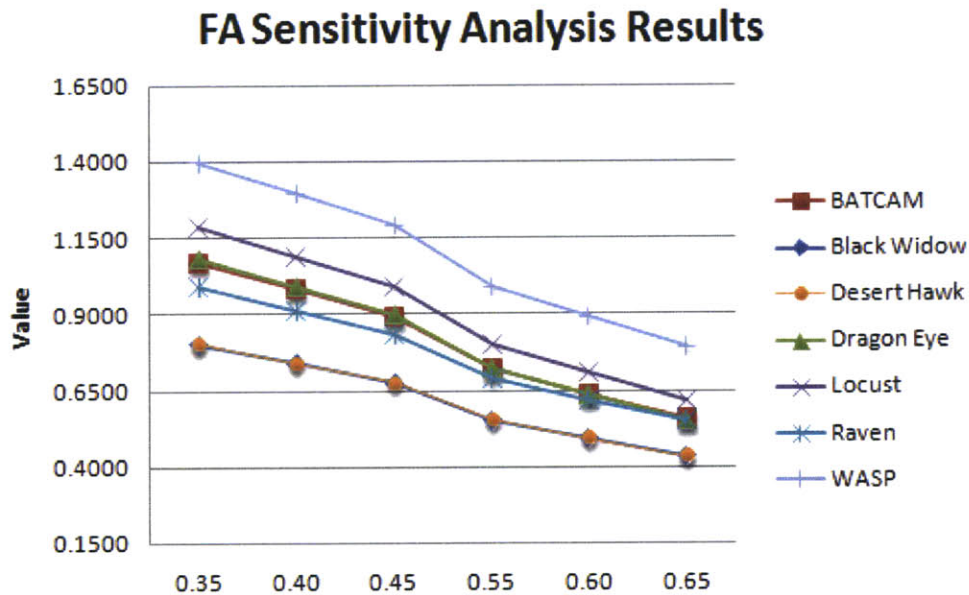


Figure 5-19: FA Sensitivity Analysis Results

Figure 5-19 illustrates that the WASP UAS does not experience crossover within 10% and, therefore is not sensitive to changes. The figure does show that some candidate solutions are sensitive to changes. This further substantiates the FA method. If the results did not show any crossover of the candidate solutions, it may indicate an error with the method. Accordingly, since the optimal solution is not sensitive to change, and other candidates in the solution space are sensitive, this validates that the solution FA produces is robust. The sensitivity analysis results confirm FA's soundness as a valid decision method. Furthermore, it can be concluded this technique provides a way to quantified flexibility inherent in engineering systems. The final step is to describe how the results FA produces gives the decision maker better information to make decisions.

5.6 Providing Better Information to the Decision Maker

The previous sections in this chapter describe the three ways FA improves the decision making process. The improvements FA provides gives the decision maker better information to make decisions. Better information expands the solution space leading to potentially innovative results [73]. The WASP is an example of this. The WASP is not a traditional UAS. The WASP is launched from an artillery tube and while in flight extends wings to become a UAV. Additionally, the information FA supplies the decision maker allows a better understanding of system properties and behaviors. Better information results in better decisions.

FA provides better information to the decision maker in three ways: 1. Visual mapping, 2. Quantifying potential and realized values, and 3. Visually representing the feasible solution space. This information allows the analyst to demonstrate to the decision maker which candidate solution is the best. All of this information is interconnected. Because it is not segmented, the decision maker can recognize system properties and behaviors.

The first piece of information is visual mapping and is composed of two parts. The first part is the system hierarchy, and the second part is the scoring tables.

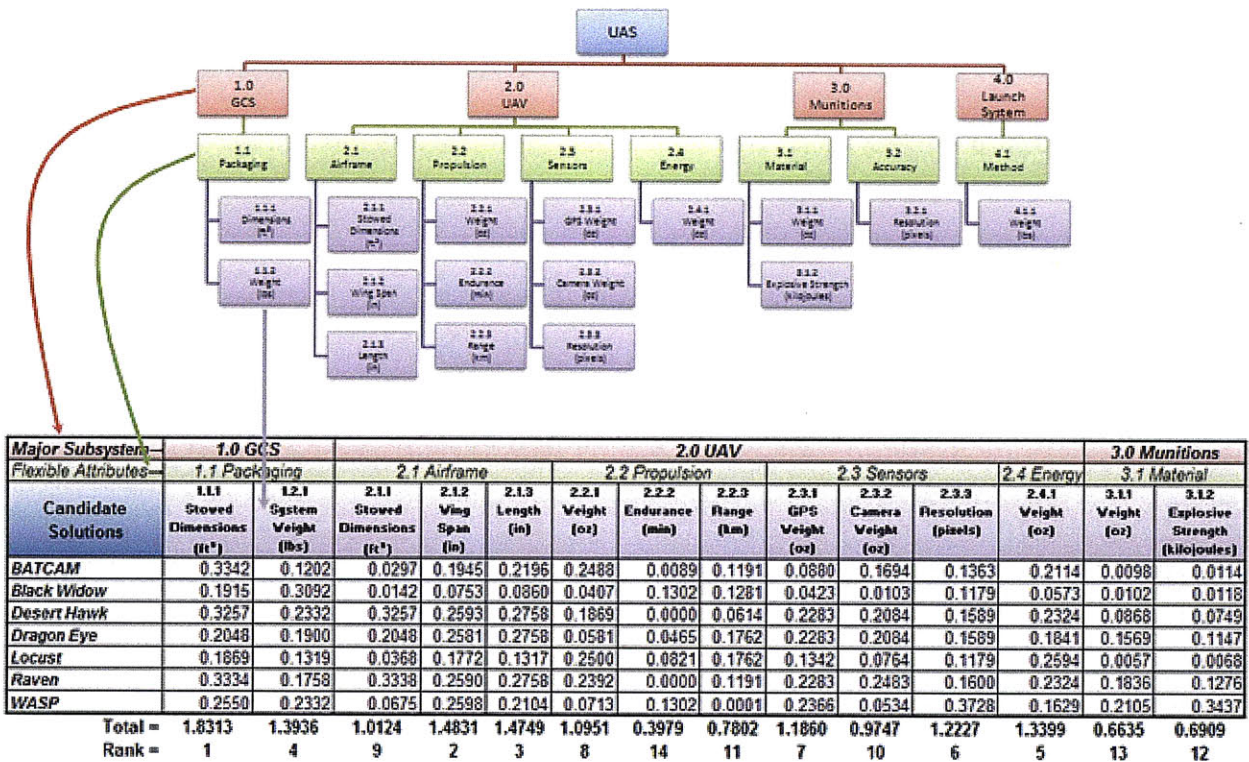


Figure 5-20: Visual Mapping of System Hierarchy to Solution Scoring

The researcher constructed the scoring tables to mirror the system hierarchy. Figure 5-20 illustrates the different levels of the hierarchy are mapped to the scoring table by position and color. The table in Figure 5-20 is the potential value scores. Mirroring the two figures after each other easily maps the calculated potential value scores to each major subsystem, flexible attribute, and MOF. Similarly, the hierarchy can be mapped to the realized value scores.

The second way FA provides better information is it quantifies potential and realized values. The figure above visually connects the potential values to each part of the UAS. At the bottom of the table are the total potential values for each MOF and how it ranks among the other MOFs. Presenting the information in this manner gives the decision maker the ability to determine which UAS has the most flexibility in each MOF. Furthermore, it shows which major subsystem, flexible attribute, and MOF have the most flexibility. Figure 5-21 presents the potential values from the table above in a more precise manner.

Potential Value of Major Subsystems

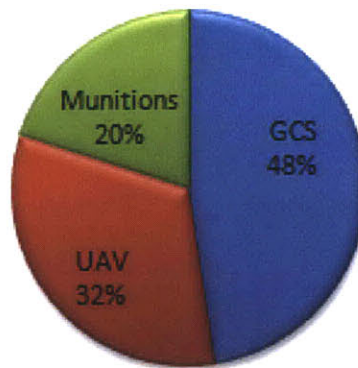


Figure 5-21: Potential Value of Major Subsystems

As Figure 5-21 shows, the GCS has the most potential value of the major subsystems. As a result, the decision maker should focus resources to improve the GCS because it has the most flexibility. For example, the following figure shows the Desert Hawk UAS's GCS.



Figure 5-22: Desert Hawk UAV and GCS [21]

The Desert Hawk represents the modal GCS in the solution space. Many candidates in the solution space are much larger but few are smaller. As the figure illustrates, the GCS is a major limiting factor of making a UAS backbackable. However, as this work shows, the GCS has the most flexibility; therefore, it is the most changeable.

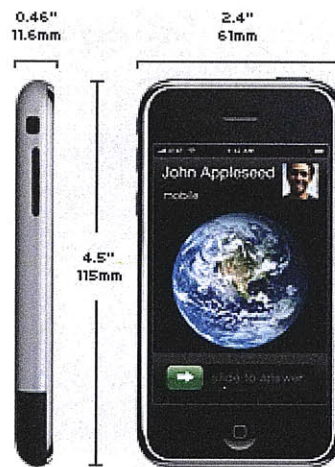


Figure 5-23: Apple iPhone [41]

Figure 5-23 shows the Apple iPhone ©. The researcher presents the iPhone in order to show that if the decision maker allocates resources to the GCS, it can result in a major improvement to the UASs. Additionally, the iPhone is a currently available commercial off the shelf system (COTS). As a result, it reduces the amount of resources needed to acquire the capability since there are no initial development costs. The figure below has the iPhone superimposed onto the Desert Hawk GCS.

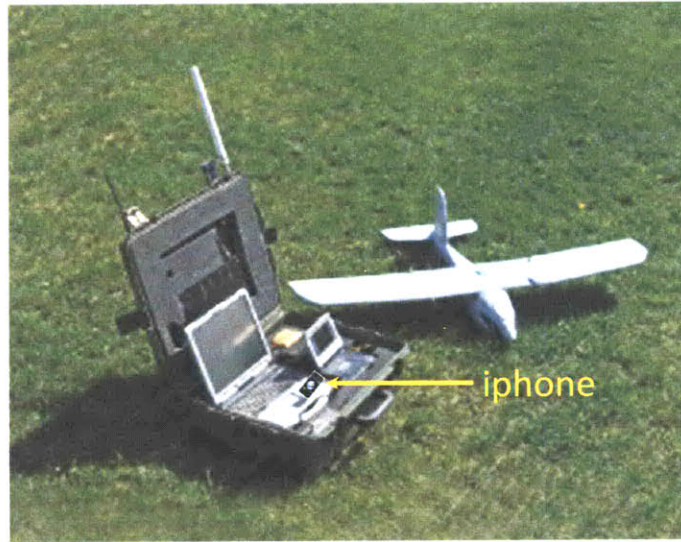


Figure 5-24: iPhone Superimposed on Desert Hawk GCS

It is evident that the iPhone is significantly smaller than the GCS. It is important to note that the researcher does not claim the iPhone, in its current form, can satisfy all the requirements of the GCS. However, the iPhone does represent a very unique system that has the capability to send and receive signals, process large amounts of data, and provide numerous user interface functions such as audio, video, and computing. Therefore, it is not inconceivable that with software changes, it could replicate the functions of the laptop on which it is superimposed.

Coupled with potential value is realized value. As described in Section 5.5.2, a system having the most potential value does not equate to the best solution. The analyst shows the decision maker which UAS has the most potential value, but then shows which UAS translates that potential value into the most realized value. Knowing the potential and realized values gives insight into system properties and behaviors. Again, using the Desert Hawk, its GCS has a lot of potential value, but the Desert Hawk does not have as much original value as other solutions. Consequently, its realized value is not as high. This is important information for the decision maker because the realized value informs them which UAS gives the most value when resources are dedicated to it. The WASP has the most realized value. Thus, the decision maker knows the best choice is to devote resources to it.

The last way FA provides better information is through the RFG. As described in Section 5.4.1, the RFG is the method the analyst uses to determine the feasible solution space. The RFG visually depicts the candidate solution space using an x-y plane format. This permits the

decision maker to see where the candidate solution is verse the constraint and the certainty level of the engineers that it can move to the ideal range.

5.7 Summary

This chapter describes in detail the method FA uses to improve the SDP. FA has three major improvements over SDP: 1. Better hierarchal representation, 2. Improved feasibility screening, and 3. Reduction of human bias in decision making. The chapter uses this method to produce an optimal solution to the UAS problem.

The chapter also presents a qualitative and quantitative system model. Additionally, the researcher describes how analysts interact with engineers in order to determine changeability estimates and how these estimates are used to create the Requirements Flexibility Graphic. Furthermore, he provides a heuristic for creating the RFG.

The last two sections of the chapter score the candidate solution space and describe how FA provides better information for the decision maker. Section 5.5 uses the method developed in the previous sections to score the candidate solution space. Both potential values and realized valued are presented and illustrated with graphics. The section concludes with the researcher validating the method with sensitivity analysis. Finally, the chapter ends with an explanation of how the information FA provides results in better decision making.

6 Analyzing and Comparing SDP and FA

The previous two chapters demonstrated decision making using the SDP and FA methodologies in order to determine the best solution to the backpackable, lethal UAS. Each method was rigorously performed in order to ensure solution accuracy. This chapter analyzes both decision methods and compares their results. First, it addresses using FA as a standalone decision method, and second it uses it in conjunction with the SDP in order to present a hybrid solution.

6.1 SDP and FA Compared

The SDP is a proven decision making method that is applicable in an eclectic number of decision problems. However, it largely relies on stakeholder preference and an unstructured feasibility screening process in order to determine the potential solution space. Additionally, it does not provide the decision maker with information about solution flexibility, and it diminishes systems focus because it defines systems by function. Conversely, FA maintains systems thinking, eliminates stakeholder preference, provides a structured method for screening the feasibility of potential candidate solutions, and evaluates each candidate's flexibility in order to present this information to the decision maker.

6.1.1 System versus Function

The first major difference between the SDP and FA that this research presented was the method each used to define the UAS. The SDP defines the UAS only by the functions it must perform. The stakeholders determine the functions the UAS must perform and then the SDP uses these functions to construct a functional hierarchy.

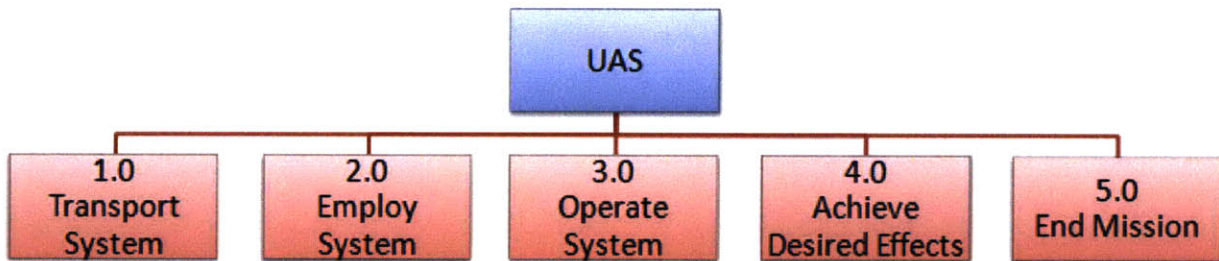


Figure 6-1: UAS Functions

Defining the UAS this way provides no information about the system of systems and results in a loss of holistic thinking. Decision analysts and decision makers become narrowly focused on functions the UAS must perform instead of the system and its properties. However, FA maintains holistic thinking because it defines the UAS by major subsystems.

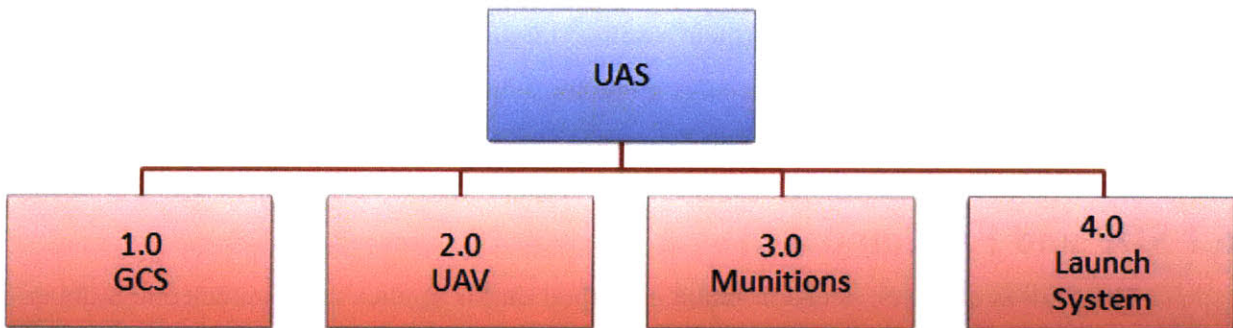


Figure 6-2: UAS Major Subsystems

During interviews, stakeholders are able to define the requirements of the UAS. The requirements of the system are the functions it must perform. If the stakeholders properly identify all the requirements, then FA is able to select a candidate solution that can perform the necessary functions. Defining the UAS by subsystems also maintains holistic thinking because the UAS is now viewed as a system of systems and not just a list of functions.

6.1.2 Preference versus Potential Value

The researcher identified stakeholder preference as a source of error when using the SDP. Stakeholders have bias and agendas that guide their preferences when confronted with decisions. Additionally, they have varying degrees of judgment skills and depth [49]. As unbiased as stakeholders may try to be, it is impossible to eliminate natural human characteristics. Even if they do not purposely try to influence a decision toward a specific outcome, personal and professional experiences shape their preferences. As described previously, half of the SDP’s quantitative model depends on stakeholder preference. As a result, there is significant potential for error that can affect the selection of the optimal solution. The SDP attempts to account for this source of error by evaluating the sensitivity of the chosen solution with respect to changes in stakeholder preferences. However, the SDP’s approach evaluates the status quo of a candidate solution’s functional value against a decision makers’ opinion of the importance or preference of that value.

$$\begin{array}{c}
 \text{Preference Weight} \\
 v(x) = \sum_{i=1}^n w_i v_i(x_i) \\
 \begin{array}{ccc}
 \uparrow & & \uparrow \\
 \text{Final Value} & & \text{Value Score}
 \end{array}
 \end{array}$$

Figure 6-3: SDP Quantitative Model

The researcher believes that replacing the human preference with a candidate solution’s potential value is better and eliminates a potential source of error. The potential value defines the flexibility of the system for the decision maker. Using this approach evaluates the status quo of a candidate solution’s functional value against the associated value gained from improving the status quo. This “realized value” provides the decision maker more information about the system. Section 6.1.4 provides more detail on the benefits of the information FA furnishes to the decision maker.

$$\begin{array}{c}
 \text{Potential Value} \\
 r(x) = \sum_{i=1}^n \delta_i v_i(x_i) \\
 \begin{array}{ccc}
 \uparrow & & \uparrow \\
 \text{Realized Value} & & \text{Value Score}
 \end{array}
 \end{array}$$

Figure 6-4: FA Quantitative Model

An added benefit of potential value over a preference weight is it does not degrade as the number of attributes increases. As they increase, the preference weight associated with each attribute becomes smaller and smaller reducing their effectiveness in optimal solution selection [8]. However, the potential value of an attribute is independent of the other attributes and therefore, does not become less effective as the system becomes more complex.

6.1.3 Feasibility Screening

A benefit of using FA over the SDP is the method it uses to create the candidate solution space. The SDP uses global constraints that candidate solutions either pass or fail. Using a global constraint does not allow evaluation of non-global subsystems of the UAS. For example, system weight is a global constraint for the UAS. The SDP considers the weight of the entire UAS rather than evaluating the weights of individual subsystems. As a result, the SDP eliminates potential best solutions because it does not provide insight into which subsystems of the UAS account for the majority of the weight. Without this knowledge, it is difficult to determine where and if modifications could bring the UAS into constraints. In contrast, FA defines the UAS by major subsystems. As a result, it is clear that the ground control station (GCS) accounts for the largest portion of the UAS weight. This then allows for the GCS to be modified because it is the quickest way to reduce weight of the UAS and bring it within limits.

Another shortcoming of the SDP is it does not use a structured method for determining the feasibility of candidate solutions that fall outside of a static constraint. It instead suggests that designers should determine whether modifications can be made to candidates that do not pass screening in order to bring them into limits [65]. However, it does not provide a method nor does it incorporate uncertainty into the feasibility of modifications. Conversely, FA supplies a structured method where the decision analyst works with the stakeholders and the design engineers in order to create a Requirements Flexibility Graphic (RFG). The RFG presents a visual depiction of where a system lies within a range of decreasing acceptability. In addition, it depicts the engineers' probability estimates of a system's ability to be changed. The stakeholders provide the analyst with the different regions of acceptability and the level of uncertainty they are willing to accept for candidate solutions that fall outside the Ideal region. The analyst then works with engineers in order to determine the probability of their system moving within the stakeholder's Ideal region. If a candidate solution lies outside the ideal region

and does not have an acceptable probability of moving to the ideal region, then it is eliminated. Figure 6-5 illustrates a RFG from Chapter 5.

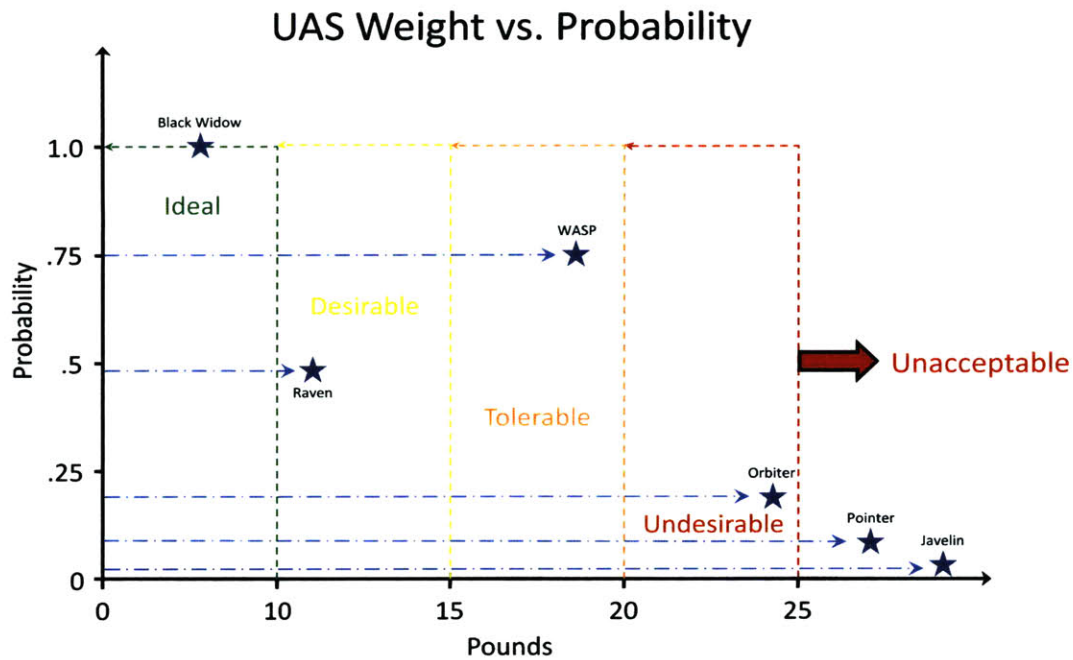


Figure 6-5: Requirements Flexibility Graphic

6.1.4 SDP and FA Results Compared

The previous three sections compared the major difference between the SDP and FA. This section compares the final results produced from those differences. The SDP reduced the solution space to three potential candidates. (The researcher increased the packable dimensions constraint which added a fourth candidate for data analysis purposes.) Using the SDP’s quantitative model shown in Section 6.1.2 produced the following results:

Candidate Solutions	Candidate Score
BATCAM	0.5314
Dragon Eye	0.3999
Locust	0.4949
Raven	0.4862

Table 6-1: SDP Candidate Scores

As previously stated, the values are a combination of stakeholder preference and value scores derived from a value function for each UAS attribute. This result supplies the decision

maker with very limited information. The information provides no understanding of system properties and behavior. It only allows him to accept the SDP's best solution or reject it.

FA, on the other hand, provides the decision maker with additional information in order to make more than an accept or reject decision. FA similarly reduces a candidate solution space but uses a structured method that includes stochastic data that prevents potentially best solutions from being eliminated. FA's quantitative model produces the following results:

Candidate Solutions	Potential Value	Realized Value
<i>BATCAM</i>	1.9014	0.8078
<i>Black Widow</i>	1.2249	0.6168
<i>Desert Hawk</i>	2.6575	0.5620
<i>Dragon Eye</i>	2.4657	0.8111
<i>Locust</i>	1.7732	0.8981
<i>Raven</i>	2.9162	0.7615
<i>WASP</i>	2.6073	1.0924

Table 6-2: FA Candidate Scores

The data in Table 6-2 provides the decision maker both an optimal solution and shows which solution has the most flexibility. The potential value column informs the decision maker which UASs provide them the most value with improvements. The realized value column gives the best solution. Additionally, by comparing the potential and realized value columns show which UASs had lower system values. For example, if the decision maker compares the Raven and Locust UASs, he can readily see that the Raven has a lower system value than the Locust because the Raven has much more potential value but less realized value. The Raven's lower realized value is due to a much lower system value than the Locust.

Furthermore, because FA maintains a systems focus, the potential value for each major subsystem can be measured. The FA analyst can provide the decision maker with information on which attribute or major subsystem has the most flexibility. The presentation of this information is addressed in further detail in Section 5.6. Supplied with this information, the decision maker knows which UAS is the best solution but also knows which UASs have the most potential value increase if changed. The decision maker can now decide to accept the selected best UAS or can decide to dedicate resources to modifying specific aspects of the optimal solution. Finally, he can decide to dedicate resources to a different UAS with significant flexibility. These decisions are possible because of the information FA presents to the decision maker.

6.2 When to Use FA

One of the stated advantages of the SDP is that it is useable in a wide assortment of decision problems. Consequently, it is important to describe when FA is appropriate for decision making. FA is appropriate to use before a physical design is created, during system development, and for system selection, as was done in this research.

Before a physical design is created, engineers can use FA in order to best choose the direction the physical design should go. During the design phase, typically more than one potential design is proposed. FA can be used to determine which proposed design has the most flexibility and which subsystem within the system of systems is the most flexible. Determining this information prior to a physical design saves time and resources. Finally, proper decisions early in the design stage can lead to significantly lower costs in the end.

Using FA during systems development is similar to how it was used in this research. For example, if the decision maker decided to select Draper Laboratories as the primary developer of a backpackable, lethal UAS, Draper could use FA in order to develop an improved WASP UAS. The current WASP design does not meet all requirements. Specifically, it does not meet the weight requirement. Therefore, using FA, Draper can define the UAS by major subsystems and then develop RFGs for each component within the WASP. The RFGs will enable engineers to assess the probability of reducing each component's weight into the Ideal region. Furthermore, the potential values for those components with the highest probability for reduction can be calculated. The potential values will show the best place in the design where they should dedicate their resources.

Finally, FA can be used as was done in this research. The researcher gathered data on 15 COTS UASs and then used FA in order to determine which COTS system was the best choice for a backpackable, lethal UAS. FA has potential application in any decision that requires a selection among numerous choices.

6.2.1 When Not to Use FA

FA should not be used with a decision that does not involve an engineering system. If an engineering system is not present, knowing flexibility is of little value, and calculating potential and realized values with any accuracy is very difficult because of the lack of appropriate value

functions. Lastly, FA should not be used if stakeholder preference is critical because it does not incorporate their preference into the calculation of the candidate solution score.

6.2.2 Using FA

Much like the SDP, all or part of the FA method can be employed. For example, an engineer may only want to depict the system hierarchy in order to assist in visualizing a complex system of systems. Similarly, developing RFGs may be important to the engineers because it depicts their estimates on the changeability of specific components. Finally, simply calculating the potential and realized values of candidate solutions can provide the engineer and decision maker significant insight into competing systems.

6.3 FA Integrated with the SDP

The goal of this thesis is to improve the decision making process. The researcher uses the SDP as an existing decision method in which to improve. As the researcher stated previously, the SDP uses a widely accepted and utilized decision analysis method. Therefore, the researcher believes that merging the SDP and FA produces a rigorous and robust decision method. The two methods would work in parallel in the initial phases of defining the problem, and later merge their quantitative models for the selection of the final solution.

In order for these processes to work in conjunction with one another, the engineer would initially create both a functional and systems hierarchy. Doing this provides a complete understanding of the system of systems and the function it must perform. The two methods continue in parallel until the feasibility screening step. At this point, the FA method of developing RFGs is used to determine the candidate solution space. Once the solution space is finalized, the methods again run in parallel. During the solution scoring phase, the methods merge in order to create a new quantitative model.

There are two potential techniques for combining the quantitative models. The first method is to run the analysis as the researcher presents in Chapter 5 and then multiply the realized value by the global weights determined from the stakeholder preferences. However, this is not feasible because global weights do not correlate well with the measures of flexibility (MOF). For example, as Chapter 5 demonstrated, MOFs do not have to be independent of each other. Many of the MOFs for the UAS involved the weight of different components. However,

the SDP requires independent measures of effectiveness (MOE) in order to prevent a single attribute like weight from dominating the global weights.

As a result, the only effective means to combine the quantitative models is to combine the potential value variable, δ , with the SDP's quantitative model. The equation that results from this is:

$$v(x) = \sum_{i=1}^n \delta_i \left(\sum_{i=1}^n w_i v_i(x_i) \right) \quad (6.1)$$

For those decisions where stakeholder preference is desired, this quantitative model incorporates the stakeholder preference, but it still provides the knowledge gained from the potential value. The same subsystem information FA supplies the decision maker is still available; however, this approach shows the additional effect of stakeholder preference. Using the combined method produces the following results:

Candidate Solutions	Potential Value	SDP Value	SDP & FA Value
<i>BATCAM</i>	1.9014	0.5314	1.0104
<i>Black Widow</i>	1.2249	0.3967	0.4859
<i>Desert Hawk</i>	2.6575	0.3859	1.0256
<i>Dragon Eye</i>	2.4657	0.3999	0.9860
<i>Locust</i>	1.7732	0.4949	0.8776
<i>Raven</i>	2.9162	0.4862	1.4180
<i>WASP</i>	2.6073	0.7146	1.8631

Table 6-3: Combined SDP and FA Results

As the table shows, the WASP is the highest scoring solution of the amalgamated decision methods. FA independently produced this same result. However, combining the two methods did result in subtle differences. For example, using just FA, the second best solution was the Locust and the BATCAM was third best. Using just the SDP, the BATCAM was the optimal solution and the Locust was next best. But, with the two methods merged, the second best choice is now the Raven. Considering both potential value and stakeholder preference result in the same optimal solution, but a reordering of the non-optimal solutions occurs. The reordering of the non-optimal solutions proves that neither potential value nor the preference weight dominate the quantitative model. If one were to dominate the model, it would mask the

affects of the other, and the non-optimal solutions would remain in the order of the governing parameter.

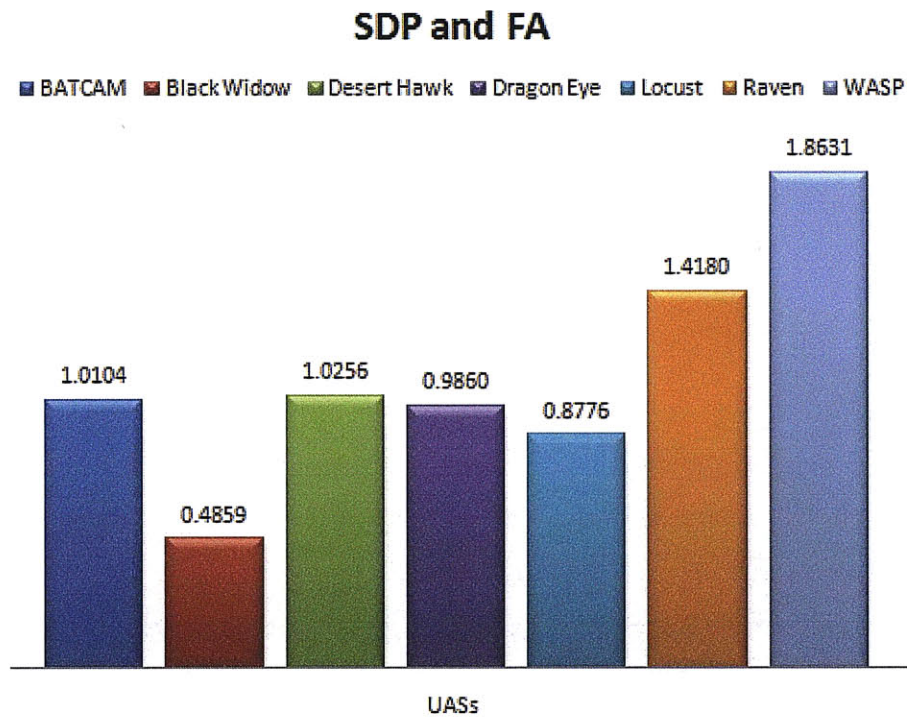


Figure 6-6: Combined SDP and FA Results

The potential error resulting from the use of stakeholder preference in the SDP remains in the combined SDP and FA approach. However, the effect the potential errors have on the final solution is now diluted because of the inclusion of potential value. Nevertheless, the desires of the stakeholders are now a contributing factor in the decision.

6.4 Summary

Chapter 4 applied the SDP to the problem of selecting a backpackable, lethal UAS from a sample of 15 COTS systems. Chapter 5 presented ways in which to improve the SDP. This chapter both analyzes and compares the results garnered from each approach.

In Section 6.1, the researcher summarizes the three major differences between the SDP and FA. With each difference, he presents the method the SDP and FA use and then describes how FA's approach improves the SDP's. At the end of the section, the optimal solution determined by each method is compared and critiqued based on how the information benefits the decision maker in his selection of a solution.

Next, the researcher addresses when it is feasible to use FA as a decision tool. Additionally, examples are provided that illustrate when FA is not appropriate for decision making. Furthermore, the researcher describes how FA can be tailored to satisfy different decision scenarios.

Finally, the researcher proposes an approach that integrates the SDP and FA. The intent is to take advantage of the strengths of the two methods. By doing this, both the system of systems and the required functions are defined. Similarly, by using FA's feasibility screening, it ensures that potential best solutions are not eliminated before they are evaluated. In order to determine an optimal solution, potential value and stakeholder preference are combined with the candidate systems value to calculate a best solution. Using this integrated method produces the same optimal solution as FA did when performed separately. However, this method presents a unique answer that considers both stakeholder preference and the flexibility inherent within each candidate solution.

7 Future Research, Summary, and Conclusions

The previous chapters have resolved the problem of selecting a COTS UAS to serve as a potential solution to a backpackable, lethal UAS. The WASP, the optimal solution chosen in this work, was the best from a solution space of 15 different systems. The most important contribution of this work is not the actual selection of a specific UAS but rather the process employed in order to arrive at an optimal solution. Nevertheless, the selection of the WASP does provide the Army valuable information because it can use the WASP as a datum in which to compare all other potential backpackable, lethal systems. This work was successful at reducing the potential candidate solution space along with presenting and validating an enhanced decision making process. The remainder of this chapter proposes areas for future work and conclusions about this research.

7.1 Future Research

The research presented in this thesis is a bridge between system value and flexibility. The process developed in this work can be used in a myriad of decision situations that involve technologically enabled, complex systems. The results and analysis supplied in Chapters 5 and 6 demonstrate the benefits FA gives to the decision maker. However, the researcher recognizes that there is further research that must be conducted in order to solidify FA as a robust decision

method. The following three areas are identified as focus areas for additional research: 1. Validating and testing the RFG, 2. Creation of an algorithm for potential value, and 3. Evaluate cost benefits of FA.

7.1.1 Validating and Testing the RFG

The RFG presented in Chapter 5 is a structured, stochastic technique for creating solution spaces. However, the RFGs used in this work were not constructed with actual engineer probability estimates. As a result, the RFG remains in a theoretical state that must be validated through application. The researcher used the RFG in order to create a solution space for UASs developed by many different companies. This presented a barrier because the majority of the companies were vying for a share of the same market space. As a result, concerns over proprietary intelligence prevented them from divulging probabilistic information about their systems. The researcher proposes two potential methods in order to validate the RFG. First, by working within the framework of one organization, one can eliminate the need to protect proprietary intelligence. An organization working internally on a design is only concerned with arriving at the best solution making probabilistic estimates readily available. The second approach to validating the RFG is with government led research. The entities chosen to participate in and receive government funding can be mandated to provide the information required to create a RFG. Selecting academic institutions as the primary participants of the funded research would further reduce proprietary concerns because universities are interested in research funding and not production funding.

In addition to validating the RFG as a global selection technique, it needs to be evaluated for non-global requirements. For example, the RFG in this work was only used in conjunction with a global constraint of the UAS weight. However, determining the feasibility and applicability of the RFG for internal system component selection represents another area for research. Because system components are rarely supplied by a single source, the RFG provides a method to evaluate feasibility of system components by different providers.

The RFG has enormous potential in solution space creation. It compiles stakeholder requirements and engineer estimates into one easily understood graphic. It also removes deterministic error and provides decision makers more information on design uncertainty. Understanding design uncertainty early in the design process should reduce project cost because

only those design options with the highest probability of success will be selected. Less certain design choices will not be selected which leads to less rework and reduces cost.

7.1.2 Potential Value Algorithm

The method the researcher used to calculate the potential value inherent in the UASs requires further development. The researcher employed a 50 percent reduction in every system attribute in order to calculate the total potential value for each UAS. However, this is unrealistic since every component within a system will not be able to change by 50 percent. Conversely, some components may be able to change more than 50 percent. As a result, the development of an algorithm is needed.

The algorithm should evolve in two phases. The first phase provides a deterministic solution. Each attribute of a system is changed independently. For example, instead of a 50 percent change across all systems, evaluate each attribute's changeability and incorporate this into the mathematical model. By doing this, the final potential value is a better measure of a system's true flexibility. The second phase determines a probabilistic solution by incorporating the information in the RFGs. This phase is more complex because the RFG must be validated and then connected to the quantitative model. Once the two are coupled, decision makers can then conduct scenario simulations. Through simulations, the decision maker can determine which scenarios provide the best probabilistic solutions. This results in decisions that take into account and mitigate uncertainty.

7.1.3 Evaluating the Cost-Benefit of FA

A topic that was not addressed in any detail was the cost-benefit of FA. The researcher demonstrated how the information FA provides the decision maker allows him to better allocate resources. However, the research did not include any quantitative value or more specifically monetary benefit derived from the FA approach. As a result, further research needs to be conducted in order to calculate the monetary benefits associated with FA. Over 75 percent of final product cost is a result of decisions made early in the design process [59]. The researcher demonstrated that FA improves decision making; therefore, it should reduce overall cost. He believes that because FA prevents the best solution from being eliminated, identifies system components most susceptible to change, and reduces rework, project cost will decrease and

product quality will increase. However, proving this is challenging because it requires FA to be used in an actual decision situation and the cost benefits extrapolated.

A possible approach in order to determine the cost benefits is to find a system that has undergone generational changes and apply the FA methodology. Almost any technologically enabled system experiences significant changes from its original form to its current form. For example, cell phones, aircraft, cars, and computers have all undergone numerous transformations since their inception. In order to apply FA, the researcher would need to set bounds on the specific timeframe in which to apply FA. For example, it is not feasible to compare the first UAS to current UASs because of the overwhelming amount of technology not available for the initial generation. However, if the researcher isolates sequential generations and evaluates them in order to determine if generations could have been skipped using FA, then a cost-benefit analysis could be performed. There are many other possible approaches to determining the cost-benefit associated with FA which further adds to the research possibilities.

7.2 Summary

The researcher's goal at the onset of this thesis was to improve an existing decision method that had broad use application and was based on widely accepted principles. This was successfully accomplished on the SDP with the development of Flexibility Analysis. The techniques presented in this work can be used for both initial design decisions and decisions involving existing COTS systems. The latter was the focus of this thesis. As the previous chapters of this work demonstrated, FA had three major enhancements. These enhancements and the researcher's final thoughts on each of them are described below.

7.2.1 Systems Focus

The first enhancement that FA made to the SDP was how to model the system. FA's approach defines the system by its major-subsystems and components. As a result, the engineered system remains the focus which allows better understanding of system properties and behaviors. Conversely, the SDP focuses on function and attempts to satisfy specified requirements. This can cause changes which reverberate throughout the system. Furthermore, because the focus is not the system, the impact of a change may not be immediately apparent. The effect may present itself by violating a different constraint and only become evident when the requirement related to that constraint is evaluated.

7.2.2 Solution Space Selection

In this work, the researcher emphasized and demonstrated the importance of not eliminating potentially optimal solutions from the solution space. Using the SDP's method for screening the candidate solution space resulted in the WASP UAS being eliminated from the final solution space. However, using RFGs, which creates the final solution space by incorporating stakeholder dictated levels of acceptability and design engineer stochastic estimates, retained the WASP into the final solution space.

Ironically, the WASP is the optimal solution regardless of whether the SDP or FA quantitative scoring model is used. Therefore, the critical discriminator in the optimal solution between the two methods was the technique employed for generating the feasible solution space.

7.2.3 Potential Value

The previous section stated that the WASP was the optimal solution for both the SDP and FA if they scored the same solution space with their respective quantitative models. However, this does not imply that replacing human preference with the calculation of potential value in the SDP's quantitative model is of no practical significance. On the contrary, because FA produces the same optimal solution as the SDP, it validates the computation integrity of FA's method. Stated differently, it validates FA's ability to find the best solution.

The significance of potential value lies in the information it provides to the decision maker. Potential value provides insight into system flexibility along with the system's properties and behaviors relative to changes. It supplies holistic knowledge about candidate solutions that is not available using the additive value model constructed of preference weightings. Therefore, it supplies valuable information that decision makers can use to more efficiently allocate resources.

7.3 Conclusions

The researcher does not dismiss the importance of preference in decision making; however, preference should not prevent dominant systems from emerging. These decisions should be based on systems and their attributes and not stakeholder preferences. FA affords the decision maker the information required to assess system flexibility and determine the appropriate allocation of finite resources.

The research presented in this work may face strong opposition by those who strongly advocate the value of stakeholder preference in decision making. The researcher understands that change is not often accepted freely; however, if FA is judged on its qualities as a decision method, it provides a venue in which to evaluate systems on their intrinsic characteristics, which are not diluted or skewed by subjectively assigned weights.

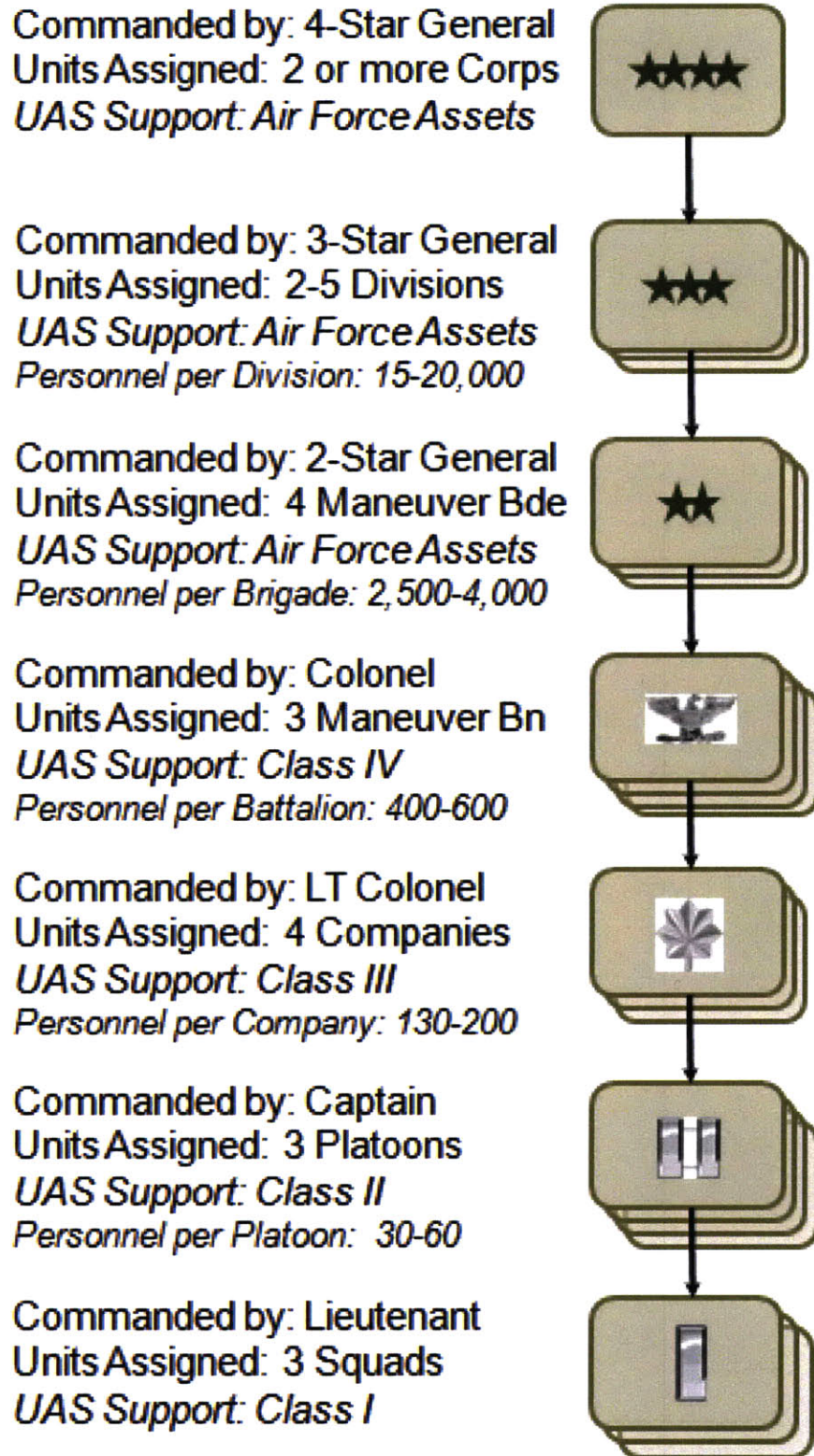
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Appendix A: Abbreviations and Acronyms

AUAS-OB	Army Unmanned Aircraft Systems Operations Branch
BCT	Brigade Combat Team
CAS	Close Air Support
CCLR	Close Combat Lethal Reconnaissance
CDA	Classical Decision Analysis
CEP	Circular Error Probable
COTS	Commercial Off The Shelf
DoD	Department of Defense
DSE	Department of System Engineering
EMI	Electromagnetic Interference
FA	Flexibility Analysis
FCS	Future Combat System
FM	Field Manual
FMI	Field Manual Interim
FPASS	Force Protections Aerial Surveillance System
GCS	Ground Control Station
GPS	Global Positioning System
GWOT	Global War on Terror
HoQ	House of Quality
INCOSE	International Council on Systems Engineering
ISR	Intelligence, Surveillance, and Reconnaissance
LP	Linear Programming
LPP	Linear Physical Programming
LTA	Lighter Than Air
MATE-CON	Multi-Attribute Tradespace Exploration with Concurrent Design
MDMP	Military Decision Making Process
MEMS	Micro-Electro-Mechanical Systems
MIT	Massachusetts Institute of Technology
MODA	Multiple Objective Decision Analysis
MOE	Measure of Effectiveness
MOF	Measure of Flexibility
MOLLE	Modular Lightweight Load-carrying Equipment
MTTF	Mean Time To Failure
NASA	National Aeronautics and Space Administration
QFD	Quality Function Deployment
RE	Relative Effectiveness
RFG	Requirements Flexibility Graphic
RTS	Returns to Scale
SDP	Systems Design Process
SLC	System Life Cycle
SOCOM	Special Operations Command
SPAD	Sonobuoy Precision Aerial Delivery
TGE	Tiny Guidance Engine





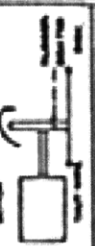


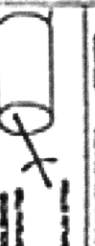
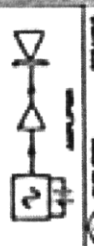
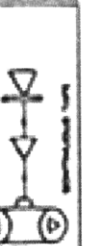
TNT	Trinitrotoluene
TRL	Technology Readiness Level
UAS	Unmanned Aircraft System
UASDD	Unmanned Aircraft Systems Development Division
UA	Unmanned Aircraft
UAV	Unmanned Aerial Vehicle
USMA	United States Military Academy
VTOL	Vertical Take-Off and Landing
WASP	Wide Area Surveillance Projectile

Appendix B: Military Organization Chart



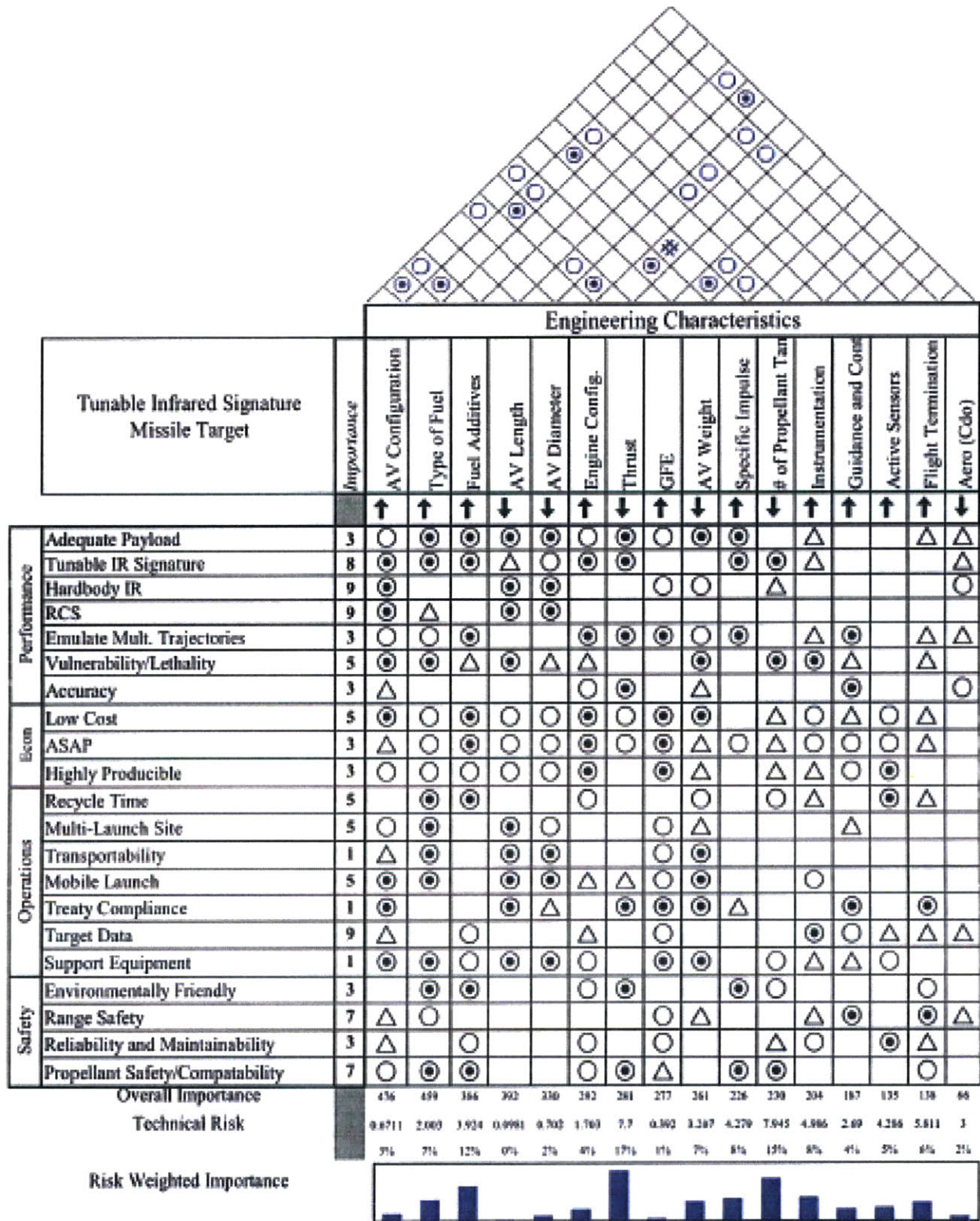
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Appendix C: Pugh Matrix

											
CRITERIA	CONCEPT	1	2	3	4	5	6	7	8	9	10
Ease of achieving 100-125 dbA	DATUM		-	-	+	-	+	-	-	+	+
Ease of achieving 2000-5000 Hz			S	S	S	-	+	S	-	+	+
Resistance to corrosion			-	-	-	-	S	-	+	S	S
Resistance to vibration			-	-	S	-	-	-	S	S	-
Resistance to temperature change			-	-	-	-	S	S	S	S	-
Simplicity of design			+	+	+	+	-	-	-	S	-
Low power consumption			-	-	-	-	+	-	-	+	+
Ease of maintenance			+	+	+	+	-	-	S	+	-
Small size			-	-	-	-	-	-	-	S	-
Long service life			-	-	S	-	-	-	-	+	-
Low manufacturing cost			S	+	+	-	-	-	S	-	-
Ease of installation			S	S	+	-	-	S	-	S	-
Long shelf life			S	S	-	S	S	S	S	S	-
Quick response time			-	-	-	-	-	-	S	+	-
Low weight			-	-	-	-	+	S	-	+	+
Small number of parts			S	S	S	-	-	-	+	+	S
Ease of operation			S	+	+	-	S	S	-	+	+
Ease of integration			S	S	+	-	-	S	S	S	S
TOTAL SCORE	POSITIVES NEGATIVES		2+ 9-	4+ 9-	7+ 7-	2+ 15-	4+ 10-	0+ 11-	2+ 9-	9+ 1-	5+ 10-

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Appendix D: House of Quality



House of Quality for a Tunable Infrared Signature Missile Target [7]

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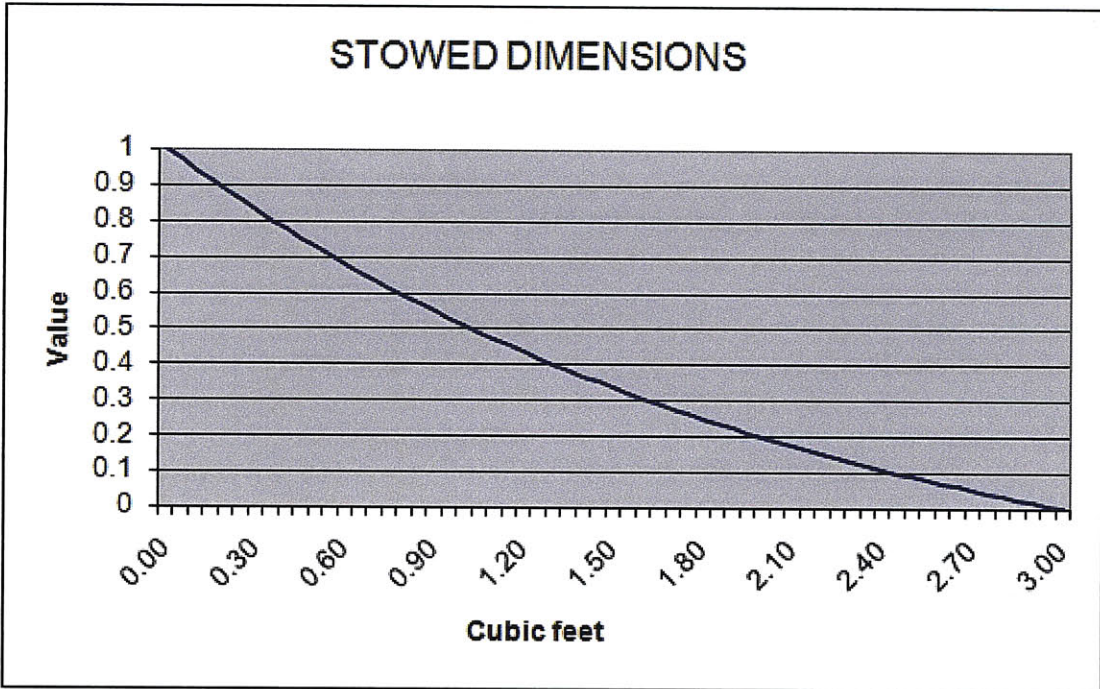
Midvalue= 5 feet/sec
z_{0.5}= 0.526
R= -6.243
ρ (rho)= -5.93E+01

Type of Scale: Proxy, Natural
Monotonicity: Increasing

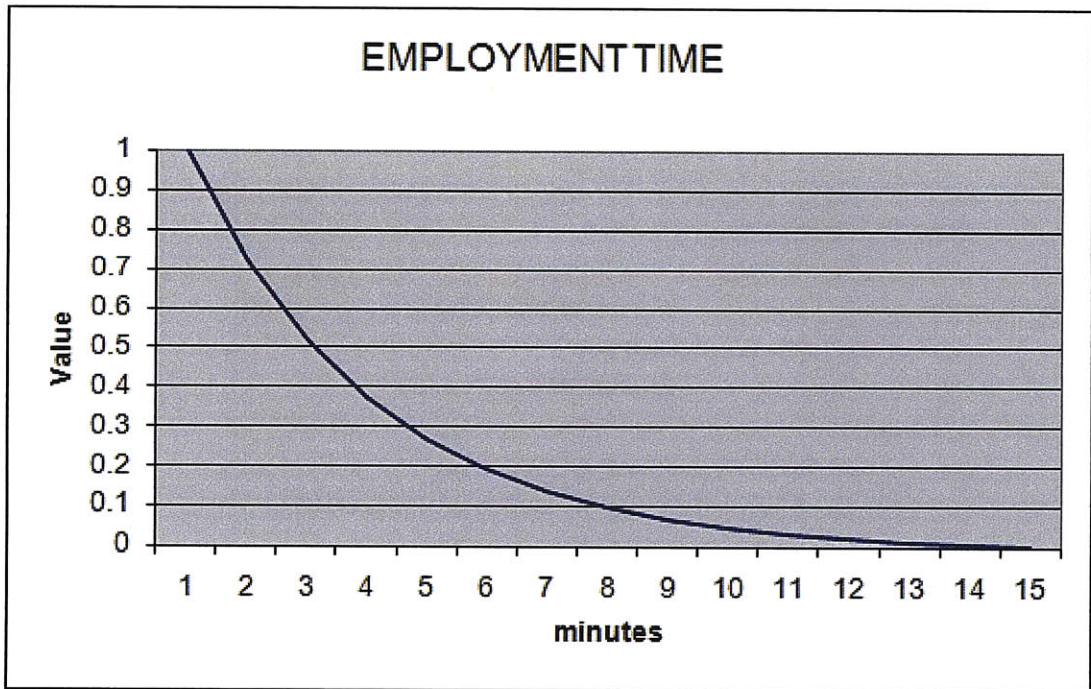
Range	Value
0.5	0
1.0	0.048734
1.5	0.09788
2.0	0.147443
2.5	0.197425
3.0	0.247831
3.5	0.298663
4.0	0.349925
4.5	0.401622
5.0	0.453756
5.5	0.506331
6.0	0.559352
6.5	0.612822
7.0	0.666744
7.5	0.721122
8.0	0.775961
8.5	0.831265
9.0	0.887036
9.5	0.94328
10.0	1



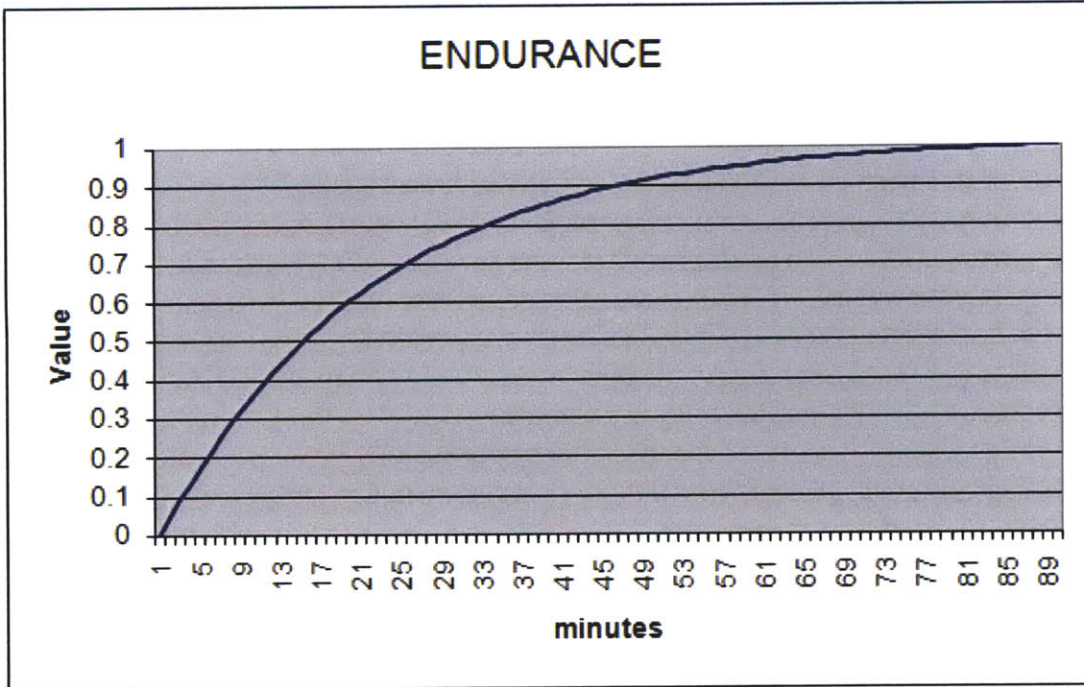
As this figure shows, each value function is constructed from many different parameters. The different



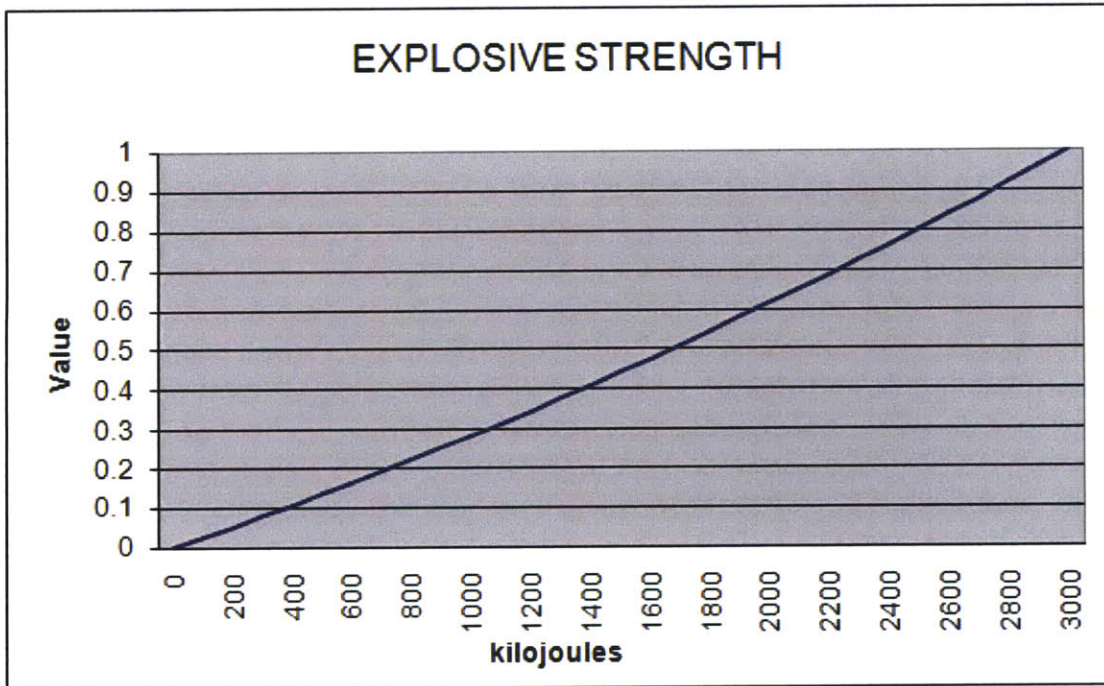
Total Stowed Dimensions of UAS



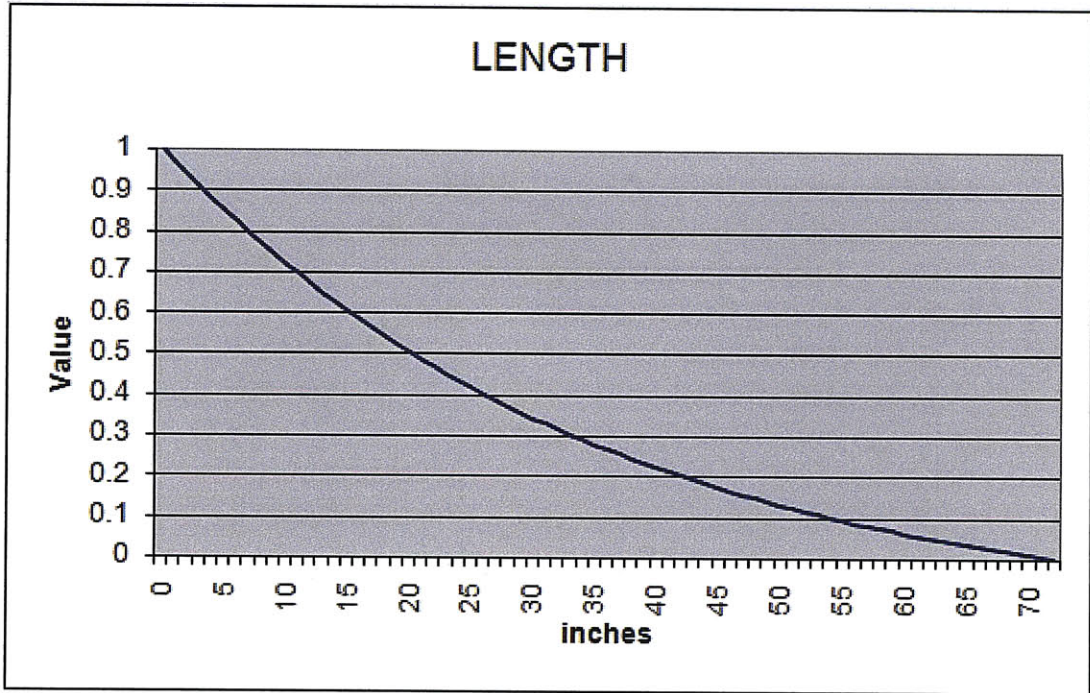
Time to Employment the UAS: Setup to Launch



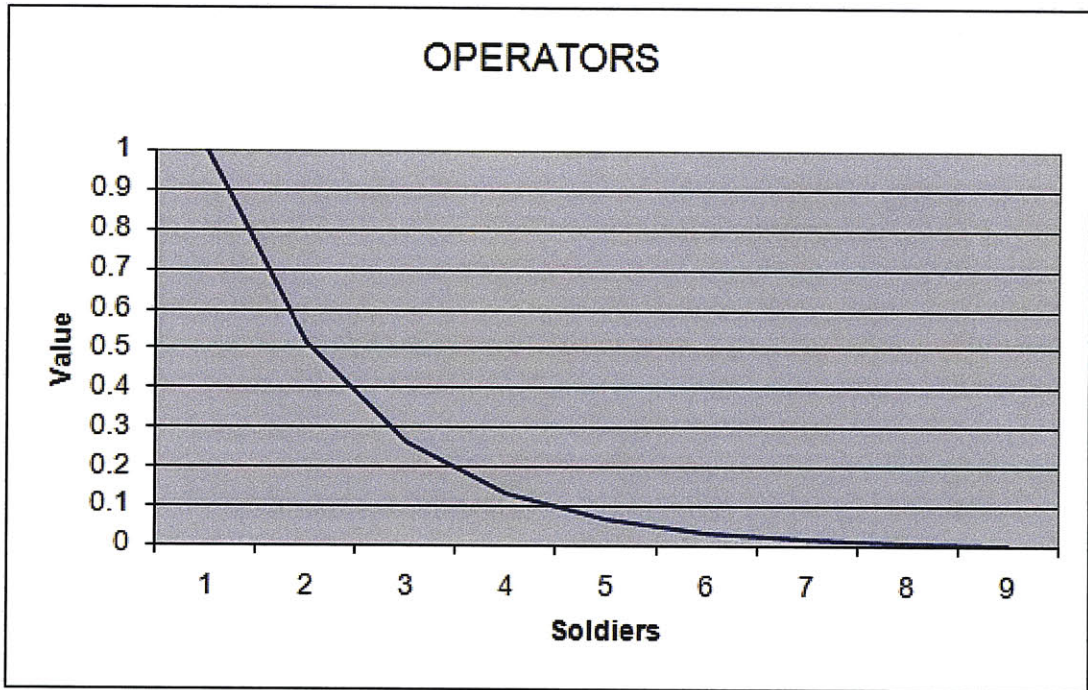
Time the UAS Can Remain Airborne



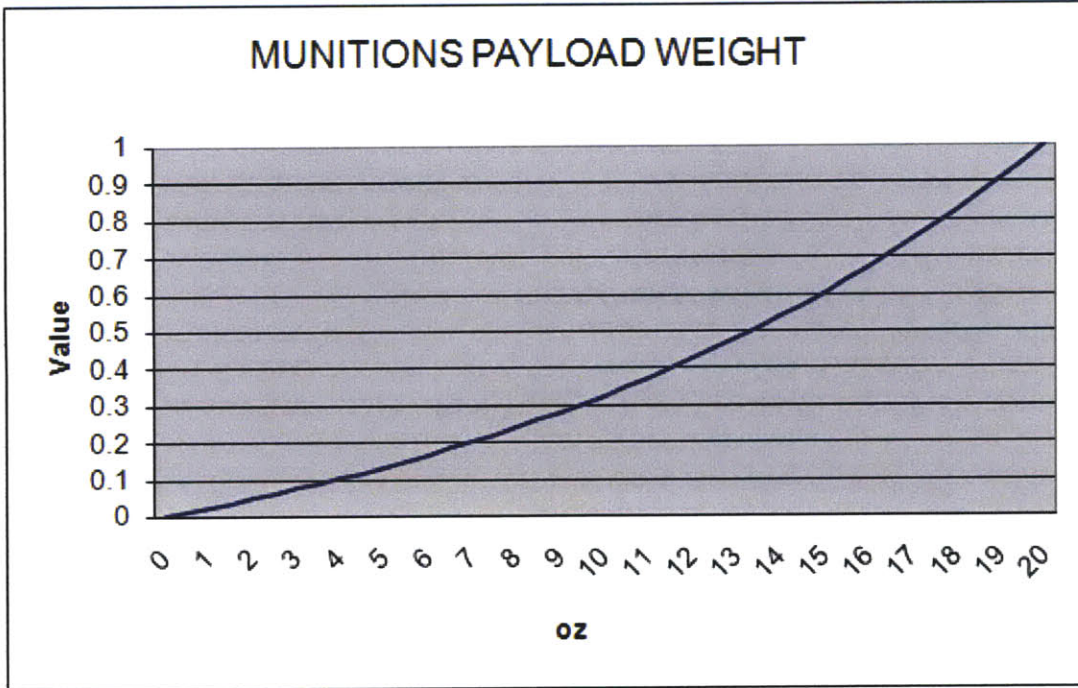
Weapon Explosive Strength of the UAS



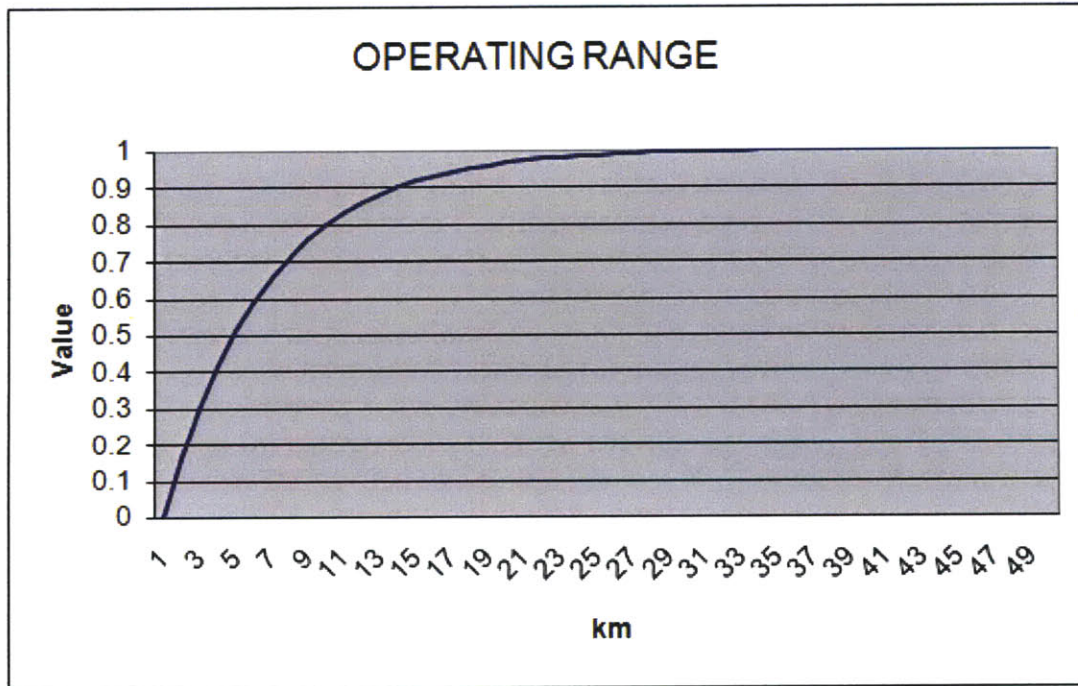
Distance from Nose to Tail of UAS



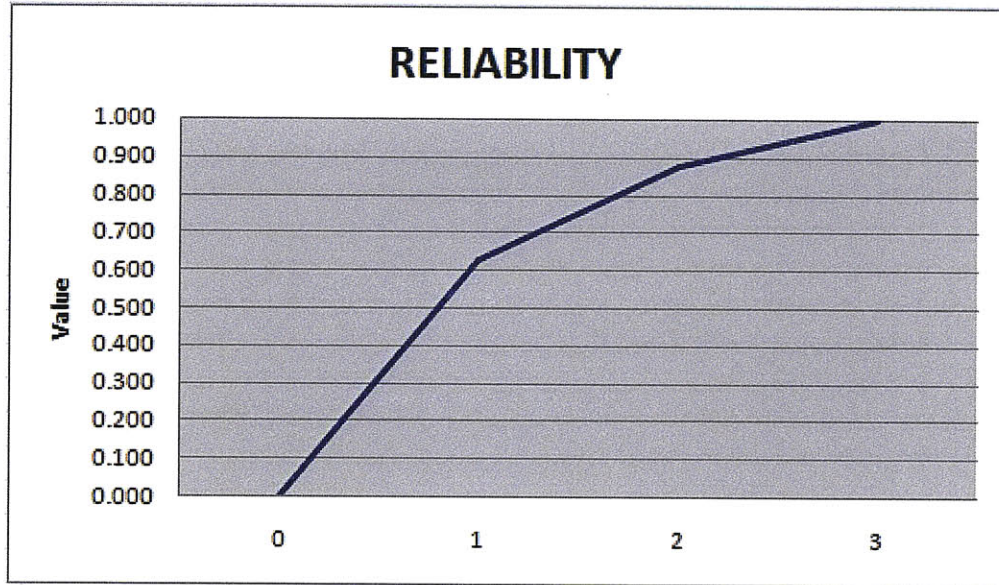
Number of Operators Required to Launch and Operate the UAS



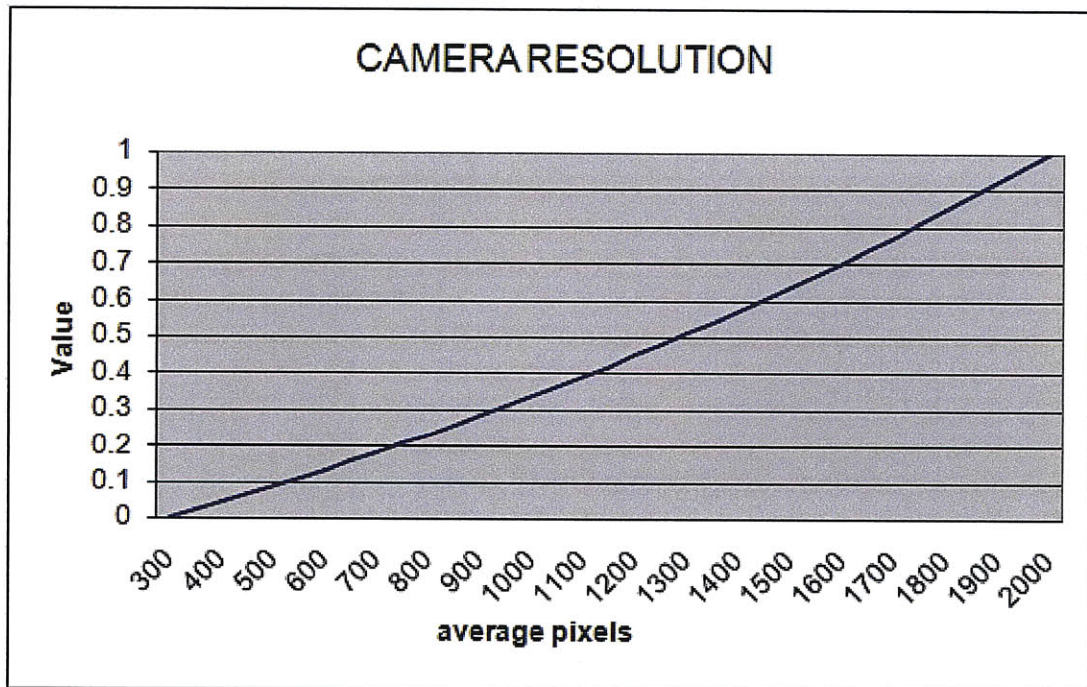
Weight of the Explosive Munition on the UAS



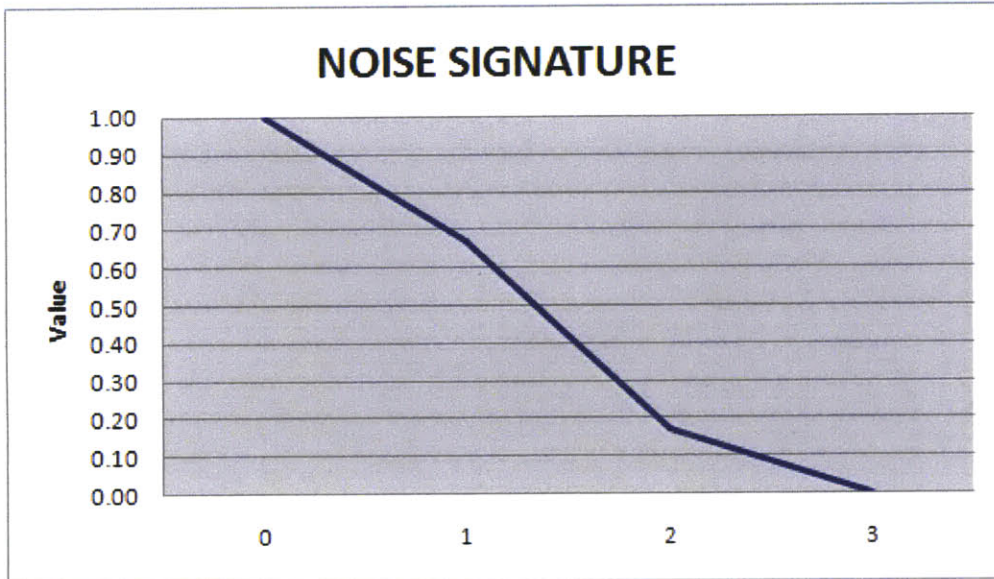
The Distance that the UAS can Travel



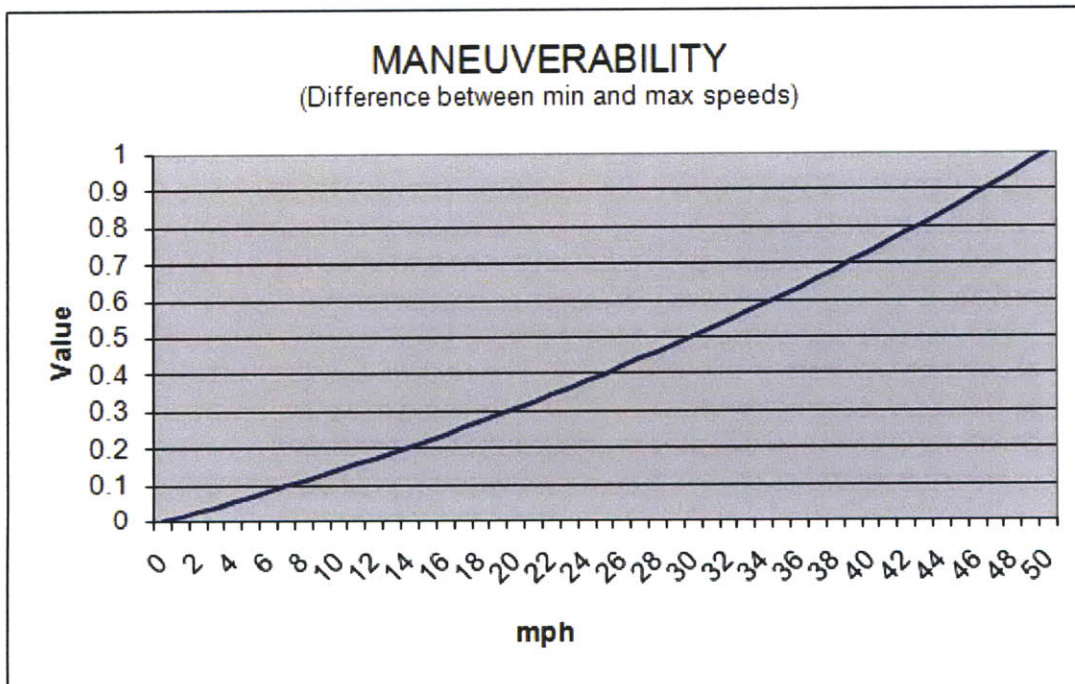
A Proxy Measure of the Reliability of the UAS Based Off Motor Type



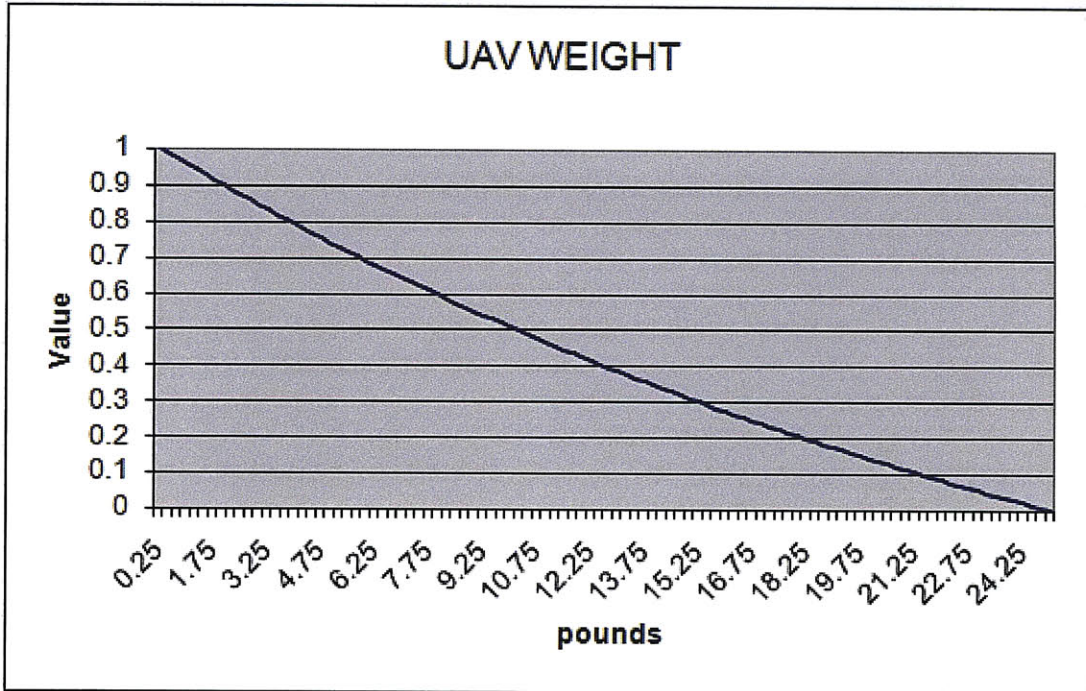
The Onboard Camera Resolution



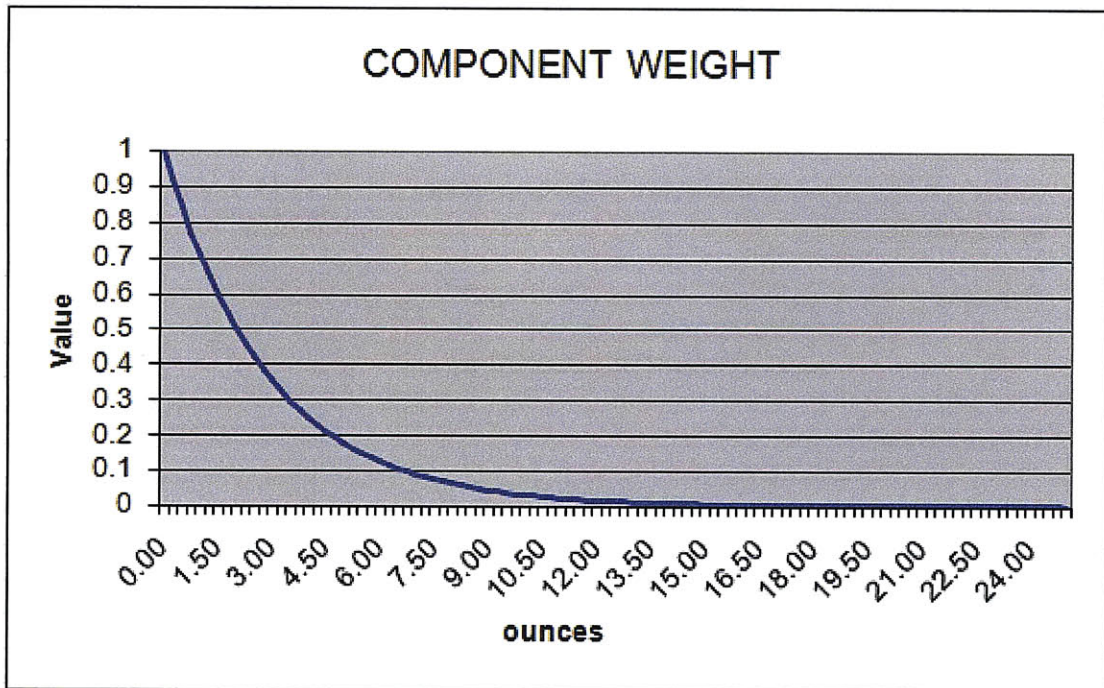
A Proxy Measure of the Noise Signature Based on Motor Type



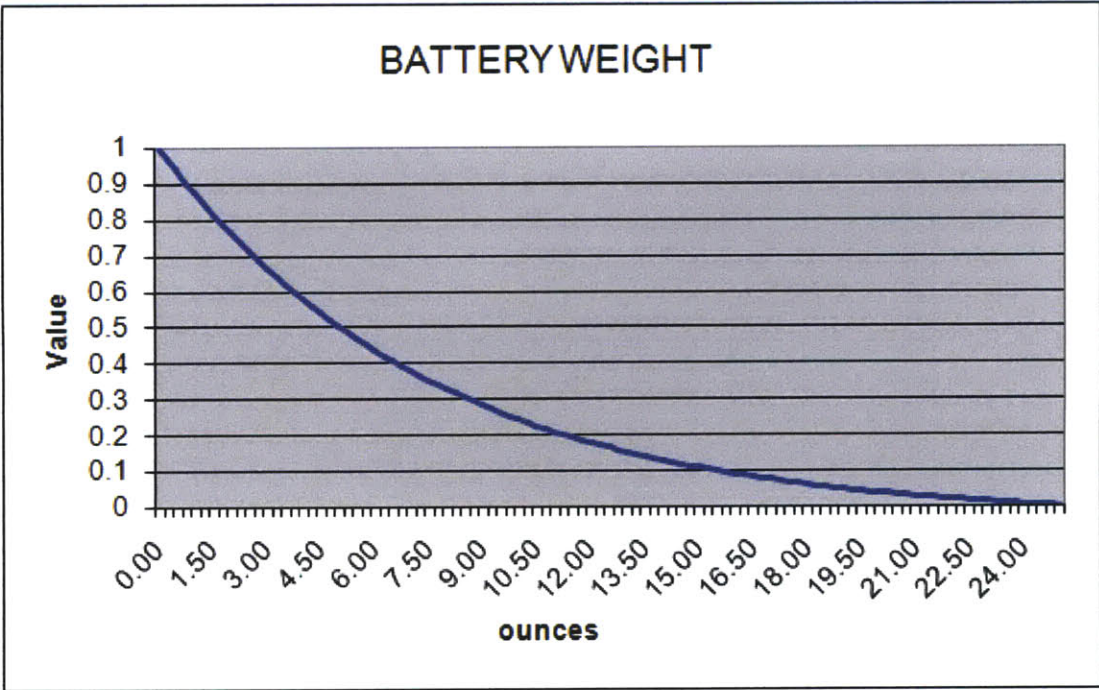
A Proxy Measure of the Maneuverability of the UAS



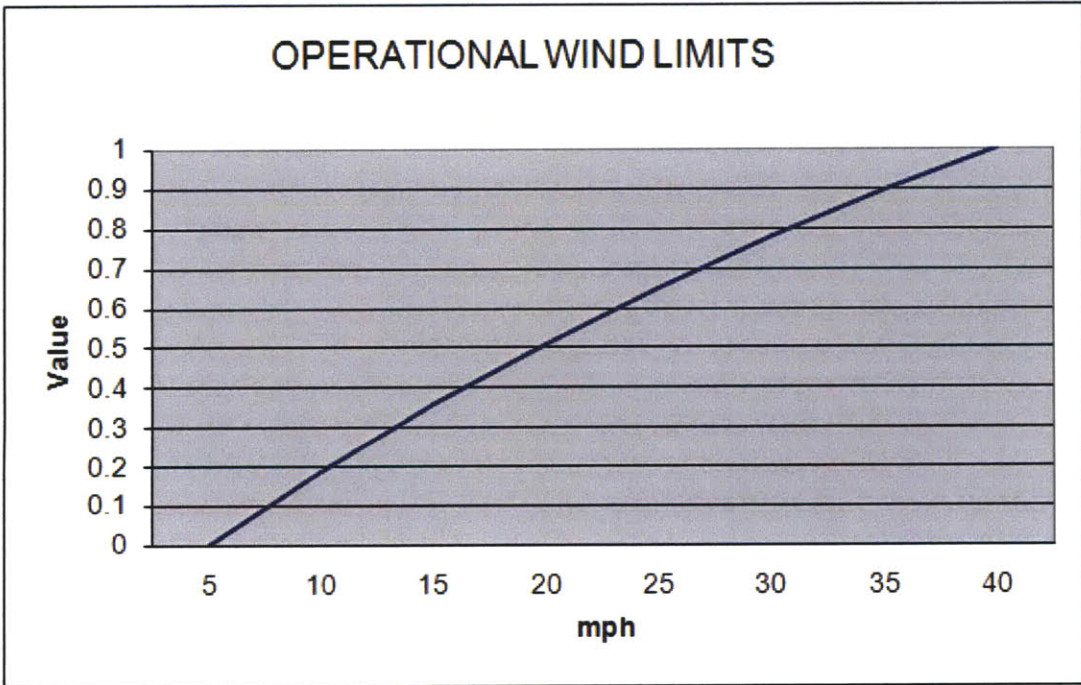
Total Weight of the UAS



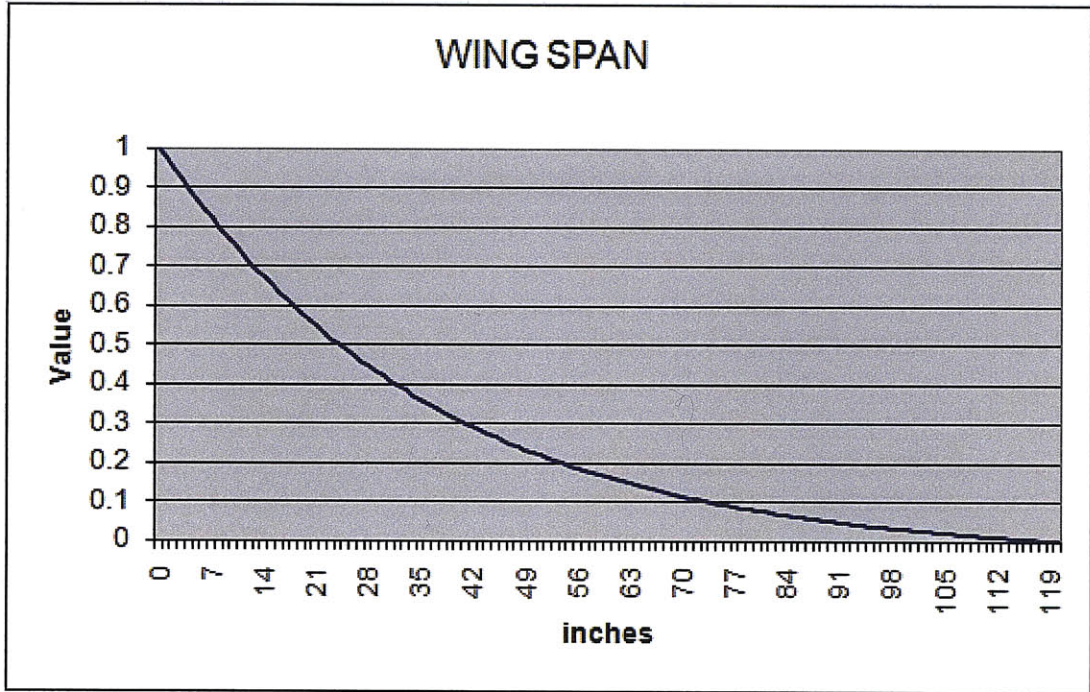
Weight of Components—Does Not Include Batteries



Weight of the UAS Batteries



The Maximum Wind Speed the UAS Can Operate



The Length of the Wings from Tip to Tip

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