AN EVOLVING-REQUIREMENTS TECHNOLOGY ASSESSMENT PROCESS FOR ADVANCED PROPULSION CONCEPTS

A Thesis
Presented to
The Academic Faculty

by

Erin Kathleen McClure

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Aerospace Engineering

Georgia Institute of Technology
August 2006

AN EVOLVING-REQUIREMENTS TECHNOLOGY ASSESSMENT PROCESS FOR ADVANCED PROPULSION CONCEPTS

Approved by:

Prof. Dimitri Mavris, Advisor
School of Aerospace Engineering
Georgia Institute of Technology

Prof. Alan Porter
School of Industrial and Systems Engineering
Georgia Institute of Technology

Prof. Daniel Schrage
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Danielle Soban
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Gary Seng
National Aeronautics and Space Administration
Glenn Research Center

Date Approved: May 04, 2006

ACKNOWLEDGEMENTS

I would first like to thank my advisor, Prof. Dimitri Mavris, for his continued support throughout my entire graduate studies. I would also like to thank Dr. Gary Seng for his help, the opportunities he gave me, and his dedication to higher education. My gratitude extends to my entire committee for their time, feedback, and support in my endeavor. I would also like to extend my thanks to all of the members of NASA's HALE conceptual design team for their input, especially Craig Nickol and Ray Morgan for their additional time and expert opinion.

My fellow graduate students have also been enormously helpful throughout the course of my studies. They not only have they helped me with my studies, but also as my friends, they have made these past few years so much more enjoyable. I would first like to thank Rob McDonald especially for his help in the early stages of my studies. I would also like to extend a special thanks to Janel, Santiago, Patrick, Hernando, and Matt for their help and friendship and help in final stages of my thesis.

Finally, I would like to thank my family and loved ones. I could never thank my parents enough for their unending love and support. My older brothers have always pushed me and I am not sure that I could have gotten to this point without having them to look up to. And last but not least, I would like to thank Ben for his love, support, and encouragement in these past few months.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

AGM	Agent Based Modeling
CDF	Cumulative Distribution Function
CI	Cross Impact Analysis
ERTA	Evolving Requirements Technology Assessment
HALE	High Altitude, Long Endurance
NASA	National Aeronautic and Space Administration
NOAA	National Oceanic and Atmospheric Administration
NPSS	Numerical Propulsion System Simulation
PDF	Probability Density Function
PEM	Proton Exchange Membrane (fuel cell)
QFD	Quality Function Deployment
RF	Relative Fitness
APSA	Advanced propulsion System Analysis
RSE	Response Surface Equation
SOFC	Solid Oxide Fuel Cell
TFA	Technology Futures Analysis
TIA	Trend Impact Analysis
TRIZ	Theory of Inventive Problem Solving
UAV	Unmanned Aerial Vehicle
UDF	Unducted Fan
P(A)	Probability that Event A will occur
$P(\overline{A})$	Probability that Event A will not occur
P(A | B)	Probability that Event A will occur, given that Event B did occur
β_i	OEC weighting for individual objective

R	Response Metric
b_o	Intercept in RSE
b_i	First order coefficient in RSE
b_{ii}	Second order coefficient in RSE
b_{ij}	Interaction Coefficient
x_i	Independent variable
$P(A_i)$	Probability Variable A will equal i
$P(A_i \mid B_j)$	Probability Variable A will equal I, given that Variable B equals j
RF_i	Relative fitness of Alternative i
$RF_{Concept\ A}$	Relative fitness of Concept A
$M_{Vehicle}$	Total mass of HALE vehicle
M_{Energy}	Mass of stored energy for HALE vehicle
$\dot{m}_{Energy}$	Flow rate of stored energy for HALE vehicle
$t_{segment}$	Length of time in flight segment
M_{Engine}	Mass of engine for HALE vehicle
P_{Max}	Maximum required power output for HALE propulsion system
W/kg	Watts per kilogram
$M_{PV\ Cells}$	Mass of Photovoltaic Cells on HALE vehicle
M_{FW}	Mass of Fixed Wing Vehicle
$\eta_{PV\ Cells}$	Efficiency of Solar Cells
W/m^2	Watts per meter squared
kg/m^2	Kilograms per meter squared
M_{PL}	Mass of Payload for HALE Vehicle
$M_{Empty\ Vehicle}$	Mass of Vehicle
$M(X_i)$	Mass of Vehicle with Propulsion System X_i

T	Thrust
D	Drag
V	Velocity
m	mass
g	Gravitational Constant (9.81 m/s^2)
h	Altitude
Z_o	Energy per unit mass ($h+V^2/2g$)
V	Velocity
T_{SL}	Sea level static thrust
m_{TO}	Takeoff mass
β	Mass fraction
α	Thrust ratio
q	Dynamic pressure
C_{DO}	Zero lift drag coefficient
K_1	Drag polar constant
S	Wing area
T_{RQD}	Required thrust
$T_{D,RQD}$	Thrust required from engine deck
$T_{D,SL}$	Sea level static thrust from engine deck
K_{Eng}	Ratio of engine size to engine deck size
ff	Flow of fuel (or stored energy)
$M_{\text{“Fuel”}}$	Mass of stored energy
b	Radius of lighter-than air envelope
D	Diameter of lighter than-air envelope
L	Length of lighter-than-air envelope

$L_{Envelope}$	Lift generated by envelope in lighter-than-air vehicle
$Vol_{Envelope}$	Volume of lighter-than-air envelope
ρ	Density
C_{DV}	Volumetric drag coefficient
P	Power required
den_{Fabric}	Density of shell for lighter-than-air vehicle
e	Eccentricity of envelope shape
$A_{Projected}$	Projected area for lighter-than-air envelope
M_{LTA}	Mass of lighter-than-air HALE vehicle
$M_{Gondola}$	Mass of gondola for lighter-than-air HALE vehicle
$M_{Env.\ Fabric}$	Mass of envelope shell for lighter-than-air HALE vehicle

SUMMARY

The following dissertation investigates the development of a methodology suitable for the evaluation of advanced propulsion concepts. At early stages of development, both the future performance of these concepts and their requirements are highly uncertain, making it difficult to forecast their future value. Developing advanced propulsion concepts requires a huge investment of resources. The methodology was developed to enhance the decision-makers understanding of the concepts, so that they could mitigate the risks associated with developing such concepts.

A systematic methodology to identify potential advanced propulsion concepts and assess their robustness is necessary to reduce the risk of developing advanced propulsion concepts. Existing advanced design methodologies have evaluated the robustness of technologies or concepts to variations in requirements, but they are not suitable to evaluate a large number of dissimilar concepts. Variations in requirements have been shown to impact the development of advanced propulsion concepts, and any method designed to evaluate these concepts must incorporate the possible variations of the requirements into the assessment. In order to do so, a methodology was formulated to be capable of accounting for two aspects of the problem. First, it had to systemically identify a probabilistic distribution for the future requirements. Such a distribution would allow decision-makers to quantify the uncertainty introduced by variations in requirements. Second, the methodology must be able to assess the robustness of the propulsion concepts as a function of that distribution.

This dissertation describes in depth these enabling elements and proceeds to synthesize them into a new method, the Evolving Requirements Technology Assessment (ERTA). As a proof of concept, the ERTA method was used to evaluate and compare advanced propulsion systems that will be capable of powering a hurricane tracking, High Altitude, Long Endurance (HALE) unmanned aerial vehicle (UAV). The use of the ERTA methodology to assess HALE UAV propulsion concepts demonstrated that potential variations in requirements do significantly impact the assessment and selection of propulsion concepts. The proof of concept also demonstrated that traditional forecasting techniques, such as the cross impact analysis, could be used to forecast the requirements for advanced propulsion concepts probabilistically. "Fitness", a measure of relative goodness, was used to evaluate the concepts. Finally, stochastic optimizations were used to evaluate the propulsion concepts across the range of requirement sets that were considered.

1 INTRODUCTION

Scientists and meteorologists are searching for new means of obtaining data from hurricanes, in hopes of improving the accuracy of hurricanes' forecasts. "Hurricane Hunters" currently fly directly into the storm to gather data, but they are expensive and do not have the endurance required to monitor the storm continuously. Satellites are not capable of accurately measuring important indicators, such as barometric pressure and wind speed. High-Altitude, Long-Endurance (HALE) unmanned aerial vehicles (UAV) could potentially fill this void, but the concept needs further development before could do so. One technological obstacle hindering the development of such vehicles is that existing propulsion systems consume too much fuel to enable the vehicles' required endurance. Numerous propulsion concepts have been proposed, but the uncertainty surrounding the future concepts' performance and the specific vehicle requirements and characteristics make it difficult for decision-makers to identify which propulsion concepts will best serve the vehicle.

The following manuscript outlines the creation of a method that will allow decision-makers to compare advanced propulsion concepts to one another *quantitatively*, given uncertainty in both the requirements and the technological capability of the concept. The Evolving Requirements Technology Assessment (ERTA) method was developed to incorporate these uncertainties into the assessment of the concepts. The high development costs and uncertainty inherent to developing such complex systems limit the number of propulsion concepts that the industry can develop. Decision-makers need to have the ability to compare advanced propulsion concepts to one another, and identify which concepts are the most robust. If such information could be provided, then they would be able to allocate resources more effectively, thus mitigating the risks associated with developing advanced propulsion concepts.

The requirements for advanced propulsion systems will be mostly dictated by vehicle characteristics and mission parameters—quantities that can be projected, but will evolve throughout the development of the propulsion system. The selection of the propulsion concept, then, had to incorporate those uncertainties into its assessment. The propulsion concept that was ultimately selected had to be robust with respect to uncertainties inherent to the development process, but it must also be robust with respect to perturbations in requirements.

Developing a method to tackle an engineering problem is an unconventional technical dissertation. Every effort was made to ensure that the development of the method followed the scientific method. The need for such a method is discussed in the introduction, and observations as to how this problem is currently addressed and shortfalls of such approaches are raised throughout the introduction, literature review and hypotheses discussion. Ten specific research questions emerged from those observations, and the answers to those questions formulated four hypotheses statements. Those hypotheses were tested when the ERTA method was used to evaluate potential HALE propulsion concepts. In the manuscript's concluding section, the success of those hypotheses is discussed.

1.1 Motivation

The ERTA method was developed to give decision-makers the ability to incorporate the uncertainty of requirements into the assessment of technological concepts. While product design and selection methods have advanced rapidly over recent years, the methods that decision-makers currently use to select technological concepts rarely incorporate the uncertainty of the requirements into the selection of concepts. If decision-makers had an understanding of how sensitive the goodness of technological concepts is to particular requirements, they could mitigate risks of development by selecting the technological concepts that are most robust to the potential variations in requirements.

1.1.1 Uncertainty Inherent to Requirements

As technology develops and systems become more complicated and intricate, the time and resources required to develop technological systems increase. This trend is especially visible in the aerospace industry. In 1986, Augustine noted that "…the cost of an individual airplane has unwaveringly grown by a factor of four every 10 years," [3] [29] while Eskew correlated the development period for a tactical aircraft with the aircraft's eventual procurement cost [29]. Throughout that period, the requirements that the technological concepts must meet do not remain stationary—they evolve. The greater the development time, the more uncertain the requirements are. Additionally, consumers such as the government often choose to extend the service life of existing systems, rather than pay to upgrade to next generation systems [67]. Throughout that extended lifespan, systems are used in different ways, adding another source of uncertainty inherent to the intended requirements.

Many of the requirements for the HALE UAV's propulsion system are quite uncertain. At what altitude should the vehicle fly? What speed should the vehicle be capable of cruising? The altitude and cruise speed will dramatically affect the performance of propulsion concepts, and need to be taken into account. Additionally, the vehicle configuration has yet to be specified. The vehicle configuration will determine the amount of drag that the vehicle produces, which determines the amount of thrust that the propulsion system must provide. The propulsion system that is developed to power the HALE vehicle should be robust to these uncertainties.

There are several examples in the aerospace industry alone of the requirements for a technological concept changing throughout its development period. Sometimes, those changes have been great enough to eliminate the need for the technological development. In other cases, the changes have been just enough to question the original concept selection. Consider the unducted fan (UDF). The UDF was conceived during the fuel crisis of the 1970's as an ultra efficient jet engine, capable of reducing fuel consumption by approximately 20% to 30% [72]. Unfortunately for the UDF, fuel prices returned to normalcy, and the requirement for fuel-efficient engines no longer superseded the need for quiet, traditional engines. Development was halted before the engine was fully developed because the requirements that made the engine a worthwhile investment changed.

Another example of technological concepts becoming obsolete throughout development is the nuclear turbojet concept. General Electric and the US government began actively developing a nuclear turbojet engine to power a large supersonic vehicle, capable of cruising subsonicly for long a period of time in 1951. By 1961, however, the military's objectives of such large system changed, and the program was cancelled as it "suffered considerably from lack of prompt decisions and from frequent changes in emphasis and goals" [97].

The industry faces similar questions in the future. The environmental constraints that governments will place on aircraft and the maximum cruise Mach number that the aircraft is allowed to fly over land will significantly impact the potential value of aeropropulsion concepts in the future. Eliminating CO_2 emissions will require the infusion of alternative fuel concepts, while the Mach number significantly affects the efficiency range of aeropropulsion concepts.

Should decision-makers consider the potential variations in requirements when they are selecting which technological concepts to develop? In conceptual design, decision-makers select the best alterative(s), given that the final product must ultimately meet one or two particular sets of requirements. As the requirements diverge from the expectations, the chance that the selected alternative is actually the best choice, or even feasible, is reduced. Decision-makers need to take uncertainty of requirements into account, when selecting technological concepts, so that they can select the concepts that are the most robust, with respect to potential variations in requirements.

This notion becomes even more important when decision-makers begin to consider advanced propulsion concepts. Advanced propulsion concepts require greater expenditures of resources and take longer periods of time to development. The longer development cycle ensures that there is more uncertainty inherent to the requirements, and the large expenditure of resources increases the stakes of the investment. In the words of Norman Augustine, "It costs a lot to build bad products," [3].

1.1.2 Methods Currently Used to Select Technological Concepts

Traditionally, commercial entities use a broad range of methodologies to select the technological concepts to which they will devote Research and Development (R&D) resources. Commercial entities make a distinction between developing technological concepts for one particular use or end product (product development) and developing technological concepts for a more general, potential applications (technological development) [8]. Selecting a propulsion system to meet the requirements of a HALE vehicle falls somewhere between the two categories. While a product is being developed for a specific purpose, commercial entities usually limit product development to proven technological capability [8]. Unfortunately, the proven technological concepts will most likely not be capable of meeting the requirements for the HALE vehicle. For this reason, the author examined the methods used to select concepts for both product development, and technological development.

The methodologies used to select technological concepts for product development vary significantly, but almost all successful methodologies have a few common steps or phases included in them [25]. First, the methodologies contain a "problem definition" phase, in which teams develop a thorough understanding of the problem, and gather necessary information. The requirements for the product are defined here. Second, the methodologies contain a "generation of alternatives" phase, where possible alternatives, or technological concepts, are identified. Third, methodologies contain an "evaluation of alternatives" phase, where decision-makers select which of the alternatives to bring forward to the next phase of development or a more detailed design. A multitude of means by which developers carry out these three essential phases of product development exist, and those means are discussed in the literature review, in sections 2.2.1, and 2.2.3. The shortfall of these methods is that they do not give the decision-maker the ability to compare technological concepts to one another, while concurrently accounting for requirements variations.

Too often, in the aerospace community, the methods that companies rely upon to select technological concepts to develop are "ad hoc or lack rigor" [49]. According to Cetron, traditional approaches to allocating R&D funding are rarely scientific or objective [15] [49]. Often funds are allocated based on which programs make the most noise, or which programs have achieved the greatest success in the past [15] [49]. While the state of the art of R&D selection methods has improved drastically over the past thirty or forty years, few industrial entities use the advanced methods [67] [49]. Some of the advancements in R&D selection methods are discussed in section 2.1. A few of the technology development methodologies discussed in that section do provide the decision-maker with the ability to compare incorporate the uncertainty of requirements into the evaluation of the technologies, but those methods cannot be used to evaluate advanced propulsion concepts.

1.1.3 Expectations for ERTA Methodology

The ERTA method is not intended to replace the methodologies currently used by industrial entities to select technological concepts for resource allocation. The ERTA method, instead, is intended to enhance the amount of information that decision-makers have when they are evaluating those concepts. The method was developed in the context of evaluating propulsion concepts that are best suited to powering a HALE vehicle. The author expects that the method could be used in other fields to enhance decision-makers' information, but demonstrating this supposition is beyond the scope of this investigation.

The ERTA method was created to assess how well each technological concept will satisfy the requirements of the future, relative to competing concepts. In order to do so, the methodology must have three components. First, the method must generate a probabilistic forecast of the requirements that future technological concepts will have to meet. The requirements for the HALE propulsion system are not fixed, and potential variations in the requirements could substantially impact the goodness each propulsion concept. It is important that the probabilistic set of requirements captures the likely variation in requirements. The robustness of each concept should be measured relative to a likely distribution of requirements instead of being measured against any distribution. Second, the method must assess the relative goodness of each concept across the distribution of requirements. Such an assessment would give decision-makers an understanding of which HALE propulsion concept(s) are best, and how sensitive that goodness is to particular requirements. Finally, the methodology must incorporate the uncertainty inherent the development of technological concepts into the assessment. The maturity of the potential propulsion concepts ranges dramatically. There is more uncertainty inherent to the less mature concepts. That uncertainty needs to be incorporated into the evaluation of technological concepts.

The ERTA method was developed specifically to tackle the problem of comparing advanced propulsion concepts to one another, given uncertain requirements. Next generation propulsion concepts are usually considered revolutionary in nature, as are fundamentally different from conventional propulsion systems. The fact that the ERTA method was developed to tackle the evaluation and comparison of advanced propulsion is significant because such technologies have to be evaluated in a different manner than evolutionary technologies or concept designs can be evaluated. There are many more variables to consider when evaluating advanced propulsion concepts, and accordingly, the design space is much larger. Also, little is known about the application or integration of such concepts, so modeling them becomes more difficult.

The author sees no reason why the methodology could not be applied to the comparison of evolutionary technological concepts, but methodologies already exist that enable decision-makers to compare such technologies to one another, and many of those methods allow decision-makers to incorporate the uncertainty inherent to the requirements into the evaluation. The author’s definitions of evolutionary and revolutionary technologies are explained in section 1.4.1.

1.2 Technical Barriers

If incorporating the variation of requirements into the analysis of technological concepts is important, why has it not been done in a methodical fashion before? There are several technical challenges preventing such a comparison. First, the problem is so large that it is difficult to grasp. Comparing a few technological concepts to one another, given a fixed set of requirements, is difficult enough in its own rite. Another challenge is the ability to forecast the requirements for future technological systems. Industrial entities are good at predicting the capability of future technological systems because those predictions are based on physical analyses. The evolution of the requirements, however, will be dictated by less tangible forces, such as government restrictions and market fluctuations. Including that uncertainty in the evaluation only increases the magnitude of the problem. Finally, traditional figures of merit will probably not be useful benchmarks, as they are often not valid across the entire range of concepts and requirements.

1.2.1 Identifying Requirements for Future Technological Concepts

In the aeropropulsion industry, advanced propulsion concepts have to be developed for years before they are ready for the market. In those fields, decision-makers must select the technological concepts to invest R&D resources into years before the concepts can be produced. The potential concepts are evaluated and compared based on the decision-maker's perception of how well each concept can meet a particular set of requirements. Unfortunately, as mentioned earlier, during the development time, those specific requirements are likely to change, or evolve. Predicting the requirements that the revolutionary technological concept will have to meet once it is developed, then, is challenging. The requirements for future technological concepts will be functions of a range of factors, from unpredictable market forces and government policies to the technological maturity of the interacting and surrounding systems. As mentioned above, the requirements for the HALE propulsion system will be dictated by the vehicle characteristics mission profile, as well as other customer requirements, such as costs and emissions constraints. It is difficult for developers to predict how those requirements will evolve with time—especially if the requirements are dictated by forces that are outside of the developer's area of expertise.

Another problem hampering the prediction of requirements for future concepts is that many of the requirements for advanced propulsion concepts are going to be highly dependent upon one another. Any forecasting will have to incorporate the dependencies of multiple requirements into its forecast—a difficult endeavor. Consider the configuration for the HALE and the cruise speed. Those two parameters are likely to be highly dependent upon one another. As cruise speed increases, the chances that the configuration will be lighter than air vehicle decreases significantly. Any forecast of requirements would have to incorporate dependencies of requirements upon one another, because the concept must be able to meet all of the requirements ***simultaneously***.

1.2.2 Justly Comparing Technological Concepts to one Another

Technological concepts, such as advanced propulsion concepts, are often fundamentally different from one another. Those differences make it difficult to compare them to one another in a just, quantitative, and methodical fashion. First and foremost, it is difficult to predict the mature capability of advanced propulsion concepts, before they have been developed. Advanced propulsion concepts are complex, highly coupled systems, completely outside of the realm of industry's experience. Unfortunately, empirical data and relationships cannot be used to evaluate advanced propulsion concepts. Analyses cannot use trends or relationships previously identified by the industry to project the performance of future advanced propulsion concepts. The evaluation of advanced propulsion concepts, then, must rely solely upon the fundamental, physical relationships upon which the concept is conceived. One problem with this analysis is that it can be highly inaccurate. While component efficiencies, material constraints, and integration losses can all be easily factored into the analysis, the values of those parameters are highly uncertain. Performance estimates can be highly sensitive to those parameters.

Another factor hindering decision-makers ability to accurately compare technological concepts to one another is that analyzing advanced propulsion concepts is simply too computationally exhaustive to allow for a full exploration of the design space of advanced propulsion concepts. Before these concepts can be truly evaluated, however, the optimal designs for each technological concept need to be identified, which presents a challenge of its own.

The magnitude of this problem cannot be overestimated. Comparisons of technological concepts can only be conducted if each of the concepts is specifically designed to meet the particular set of requirements that the concepts must meet. Each concept has a different, but lengthy, set of design variables; all of which must be optimized. In the context of a traditional turbofan engine, the pressure ratio of the compressors and bypass ratio of the engine must be optimized to the specific mission profile of the aircraft. Because system parameters are not simple functions of the design variables, this is an exhaustive task. This challenge has been overcome in order to optimize conventional, well-understood concepts by using sophisticated modeling techniques. Even when these techniques are employed, optimizing the local design variables is time consuming and the process is particular to the individual concepts that are being optimized. It is not feasible to automate the process to optimize and evaluate an unspecified number of advanced propulsion concepts.

Another technical challenge preventing the comparison of advanced propulsion concepts to one another is the unknown mature performance of each of the advanced propulsion concepts. Advanced propulsion concepts are immature by definition. There is a high degree of uncertainty associated with developing each of the components and integrating them into one, cohesive, concept. The efficiency, the volume, and the weight of the aeropropulsion concepts, for example, are difficult to predict at early stages of development. Those parameters will significantly impact the evaluation of the concepts.

Finally, comparing multiple advanced propulsion concepts to one another requires some figure of merit that is applicable over the entire range of concepts being considered. Often times, the traditional metrics used to evaluate goodness have no meaning when applied to advanced propulsion concepts. Consider the figure of merit traditionally used to evaluate propulsion systems, fuel consumption. When evaluating advance propulsion systems that rely upon solar energy or hydrogen, fuel consumption has no meaning. Before the HALE propulsion alternatives can be compared to one another, a figure of merit applicable across the entire range of alternatives must be generated.

1.2.3 Incorporating the Variation of Requirements

As discussed above, the analysis required to compare technological concepts is exhaustive; each concept must be specifically designed to meet each particular set of requirements, and the uncertainty associated with the concept's development must somehow be considered in the comparison. Unfortunately, an infinite number of potential requirement sets that the advanced propulsion concepts may have to meet exist. It is infeasible to conduct an exhaustive comparison of all technological concepts, given each potential set of requirements. How then, can the impact of the potential variation of requirements be considered when evaluating advanced propulsion concepts?

1.3 High-Altitude, Long-Endurance Vehicle

As discussed above, the ERTA method was developed to enable the comparison of various propulsion concepts proposed to propel a HALE vehicle. The vehicle itself is being developed to track hurricanes and cyclones, with the intention of studying and learning more about their formation. Selecting a propulsion system for the HALE is a difficult problem worthy of investigation because conventional aeropropulsion concepts will most likely not be capable of propelling such a vehicle. Conventional propulsion systems are simply not efficient enough to give the vehicle the endurance it would need to track the hurricanes. If such a vehicle is to be developed, advanced propulsion concepts will also need to be developed in order to propel the vehicle, and decision-makers are not sure as to which of the numerous proposed concepts offers the greatest chance of success.

Existing conventional propulsion concepts are currently driven by the combustion of hydrocarbon fuels. Such processes, while mature, reliable and cheap, are not fuel efficient enough to give the vehicle the endurance that is required. Even if the concepts are dramatically improved, they would probably not be capable of monitoring the tropical storm area for more than a few days, without refueling. Alternative energy sources, such as regenerative fuel cells, will most likely be required. The likely requirements for the hurricane-tracker will be investigated and forecasted, and used to assess the value of advanced propulsion concepts.

1.4 Background

The following section provides background information that may be helpful for reading later sections of this paper. First, the terms evolutionary and revolutionary are defined as they apply to technology in this manuscript. Second, the evolution of the term "robustness" is discussed. While most of the terms used in this investigation are common and widely used, there may be some ambiguity associated with them. Also, they may take on a new meaning in the context of this dissertation. The following section attempts to eliminate any potential confusion by clearly defining some of those terms.

1.4.1 Evolutionary and Revolutionary Technology

Most people have an intuitive understanding of the differences between evolutionary technology and revolutionary technology, but it is not always easy to classify a technological development as evolutionary revolutionary. The difference between the two is partially subjective. Merriam-Webster defines the terms evolution and revolutionary appropriately below:

> Evolution: a process of continuous change from a lower, simpler, or worse to a higher, more complex, or better state
>
> Revolutionary: constituting or bringing about a major or fundamental change

These definitions lay the foundation for defining revolutionary and evolutionary technology, but alone, they are not sufficient. Revolutionary technology can be described as a system that replaces or fundamentally changes the existing system, but revolutionary technologies will require evolutional development before they can produce feasible alternatives. Should the technological developments that incrementally advance revolutionary systems be considered revolutionary or evolutionary? It is the author's supposition that the incremental technological developments that improve the performance of one component of a new or revolutionary system are evolutionary in nature. Revolutionary technologies, then, can be limited to the theoretical concepts that will replace existing systems, developments that initiate fundamental changes to the existing system, and advancements that integrate the entire revolutionary system. The author's classification of evolutionary and revolutionary technology is detailed below.

> Evolutionary Technology: a technological development that will incrementally advance the state of the art by improving upon one element of a system
>
> Revolutionary Technology: a technological development or theoretical concept that initiates a fundamental change in the way that the existing system operates or makes such a change possible

Unfortunately, these definitions alone are not enough to clarify the differences between revolutionary and evolutionary technology completely. A perspective of system definition is required before the discrepancy can truly be made. For example, consider a technology that would replace the way that the fuel is ignited in a traditional turbofan engine, while allowing the entire rest of the system to operate as usual. If the entire engine were considered “the system”, the technology would be considered evolutionary, because it would allow for the incremental improvement of the entire system through the improvement of one its parts. If, on the other hand, just the combustor were considered “the system”, the technology would be revolutionary, as it would necessitate a fundamental change in the way that the system operates.

A similar and appropriate example of how revolutionary technology can be confused with evolutionary technology given different points of references is the switch from examining the entire aircraft to considering just the aircraft engine as the system. When the box is drawn around the entire vehicle, (in a fashion similar to a control volume) novel propulsion concepts are simply evolutionary advancements. When the box is drawn around only the propulsion system, however, those novel concepts become revolutionary technologies. Clearly defining “the system” paves the way for unmistakable distinction between evolutionary and revolutionary technologies.

Because the definitions of evolutionary and revolutionary technologies are dependent upon the system reference, it makes sense to clarify the term system. A system can be defined for this purpose as a group of components or processes that are interconnected to serve one purpose. Throughout this paper, the term system refers to the integrated engine that is necessary to fulfill the requirements. From hereon, the term alternative, or solution, will be used to refer to one specific configuration for a system. A concept, on the hand, will refer to the set of alternatives that all fit into a specific classification. For example, a turbofan engine with a bypass ratio of 5 and an overall pressure ratio of 40 is one alternative. A turbofan engine with a bypass ratio of 1 and a overall pressure ratio of 15 is another alternative. Both alternatives are different types of the same concept, a dual-spool turbofan engine. Evolutionary technologies allow for alternatives that are derivatives of the conventional concept to be created. Revolutionary technologies allow entirely new concepts to be created. The advanced propulsion concepts investigated in this paper are revolutionary concepts.

1.4.2 Evolution of "Robustness" in Engineering

The ERTA method was developed so that decision-makers could measure the ***robustness*** of advanced propulsion concepts, given uncertainty in requirements. Robustness first emerged in the engineering world as a term to reflect products' ability to withstand uncontrollable variations in production and usage. The term has taken on many applications since is original usage, and given the current state of the aerospace engineering industry, a new meaning of robustness has evolved. Robustness can now be used to refer to the ability of a concept to withstand changes in requirements that evolve though time.

Since robustness was first introduced to engineering, entire fields of study have emerged that focus on increasing value through a more intelligent early development process. Designing for Six Sigma has become the catch phrase that refers to ensuring that the acceptable lower and upper boundaries for product characteristics are each at least six standard deviations from the nominal target—ensuring fewer than 3.4 defects per million products. Six Sigma incorporates many methods developed over the past few decades to ensure robustness. The Taguchi Method identified which product characteristics were least sensitive to uncontrollable variations, and associated a loss function with that deviation. Quality Function Deployment (QFD) sought to fully grasp customer requirements and then translate those requirements into product and process design.

Today, development of aerospace engineering products can span across decades—not just years. Most aerospace vehicles are expected to have lifetimes of thirty years or longer. Frequently, those same vehicles remain in service even longer than they were originally intended. For this reason, when designing vehicles, decision-makers now need to incorporate the robustness of systems to variations in requirements. The ability of an aerospace vehicle to adapt and be capable of meeting a different sets of requirements from which it was originally intended is an attribute that should be sought after and designed for. Similarly, when selecting which advanced propulsion concepts to develop the potential for derivatives of the original concept to meet the evolving demands—the robustness of a concept to evolving requirements—needs to be considered.

2 LITERATURE REVIEW

Before potential advanced propulsion concepts could be investigated, a systematic methodology to identify potential advanced propulsion concepts and assess their robustness was needed. The author first investigated existing advanced design methodologies to determine whether current methods could be used to evaluate the robustness of advanced propulsion concepts. The following chapter overviews advanced design methodologies that have been used to identify or evaluate technological systems in the past. Unfortunately, none of the methods was suitable for the evaluation of the immature advanced propulsion concepts either because it would be difficult to employ to evaluate a large number of concepts, or because it was not well suited to assessing the robustness of a concept with respect to requirements. This chapter is broken down into two main sections: a review of methodologies that help decision-makers identify and evaluate future concepts and technology, and an exploration of tools that may be used to understand and forecast requirements and tools that can be used to enhance the understand of complex design spaces.

2.1 Current State of the Art in Technology Forecasting

The following section investigates advanced design methodologies that have been developed to identify and or evaluate advanced technological concepts. The first methodology, the Theory of Inventive Problem Solving (TRIZ) was developed to identify new solutions or concepts capable of satisfying a set of posed requirements. TRIZ is noteworthy because it is an attempt at systematically identifying the best concepts. The other methodologies discussed use qualitative assessments to evaluate the technology or concept. These methodologies measure the robustness of each technology or concept to potential variations in requirements or technological maturity.

2.1.1 Theory of Inventive Problem Solving (TRIZ)

The Theory of Inventive Problem Solving (TRIZ) is primarily a technique for concept generation. Altshuller developed the TRIZ as a systematic approach toward creative problem solving [91]. TRIZ encompasses many theories and methodologies, but the basis of it is applying "inventive principles" to tackle current, complex engineering problems [63].

Altshuller, a patent expert, analyzed thousands of patents and identified physical contradictions that occurred across industries and tracked their solutions [63]. He labeled the innovative solutions that occurred over and over "inventive principles". He then came up with is a systematic problem solving process that breaks the problem down an existing system. Problems within the system are compared to similar problems encountered previously in other industries. TRIZ identifies the physical contradictions in those systems, and uses inventive principles to identify a solution [91].

TRIZ is noteworthy because it is a novel approach to identifying new solutions or new concepts. Unfortunately, TRIZ does not provide any insight into determining which of the proposed alternative solutions would be best to implement. Within the aeropropulsion industry, many concepts have been proposed as next generation alternatives, but a significant amount of resources are required to develop any of those alternatives. TRIZ does not give developers guidance in making a sophisticated distinction between the proposed concepts. Additionally, TRIZ is best suited toward improving existing systems, not identifying revolutionary systems. Finally, TRIZ is not easy to conduct; it requires breaking a system down into a “cause and effect” diagram which is cumbersome and difficult to automate.

2.1.2 Quantitative Technology Forecasting Methods

While the main intention of TRIZ was to identify new solutions or concepts, other noteworthy methodologies have been developed to quantitatively evaluate technological concepts. These methods employ rigorous modeling and simulation to forecast the impact of future technological concepts. Those impacts are then used to evaluate the technological concepts. A few of these methods are described below.

All of the methods described use “k-factors” or technology dials to model the level of technological maturity of a subsystem or component. K-factors are dimensionless numbers that are used to perturb disciplinary metrics slightly within complex designs [58]. The setting for disciplinary metrics reflect the state of the art being modeled; they are often referred to as “technology dials” because they can be changed to reflect the level of technology infused into the system [62]. An example of the use of a k factor can be easily seen within a turbojet propulsion system. The efficiency of one of the main components, the high-pressure compressor (HPC), can be considered a disciplinary metric. Throughout time, the efficiency of that component will most likely increase. Raising that efficiency in a model through use of a k-factor shows advancement in the state of the art, or an infusion of technology into the design. The overall impact of a technology that allows the HPC to operate more efficiently can thus be quantified by using appropriate k-factors to perturb the suitable disciplinary metrics. It is important to note that technology k-factors can be used to model degradations associated with new technologies as well. For example, consider the same hypothetical technology that improved the performance of the HPC. That technology may negatively affect other disciplinary metrics, such as the weight of the HPC. To model that degradation, another k-factor is used which affects the forecasted weight of the HPC directly. The system level analysis will allow developers to quantify the overall system level impact of advancing and degrading various disciplinary metrics will have on the overall system.

K-factors can be used to model the impact of specific technologies, as is done in exploratory forecasting, or they can be used to conduct gap analyses [51]. Decision-makers can use k-factors normatively to play "what if" games—meaning that they can quantitatively answer the question of ***what*** would happen to system level metrics ***if*** various metrics were improved or degraded.

2.1.2.1 Unified Tradeoff Environment

Baker developed a technique referred to as the Unified Tradeoff Environment (UTE) to quantify the impact of changes in requirements, vehicle attributes and technologies to system-level metrics [4]. Essentially, he created a surrogate model that captured the variation of the responses with respect to the variability of the independent requirement (mission parameters), concept parameters, as well as technology variables. The surrogate model served as the basis for an interactive environment that allowed decision-makers to see the impact of small changes upon the design in real time. A generic example of the real time environment is shown in Figure 1.

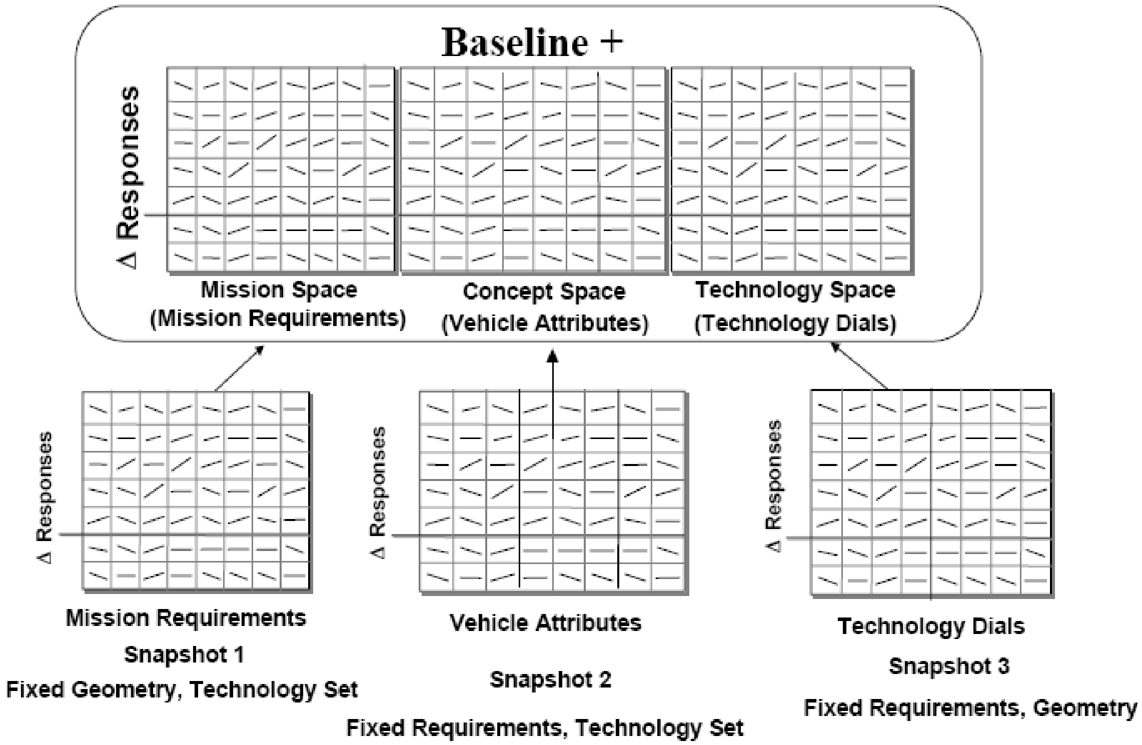


Figure 1: Unified Tradeoff Environment Example [4]

UTE is a noteworthy methodology because it gives decision-makers the capability to identify the sensitivity of system-level metrics to variations in requirements, vehicle attributes and technology. Unfortunately, because UTE relies on surrogate models, in requires that the system-level metrics are well behaved with respect to the variables and the variable ranges. Additionally, UTE requires the development of a surrogate model for each concept under consideration. Finally, UTE does not incorporate a systematic strategy to account for the variability in requirements in its analysis.

2.1.2.2 Joint Probability Decision Making

Bandte developed Joint Probability Decision Making (JPDM) as a decision-making methodology that uses the Probability of Success (POS) as a means of designing and evaluating a concept [5]. Instead of lumping all criteria together into one overall measure of goodness, JPDM allows decision-makers to evaluate the potential of a concept to meet multiple requirements simultaneously [5]. For each specific set of requirements, JPDM measures whether a specific design will be feasible (can satisfy all of the requirements simultaneously). A noise distribution is then placed upon the requirement variables, and Monte Carlo trials are used to calculate the likelihood that an alternative will be feasible. This likelihood is defined as the POS. POS, once calculated, can be used as a single, all-inclusive figure of merit to evaluate different designs. Because JPDM requires the use of thousands of Monte Carlo trials to accurately measure the POS, the analysis that calculates feasibility must not be too computationally exhaustive. Surrogate models can be used to relate the variation in system-level metrics to the variability of requirements and vehicle attributes.

JPDM is an effective methodology for evaluating technological systems, given an uncertain set of requirements, but it would be difficult to employ when evaluating advanced propulsion concepts for a HALE vehicle. First, a new model has to be created for each concept under consideration, which would be time-consuming. Additionally, JPDM does not incorporate a likely distribution of requirements into the assessment. Finally, JPDM's figure of merit, POS, does not capture the relative goodness of feasible alternatives. When two alternatives can satisfy a fixed set of requirements, one of those alternatives may still be superior to the other. POS does not capture the relative goodness of each alternative, only whether it is feasible. Even though two alternatives could have an approximately equivalent likelihood of being feasible, one alternative could be superior.

2.1.2.3 Technology Identification, Evaluation and Selection

The Technology Identification, Evaluation and Selection (TIES) methodology was created to give developers a systematic method of exploring complex design space, determining whether new technologies need to be developed, and identifying which technologies would be best suited to the design. TIES has been well documented by Kirby and Figure 2 shows an overview of the methodology [49]. In the first few steps of TIES, the problem solver strives to understand the problem fully [49]. This involves identifying the system-level requirements and the defining the concept parameters, or independent variables, that make up the design space are determined. Some of those variables are continuous, while others are discrete. Next, the developer sets up the system level analysis that will be use to prorogate the changes of design variables to system level metrics (response) [49].

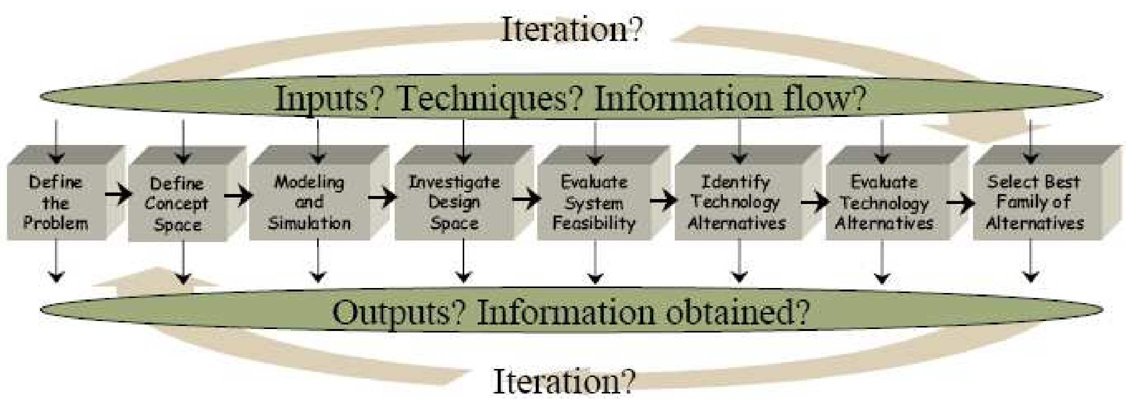


Figure 2: Overview of TIES Methodology [49]

In complex systems, the analysis will be exhaustive; consequently, statistical models that accurately capture the variation of the responses as functions of the variability of the independent variables are used to explore the design space thoroughly. Armed with the statistical model, the developer can determine, quickly and accurately, whether there is feasible design space with current, off the shelf, technology [50]. If that is the case, the problem is solved, as the developer can optimize the solution within the feasible design space using the optimization method of his choice.

In most complex problems, however, there is no feasible space, and technologies need to be considered to "open up" the design space and ensure that it contains feasible solutions [49]. If that is the case, potential technologies need to be identified, and their expected impacts on appropriate disciplinary metrics—or k-factors—need to be determined. Each technology essentially becomes characterized by a particular set of k-factors. At this point, a new statistical model is created to relate the system level metrics, or responses, to the k-factors [49]. The impact of infusing each technology can be determined in real time by generating a second statistical model that relates the variability of the system level metrics to the variation of the k-factors [62].

In order to model the infusion of multiple technologies to a design, the set of k-factors required to model each technology are added together. For example, consider two technologies, A and B. Technology A is expected to increase the efficiency and weight of the HPC by 2% and 5%, respectively, while Technology B is expected to increase the efficiency and weight of the HPC by 3% and 4%, respectively. If Technologies A and B are compatible, together they would increase the efficiency and weight of the HPC by 5% and 9% respectively. In TIES, multiple technologies are characterized by the sum of the k-factors that represent each technology contained in the set. The developer can quickly quantify the impact of infusing any set of technologies to the design space using the statistical model that relates the variation in system metrics to the variability of the k-factors. Armed with that information, the problem solvers can make informed and objective decisions as to which technologies to develop further.

Unfortunately, it would be difficult to use TIES to evaluate advanced propulsion concepts. First, it assumes an existing baseline concept. While the baseline concept is optimized, if the decision-maker originally considered an inferior concept, he or she would be stuck with the concept later on. Second, TIES best suited for evaluating the impact of evolutionary technologies, or technologies that are applied to an existing baseline. TIES can only model technologies that improve or degrade small parts of the existing system. It cannot model technologies that replace the system, or require the infusion of an entirely new system.

2.1.2.4 Summary of Quantitative Technology Forecasting Methods

None of the existing qualitative forecasting methods that were investigated was well suited for the evaluation of HALE propulsion concepts. The propulsion concepts under consideration are very immature. Little is known about the future performance of the advanced propulsion concepts, and consequently, the modeling and simulation environments that can be used to assess them are limited. Additionally, none of the methodologies systematically generates a distribution of requirements. JPDM and TIES quantify uncertainty with respect to noise distributions in the requirement and technology variables.

Additionally, none of the methodologies is suitable for comparing fundamentally different concepts to one another, given an uncertain set of requirements. UTE can be used to compare a small number of concepts to one another, but the need to create a surrogate model for each concept prohibits decision-makers from considering a large number of concepts. It would be difficult to use JPDM to evaluate a large number of concepts, as a surrogate model will have to be developed for each concept. Additionally, decision-makers could not use JPDM to compare feasible alternatives or concepts to one another. POS only measures whether an alternative is feasible—not how good a feasible alternative is. Finally, TIES is only suitable to evaluating technologies that incrementally improve existing systems—not technologies that replace existing systems.

2.2 Literature Search of Tools

The previous section overviewed methods that have been used to increase the amount of information decision-makers have to evaluate technological systems. Most of the methods discussed above enhance the information that is provided to decision-makers, but are not alone sufficient to differentiate between dissimilar concepts in the presence of uncertain requirements. The following section explores some tools that could be used to enhance the information that decision-makers have when comparing advanced propulsion concepts to one another.

The author first turned to an emerging field of research, entitled Technology Futures Analysis (TFA) [77]. TFA was an initiative to unite various forecasting methods aimed at predicting the impact of technology. The TFA methods discussed in this secton are broken into three categories. The first grouping of methods discussed below can be best described as brainstorming organization methods, as they organize and synthesize information from disciplinary experts. The second classification of methods discussed below can be used to forecast future states or conditions. These methods use information currently available, such as trends or expert opinion, and project that information to create a forecast of the future. The third classification of methods discussed in this paper are those which aid in decision-making, given a set of objectives.

Unfortunately, most TFA methods have not addressed the problem of analyzing and modeling the increasingly complex technological systems—an essential step to forecasting technology of the future. Consequently, this section also explores some mathematical and statistical techniques that can be used for this purpose. Exploration methodologies specifically examine methods aimed at introducing as much knowledge about the multi-dimensional space as efficiently as possible. Meta-modeling techniques look at surrogate models that can be used to reduce the computational time required to model technological concepts. Finally a few common stochastic optimizations are examined. These methods can be used to optimize multimodal spaces.

2.2.1 Gathering, Organizing & Synthesizing Information

The first group of TFA methods that are discussed aid in the synthesizing and organization of expert information or problem definition. These methods have been particularly valuable in the arena of systems engineering, where alternatives and requirements are too complex to be intuitively understood. They can be used directly to forecast the future, as sometimes is the case with Delphi, but they are usually used to identify alternatives, or understand requirements or relationships between requirements, alternatives, and potential scenarios.

2.2.1.1 Delphi Technique

The Delphi technique is a surveying method developed in the 1940s for military applications by the Rand Corporation [87]. Since it has been declassified, it has been widely used for technology forecasting [78]. In the same way that it has been used to forecast technology, it can be used to forecast the requirements that complex technological systems will eventually face. The Delphi technique surveys experts, usually through mail. The answers to the surveys are collected and analyzed. Participants are given feedback that includes the range of responses and rationales for various answers and then asked to answer the questions again, in light of the new information, but feedback allows the experts' opinion to remain anonymous [78]. The process repeats itself until the experts' opinions stabilize. Two aspects to the Delphi technique make it so successful. First, participation is usually anonymous, which prevents participants' egos from forcing them to continue to promote shaky arguments [78], [87]. Second, both statistical evaluations of the responses and rationales are fed back to the participants, allowing them to understand both the degree of difference in the group, and the arguments for various positions [87].

The Delphi technique is certainly not perfect. Carelessness in the preparation of the survey or feedback can make the technique less accurate. The iterative process is time consuming, and requires a fair number of participants [78]. Finally, the only way that the correlation between interdependent events can be accounted for is if the experts can account for it in their assessment [78]. The following technique attempts to capture experts' opinions, but also account for the joint probability of dependent events.

2.2.1.2 Morphological Analysis

Morphological analyses break a system down into its required parts, or subsystems. A morphological matrix is a chart that identifies all of the possible concepts or systems. It can be easily adapted to identify revolutionary alternative technologies. A morphological matrix is created by listing all of the required parts or subfunctions in one column [25]. For each part or subfunction, the alternatives are listed across that row [25]. A concept is made up of one unique set of alternates. Table 1 shows a morphological matrix for a shoe. The shoe is broken down into three parts, the sole, the upper material, and the fastener that keeps the shoe on the foot.

Table 1: Generic Morphological Chart

	Alternative 1	Alternative 2	Alternative 3
Sole Material	Rubber	Leather	Wood
Upper Material	Canvas	Leather	Nylon
Fastener	String	Velcro	Buckle

The morphological matrix is a technique that spurs creative thinking, but it also gives problem-solvers an understanding of how complex the problem actually is. The total number of concepts is equal to the product of all of the solutions to each part. For the shoe example shown in Table 1, there would be $3 \times 3 \times 3$ or 27, alternatives. Obviously, as a system is examined in greater detail or becomes more complex, the number of concepts grows exponentially.

The functional breakdown employed by morphological charts ensures that they are well suited to identifying advanced propulsion concepts. Advanced propulsion concepts usually consist of well-understood components—just assembled in a different manner. Table 2 is a simplified morphological chart that can be used to break down a propulsion system. This chart is by no means complete, but it serves as a simplified example of how morphological charts can be used to identify revolutionary technologies or concepts. Many advanced propulsion concepts are listed within the morphological chart, but not by name. In Table 2, most of the subfunctions are self-explanatory; thrust can be produced via either expanded exhaust, a propeller, acceleration of bypass air, or some combination of the previous three. Some of the other subfunctions, such as power source for thrust production, are less intuitive. This subfunction refers to the form of energy that is converted into thrust. For example, if a propeller is used to generate thrust, that propeller can be driven either by a motor, which uses electrical energy, or directly by shaft work potential. Even though the morphological chart displayed in Table 2 is simple, it contains 21,600 combinations of alternatives.

Table 2: Simplified Morphological Chart of Propulsion System

	(1)	(2)	(3)	(4)	(5)
Thrust Production	Propeller	Expand Exhaust	Bypass Air & Exhaust	Propeller & Exhaust	
Thrust Type	Distributed	Concentrated			
Energy Source	Hydrocarbon	Hydrogen	Nuclear Fuel	Solar	Stored Electrical Energy
Energy Extraction	Combustion	Fuel Cell Rxn	Nuclear Rxn	Photovoltaic Cell	Motor
Combustion Type	Steady (Constant Pressure)	Unsteady Detonation	Unsteady Deflagration	None	
Oxidizer Supply	On-board	Ambient	None		
Work Performed on Oxidizer	Compression	Heat Exchange	None		
Power Source for Thrust Production	Electricity	Shaft Work	Mechanical Nonequilibrium		

It is important to note that not all of the combinations of alternatives shown in the morphological chart would produce feasible solutions. For example, if energy is stored in the form of nuclear fuel, it cannot be extracted via combustion, and an oxidizer would not be required. In that case, the only feasible alternative for those subfunctions would be “None”. Each alternative consists of one combination of alternative for each subfunction. The selection of alternatives that make up the conventional turbofan engine are shown below in Table 3.

Table 3: Morphological Selection of Turbofan Engine

	(1)	(2)	(3)	(4)	(5)
Thrust Production	Propeller	Expand Exhaust	Bypass Air & Exhaust	Propeller & Exhaust	
Thrust Type	Distributed	Concentrated			
Energy Source	Hydrocarbon	Hydrogen	Nuclear Fuel	Solar	Stored Electrical Energy
Energy Extraction	Combustion	Fuel Cell Rxn	Nuclear Rxn	Photovoltaic Cell	Motor
Combustion Type	Steady (Constant Pressure)	Unsteady Detonation	Unsteady Deflagration	None	
Oxidizer Supply	On-board	Ambient	None		
Work Performed on Oxidizer	Compression	Heat Exchange	None		
Power Source for Thrust Production	Electricity	Shaft Work	Mechanical Nonequilibrium		

Another advanced propulsion concept that has generated much attention over the years is a Pulse Detonation Engine (PDE). The PDE is a relatively simple concept that uses detonation waves of combustion to add heat to the air and increase the pressure of the working fluid. Instead of producing a steady stream of thrust, the PDE produces a high frequency pulse of thrust. Table 4 shows the subfunction alternatives that make up the PDE.

Table 4: Morphological Selection of Pulse Detonation Engine

	(1)	(2)	(3)	(4)	(5)
Thrust Production	Propeller	Expand Exhaust	Bypass Air & Exhaust	Propeller & Exhaust	
Thrust Type	Distributed	Concentrated			
Energy Source	Hydrocarbon	Hydrogen	Nuclear Fuel	Solar	Stored Electrical Energy
Energy Extraction	Combustion	Fuel Cell Rxn	Nuclear Rxn	Photovoltaic Cell	Motor
Combustion Type	Steady (Constant Pressure)	Unsteady Detonation	Unsteady Deflagration	None	
Oxidizer Supply	On-board	Ambient	None		
Work Performed on Oxidizer	Compression	Heat Exchange	None		
Power Source for Thrust Production	Electricity	Shaft Work	Mechanical Nonequilibrium		

Morphological charts give developers a means of breaking the problem down functionally, so that the entire spectrum of solutions can be examined. The morphological chart does not give the developer the capability to identify new solutions to problems.

2.2.1.3 Future Wheels

A Future Wheel is another organized brainstorming technique. A trend, objective, or event is placed in the middle of a workable space. The primary consequences or impacts of that central objective or event are listed in a circle around the central objective or event, and are connected with "spokes". The secondary consequences or impacts, caused by the primary consequences, are then listed in a secondary circle around the primary circle. This growth continues, until all impacts are understood. Figure 3 shows a generic decision tree with two levels of impacts. Notice how the impacts circle the central event.

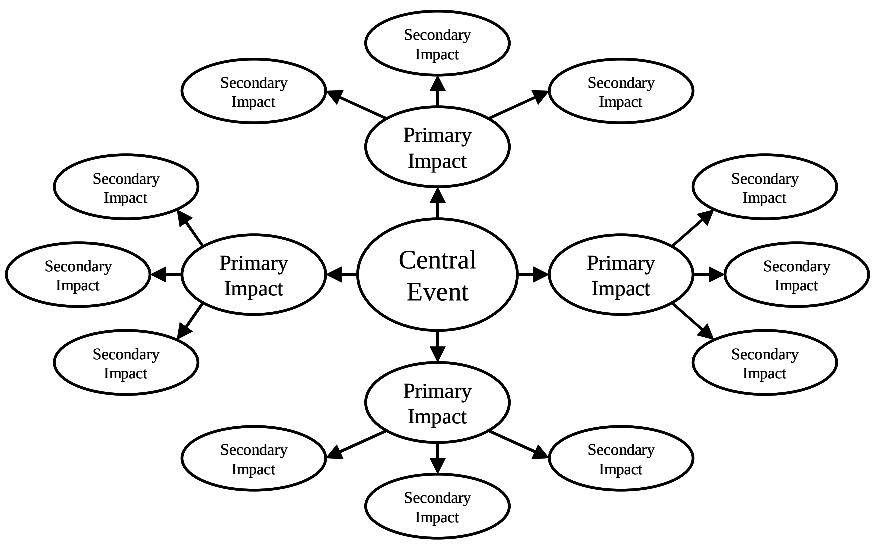


Figure 3: Generic Decision Tree

Future wheels have can be used for many different things. First, they can be used to identify possible consequences of trends or events in a logical fashion. For example, if a corporation is considering raising prices for one of their products, they could first identify all of the potential consequences of that price increase, such as alienating customers, and increased revenue per product. Secondary consequences would then also be identified. The corporation would be left with a logical understanding of all of the potential impacts of raising their prices.

Future wheels can also be used to forecast potential scenarios such as future markets. Future wheels can also be used to identify and understand complex relationships between systems or objectives. Basically, it is a method to organize brainstorming activity, so that potential impacts of a central theme, objective, or event can be better understood.

2.2.1.4 Relevance Trees

Relevance trees are a means for hierarchical decompositions of topics or states or objectives. They can be used simply to decompose a system or a topic into simpler topics or subsystems, or in conjunction with scenarios to identify possible paths to achieving scenarios or objectives. Relevance trees begin with imagining a state or objective, and then working backward to imagine all of the circumstances that could lead up to that the objective or state.

Relevance trees can be used to identify the subfunctions in a morphological matrix. They can also be used to identify possible paths that corporations may take to reach a certain end goal or objectives. They are another relatively simple tool that increases the decision-makers' understanding of problems at hand.

2.2.1.5 Scenario Approaches

The scenario approach consists of carefully constructing a set of potential future states, or scenarios. The potential scenarios and their ranges give decision-makers an understanding of what the future may have in store, but they also give an idea as to how uncertain the future actually is. Each scenario is created from a carefully crafted, logical set of events. Scenarios are an extremely popular tool for government planners, military analysts, and corporate decision-makers [65]. It is important to note that scenarios do not predict the future, but instead highlight potential futures for strategists [65].

There are different definitions of scenarios, as well, as differing views of what scenario approaches are. Some experts have defined scenarios as descriptions of future situations, which aid in moving forward to the future. Other experts define scenarios as narrative descriptions of potential states or developments. Scenarios are considered by some to be a tool that helps to clarify alternatives, while others consider it to offer foresight into the future.

Scenario approaches were first used by military strategists immediately after World War II. U.S. military imagined what opponents might do, and used those scenarios to plan possible alternative tactics. Scenario approaches also gained more notoriety in the early 1970s when Pierre Wack, a planner in the London offices of Royal Dutch/Shell, began to identify possible scenarios that would significantly drive oil prices up, such as the emerging power of OPEC. His group identified two possible scenarios: first, that oil prices remain stable and second that oil prices are driven up significantly by OPEC. His group also figured that in order for the former scenario to occur, something unexpected must happen, such as the discovery of new oil fields outside of Arab control [65]. The identification of the scenarios ultimately gave Shell a significant advantage over its competitors in the following oil crisis.

Numerous experts have proposed methodical approaches to building and using scenario techniques. A list of such methods was compiled by Mietzner and Reger, and it can be found in source [65]. First, the methods specify that information is gathered and clarified and that key issues are identified. Second, the driving foces and critical uncertainties are identified. Next, potential plots that lead to plausible alternative futures are fabricated. Finally, the key decisions or events that would guide the future in the direction of one scenario or another are identified.

Regardless of the various details of scenario approaches, they increase the information that decision-makers have. Decision-makers have an understanding of what the future might possibly look like, as well as a potential set of events that could have led up to those circumstances. The range of potential scenarios gives an idea of how uncertain the future is. Finally, the scenarios provide decision-makers with an environment that would allow them to identify decisions that might need to be made in the future and to test the effectiveness of those decisions under certain circumstances.

2.2.2 Forecasting Methods

Another set of TFA best fall into the category of forecasting techniques. These methods use the information available from historical trends and or expert opinion in conjunction with modeling and simulation to identify future scenarios and their likelihoods. Three forecasting methods are discussed below: time series estimation, cross impact analysis (CI), and Trend Impact Analysis (TIA). Plenty of other forecasting methods have been developed, to better understand or predict the future, such as Agent-Based Modeling (ABM). More information can be obtained on ABM methods in Gordon and Glenn from sources [38] and [34]. Time series estimation regresses the historical trends observed in metrics against one or more variables. Those trends are then extrapolated to predict future changes to the metric. The cross impact analysis (CI) method incorporates simulation and expert opinion to forecast the overall likelihood of events happening, given that the events are dependent upon one another. TIA is a modified trend extrapolation that takes expected impacts of future events into account. ABM is a modeling and simulation technique that yields a probabilistic forecast. Forecasting methods can be combined to obtain the best prediction of the future requirements for complex systems.

2.2.2.1 Time Series Estimation

Time series estimation is a sophisticated trend extrapolation. Variations exist within any observed trend. Time series forecasting distinguishes the systematic variation from the random variation. The systematic variation is then used to forecast the future value of the metric being forecasted. The systematic variations can be explained by seasonal effects, periodic cycles, random effects, or many other causes [66]. Simple historical trends and seasonal effects can be modeled using simple coefficients and seasonal dummy variables. Seasonal dummy variables are simple variables, set either to 0 or 1, to indicate which season it is. For example, if the model is broken into four seasons, four dummy variables would be required to specify which season it currently is. The values of the example dummy variables are below 24].

$$D_1 = (1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,\dots)$$
$$D_2 = (0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,\dots)$$
$$D_3 = (0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0,\dots)$$
$$D_4 = (0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1,\dots)$$

At time t=1 the setting for each of the dummy variables would be as follows: $D_{11} = 1$, while D_{21}, D_{31}, D_{41}, = 0. Statistical tools can be used in conjunction with historical data to determine the coefficients for the main independent variable, time, and the seasonal variables; the model can then be used to calculate metric *y*. A linear example of this model is shown in Equation 1 below for any time *t*., but the regression equation does not need to be linear; it could be quadratic, logarithmic, exponential, etc. The coefficients in Equation 1 are represented with β_1 and γ_i, where the former is the coefficient for the main independent variable and the later is the set of coefficients that correspond to the set of dummy variables. $\underline{y_t}$ is the metric that is being forecasted. Notice in Equation 1 that there is no intercept term. An intercept term would be redundant because a dummy variable exists for each season.

$$y_t = \beta_1 \mathrm{TIME}_t + \sum_{i=1}^{s} \gamma_i D_{it} + \varepsilon_{\mathrm{t}} \quad \textbf{(1)}^{\textbf{[24]}}$$

In Equation 1, the term ε_t shows the variation in the data that cannot be explained either through the main trend or through the seasonality. Time series forecasting attempts to identify the portion of that variation that is systematic and models it. Several statistical techniques have been used to model systematic variation, including moving averages, autoregressive functions, and multivariate analyses. Statistical software packages, such as JMP, a product of the SAS Institute, can aid in the regressions.

Regression analysis is a particular form of time series forecasting, where the metric is regressed against one or more exploratory variables instead of time. In a similar manner as above, historical data that relates the metric to the independent variables is collected and regressed against the historical variables. The curve fit that best approximates the trend is used to model the metric. Statistical software packages can again be used to aid in the regression. Regression analyses can be highly accurate because they include a degree of causality. The problem with using them to forecast future values of metrics is that they can only be effective if the user is capable of forecasting the values of the explanatory variables with a degree of accuracy.

2.2.2.2 Cross Impact Analysis

Cross Impact (CI) analysis integrates expert opinion with Monte Carlo simulation to identify a probabilistic forecast. First developed in 1966, it has been widely used in various fields to forecast probabilities associated with future events happening [43], [78]. The key to the CI analysis is that it allows analysts to capture the dependencies of possible future events upon one another, without a rigorous, physics-based analysis.

CI accounts for the dependencies by recording the conditional probability of each event occurring, given that each other event did or did not occur. The probability that an event occurs is the likelihood that the event will occur; the probability of event A occurring is written as P(A). The conditional probability is the probability that one event, will occur, given that another event did occur. This conditional probability of event A occurring given that event B did occur is written as $P(A | B)$. CI analyses ask experts to estimate both the probability of events occurring and the conditional probability of each set of events occurring. Estimating the overall probability that an event will occur is difficult for experts because they must take its dependency upon all other events into account. Estimating the conditional probability, however, is a simpler problem for experts. The CI analysis, then, is advantageous because the importance of the estimated probability is reduced.

The CI formulates a forecast by both the expert-estimated probability and expert-estimated conditional probability. In order to do so, the probabilities and conditional probabilities must be estimated for each event. Consider an example with three events, labeled A, B and C. The initial probability estimates are shown in Table 5 below.

Table 5: Marginal Probabilities for Events A-C

Event	P(Event)
A	P(A)
B	P(B)
C	P(C)

The conditional probability for each event is shown in Table 6. The probability in each cell is the probability that the event row will occur, given that the event column did occur. For example, the cell that intersects column A with row B is the conditional probability that event B occurs, given that event A did occur. Notice that the values along the diagonals are all equal to one. This is because the probability of an event occurring, given that the event did occur, is 100%.

Table 6: Conditional Probabilities for Events A-C

	A	B	C
A	1	P (A | B)	P (A | C)
B	P (B | A)	1	P (B | C)
C	P (C | A)	P (C | B)	1

CI also requires that experts forecast the negative conditional probability. These values are the likelihood that an event will occur, given that another event did NOT occur. Table 7 records the negative conditional probabilities.

Table 7: Negative Conditional Probabilities for Events A-C

	A	B	C
$\overline{A}$	0	P (A | $\overline{B}$)	P (A | $\overline{C}$)
$\overline{B}$	P (B | $\overline{A}$)	0	P (B | $\overline{C}$)
$\overline{C}$	P (C | $\overline{A}$)	P (C | $\overline{B}$)	0

Notice in Table 7 that the negative conditional probabilities are all zero along the diagonals. This simply shows that the $P(A \mid \overline{A})$ must be 0, meaning that A must not occur, given that A did not occur.

After the required information in Table 5, Table 6, and Table 7 is obtained, a Monte Carlo simulation is used to estimate the probability of different scenarios occurring. In each simulation, one event is chosen at random, and whether or not it "occurred" is determined probabilistically, based on the initially guessed marginal probability. If that event is chosen to occur, the probability of the remaining events occurring then becomes the conditional probability, given that the first event did occur. If the first event was chosen *not* to occur, the probability of each of the remaining events happening is replaced with the negative conditional probability, or the conditional probability of the event happening, given that the first event did *not* occur. Each of the remaining events is considered in a similar manner, in a random order. Each simulation trial will produce one scenario. For a further explanation of the Monte Carlo trials, see source 3. Thousands of trials will yield a distribution of scenarios that reflect the integration of expert opinion of both individual probabilities and conditional probabilities.

CI breaks the future down into a series of events that may happen one-at-a-time. Each event can happen only once. In order to handle events that might occur multiple times, the subsequent occurrences of an event needs to be considered multiple events. For example, if finding a new source of oil reserves is one possible event and the decision maker wants to consider the possibility of finding multiple new sources of oil reserves, event A could be finding a first new reserve source. A second event, B, could be finding the second set of reserves. Obviously, in this case, event B could only happen once event A has already happened. In that case, the conditional probability of event A given event B would be 1, and the conditional probability of event B given that event A had not happened would be zero.

As stated above, CI integrates the expert-estimated marginal and conditional probabilities, as it is unlikely that those values would initially match up for any set of events. The values for conditional probabilities are bound by the laws that govern conditional probabilities, i.e., there are maximum and minimal acceptable values for conditional probabilities given the marginal probabilities of both events. If the expert-predicted conditional probability falls into the acceptable range, given the expert-predicted marginal probabilities, they are accepted. If not, a decision needs to be made to accept or not accept the conditional probability. If there is strong evidence for the conditional probability value being outside of the acceptable range, it is accepted, and the marginal probabilities will be changed later to reflect the difference. Bayes' rule can also be used to ensure that the probability of event A given event B, $P(A \mid B)$, and the probability of event B, given event A, P(B | A), are correctly related. Bayes' rule is shown below in Equation 2.

$$P(A \mid B) = \left(\frac{P(B \mid A)}{P(B)} \right) P(A) \tag{2}$$

Where: P(A) = probability of A

P(B) = probability of B

P(A | B) = probability of A given B

After the conditional probabilities are computed, the negative conditional probabilities need to be determined. These can be calculated directly from the conditional probabilities, as shown below in Equation 3.

$$P(A \mid \overline{B}) = \left(\frac{1 - P(B \mid A)}{1 - P(B)} \right) P(A) \tag{3}$$

As was mentioned earlier, if the conditional probabilities do not all fall into the acceptable ranges some sort of iteration scheme is going to be needed to ensure that the marginal probabilities and the conditional probabilities are consistent.

Traditionally, CI uses a Monte Carlo simulation to estimate the marginal probabilities. The process for using a Monte Carlo Simulation to determine the marginal probabilities is outlined below. Porter further detailed this process in *Forecasting and Management of Technology* [78].

1) Select one of the events at random (Event i)
2) Determine whether that event occurs or does not occur (using a random number generator—i will occur P(i) percent of the time).
3) Select a second event (Event j) from the remaining events, and determine whether that event occurs or not.

   If i occurred, P(j) = P (j | i); otherwise, P(j) = P(j | $\bar{i}$)

4) Steps 1-3 are repeated until all events have been selected

5) Record whether event i and event j occurred, and repeat steps 1-4, as a Monte Carlo simulation typically does.

The CI calculated marginal probability of each event occurring is the ratio of the number of times the event occurred in each trial divided by the total number of trials. Once completed, CI yields a probabilistic estimate of the probability of each event occurring.

2.2.2.3 Trend Impact Analysis

Trend Impact Analysis (TIA) uses past trends to predict the future, as do time-series forecasting methods. Unlike time-series forecasting methods, however, TIA accounts for the impacts of potential future events upon the future trends. Potential future events are considered interruptions, and experts help analysts forecast the impact of the interruptions on the trends, thus forecasting the impacts of the interruptions on the outputs.

The first step to TIA is creating an uninterrupted forecast of the variable of interest, using time series forecasting. A curve is fitted to historical data and that curve is used to predict the future value of the variable. Time-series forecasting is discussed in section 2.2.2.1. That prediction represents the uninterrupted forecast, meaning the expected future value of the variable, given no future events impact that trend. The second step of TIA is to identify a set of events that would impact those trends, and predict the impact that those events would have. Parameters that dictate the time and degree to which a future event will impact the expected trends must be identified or predicted. Specifically, the expected time that the event will initially impact the trend, the time that the maximum impact will occur, and the time that the steady-state impact will begin all need to be calculated. In addition to those times, the maximum impact to the trend and the steady-state impact must be assessed. Figure 4 shows a generic impact to a trend, in percentage of the trend. In this figure, the maximum impact is positive, meaning that event increases the value or amount of the variable, but the long-term impact actually is negative to value of amount of the variable.

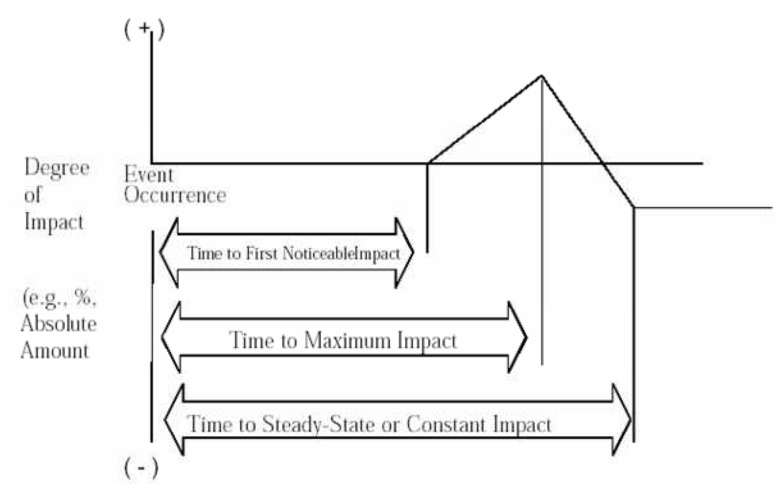


Figure 4: Typical Event Impact Parameters [35]

The impact shown in Figure 4 could follow the price of a product, in the event that something disrupted the supply of that product. In the short term, the prices would increase, as supply is reduced, but ultimately, the demand is decreased, and prices are reduced in the long-term.

After the uninterrupted, time-series forecast is created and the impacts of future events are forecasted, computer programs combines them to identify an adjusted extrapolation. The effect of different potential events can be calculated alone, independently, or the events can be coupled. The expected value of the forecasted variable is tracked by summing up the potential future values and their probabilities. The combined variance is also tracked, and certainty percentiles can be placed on the variables.

TIA allows decision-makers to use historical trends intelligently to predict the future value of variables. Like any forecast, it is dependent upon the assumptions that go into calculating it. TIA can only predict the impact of events that can be ***foreseen***.

2.2.3 Decision Making Methods

Decision-makers have developed many methodologies to evaluate and select the best alternatives, given a set of objectives or criteria. These methods are often referred to as Multi-Attribute Decision Making (MADM) techniques. MADM techniques were investigated as a means of evaluating the advanced propulsion concepts given the multiple criteria.

The first MADM technique reviewed is commonly referred to as the Overall Evaluation Criterion (OEC) equation. An OEC gives decision-makers a single measure by which to compare the overall goodness of various alternatives. Each alternative's ability to meat each criterion is measured relative to some baseline. Each criterion is weighted appropriately relative to the other criteria. Finally, the values for each criterion are summed to form one, single measure of goodness for each alternative. Equation 4 shows a hypothetical OEC for Alternative *i*, relative to a baseline. The β term represents the weighting on each term. In Equation 4, all of the objectives should be maximized.

$$\mathrm{OEC}_{Alt.\,i} = \beta_1 \frac{\mathrm{Objective}_{1,Alt.\,i}}{\mathrm{Objective}_{1,Baseline}} + \beta_2 \frac{\mathrm{Objective}_{2,Alt.\,i}}{\mathrm{Objective}_{2,Baseline}} + ...\beta_n \frac{\mathrm{Objective}_{n,Alt.\,i}}{\mathrm{Objective}_{n,Baseline}} \qquad (4)$$

If an objective is to be minimized, the terms for that objective would be the inverse of what is shown in Equation 4. If instead it is desirable to exactly meet a target, the absolute value of the relative difference of the alternative's value to the target could be used in place of the terms shown. OEC equations are simple, but effect measures from which to compare various alternatives.

Another MADM tool for ranking alternatives is the Technique for Ordered Preference by Similarity to the Ideal Solution (TOPSIS). TOPSIS normalizes all of the metrics that measure the alternatives ability to meet each objective [44]. A positive ideal solution that has the best attributes from each of the alternatives is created, and a negative ideal solution that has the worst attributes from each of the alternatives is created. Each of those normalized metrics is then weighted based on the relative importance of the objective. The Euclidean distance of each alternative from to the positive and negative ideals is calculated, and the alternatives are ranked based on those distances. The closer an alternative is to the positive ideal and farther away it is from the negative ideal, the better its ranking.

TOPSIS and the OEC techniques are both heavily dependent upon the weightings that are given to the objectives. Those weightings are subjective. While decision-makers can choose the weightings, another MADM tool, Analytic Hierarchy Process (AHP), can calculate those weightings [86]. In AHP, the importance of each objective is ranked relative to all of the other objectives, on a scale of 1 to 9. A matrix is created that contains all of the relative rankings. The matrix is then normalized, and the average value of the row in the normalized matrix is used as the ranking for that objective.

2.2.4 Exploration Techniques

Complex design spaces can be explored by simply sampling portions of the space. Before those techniques are discussed, it makes sense to explain a few terms. Design space can be defined as the entire set of possible alternatives. In a more mathematical sense, it is the entire multidimensional range of independent variables. The variables can be either continuous or discrete. A response is the output of the analysis for a unique design variable setting, or alternative. The responses' values are ultimately what the decision-maker is interested in finding out about the design space.

The sampling techniques will produce a set of results, along with the input variables that produced those results. The sampling can be done at regular intervals, deterministically, or it can be random and probabilistic. Intelligent, predefined design space explorations, or Designs of Experiments, can be used to obtain all of the required information about the design space, while running the fewest cases, or samples possible [68]. Design space sampling can be used simply to understand the design space, perform ad hoc optimizations, or forecast distributions of output responses.

2.2.4.1 Grid and Random Searches

Grid searches are the most basic and thorough explorations of design space through sampling. Each dimension of the space is divided up into regular intervals and the outputs are calculated for every possible combination of those variable settings. Grid searches got their name because if used in a two-dimensional space, the points that must be tested form a grid. Simple grid searches provide decision-makers with a quick, but thorough understanding of the space. The problem with grid searches is that thorough explorations require fine grids, and the number of cases to be analyzed increase exponentially as the dimensions of the problem increase.

Grid searches can serve as the basis for ad hoc optimization methods. Initially, the space is divided into a coarse grid, and the prescribed points are tested. From the initial grid search, the decision maker identifies areas of the design space where the optimal solution is likely to exist. Finer grids are drawn in those areas, and the process repeats itself. The optimization continues until the decision-maker is content with the resolution of the optimization.

Instead of searching the design space rigidly with a grid, random searches can be used. In random searches, the values for the independent variables that are sampled are determined randomly. Random searches produce a good sampling of the design space, and require little overhead to set up. The understanding of the design space that is explored is purely tied to how many points are examined in the random search. Searches can easily be tailored to the number of designs being examined.

2.2.4.2 Design of Experiments

A DoE is a prescribed set of experiments that will yield enough information about the design space to data to ensure that the variability of the responses can be properly correlated to the variation of the input parameters [68]. The inputs to the DoE are orthogonal to ensure that the effects of each term the experimenter is regressing against are not correlated with one another. In the case of analyzing complex systems, a computer simulation is run in the place of conducting an experiment. Using a DoE to identify the "experiments" to be conducted via simulation allows decision-makers to create meta-models more efficiently.

There are several different classes of DoEs; each provides varying amounts of information about different parts of the design space. As the number of experiments that the DoE requires increases, the fidelity of the subsequently generated RSE will increase as well. It should be noted, however, that the meta-model could still have a poor fit if the analysis does not behave as the meta-model predicted. A full factorial DoE, an experiment in which every combination of discrete variables is tested, would be the most complete experiment possible, and would produce the highest fidelity meta-model. A full factorial DoE would capture all possible interactions between all of the variables. Such a DoE, however, usually requires too many test cases to be practical. For an experiment that investigates the impact n variables, each variable has i discrete settings, requires i^n test cases. If there were 12 variables, each with 3 settings, 531,441 cases would need to be run.

As the number of experiments in a DoE is reduced, the fidelity of the meta-model produced will decrease. Box-Behnken Designs, and Central Composite Designs (CCD) are just two DoEs developed to reduce the number of simulations that are required to be run [49]. These DoE methods reduce the number of simulations for 12 variables, each consisting of 3 settings, from 531,441 in a full factorial to 2,187 and 4,121, respectively. Additional information about these DoEs can be found in Empirical Model-Building and Response Surfaces [49], [10]. It should be noted that the fidelity of the meta-model varies throughout the design space. DoEs that examine fewer cases at the interior of the design space yield RSEs with lower accuracy throughout the interior, while DoEs that concentrate more of the cases in the interior of the design space may produce RSEs that are less accurate throughout the space, but do not rely upon extrapolation as much for the extreme boundaries of the space.

2.2.4.3 Monte Carlo Techniques

Monte Carlo techniques are random samplings designed to simulate reality. They use computational simulations to determine the distribution of computer outputs, or responses, experimentally. For each simulation, the independent variable inputs are generated randomly from a predetermined distribution, designed to reflect the actual distribution of the inputs. For a large number of simulations, the distribution of the output responses can be found with a high degree of accuracy.

Monte Carlo techniques are not traditionally used for optimization, but for exploration. The simplest version of a Monte Carlo technique is a random sampling. In order to produce a random sampling, a uniform distribution is used to generate each independent variable for each case that is simulated. The final set of cases should uniformly reflect the entire design space. Random samplings are similar to grid samplings, but the points are randomly chosen and not discretely dispersed throughout the design space.

Monte Carlo simulations allow decision-makers to calculate the distribution of probabilistic outputs based on assumed distributions of probabilistic inputs. This simulation is ideal for quantifying the uncertainty inherent to any analysis. Cumulative Distribution Functions (CDFs) of the outputs, or integrals of the probability density function, quantify the probability of meeting characteristic requirement constraints. Monte Carlo simulations can also be used to identify regions of multidimensional space. For example, if uniform distributions are placed on all of the independent variables, the percentage of the designs that meet multiple constraints or requirements simultaneously can easily be determined.

Because Monte Carlo techniques require a large number of test cases, or simulations, to portray the distribution of responses accurately, they are difficult to employ with complex analyses. For this reason, they are frequently used in conjunction with RSEs or other meta-modeling techniques. Thousands of cases can be run when the analysis consists only of simple equations, yielding a good estimate of the probability distribution of the response.

2.2.5 Meta-models

As technological systems become more and more complex, the analyses needed to evaluate these systems likewise become more and more complex. Design spaces cannot be fully explored, because analyzing each alternative within the design space is simply too time consuming. Fortunately, several methods have been developed over the years to tackle the problem of evaluating large sets of complex systems. The simplest means of handling these problems is to first develop a meta-model of the complex analysis, and thoroughly explore the entire design space using the simplified meta-model. The development of the meta-model is discussed below. Two meta-modeling techniques are described below.

2.2.5.1 Response Surface Equations

The most commonly employed meta-model is a Response Surface Equations (RSE), or a quadratic regression of a complex model. RSEs are essentially simplified models of more complex analyses, or meta-models. They capture the dependencies of responses, or output metrics, to the independent variables, or input parameters [49]. RSEs are created by regressing the responses against the independent variables of interest. Once an RSE is created, it can be used in place of time consuming, complex analyses. While a quadratic RSE is most often used, the RSE can be linear, include higher order terms, or not be quadratic at all. A quadratic RSE is shown below:

$$R = b_o + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ji} x_i x_j + \varepsilon$$

Where: R = Response
b_o = intercept term
b_i = 1st order coefficient
b_{ii} = 2nd order coefficient
b_{ij} = interaction coefficient
x_i = independent variable

The creation of RSEs has been greatly aided by the development of DoEs. There are a few limitations to RSE meta-models to represent the design space. First, the number of independent variables that can be considered is limited. Although DoEs can be and have been designed for large sets of variables (100 variables), they become more difficult to come by, and often have to be generated specifically for the intended purpose. Second, and perhaps even more limiting, is the notion that the design space represented by RSEs must be smooth, continuous, and well behaved. As the range of variables considered in the design space increases, and the responses behave less linearly, meta-models usually lose their ability to capture the variability of the response as a function of the variation of the independent variables accurately. Finally, RSEs simply cannot model discontinuous space.

Once RSEs have been generated, they offer the decision maker the ability to conduct a plethora of analyses. First, they can be used to quantify the sensitivity of the responses to the independent variables in the. Often in highly coupled, complex analyses, that sensitivity is a function of the other variable settings and cannot be determined intuitively. Second, the RSEs can be used in place of the complicated analysis for the purpose of optimization. Because the RSEs provide direct and simple equations to represent each response, straightforward mathematical optimizations can used to find optimized design settings. Finally, RSEs can be used in conjunction with Monte Carlo techniques (discussed below) to generate distributions of outputs based on assumed distributions of inputs.

2.2.5.2 Artificial Neural Networks

Another type of meta-model that is quickly gaining popularity for its ability to model non-linear spaces is the artificial neural network [47]. Artificial neural networks are mathematical models that were inspired the biological neural network that connects neurons in the nervous system.

Artificial neural networks are actually simple mathematical models. They define a function $f : X \rightarrow Y$. The function f actually represents a composition of functions $g_i(x)$, which can also be further decomposed into a network structure, as is shown in Figure 5 [99]. In this form, the output F is ultimately a function only of X, because $\mathrm{F} = f(\mathrm{G})$, $\mathrm{G} = g(\mathrm{H})$, and $\mathrm{H} = h(\mathrm{X})$.

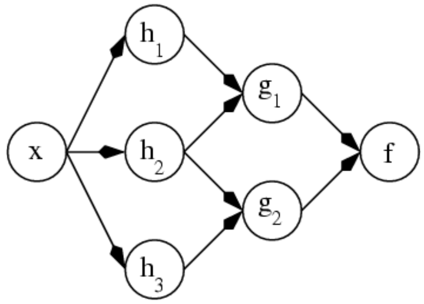


Figure 5: Generic Artificial Neural Network Dependency [99]

There are multiple types of Neural Networks, and they vary in their complexity and ability to model various nonlinear functions [47]. They can provide a basis for the creation of meta-models, and they can even be used to optimize functions.

2.2.6 Stochastic Optimizations

Stochastic optimizations consist of probabilistic solutions that successively improve from generation to generation. They usually attempt to mimic real development or improvement processes, such as evolution. Two stochastic optimization methods are discussed below: simulated annealing and genetic algorithms.

2.2.6.1 Simulated Annealing

Simulated annealing is a sophisticated stochastic optimization aimed at finding an optimal solution within a multimodal design space. Annealing is the processes of heating metal and then cooling it slowly. When the metal is hot, it is very pliable, and can be shaped easily. As the metal cools, however, it becomes more rigid, and less pliable. Simulated annealing has been developed especially to handle multimodal spaces, as the design points can move from good points to worse points when the temperature is hot, or the process is just beginning, to escape potentially local, but inferior minima.

Simulated annealing was proposed by Kirpatrick as an optimization routine meant to mimic the real process of annealing in 1983 [52]. Points within the space are selected at random to be the design points, and the objective function is calculated for the design point. A small step is taken in a random direction away from the design point, and the objective function is tested at the new point. If the objective function of the new point, or offspring, is better than the objective function for the design point, or parent, the design point moves to the new point. Essentially, the offspring survives, and kills off the parent. If the objective function for the offspring is worse than that of the parent, usually the parent will survive over the offspring, but there is still a chance that the offspring will survive. In that case, the probability that the offspring survives decreases as the gap between the parent' function value and the offspring' function value widens.

Figure 6 depicts a hypothetical multimodal function in one-dimensional space that is to be minimized. Two initial points were selected at random.

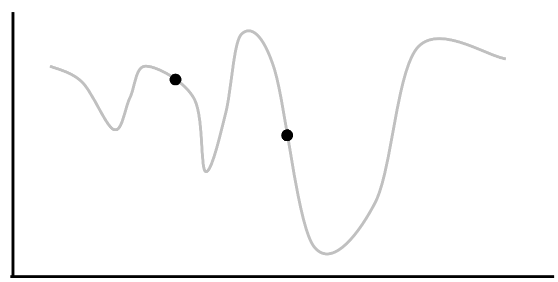


Figure 6: Hypothetical Multimodal Objective Function

Notice that the objective function in Figure 6 has three local minima. Figure 7 shows the movement from the originally selected two points to the two new points. Notice that one of the points is actually worse than the original, while the other point is better. Because it is early in the process—the first iteration—and the offspring is not significantly worse than the parent, it is likely that the offspring will survive and the design point will shift from the original point to the new point. For the second set of points, the offspring is lower, or better, than the original point, so the offspring will definitely survive, and the design point will shift.

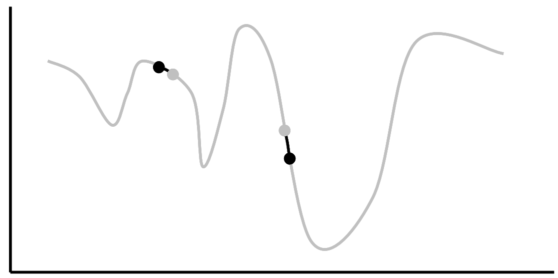


Figure 7: Initial Iteration of Simulated Annealing on Hypothetical Multimodal Objective Function

The process described above continues for several iterations. Eventually, after several iterations, each of the design points will likely settle into local minima. This process is shown in Figure 8.

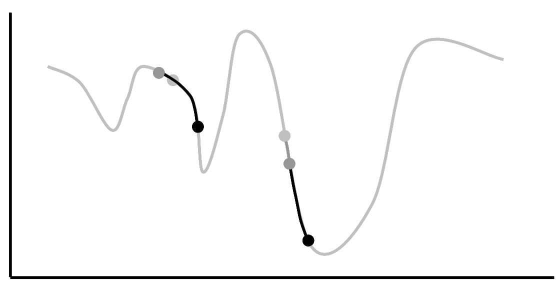


Figure 8: Progression of Simulated Annealing on Hypothetical Multimodal Objective Function

Complex optimization schemes, such as simulated annealing, are only used when the actual objective function cannot be quantitatively visualized. If the decision maker truly understood the shape of the objective function, optimization techniques would not be required. Unfortunately, decision–makers cannot use a convergence tolerance to identify whether stochastic optimizers are approaching the global minimum. The global minimum is unknown, and the optimal solution found in stochastic optimization will not improve continuously throughout successive iterations. Tens or hundreds of iterations can take place with no improvement over the best design of the set, and then suddenly, a new, “optimal” design point can emerge. For this reason, decision-makers usually run as many simulated annealing trials as the decision maker can afford to run.

2.2.6.2 Genetic Algorithms

Optimization schemes that simulate the process of evolution by natural selection have generated much attention lately and have emerged as promising new techniques for handling multimodal spaces. As simulated annealing mimics the real process of annealing, genetic algorithms attempt to mimic the process of biological evolution.

The theory behind genetic algorithms is that the "fittest" solutions in a gene pool will survive each generation. "Fitness" in this case is directly related to the object function and is greater for solutions closer to the global maximum (or minimum for functions that are minimized). Initially the pool consists of randomly selected solutions, or alternatives, but it "evolves" into a better pool through time. Throughout each successive generation, the pool members are mutated, crossed with themselves, and reproduced selectively. These processes allow the overall fitness of the pool to improve.

The concept driving genetic algorithms is simple, but the actual implementation of genetic algorithms can vary substantially. Each independent variable required to define a solution is discretized into settings. Each setting is represented by a binary number. The binary numbers that reflect the setting for each independent variable are combined into one long, binary string. The pool, then, is the set of binary strings that each define one solution or alternative. In mutation, part of the binary string, or genetic makeup of some of the pool members is altered. A zero switches to a one, or a one becomes a zero. As the process advances, pools can head toward homogeneousness. Mutations ensure that there will be some diversity among the pool. When pool members are crossed with one another, portions of the string from one pool member is switched with the same portion of binary string from a second pool member. As the pool advances and becomes more homogenous, the impacts of crossover will become less and less evident. Selective reproduction can be completed in a number of ways. A "tournament selection" pairs pool members up randomly, and takes the best of the alternatives as the next generation pool member. Proportional replacement is a deterministic reproduction method that uses a formula to determine the percentage of the next generation pool that will be made up each pool member. The proportional replacement formula is shown below.

$$N_i = \mathrm{N}_p \frac{F_i}{\sum F_i} \qquad \text{where} \quad \begin{array}{l} F_i = F(\overline{\mathrm{x}}_\mathrm{i}) \text{ if } F \text{ is to be maximized} \\ F_i = 1 \big/ F(\overline{\mathrm{x}}_\mathrm{i}) \text{ if } F \text{ is to be minimized} \\ \mathrm{N_p} = \text{Pool Size} \\ \mathrm{N_i} = \text{Number of "i" solutions in next generation pool} \end{array}$$

N_i needs to be rounded, as it will not usually end up as a whole number. Additionally, the sum of all of the N_i's does not necessarily add up to N_P. If this is the case, either some of the designs that should be included in the next generation will not be, or additional pool members will have to be added to the pool, to ensure that the number in the pool is held constant. While there is no single best optimization algorithm, genetic algorithms have been shown to be effective for a wide range of problems [64].

3 HYPOTHESES & RESEARCH QUESTIONS

The following chapter discusses ten research questions that emerged while attempting to evaluate and compare advanced propulsion concepts. The discussion that follows the questions investigate the answers to those questions. The answers to each question lead or partially lead up to one of four hypotheses, listed below. Hypothesis I is the main hypothesis that sets up the requirements for the Evolving Requirement Technology Assessment (ERTA) methodology. The remaining hypotheses laid the foundation for the ERTA methodology.

> **Hypothesis I:** Any method designed to evaluate advanced propulsion concepts must incorporate the possible variations of the requirements into the assessment.

> **Hypothesis II:** Shape functions depicting distributions of future requirements can be defined using traditional, forecasting techniques.

> **Hypothesis III:** "Fitness", a technological concept's ability to meet a set of requirements relative to other potential concepts, can be used to forecast an advanced propulsion concept's likelihood of successful development.

Hypothesis IV: Stochastic optimizations can be used to calculate fitness as a function of requirements, enhancing decision-makers' understanding of future technological concepts.

3.1 Hypothesis I

In order to identify the propulsion concept best suited to propelling the HALE vehicle, the vehicle system and mission requirements must be known. Given those parameters, analyses can be conducted to evaluate each concept, and decision-making tools can be used to select the concept that is best overall. Unfortunately, the values of those parameters that are used to evaluate each concept are uncertain. How sensitive is the comparison of each concept to the potential variations in those requirements? Would the decision-makers come to a different conclusion if the requirements were only slightly perturbed? These observations and questions are formalized by the research question below.

3.1.1 Research Questions

1) Does the uncertainty inherent to the requirements for technological concepts significantly impact the goodness of advanced propulsion concepts?
    - The impact that uncertainty in the requirements has on the goodness of propulsion concepts is a function of how greatly the requirements will vary. If the propulsion concepts require only a short development period, changes in requirements will be minor, and the evaluation of the concept will not be impacted. If, on the other hand, the development will span across years, the requirements for the concept could vary significantly, and the concept's ability to meet the requirements could diminish.

2) Should the uncertainty in the requirements for advanced propulsion concepts be incorporated into the evaluation of technological concepts?

    - The uncertainty inherent to the requirements should only be taken into account if there is a good chance that the requirements will deviate significantly from their original expectations. Otherwise, the impact of requirements' variation will be negligible. Advanced propulsion concepts will require years to develop, and the requirements for such concepts could vary dramatically.

3.1.2 Hypothesis Statement

Any method designed to evaluate advanced propulsion concepts must incorporate the possible variations of the requirements into the assessment.

The goodness of advanced propulsion concepts can only be measured relative to the concepts' abilities to meet the requirements for the system. Because advanced propulsion concepts require a significant amount of time and resources to be fully developed, the requirements that they are developed to meet can significantly change during the development phase. As the requirements change, so too might the potential worth of any advanced propulsion concept.

Requirements can change, new requirements can be created, or the relative importance of individual requirements can fluctuate. Consider the design of a propulsion system designed for a civilian aircraft. If jets are allowed to travel supersonically over land, or if the aerodynamics discipline develops an aircraft shape that produces a low enough overhead pressure to allow for supersonic flight over land, the goodness of any engine is going to be significantly impacted. Simply changing the relative importance of individual requirements can impact the goodness of advanced propulsion concepts.

While resources may be devoted to developing many advanced propulsion concepts, the concepts that ultimately “survive” to become viable operating systems are the concepts that are most robustly capable of meeting the evolving set of requirements. Whether the changes in requirements stem from government policy changes, market forces, or enabling technology capability, they will significantly impact the worth, or potential goodness, of future systems. Throughout development, changes in requirements could make advanced propulsion concepts obsolete before they are even fully developed.

There are numerous examples of technologies becoming obsolete before they ever had a chance to make it to the market within aeropropulsion systems alone. Consider the example of the nuclear jet engine or the unducted fan (UDF). While the testing and development of the nuclear jet went fairly well, perception of nuclear power and the requirements for such a large system changed throughout the development cycle. The program was dropped entirely. Unfortunately for the UDF, fuel prices returned to normalcy, and the requirement for fuel-efficient engines no longer superseded the need for quiet engines.

In order to capture the variation of requirements into the assessment of advanced propulsion concepts, two things need to be done. First, a probabilistic distribution of the requirements needs to be identified. The impact of uncertainty of requirements cannot truly be accounted for unless the uncertainty in the requirements itself is understood. Second, decision-makers must develop the ability to assess the robustness of the propulsion concepts as a function of that distribution. The remaining research questions were developed while attempting to find a means of forecasting a distribution of the requirements, and evaluating the concepts, given that distribution of the requirements.

3.2 Hypothesis II

Once the impact of the evolution of requirements upon the selection of advanced propulsion concepts is established, a probabilistic understanding of the likely future requirements must be developed. Identifying a probabilistic distribution for those requirements is a sufficient means for means of quantifying uncertainty at the early phases of technology forecasting. Identifying such a distribution, however, is not trivial. The following questions arose when attempting to develop a probabilistic distribution of the requirements.

3.2.1 Research Questions

3) How can the evolution of requirements for complex systems be predicted?

    - Forecasting techniques have been developed and used for years in a variety of fields. Technology Futures Analysis (TFA) is an initiative aimed at organizing the research to advance such methods. There are several types of these methods, ranging from expert-opinion based methodologies to complex, sophisticated modeling and simulation based methodologies. A few of these methods are discussed below.
        - Requirements can be directly forecasted using expert opinion. The Delphi Technique is one example of methodology that could use expert opinion to forecast requirements directly. It is tailored toward sampling expert opinion from a wide range of experts. It was discussed in section 2.2.1.1.
        - Trend extrapolation can be use to project historical trends into the future to predict the value of particular requirements. Time-series estimation is a good example of a trend extrapolation. It was discussed in section 2.2.2.1.

- Scenario approaches can also be used to identify a few key scenarios. The divergence of the performances of the concepts under each of the key scenarios can eventually be used to understand the uncertainty associated with the various concepts. Scenario approaches are discussed in section 2.2.1.5.

4) How can the interdependent nature of the individual requirements be captured?
   - Requirements for complex systems, such as the HALE propulsion system are partially dictated by the larger-level, integrated super-system. In the case of the HALE, the larger integrated super-system is the entire vehicle and mission. The individual parameters in the super-system are highly interdependent upon one another, as they are highly coupled. Any forecasting method used to place a distribution on those parameters should capture those dependencies. Because identifying the requirements is only one part of evaluating advanced propulsion cocnepts, the forecasting method should be relatively simple, and easy to execute.
   - The Trend-Impact Analysis (TIA) can be used to forecast the value of continuous variables that are dependent upon events or other variables. TIA was discussed in section 2.2.2.3. Unfortunately, TIA cannot be used to forecast the distribution of discrete variables.
   - The cross impact (CI) analysis is a forecasting method that can be used to identify a probabilistic forecast of multiple, dependent events. CI was discussed in section 2.2.2.2. With a few modifications, the CI analysis can capture the dependencies of requirements along in its forecast.

3.2.2 Hypothesis Statement

> Shape functions depicting distributions of future requirements for the HALE propulsion system can be defined using traditional, forecasting techniques.

Forecasting methods have been widely used in many industries for years. Entire fields of research have been devoted to developing such methods, and the research has produced numerous viable methods. The types of requirements for complex systems and their roots are going to vary dramatically. Some requirements will be caused by government policies, and some will be functions of the free economy. Still other requirements are functions of the technological development (or lack of development) in tangential technological systems. Because the requirements come from such different sources, forecasting all of them simultaneously may be challenging.

Forecasting the requirements is only one part of assessing the advanced propulsion concepts as a whole. As decision-makers have more time and energy to devote to the forecasting of requirements, the methods can become more elaborate and exhaustive. For the purposes of the ERTA method, a forecasting method must be simple to implement, but still methodical, and the forecasting method should integrate past trends with future expert expectations. Finally, the forecasting method needs to be transparent and traceable, so that all assumptions can be clearly stated and understood.

While it is difficult to validate any forecasting method, the author believes a useful forecast of requirements can be derived from the plethora of methods that the forecasting research has developed. Table 9 compares a few forecasting techniques. The symbols used to evaluate each forecasting technique are explained in Table 8.

Table 8: Legend Methodology Alternative Ratings

⊗	Completely Incapable of Meeting Requirement
—	Poorly Meets Requirement
○	Sufficiently Meets Requirement
◉	Meets Requirement Well
●	Meets Requirement Exceptionally

Table 9: Types of Forecasting Methods

	Ease of Implementation	Probabilistic	Transparency	Avoid Biases	Capture Dependencies
Expert Opinion	●	○	⊗	⊗	⊗
Time-Series Forecasting	○	◉	○	○	◉
Trend Impact Analysis	—	◉	◉	◉	◉
Cross Impact Analysis	—	●	◉	◉	●
Scenario Forecast	—	○	○	○	○
None	●	⊗	⊗	●	⊗

The cross impact analysis integrates simulation with expert opinion to identify a probabilistic forecast. CI is attractive because the experts forecast the likelihood of each event occurring, as well as the conditional probability of each set of events occurring. The dependencies of individual requirements can be captured and integrated into the overall forecast.

3.3 Hypothesis III

Once a probabilistic set of requirements is established, the ability of the technological concepts to meet those requirements must be assessed. That assessment can then be used to compare the concepts to one another. Before those concepts can be compared on a just, “apples to apples” basis, a figure of merit that is applicable for each propulsion concept, across every set of requirements must be found.

3.3.1 Research Questions

5) What figures of merit are universal enough to be used to evaluate advanced propulsion concepts against one another?

    - Any metric used to compare advanced propulsion concepts to one another must be applicable and directly comparable across every concept, and every set of requirements. Metrics that are specific to conventional concepts, such as thrust specific fuel consumption, often have no meaning when evaluating alternative concepts, such as solar vehicles.
    - System level metrics, such as vehicle weight, or emissions could be applicable across all requirements and concepts, but might still not be appropriate because the values cannot be directly compared across different sets of requirements. For example, it does not make sense to compare gross vehicle weight, when the vehicle has to fly different missions. The assumptions that go into the calculation of that parameter are different, and thus, can only be used to compare concepts to one another if the requirements are fixed.
    - Probability of Success (POS) was identified by Bandte as a figure of merit from which to assess various concepts. It measured the likelihood that a concept would be feasible, given a noise distribution on the requirements. The problem with POS is that it does not give a measure of how much better or worse a concept is given that both are feasible.
    - “Fitness” is a relative figure of merit that specifies how well each concept meets the specific set of requirements relative to other potential advanced

propulsion concepts being considered. Fitness can be used in conjunction with any quantifiable measure, or even a conglomerate measure, such as an overall evaluation criterion (OEC) function.

3.3.2 Hypothesis Statement

"Fitness", a concept's ability to meet a set of requirements relative to other potential concepts, can be used to forecast a propulsion concept's likelihood of successful development.

Traditionally, the goodness of technological concepts is measured in terms of physical characteristics that reflect the capability of the concept. For example, fuel consumption is often used to evaluate aircraft engines. Cruise lift to drag ratio is often used to evaluate aircraft. These metrics are useful when comparing different alternatives that are part of the same basic concept, but cannot be used to evaluate fundamentally different concepts. Propulsion systems that convert solar energy to thrust cannot be evaluated based on their fuel consumption, just as lighter-than-air vehicles cannot be evaluated based on their lift to drag characteristics.

Instead of comparing physical parameters, decision-makers need to have a universal figure of merit that allows them to compare fundamentally different concepts to one another. Table 10 compares various figures of merit. The figures of merit were first evaluated based on how easy they were to determine. The second category measures whether the figure of merit was suitable for evaluating a number of criteria. The third category measured whether the Figure of merit was applicable across the entire range of concepts, and the final category measured whether the figure of merit was suitable to measure across a range of requirements. Fitness and POS are the only figures of merit that are always applicable, but only fitness gives decision-makers an understanding of how multiple feasible concepts compare against one another.

Table 10: Figures of Merit

	Ease of Determination	Ability to Measure Multiple Criteria	Applicability Across Range of Concepts	Applicability Across Range of Requirements
Physical Characteristic	○	◎	—	—
OEC	○	●	—	—
POS	—	◎	●	●
Fitness	—	◎	●	●

Fitness measures how well a concept meets the requirements relative to the other, competing concepts. There are different ways that fitness can be measured, but the ERTA method will use a proportional measure of fitness to evaluate how well each concept can meet the requirements relative to other concepts.

Fitness is a good indicator of how likely a concept is to be successfully developed because it first measures whether or not a concept is capable of meeting the specific requirements. If a concept cannot meet the requirements, its fitness is zero. Second, measuring fitness gives decision-makers an idea of how much better (or worse) a concept is than the other options. Fitness can be used to directly compare fundamentally different concepts in an “apples to apples” fashion, because only system level metrics that pertain specifically to requirements are examined. Finally, while fitness does measure the ability of a concept to meet a particular set of requirements, it is applicable across any set of requirements, as long as at least one metric should be optimized, and not just constrained. The calculation of fitness is described in sections 4.2.2.

3.4 Hypothesis IV

Now that we have found a means of identifying a requirements distribution and found a figure of merit that is suitable to evaluate concepts (fitness), given the varying requirements, the remaining questions deal with actually measuring the fitness of each concept, given the uncertainty inherent to the requirements, and the development of the propulsion concepts. Before any of this can be cone, however, the propulsion concepts that are being considered need to be identified. Once those concepts are identified, their performance needs to be assessed, and they have to be designed to meet the specific set of requirements. Comparing concepts that are not designed specifically to each set of requirements will result in an unfair comparison of concepts. Next, the fitness of each concept needs to be calculated. That calculation, however, must incorporate the possible fluctuation of requirements and the uncertainty inherent to the development of each concept. More accurate performance capabilities can be assessed for concepts that are more mature. The varying level of uncertainty needs to be taken into account.

3.4.1 Research Questions

6) How does one identify and define potential propulsion concepts?

    - Identifying advanced propulsion concepts is not always necessary; the specific concepts being considered could be obvious. Limiting the concepts, however, may prevent decision-makers from understanding an important piece of the puzzle. Advanced propulsion concepts other than those specified could eventually become the mainstream technology, making all of the specified advanced propulsion concepts obsolete.
    - Methods for identifying propulsion concepts must be easy to implement and objective. Biases can prevent decision-makers from identifying quality solution. Also, the methodology should be well tailored to the

physical assessment, or modeling of the concept. Table 11 compares various alternatives for identifying potential concepts.

Table 11: Methods for Identifying Concepts

	Ease of Implantation	Objective	Range of Concepts
Provided by Customer	●	—	⊗
Brainstorming	◉	○	○
Morphological Matrixes	◉	◉	◉
TRIZ	—	◉	○

- TRIZ is one possible method for identifying advanced propulsion concepts, but is difficult to automate. Morphological matrices (explained in section 2.2.1.2) may be more helpful. By breaking a system down into the required subfunctions or subsystems, decision-makers can systematically organize all of the possible solutions to a problem. One concept can be defined as one unique set of alternatives from the morphological matrix. Categorizing alternatives in this way will prevent decision-makers' bias from wrongly eliminating concepts.

7) How can the mature performance of advanced propulsion concepts be assessed?

- The modeling tools used to assess advanced propulsion concepts must be flexible enough to assess the entire range of advanced propulsion concepts under consideration. Because many of the concepts are revolutionary in nature, empirical relationships or data cannot be used to assess these concepts. A few assessment methods are compared below in Table 12.

Table 12: Methods for Assessing Revolutionary Concepts

	Ease of Implementation	Accuracy	Ability to Evaluate Entire Range of Concepts	Model Future, Mature Performance
Qualitative Assessment	◉	—	●	○
Empirical Model	○	◉	⊗	—
Empirical and Physics-Based Modeling	○	◉	—	◉
Physics-Based Modeling	—	○	◉	●
Qualitative and Physics-Based Modeling	—	○	◉	◉

- The only real way to analyze and predict performance of advanced propulsion concepts is through first principles analyses. Such analyses can be validated using controlled experiments along with initial tests of immature technology. Predicting the mature performance of the concepts after they have been developed, however, affords no such validation. Research has been done to assess mature performance of aeropropulsion systems at early stages of development, based on the theoretical limitations of the concepts [60]. That research shows that mature performance will be dominated by the physical limitations inherent to the concept. The concepts can be modeled using the simple physical and thermodynamic relationships that define them, in conjunction with key disciplinary metrics that measure how mature the process is, such as efficiencies, and material limitations

- Using the simple physical and thermodynamic relationships is also likely to increase the computational speed, allowing for a more thorough examination of the revolutionary design space. A combination of first principles analyses and qualitative assessments might also be useful. Depending on how much information and experience decision-makers have, qualitative assessments can enhance the physics-based assessment.

8) How can one systematically find optimized propulsion concepts to ensure that the comparison is on an "apples to apples" basis?
    - Advanced propulsion concepts can only be compared to one another if they are both optimized to meet the specific set of requirements. Otherwise, the comparison would be biased. From hereon, the specific alternative within a particular concept that is designed to best meet the specific set of requirements is referred to as the optimized concept. Optimized concepts can be considered as local minima in the entire concept space.
    - Identifying the optimized concept, however, is exhaustive. Optimization methods can be used to identify the optimal concept. Traditionally, optimization methods are judged for their ability to avoid local minima. In this case, they will be required to identify the local minima so that the optimized concepts can be compared. An optimization method should first and foremost be capable of identify the local minima. Additionally, it should be robust, and not require too much time to complete. Optimization routines are compared below in Table 13.

Table 13: Optimization Methods

	Set Up Time	Computational Time	Identify Local Minima?	Robustness
Gradient-Based Methods	—	○	⊗	—
Random Search	◉	○	○	◉
Genetic Algorithm	○	—	—	◉
Simulated Annealing	○	—	◉	◉
None	●	●	⊗	⊗

- Gradient-based methods are notorious for getting "stuck" in local minima, but they are deterministic in nature, so the decision-maker would have to run one optimization for each concept under consideration to find all local minima.
- Stochastic optimizing methods can help decision-makers identify the optimal design variable settings for advanced propulsion concepts, so that that the concepts are compared in an "apples to apples" fashion. Simulated annealing, in particular, can identify local minima within a design space, or optimized concepts from the entire space. Once the optimized concepts are identified, the goodness of each concept can then be assessed relative to one another.

9) How can the robustness of HALE propulsion concepts to variations in requirements be incorporated into the overall goodness of advanced propulsion concepts?

    - Fitness measures how well a concept meets the particular set of requirements relative to the other concepts that are considered. The distribution of fitness as a function of the probabilistic distribution of requirements can give decision-makers a quantitative understanding of how robust each concept is to variations in requirements.

- The easiest, most accurate way to identify an output distribution is to use Monte Carlo (MC) trials. Monte Carlo techniques are discussed in section 2.2.4.3. Unfortunately, they require thousands of trials to predict output distributions. Conducting Monte Carlo trials in with the actual assessment is infeasible, as the assessment will likely be computationally exhaustive.
- Fast Probability Integration (FPI) is a method that approximates a Monte Carlo simulation to identify a distribution of an output as a function of the distribution of the input. FPI works by identifying the most probable FPI, and approximating the cumulative distribution function (CDF). More information about FPI can be found in source [49].
- Instead of approximating the Monte Carlo trials, the actual assessment can be approximated using a meta-model. Two popular meta-models were considered: Response Surface Equations (RSE) and Neural Networks, described in section 2.2.5.1 and 2.2.5.2, respectively.
- Different means for identifying the distribution of fitness as a function of the distribution of requirements are compared in Table 14.

Table 14: Calculating the Distribution of Fitness

	Time	Thoroughness of Exploration	Ability to Assess Multiple Criteria	Accuracy (In Linear Space)
MC + Assessment	⊗	●	⭘	●
FPI + Assessment	⭘	○	⊗	⭘
MC + RSE	⭘	⭘	●	⭘

MC + Neural Network	○	◉	●	○

- Monte Carlo trials were conducted using a meta-model because meta-models can be highly accurate, but require only a fraction of the computational time of the actual assessment. RSE was selected as the meta-model because the fitness of each concept is expected to behave relatively linearly with respect to the range of requirements. The fitness is a relative normalization of system-level metrics, and thus should be much more linearly.

10) How can the uncertainty associated with the development of advanced propulsion concepts be incorporated into the comparison of the concepts?
    - Once the uncertainty can be measured at system-level scale and quantified that uncertainty can be reflected in the fitness of an advanced propulsion concept. The sensitivity of fitness to the maturity of disciplinary metrics can also be measured. Ultimately, however, uncertainty can be taken into account by aggregating the fitness of a concept over the potential distribution of key disciplinary metrics.
    - The distribution of fitness with respect to disciplinary metrics can be calculated using the same methods that were used to calculate the distribution of fitness as a function of requirements.

3.4.2 Hypothesis Statement

Stochastic optimizations can be used to calculate fitness as a function of requirements, enhancing decision-makers' understanding of future technological concepts.

The final hypothesis statement encompasses the answers to that were found to questions 6-10. In the third hypothesis, fitness was proposed as a figure of merit that can be used to evaluate advanced propulsion concepts. The fourth hypothesis proposes a means of calculating the distribution of fitness as a function of the distribution of requirements.

Table 15 summarizes all of the means of assessing advanced propulsion concepts. The ERTA methodology uses all of the highlighted elements to assess each concept.

Table 15: Morphological Matrix of Alternatives for Assessing Concepts

Define Concepts	Provided by Customer	Brainstorming	Functional Decomposition	TRIZ	
Model Technological Concepts	Qualitative Assessment	Empirical Model	Empirical and Physics-Based Modeling	First Principles	Combination
Identify Optimal Concept	Expert Identification	Design Space Exploration for each Concept	Optimization Routine	Other	
Optimization Routine	Gradient-Based Methods	Random Search	Genetic Algorithm	Simulated Annealing	None
Figure of Merit	Physical Characteristic	OEC	PoS	Fitness	
Capture Maturity/ Capability	Deterministic Disciplinary Metrics	Probabilistic Disciplinary Metrics			
Assess Merit Across Distribution of Requirements	MC + Assessment	FPI + Assessment	MC + Meta-Model		
Meta-Model	None	RSE	Neural Network		

A functional decomposition was chosen to identify the concepts because it is an effective method for identifying a wide range of alternatives. A first principles assessment was used to model each of the concepts because it is applicable across the entire range of concepts under consideration, both conventional and revolutionary. The optimal concept for each set of requirements was identified using a simulated annealing optimization routine, and the fitness of each concept will be calculated from the set of optimized alternatives. Finally, the distribution of fitness as a function of the requirements and the disciplinary metrics will be used to evaluate each of the concepts. The distribution of fitness will give decision-makers an understanding of how likely a concept is to be feasible in the future, and how that concept compares to competing concepts.

It was already determined in section 3.1.2 that any meaningful forecast of advanced propulsion concepts must consider the variability of the requirements. Advanced propulsion concepts that are feasible and viable to a wider range of requirements will have a greater chance of succeeding and making it to market. Decision-makers need a quantitative understanding of how well the advanced propulsion concepts would perform given varying requirements. That, combined with a probabilistic understanding of how the requirements are likely to vary would yield an unbiased predictor of how likely to succeed various advanced propulsion concepts are. Such knowledge would serve as a basis for comparison between fundamentally different advanced propulsion concepts, thus serving as an aid for decision-makers when allocating funds for research.

3.5 Summary of Hypotheses

The first hypothesis stated, “any method designed to evaluate advanced propulsion concepts must incorporate the possible variations of the requirements into the assessment”. This hypothesis established the need to develop a methodology to evaluate advanced propulsion concepts that took into account the uncertain nature of the requirements. In order to do so, such a method would have to identify a probabilistic distribution for the requirements and assess the goodness of each concept as a function of that distribution. The second, third and forth hypotheses were proposed as means of completing those two tasks.

The second hypothesis proposed the means of calculating the distribution of the requirements. The hypothesis stated "shape functions depicting the distributions of future requirements for propulsion systems can be defined using traditional, forecasting techniques." The cross impact analysis was specifically proposed as a means of forecasting the requirements because it is a relatively simple forecasting technique that takes the dependent nature of the requirements into account.

The third hypothesis proposed a figure of merit to be used to compare the advanced propulsion concepts to one another. The hypothesis stated "'Fitness' can be used to forecast a propulsion concept's likelihood of successful development." Fitness was proposed as a figure of merit because it directly measures how well a concept satisfies a specific set of requirements. It is applicable and comparable across all potential requirements

The final hypothesis identified a means of evaluating each of the concepts, given the distribution of the requirements. The hypothesis stated "stochastic optimizations can be used to calculate distribution of fitness for advanced concepts, enhancing decision-makers' understanding of future technological concepts." A simulated annealing program was proposed as a means of identifying the set optimized concepts as a function of the requirements and disciplinary metrics. Fitness could then be calculated from the set of optimized concepts. Monte Carlo methods were proposed as a means of calculating the distribution of fitness as a function of the distribution of requirements and disciplinary metrics. The distribution of fitness could then be used to evaluate the concepts. Decision-makers would have an understanding of how likely a concept is to satisfy the future requirements, as well as an understanding of how competing concepts compare against one another.

4 METHODOLOGY

In Chapter 2, a review of advanced design methodologies revealed that no existing methodology is suitable for evaluating advanced propulsion concepts given an uncertain set of requirements. The previous chapter hypothesized the need for such a methodology, and set up the basis for a process. The following chapter discusses the Evolving Requirements Technology Assessment (ERTA) methodology itself.

Any method designed to assess advanced propulsion concepts, given uncertain requirements has to have two main elements. First, the requirements for future propulsion systems must be determined. Second, the propulsion concepts must be assessed with respect to that likely distribution of requirements. As discussed in Chapter 3, that assessment will use fitness as a figure of merit to evaluate the concepts. Fitness will allow decision-makers to directly measure how well a concept meets the specific set of requirements. Comparing the fitness of competing concepts will give decision-makers an understanding of how good each concept is relative to competing concepts. Finally, the distribution of fitness, as a function of the distribution of requirements, will give the decision-makers an understanding of how likely each concept is to satisfy the requirements and how sensitive each concept is to variations in the requirements.

4.1 Defining the Requirements

The first step to solving any problem is identifying and fully understanding the requirements. The requirements for complex systems can be formulated in several ways. The ERTA methodology forecasts the requirements probabilistically, so that the uncertainty inherent to the requirements can be captured. Probabilistic requirements can be obtained in several different ways. They could be obtained directly from the customer, forecasted, or found through an exhaustive requirements analysis. The ERTA methodology uses a requirements analysis in conjunction with a forecasting method to identify the probabilistic requirements. While a forecasting method would be capable of identifying the probabilistic distribution for the requirements, a requirements analysis is required to identify the possible requirements. Table 16 shows a breakdown of methods that can be used to formulate requirements. The specific means that were selected for each category are highlighted.

Table 16: Morphological Matrix of Formulating Requirements

Type of Requirements	Deterministic (Single Mission)	Multiple Missions or Scenarios	Probabilistic			
Requirements Formulation	Provided by Customer	Requirements Analyses	Forecast	Requirements Analysis/ Forecast		
Forecasting Methods	Expert Opinion	Time-Series Forecasting	Trend Impact Analysis	Cross Impact Analysis	Scenario Forecast	None
Requirements Analyses	Integrated Product Teams	QFD	Morphological Study	Systems Engineering Studies	None	

The selections made in Table 16 that together specify the method of formulating the requirements were identified logically. Each selection made in Table 16 is defended below. For each of the categories, the different method alternatives were compared. Table 17 explains what each of the marks used in the comparisons mean.

Table 17: Legend Methodology Alternative Ratings

⊗	Completely Incapable of Meeting Requirement
▬	Poorly Meets Requirement
○	Sufficiently Meets Requirement
◉	Meets Requirement Well
●	Meets Requirement Exceptionally

The ERTA method needs requirements to be defined probabilistically. Table 18 compares different ways that requirements can be defined. Determining requirements deterministically refers to developing only one, set of requirements from which the alternatives will be compared. While deterministic sets of requirements are simple to formulate, they are entirely incapable of allowing for the incorporation of uncertainty. Multiple missions or scenarios are often used to compare concepts that must be capable of meeting multiple sets of requirements. Multiple missions or sets of requirements are easier to identify, and have some ability to incorporate uncertainty, but probabilistically defined missions provide a much better basis for incorporating uncertainty into the analysis.

Table 18: Types of Requirements Forecasts

	Develop Understanding of Problem	Ease of Identification	Incorporation of Uncertainty
Deterministic (Single Mission)	⊗	◉	⊗
Multiple Missions or Scenarios	◉	○	○
Probabilistic	◉	▬	●

Probabilistically defined requirements not only provide multiple sets of requirements, but they also specify a likely distribution for the different requirement sets. The requirements for complex systems are uncertain in nature and thus must be considered probabilistically. As systems become more complex, the time and resources required to develop them fully increase. As this time increases, the requirements placed upon that system are given more time to evolve and become less certain. Additionally, it is likely that the systems will ultimately be required to serve more than one purpose. Because the requirements for advanced propulsion concepts are so uncertain, evaluations of these systems must consider an array of requirements, not just one determinant set of requirements or even a few dominant sets of requirements.

Table 19 compares the different methods used to formulate the requirements. Each method was first compared based on how much how easy it was to conduct. The methods were then compared based on how available the information was, and how suited each was to incorporate uncertainty. The column "Availability" refers to how often such methods can be used to formulate requirements. Notice that the customer directly providing the requirements is by far the simplest method, but the method is inadequate in every other category, as it develops little understanding of the problem, is unsuitable for incorporating uncertainty, and such a method is not always available.

Table 19: Requirements Formulation Methods

	Ease of Implementation	Availability	Incorporation of Uncertainty
Provided by Customer	●	—	⊗
Requirements Analyses	—	●	○
Forecast	○	◉	●
Forecast/ Requirements Analysis	○	◉	●

Performing a requirements analysis develops a strong understanding of the requirements, and they can always be performed. The problem with such an approach is that they are difficult to perform, and are not as well suited to incorporate uncertainty as forecast based methods are. The problem with forecast-based methods is that they do not develop as good of an understanding of the problem. If no experts are available to give their input, or if no historical trends exist to project into the future, forecasting is difficult. A combination of forecasting and requirements analysis is the best of both worlds, however. Simplified requirements analysis can be performed to identify possible requirements, and forecasting methods can be used to identify the likelihood of each possible requirement.

As mentioned above, a requirements analysis is necessary to identify potential requirements. Performing a requirements analysis develops a strong understanding of the requirements, and they can always be performed. The problem with such an approach is that they can be difficult to perform and time consuming. A few requirement analyses are listed and compared in Table 20. These methods can be performed in conjunction with one another—they are not mutually exclusive.

Table 20: Types of Requirements Analyses

	Ease of Implantation	Avoid Biases	Incorporation of Uncertainty	Integration with Forecasting Method
Integrated Product Teams	○	⊗	⊗	○
QFD	○	▬	○	○
Morphological Study	◉	●	◉	●
None	●	⊗	⊗	⊗
Systems Engineering Studies	⊗	◉	◉	○

Experts in a variety of fields are brought together to discuss and agree upon requirements in Integrated Product Teams (IPT). While they are usually beneficial, the most outspoken people usually dominate the group, making them very biased. Quality Functional Deployment (QFD) is an encompassing method geared toward relating requirements to product characteristics. Certain parts of QFD, however, are specifically geared toward identifying requirements. These methods are relatively simple to implement, but they cannot be incorporated with the forecasting methods as well, and they are not well suited to incorporating uncertainty. Systems engineering studies refer to the rigorous quantitative analyses of requirements. The problem with these methods is that they are difficult and time consuming to implement. Also, often, the requirements may lie outside of the decision-makers area of expertise. Morphological studies are perfect requirement analyses because they identify all of the possible sets of requirements in an organized fashion, and they can be integrated with the forecasting methods easily.

While the requirements analysis identified potential requirements, a forecasting method is necessary to identify the likelihood of each of the potential requirements. Forecasting the future is a difficult task. Forecasting the evolution of requirements is a complicated endeavor on its own. Entire fields of research have been devoted to developing methods to predict the future, and the research has produced numerous viable methods [66]. Some of these methods were discussed in section 2.2.2. The method that is most suitable depends upon the type of requirements being assessed as well as the time and energy that the decision maker has to devote to the forecast. It is important to note that many of the requirement changes may be caused by one of a few factors: changes in expected horizontal technological capability, market changes, or societal policy changes. Horizontal technological capability refers to capability of systems or disciplines that work alongside of the system in a larger, integrated super-system. For example, the aerodynamic and structural systems are two horizontal disciplines where technological progress could significantly impact the requirements placed upon a propulsion system. Societal policy refers to requirements driven by society or government, such as elimination of emissions or other environmental regulations with which the technology must be compliant.

Table 21 compares a few forecasting methods. The methods are compared based on how easy they are to implement, and how good the forecast is. It should be noted that quality is a difficult figure to measure, as the accuracy of forecasting methods cannot really be determined. The ability of the methods to become probabilistic is also noted. Transparency is important in a forecasting method because any method is going to rely upon many assumptions. Additionally, the ability of the method to avoid biases is reflected below. Finally, the ability of the method to capture decencies between various requirements is also tracked. This trait is important because many of the requirements for complex systems will be highly dependent upon one another. The methods are explained in greater depth in the literature search section 2.2.2.

Table 21: Types of Forecasting Methods

	Ease of Implementation	Probabilistic	Transparency	Avoid Biases	Capture Dependencies
Expert Opinion	●	○	⊗	⊗	⊗
Time-Series Forecasting	○	◉	○	○	—
Trend Impact Analysis	—	◉	◉	◉	◉
Cross Impact Analysis	—	●	◉	◉	●
Scenario Forecast	—	○	○	○	○
CI Based on Requirements Analysis	—	●	◉	●	●
None	●	⊗	⊗	⊗	⊗

Notice that only the methods that capture dependencies and are somewhat probabilistic are feasible forecasting methods for the ERTA method. Time-series forecasting and TIA were not selected because they require that the requirement be a continuous numeric value. This may be the case for some requirements, but will not always be the case. Scenario forecasts do not really give a good idea of the likelihood of each of the scenarios, sot they are not as geared toward the ERTA method. The CI analysis gives a probabilistic set of requirements, and captures dependencies, but as discussed in earlier in section 2.2.2.2, CI requires that the forecast be broken down into a series of discrete events. Expert opinion and simulation is then used to determine whether each event occurs or does not occur. Unfortunately, this assumption may be too simplistic to be of much use. For this reason, the author proposes modifying the CI analysis and basing it specifically on the requirements analysis to make it more applicable to forecasting the requirements for complex revolutionary systems. The modification of the CI method is discussed in section 4.1.1. The modified CI approach was selected because it allowed the decision-makers to capture the dependencies of various requirements, while also being transparent, and capable of forecasting discrete parameters.

4.1.1 Modifying the Cross Impact Analysis

Unfortunately, traditional CI is probably too simplistic to be of much use when evaluating complex system requirements. Individual requirements could be continuous, or have more than two likely settings. Creative methods could be employed to convert these requirements to sets of simple events, that either happen or do not happen, but doing so would probably be cumbersome. Instead, the CI analysis could be adapted to include a capability to forecast the probability of events when more than two outcomes are possible. Look at each event as a variable with two settings: occurring or non-occurring. The settings are mutually exclusive, but their probabilities must add up to one. That idea can be extended. Instead of having only two mutually exclusive settings for each variable, more settings can be considered, but the must still be mutually exclusive, with a total probability adding up to one. Consider a generic event, or variable, A. that has three possible settings, A_1, A_2, and A_3. The probability of each occurring individually must sum up to one, as shown in Equation 5.

$$\sum_{i=1}^{3} P(A_i) = 1 \tag{5}$$

In traditional CI, only the probability and conditional probability need to be estimated. The probability of the event not occurring is one minus the former, as the event must either occur or not occur. When a variable has more than one setting, however, the experts must estimate the probability of each setting. The probability of each setting, or value, occurring reflects a probability distribution. The sum of the distribution then must add up to one. Table 22 shows such probabilities for three generic variables, A, B, and C. Variables A and C have three settings, while Variable B only has two.

Table 22: Estimated Probabilities

	1	2	3
A	$P(A_1)$	$P(A_2)$	$P(A_3)$
B	$P(B_1)$	$P(B_2)$	
C	$P(C_1)$	$P(C_2)$	$P(C_3)$

One positive and one negative conditional probability matrix would not be sufficient to record all of the conditional probabilities when each variable has more than one setting; a more comprehensive matrix is needed. Table 23 shows the conditional probability for the same three generic variables shown in Table 22. In Table 23, the row indicates the variable setting that is given, and the column marks the variable setting that is being considered. The value that is in the cell at the intersection of row A1 and column B1 is the conditional probability that B will equal one, given that A equals one. All of the information contained in the positive and negative conditional probability matrixes is also contained in Table 23, but it is expanded to consider third possibilities for variables

A and B. In Table 23, notice that the conditional probabilities along the diagonals are one and the conditional probabilities of two variables in one setting is zero.

Table 23: Conditional Probability Matrix

		A			B		C		
		A1	A2	A3	B1	B2	C1	C2	C3
A	A	1	0	0	$P(A_1 \mid B_1)$	$P(A_1 \mid B_2)$	$P(A_1 \mid C_1)$	$P(A_1 \mid C_2)$	$P(A_1 \mid C_3)$
	A2	0	1	0	$P(A_2 \mid B_1)$	$P(A_2 \mid B_2)$	$P(A_2 \mid C_1)$	$P(A_2 \mid C_2)$	$P(A_2 \mid C_3)$
	A3	0	0	1	$P(A_3 \mid B_1)$	$P(A_3 \mid B_2)$	$P(A_3 \mid C_1)$	$P(A_3 \mid C_2)$	$P(A_3 \mid C_3)$
B	B1	$P(B_1 \mid A_1)$	$P(B_1 \mid A_2)$	$P(B_1 \mid A_3)$	1	0	$P(B_1 \mid C_1)$	$P(B_1 \mid C_2)$	$P(B_1 \mid C_3)$
	B2	$P(B_2 \mid A_1)$	$P(B_2 \mid A_2)$	$P(B_2 \mid A_3)$	0	1	$P(B_2 \mid C_1)$	$P(B_2 \mid C_2)$	$P(B_2 \mid C_3)$
C	C1	$P(C_1 \mid A_1)$	$P(C_1 \mid A_2)$	$P(C_1 \mid A_3)$	$P(C_1 \mid B_1)$	$P(C_1 \mid B_2)$	1	0	0
	C2	$P(C_2 \mid A_1)$	$P(C_2 \mid A_2)$	$P(C_2 \mid A_3)$	$P(C_2 \mid B_1)$	$P(C_2 \mid B_2)$	0	1	0
	C3	$P(C_3 \mid A_1)$	$P(C_3 \mid A_2)$	$P(A_3 \mid A_3)$	$P(C_3 \mid B_1)$	$P(C_3 \mid B_2)$	0	0	1

The cells in Table 23 that connect variable settings for the same variables are shaded and are trivial to determine, as they must be either ones or zeros. The values for cells that connect different variables, however, must be determined. These values would most likely be obtained from expert opinion. It is important to note, however, that the sum of all of the conditional probabilities for one variable must add up to one. Equation 6 and Equation 7 show this principle for Variable A. Equivalent conditions would hold for Variable B and Variable C.

$$\sum_{i=1}^{2} \mathrm{P}\left(\mathrm{B}_i \mid \mathrm{A}_j\right) = 1 \quad \text{for } j = 1, 2, 3 \tag{6}$$

$$\sum_{i=1}^{3} \mathrm{P}\left(\mathrm{C}_i \mid \mathrm{A}_j\right) = 1 \quad \text{for } j = 1, 2, 3 \tag{7}$$

Each Monte Carlo trial would be conducted in a manner similar to that of a traditional CI. One variable would be selected at random, and its value would be determined, based on the probabilities estimated in Table 22. The probability distribution of the remaining variables would be replaced with the appropriate conditional probability distribution, and a second variable would be selected and from the remaining variables. Estimating the probability distribution of the first and second variables is trivial; the former is given in Table 23, and the later can be found in Table 23. Determining the value of the remaining variables becomes more involved. The true probability distribution for the third variable is the conditional upon both the first variable assessed and the value of the second variable assessed. Unfortunately, Table 23 does not provide that information; instead, it has to be estimated. One means of estimating that probability would be to consider only the conditional probability distribution as determined from *one* of the variables that have already been determined. Realistically, this would be either the first or the last variable that was assessed. The biggest problem with this simplification is that infeasible, or impossible, combinations could be created. Assume that two different variable values are incompatible with one another, or that the conditional probability for the combination is zero. If the probability distribution is found as a function of only one of the previously determined variable values, this incompatibility could be overlooked.

Another approach to calculating the conditional probability distribution of one variable upon multiple other variables would be to average the conditional probabilities of all of the previous variables. The calculation of a simple average is shown in Equation 8. In this equation, the probability distribution is determined for the n^{th} randomly selected variable; $X_{1,2,\ 3\ldots n\text{-}1}$ represent all of the variables that have previously been determined.

$$P\left(X_n \mid \left[X_1 \cap X_2 \cap \ldots X_{n-1}\right]\right) \approx \frac{P\left(X_n \mid X_1\right) + P\left(X_n \mid X_2\right) + \ldots P\left(X_n \mid X_{n-1}\right)}{n-1} \qquad (8)$$

Simple averages would ensure that the dependency of all of the previous variables would be accounted for, but would not eliminate impossible or infeasible combinations. In order to do so, the calculated conditional probability would have to equal zero if any of the specific condition probabilities equal zero, as shown in Equation 9.

$$\text{if } P\left(X_n \mid X_i\right) = 0 \text{ for any } i\text{, where } 1 \geq i > n \quad P\left(X_n \mid \left[X_1 \cap X_2 \cap \ldots X_{n-1}\right]\right) = 0 \qquad (9)$$

Logic can be introduced to the averaging of conditional probabilities, in order to ensure that incompatible combinations are not generated. If the conditional probability of any variable value upon the previously determined variables equals zero, the new probability of that variable value equals zero. Otherwise, the probability would be a simple average. This logic, however, could potentially cause problems for the Monte Carlo trials. It would introduce conditions under which the constraint that all possible conditional probabilities sum up to 1, as shown in Equation 6 and Equation 7 is violated. A simple normalization of the non-zero conditional probabilities would eliminate this problem. Equation 10 shows this normalization for the n^{th} selected variable that has m potential variable settings.

$$P_{norm}\left(X_{n_j} \mid [X_1 \cap X_2 \cap \ldots X_{n-1}]\right) = \frac{P\left(X_{n_j} \mid [X_1 \cap X_2 \cap \ldots X_{n-1}]\right)}{\sum_{i=1}^{m} P\left(X_{n_i} \mid [X_1 \cap X_2 \cap \ldots X_{n-1}]\right)} \tag{10}$$

Once this logic is in place, Monte Carlo trials can commence. As mentioned above, an initial variable is selected at random, and its value is determined probabilistically from the variable's probability distribution. A second variable is selected from those remaining, and its value is determined from the appropriate conditional probability distribution. Values are found for each of the remaining variables probabilistically, in a random order. For each of these variables, however, the intelligent, normalized conditional probability distribution is used.

It should be noted that CI alone may not be sufficient to forecast the future requirements. Particular requirements may be better forecasted using other techniques, such as a trend regression. For example, if a particular requirement is thought to be independent and can be represented by a continuous variable, it might make sense to use a time series forecast to model the evolution of that particular requirement.

4.2 Assessing Advanced Propulsion Concepts

Once the requirements for advanced propulsion concepts have been identified, decision-makers can begin to assess each propulsion concept. Hypothesis III proposed that fitness be used as a figure of merit to evaluate the advanced propulsion concepts. Hypothesis IV proposed that the distribution of fitness, as a function of the requirements, be used to understand how robust each concept is to variations in requirements. It also outlined a process by which to identify that distribution.

In order to calculate the distribution of fitness for each concept, decision-makers must develop a means of calculating fitness as a function of the requirements. Once that is done, a Monte Carlo simulation can be used to identify the distribution of fitness. Directly relating fitness of each concept to requirements is not simple, however. For each specific set of requirements, the optimal concepts, or the concepts' designs that are optimized to the specific requirements, must be found. This requires the ability to measure each advanced propulsion concept's performance, as well as the ability to identify each optimal concept. Once each optimal concept is identified, the fitness of each concept can be found.

Calculating fitness as a function of the requirements is computationally exhaustive. For this reason, a surrogate model should be created to relate fitness directly to the variability of requirements in a less computationally exhaustive fashion. Because the maturities of advanced propulsion concepts vary significantly, decision-makers will also have to incorporate the uncertainty inherent to technological development. The surrogate model can also capture the variation in fitness as a function of the variability of key technological metrics. The following section discusses the identification of the optimal concepts, the calculation of fitness, and the incorporation of uncertainty into the calculation of fitness for advanced propulsion concepts.

4.2.1 Identifying Optimal Concepts

Identifying the optimal concepts is not a simple endeavor. Each advanced propulsion concept must be optimized to meet the specific set of requirements.

Optimizations are difficult tasks. Identify concepts under consideration. Assess the concepts. Use a simulated annealing program to identify the optimal concepts.

4.2.1.1 Identifying the Advanced Propulsion Concepts

Before the advanced propulsion concepts can be assessed, they must be identified or defined. Sometimes, decision-makers are only interested in comparing a few concepts to one another. If that is the case, defining the concepts is trivial. If problem is broader, defining the concepts becomes more difficult.

Brainstorming is an easy way to generate concepts, but the brainstormers' biases will most likely prevent them from considering all possible alternatives. TRIZ, which was explained in section 2.1.1, is a method intended to stimulate creativity and identify novel solutions to problems developers incur. The problem with TRIZ is that it difficult to implement. Also, while several solutions are usually identified, the range of solutions is not as encompassing as the author would like for the ERTA method. Functional decomposition is the best way to identify concepts. It is easy to implement and biases are reduced because the decision-maker functionally steps through the system and identifies all necessary parts or subfunctions. When all of the means of accomplishing those subfunctions are identified, the set of possible combinations makes up a large combinatorial space that defines the possible set of concepts.

4.2.1.2 Modeling Advanced Propulsion Concepts

Once the concepts have been identified or defined, the ability of each to satisfy the requirements must be assessed. In order to do so, decision-makers must have the ability to model each concept and forecast how well it would perform, given specific sets of requirements. Such a modeling method must be applicable to the entire range of concepts under consideration, and should be as accurate as possible. They should also be able to model the mature performance estimates of technology, even when the technology is immature.

The ERTA methodology proposes modeling the basic physics behind advanced propulsion concepts in order to forecast how well each concept will be able to satisfy the requirements. Qualitative assessments are easy to implement and can be used to evaluate all of the concepts, but they lack the physics-based analysis that allows for an accurate comparison. Empirical models cannot be used to evaluate advanced propulsion concepts, as many of the concepts are outside of the historical database. Models that rely upon a combination of empirical modeling and physics-based modeling might be capable of assessing most concepts, and would be more accurate at modeling conventional concepts, because they would be based on empirical data. Such methods, however, would be biased toward today's performance, and it would be difficult to assess the future, mature capability of certain concepts. Physics-based analyses are best suited toward predicting the mature performance of advanced propulsion concepts [60]. The performance of concepts will improve throughout time, but will ultimately be limited by the physical principles that govern the concept. Combination methods that combine physics-based analyses with qualitative assessments might also be worthy, because decision-makers could include assessments that cannot easily be modeled by using physics-based principles, such as cost and ease of development or integration.

4.2.1.3 Optimizing Advanced Propulsion Concepts

Once all of the concepts have been identified, a method by which to model each alternative and assess its ability to satisfy the requirements has been developed, each concept can be optimized to best satisfy the specific requirements. As was proposed in Hypothesis IV, a simulated annealing program can be used to ease the process of identifying optimal concepts. As was discussed earlier, a concept is a classification, or grouping, of alternatives. An alternative is a unique setting of design variables, or unique engine. In order to compare concepts to one another in an "apples to apples" fashion, decision-makers must be able to identify the optimal concept. Finding those optimal concepts accurately, however, is not simple. Theoretically, if the concepts were well enough understood, expert opinion could be used to instead of an optimization to find the optimal concept. Unfortunately, expert opinion incorporates biases into the evaluation of the concepts, and is not very accurate. Several methods can be used to identify the alternative that is used to compare each concept. They are shown in Table 24. The methods are evaluated based on how easy they are to implement, whether or not they can easily be automated, how accurately they identify the optimal concept, and how quick they are. They are also evaluated based on how able they are at finding all of the optimal concepts simultaneously. Gradient-based optimization methods are robust optimizations to find the optimal design of one concept, however, they cannot easily find all of the optimal concepts.

Table 24: Methods to Identify Optimal Alternatives within Concept

	Ease of Implementation	Automation	Avoid Biases	Speed	Ability to Find Optimal Concepts Simultaneously
Expert Identification	●	⊗	⊗	●	●
Design Space Exploration	⊗	○	◉	⊗	⊗
Gradient-Based Optimization	○	◉	◉	○	—
Stochastic Optimization	○	◉	◉	◉	◉

The optimal concept identified by experts, but given the complex nature of the concepts that are being identified, it is unlikely that experts would be able to accurately identify the optimal alternatives within the concept. Design space exploration is a robust method for finding optimal or near optimal design variable settings, but it is a laborious process, and could not easily be automated. Design space exploration requires evaluating the entire potential space, usually through the use of a surrogate model, and identifying if a feasible solution exists. If multiple feasible alternatives exist, design space exploration finds the optimal alternative. If no feasible alternatives exist, design space exploration identifies the best alternatives. It is not practical to perform design space exploration on all possible concepts, when more than a few concepts are being considered. Optimization routines, on the other hand, can identify the optimal settings robustly and automatically. The optimization routines are discussed below.

The ERTA method uses optimization routines to identify the optimal alternatives within each concept. Instead of performing an individual optimization on every possible concept, the ERTA method seeks to perform one optimization method on the entire revolutionary design space. An optimization routine, then, would have to be capable of the local minima in the space, as each local minimum reflects one optimized concept. The optimization routines also have to be robust enough to handle discontinuous spaces, as the revolutionary design space is most likely highly discontinuous. Table 25 compares a few optimization routines.

Table 25: Optimization Methods

	Set Up Time	Computational Time	Identify Local Minima?	Robustness
Gradient-Based Methods	—	○	⊗	—
Random Search	◉	○	○	◉
Genetic Algorithm	○	—	—	◉
Simulated Annealing	○	—	◉	◉
None	●	●	⊗	⊗

Gradient-based optimization methods are proven, deterministic optimization methods, but they are not appropriate for identifying the optimal alternatives within each concept. First, gradient-based methods use the derivative objective function to identify a direction to move. The revolutionary design space will be discontinuous, and consequently, the derivative will not always exist. Second, gradient-based methods get stuck in local minima, but because they are deterministic, it is difficult to identify multiple local minima. If multiple gradient-based optimizations were run, each starting at a different point, the local minima could theoretically be found, but this would be a cumbersome approach.

Random searches would give the decision-maker a good idea of what the design space looks like, but other optimization routines are more efficient. Both genetic algorithms and simulated annealing would allow the decision maker to replicate the evolution of individual technological concepts probabilistically, but in very different ways. As was discussed in section 2.2.6.2, genetic algorithms optimize by simulating a "pool" of solutions that evolve together, and thus improve throughout time. In each subsequent generation, the pool members are crossed with each other and then reproduce, ensuring that the pool will become a more homogenous mixture of the best of the pool members. While simulated annealing also consists of a "pool" of solutions that will hopefully evolve through time, those solutions evolve independently. There is no crossing of solutions; whether or not an "off-spring" that is reproduced survives into the next generation is ONLY a function of the "goodness" of the offspring relative to the "goodness" of the parent. In that way, the difference between genetic algorithms and simulated annealing can be related to the differences between sexual and asexual reproduction. Each offspring would be essentially a mutation of the parent.

Advanced concepts will evolve as resources are invested in advancing them, but they will most likely evolve as isolated entities. Because of the intricacies of interconnecting different parts of technological concepts, it is unlikely that parts of concept A will be able to be merged with parts of concept B to produce an evolved concept C. Simulated annealing replicates evolution without crossing solutions in the pool; therefore, the author proposes using it to replicate the evolution of individual technological concepts, as it more accurately imitates reality. Because the simulated annealing routine is stochastic, it will allow decision-makers to identify alternatives very near each of the optimum concepts, but it will most likely not identify each optimal concept.

The simulated annealing algorithm begins with a pool of completely random solutions. In each consecutive iteration, one variable in each solution is perturbed slightly, or mutated, to produce an offspring. If the offspring is more fit than the parent, the offspring survives to the next generation, and the parent is killed off. If the offspring is less fit, the probability that the offspring survives is a function of how much less fit it is, and how far into the evolutionary process the algorithm is. As the algorithm moves forward, just like in simulated annealing, the likelihood of an inferior offspring surviving over a superior parent is less and less.

Throughout the process, the solutions that the pool consists of will slide into local minima, or valley, assuming that the objective function is to be minimized. The percentage of the solutions that fall into each local minima will be directly related to the percentage of the design space that is take up by the global minima (breadth), and the steepness of the walls on either side of the minima. The fitness of the points trapped in each valley will be directly related to the fitness of the optimal point in the valley (depth). Consider a generic, one-dimensional objective function that has three local minima as shown in Figure 9.

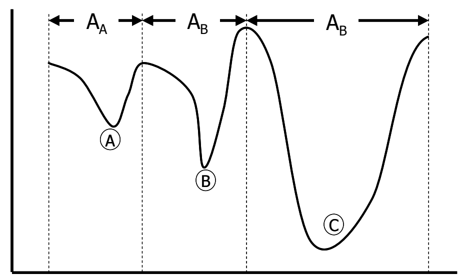


Figure 9: Generic One-dimensional Objective Function

Given the function shown in Figure 9, the points in a simulated annealing pool would theoretically get “stuck” in the valleys labeled “A”, “B”, and “C”. Because the points in the pool are generated randomly from a uniform distribution of the space, the percentage of the pool members stuck in Valley A would be equal to the ratio of Area A to the total space of A_A, A_B, and A_C. Because the simulated annealing program is stochastic in nature, the percentage of points in valley A would mostly likely not exactly equal the ratio, but it would approach it. The simulated annealing program would ultimately identify the optimal concepts, which can later be used to fairly compare concepts to one another.

4.2.2 Calculation of Fitness

Once the set of optimal concepts is known, the fitness of each concept can be calculated for a specific set of requirements. The pool of optimized concepts is actually a pool of optimized alternatives. The fitness of each alternative in the pool is a function of how well that alternative satisfies the requirements, as well as a function of how well the other competing alternatives satisfy the requirements. The relative fitness of each alternative, RF_i, is a measure of the proportional goodness of each concept. The formula for the relative fitness is the same formula that was used in genetic algorithms for proportional replacement, and can be seen below in Equation 11.

$$RF_i = \frac{f(X_i)}{\sum f_k} \tag{11}$$

Where: RF_i = relative fitness of alternative i

$f(\overline{X}_i)$ = objective function

$$f_i = \begin{cases} f(\overline{X}_i) & \text{if } f(\overline{X}_i) \text{ is to be maximized} \\ 1/f(\overline{X}_i) & \text{if } f(\overline{X}_i) \text{ is to be minimized} \end{cases}$$

As was stated earlier, an advanced propulsion concept is really a set of propulsion alternatives. In the generic objective function shown in Figure 9, the "valleys" could each be considered subsets of the design space, and thus technological concepts.

After the simulated annealing algorithm progresses through a sufficient number of iterations, the decision maker can use the makeup of the final pool to forecast the fitness of each of the concepts for the specified requirements. The alternatives present in the pool can each be classified into a concept, depending on the classification scheme that the decision maker chooses. The overall relative fitness of a technological concept equals the sum of the relative fitness of the entire set of alternatives present in the final pool, as is shown in Equation 12.

$$RF_{\text{Concept A}} = \sum_{\substack{\text{All Alternatives} \\ \text{Contained In A}}} RF_i \tag{12}$$

The relative fitness of each concepts contains a measure how good the concept is, as the fitness of each concepts is a relative measure of goodness. The fitness of each concept also incorporates a measure of how "easy" a concept is to implement. As was described above using Figure 9, the percentage of the alternatives in the optimal pool that are part of each concept is a function of how much of the feasible space is made up by that concept. As the percentage of the optimal pool that is made up of a concept increases, the fitness of that concept will also increase because there are more alternatives' fitness to sum. If two or more technological concepts are mutually exclusive and make up the entire concept space, the relative fitness of those concepts will sum up to one. This can be shown through the commutative property of addition, as the relative fitness of all of the alternatives present in the final pool will sum up to one by definition of the relative fitness in Equation 11. The relative fitness of each technological concept reflects how likely it is to survive if it were allowed to mature, given the requirements that the analysis was based upon.

4.2.3 Incorporating Uncertainty into Assessment of Concepts

The previous section detailed a method created to give decision-makers the ability to compare fundamentally disparate technological concepts, and determine the fittest concept for a set of requirements. As was discussed earlier, however, the future requirements that a technological concept is required to meet are highly uncertain, especially given the long gestation period required to develop complex systems. Selecting the fittest advanced propulsion concept based on one set of requirements is naïve, as the decision maker would have no idea how sensitive the fitness of each concept is to the specific set of requirements. In order to understand the fitness of various advanced propulsion concepts fully, the problem solver must consider the variability of the requirements when assessing the fitness of technological concepts.

While the requirements for future technological concepts are uncertain, the maturity of the concepts is also uncertain. The maturity of advanced propulsion concepts can be modeled by inputting disciplinary metrics into the analysis of the concept. Disciplinary metrics are variables and constraints that can be included in the physics-based analysis. Component efficiencies are good examples of disciplinary metrics. Maximum temperatures or elasticity of materials are also good examples of disciplinary metrics. They allow the decision-maker to propagate elementary improvements in technology up to system level metrics. The uncertainty in maturity of concepts can be measured by placing distributions on disciplinary metrics.

Decision-makers must also consider the uncertainty inherent to both the future requirements for the concept and the development of the concepts, to fully understand the goodness of any concept. Both sources of uncertainty can be incorporated into the analysis by calculating the distribution of fitness as a function of both the distribution of requirements and the distribution of disciplinary metrics. Performing such a calculation, however, is not simple. The method to assess the fitness of technological concepts as a function of requirements is not a trivial analysis—it is a computationally exhaustive effort. Methods discussed in Section 2.2.6 can be used to give the decision maker a quantitative understanding the fitness of these advanced propulsion concepts as a function of a ***distribution*** of sets of requirements.

4.2.3.1 Calculating the Distribution of Fitness

The possible methods for identifying the distribution of an output as a function of the distribution of an input are listed and compared in Table 26. Monte Carlo simulations are the simplest, most accurate means of forecasting the distribution of an output as a function of the distribution of inputs. In order the forecast to be accurate, however, a large number of simulations need to be run. Running Monte Carlo simulations with the actual assessment is incredibly time consuming. Fast Probability Integration (FPI) is a method that approximates a Monte Carlo simulation to identify a distribution of an output as a function of the distribution of the input. FPI works by identifying the most probable FPI, and approximating the cumulative distribution function (CDF). More information about FPI can be found in source [49]. FPI is an accurate method of approximating Monte Carlo simulations, and it reduces the number of runs necessary to identify a distribution by thousands. Unfortunately, however, FPI is specific to individual metrics. Because decision-makers need to find the fitness of many concepts, FPI must be conducted for each concept. Table 26 compares the three ways that the distribution of outputs can be calculated as a function of the distribution of the inputs.

Table 26: Calculating Distribution of Fitness

	Set Up Time	Computational Time	Thoroughness of Exploration	Ability to Assess Multiple Criteria	Accuracy (In Linear Space)
MC + Assessment	◉	⊗	▬	◉	●
FPI + Assessment	○	▬	○	⊗	◉
MC + Meta-Model	▬	○	◉	●	◉

Notice in Table 26 that a Monte Carlo in conjunction with the actual assessment is the most accurate means of calculating the distribution of the fitness. This method however, is simply too computationally exhaustive to use. The Monte Carlo trials take thousands of trials to calculate a distribution, and each assessment takes approximately 30 minutes to calculate. At that rate, it would take 200 days to run 10,000 Monte Carlo trials. FPI in conjunction with the assessment would be much quicker, but the fitness of each concept must be determined. FPI analyses would have to be conducted individually for each concept's fitness, which is also infeasible. Monte Carlo trials in conjunction with a meta-model, or surrogate model, however, would be a good way to model the distribution of the fitness. It was infeasible to represent the variability of the revolutionary design space as a function of the variation in the design variables using a meta-model because the revolutionary design space is highly discontinuous. The variability of the fitness of the technological concepts as a function of the variability of the requirements and disciplinary metrics, however, is a more behaved space that would most likely be able to be captured with a meta-model.

4.2.3.2 Creating a Meta-Model

There are a few types of meta-models that can be used in place of the actual model to calculate fitness. Table 27 compares two such methods: Response Surface Equations and Neural Networks.

Table 27: Meta-Model Alternatives

	Setup Time	Computational Time	Accuracy (In Linear Space)	Degrees of Freedom
None	●	⊗	●	●
RSE	○	●	●	○
Neural Network	—	◉	◉	○

The row labeled “None Meta-model refers to using the actual analysis. Notice that using no meta-model is time consuming but affords many degrees of freedom, and is highly accurate. Unfortunately, it is too computationally exhaustive to use in conjunction with a Monte Carlo Simulation. Neural Networks are good for describing non-linear spaces, but the fitness of the concepts within the range of requirements and disciplinary metrics should be linear. RSEs were chosen to as a surrogate model because they are easier to formulate, and should be accurate. Neural Networks could replace RSEs, however, without a disruption to the method.

In order to develop a meta-model that relates variability of the fitness of each concept to the variation of in the requirements, the decision maker needs to follow the steps of Response Surface Methodology (RSM). First, the decision maker needs to identify the independent variables and their ranges; in this case, the independent variables will be the requirements used to design system. Next, the data that relates the response, in this case concept fitness, to the variation in the requirements needs to be generated. A DoE is used to select the design settings for requirements (independent variables) that must be run. Then, the decision maker needs to regress the responses against the requirements, and check the validity of the meta-model.

Once the meta-model has been created, the decision maker can quantitatively observe the sensitivity of each concept's fitness to the requirements and disciplinary metrics. This will serve as a sanity check for the overall system, as erroneous physical correlations will become obvious, and it will increase the decision-maker's understanding of the problem. More importantly, the meta-model will serve as the analysis used in the Monte Carlo simulation that allows the decision maker to calculate the overall distribution of each concept's fitness as a function of the forecasted distribution of the requirements.

The nature of the fitness parameter requires that it be treated carefully with a meta-model. As was stated earlier, the fitness of each concept will vary between 0 and 1, and the sum of the fitness parameters from mutually exclusive concepts that total the entire space must be 1. The relative fitness parameters of these concepts are NOT independent. For this reason, the author suggests post-processing the fitness parameters generated by the meta-model to ensure that the fitness parameters are bounded correctly. The proposed post-processing routine is simple. The following is conducted for the set of mutually exclusive concepts that sum up to the entire space. If the minimum of the relative fitness parameters is less than zero, that parameter value is subtracted from all of the fitness parameters. Equation 12 shows the calculation of the minimum fitness parameter, Z.

$$Z = \min\left[\min\left(\overline{RF_m}\right), 0\right] \qquad (13)$$

Where: $\overline{RF_m}$ = set of RF_i as calculated from meta-model

The minimum fitness parameter, Z, is subtracted from all of the meta-model calculated fitness parameters, to ensure that all of the relative fitness parameters are positive or zero. Then, the parameters are normalized by the sum of all of the new relative fitness parameters. Equation 14 shows the calculation of the relative fitness parameters from the meta-model predicted relative fitness parameters.

$$RF_i = \frac{RF_{m,i} - Z}{\sum\left(RF_{m,i} - Z\right)} \qquad (14)$$

Where: RF_i = relative fitness of alternative i

$RF_{m,i}$ = meta-model predicted RF of alternative i

Z = minimum of RF parameters per Equation 13

Once the decision maker has the ability to relate the relative fitness of each concept to the set of requirements that the concept has to meet quickly, the decision maker can run the Monte Carlo simulation on the prescribed distribution for the requirements. The distribution of relative fitness for each concept can be examined, or it can be used to determine an integrated overall relative fitness given the distribution of the requirements.

4.2.3.3 Evaluating the Distribution of Fitness

As discussed above, the fitness of each concept will measures how well the concept meets a specific set of requirements. Figure 10 shows the fitness of three generic concepts, given a fixed set of requirements and technological maturity metrics. Figure 10 is actually a probability density function, where the fitness value for each concept is shown in the x-axis, and the likelihood of that value is shown in the y-axis. Because Figure 10 depicts the fitness of three concepts for a fixed set of requirements and technology, there is no uncertainty in the fitness measures. Concept A is infeasible, because its fitness is zero—it is not capable of satisfying the requirements. Concept B and Concept C are both capable of satisfying the requirements, but Concept C is a slightly better alternative.

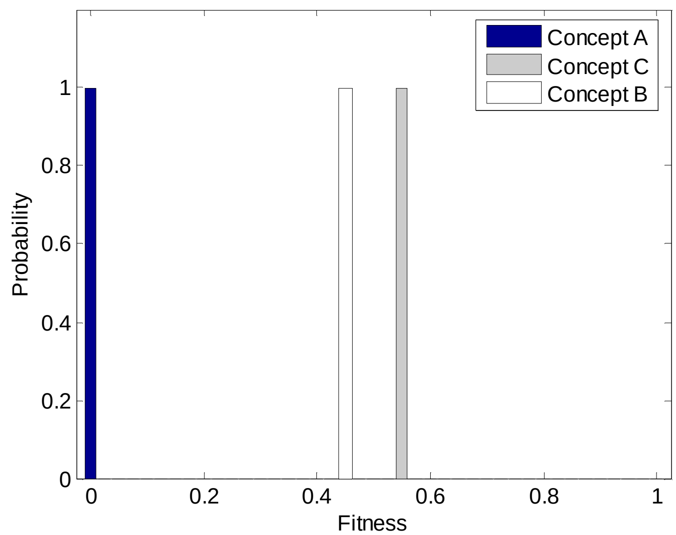


Figure 10: Fitness of Three Generic Concepts for Fixed Requirements

In Figure 10, only three concepts were evaluated and all three concepts are mutually exclusive. The fitness of each concept must then sum up to one. Notice from the figure, that this constraint was enforced.

Figure 10 shows that Concept C is more attractive for the specific set of requirements and technology, but the figure does not give the decision-maker an understanding of how sensitive each concept is to variations in the requirements. Decision-makers must know how the uncertainty in the requirements impacts the distribution of fitness for each concept. Figure 11 shows a generic distribution of the fitness for the same three concepts.

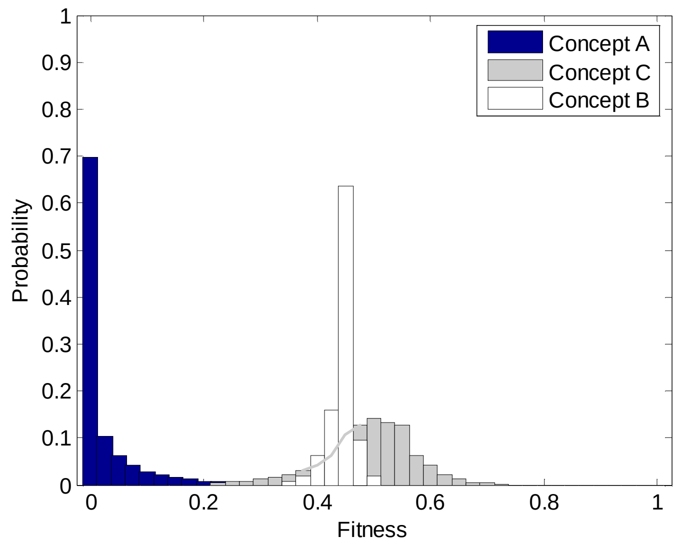


Figure 11: Fitness of Three Generic Concepts for Distribution of Requirements

Notice in Figure 11 that Concept C still appears to be more attractive than Concept B. The figure also shows, however, that the goodness of Concept B is much more certain that the goodness of Concept C. This is because the distribution of fitness for concept B is much tighter. Decision-makers could use this information when evaluating advanced propulsion concepts at early stages of development. The uncertainty in fitness can be directly related to the risks associated with developing advanced propulsion concepts. Decision-makers can use the distribution of fitness for each concept as another figure of merit when evaluating these concepts.

4.3 Method Overview and Summary

The ERTA method was developed as a means of comparing fundamentally different technological concepts, given an uncertain set of requirements. The method can be broken down into two main parts, formulating the requirements and assessing advanced propulsion concepts, based on each concept's fitness. Figure 12 shows a flow chart of the ERTA methodology.

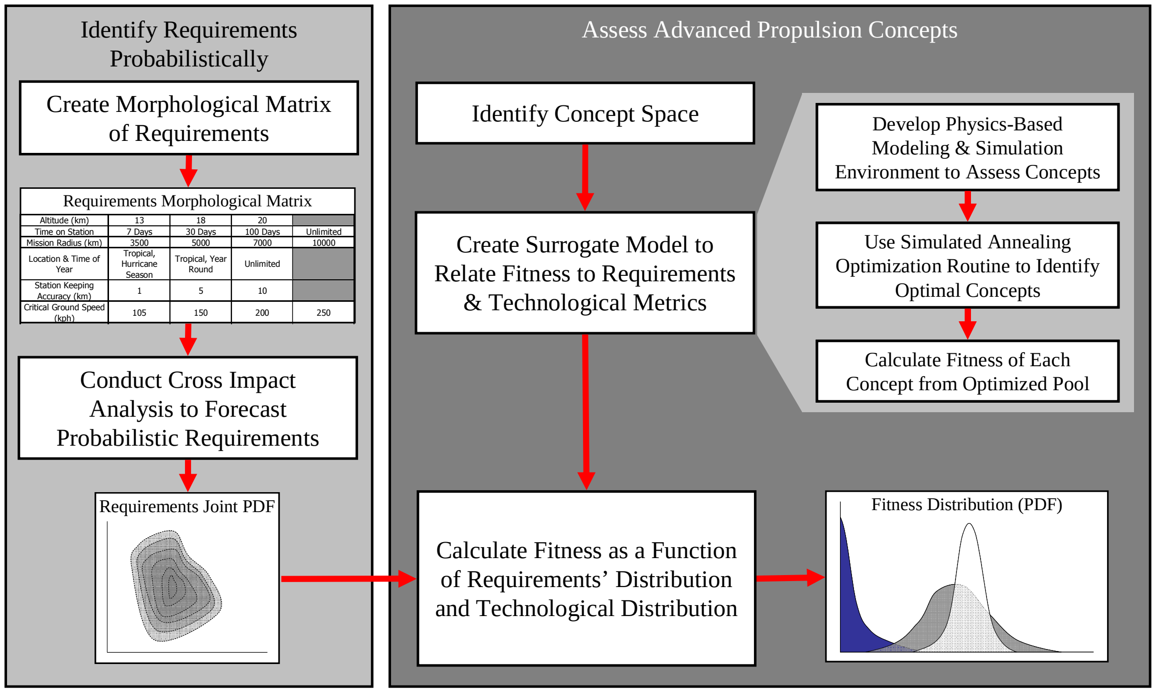


Figure 12: Flow Chart of ERTA Methodology

Notice how in Figure 12, the ERTA methodology is broken into two main parts, identifying the requirements probabilistically, and assessing the propulsion concepts, given the distribution of requirements. A morphological matrix was used to identify potential requirements, and a cross impact analysis was conducted to identify the probabilistic distribution of those requirements. After the concepts were identified, a surrogate model was created that calculated fitness as a function of requirements and disciplinary metrics. That surrogate was used in conjunction with Monte Carlo techniques to identify the distribution of fitness for each concept. The distribution of fitness could then be used to evaluate how good each concept will be, and how robust that goodness is to likely variations in the requirements.

Advanced propulsion concepts could be evaluated using a number of different methodologies, but the ERTA methodology is a novel approach to assessing advanced propulsion concepts, because it sought to assess the robustness of each concept to the likely distribution of the requirements. Table 28 shows a morphological matrix of alternatives for evaluating advanced concepts. Table 28 is a relatively simple account of such methodologies, but it shows that there are 41,472,000 different methodologies that could be used to evaluate the concepts. The alternatives chosen in the ERTA methodology are highlighted.

Table 28: Complete Methodology Morphological Matrix

Requirements Formulation	Provided by Customer	Requirements Analyses	Forecast	Forecast/ Requirements Analysis	
Type of Requirements	Deterministic	Multiple Missions	Probabilistic		
Forecasting Methods	Expert Opinion	Time-Series Forecasting	Trend Impact Analysis	Cross Impact Analysis	Scenario Forecast
	None				
Requirements Analyses	Integrated Product Teams	QFD	Morphological Study	None	Systems Engineering Studies
Need Advanced propulsion concepts?	Expert Opinion	JPDM	Likelihood of Meeting Requirements	Use Technological Assessment	
Figure of Merit	Physical Characteristic	OEC	POS	Fitness	
Define Concepts	Provided by Customer	Brainstorming	Functional Decomposition	TRIZ	
Model Technological Concepts	Qualitative Assessment	Empirical Model	Empirical and Physics-Based Modeling	First Principles	Combination
Identify "Best" Alternatives	Expert Identification	Design Space Exploration	Optimization Routine	Other	
Optimization Routine	Gradient-Based Methods	Random Search	Genetic Algorithm	Simulated annealing	None
Measure Maturity	Deterministic Disciplinary Metrics	Probabilistic Disciplinary Metrics			
Find Distribution of Metrics	MC + Assessment	FPI + Assessment	MC + Meta-Model		
Meta-Model	None	RSE	Neural Network		

The ERTA method combined simple requirements analyses and stochastic forecasting techniques to identify a probabilistic forecast of the requirements. A morphological matrix was selected to identify the possible sets of requirements, because it is a simple, but organized, method of identifying all possibilities. A cross impact analysis was used to forecast the likelihood of each of the requirements, because it uses expert opinion and it is a simple, but effective method for accounting for dependencies between requirements.

The ERTA method assesses advanced propulsion concepts by evaluating the distribution of fitness across the distribution of requirements. Fitness gives a measure of the likelihood that the concept will produce feasible alternatives, as well as an understanding of how "good" it is, relative to competing concepts. If the fitness of a concept is zero for a significant portion of the requirement space, the concept is most likely not a feasible alternative. The outputs of this analysis give decision-makers an understanding of how sensitive the fitness of any concept is to any particular requirements. Concepts that have a relatively good fitness across a wide variety of requirements are robust to variation in requirements. Robustness is a key indicator of how successful an advanced propulsion concept could become, if developed.

5 PROOF OF CONCEPT

The ERTA method was used to assess various advanced propulsion concepts' ability to supply a HALE Hurricane tracking UAV with power and propulsion. The requirements for such a propulsion system will be dictated by the vehicle, mission and NOAA requirements, all of which are uncertain. Such an analysis served as an excellent demonstration example of the ERTA method because the requirements for the propulsion system are uncertain, yet complex and correlated. Also, the results of such an analysis will be of interest to the aerospace industry.

5.1 Hurricane Tracking HALE Vehicle

Hurricanes have become an increasingly destructive force in recent years. The strong winds and storm surge that accompany the storms are dangerous and can cause millions of dollars of damage to infrastructure along the coast. Unfortunately, hurricane forecasters are still not capable of predicting exactly when and where hurricanes will make landfall. To ensure that the people are safely out of each hurricane's path, miles of extra coastline are evacuated, to account for the uncertainty in the storms trajectory. A hurricane-tracking vehicle could vastly increase science's knowledge of the formation and path of hurricanes. This information could be used to increase the accuracy of the storm's predictions and eventually reduce the cost associated with evacuation.

According to NOAA, an average year will produce 11 named storms, six hurricanes—two of which can be categorized as major [74]. Recently, however, the warm waters and the wind patterns have been responsible for producing more tropical storms with greater intensity. "In 2005, the Atlantic hurricane season contained a record 28 storms, including 15 hurricanes," [74]. Figure 13 shows the tracks that 2005 hurricanes took.

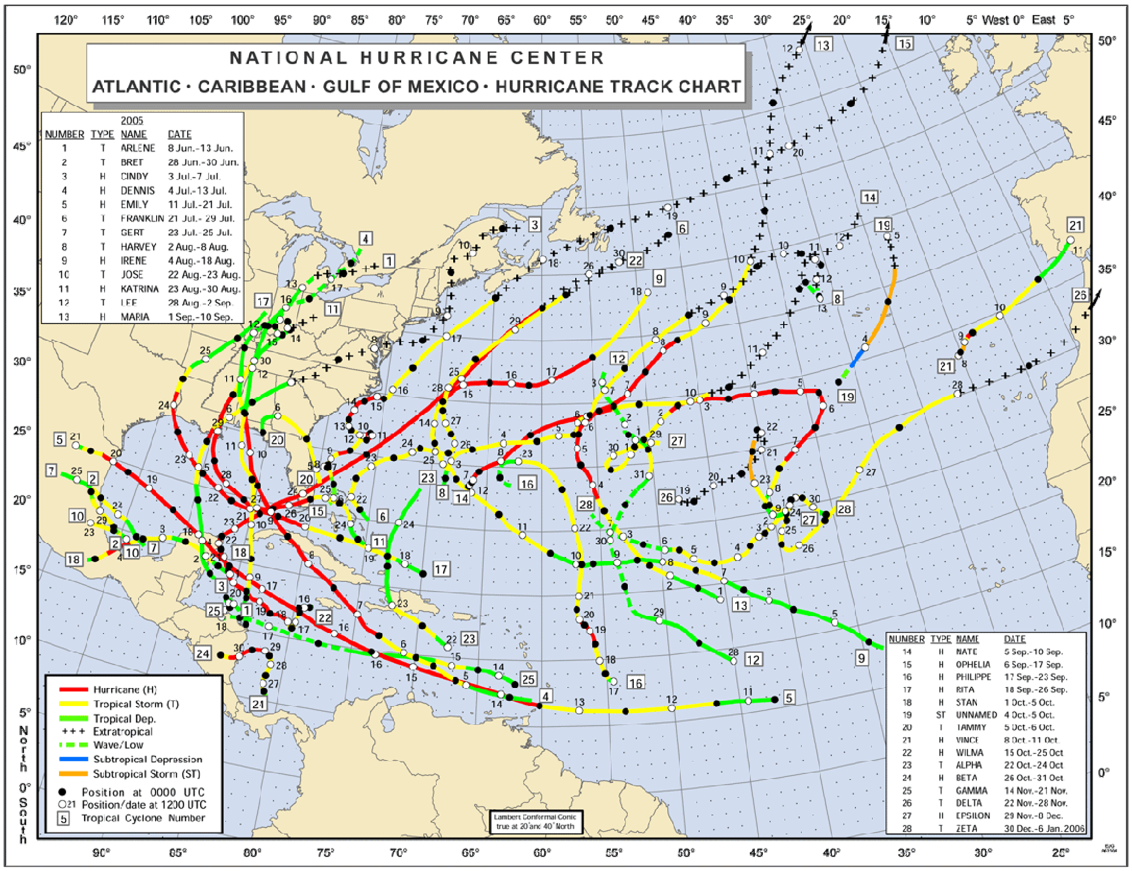


Figure 13: 2005 Hurricane Tracks [71]

Before the 2005 hurricane season, NOAA predicted that the season would be more active than usual, but even then, only expected 12-15 tropical storms [73]. NOAA is predicting an active hurricane season for 2006 as well, and expects 13-15 named storms [74].

Scientists today are able to track the development of hurricanes through many sources, including ships and buoys in the water, geostationary satellites, and "Hurricane Hunters" that fly into the actual hurricane. Unfortunately, none of these sources are able to continuously track and monitor the hurricane. Satellites cannot detect important information accurately, such as barometric pressure and wind speed. Ships are limited because they are slow and vulnerable to large storm waves. The Hurricane Hunters are effective, but their missions are expensive, and they cannot continuously monitor the hurricane. If a vehicle could be developed that could loiter over the development of a hurricane, and track it though its entire cycle, meteorologists could generate much more knowledge about hurricanes. That information could be inputted into forecasting models and eventually reduce the uncertainty in the models' predictions. The industry currently estimates that evacuating one mile of coastline costs on average one million dollars. Increasing the accuracy of hurricanes' forecast even slightly could reduce the amount of coastline that has to evacuate, saving millions of dollars for each hurricane.

5.1.1 Vehicle Mission and Overview

The hurricane tracking HALE vehicle is intended to provide continuous coverage of the development and lifecycle of hurricanes. It would ultimately be responsible for loitering over the "hot zone" where hurricanes are formed, and following a hurricane once it has be developed. Active Doppler Radar, infrared imaging sensors, and Electro-optical imaging sensors can all be used to observe the cyclone from above. Expendable observation devices, such as non-maneuvering dropsondes and small autonomous UAVs, can be dropped into the storm to gather information. The small UAVs could maneuver in and around the cyclone eye-wall to provide a 3-dimensional map of the wind speed, direction, pressure, etc. Ultimately, the vehicle, or system of vehicles, must be capable of taking off from the US mainland and monitoring areas over which most hurricanes develop.

The actual required speed, range, and endurance of the vehicle are currently still being investigated. They could vary, depending on the required monitoring activities of the HALE and the capabilities of the technology used to develop the HALE aircraft. The vehicle would have fly at an altitude high enough to be safely above the hurricane, and it would have to travel quickly enough to keep up with the hurricane, despite any potential winds aloft. The target velocity for the HALE aircraft is between 105 and 215 km/hr. The vehicle would also have to have an endurance that is great enough last through a decent portion of the hurricane season. NASA is currently looking at mission lengths between 7 and 100 days. Once the HALE identifies a cyclone, it will have to follow the cyclone at an unspecified speed, dropping the expendable payload as it goes. NOAA has not specified what type of vehicle they are interested in pursing, meaning that the vehicle could ultimately appear to be anything from a helicopter to a traditional airplane to a blimp. Figure 14 shows a schematic overview of the HALE UAV's mission.

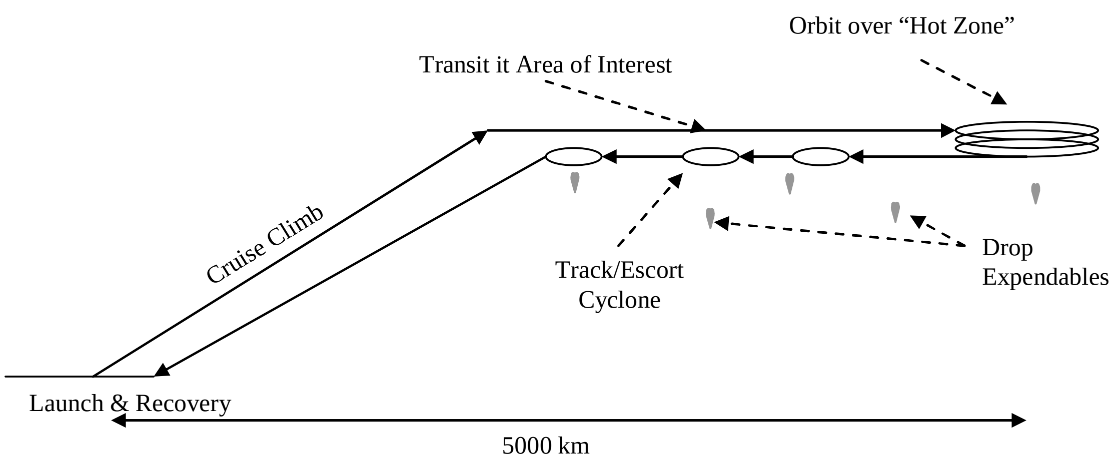


Figure 14: Mission Overview for HALE UAV

5.1.2 NASA Conceptual Design Team

Fortunately, the demand for a high altitude, long endurance vehicle is not unique to NOAA. National security would benefit from having such a vehicle to provide surveillance for borders and other sensitive areas. Society in general would benefit from having a HALE vehicle provide communications relay. HALE vehicles could provide more powerful coverage than satellites, but be more flexible and easier to upgrade than towers. Additionally, they could serve as the communications infrastructure in a catastrophic situation, such as Hurricane Katrina. Emergency relief was hindered there by the failure of the cellular telephone infrastructure.

Because of the interest in a HALE vehicle, NASA assembled a conceptual design team to investigate the requirements and assess the feasibility of such a vehicle. The design team consisted of experts across a broad range of disciplines, ranging from propulsion to structures to electronics, navigation and control.

5.2 Identifying a Probabilistic Requirements Forecast

Before advanced propulsion concepts could be assessed, the requirement that the concepts will have to meet must be understood. As prescribed in section 4.1, a morphological analysis was conducted to understand the requirements, and a cross impact analysis was conducted to calculate the potential distribution of those requirements. The probabilistic forecast of the requirements that the CI analysis yielded enhanced the understanding of the requirements and later served as a distribution from which to evaluate the potential propulsion concepts.

One of the difficulties of conducting a forecasting method that requires expert opinion is actually obtaining the opinion from qualified experts. Fortunately, the conceptual design team workshop that NASA held at Georgia Tech, with the aid of Dr. Mavris and Dr. Kirby presented a unique and fortunate opportunity to directly query experts from a diverse, but applicable set of disciplines. Before the workshop, each NASA HALE Concept Design Team member investigated and researched the requirements that pertained to his or her area of expertise. They also investigated possible alternatives for subsystems within their area of expertise. At the workshop, they were able meet and together further investigate the requirements for such a vehicle, and investigate the feasibility of various vehicle concepts.

Part of that workshop entailed the development of a morphological matrix that identified all of the possible mission parameters for the UAV. The experts were also asked to give their input as to the likelihood of the various mission parameters. Similarly, the design team developed a morphological matrix that identified all of the possible vehicle characteristics. For each possible vehicle characteristic, experts rated the alternatives according to appropriate metrics, and used that to come up with a normalized measure of goodness.

The requirements for a HALE propulsion system will be dictated by the mission parameters and vehicle characteristics. Accordingly, the workshop provided a basis from which to formulate the requirements for advanced propulsion concept. The possible requirements came directly from the morphological matrix, and the distribution of the requirements was found through a cross impact analysis. Most of the expert opinion required for the CI analysis came directly from the workshop, as the design team did compare alternatives. The design team also examined the vehicle characteristics and mission parameters that were interdependent. The conditional probability estimates were derived from this examination. Finally, a modified CI analysis was performed on a selected set of the mission parameters and vehicle characteristics to formulate a probabilistic set of relevant requirements for the aeropropulsion system.

5.2.1 Identifying Potential Requirements

The HALE Concept Design Team's first task was to create two morphological matrixes, one of the mission parameters, and one for the HALE concept alternatives. This matrix enabled the design team to better understand the system requirements and alternatives, but it also served as a basis for establishing the requirements for the propulsion systems evaluated in this study. In the mission parameters matrix, the mission that the HALE aircraft would have to perform was broken down into the major mission segments or parameters, and alternatives for each segment or parameter we listed. The mission parameters morphological matrix is shown in Table 29. The number of missions described in Table 29 (as found by all of the unique combination of alternatives) is almost 516 billion missions.

Table 29: HALE Mission Parameters Morphological Matrix

Altitude	>13 km	>18 km	> 20 km	
Time On station	~7 days	~30 days	~100 days	Unlimited
Mission Radius	~3500 km	~5000 km	~7000 km	~10000 km
Location and Time of Year	Tropical, Hurricane Season	Tropical, Year Round	Unlimited CONUS	
Station Keeping Accuracy	~1 km	~5 km	~10 km	
Critical Ground Speed	105 kph	150 kph	200 kph	250 kph
Wind Tol: Launch and Recovery	10 kph	25 kph	50 kph	
Wind Tol: Sustained	< 100 kph	~ 100 kph	~150 kph	~200 kph
Gust tolerance: Uniform	<7.5 mps	<15 mps	<22.5 mps	
Service Life	~3000 hrs	>7500 hrs	>10000 hrs	>40000 hrs
Expendable Payload	Dropsondes	Mini-UAV	Drop and UAV	None
Fixed Payload	Hurricane-Doppler	Disaster - Monitoring	Hurricane Package	
	Broadband	Cell Phone		
Weather	Standard Day	Near All Weather	All Weather	
Completion Rate	>90%	>95%	>99%	
	>99.9%	>99.99%		
Mission Operational Concepts	Auxiliary-powered Deployment	Refueled in Flight	Single Vehicle	Formation Flight
	Serial Flight	Tip-joined Multi-Vehicle		
Operating Environment	Mil Std 210 Std Day	Mil Std 210 Cold Day	Mil Std 210 Hot Day	Mil Std 210 Tropical Day
Runway length	<150 m	<1500 m	<2000 m	Circular
Recovery	None	Wheeled Runway Landing	Parachute	Parasail
	Skid Gear	In Air Recovery	Water Landing	Stall and Drop from Low Alt.
Launch	Towed	Wheeled Runway Launch	Dolly	
Runway width	< 45 m	<60 m	Circular	

The vehicle characteristics morphological matrix is shown in Table 30. Notice that the morphological matrix is broken down into subcategories of configuration, command, control, and data link and actuation. Notice that a major discipline of the UAV is missing from Table 30. The propulsion system characteristics are not considered. While the HALE Concepts Design Team did identify the potential propulsion system characteristics, they were left out of this analysis, as the ultimate point of the exercise is to establish the requirements for the propulsion system. A morphological matrix was created that defined all of the possible propulsion concepts that were considered in the analysis. Ignoring the propulsion systems, the number of vehicle systems identified in Table 30 numbered almost 2.8 trillion.

Table 30: HALE Vehicle Characteristics Morphological Matrix

Configuration	**Variable Geometry**	**None**	**Span**	**Sweep**	**Dihedral**
		Chord	**Aux surfaces**		
	Rotorcraft	**None**	**Helicopter**	**Autogyro**	**Tiltrotor**
	Fixed Wing	**None**	**W-B-T/C**	**Bi-plane**	**All wing**
		Three surface + B	**Joined wing**		
	Airship (LTA)	**None**	**Dirigible**	**Blimp**	
		Hybrid	**Powered Balloons**		
	Detect and Avoid	**Radar**	**Chase**	**EO**	**IR**
		Laser	**Ultrasonic**	**IFF/Transponder**	**Tip lighting**
	Health Management	**None**	**Federated**	**Integrated**	
	Flight Control Sensors	**Flight control level**	**Precise Pointing**	**GPS only**	**GPS + compass**
Command	**Command Mission Termination Systems**	**None**	**Controlled Return**	**Controlled Ditch**	**Parachute**
		Pyrotechnic	**Autonomous Safe**	**Control Hard Over**	
	Command Link: Line of Sight	**None**	**Single channel**	**Dual channel**	**Freq Hopping**
		Single Down-Dual Up	**Mil band**	**Commercial Band**	
	Command Link: Beyond Line of Sight	**None**	**Relay**	**HF**	**GEO**
		LEO	**VLF**	**LF**	
Control	**Climb & Descent**	**Controlled: LOS**	**Controlled: Non-LOS**	**Controlled: Pitch Roll Rate Inputs**	**Semi-Auto: Pre-programmed Static Mission**
		Semi-Auto: Heading, Alt., Speed inputs	**Fully Auto: IVHM**	**Fully Auto: Mission Management**	
	Cruise	**Controlled: LOS**	**Controlled: Non-LOS**	**Controlled: Pitch Roll Rate Inputs**	**Semi-Auto: Pre-programmed Static Mission**
		Semi-Auto: Heading, Alt., Speed inputs	**Fully Auto: IVHM**	**Fully Auto: Mission Management**	
	Take-off and Landing	**Controlled: LOS**	**Controlled: Non-LOS**	**Controlled: Pitch Roll Rate Inputs**	**Semi-Auto: Pre-programmed Static Mission**
		Semi-Auto: Heading, Alt., Speed inputs	**Fully Auto: IVHM**	**Fully Auto: Mission Management**	

Data Link	Data Link: Line of Sight	None	Single channel	Dual channel	Freq Hopping
		Single Down-Dual Up	Mil band	Commercial Band	
	Data Link: Beyond Line of Sight	None	Relay	HF	
		GEO	LEO		

Actuation	Actuation Systems	Differential Thrust	Electric Motor	Pneumatic/ Hydraulic	
		Piezoelectric	SMA		

The morphological matrix created by the HALE Concepts Design Team was an excellent basis from which to formulate the requirements for the HALE propulsion system, but it needed to be modified slightly. The matrix contained many system level parameters or characteristics were not considered in the early analysis of the propulsion system, either because the differences in the alternatives did not have significant impact on the propulsion system, or because the author simply did not have the capability to analyze the impact of the different alternatives. Those parameters and characteristics were removed from the analysis. Because they were not modeled, they could not impact the result, and they complicated the CI analysis.

The remaining portions of the morphological matrixes were combined to form one morphological matrix that defined and organized the potential requirements for the HALE UAV's propulsion system, as shown in Table 31. The morphological matrix took parts of the morphological matrixes in Table 29 and Table 30. Not all of the elements that will not significantly impact the goodness of each of the potential propulsion systems, but they were included because the author believed that they could have an impact on the propulsion system. It is better to have a variable and ignore it in the analysis than it is to ignore it initially and need it later. Over 2 trillion systems were identified in Table 31.

Table 31: HALE Propulsion System Requirements Morphological Matrix

Altitude	>13 km	>18 km	> 20 km	
Time On Station	~7 days	~30 days	~100 days	Unlimited
Mission Radius	~3500 km	~5000 km	~7000 km	~10000 km
Location and Time of Year	Tropical, Hurricane Season	Tropical, Year Round	Unlimited CONUS	
Station Keeping Accuracy	~1 km	~5 km	~10 km	
Critical Ground Speed	105 kph	150 kph	200 kph	250 kph
Service Life	~3000 hrs	>7500 hrs	>10000 hrs	>40000 hrs
Expendable Payload	Dropsondes	Mini-UAV	Drop and UAV	None
Fixed Payload	Broadband	Cell Phone	Hurricane Package	
	Hurricane-Doppler	Disaster Monitoring		
Weather	Standard Day	Near All Weather	All Weather	
Mission Operational Concepts	Auxiliary-powered Deployment	Refueled in Flight	Formation Flight	Tip-joined Multi-Vehicle
	Serial Flight	Single Vehicle		
Operating Environment	Mil Std 210 Std Day	Mil Std 210 Cold Day	Mil Std 210 Hot Day	Mil Std 210 Tropical Day
Runway Length	<150 m	<1500 m	<2000 m	Circular
Recovery	None	Wheeled Runway Landing	Parachute	Stall and Drop from Low Alt
	Skid gear	In air Recovery	Water Landing	Parasail
Launch	Towed	Wheeled Runway Launch	Dolly	
Runway Width	< 45 m	<60 m	Circular	
Variable Geometry	None	Span	Sweep	Dihedral
	Chord	Aux Surfaces		
Rotorcraft	None	Helicopter	Autogyro	Tiltrotor
Fixed Wing	None	W-B-T/C	Bi-plane	All Wing
	Three surface + Body	Joined wing		
Airship (LTA)	None	Dirigible	Blimp	
	Hybrid	Powered Balloons		

5.2.2 Initial Probabilities

Once the possible requirements were defined (Table 31), the probability of each possible requirement had to be forecasted. The CI analysis uses expert opinion to identify the initial probability of each mission parameter or vehicle characteristic actually becoming part of the future system, and hence, a future requirement. The cross impact analysis assumes that only one and only of the possible outcomes that is listed in each element will occur. This means that two potential alternatives in the same element cannot occur simultaneously, or the alternatives are mutually exclusive, and that one of the alternatives must occur. For example, the HALE vehicle must cruise at an altitude of 13 km, 18 km, or 21 km. The probability of all of the alternatives that comprise one element or parameter, consequently, must sum up to one. The expert estimated initial probability for two of the mission parameters, altitude and ground speed, are listed below in Table 32.

Table 32: Selected Probabilities of Mission Characteristics

Altitude	>13 km	>18 km	> 20 km	
Probability	0.1	0.5	0.4	

Critical Ground Speed	105 kph	150 kph	200 kph	250 kph
Probability	0.15	0.8	0.04	0.01

A full list of the initial probably estimates for the potential requirements settings can be found in APPENDIX B.

5.2.3 Compatibility Matrix

The modified CI analysis also takes into account the dependencies of the different potential requirements on one another. Certain alternatives will not be compatible with one another. For example, it is unrealistic to forecast that the UAV will be a lighter than air vehicle that will travel 250 kph. In addition to the incompatibilities, certain alternatives will be correlated with one another, meaning that if one alternative is part of the system, there is a greater chance that another alternative will also be part of the system. An example of correlated mission parameters may be critical ground speed and altitude. The chances of a lower ground speed are much higher at low altitudes, because the density of the altitude is greater and therefore the power required to propel the UAV would be much greater. There are also negative correlations between alternatives of different elements. Finally, some of the elements truly are independent of one another, meaning that if one alternative is part of the larger system, the likelihood of alternatives from another element being part of the system is unchanged.

A large compatibility matrix was formed that related the conditional probabilities of alternatives in each of the elements to alternatives in another. The entire matrix is cumbersome, as one row and one column are required for each of the alternative present in the matrix. A few excerpts from the compatibility matrix are shown below. The compatibility matrix relates the conditional probability of each alternative in the row, given that the alternative in the column heading is part of the system. The probability listed on the far left is the initial probability for the alternative, as predicted by experts. Table 33 shows the conditional probability for two ***independent*** variables, Altitude and Service Life. Because the variables are independent, the conditional probability for each alternative is equal to the initially estimated probability, as selecting one of the alternatives had no bearing on the selection of the other. Also notice that the alternatives within each element, are mutually exclusive. The likelihood of the altitude being under 13 km, given that it is 18 km is zero.

Table 33: Excerpt from Conditional Matrix (Independent Variables)

			Altitude			Service Life			
Element	Probability	Alternative	>13 km	>18 km	> 20 km	~3000 hrs	>7500 hrs	>10000 hrs	>40000 hrs
Altitude	0.1	>13 km	1	0	0	0.1	0.1	0.1	0.1
	0.5	>18 km	0	1	0	0.5	0.5	0.5	0.5
	0.4	> 20 km	0	0	1	0.4	0.4	0.4	0.4
Service Life	0.1	~3000 hrs	0.1	0.1	0.1	1	0	0	0
	0.15	>7500 hrs	0.15	0.15	0.15	0	1	0	0
	0.5	>10000 hrs	0.5	0.5	0.5	0	0	1	0
	0.25	>40000 hrs	0.25	0.25	0.25	0	0	0	1

Figure 15 shows the joint distribution for the two variables shown in Table 33. Notice in Figure 15, that the two variables really do appear to be independent. This can be determined, because the ratio of the probability of the various altitudes appear to be the same, regardless of what the service life is. At the same time, the ratios between the probabilities of the service life settings are the same, regardless of what altitude has been selected.

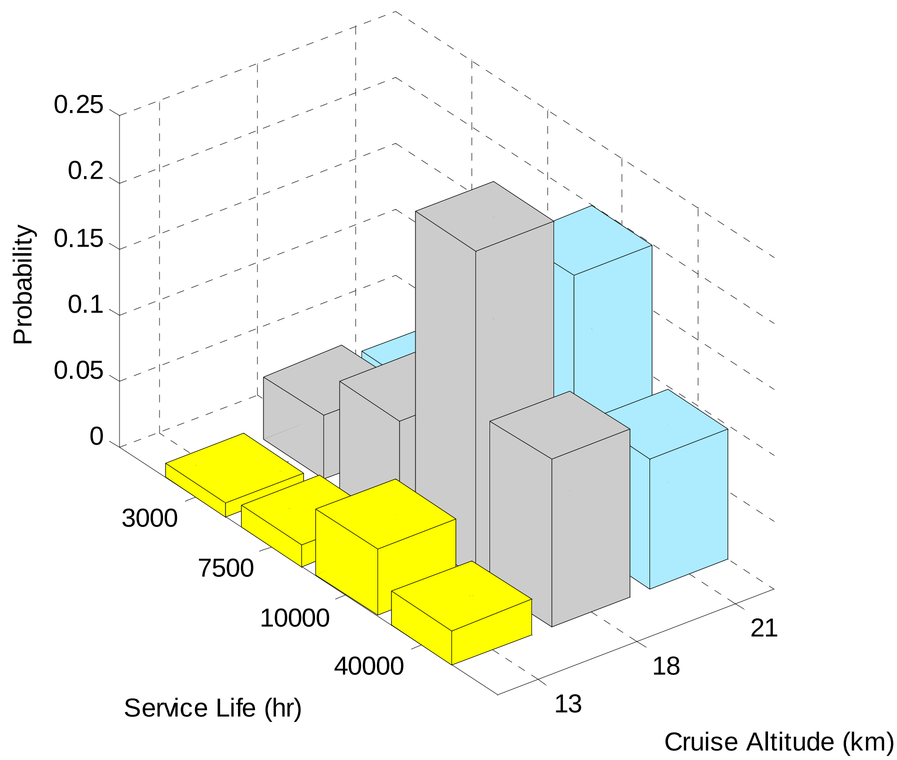


Figure 15: Joint Probability Distribution for Service for Independent Variables

Table 34 is another excerpt from the compatibility matrix. Table 34 however, shows two variables that are dependent upon one another, Altitude and Critical Ground speed. Notice in Table 34 that there is a positive correlation between increasing altitude and increasing ground speed. As the latitude that is selected increases, the probability that the speed will be higher increases as well.

Table 34: Excerpt from Conditional Matrix (Independent Variables)

Element	Probability	Alternative	Altitude >13 km	Altitude >18 km	Altitude > 20 km	Critical Ground Speed 105 kph	Critical Ground Speed 150 kph	Critical Ground Speed 200 kph	Critical Ground Speed 250 kph
Altitude	0.1	>13 km	1	0	0	0.1	0.1	0.1	**0**
	0.5	>18 km	0	1	0	0.5	0.5	0.5	0.55
	0.4	> 20 km	0	0	1	0.4	0.4	0.4	0.45
Critical Ground Speed	0.15	105 kph	0.19	0.15	0.1	1	0	0	0
	0.8	150 kph	0.8	0.8	0.6	0	1	0	0
	0.04	200 kph	0.01	0.04	0.2	0	0	1	0
	0.01	250 kph	**0**	0.01	0.1	0	0	0	1

The entire compatibility matrix is not shown in any appendices, simply because it is too large to readily show on paper. Figure 16 shows the joint distribution of the two variables shown in Table 34. The joint probability shows that the two variables are clearly correlated. Notice that the likelihood of the speed being 250 kph at an altitude of 13 km is zero.

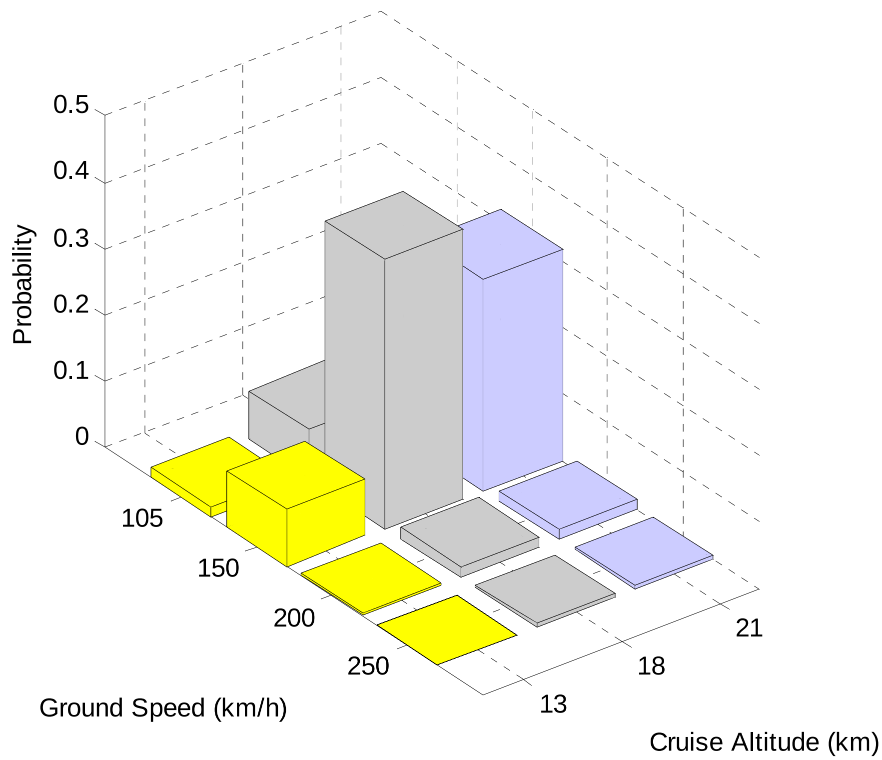


Figure 16: Joint Probability Distribution for Dependent Variables

5.3 Evaluating Advanced Propulsion Concepts

In order to evaluate the fitness of propulsion concepts a tool that can assess the range of potential concepts, under the variety of potential requirements, is required. Unfortunately, while several propulsion analysis programs exist, a tool that was flexible enough, robust enough, and simple enough to implement did not exist before this research initiative began. Consequently, an analysis environment was created, based on the physical and thermodynamic processes that occur in a propulsion system. The environment essentially evaluates the propulsion system and creates a simplistic, engine deck. That deck is then used to size a parametrically specified aircraft or air-vehicle. The fitness of each concept is then calculated, using the propulsion analysis and vehicle-sizing program. The basic principles of the assessment environment, the Advanced Propulsion System Analysis (APSA), are described below.

5.3.1 Identifying Advanced Propulsion Concept Space

The first step to assessing the advanced propulsion concepts was identifying the concept space. The In order to do this, the propulsion system was broken down into the fundamental processes that must be present in a propulsion system. Table 35 shows the breakdown of the advanced propulsion concepts. Table 35 broke propulsion concepts into a few main subfunctions. First, the "combustion" subfunction examined how the engine extracted the energy from any sort of onboard fuel. If a battery was the main energy source, combustion was not necessary. Various fuel types were examined. Additionally, if combustion occurred, an oxidizer was required. Either that oxidizer could be taken from ambient air, or it could be stored onboard. Additionally, because of the long duration required for the vehicles, energy needed to be replenished. The energy renewal subfunction lists alternatives for renewing the energy of the propulsion system. Finally, the vehicle must convert electrical or shaft energy to thrust. Main methods behind this conversion are also listed.

The combustion processes discussed in Table 35 approximate combustion processes. Pressure is not truly conserved in constant pressure combustion processes. A small percentage of the total pressure is lost in the combustion process. Similarly, constant volume combustion processes are combustion processes that can be approximated as occurring at a constant volume, such as the combustion in a four-stroke engine.

Notice in Table 35 that the propulsion concepts are limited. Nuclear propulsion concepts were ignored both because of the complexity involved in such engines, and the low likelihood that the engines would be considered. Also, while batteries were considered as the basis for thrust generations, the author assumed that batteries alone would not provide enough energy efficiently enough to power the HALE vehicles.

Table 35: APSA Morphological Matrix

Solution Space	Combustion Type	None	Fuel Cell	Constant Pressure Combustion	Constant Volume Combustio n	
	Fuel Type	None	H_2	Jet-A	CH_4	C_3H_8
	Battery Type	None	Nickel-Cadmium	Nickel-Metal Hydride	Lithium Polymer	Zinc-Bromide
	Oxidizer	None	Ambient Air	Stored O_2		
	Oxidizer Preparation	None	Heat Addition	Compression		
	Energy Renewal	None	Solar	Refueling	Beamed Energy	
	Thrust Production	Propeller	Bypass Jet	Pure Jet		

There are 10800 propulsion concepts identified in Table 35.

5.3.2 Creating a Surrogate Model to Relate Fitness to Requirements

The ERTA method strives to give decision-makers an understanding of how robust advanced propulsion concepts are to variations in requirements. In order to do so, the ERTA method calculates the distribution of fitness as a function of the distribution of requirements. Before that can be done, a surrogate model must be built to directly relate each concept's fitness to variations in the requirements. The following section discusses the development of this surrogate model.

In order to develop a surrogate model, first, decision-makers must have the ability to assess each concept. Because most of the concepts under consideration are very immature, and because the author could not find a suitable modeling environment that enabled her to evaluate the entire range of concepts under consideration, she developed her own modeling environment. This environment models the engine cycle by building an engine deck. That deck is then used to size a vehicle to fly a mission. If the engine was capable of powering the vehicle and allowing it to complete the mission, the gross weight of the vehicle was used as a discriminator compare feasible engines.

Once this environment existed, a simulated annealing program was written to find an optimal set of propulsion alternatives for a particular set of requirements and setting of disciplinary metrics. That optimized set of alternatives was used to calculate the fitness of each concept. A meta-model was then created to relate the variation in the fitness of each concept to the variability of the requirements and disciplinary metrics.

5.3.2.1 Assessing Alternatives' Ability to Meet Requirements

Before one can measure how well a propulsion concept can meet a specific set of requirements, one has to have a modeling and simulation environment that can be used to assess the concepts. As was discussed in section 4.2.1.2, a first principles analysis was used to evaluate the propulsion concepts. The author could not find an existing modeling and simulation environment that was flexible and fast enough to model the entire range of propulsion concepts under consideration, so one was created. Modeling the engine cycle alone, however, is not sufficient to assess the propulsion system. The performance of the cycle throughout the mission, and the interactions between the vehicle and the propulsion system must be accounted for in order to assess the engine's ability to satisfy the requirements. Both the modeling of the propulsion system and the modeling of the vehicle integration are discussed in this section.

5.3.2.1.1 Modeling the Propulsion Cycle

The ultimate function of a propulsion system is to convert energy that is either stored onboard, or continuously acquired, into some form of propulsion. Propulsion systems have several basic components that help enable this task to be carried out. Rarely is the stored energy converted directly to thrust. Usually, it is first converted to heat energy, and then in turn converted to mechanical energy. In the case of a fuel cell or battery system, the stored energy is first converted to electromagnetic current, and then converted to mechanical energy.

An assessment environment was created that was capable of evaluating the entire range of possible alternatives. In order to do this, the propulsion system was broken down into the fundamental processes that must be present in a propulsion system. Those processes were then modeled using the fundamental physical and thermodynamic relationships that govern them. The processes were connected by modeling the transfer of energy between them, either in the form of shaft horsepower, electromagnetic energy, or fluid properties. The basic format of the environment is similar to Numerical Propulsion System Simulation (NPSS), a NASA developed propulsion cycle analysis code, accepted across the industry and government. The differences between APSA and NPSS are the level of fidelity of the analysis, the degree of the system that must be specified and the reliance upon empirical data. APSA relies on lower fidelity, physics-based analyses for all of its calculations. Differentiations in maturity are modeled through simple disciplinary metrics, individually specified for each potential process. Increasing the fidelity of APSA requires that more information about the concept is specified at an earlier stage, which is difficult and usually unnecessary when assessing advanced propulsion concepts that little is known about. Finally, APSA does not use any empirical relationships, simply because most of the concepts that are being evaluated are outside of the realm of experience.

The APSA is currently capable of assessing the entire range of propulsion concepts identified in Table 35. Notice that far out concepts, such as ion-propulsion systems and nuclear jets or rockets, were left out of the APSA because those concepts were not expected to be legitimate contending concepts. Traditional concepts, such as a turbofan are included. Each alternative is the space is represented by a unique combination of morphological matrix alternatives. A turbofan concept, for example, would be modeled as a constant-pressure combustion process, using Jet A fuel, no battery, ambient air, and compression. There would be no source of energy renewal, and thrust would be produced using a bypass jet. Similarly, rockets, turboprops, and various fuel cell concepts can all be modeled.

The combustion processes discussed in Table 35 are approximations of combustion processes. Pressure is not truly conserved in constant pressure combustion processes. A small percentage of the total pressure is lost in the combustion process. Similarly, constant volume combustion processes are combustion processes that can be approximated as occurring at a constant volume, such as the combustion in a four-stroke engine.

In addition to the processes shown in Table 35, APSA also continuous variables that further define the system. These variables specify the equivalence ratio of the engine, the compression ratio of the compressor if one exists, as well as other key cycle parameters.

The APSA was used to create an engine deck for each propulsion system. The engine deck recorded how much power and thrust could be generated at several specified flows of energy, at different altitudes, and at different speeds. The deck also recorded the ratio of the engine to power output. The information in the deck was used to size parametrically defined vehicles.

5.3.2.1.2 Vehicle Sizing Algorithm

Unfortunately, calculating the cycle of a propulsion system is not sufficient to evaluate a propulsion system. The only way to evaluate these fundamentally different concepts fairly is to measure how well they allow the entire vehicle system to meet the system-level requirements. This can only be measured by evaluating the integration of the propulsion system with the vehicle and the mission. Instead of evaluating a propulsion concept independently, propulsion concepts will be evaluated based on their ability to allow the entire vehicle system to meet the system-level requirements simultaneously. The ability of a vehicle system to meet the system level requirements can be measured by a number of metrics. Any system-level metric that is calculated can be used as a metric from which to evaluate propulsion systems, but for this analysis, total vehicle weight was used as a metric to assess how well the propulsion system met the requirements. If the vehicle is was incapable of satisfying all of the mission requirements simultaneously, vehicle weight would be infinite.

The vehicle sizing portion of the ASPA environment uses the engine deck, found in the propulsion cycle analysis, and an energy-based sizing method to size a vehicle to satisfy a parametrically defined. As mentioned above, total vehicle weight was used as a metric to compare different propulsion systems to one another. While other figures could have been considered or simultaneously introduced, gross weight introduces a measure of life cycle cost and technological maturity, as the component weights of propulsion systems are reduced when the concept becomes more mature. Emissions were initially considered in the study, but they eliminated as a metric. Carbon based emissions are closely tied to fuel type and overall efficiency, so the metric was redundant. Nitrogen based emissions were ignored because they are usually only considered at takeoff and landing and the author had trouble predicting the nitrogen emissions for immature propulsion technology. While gross weight is the outputted system-level metric, is NOT the only metric used to assess the concept. If the propulsion system is not capable of meeting all of the requirements or constraints (located in a wide variety of fields) ***simultaneously***, the gross weight is not computed, and thus, the infeasibility of the alternative becomes apparent. Vehicle weight was used to compare propulsion systems, but the values were only directly compared when the requirements and vehicle configuration was held constant.

An energy based sizing method was used to size the various types of air vehicles. In order to keep the analysis running quickly enough to be of use, vehicles were specified parametrically. Three different classes of vehicles were considered, fixed wing aircraft, lighter-than-air vehicles, and hybrids. Helicopter-based systems were not included in the analysis because the experts involved in the NASA conceptual design study determined that they were not feasible alternatives to meet the HALE's system-level requirements.

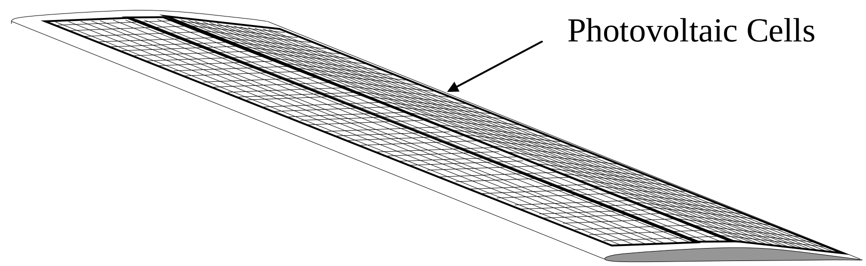
The theory behind the sizing algorithms for each vehicle class was universal, but the implementation of that theory differed based on the vehicle class. An overview of the methodology is discussed in APPENDIX C. The generation of lift and drag is different for fixed wing and lighter-than-air vehicles; consequently, the each sizing algorithm reflected those differences. Also, each class of vehicles required a different set of parameters to define them. Finally, the mission parameters that significantly impacted the vehicle sizing differed for the vehicle class. The sizing algorithms used to size fixed and lighter-than-air vehicles are explained in further detail in APPENDIX D and APPENDIX E, respectively. An overview of the sizing and synthesis environment is discussed below.

The basis for each sizing algorithm was to calculate the power required to propel the vehicle at each point in flight. The engine deck was used to relate that power to a flow of "fuel". Fuel referred to any stored energy, from Jet-A to H_2 to electrolyzer. That flow was integrated across the entire mission to calculate the portion of the vehicle mass that needed to be fuel. That ratio was then used to size the vehicle.

In order to calculate the power required at any point in the mission, the drag generated by the vehicle was calculated as a function of the mass. For the fixed wing vehicle, drag was a function of the dynamic pressure, wing loading, and the drag polar, shown below in Equation 15. In the equation, $C_{D,O}$ is the zero lift drag coefficient and K_1 is a constant.

$$C_D = C_{D,o} + K_1 C_L^{\ 2} \qquad 15$$

Equation 15 can be used to calculate drag as a function of mass, by multiplying the drag coefficient by dynamic pressure, and dividing it by the wing loading. The constants in the equation, $C_{D,o}$ and K_1 are functions of the geometry of the vehicle. According to the requirements that were developed by the NASA conceptual design team, several fixed wing vehicles were considered, from a flying wing, to a traditional fuselage-wing body. Defining the vehicle configuration defined the parameters in Equation 15. A solar flying-wing structure is shown below in Figure 17



.

Figure 17: Flying Wing Schematic

Once the drag polar constants were determined, the drag could be normalized by the vehicle mass, as shown in Equation 16. In the equation, m_{TO} refers to takeoff gross weight. The variable S refers to wing area. The wing loading, then is the ratio between the m_{TO} and S.

$$\frac{\text{Drag}}{m_{TO}} = \frac{q\, C_{Do}}{m_{TO}/S} + \frac{K_1\, g^2}{q}\left(m_{TO}/S\right) \qquad (16)$$

Equation 16 can be used to calculate the drag at any straight, level, constant speed flight. Additional terms need to be considered if the vehicle is climbing or accelerating (including turning).

Lighter-than-air vehicles do not rely upon lift generated by a wing to stay up in the air. Instead, they rely upon the buoyant forces to sty in the air. Because of this, lighter-than-air vehicles do not generate large amounts of drag due to the creation of lift.

Instead, they generate drag by pushing a large volume through the air. An airship schematic is shown below in Figure 18.

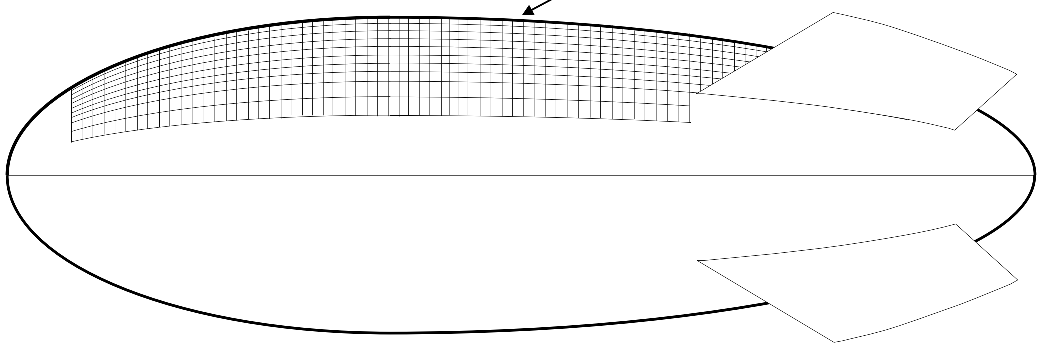


Figure 18: Solar Airship Schematic

The drag generated by lighter-than-air vehicles was calculated using a volumetric drag coefficient, C_{DV} [48]. The volumetric drag coefficient is found by normalizing the drag both they dynamic pressure and the envelope volume, raised to the 2/3rd power, as is shown in Equation 17.

$$C_{DV} = \frac{\text{Drag}}{\frac{1}{2}\rho V^2 \left(\text{Volume}\right)^{2/3}} \tag{17}$$

The flow of energy that was required to provide that power was obtained from the engine deck, and the ratio of stored energy to mass and engine weight to mass was calculated. By normalizing the flow of energy by the total vehicle mass and integrating that flow across the entire span of the mission that the engine last, the ratio of energy weight to vehicle weight could be found. The ratio of stored energy to vehicle weight was recorded for each segment, as is shown in Equation 18.

$$\frac{M_{\text{Energy}}}{M_{\text{Vehicle}}} = \frac{\dot{m}_{\text{Energy}}}{M_{\text{Vehicle}}} t_{segment} \tag{18}$$

The total ratio of stored energy for the vehicle was found by determining the greatest possible stored energy ratio for the mission. In most cases, that segment occurred between energy renewals. Energy renewal could come in the form of mid-air refueling or solar energy.

Additionally, the maximum power to weight ratio for the mission was found. This parameter was used in conjunction with the power to weight ratio of the engine (the specific power) that was tabulated in the engine deck. The calculation of the engine mass ratio is shown in Equation 19.

$$\frac{\mathrm{M}_{\mathrm{Engine}}}{\mathrm{M}_{\mathrm{Vehicle}}} = \frac{\mathrm{P}_{\mathrm{Max}}}{\mathrm{M}_{\mathrm{Vehicle}}} \text{Specific Power}_{\mathrm{Engine}}\,(\mathrm{W/kg}) \tag{19}$$

Other mass ratios, such as the empty mass ratio, were assumed parameters in the analysis. If solar energy was to renew the energy, the required area of solar cells was found. This area was also normalized the by mass of the vehicle. The solar cells had to capture enough solar energy to replenish the stored energy consumed during the non-solar hours and power the vehicle during the solar hours. The density of the solar cells was parameterized to calculate the ratio of solar cell mass to vehicle mass, as shown below in Equation 20. In Equation 20, Solar Energy refers to the intensity of solar energy. Cell density refers to how heavy the cells are (per unit area).

$$\frac{M_{PV\ Cells}}{M_{FW}} = \frac{\text{Energy}}{M_{Vehicle}} \frac{1}{\text{Solar Energy}\,(\mathrm{W/m^2})} \frac{1}{\eta_{PV\ Cells}} \text{Cell Density}(\mathrm{kg/m^2}) \tag{20}$$

The ratio of empty mass to vehicle mass was parameterized, and the payload was known. For a fixed payload mass, the engine and vehicle were sized in a rubber fashion until the remaining mass fraction equaled the ratio of payload to gross vehicle weight. The equation for calculating vehicle weight is shown below in Equation 21.

$$M_{Vehicle} = \frac{M_{PL}}{1 - \dfrac{M_{Empty\ Vehicle}}{M_{Vehicle}} - \dfrac{M_{"Fuel"}}{M_{Vehicle}} - \dfrac{M_{Engine}}{M_{Vehicle}} - \dfrac{M_{PV\ Cells}}{M_{Vehicle}}} \tag{21}$$

As was mentioned earlier, the total vehicle weight was used as a measure of how well the propulsion system met the requirements. As was stated earlier, the sizing algorithms used for both fixed and lighter-than-air vehicles are further explained APPENDIX D and APPENDIX E, respectively. A discussion of the theory behind the algorithms is discussed in APPENDIX C.

If the propulsion system were unable to meet all of the requirements, vehicle weight could not be calculated, and the optimization would realize that no feasible alternatives were produced. The best feasible propulsion system would produce the smallest vehicle, for each specific set of requirements. Fitness, then, was calculated as a function of gross vehicle weight. The inverse of total vehicle weight was used to calculate fitness, as is shown in Equation 22.

$$F(X_i) = \frac{1}{M(X_i)} \tag{22}$$

It is important to realize that the mass of the vehicles could only be used as a figure of merit to compare propulsion systems under a consistent set of propulsion system requirements (or vehicle and mission parameters). As the vehicle and mission parameters change, the expected weights of those vehicles will change. It is important to compare the propulsion systems on an "apples to apples" basis.

5.3.2.1.3 Validating the APSA Environment

Unfortunately, because the APSA environment models very advanced, immature technology, the environment itself is difficult to validate. In most cases, similar systems have not been built yet, so the results cannot be compared to existing systems. Even in the few cases where systems exist, either operational or prototype systems, it is difficult to generate enough information about the system to replicate the results. Producing high fidelity solutions, while desirable, is not essential. The vehicles are only being sized conceptually, and errors in the analysis will be consistent, thus not affecting the comparison. The APSA environment was used to size three vehicle classes: a large, long-range commercial jet, comparable to the Airbus 340; a flying wing solar vehicle, comparable to the Helios; and a solar airship comparable to a solar airship that was conceptually designed by NASA.

The fixed wing vehicle was designed to carry a payload of 46,000 a distance of kg 14,000 km. The vehicle has a wing loading of 760 kg/m^2 [96]. The aircraft uses four high bypass ratio turbofan CFM56 series engines, made by CFM International. The engines have a bypass ratio of 6.6 and an overall pressure ratio of 37.4 [16]. The Airbus A340-200 weighs 275,015 kg, completely loaded, 129,000 kg empty, and can carry 100,100 kg of fuel [96]. The drag characteristics of the vehicle were unknown, but were estimated from similar configurations. The cruise zero lift drag coefficient, $C_{D,o}$, was estimated to be 0.014, and the K_1 parameter was estimated to be 0.028 [57], [83]. The mission parameters and vehicle configuration details were inputted into the sizing and synthesis code, to calculate the total gross weight required to perform the mission. The sizing and synthesis found that the vehicle would have to weigh 273,440 kg, with 93,705 kg of fuel. The empty weight of the vehicle was 133,716 kg. The greatest error in the assessment was the fuel consumption, and that was still only a 6.4% error with respect to the Airbus A-340.

The APSA environment was next used to size a vehicle comparable in size and performance to the Helios, a NASA prototype solar vehicle. The Helios was intended to be the first regenerative fuel cell system powered vehicle, but it crashed before it could be fitted with a regenerative fuel cell. Before it crashed, however, it served as a prototype for a solar vehicle. The vehicle was a flying wing configuration

The Helios weighed 1322 lb, and carried a payload of up to 726 lb, making a gross weight of 2048 lb, or 929 kg. The vehicle had a wingspan of 247 ft (75 m) and a wing area of 1976 ft^2 (184 m^2). It was estimated that the vehicle flew at a lift coefficient C_L of 0.8. The APSA environment was used to size such a solar vehicle. The designed vehicle weighed 884 kg, with an empty weight of 555 kg. The vehicle had a required wing area of 170 m^2, and a wingspan of 72 m. the greatest error in the estimation was the gross weigh, which was 8.1% off of NASA Helios.

Finally, the APSA environment was used to size a solar airship. The airship was designed to be comparable to a NASA conceptually designed airship. The airship in the study had a payload of 2000 kg and a solar array with an efficiency of 8% [21]. The Fuel cell efficiency was 50% [21]. The airship used helium as a lifting gas, and the envelope was 185 m long, and 46 m in diameter [21]. The volume was $2.8x10^5$ m^3 [21]. Unfortunately, the operating altitude and the required velocity were not specified. The APSA environment sized an airship enveloped to be 40 m in diameter, and 160 m in length. The volume of the airship was $2.58x10^5$. The error of the APSA environment relative to the NASA conceptual study was at most 7.9%.

The validation of the APSA environment showed that it consistently sized a broad range of vehicles with only a 5% to 10% error relative to existing systems, or intensive conceptual designs. The vehicles are sized at the conceptual level, so errors of up to 5% to 10% are acceptable. Additionally, the propulsion systems will only be directly compared to one another under a constant set of assumptions. The errors in the analysis will be consistent, and thus should not impact the comparison.

5.3.2.2 Identifying Set of Optimal Alternatives

Once decision-makers can directly measure how well each alterative meets the sets of requirements, an optimized set of propulsion alternatives can be found. For a particular set of requirements, a simulated annealing program was used to identify a set of propulsion alternatives that were optimized for a specific set of requirements. As was described earlier, simulated annealing programs often get “stuck” at local minima. In the entire concept space, each optimized alternative within each concept is represented by a local minimum. It is important that the optimized set of alternatives found by the simulated annealing program is truly reflective of the optimized propulsion concepts. Unfortunately, simulated annealing is a stochastic process, and consequently, that will not always be the case. A small percentage of the time, the simulated annealing program will simply not produce a good set of optimized alternatives.

The amount of time that this occurs can be reduced by way that the simulated annealing program is conducted. Remember from section 2.2.6.1 that simulated annealing programs randomly generate a population of alternatives and then improve each alternative individually each generation. In each generation, evolution consists of slightly perturbing each alternative and then calculating whether the offspring is better than the original parent alternative. If this is the case, the new alternative survives and becomes part of the next generation. If this is not the case, the optimizer probabilistically determines whether to keep the original alternative, or allow the new alternative to be part of the next generation. Traditionally, experts suggest that the probability with which "worse new alternatives" survive to the next generation be high in early generations, and drop to almost zero for late generations. Doing so helps the optimizer to avoid getting stuck in local minima. Because the point of this process is to find the local minima, the probability that "worse new alternatives" survive was kept relatively low throughout the entire optimization. The number of alternatives in the population and the number of generations that are allowed to run also play large roles in how well the optimizer finds a set of alternatives that are reflective of the truly optimized population. Unfortunately, increasing the number of alternatives considered and generations that are ran also increases the computational time required to perform the optimization. For this reason, these numbers have to be balanced with the computational time available. In this case, each optimized population consisted of 30 alternatives, and they were allowed to evolve through 300 generations. An explanation of the simulated annealing program and the MATLAB code used to conduct the program can be found in APPENDIX F.

5.3.2.3 Calculating Fitness

Once the optimized population was found, the relative fitness for each concept was determined. In order for this to occur, the alternatives present in the final pool had to be grouped into subsets, or concepts. Several different types of concepts were defined, and many of those concepts overlap with one another. First, concepts were broken down by the type of combustion process from which they derived most of their power. A review of Table 35 shows that there were four main types of combustion processes, none, (implying a battery) a fuel cell reaction, a constant pressure combustion reaction, and a constant volume combustion reaction. Another way in which propulsion alternatives were grouped into concepts was by the means of propulsion. Three systems were considered, propeller based systems, pure jets—where only the exhaust was accelerated to produce thrust, and bypass jets—where ambient air was compressed in a duct, and accelerated with a nozzle to produce additional thrust. The fitness of more conventionally defined concepts, such as turbojet engines, rocket engines could and piston/propeller engines could be identified by finding the fitness of the proper combination of components.

The relative fitness, as defined in section 4.2.2 was found for each alternative in the optimized pool through Equation 23, shown below. $F(X_i)$ refers to the function found in Equation 23. The fitness of each concept is found by finding the ratio of the function value to the sum of the function values for all alternatives contained in the optimized pool.

$$RF_{Alt.i} = \frac{F(X_i)}{\sum_{j=1}^{n} F(X_j)} \tag{23}$$

Once the fitness of each alternative is found, the fitness of each concept was found by adding up the fitness of each of the alternatives that were classified into the particular concept, or subset, as is shown in Equation 24.

$$RF_{Concept\ A} = \sum_{i=1} RF_i \tag{24}$$

The fitness found in Equation 24 is function of the requirements that were used to assess the propulsion concepts. Once the ability to calculate fitness was developed, a meta-model was created that calculated fitness as a direct function of the requirements.

5.3.2.4 Creating a Meta-model

Unfortunately, the process to calculate the relative fitness of each concept as a function of the requirements, or set of disciplinary metrics is time consuming. It was not feasible to calculate the fitness for each concept for each set of requirements of interest. Instead, a meta-model was created that related the variability of the fitness to the variation in the requirements and disciplinary metrics. That meta-model was then used to calculate fitness for each concept, across the distribution of requirements. As was mentioned above in section 4.2.3.2, a quadratic curve fit, or RSE, was used as a meta-model. RSEs were discussed in section 2.2.5.1.

The meta-model had to capture not only the variability of the fitness of each concept as a function of the requirements, but it had to capture the variability of the fitness as a function of the technical maturity of each of the propulsion concepts. Because each of the advanced propulsion concepts are so immature, the uncertainty inherent to the maturation will greatly impact the fitness of each concept. Thirteen variables that captured the technological maturity that were also found to significantly impact the fitness of the concepts. Those variables are shown Table 36.

Table 36: Disciplinary Metrics

	Min	Max	Unit
Fuel Cell Efficiency	0.6	0.9	
Fuel Reformation Efficiency	0.6	0.9	
Maximum Combustion Temperature	2000	4000	°K
% of Gas Absorbed in Fuel Cell	0.4	0.8	
Fuel Regeneration Efficiency	0.7	0.9	
Solar Energy Absorption Efficiency	0.2	0.6	
Radiation of Beamed Energy	1000	3000	
Rate of Refueling	½	3	Refuels/day
Specific Weight of Photovoltaic Cells	0.2	0.8	kg/m^2
Specific Weight of Const. Pressure Combustion System	300	10000	W/kg
Specific Weight of Const. Volume Combustion System	100	10000	W/kg
Specific Weight of Fuel Cell System	100	1000	W/kg
Fuel Storage Temperature	200	300	°K

The requirements for the propulsion system were parameterized with 5 continuous variables and 4 discrete variables. These variables do not necessarily directly translate to the requirements found in 5.2.1, but the varying requirements will change the settings of each of the variables. The continuous variables are shown in Table 37 and the discrete variables are shown in Table 38.

Table 37: Continuous Variables Derived from Propulsion System Requirements

	Min	Max	Unit
Speed	105	200	km/hr
C_L (If Fixed Wing)	0.8	1.2	
Cruse Altitude	13	21	km
Solar Hours	6	14	hr
Takeoff Field Length (If Fixed Wing)	150	2000	m

Table 38: Discrete Variables Derived from Propulsion System Requirements

	Settings		
	1	2	3
Energy Renewal Available	Refueling	None	"Beamed Energy"
Vehicle Type	Fixed Wing	Hybrid	Lighter than Air
Takeoff Means	Powered Takeoff	Launch at Altitude	-
Takeoff Weather	All Weather	Sunny Conditions	-

In order to generate enough data to accurately relate fitness to all of the requirement variables and the disciplinary metrics, a DoE identified the inputs for 557 orthogonal cases. DoEs were discussed in section 2.2.4.2. Unfortunately, there are not feasible alternatives for all of the space. Lighter-than-air vehicles, for example, cannot realistically be sized to fly at airspeeds of 200 km/hr or greater. Because the DoE was orthogonal, but the feasible space was not, many of the experiments specified in the DoE produced no results. Additionally, because the simulated annealing is stochastic in nature, a few of the experimental runs produced poor results. For these reasons, 235 additional, randomly generated, space filling experiments were conducted.

For each experiment, the optimized pool of alternatives was used to calculate the fitness of each of the concepts. The fitness outputs were regressed against the input parameters, to produce one, simple model that calculated fitness as a function of the inputs, assuming that the inputs were within the predefined range. Two meta-models were actually created. One set captured the variability of the fitness metrics when the vehicles could refuel if necessary. The second set capture the variability of the fitness metrics when only solar energy was available and electromagnetic energy could be "beamed" to the vehicle. The other continuous variables were captured with "dummy" variables in the RSEs.

The fit of the quadratic models was not exceptional, but it was sufficient for the purposes of identifying fitness as a function of the requirements. It is difficult to create a quadratic model of a stochastic analysis, primarily because stochastic processes are inherently uncertain. There is a degree of error in the actual analysis, and that error will be propagated into the meta-model.

Figure 19 shows how well the model fits for one class of alternatives, the fuel cell propulsion systems. Notice that while the fit is not superb, the error terms are within a few percentage points of the meta-model predicted results. Figure 19 reflects the fitness of the fuel cell concepts when refueling is available.

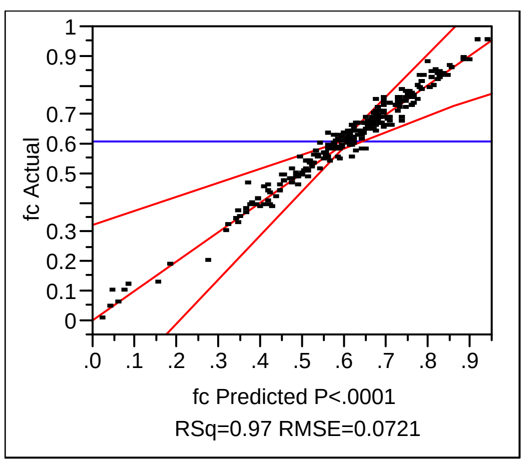


Figure 19: Goodness of Fit for Fuel Cell Concepts' Fitness

Figure 20 shows the goodness of fit for solar based concepts when refueling is available. Even when refueling was an option, solar powered vehicles were still capable of meeting the requirements. They are not preferable, however, as the solar cells offer additional weight, and depending on the frequency of the refueling, they might not be competitive. Notice that this trend is reflected in the lower average of solar powered vehicles.

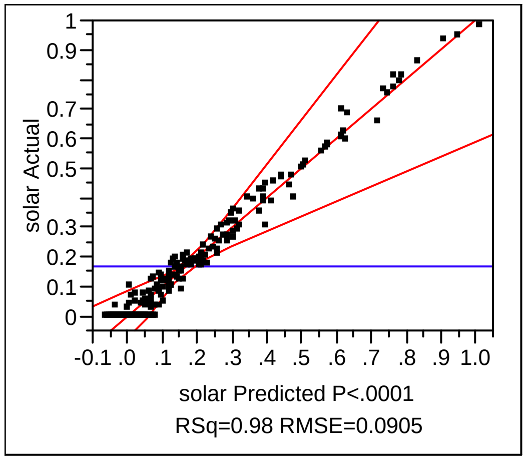


Figure 20: Goodness of Fit for Solar Concepts' Fitness when Refueling is Available

Figure 21 shows the Prediction Profiler of different combustion processes and energy renewal options as a function of a few requirement variables and a few disciplinary metrics. The set requirement variables and disciplinary metrics shown in Figure 19 is not complete. The entire set of prediction profilers is too large to examine thoughtfully. The set of RSEs represented in Figure 21 are those from when refueling is an option. A prediction profiler maps the curve fit along one dimension, to show the sensitivity of the response to the variables. In Figure 21 , the row labeled fc models the fitness of all fuel cell processes. The rows labeled P_comb and V_comb model the fitness of constant pressure and constant volume combustion processes, respectively. Constant volume combustion processes include pure jet engines, turbojet engines, and turboprop engines. Constant volume combustion processes are those processes that are modeled using a constant volume model, ranging from internal combustion processes to pulsed detonation processes. The row labeled solar refers to all concepts that use solar energy to renew their energy, and the row that is labeled refuel actually makes use of the refueling option.

In Figure 21 the column labeled η_{FC} is the efficiency of the actual fuel cell. The column labeled η_{Solar} is the efficiency of the photovoltaic cells. Speed is the cruise speed, in m/s; Altitude is the cruise altitude in ft. Solar Hours is the minimum amount of solar hours that to which the vehicle will be exposed. This metric will change as the geographic operating location and operating season changes. Finally, Log($^{RF}/_{Day}$) is the log of the number of refuels available to the vehicle per day.

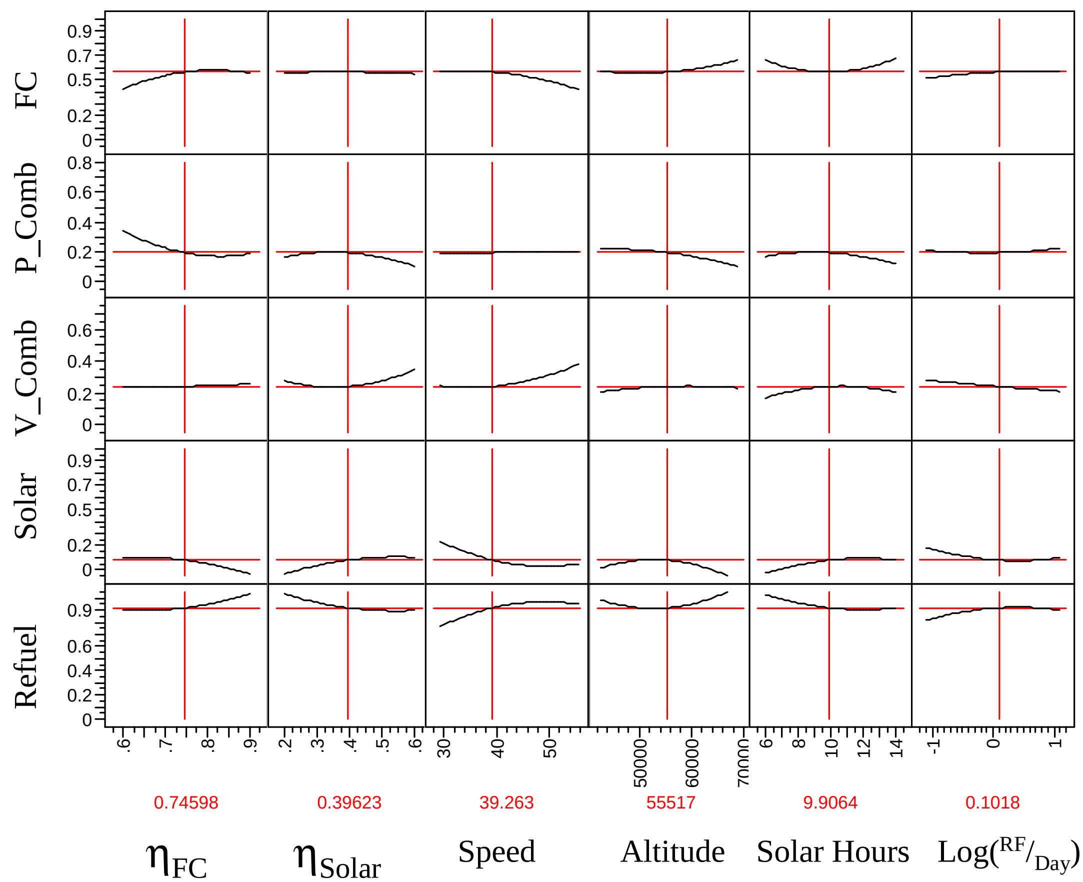


Figure 21: Prediction Profile When Refueling is Available

Notice that the trends in Figure 21 make sense. As the efficiency of the fuel cell increases, the fitness of the fuel cell increases, while the fitness of the constant pressure combustion processes decrease. Also, as the number of solar hours in a day increase, the fitness of solar concepts increase. Another helpful observation is that as the speed increases, the fitness of solar based concepts drops dramatically. Solar based concepts do not appear to be feasible at the high speeds.

At first thought, it does not make sense to relate the fitness of one concept to the component disciplinary metric of another concepts. The fitness of constant pressure combustion processes should not depend upon the efficiency of fuel cells. As a fuel cell becomes more efficient, however, fuel cell processes become more attractive. The two concepts are competing against one another. As fuel cell processes become more attractive, combustion processes become less attractive. The trends make sense. One interesting note is that increasing the efficiency of the fuel cell only increases the fitness of fuel cell concepts to a point. Pushing the efficiency beyond approximately 75% seems to have no additional impact on the attractiveness of fuel cell concepts over traditional combustion based processes.

After observing the two meta-model, a few questions arose. Using solar energy as a source of energy renewal did not make constant pressure and constant volume combustion processes infeasible. This trend puzzled the author; as regenerative processes are only really considered in conjunction with fuel cells. The author to date has never found a proposal of an aeropropulsion engine that combusts the fuel, and then uses the products of combustion to regenerate fuel, using solar energy.

Figure 22 and Figure 23 show portions of the prediction profiler for the second set of RSEs. In this set of RSEs, refueling is not an option. The only options for energy renewal are solar power and auxiliary power “beamed” up to the aircraft. The variable “Beamed?” refers to whether beamed electromagnetic energy is or is not available. When that variable is set to zero, no beamed energy is available.

Figure 22 shows the values for the combustion classes and the energy renewal classes when the “Beam?” variable is set to zero—implying that no beamed energy is available. The only row that is different from Figure 21 above is the last row, labeled em.

This row represents the concepts that receive their energy renewal through beamed electromagnetic energy. Notice that when the Beam? Variable is set to zero, the em response is zero and insensitive to all other variables. The lone exception to this is em's dependence on speed. Unfortunately, this trend is due to an error in the mapping of the design space. Solar power is simply not capable of providing enough energy to power flight at the highest range of the speed. The infeasibility of this space ensured that no feasible design points were found in this range; therefore, the model is inaccurate in this area of the space.

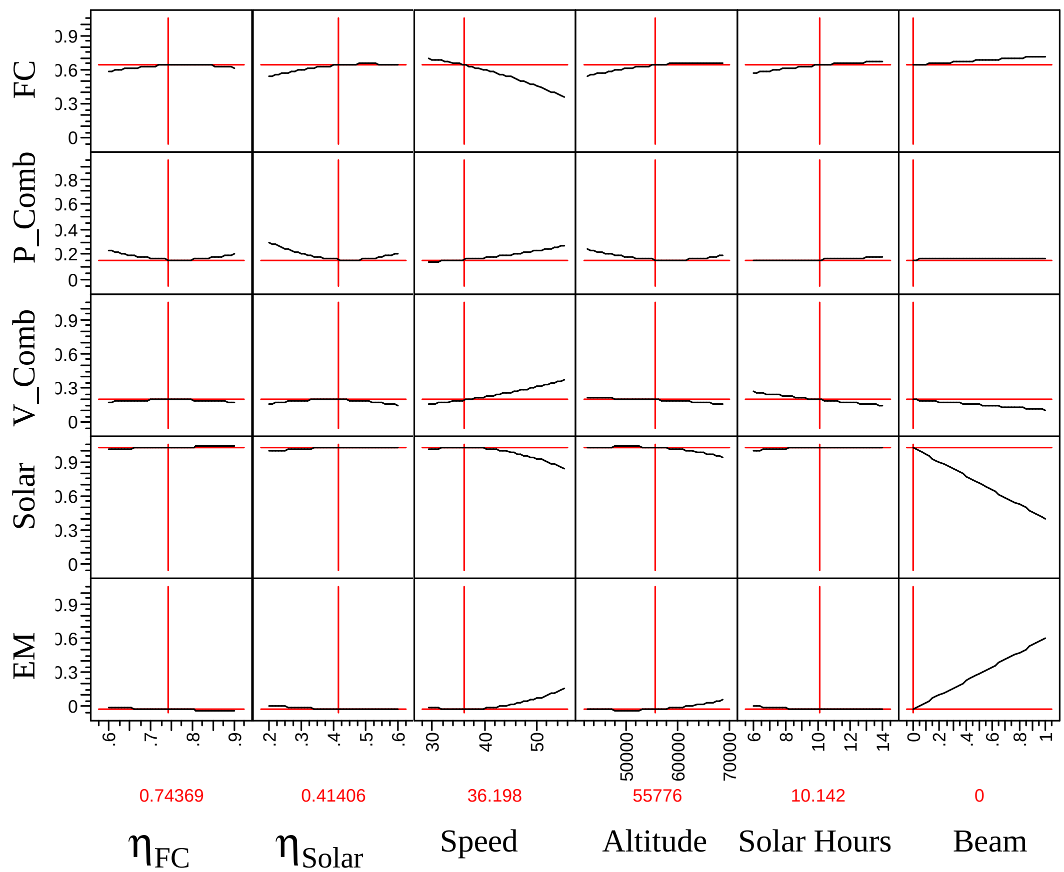


Figure 22: Prediction Profile of when Only Solar Power is Available

Figure 23 is the same as Figure 22 except that the Beam? variable is set to one, implying that beamed energy is available. Notice in Figure 23 that the value of the em response is significantly higher. Also notice that both em and solar metrics are insensitive to the solar efficiency. Both sources of energy renewal require the use of photovoltaic cells, so the efficiency should of the cells should not impact the competitiveness of one concept with another.

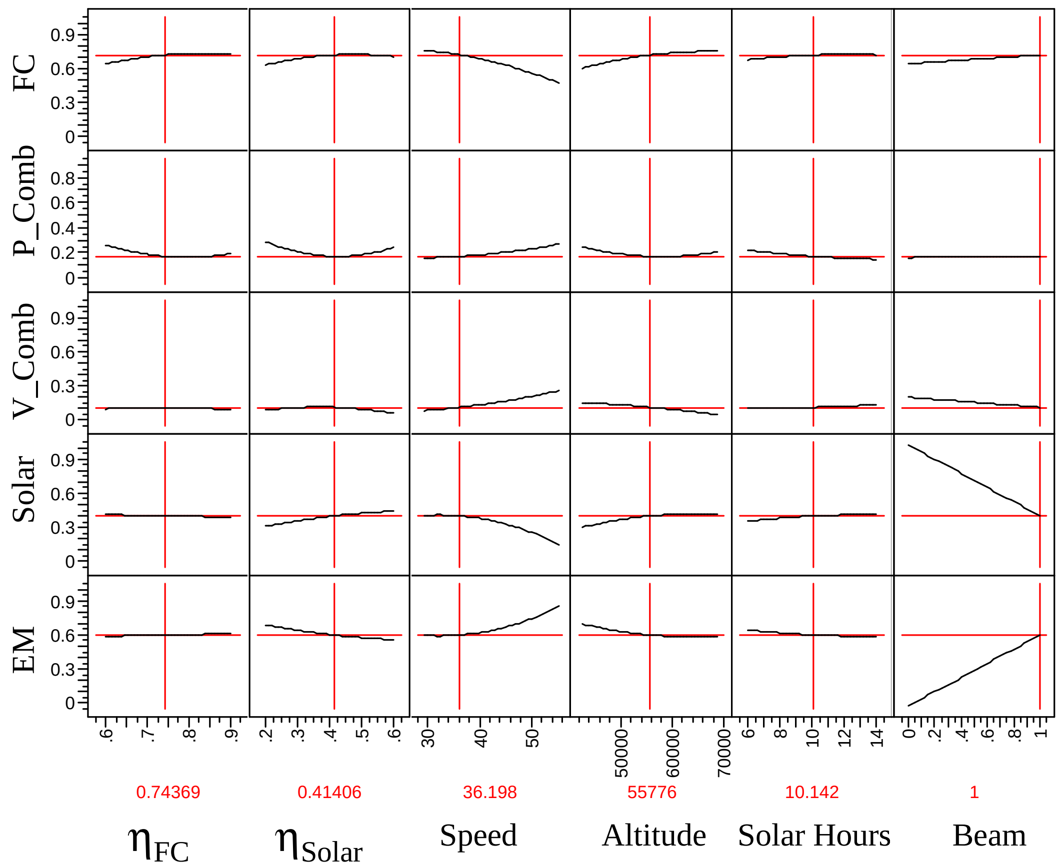


Figure 23: Prediction Profile of when Beamed Power is Available

5.3.3 Calculating the Distribution of Fitness

Once a meta-model was created, the distribution of fitness for each concept was found by employing Monte Carlo techniques. An earlier section discussed how the probabilistic distribution of requirements was found using the CI analysis. A triangular distribution was placed upon the disciplinary metrics. The minimum value, maximum value and median vale of each of those metrics is shown below in Table 39. The ranges depicted in Table 36 are not identical to the ranges that were used to create the meta-model. This is because the author determined some of the ranges in the disciplinary metrics were too large to accurately portray reality.

Table 39: Distribution of Disciplinary Metrics

	Min	Median	Max	Unit
Fuel Cell Efficiency	0.6	0.7	0.8	
Fuel Reformation Efficiency	0.7	0.71	0.8	
Maximum Combustion Temperature	2000	3000	3500	°K
% of Gas Absorbed in Fuel Cell	0.4	0.6	0.8	
Fuel Regeneration Efficiency	0.7	0.8	0.9	
Solar Energy Absorption Efficiency	0.2	0.22	0.6	
Radiation of Beamed Energy	1000	1100	1400	
Rate of Refueling	½		3	Refuels/day
Specific Weight of Photovoltaic Cells	0.3	0.7	0.8	kg/m^2
Specific Weight of Const. Pressure Combustion System	300	1000	10000	W/kg
Specific Weight of Const. Volume Combustion System	100	500	10000	W/kg
Specific Weight of Fuel Cell System	100	150	1000	W/kg
Fuel Storage Temperature	200	299	300	°K

The Monte Carlo trials sampled requirements from the distribution identified in the CI analysis and sampled disciplinary metrics from the triangular distribution described in Table 39. The results are discussed and interpreted below.

5.4 Interpreting the Results

The first propulsion concepts that investigated were conventional propulsion concepts. If conventional propulsion concepts are likely to satisfy the requirements, decision-makers would most likely not be interested in investing the time and resources required to develop advanced propulsion concepts. Unfortunately, conventional concepts were proven to have a low likelihood of satisfying the requirements. For this reason, the author then investigated the fitness of other advanced propulsion concepts.

5.4.1 Defining Conventional Propulsion Concepts

The author defined conventional concepts to be those that are evolutionary derivatives of technology currently used in the industry. Turboprop, turbofan, and turbojet engines have all been built and successfully used to power aircraft. The core of these engine concepts is that ambient fluid is compressed, used to oxidize the fuel, and the resulting fluid drives a turbine. The means of thrust generation, however, is different for each concept. Reciprocating engines and propeller combinations have also been widely use to power aircraft. These concepts rely upon an approximately constant volume combustion process to extract the chemical energy out of fuel, but use the pressure spike of the fluid to drive a shaft. Combinations of the two classes described above, however, are distinctly unconventional. Constant volume combustion processes cannot easily be combined with compressor/turbine systems because constant volume combustion is not a steady-state process, and researchers have not been able to efficiently and safely combine the non-steady state combustion with the steady state compressor/turbine. Fuel cell based propulsion systems and battery based propulsion systems are all considered to be advanced propulsion concepts, simply because the concepts have either not been used to power full sized aircraft, and are far from power system.

For the purpose of this study, any sort of regenerative system will be considered revolutionary. Additionally, any alternative that uses a fuel cell or a battery as its primary form of energy conversion will also be considered revolutionary. Non-regenerative alternatives that rely upon, constant pressure propulsion systems will be considered evolutionary, as they are similar to existing systems today. Additionally, for simplicity's sake, non-regenerative alternatives that rely upon constant volume combustion processes will also be considered conventional.

5.4.2 Assessing Conventional Concepts

Conventional propulsion concepts can classified as concepts that rely upon non-regenerative combustion processes to generate thrust. The distribution of fitness for two subclasses of these concepts is shown in Figure 24. The fitness of constant pressure combustion based alternatives is slightly worse than that of constant volume combustion based alternatives. Constant volume combustion is a more efficient process. The vehicle would consume less fuel throughout the mission, implying that constant combustion process-based concepts should be more attractive. The only caveat to this notion is that the specific power density, or the ratio of energy output to engine mass, for constant volume combustion processes was given a slightly higher distribution. Much of the increased fuel efficiency could be offset by the increased weight of the engine.

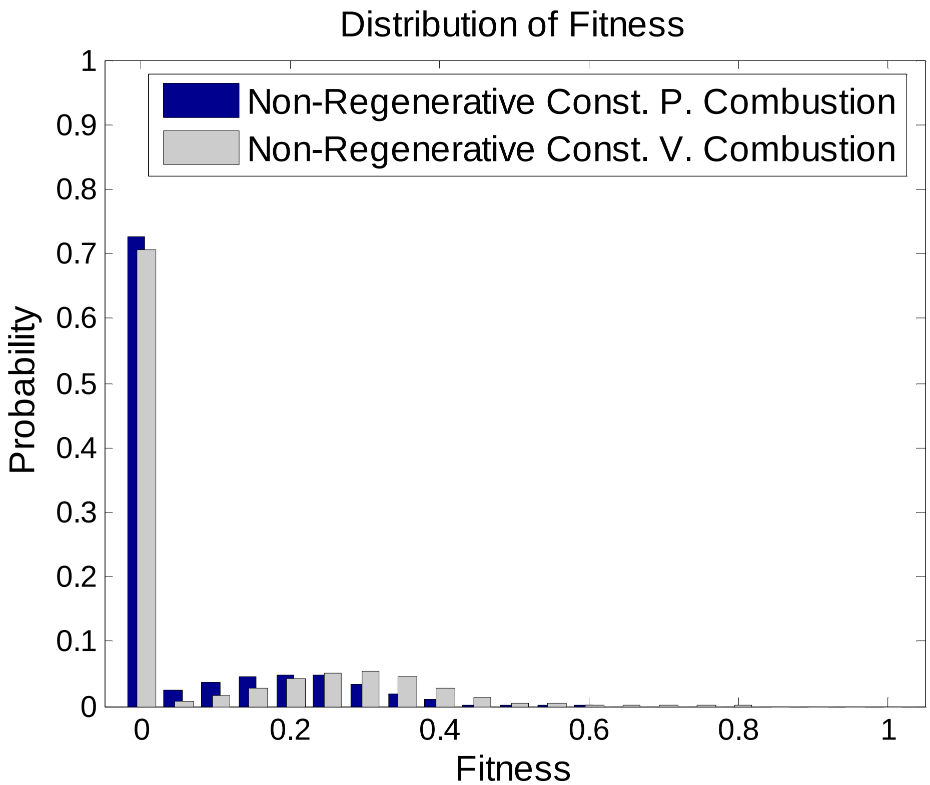


Figure 24: Fitness for Conventional Propulsion Concepts

Neither of the non-regenerative concepts will be sufficient to meet approximately 70% of the potential sets of requirements. This outcome is primarily a function of one requirement, the operation parameter. This parameter dictated how the mission operation would take place. The Mission Operational Parameter alternatives and their associated probabilities are shown below in Table 40. The "Auxiliary-Powered Deployment" alternative implied that power could be "beamed" to the aircraft. The "Refueled in Flight" option meant that refueling would be available to the vehicle. "Single Vehicle", "Formation Flight" and "Tip-joined Multi-Vehicles" had no means or energy renewal except for the available solar power. The "Serial Flight" option implied that multiple vehicles would be responsible for covering the terrain; one vehicle would not have spend the entire mission duration above the hurricane.

Table 40: Mission Operation Requirements and Probabilities

	Selection	Probability
Mission Operational Concepts	Auxiliary-Powered Deployment	0.08
	Refueled in Fight	0.2
	Single Vehicle	0.6
	Formation Flight	0.01
	Serial Flight	0.1
	Tip-joined Multi-Vehicle	0.01

The only time cases enabled non-regenerative alternatives to be feasible propulsion systems were the ones that allowed for refueling, either by mid-air refueling, or by making multiple trips and refueling back at base.

Figure 25 shows the fitness of conventional alternatives (non-regenerative combustion-based alternatives) under two conditions: when mid-air refueling is available and when mid-air refueling is not available. Figure 25 shows that in some cases where mid-air refueling is not available conventional concepts will be capable of meeting the requirements. In each of those cases, however, serial flights were employed as a mission concept.

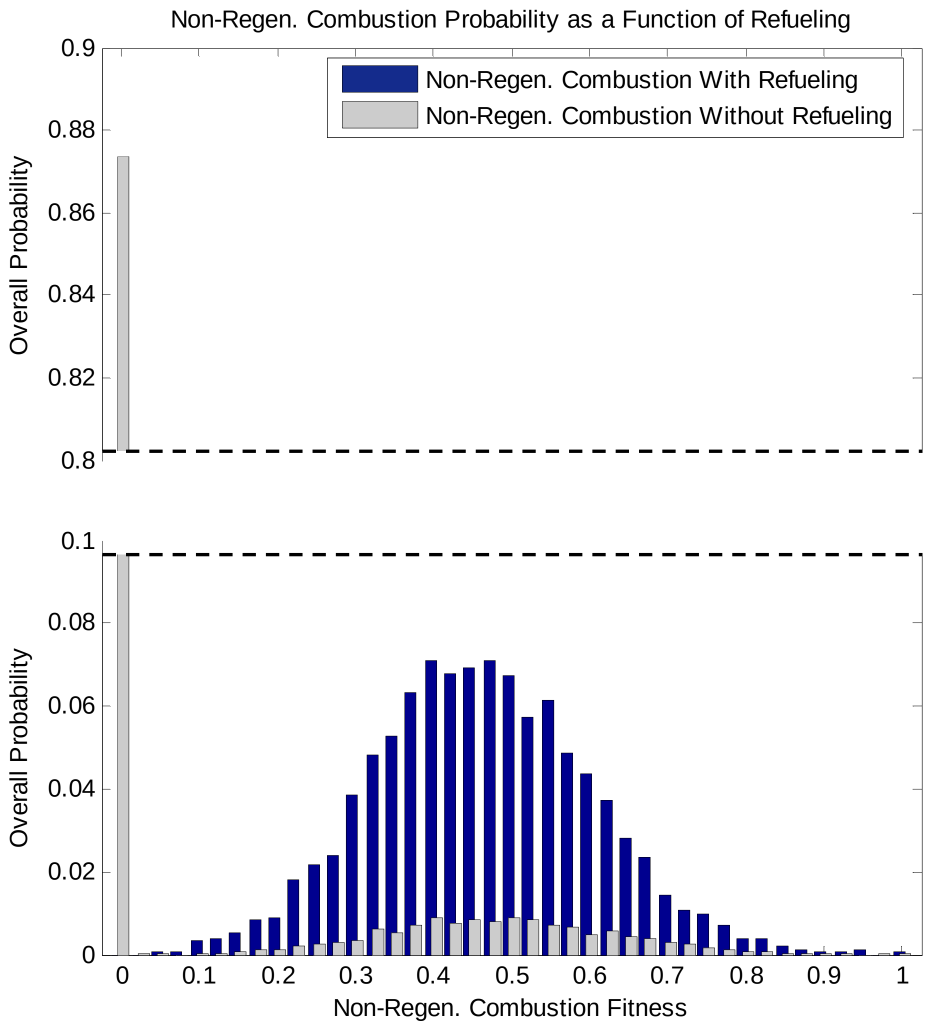


Figure 25: Fitness of Non-Regenerative Combustion Concepts

The overall distribution of fitness for any conventional alternative is shown in Figure 26. Notice that conventional concepts are incapable of meeting 70% of the potential requirement sets.

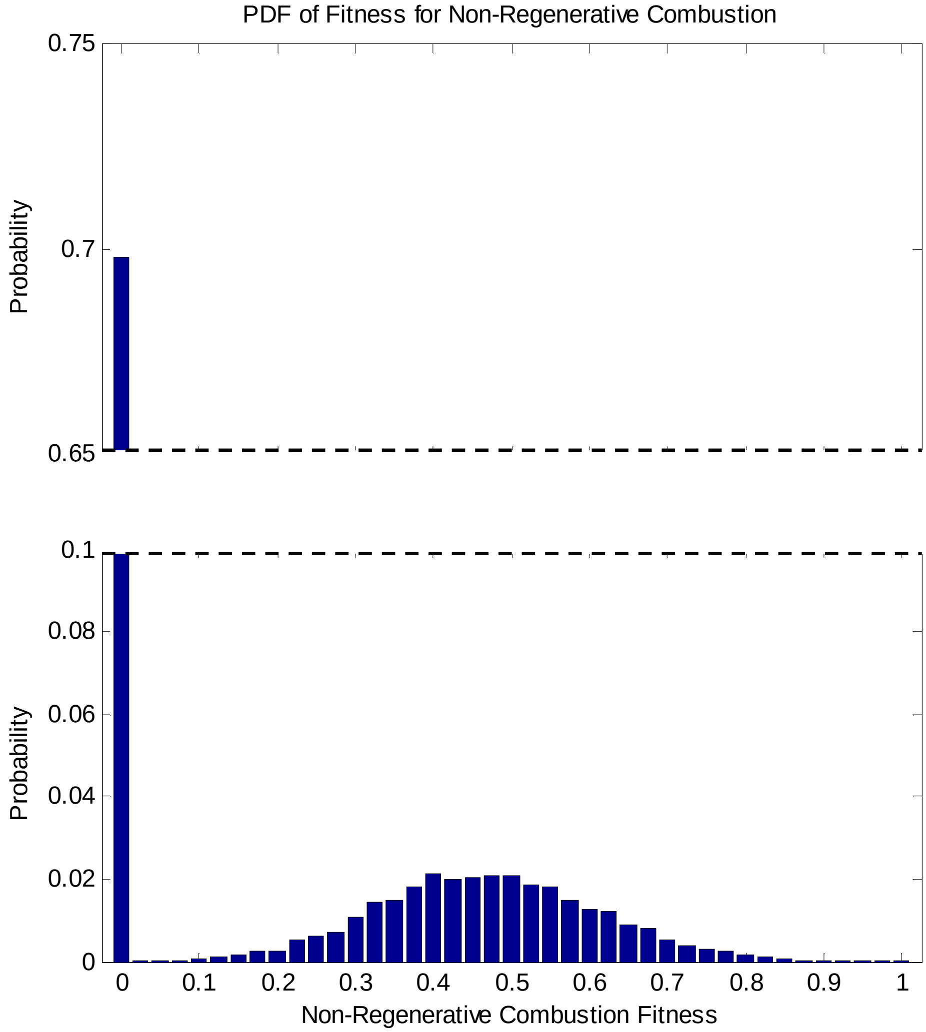


Figure 26: Fitness of Non-Regenerative Combustion Alternatives

Evolutionary derivatives of conventional concepts, then, would be capable of meeting only 30% of the potential requirement sets. In the 30% of the requirement sets that conventional concepts are feasible, they are still not necessarily the best alternatives. Regenerative systems and fuel cell based systems may be more fit to propel the HALE vehicles. If decision-makers want a greater chance at meeting the likely future requirements for the hurricane tracking HALE vehicle they will have to invest in advanced propulsion concepts.

Even if the decision-makers were content with the 30% of meeting the requirements with conventional technology, he or she needs to consider how much improvement revolutionary technologies could offer over conventional technologies. Figure 27 compares the fitness of conventional combustion processes with regenerative combustion processes and fuel cell concepts. Notice that given the entire likely distribution of requirements and technological maturity, fuel cell concepts still offer a greater fitness.

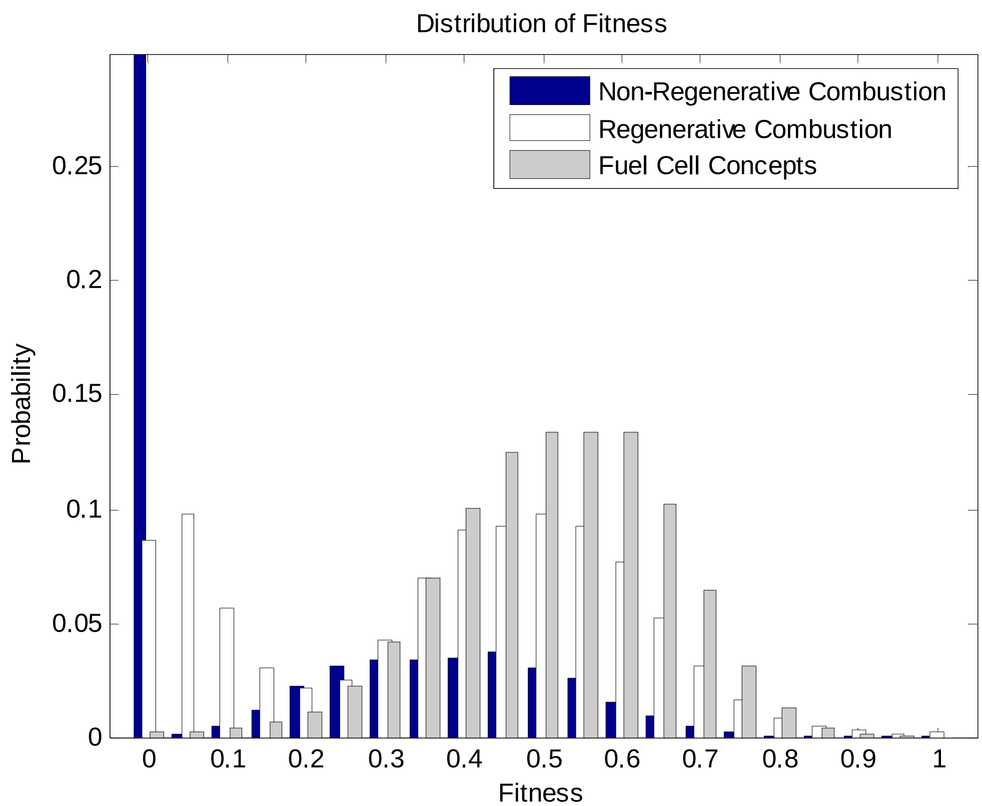


Figure 27: Distribution of Fitness for Conventional and Advanced Propulsion Concepts

The author considered Figure 26 and Figure 27 to be sufficient reason to consider advanced propulsion alternatives to power the HALE vehicle. In the next section, the fitness of each of the possible revolutionary alternatives is investigated.

5.4.3 Identifying Fitness of Advanced propulsion concepts

Once decision-makers have established that advanced propulsion concepts will need to be developed, they have to determine which concept they would like to invest in, and justify that decision.

As was mentioned earlier, the feasibility of regenerative combustion-based alternatives was not determined. Two meta-models were created, the first assumed that such processes were feasible and the second assumed that such processes were infeasible.

5.4.3.1 Analysis I (Assumes that Combustion/Regeneration is Feasible)

In the first analysis, alternatives that used combustion as their main means of energy conversion could store the products of combustion and perform electrolysis on them to produce hydrogen and oxygen—or a source of stored chemical energy. This analysis generated several feasible alternatives. Before investigating the feasible alternatives, however, the potential fuels were examined. Figure 28 compares the fitness of four types of fuel, CH_4, Jet A, H_2, and C_3H_8. Figure 28 might be difficult to read because of the amount of distributions that are shown, but H_2 emerges as the only fuel that was feasible for all sets of requirements. The propulsion analysis assumed that only H_2 could be regenerated; consequently, it was the only fuel option that was feasible when neither refueling nor serial flights were a requirement option. Fortunately, Figure 28 also shows that H_2 fuel was also the most fit, even when those requirement options were part of the requirement set. The analysis did not consider the volume of the fuel in the vehicle sizing, however, which may account for this outcome.

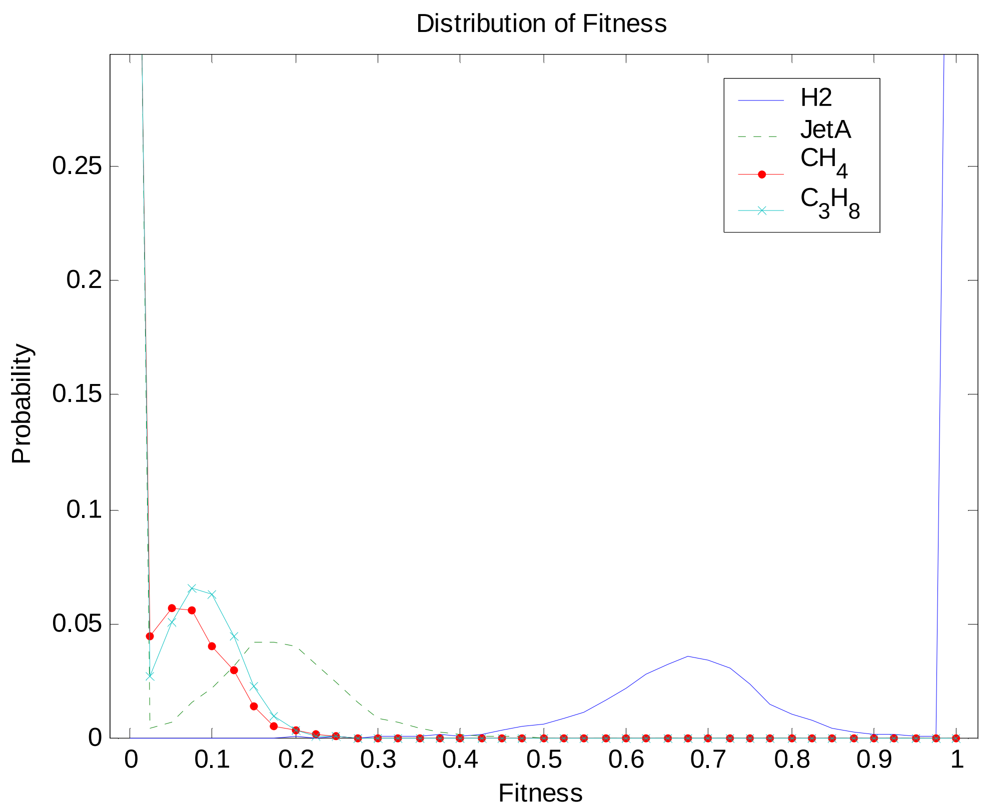


Figure 28: Fitness of Fuel Types

Because H_2 is the only fuel option that is feasible given the entire range of concepts, it is an obvious choice to be part of the concepts selected for future development. Identifying the need for H_2 has many implications for the entire future vehicle system. Safely and efficiently designing the storage tanks for H_2 will require further development in many disciplines.

In section 5.4.2, it was determined that not-regenerative concepts were not feasible over enough of the potential requirement sets to be seriously considered. Figure 29 shows the probability distribution of three main classifications of feasible alternatives, regenerative fuel cells, regenerative constant pressure combustion processes, and regenerative constant volume combustion processes. The “double M” shape of the chart is a function of whether refueling was allowed or not. When the systems are capable of refueling, the fitness of each of the regenerative concepts is going to be reduced. Non-regenerative concepts are then allowed to compete with them. From the chart, regenerative constant fuel cell processes are the most fit. The primary reason that fuel cells are more fit than conventional combustion processes is most likely a function of the fact that fuel cell's direct conversion of chemical energy to electromagnetic energy is an inherently more efficient process than converting chemical energy to heat, and then to mechanical energy.

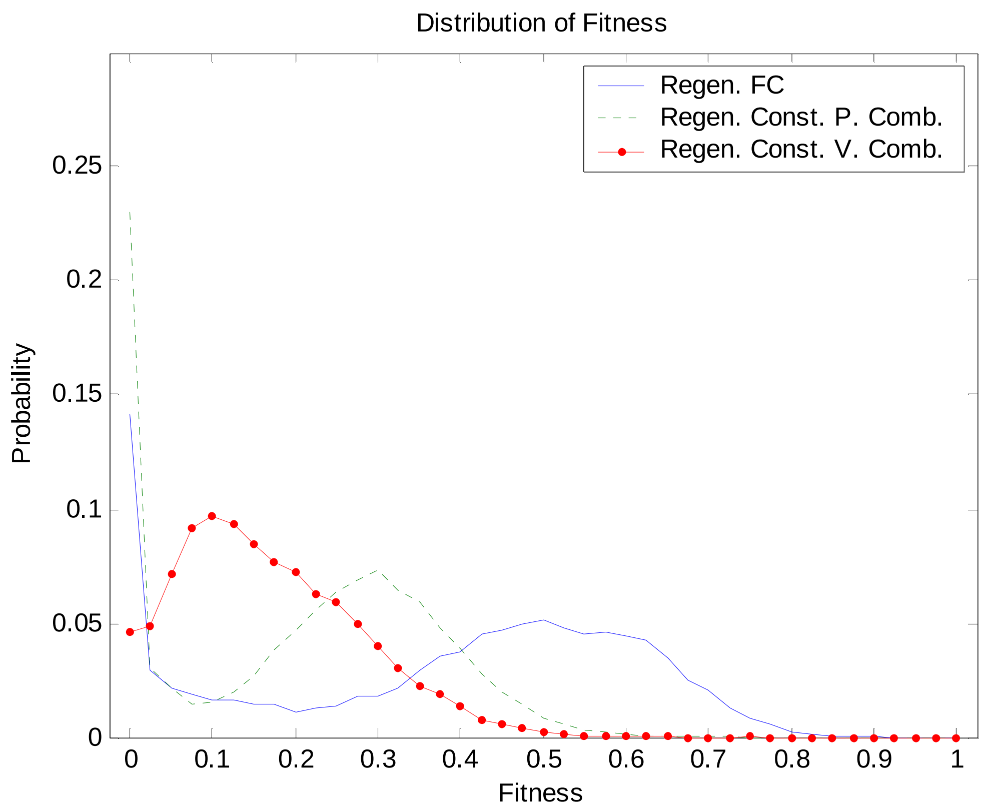


Figure 29: Fitness of Fuel Cell and Combustion Concepts

Another interesting result of this analysis is that when examining regenerative concepts, constant pressure combustion processes appear to be much more fit than constant pressure combustion processes. This is most likely a function of the specific weight parameters given to both constant pressure combustion and constant volume combustion processes. Looking back at Table 39 shows that distribution of specific weight for constant pressure combustion processes was higher than the distribution of weight for constant volume combustion processes.

The distribution of fitness for regenerative fuel cell concepts is shown in Figure 30. Two distributions are shown: one for when refueling is available, and one for when refueling is not available. The fitness distribution is much lower when refueling is available, simply because the concept competes with non-regenerative concepts. The left-side tail of the non-refueling distribution can be explained by the percentage of the requirement sets that allow multiple vehicles to cover the aerial observation.

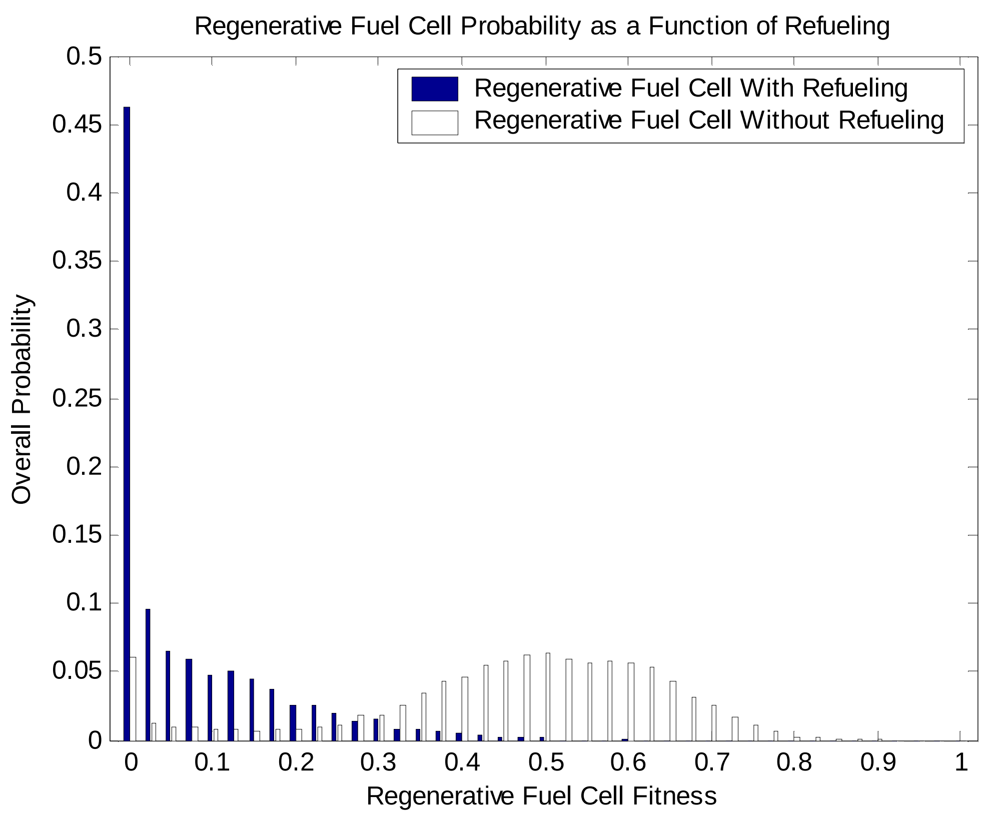


Figure 30: Fitness of Regenerative Fuel Cells

Figure 31 compares the distribution of fitness for regenerative constant pressure combustion, for both the case of refueling and no refueling. The median distribution for constant pressure combustion is significantly higher than that of fuel cell based concepts.

As was discussed above, this is a function of the distribution placed upon the disciplinary metrics that define the concepts' maturity.

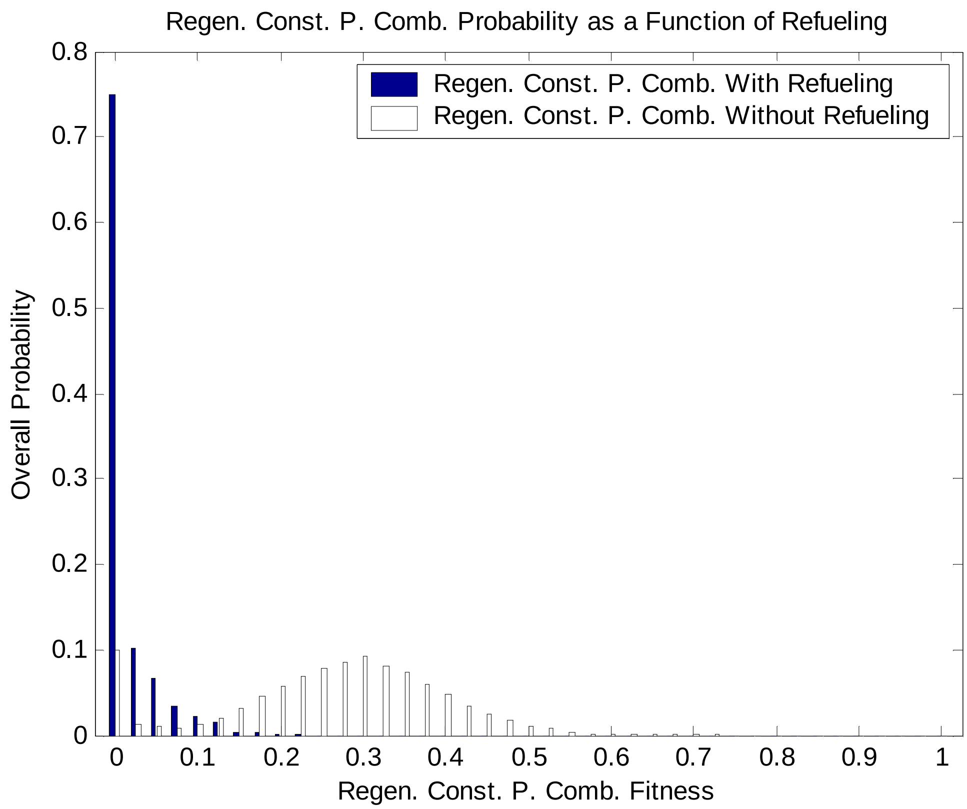


Figure 31: Fitness of Regenerative Constant Pressure Combustion Processes

Finally, Figure 32 shows the distribution of regenerative constant volume combustion processes, both for when refueling is available and when it is not. The median fitness for the requirements distribution is slightly lower than that of the regenerative fuel cells, and distinctly lower than that of the regenerative constant pressure combustion processes.

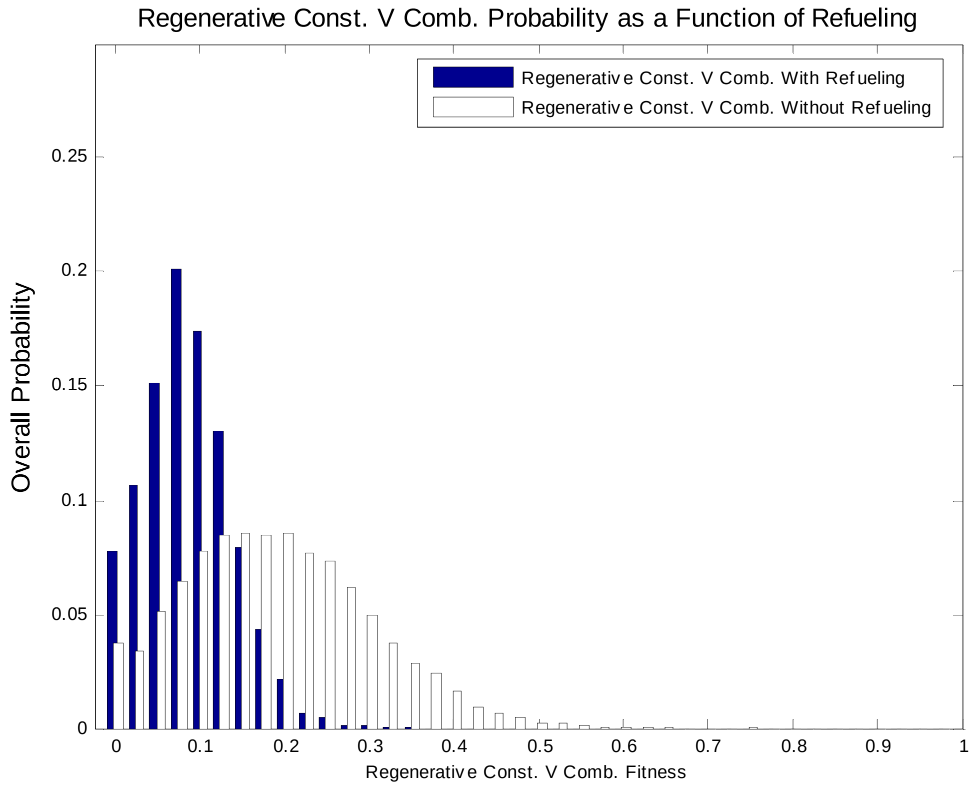


Figure 32: Fitness of Regenerative Constant Volume Combustion Processes

In the first analysis, which assumed that the products of combustion could be stored and converted back into H_2 and O_2, constant pressure combustion emerged as the most promising main form of energy conversion. This determination was a function of the maturity of fuel cells, however, and as more information is determined about future capability of fuel cells, this result should be reexamined.

At this point, the author has determined that H_2 is the only real fuel alternative, and that fuel cells are the fittest main form of energy conversion. Other aspects of the concepts, however, should also be investigated, such auxiliary processes that make the energy conversion more efficient, and the means of producing thrust. First, let us examine the possible means of thrust production. Three means of producing thrust were considered: driving a propeller, pressurizing and accelerating ambient air through a bypass duct, and accelerating the combustion products through a nozzle. The third means proved to be infeasible in all of the cases, considering the slow cruise speed and need to contain combustion products to regenerate fuel. Figure 33 shows the fitness of the three concepts.

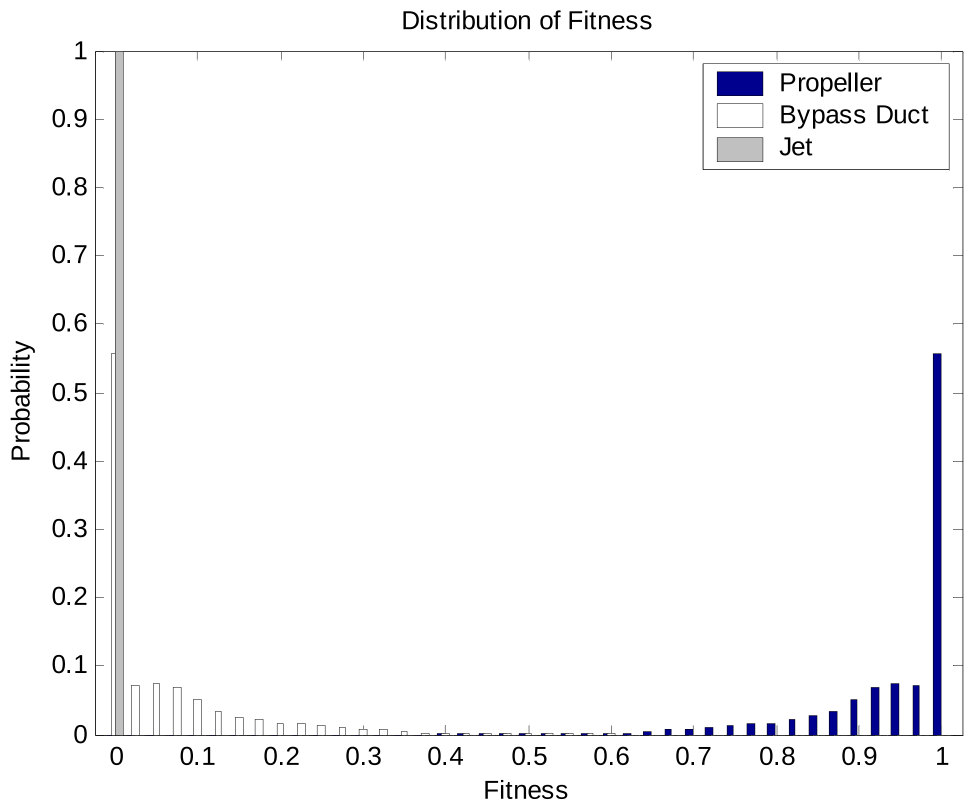


Figure 33: Fitness of Thrust Production Methods

Propellers are really the only feasible thrust production alternative. Accelerating the thrust through a bypass duct, as in a turbofan engine is simply not an efficient form of thrust generation at the low range of speeds that the hurricane-tracking vehicle would travel.

Figure 34 investigates the fitness of using heat exchangers to heat the oxidizer and fuel. Using heat exchangers alone to prepare the combustion reactants is not a feasible alternative. While combining them with fuel cells is viable, combining them with combustion is not truly an option, as the fitness of these combinations is essentially zero for all requirement alternatives.

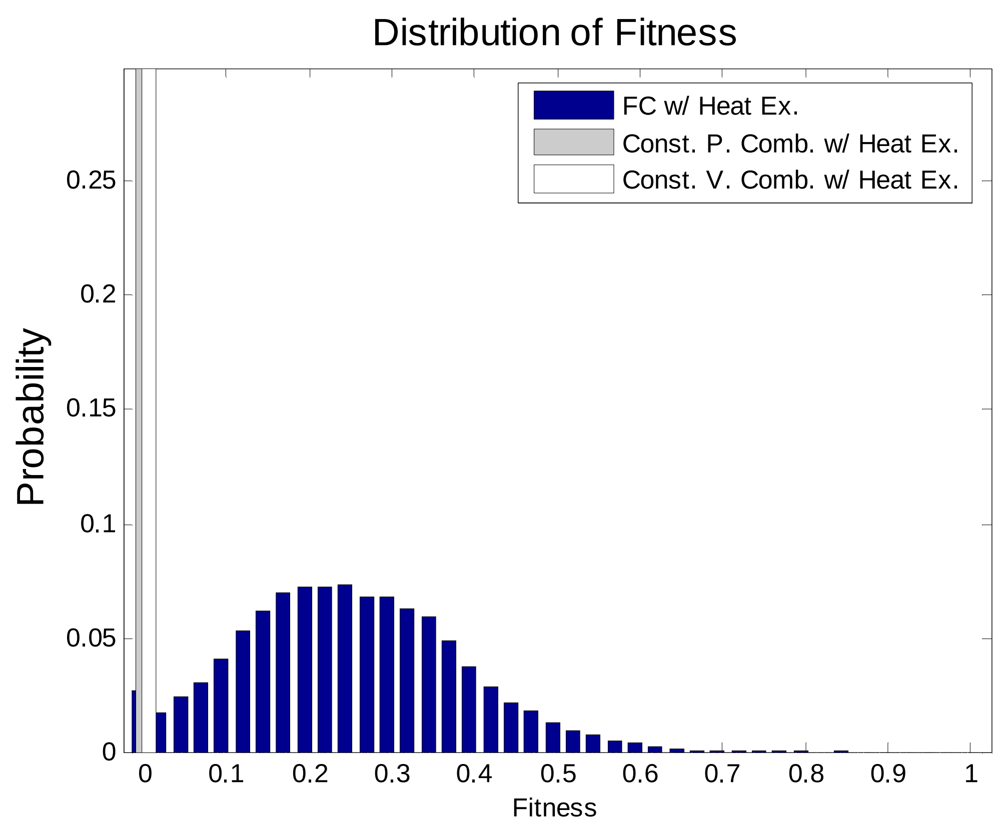


Figure 34: Fitness of Concepts Using Heat Exchangers

Using a heat exchanger as a means of making the fuel cell process more efficient is a viable concept. Using a compressor to energize the ambient stream is also a viable concept for a fuel cell propulsion system. The two concepts are essentially competing, and from this point on will be considered competing alternatives. Figure 35 compares the two competing concepts. Notice on average that the compressor seems to be a slightly better concept both because there is less uncertainty associated with it and on average, it is a more fit alternative. The heat exchanger/fuel cell combination has the potential to be a very competitive alternative.

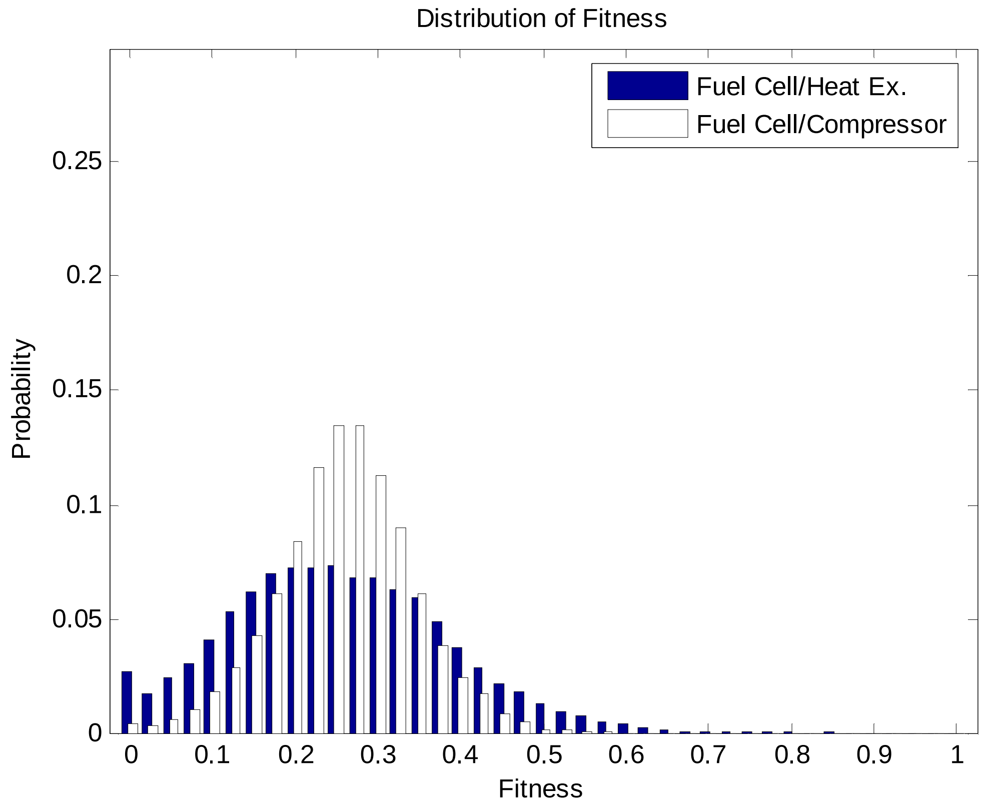


Figure 35: Fuel Cell with Heat Exchanger or Compressor

The distribution of fitness for the fuel cell/compressor/propeller distribution is shown alone in Figure 36.

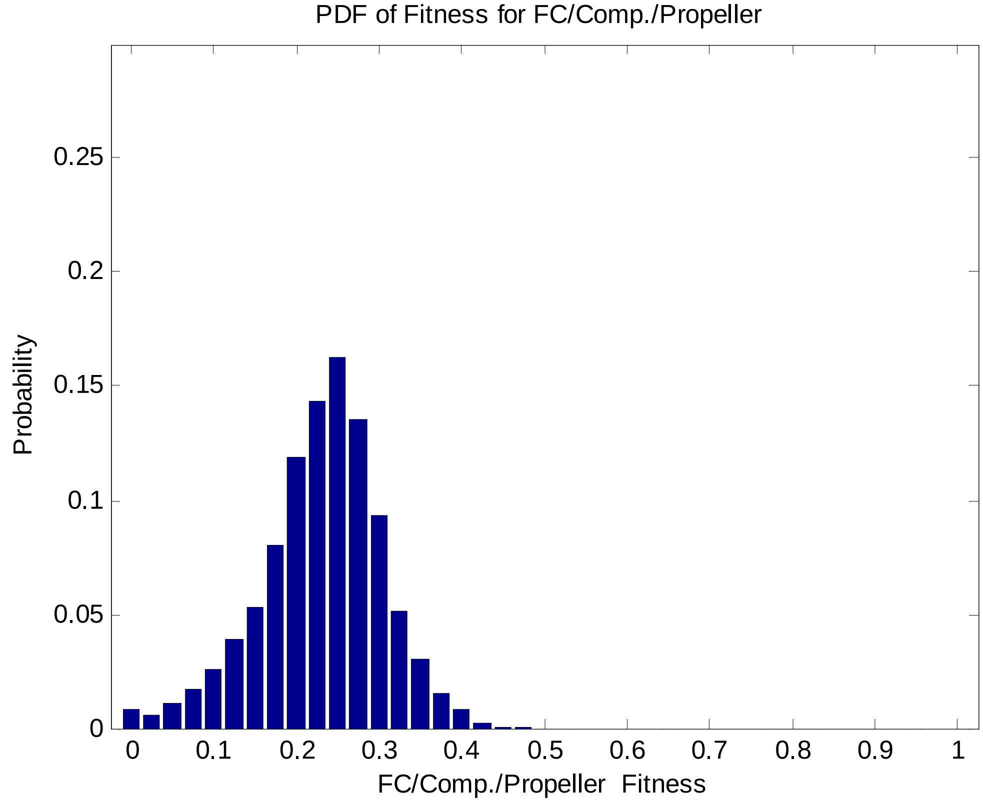


Figure 36: Distribution of Compressed Fuel Cells that Drive a Propeller

The distribution of fitness for constant pressure combustion systems that use compressors and turbines to increase the pressure of the gas in the combustion chamber and propel the vehicle with a propeller are shown in Figure 37. How does the fitness of the compressed fuel cell concept that drives a propeller compare to other alternatives?

Figure 37 shows the distribution of fitness for a constant pressure combustion process, combined with a compressor/turbine that creates shaft power to drive a propeller. This concept essentially defines a turboprop engine. The only difference between the concepts listed in Figure 37 and conventional turboprops is that the concepts in Figure 37 include regenerative turboprop concepts. In the regenerative concepts, the exhaust would somehow have to be stored, and a reformation process would have to be conducted to convert the exhaust H_2O back into H_2 and O_2. The feasibility of this concept is unknown.

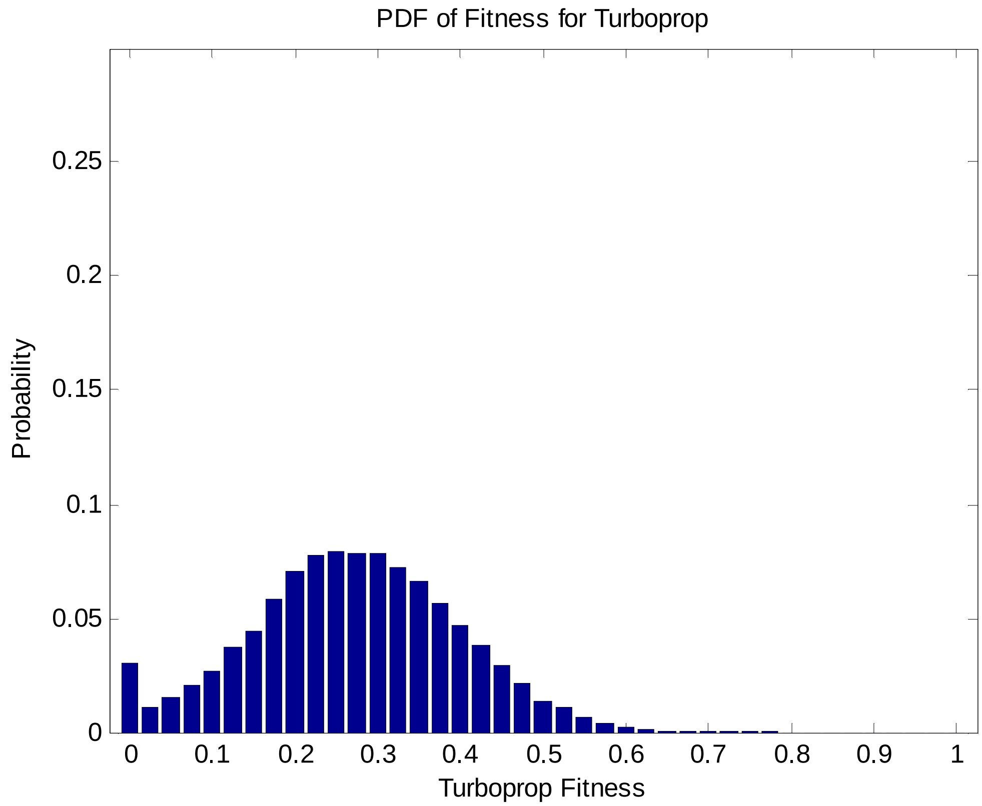


Figure 37: Distribution of Fitness for a Constant Pressure/Compression/Propeller Concept

A rotary piston/propeller combination would be classed as a constant volume combustion process, combined with a compression process, to drive a shaft. The distribution of fitness for such a concept is shown below in Figure 38. As was the case in Figure 37, Figure 38 combines the distribution of both regenerative concepts with non-regenerative concepts in the figure.

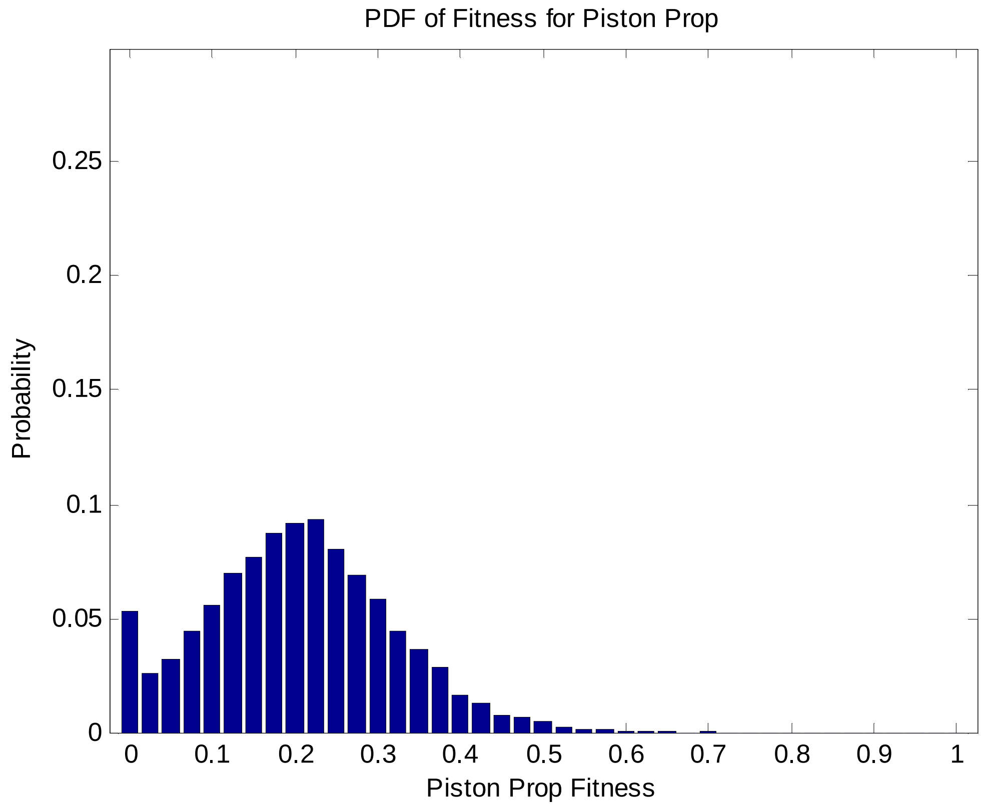


Figure 38: Distribution of Fitness for a Constant Volume/Compression/Propeller Concept

Finally, Figure 39 compares the distribution of all of the mentioned concepts to one another, given the distribution of requirements and technological maturation. Notice when the two types of fuel cells are considered separately, the fitness for each concept is considerably less than that of the fuel cell concept in general. This is because the two concepts are now considered to be competing concepts, and the fitness of one takes away from the fitness of the other.

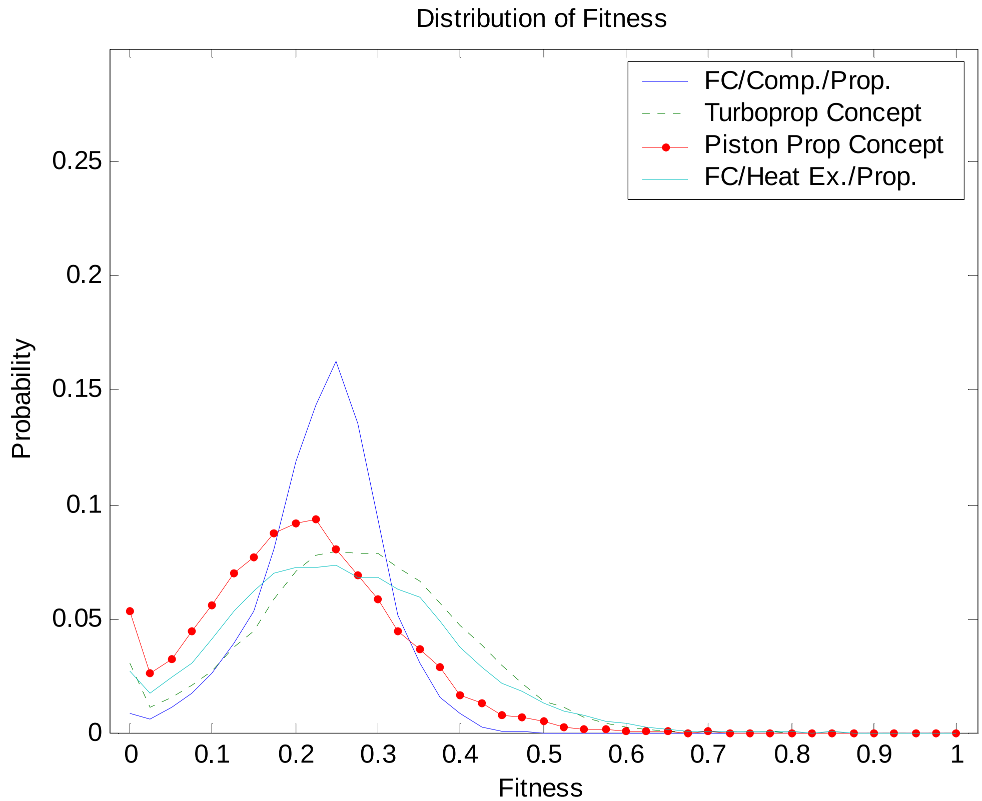


Figure 39: Comparison of Commonly Considered Propulsion Concepts

Given this analysis, each of the concepts seems to be reasonable alternatives. The least uncertainty surrounds the fuel cell/compression concept, but constant pressure combustion/compression/propeller concept has a good chance of better meeting the requirements. Remember, that this should not be considered as a conventional concept, because the cycle may have to be regenerative in nature. The tradeoffs between the four concepts must ultimately be taken into account by the decision-maker.

Notice that the turboprop concept appears to be the best overall concept. This outcome seems to contradict the outcome observed in Figure 24 where it showed that constant volume combustion processes were more fit than constant volume combustion processes. It is important to remember, however, that Figure 39 shows the distribution of all turboprop and piston/prop engines—conventional and regenerative. Wile conventional piston props are more fit than conventional turboprops, Figure 31 and

Figure 32 showed that the regenerative turboprops are more fit than conventional turboprops.

This analysis shows that all four proposed concepts are legitimate concepts, and does not truly discern between the four concepts. This analysis, however, was conducted assuming that regenerative combustion-based propulsion concepts are feasible. The following analysis investigates the very same concepts, but assumes that regenerative combustion –based concepts are infeasible.

5.4.3.2 Analysis II (Assumes that Combustion/Regeneration is Infeasible)

The second analysis was similar to that of the initial assumption, however, the analysis assumed that the products of combustion could not be stored and converted back to fuel to propel the aircraft during non-solar hours. That assumption ensures that only fuel cell based alternatives will be feasible across the entire range of requirement sets. Figure 40 displays the distribution of fitness for each of the three concepts, given the distribution of requirements and disciplinary metrics.

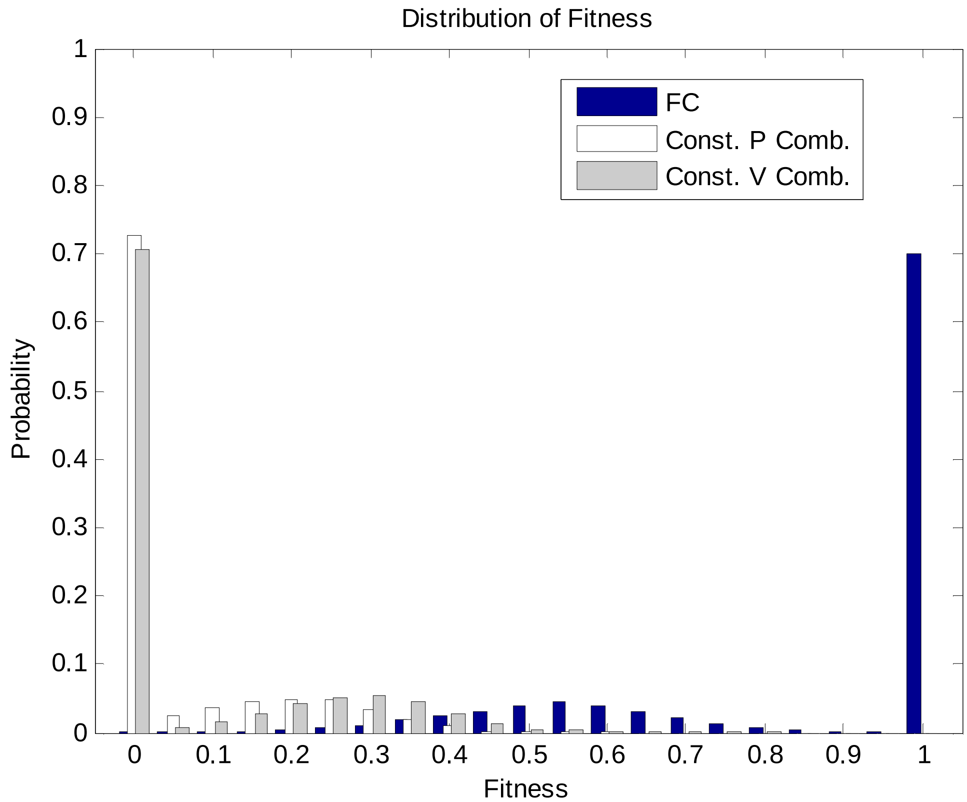


Figure 40: Fitness of Combustion Processes

Figure 40 shows not only that fuel cell processes are the only processes that are feasible across the entire range of requirements, but they are usually better alternatives. Figure 41 examines the distribution of the three concepts, and compares the distribution of fitness when refueling is available to the distribution of fitness when refueling is not available.

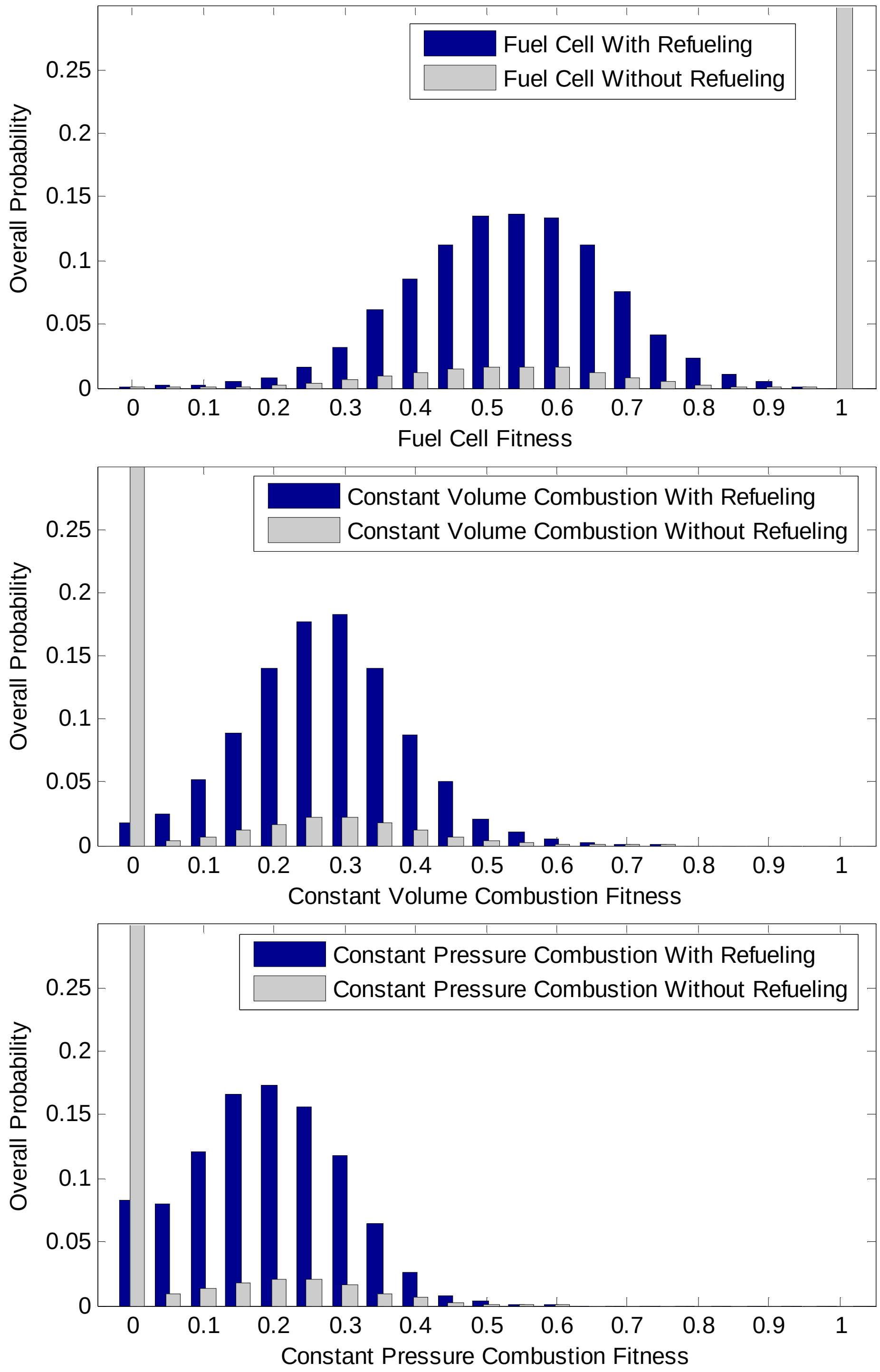


Figure 41: Comparison of Combustion Processes

Figure 41 shows the distribution of fitness for the three concepts in greater detail. Even when refueling is not an option for the vehicle, the two combustion-based concepts had some degree of fitness. This is because approximately 10% of those sets of requirements used multiple vehicles in serial flights to loiter over the area. Figure 41 clearly shows the improvement that constant volume combustion offers over constant pressure combustion, as well as the improvement that fuel cells offered over combustion. The main form of energy conversion for the propulsion system should be a fuel cell concept, because they are feasible over the entire range of requirements, and they are more fit, even with combustion is an option.

While fuel cells have been chosen as the main power generation for the propulsion concept and that decision has been justified in Figure 41, other aspects of the cycle still need to be investigated. The differences in the two analyses did not impact the fitness of thrust generation methods, or the fitness of different fuel alternatives. The distribution of fuel types shown in Figure 28 is representative of the distribution of fuel alternatives. Figure 28 showed that H_2 is the only fuel alternative that is feasible across the entire range of requirements. Figure 33 showed the fitness for two types of thrust generation methods, and similarly showed that using a propeller to generate thrust is the only means of producing thrust that is feasible across the entire range of potential requirement sets.

First, let us investigate the fitness of using only heat exchangers to prepare the gas that enters the fuel cell. Figure 42 shows the fitness of such propulsion systems with propellers.

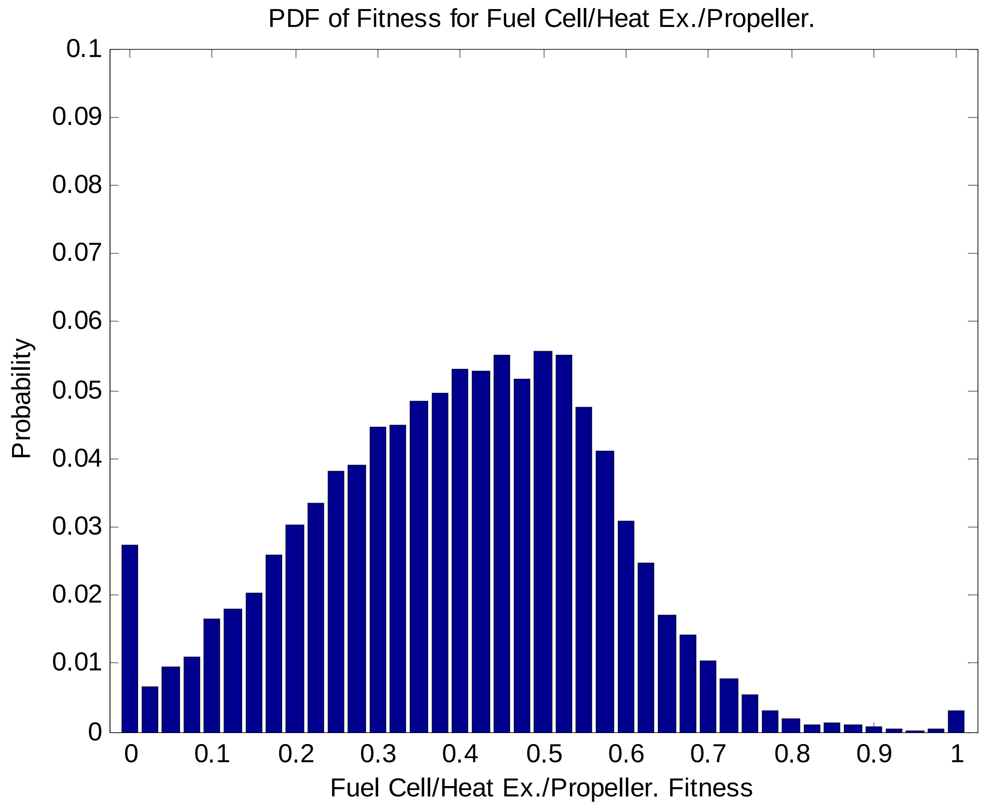


Figure 42: Fitness of Fuel Cell with Heat Exchanger and Propeller

Figure 42 shows that using a simple fuel cell cycle—only using a heat exchanger to heat the reactants in the fuel cell and generating electric current to power the fuel cell is an attractive alternative. The distribution of fitness is an odd shape, however, so the author broke down the distribution into different parts. Figure 43 shows the distribution of fitness for this same concept in the two main requirement circumstances—when refueling was an option, and when refueling was not an option.

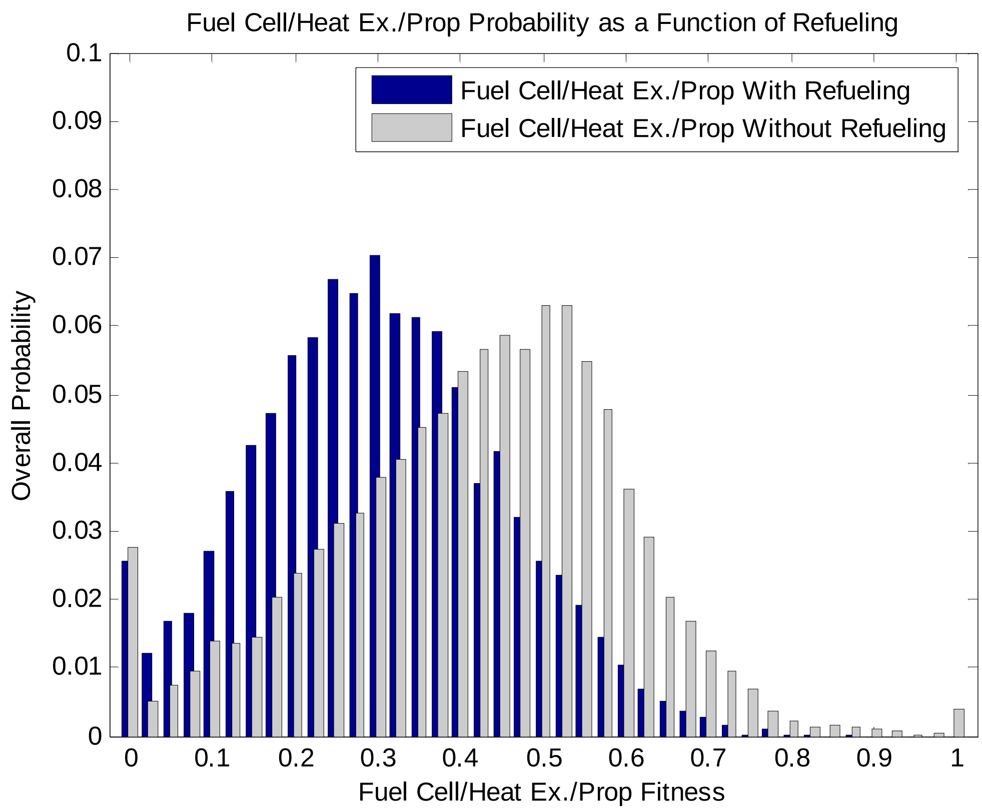


Figure 43: Fitness of Fuel Cell Concept with and without Refueling

It is easy to see how the two distributions in Figure 43 could sum up to the distribution in Figure 42. Notice that the fuel cell/propeller combination is slightly less attractive when refueling is available. This is because combustion based concepts are feasible given these requirements, and combustion based processes have to compete with them.

The study also investigated using a compressor in addition to heat exchangers to prepare the reactants that entered the fuel cell. Figure 44 shows the fitness of these concepts that were fitted with a propeller to generate thrust. Figure 44 has a very distinct “double M” shape to its distribution.

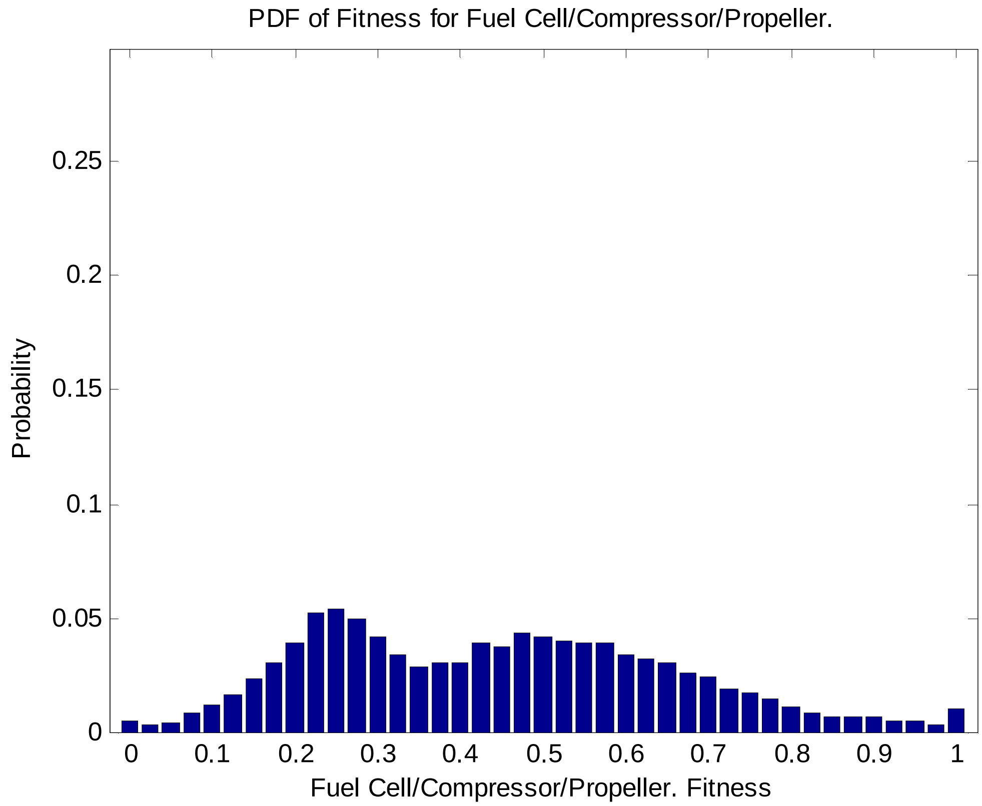


Figure 44: Fitness of Fuel Cell with Compression and a Propeller

Multi-modal distributions are often worrisome, as they can often indicate an error in the analysis. The author further investigated the cause of the "double M" shape in Figure 44. Figure 45 below breaks the fitness distribution down into two fitness distributions: one when refueling is an option, and one when refueling is not an option for the vehicle.

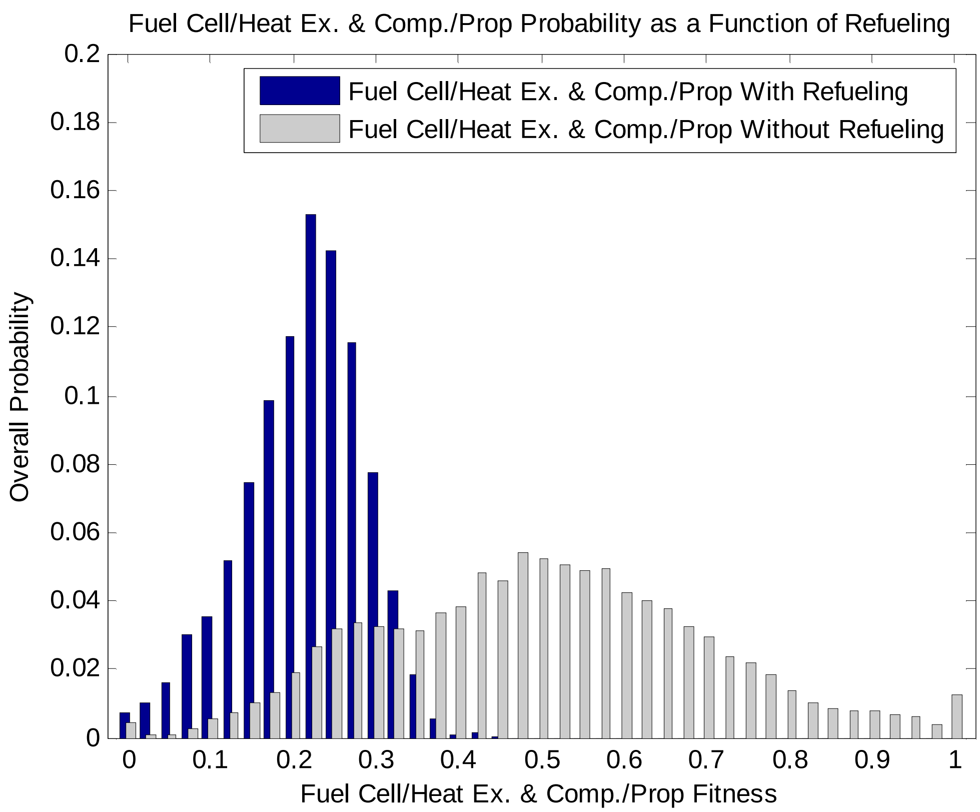


Figure 45: Fitness of Fuel Cell Concept with Compression as a Function of Refueling

Figure 45 clearly shows that the multimodal behavior observed in Figure 44 is a function of whether or not refueling was an option for the vehicle. As was the case with the fuel cell concepts that did not use compression to energize the fluids entering the fuel cell, the concepts are much more fit when refueling is not an option. Again, this trend occurs because when refueling is an option, combustion is a feasible alternative, and fuel cell concepts have to compete with combustion-based concepts.

A regenerative fuel cell concept that uses heat exchange and a compressor to energize the gas that enters the fuel cell and generates an electric current to drive the propeller with electricity generated in the fuel cell is an attractive concept. It does not, however, appear to be significantly more fit than a fuel cell/propeller concepts that only use heat exchangers to excite the fluid. Both concepts are robust enough to meet almost all of the potential set of requirements. The fuel cell/heat exchanger/propeller concept has a high degree of uncertainty associated with it, as it is an immature, revolutionary concept. The concept actually appears to have a slightly lower uncertainty associated with it than the fuel cell/compressor/propeller combination does. This assessment, however, assumes that a regenerative combustion process is not feasible. Figure 46 directly compares the fitness of the fuel cell/heat exchanging concepts with the fuel cell/compression concepts.

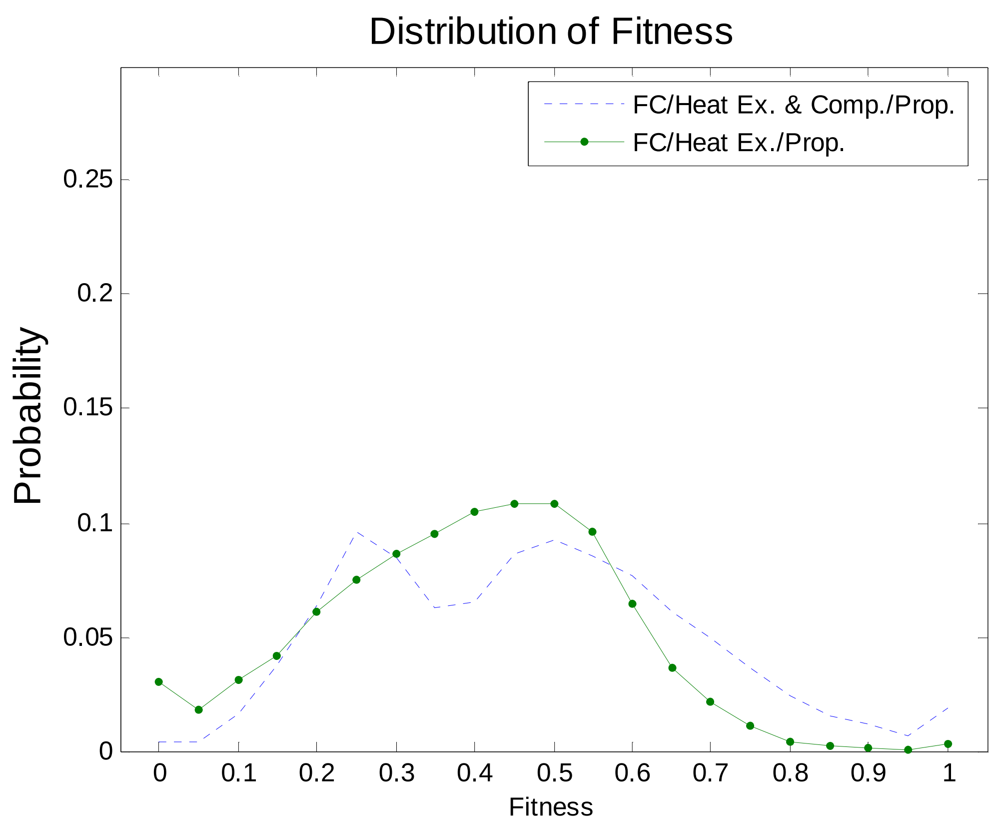


Figure 46: Comparison of Heat Exchanger to Compressor with Fuel Cell

Each concept is only considered in conjunction with a propeller to produce thrust. Notice in Figure 46 that the fuel cell/heat exchanger system appears to advantageous over the concepts that use heat exchangers. Finally, the distribution of fitness for the fuel cell/compression/heat exchanger is compared to conventional concepts in Figure 47.

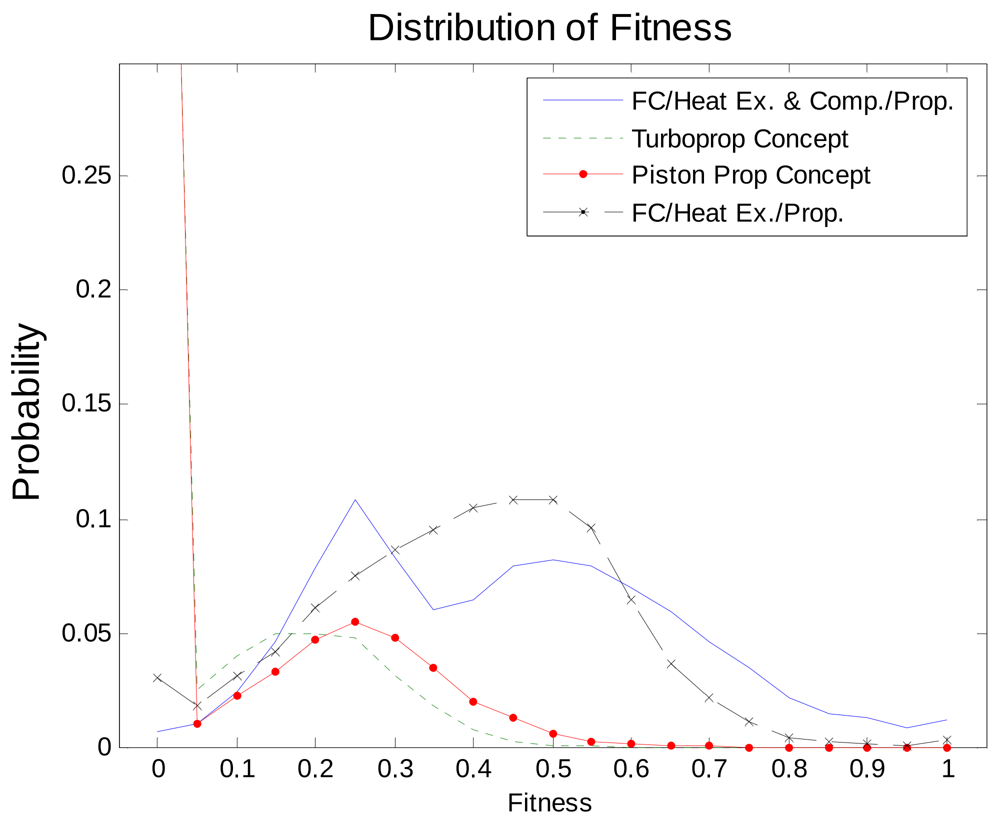


Figure 47: Comparison of Fuel Cell to Competing Concepts

Unlike Figure 39, the conventionally named concepts in Figure 47 truly are conventional. Because this analysis assumed that the only feasible regenerative concepts are fuel cell based concepts, the turboprop and piston/propeller engines analyzed in Figure 47 truly are conventional.

The information generated in this analysis shows that the most fit propulsion concept for the HALE vehicle is a fuel cell concept that drives a propeller with the electrical energy generated in the fuel cell. This analysis gives the decision-maker a quantitative understanding of how the goodness of each propulsion concept varies with the requirements and with the technological maturity of each concept. The assumptions made in the analysis to arrive at this conclusion have been transparent. Ultimately, it is up to the decision-maker to select which propulsion concept or concept to bring forward to the next phase of development.

6 CONCLUSIONS

The Evolving Requirements Technology Assessment method was developed to give decision-makers the ability to compare advanced propulsion concepts to one another on another, given the uncertain nature of the requirements that the advanced propulsion concepts must meet. In using the ERTA method to evaluate and compare the various propulsion concepts for use on the HALE hurricane tracker, the four hypotheses statements were successfully tested. The overarching Research Question was demonstrated, substantiating research questions were addressed, and the four hypothesis posed were found to hold true.

In the introduction, several goals for the successful development of the ERTA method were laid out. Ultimately, the method had to give decision-makers an understanding of how robust the goodness of each propulsion concept was to potential variations in the requirements. In order to do this, the method had to do three things. First, it had to generate a probabilistic forecast of the requirements. The ERTA method does so by combining requirements analyses with forecasting methods. The resulting modified cross impact analysis provides a probabilistic set of requirements that incorporated the interdependencies of individual requirements into the forecast.

Second, the method had to assess the relative goodness of each concept across the distribution of requirements. The ERTA method achieved this by calculating the fitness of each concept, as a function of the requirements. The distribution of each concept’s fitness was then calculated as a function of the distribution of the requirements.

Finally, the method had to incorporate the uncertainty inherent the development of technological concepts into the assessment. The propulsion concepts for the HALE propulsion system range dramatically in maturity. The ERTA method met this requirement by placing a distribution on the disciplinary metrics used in the concept assessment. The uncertainty was incorporated into the overall distribution of fitness for each concept. More mature concepts had tighter distributions.

Overall, the ERTA method gave decision-makers the ability to measure the robustness of each concept to the potential variation in requirements. The assessment will enhance the information that decision-makers have when selecting which concepts to allocate funds. Such evaluations will allow decision-makers to more efficiently allocate funds to potential advanced propulsion concepts, and allow them to justify their decisions with a logical, transparent methodology.

6.1 Assessing the Hypotheses Statements

Four hypotheses statements were inferred throughout the manuscript. The first, statement was the most general. It is restated below.

> Any method designed to evaluate advanced propulsion concepts must incorporate the possible variations of the requirements into the assessment.

This first statement provided the need for the ERTA methodology. While the statement is difficult to prove, evidence for the statement exists in historically unsuccessful developments. Consider again the numerous technological concepts that became obsolete before they could be fully developed because the requirements for such systems changed. The (UDF), a revolutionary aeropropulsion system that promised to reduce fuel consumption by 20% to 30% was dropped when the fuel crisis ended and the demand for quiet, aesthetic engines superseded the drive for efficiency [72]. The nuclear jet, another relatively promising concept was dropped after the demand for ultra-large aircraft was reduced and anxiety of nuclear power set in [97]. Similarly, there are historic examples of technological concepts being only adequate because the actual requirements for the concept differ from what the concept was intentionally designed to meet. The US Navy originally intended the F-18 to be primarily a payload-delivering vehicle, not a air-superiority vehicle. It was intended to work in conjunction with the F-14. As the F-14 was phased out, however, the F-18 has to perform both missions [9].

The analysis conducted on the HALE propulsion concepts also supported the hypothesis. The fitness of each of the propulsion concepts were very sensitive to particular requirements. How useful a fuel cell concept will be to the future HALE vehicle depends highly upon the speed that the vehicle must travel and whether or not the vehicle will be capable or refueling in the air. Additionally, the future usefulness of a solar vehicle will also depend strongly on those requirements.

The second hypothesis statement was much more tangible, but still difficult to ***prove***. The statement is restated below:

> Shape functions depicting distributions of future requirements for the HALE propulsion system can be defined using traditional, forecasting techniques.

The ERTA method was used to generate a probabilistic distribution of the requirements for the HALE propulsion system. Unfortunately, it is difficult to prove that this distribution is truly reflective of the actual distribution, because the actual probability of each requirement occurring is unknown. The interdependencies of the individual requirements were seen in the distribution, and unlikely requirements did have a low probability of occurring. One important feature of a forecasting methodology is that the assumptions that it uses to generate the forecast be transparent. The assumptions that the modified cross impact analysis used are all

The third hypothesis introduced the notion of using fitness to compare HALE propulsion concepts to one another. The hypothesis is restated below:

> “Fitness”, a concept’s ability to meet a set of requirements relative to other potential concepts, can be used to forecast a propulsion concept’s likelihood of successful development.

Again, this statement is difficult to prove, but the use of the ERTA method to evaluate the propulsion systems serves as evidence that fitness can measure the ability of a concept to meet the specific set of requirements, relative to competing concepts. The fitness parameter also incorporated a measure of how “easy” it is to produce a feasible alternative for each concept. Concepts which are easier to develop will have a greater fitness because more of the alternatives in the optimized pool will be classified as those concepts. Fitness quantifies both a concept’s ability to meet the requirements and how easy it is to produce a feasible alternative—two metrics that in a perfect world, would predict the success of a concept. In an imperfect world, were decisions are made based on political motivations, the fitness can serve as a methodical and analytical justification for allocating resources to particular technological concepts.

The final hypothesis statement outlines the foundation of the ERTA method. The hypothesis is stated below:

> Stochastic optimizations can be used to calculate fitness as a function of requirements, enhancing decision-makers’ understanding of future technological concepts.

Stochastic optimizations provided the means by which the propulsion concepts were optimized to meet specific sets of requirements. A simulated annealing program was used to identify an optimized set of alternatives. Simulated annealing is a stochastic optimization routine that begins with several random alternatives, and allows those alternatives to evolve individually throughout the routine. The final “optimized” set of alternatives was the used to calculate the fitness for each concept, given a particular set of requirements. While it is difficult to compare the optimized concepts that the simulated annealing program identified, the results made sense, and the optimization was accepted. Overall, the process successfully identified the optimized alternatives for each concept. Stochastic processes were again used to identify the distribution of fitness as a function of the distribution of requirements.

6.2 Results of Demonstration

The ERTA method was developed to allow the author to compare potential advanced propulsion concepts as a means of propelling a HALE hurricane tracker. Requirements for the propulsion system were defined by the mission of the vehicle, and the vehicle characteristics. NASA assembled an interdisciplinary team of experts to investigate the feasibility of such a vehicle. As part of that mission, the NASA experts conducted a workshop to better specify system level requirements and possible vehicle characteristics. Results of that workshop were used as the basis to establish possible propulsion system requirements. A cross impact analysis was conducted to identify a probabilistic set of requirements, and those requirements were eventually used to forecast the fitness of each of the proposed propulsion concepts.

The long duration of the mission dictated that several of the potential propulsion concepts were incapable of meeting most of the requirement sets. Assuming that conventional concepts are limited to non-regenerative combustion based engines, conventional concepts would only be capable of meeting approximately 30 % of the requirement sets. Due to the long mission durations, only regenerative propulsion systems (those that "recharged" the fuel) were serious contending concepts. Fuel cell concepts that compress O_2 and H_2 before they enter a fuel cell and produce electricity to drive a propeller are by far the most fit concepts, given the potential set of requirements. They are feasible alternatives across the entire range of requirements, and are best able to meet the requirements in several of the requirement sets.

6.3 Recommendations

The ERTA method has proven as a methodical means of comparing advanced propulsion concepts, given an uncertain set of requirements. The author has identified a few research directions that could possibly improve decision-makers ability to compare advanced propulsion concepts.

First, the requirements were forecasted using a modified version of a cross-impact analysis. Other probabilistic forecasting techniques could potentially be used to identify the requirement sets. Most notably, the technology impact analysis (TIA) could be used in conjunction with cross impact analysis to model some of the individual requirements. TIA uses time-series forecasting to predict future distributions of continuous variables. The value of discrete requirement variables could be inputs to the TIA analysis to forecast specific, continuous variable requirements. Such a method would allow the dependency of the requirements to be modeled, but it would also allow the requirement value to be continuous. The applicability of other forecasting techniques could also be investigated.

A second research direction is in the means of forecasting the ability of the conventional technology to meet the future sets of requirements. Because more is known about the conventional technology, a more thorough investigation of the space surrounding the evolutionary concept can take place. The investigation could then consider a combination of empirical data and physics-based methods to better assess the ability of the conventional concept to meet the future requirements.

Finally, different ways of calculating fitness for each concept and set of requirements can be explored. The ERTA method currently uses a simulated annealing optimization routine to identify a nearly optimized pool of alternatives. The fitness of the concepts was calculated from the optimized pool. A meta-model was created to relate the variability of the fitness to the variation in the requirements. Unfortunately, this introduces two sources of error. Error is inherent to the simulated annealing program, as it is a stochastic process. That error regressed into the meta-model, and the meta-model adds an additional source of error. As computational power grows and storage capacity increases, other methods might replace the simulated annealing optimization. A grid search could be used conducted on each space exploration for each set of requirements. Depending on the fineness of the grid search, it could add thousands of cases to each optimization, and require much more storage space, but if possible, it would reduce some of the stochastic nature of the problem, and increase the accuracy of the meta-model.

There is also much research to be done in the line of developing means of comparing advanced propulsion concepts. Fitness has been proposed as a figure of merit, simply because of its broad applicability to all requirement sets and concepts. Much work remains to give decision-makers a more intuitive understanding the relative differences between potential concepts, and an understanding of the uncertainty inherent to the problem.

APPENDIX A: NASA HALE UAV WORKSHOP

NASA conducted a conceptual design workshop on November 2-4, 2005 at the Aerospace Systems Design Laboratory's (ASDL), Georgia Institute of Technology to enhance their understanding of the requirements and feasibility of a high altitude, long endurance (HALE) aerial vehicle. Thirteen NASA experts from a wide variety of disciplines attended. Ultimately, the output of the workshop was to assist in the technology prioritization and planning to the Unmanned Aerial Vehicles (UAV) sector of NASA's Vehicle Systems Program.

The UAV Sector encompasses a broad range of vehicle and mission types, from terrestrial HALE vehicles to planetary exploration vehicles. The information gained in the workshop was used to assess the technologies being developed so that the various technologies could be prioritized based on their ability to further the state of the art. Unfortunately, current modeling and simulation tools cannot adequately address the full range of vehicle types in the UAV Sector. This workshop was intended to serve in the place of modeling and simulation as the as the assessment of each technology, which was necessary to evaluate the technologies.

Each of the attendees came from NASA or company working closely with NASA on the HALE UAVE development. Table 41 lists the NASA employees who attended the workshop.

Table 41: List of NASA Workshop Attendees

Attendee	Organization
Tom Ozoroski	NASA Langley Research Center
Mike Logan	NASA Langley Research Center
Salvatore Buccellato	NASA Langley Research Center
Mark Motter	NASA Langley Research Center
Bob Clarke	NASA Langley Research Center
Joel Campbell	NASA Langley Research Center
Steve Smith	NASA Ames Research Center
Ray Morgan	Morgan Aircraft Consulting
Dave Paddock	NASA Langley Research Center
Ron Busan	NASA Langley Research Center
Mark Guynn	NASA Langley Research Center
Lisa Kohout	NASA Glenn Research Center
Craig Nickol	NASA Langley Research Center

On the first day of the workshop, the attendees reviewed the requirements for a HALE hurricane-tracking UAV and a communications relay HALE UAV. Once they understood the requirements and the ASDL methodology, they created an Interactive Reconfigurable Matrix of Alternatives (IRMA). An IRMA is actually an interactive, reconfigurable morphological assessment. In order to do this, the attendees first performed a functional decomposition of the mission. This breakdown is shown below in Figure 48

Mission	Altitude
	Time On station (ie, chase or loiter time)
	Mission Radius
	Location and time of year (energy availability)
	Station keeping accuracy
	Critical Ground Speed
	Wind Tol: Launch and Recovery
	Wind Tol: Sustained
	Gust tolerance: Uniform
	Gust tolerance: Non-uniform
	Service Life
	Expendable Payload
	Fixed payload
	Weather
	Completion rate
	Mission operational concepts
	Operating environment
	Runway length
	Recovery
	Launch
	Runway width

Figure 48: Mission Breakdown

The attendees also broke the vehicle systems down into the required systems, including:

1) Propulsion and Power
2) Configuration
3) Sensors
4) Avionics and Instrumentation
5) Command
6) Control
7) Data Link
8) Actuation

Once the vehicle was decomposed into systems, the attendees broke into groups to break the systems down further into subsystems and they identified alternatives for each subsystem. The resulting system and subsystems are shown below in Figure 49.

Power and Propulsion	Power source
	Energy conversion
	Energy storage
	Thrust generation-propulsors
	Auxiliary power generation
	Fuel
Configuration	Variable Geometry
	Rotorcraft
	Fixed Wing
	Airship (LTA)
Sensors, Avionics, and Instrumentation	Detect and Avoid
	Health management
	Flight control sensors
Command	Command mission termination systems
	Command link: line of sight
	Command link: beyond line of sight
Control	Climb & Descent
	Cruise
	Take-off and landing
Data Link	Data Link: line of sight
	Data Link: beyond line of sight
Actuation	Actuation systems

Figure 49: Vehicle System Breakdown

Once the vehicle and mission were broken down, the attendees ranked the importance of each mission parameter and assessed the alternatives for each vehicle subsystem alternative. This was done both individually during a break in the workshop, and collectively after the attendees considered the problem individually.

On the final day of the workshop, the dependent relationships between the mission parameters and vehicle subsystem alternatives were investigated. The attendees identified each of the dependent sets of alternatives, and fist noted all of the incompatible combinations. Then, they investigated which of the alternatives were correlated.

The outputs of the workshop served as an assessment of each of the technologies currently being developed for the terrestrial HALE UAV vehicle. Throughout the process the NASA attendees enhanced their understanding of the requirements, vehicle system alternatives, and the interaction between the two. The IRMA that was developed can be used in the future when evaluating UAV technologies. It is interactive, so that decision-makers can use it to play “what if” games with various alternatives. Additionally, it can be updated in the future to reflect additional information and technologies. Finally, the workshop also served as the basis for the requirements development for the hurricane tracking HALE propulsion system.

APPENDIX B: PROBABILITY ESTIMATES FOR REQUIREMENTS

The following tables list the initial probability estimates that were used to determine the requirements for the HALE propulsion system. The parameters were identified in the NASA HALE Conceptual Design Team Workshop. The probability estimates were determined in part at the workshop, and in part with the help of Craig Nickol and Ray Morgan after the conclusion of the workshop.

Element	Alternative	Probability
Altitude	>13 km	0.1
	>18 km	0.5
	> 20 km	0.4
Time On Station	~7 days	0.2
	~30 days	0.3
	~100 days	0.49
	Unlimited	0.01
Mission Radius	~3500 km	0.2
	~5000 km	0.4
	~7000 km	0.2
	~10000 km	0.1
Location and Time of Year	Tropical, Hurr Season	0.7
	Tropical, Year Round	0.19
	Unlimited CONUS	0.11
Station Keeping Accuracy	~1 km	0.5
	~5 km	0.3
	~10 km	0.2
Critical Ground Speed	105 kph	0.15
	150 kph	0.8
	200 kph	0.04
	250 kph	0.01
Service Life	~3000 hrs	0.1
	>7500 hrs	0.15
	>10000 hrs	0.5
	>40000 hrs	0.25
Expendable Payload	Dropsondes	0.7
	Mini-UAV	0.1
	Drop and UAV	0.19
	None	0.01
Fixed Payload	Broadband	0.2
	Cell Phone	0.2
	Hurricane Package	0.2
	Hurricane-Doppler	0.2
	Disaster Monitoring	0.2
Weather	Standard Day	0.59
	Near All Weather	0.4
	All Weather	0.01
Mission Operational Concepts	Auxiliary-Powered	0.08
	Refueled in Flight	0.2
	Single Vehicle	0.6
	Formation Flight	0.01
	Serial Flight	0.1
	Tip-Joined Multi-Vehicle	0.01

Element	Alternative	Probability
Operating Environment	Mil Std 210 Std Day	0.25
	Mil Std 210 Cold Day	0.25
	Mil Std 210 Hot Day	0.25
	Mil Std 210 Tropical Day	0.25
Runway Length	<150 m	0.01
	<1500 m	0.3
	<2000 m	0.68
	circular	0.01
Recovery	None	0.01
	Wheeled Runway Landing	0.7
	Parachute	0.1
	Parasail	0.01
	Skid gear	0.11
	In Air Recovery	0.01
	Water Landing	0.1
	Stall and Drop (Low Alt.)	0.01
Launch	Towed	0.1
	Wheeled Runway Launch	0.6
	Dolly	0.3
Runway Width	< 45 m	0.19
	<60 m	0.8
	Circular	0.01
Variable Geometry	None	0.1859911
	Span	0.1446011
	Sweep	0.1386138
	Dihedral	0.28
	Chord	0.06
	Aux. Surfaces	0.1940518
Rotorcraft	None	1
	Helicopter	0
	Autogyro	0
	Tiltrotor	0
Fixed Wing	None	0.02
	W-B-T/C	0.2
	Bi-plane	0.3
	All wing	0.4
	Three surface + B	0.05
	Joined wing	0.03
Airship (LTA)	None	0.2
	Dirigible	0.2
	Blimp	0.49
	Hybrid	0.1
	Powered Balloons	0.01

APPENDIX C: SIZING ALGORITHM OVERVIEW

High Altitude, Long Endurance (HALE) vehicles were sized using an energy-based sizing algorithm. The drag that was generated at each point in the mission was calculated as a function of the vehicle mass. The power necessary to overcome that drag at he specified velocity was used to calculate the normalized power output of the engine at different points in the mission. For fixed wing vehicles, drag was purely a function of weight and the appropriate drag polar. For the lighter-than-air vehicles, drag was a function of the d/l ratio, and the envelope volume. For hybrid vehicles, the ratio of the weight that was carried by "lift" was calculated, and the rest of the weight was supported by an envelope filled with helium. The drag from the lift generation and envelope were added together to calculate a total drag. Once the drag was calculated at different parts of the mission, the vehicles were essentially sized in the same manner.

For each vehicle class, at each point in the mission, the thrust or power required to perform the mission parameter was calculated. The instantaneous amount of fuel, or stored energy, required to provide that thrust or power was then taken from the engine deck, and tracked in terms of percentage of the vehicle weight. The instantaneous amount of stored energy was found for each mission segment and integrated across an entire part of the mission. The duration of the mission was long enough that each propulsion system required some sort of energy renewal, (with the exception of the serial flight option), whether that energy was obtained through the sun, through refueling, or by receiving electromagnetic energy that is "beamed" to the vehicle. Because each vehicle received some sort of energy renewal, the vehicles only had to store enough energy to provide the vehicle with power between renewal encounters. One of the mission operation alternatives was to observe the hurricane area using multiple vehicles in serial flight. When this was the case, no renewal was needed. In these cases, the vehicle was sized to perform a subset of the mission, and allowed to refuel an allotted period of time.

If the source of energy renewal was solar, the vehicle needed to have enough surface area to provide enough energy to convert all of the “spent fuel” back into usable fuel, while also powering the vehicle during the solar hours. The percentage of the total vehicle weight that was fuel was calculated by determining the amount of fuel required to propel the vehicle through the “non-solar” hours. The number of solar hours in a day was a function of the geographic operating location and operating time of year. Also, if the vehicle had to take off in poor conditions, a check was performed to ensure that the vehicle had enough fuel to get to cruise altitude without the help of solar energy.

If the vehicle renewal source was mid-air refueling, the vehicle simply replenished the fuel that it used since the last refueling session. The percentage of the vehicle weight that was reserved for fuel was measured by ensuring that the vehicle could perform all of the mission requirements between refueling sessions. The frequency of refueling was left as metric, and varied between refueling every 3 days to every 1/3rd of a day. A triangular distribution was placed on the log of the frequency.

Vehicles that received their energy renewal through “beamed” energy were sized in a manner similar to those of solar powered vehicles, since the premise was the same. The amount of power required also had an impact on sizing the engines. Each basic engine concept was given a power density figure. The maximum power required in the mission was calculated as a function of total vehicle weight. The power density was then used to identify the engine weight as a percentage of total vehicle weight. If photovoltaic cells were required, as in the case of solar and beamed renewals, the weight of the photovoltaic cells was also included.

For each of the three cases, the weight of the engine was calculated as a function of the total vehicle weight by using energy density parameters for the engine type and the maximum required power to weight ratios of the vehicle. The sizing of each specific vehicle is discussed in APPENDIX D and APPENDIX E.

APPENDIX D: SIZING ALGORITHM FOR FIXED WING AIRCRAFT

The sizing algorithm for fixed winged aircraft was generated using fundamental physical principles. The sizing algorithm was similar to that developed by Choi [17], but it was tailored specifically to work with an alternative energy "engine deck". Ensuring that lift generated by the aircraft equals the weight of the aircraft and that the thrust provided by the propulsion system equals the drag produced by the lift generation and mission requirements. First, the thrust to weight ratio is calculated. In order to do this, the algorithm compares the maximum thrust at different sizing conditions to the thrust to weight ratios required. These ratios can be calculated using derivatives of Mattingly's Master Equation [57]. This equation calculates the minimum thrust to weight ratio as a function of the current mass fraction, storage rate of energy, drag polar and velocity. Mattingly's equation can be derived from the conservation of energy equation; the storage rate of kinetic and potential energy equals the excess power.

$$\left(\mathrm{T}-\mathrm{D}\right)\mathrm{V}=\frac{d}{dt}\left(\mathrm{m}gh+\frac{\mathrm{mV}^2}{2}\right) \quad \text{or} \quad \left(\mathrm{T}-\mathrm{D}\right)\mathrm{V}=\mathrm{m}g\frac{d}{dt}\left(Z_o\right) \tag{25}$$

Where:
T = thrust
D = drag
V = velocity
m = aircraft mass
g = gravitational constant
h = height (altitude)
Z_o= total energy per weight, or $\left(h+\mathrm{V}^2/2g\right)$

Assuming that K'' from the drag polar is negligible, the Master Equation below (shown in metric form) can be derived from the above equation.

$$\frac{T_{SL}}{m_{TO}} = \frac{\beta}{\alpha}\left\{\frac{q\,C_{Do}}{\beta\, {m_{TO}}/{S}} + \frac{K_1\,\beta\, g^2}{q}\left({m_{TO}}/{S}\right) + \frac{g}{V}\frac{d}{dt}(Z_o)\right\} \tag{26}$$

Where: m_{TO} = takeoff mass

T_{SL} = sea level static thrust

β = mass fraction, or ${m}/{m_{TO}}$

α = thrust ratio, or ${T}/{T_{SL}}$

S = wing area

C_{Do} = zero lift drag coefficient

K_1 = drag polar constant

For various key points throughout the mission, the algorithm works by ultimately determining the amount of fuel flow required to provide enough thrust. In order to do, the algorithm must determine the amount of thrust required, and match from the engine deck the amount of fuel flow required to produce that much thrust. The thrust data in the engine deck is not scaled yet, but that is irrelevant, as fuel flow is calculated per takeoff gross mass. The unscaled thrust value required from the deck can be calculated using the Master Equation shown in Equation 26 and the fact that $T_{RQD} = \alpha\, T_{SL}$. Equation 27 shows Equation 26 manipulated to calculate α.

$$\alpha = \frac{\beta}{{T_{SL}}/{m_{TO}}}\left\{\frac{q\,C_{Do}}{\beta\, {m_{TO}}/{S}} + \frac{K_1\,\beta\, g^2}{q}\left({m_{TO}}/{S}\right) + \frac{g}{V}\frac{d}{dt}(Z_o)\right\} \tag{27}$$

Equation 28 identifies the thrust required as a function of the sea level static thrust.

$$T_{RQD} = \frac{\beta\, T_{SL}}{{T_{SL}}/{m_{TO}}}\left\{\frac{q\,C_{Do}}{\beta\, {m_{TO}}/{S}} + \frac{K_1\,\beta\, g^2}{q}\left({m_{TO}}/{S}\right) + \frac{g}{V}\frac{d}{dt}(Z_o)\right\} \tag{28}$$

Where: T_{RQD} = thrust required

The engine is assumed to be rubberized, meaning that it can be scaled. The factor used to size up the engine detailed in the deck can be scaled up to the true engine by multiplying it by a constant factor. That factor can be divided by both sides to give the same equation, but scaled for the engine deck, as seen in Equation 29.

$$T_{D,RQD} = \frac{\beta\, T_{D,SL}}{T_{SL}/m_{TO}} \left\{ \frac{q\, C_{Do}}{\beta\, m_{TO}/S} + \frac{K_1\, \beta\, g^2}{q} \left(m_{TO}/S \right) + \frac{g}{V} \frac{d}{dt} \left(Z_o \right) \right\} \tag{29}$$

Where: $T_{D,RQD}$ = thrust required from engine deck

$T_{D,SL}$ = sea level static thrust from engine deck

At this point in the algorithm, a new parameter, K_{Eng} is introduced. K_{Eng} is the factor by which the engine is scaled, or the ratio between the actual sea level static thrust, T_{SL} and the deck reported, unscaled seal level static thrust, $T_{D,SL}$. If both K_{Eng} and that ratio are divided by the takeoff gross mass of the aircraft, Equation 30 can be derived.

$$\frac{T_{SL}/m_{TO}}{T_{D,SL}} = \frac{K_{Eng}}{m_{TO}} \tag{30}$$

The fuel flow per takeoff gross aircraft mass can be found using that same ratio, K_{Eng}. Once the engine deck thrust required, $T_{D,RQD}$, is found, the fuel flow from the deck, ff_D can be found as a linear interpolation from the engine deck. Since the aircraft has yet to be sized, the measure of fuel flow should be on a per takeoff gross mass basis. In order to find this value, ff_D needs to be multiplied first by the K_{Eng}, and then divided by the takeoff gross mass, m_{TO}. Equation 31 shows this relationship. The ratio of K_{Eng} to m_{TO} can be found in Equation 30, where the thrust to mass ratio was calculated by the mission parameters, and and the seal level static engine deck thrust was calculated by the propulsion analysis algorithm.

$$\frac{ff}{m_{TO}} = ff_D \frac{K_{Eng}}{m_{TO}} \tag{31}$$

The total fuel consumed over the segment per takeoff gross mass equals the quantity found in Equation 31 multiplied by the time of that segment. It should be noted here that the greater number of segments the flight is broken into, the more accurate the sizing algorithm is, as conditions continuously change throughout flight. Even if the altitude and Mach number remain constant, the lift, and consequently the drag, will vary as the weight is reduced because fuel is consumed. There is a tradeoff, however, as the more segments that the flight is broken into, the longer the algorithm takes to run for each sizing analysis. Considering the low fidelity of the analysis being used, it does not make sense to break the mission into too many segments. Also, because the flight conditions are measured at the beginning of each segment, the fewer segments that the flight is broken into, the more conservative the assessment is, as the weight of the aircraft will continue to decrease as fuel is consumed.

Assuming that no payload is dropped throughout the mission, the only reduction of mass is the consumption of fuel. If the aircraft stored oxidizer onboard, or if the byproducts of the process are retained onboard, this would not be the case, and the algorithm would need to be varied. Assuming that the only reduction of mass is through the consumption of fuel, the weight fraction β for each segment can be easily calculated from the β for the previous segment and the ratio of fuel consumed for the segment over the takeoff gross mass, as is shown in Equation 32.

$$\beta_{i+1} = \beta_i - \frac{\mathrm{ff}}{\mathrm{m}_{\mathrm{TO}}} \qquad (32)$$

The algorithm iterates through the mission beginning with takeoff, and calculates the β fraction for the next flight segment. Once the final β fraction is calculated, the empty weight fractions and payload can be used to identify the takeoff gross mass of the aircraft. The empty weight fractions reflect the current state of the art for the structural subsystem of the aircraft.

Once the fuel weight percentage, engine weight ratio, and photovoltaic cell weight ratio were calculated known, the vehicles were sized using slightly different algorithms. The empty weight fraction for fixed winged vehicles was given parametrically. Equation 33 shows the totaling of aircraft weigh t for fixed wing vehicles.

$$M_{FW} = M_{PL} + M_{Empty\ Vehicle} + M_{"Fuel"} + M_{Power\ System} + M_{PV\ Cells} \qquad (33)$$

Equation 34 is a manipulated version of Equation 33 that allows the total vehicle weight, M_{FW}, as a function of payload and the weight ratios discussed above.

$$M_{FW} = \frac{M_{PL}}{1 - \frac{M_{Empty\ Vehicle}}{M_{FW}} - \frac{M_{"Fuel"}}{M_{FW}} - \frac{M_{Power\ System}}{M_{FW}} - \frac{M_{PV\ Cells}}{M_{FW}}} \qquad (34)$$

While the expected empty weight fractions may vary with the propulsion system as complexity increases or decreases, at this point, the algorithm assumes that the empty weight fractions are the same for each type of propulsion system. The total fuel consumed throughout the mission, the takeoff gross mass of the aircraft, and the total emissions emitted into the atmosphere throughout the flight are all calculated in the algorithm and could ultimately be used as figures of merit when selecting the "fittest" propulsion systems.

Figure 50 summarizes the sizing and synthesis routine used to conceptually size the fixed wing vehicles.

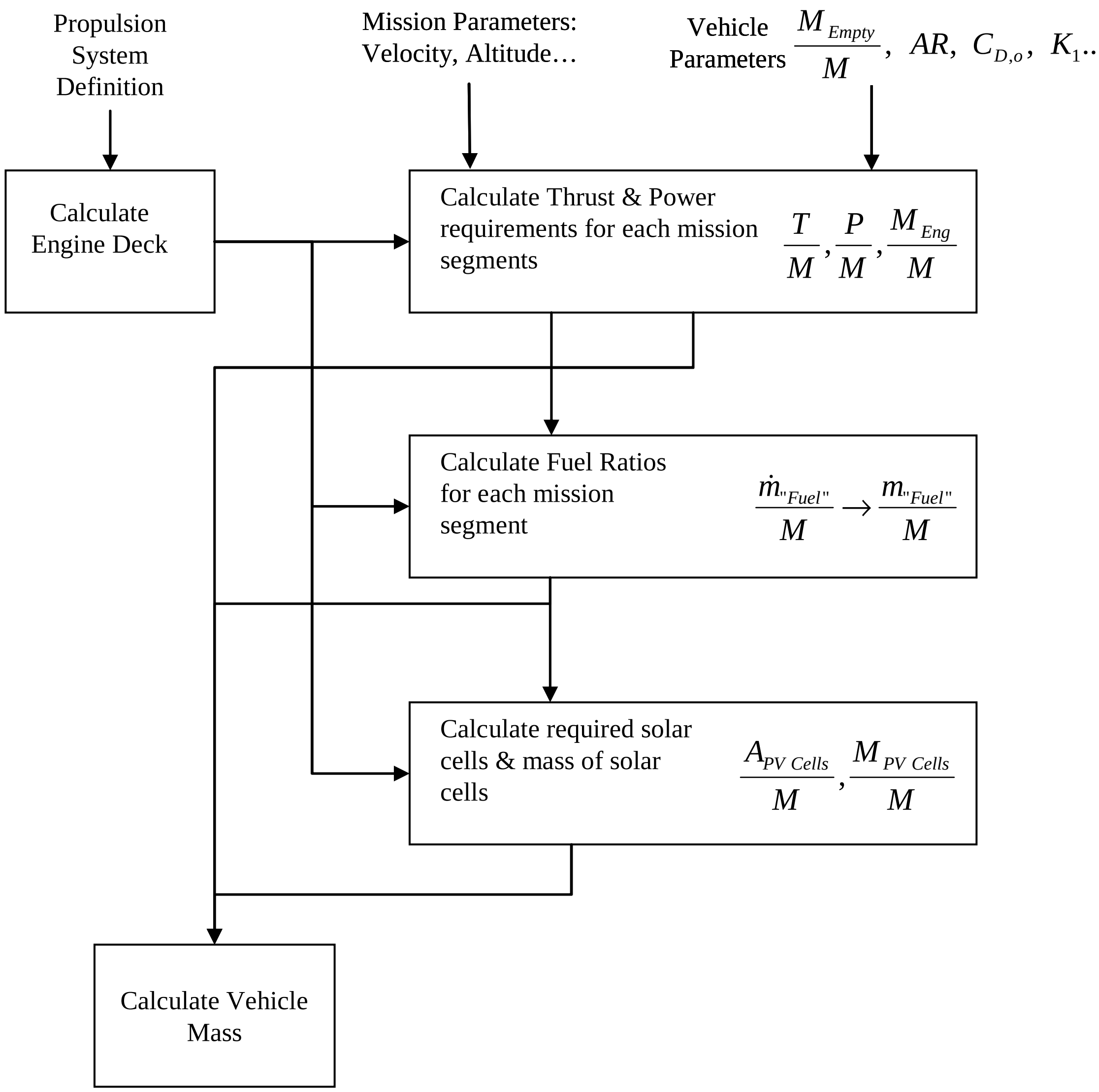


Figure 50: Flow Chart of Sizing and Synthesis Routine for Fixed Wing

APPENDIX E: SIZING ALGORITHM FOR LIGHTER-THAN-AIR VEHICLES

An energy based sizing algorithm was used to size lighter-than-air vehicles. Because little was known about the vehicles, and the author desired the sizing algorithm to be fast enough for a thorough design space investigation, the sizing algorithm had to be simplified. The assumptions used to size the vehicles, however, were consistent, and thus the assumptions and simplicity of the analysis should not impact the evaluation of the propulsion system.

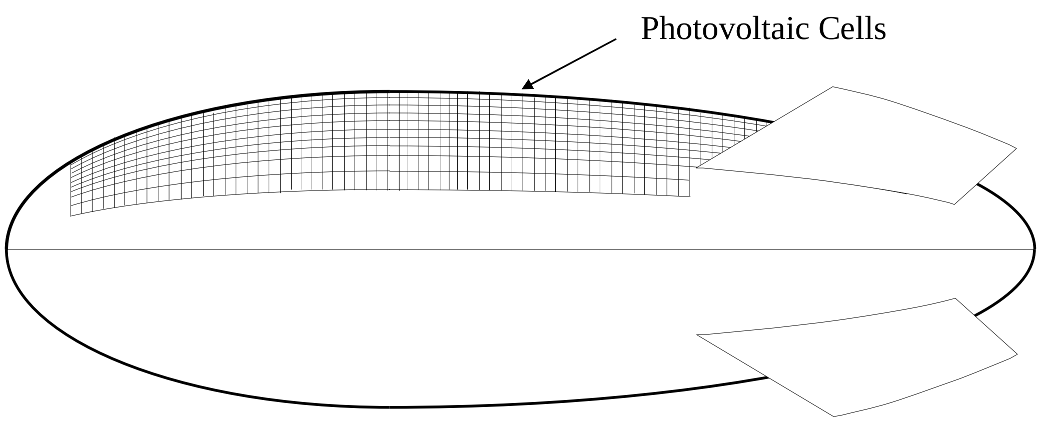


Figure 51: Solar Airship Schematic

Each of the airships were shaped to minimize the drag. Khoury noted that the National Physical Laboratory in England found that the drag of an airship can be minimized by shaping it as shown below in Figure 52 [48]. The ratio of D/L was parametric, but ranged between 0.15 and 0.30.

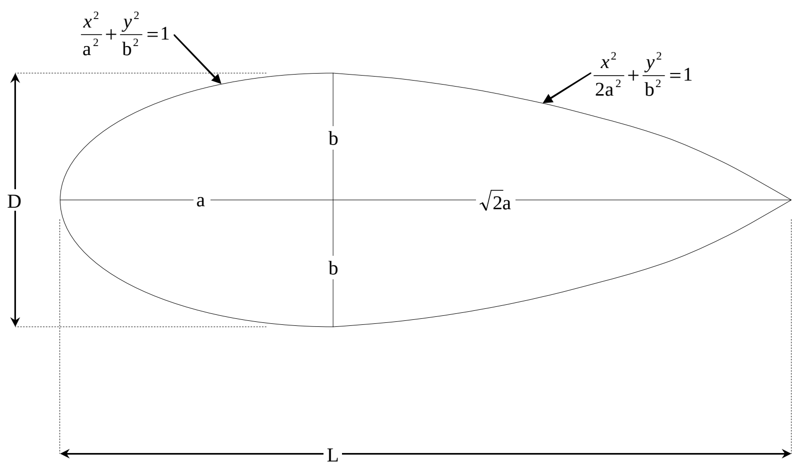


Figure 52: Optimal Shape for Airship

The shape shown in Figure 52 served as the predominant shape for the lighter-than-air envelopes.

The ratio of envelope volume to vehicle mass was calculated by as a function of the difference in density between the ambient air and the helium at the maximum altitude. The derivation of the relationship is shown below in Equations 35, 36 and 37.

$$L_{Envelope} = m_{Vehicle}\, g \tag{35}$$

$$gVol_{Envelope}\left(\rho_{Ambient} - \rho_{He}\right) = m_{Vehicle}\, g \tag{36}$$

$$\frac{Vol}{M_{Vehicle}} = \frac{1}{\left(\rho_{Ambient} - \rho_{He}\right)} \tag{37}$$

Drag was calculated as a function of the envelope volume, Vol, the velocity, the ambient density, and the volumetric drag coefficient, as determined by Hoerner [48].

$$D = \frac{1}{2}\rho V^2 \left(Vol\right)^{2/3} C_{DV} \tag{38}$$

The drag of the vehicle was required to calculate the amount of power that the vehicle must overcome at each point in the mission, by multiplying the drag by the velocity. The power was then normalized by the vehicle mass. Unfortunately, this was not simple. The drag coefficient is normalized by the volume raised to the 2/3rd power, as is shown in Equation 39.

$$\frac{P}{M_{Vehicle}} = \frac{1}{2}\rho V^3 \frac{(Vol)^{2/3}}{M_{Vehicle}} \frac{C_{DV}}{(Vol)^{2/3}} \tag{39}$$

In order to normalize the required power by mass, the ratio between the volume raised to the 2/3rd power and mass had to be determined. To identify such a relationship, the author investigated the shape of the enveloped. The volume of the airship can be found by rotating the shapes shown in Figure 52 and Figure 53 around the axis 180º. The volume, then, must be proportional to b^2 and L. Equation 40 shows the volume calculation for the shaded region in Figure 53.

$$Vol_{Shaded} = \frac{4}{3}\pi \, b^2 a \tag{40}$$

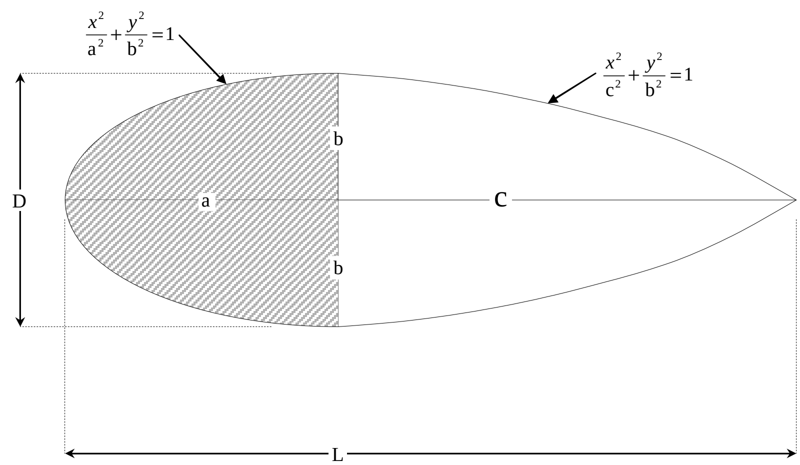


Figure 53: Generic Airship Shape

The volume of the unshaded region in Figure 53 is calculated in the exact same manner as the volume of the shaded region. The two volumes can be added together to find the total volume of the envelope, as shown below in Equation 41.

$$Vol = \frac{4}{3}\pi \, b^2 a + \frac{4}{3}\pi \, b^2 c \tag{41}$$

Because the length a and length c sum to the total length of the airship, L can replace the "a" and "c" terms in Equation 41 to create Equation 42.

$$Vol = \frac{4}{3}\pi\,\mathrm{b}^2(\mathrm{a}+\mathrm{c}) \qquad \Rightarrow \qquad Vol = \frac{4}{3}\pi\,\mathrm{b}^2\mathrm{L} \tag{42}$$

If the ratio of D to L is known and fixed, it can be used to remove L from Equation 42 and make Volume only a function of b^3. This function is shown below Equation 43.

$$Vol = \frac{8}{3}\frac{\pi}{D/L}\mathrm{b}^3 \tag{43}$$

Notice in Equation 43 that the volume is only a cubic function of b. Volume raised to the 2/3rd power can now easily be found. The author introduced the relationship between the square of the b and the mass, b^2/M, so that the calculation of volume to the 2/3 power divided by mass could be calculated for Equation 39. This relationship is shown below in Equation 44.

$$\frac{(Vol)^{2/3}}{M} = \left(\frac{8}{3}\frac{\pi}{D/L}\right)^{2/3}\frac{\mathrm{b}^2}{\mathrm{M}} \tag{44}$$

By guessing a ratio of b^2/M, the ratio of volume to the 2/3rd to mass could be calculated. The author could then use that value, found in Equation 44, to calculate the power required for the airship at each point in the mission, using Equation 39. The b^2/M term was initially guessed, but later would be iterated upon.

Once the ratio of volume to the 2/3rd power and Mass were known, the author was able to calculate the power required at key points in the mission. The required power was then used to identify the flow of energy that was required at each point in the mission. That flow energy was multiplied by the duration of the mission segment to identify the required stored energy to vehicle mass ratio.

The envelope to vehicle mass ratio was calculated by first calculating the surface area, of the envelope, normalizing it by the mass, and multiplying it by the parametric fabric density, measured in mass to surface area. Because surface area is directly proportional to b^2/M, this calculation was also made easier with the introduction of the new variable. The calculation can be found by rotating the surface area Figure 52 360 degrees. Equation 45 shows the derived relationship.

$$\frac{M_{Rnvelope}}{M_{Vehicle}} = \left(\frac{b^2}{M_{Vehicle}} 2\pi \left(\frac{1 + \arcsin(e)}{{}^{d}\!/_{l}\, e} \right) \right) den_{Fabric} \tag{45}$$

The quantity e Equation 45 is the eccentricity, and it is a function of the ratio of d/l. Equation 46 shows how the eccentricity calculation.

$$e = \sqrt{1 - {}^{d}\!/_{l}} \tag{46}$$

Another important factor in the sizing of airships is the projected area. If the vehicle relies upon solar energy, a check must occur to ensure that the vehicle has enough projected area to capture enough solar energy to power the vehicle.

$$\frac{A_{\mathrm{Projected}}}{M_{Vehicle}} = \frac{1}{4} \pi \frac{b^2}{M_{Vehicle}} \tag{47}$$

The ratio of the solar cells to the vehicle mass could also be calculated once the area of solar cells that is required is calculated. This was done using a parametric density of the solar cells, just as was done in for the fabric density. Finally, the engine to vehicle mass ratio was calculated by knowing using the maximum power output and the parametric specific density of the vehicle.

For lighter-than-air vehicles, the fabric density was given parametrically, and the empty gondola weight fraction was known. Equation 48 shows the total vehicle weight, M_{LTA}, as a sum of the component weights.

$$M_{LTA} = M_{PL} + M_{Gondola} + M_{"Fuel"} + M_{Power\ System} + M_{PV\ Cells} + M_{Envelope\ Fabric} \tag{48}$$

This analysis assumed that the gondola weight is a function of the items held in the gondola. The ratio of empty gondola weight to the filled gondola (compromised of the gondola, fuel, power source, and payload) was constant. Gondola weight, then, can be removed from Equation 48 and replaced with the known ratios. Equation 49 shows a manipulation of Equation 48 that allows takeoff vehicle weight to be calculated as a function of payload, fuel ratio, power system ratio, fabric density, and the empty gondola weight ratio.

$$M_{LTA} = \frac{M_{PL} \Big/ \left(1 - \dfrac{M_{Gondola}}{M_{Gondola} + M_{"Fuel"} + M_{PowerSystem} + M_{PL}}\right)}{1 - \dfrac{\left(M_{"Fuel"} + M_{Power\ System}\right) \Big/ M_{LTA}}{1 - \dfrac{M_{Gondola}}{M_{Gondola} + M_{"Fuel"} + M_{PowerSystem} + M_{PL}}} - \dfrac{M_{Fabric}}{M_{LTA}} \dfrac{M_{PV\ Cells}}{M_{LTA}}} \tag{49}$$

The airships were sized parametrically using Equation 48. The calculation of the mass ratios in Equation 48 required the use of a b^2/M value, which was guessed. After the vehicle was sized, the actual b^2/M value could be found. A fixed point iteration process was used to ensure that the guessed b^2/M value equaled the found b^2/M value. Once the difference was limited to a specified tolerance, the sizing was complete.

The entire sizing methodology for lighter-than-air vehicles is shown in Figure 54. Notice, that the process is iterative. The variable b^2/M is initially guessed, and iterated upon until the guessed value matches the estimated value.

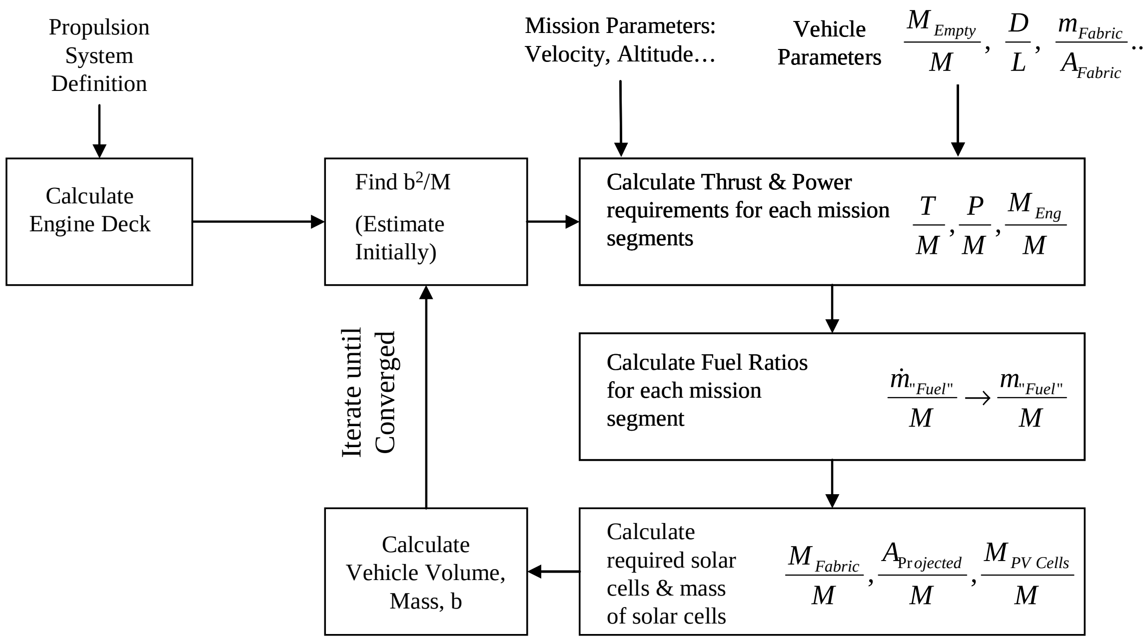


Figure 54: Flow Chart of Sizing and Synthesis Routine for LTA

APPENDIX F: SIMULATED ANNEALING DISCUSSION

The following simulated annealing program was used to find the optimal set of propulsion systems for each fixed set of requirements. The program is a MATLAB function, and it does use a couple of functions that were created by the user, but are not shown here. In general, the optimizer initially generates a random set of solutions, or engines. Throughout each generation, the optimizer slightly perturbs each solution to produce an offspring. If the offspring is better than the parent is, it survives to the next generation. If the offspring is worse, there is a small chance that the new solution will be kept. That probability is dictated by the “Temperature”. At the beginning of the optimization (early generations) the “Temperature” is high, and there is a good chance that the inferior offspring will survive. Throughout each generation, however, the “Temperature” cools, and the likelihood that an inferior offspring survives decreases.

The simulated annealing function requires input as to the number of generations, the pool size, and requirement variables that are taken into account by the optimization function. The function then defines the boundaries for the randomly generated initial pool, and generates the pool. The, the optimizer calculates the function values for each pool member.

For each generation, the optimizer slightly perturbs the pool members to produce offspring, or a “trial_pool”. The function values for each solution in the “trial_pool” are calculated, and the optimizer determines which members of the trial pool replace their parents in the “new_pool”. This process is repeated in the next generation. The results determined in the thesis used a pool size of 30 alternatives, and ran through 300 generations.

```
function data = sa_doe(generations,pool_size,...
        mission_parameters,tech_limitations,iiii)

%% Set Boundaries
%% Boundaries identify whether variables are discrete or continuous
%% Boundaries also set mins and maxes for continuous variables
bounds=[1,1,1,1,0,1,0,1;   4,4,2,2,1,2,1,3];
[a,dimensions]=size(bounds);

%% Generate iiitial pool of engines, defined by indpendent variables.
pool=make_pool(bounds,pool_size);



%% Define Likelihood Poorer solution will be kept
typical_delta=2000; %% Typical difference in F(x) for two solutions
%% Probability inferior solution kept at end of optimization
p_min=.01;
%% Probability inferior solution kept at begining of optimization
p_max=.05;
b=(log(p_max)/log(p_min))^(1/(generations-1));
b=(log(p_max)/log(p_min))^(1/(generations-2));
A=-log(p_max)*typical_delta/b;
A=-typical_delta/b^2/log(p_max);

%% Define the min & max step size for solution pertubations
t_step_max=.3;
t_step_min=.02;

%% Find the function values for each pool member
%% Author created function to do so, shown below
z(:,1)=find_function_values(pool,pool_size,...
   mission_parameters,tech_limitations)';

%% Find best solution of entire pool
[z_min(1),index]=min(z(:,1));
%% Find best engine of total optimization
best_engine(:,1)=pool(index,:)';
best_engine(dimensions+1,1)=z(index,1);
best_overall(:,1)=best_engine;

%% Find average F(x) for current pool
z_avg(1)=mean(z(:,1));

for i=2:generations
        t1=cputime;
        %% Probability of accepting inveferior solution is dictated by
        %% Temperature (T)
        T=A*b^(i);
        step_size=t_step_max-(t_step_max-t_step_min)/(generations-2)*(i-2);
        P_bar=exp(-typical_delta/T);

        %% Create a pool of offspring solutions (user defined function)
        trial_pool=vary_pool(pool,bounds,step_size,...
                pool_size,dimensions,z(:,i-1));
```

```
		%% Find function values for each new solution
		trial_z=find_function_values(trial_pool,pool_size,...
			mission_parameters,tech_limitations)';


		%% For each pool member, identify whether new solution is better or
		%% worse.  If worse, determine whether accepted or rejected (using
		%% Temperature calculated above.
		for j=1:pool_size
			if trial_z(j) <=z(j,i-1)
				new_pool(j,:)=trial_pool(j,:);
				new_z(j)=trial_z(j);
			else
				delta=trial_z(j)-z(j,i-1);
				P_accept=exp(-delta/T);
				if rand<=P_accept
					new_pool(j,:)=trial_pool(j,:);
					new_z(j)=trial_z(j);
				else
					new_pool(j,:)=pool(j,:);
					new_z(j)=z(j,i-1);
				end
			end
		end

		%% Define next generation pool, find generation minimum  & average.
		%% Also, see if total optimization minimum was improved upon.
		pool=new_pool;
		z(:,i)=new_z';
		[z_min(i),index]=min(z(:,i));
		best_engine(1:dimensions,i)=pool(index,:)';
		best_engine(dimensions+1,i)=z(index,i);
		%% See if total optimization minimum was improved upon.
		if z_min(i)<=best_overall(dimensions+1,i-1)
			best_overall(:,i)=best_engine(:,i);
		else
			best_overall(:,i)=best_overall(:,i-1);
		end
		z_avg(i)=mean(z(:,i));
		%% Move on to next generation
	end

	data=pool;
	data(:,dimensions+1)=z(:,i);
	data(pool_size+1,:)=best_overall(:,i)';



	%------------------------------ FUNCTIONS --------------------------------%
	function pool=make_pool(bounds,pool_size)
	[a,b]=size(bounds);
	for i=1:pool_size
		for j=1:b
```

```
            if bounds(1,j)==0 pool(i,j)=rand;
            else pool(i,j)= randint(1,1,[bounds(1,j),bounds(2,j)]);
            end
        end
end
return

function z=find_function_values(pool,pool_size,...
        mission_parameters,tech_limitations);
good_ct=0;
for i=1:pool_size
        %% fly_mission is the function to calculate total vehicle mass.
        zz(i,:)=fly_mission(pool(i,:),mission_parameters,tech_limitations) ;
        if zz(i,1)==0
            zz(i,1)=1e10;
        else good_ct=good_ct+1;
        end
        z(i)=zz(i,1);
end
return
```

APPENDIX G: DISCIPLINARY METRIC VALUES

Disciplinary Metric	Explanation	Value	Unit
η_{Inlet}	Inlet Efficiency	0.99	
$\eta_{Compressor}$	Compressor Efficiency	0.9	
% $Q_{Loss, Heat Exchange}$	Percent Heat Lost in Heat Exchange	0.045	
$\eta_{Combustion}$	Combustor Efficiency	0.995	
η_{Motor}	Motor Efficiency	0.8	
$\eta_{Generator}$	Generator Efficiency	0.9	
$\eta_{Turbine}$	Turbine Efficiency	0.93	
η_{Shaft}	Shaft Efficiency	0.99	
η_{Nozzle}	Nozzle Efficiency	0.99	
$\eta_{Propeller}$	Propeller Efficiency	0.85	
η_{Fan}	Fan Efficiency	0.9	
$\Delta P_{O, Fuel Cell}$	Pressure Drop in Fuel Cell	0.6	
$T_{Max,FC}$	Maximum Temperature in Fuel Cell	1200	^oK
% $\Delta P_{O, Heat Addition}$	Pressure Drop in Heat Addition	0.8	
% $\Delta P_{O, Combustion}$	Pressure Drop in Combustion	0.96	
C_{Do}	Zero Drag Lift Coefficient	0.02	
AR	Aspect Ratio	20	
e_{AR}	Factor used in drag polar	0.9	
M_{Empty}/M_{Gross}	Ratio of empty mass to total mass	0.25	K
$M_{Payload}$	Payload Mass	1500	Kg
Fabric Density (for LTA)	Mass of LTA fabric per unit area	0.3	Kg/m^2
$M_{Gondola}/M_{Gross}$	Ratio of gondola mass to total mass	0.25	
d/l (for LTA)	Diameter to length ratio for LTA	0.25	
$C_{L,max}$ (for some FW)	Maximum lift Coefficient	2	

REFERENCES

[1] Aerospace-Technology.com "Airbus A340-200 and A340-300 Wide Bodied Four Engine Airliners, Europe", <http://www.aerospace-technology.com/projects/a340-200/>, Retrieved January 2006.

[2] Asthana, Praveen "Jumping the Technology S-curve" *IEEE Spectrum*, Volume 32, Number 6, June, 1995, p 49-54.

[3] Augustine, N. R, *Augustine's Laws*, Viking Penguin, New York, 1986.

[4] Baker, A.P. *The Role of Mission Requirements, Vehicle Attributes, Technologies, and uncertainty in Rotorcraft System Design*. PhD thesis, Georgia Institute of Technology, 2002.

[5] Bandte, O., *Probabilistic Multi-Criteria Decision Making Technique for Conceptual and Preliminary Aerospace Systems Design*. PhD thesis, Georgia Institute of Technology, September 2000.

[6] Barbir, F., L. Dalton, T. Molter. "Regenerative Fuel Cells for Energy Storage: Efficiency and Weight Trade-offs" Presented at the 1st International Energy Conversion Engineering Conference (IECEC), Portsmouth, Virginia, August 17-21, 2003. Paper Number: AIAA-2003-5937.

[7] Best Practices: Successful Application to Weapon Acquisitions Requires Changes in DoD's Environment, GAO/NSIAD-98-56, February 1998.

[8] Best Practices: Successful Application to Weapon Acquisitions Requires Changes in DoD's Environment, GAO/NSIAD-98-56, February 1998.

[9] Birkler, J., J.C. Graser, M.V Arena, et. al. "Assessing Competitive Strategies for the Joint Strike Fighter: Opportunities and Options" RAND, 2001.

[10] Box, G.E.P., N.R. Draper, *Empirical Model-Building and Response Surfaces*, Wiley & Sons, New York, 1987.

[11] Briceno, S.I., D.N. Mavris, "Implementation of a Physics-Based Decision-Making Framework for Evaluation of the Multidisciplinary Aircraft Uncertainty," Presented at the SAE World Aviation Congress, Montreal, Canada, September 9-12, 2003.

[12] Campbell, D. "Revolutionary Power and Propulsion for 21st Century Aviation" Presented at the AIAA International Air and Space Symposium and Exposition: The Next 100 Years, Dayton, OH, July 14-17, 2003. Paper Number: AIAA-2003-2561.

[13] Carpio, R.S. “NASA Cost Estimation and Analysis Strategy” Presented at the AIAA Space 2001 - Conference and Exposition, Albuquerque, NM, August 28-30, 2001. Paper Number: AIAA-2001-4712.

[14] Casani E.K., B Wilson “The New Millennium Program - Technology Development for the 21st Century” Presented at the Aerospace Sciences Meeting and Exhibit, 34th, Reno, NV, January 15-18, 1996. Paper Number: AIAA-1996-696.

[15] Cetron, M.J., “Technology Forecasting for the Military Manager”, An Introduction to Technological Forecasting, Edited by J.P. Martino, Gordon & Breach, London, 1972.

[16] CFM International “CFM56-5C TECHNOLOGY”, <http://www.cfm56.com/engines/cfm56-5c/tech.html>, Retrieved January 2006.

[17] Choi, T., D. Soban, and D. Mavris, “Creation of a Design Framework for All-Electric Aircraft Propulsion Architectures”. 3rd International Energy Conversion Engineering Conference, San Francisco, California, Aug. 15-18, 2005.

[18] Christensen, C.M. *The Innovator’s Dilemma*. 2000. HarperBusiness Essentials.

[19] Clausing, D.P. “The Role of TRIZ in Technology Development” Presented at Altshuller Institute Conference, March 2001.

[20] Coldrick, S., P. Longhurst, P. Ivey, J. Hannis. “An R&D Options Selection Model For Investment Decisions” *Technovation*, Volume 25, Number 3, March, 2005, p 185-193.

[21] Colozza, A., J.L. Dolce, “High-Altitude, Long-Endurance Airships for Coastal Surveillance”, NASA Center for Aerospace Information, February 2005, <http://gltrs.grc.nasa.gov>, Retrieved September 2005.

[22] Davis, S.C., S.W. Diegel. “Transportation Energy Data Book, Edition 23”. Center for Transportation Analysis. October 2003. Prepared for the Office of Planning, Budget Formulation and Analysis, U.S. Department of Defense.

[23] Dean, E.B., “Quality Function Deployment for Large Systems”. Presented at the International Engineering Management Conference: Managing in a Global Environment. Eatontown, NJ, October 25-28, 1992.

[24] Diebold, F.X. *Elements of Forecasting, 2nd Edition*. South-Western, a division of Thomson Learning, Cincinnati, Ohio, 2001.

[25] Dieter, G.E., *Engineering Design: A Materials and Processing Approach, 3rd Edition* McGraw-Hill Higher Education. 2000.

[26] Drew, P. et.al. "Technology Drivers for 21st Century Air Transportation Systems" Presented at the AIAA International Air and Space Symposium and Exposition: The Next 100 Years, Dayton, OH, July 14-17, 2003. Paper Number: AIAA-2003-2558.

[27] Dunning J., S. Benson "NASA's Electric Propulsion Program" Presented at 38th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, Indianapolis, Indiana, July 7-10, 2002. Paper Number AIAA-2002-3557.

[28] Dunning, J. "NASA's Electric Propulsion Program - Technology Investments for the New Millennium" Presented at the AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, 37th, Salt Lake City, UT, July 8-11, 2001. Paper Number: AIAA-2001-3224.

[29] Eskew, H.L., "Aircraft Cost Growth And Development Program Length: Some Augustinian Propositions Revisited - Statistical Data Included", Acquisition Review Quarterly, Summer, 2000.

[30] Fey, V.R., E.I. Rivin. "Guided Technology Evolution (TRIZ Technology Forecasting)" *The TRIZ Journal*. January 1999.

[31] Garcia, E., D.N. Mavris,"Formulation of a Method to Assess Capacity Enhancing Technologies" Presented at the AIAA/ICAS International Air and Space Symposium and Exposition: The Next 100 Years, Dayton, OH, July 14-16, 2003. Paper Number: AIAA 2003-2677.

[32] Geroski, P.A. "Models of Technology Diffusion". *Research Policy*, Volume 29, Number 4-5, April, 2000, p 603-625.

[33] Goldby, S.D. "Strategic Approaches to Technology Adoption" *Laboratory Robotics and Automation* Volume 11, Issue 6, 1999, p 330-334.

[34] Gordon, T.J. "A Simple Agent Model of an Epidemic" *Technology Forecasting Social Change*. Volume 70, 2003, p 397-417.

[35] Gordon, T.J. "Trend Impact Analysis" AC/UNU Millennium Project Futures Research Methodology. Futures Research Methodology. 1994.

[36] Gordon, T.J. "Trend Impact Analysis" AC/UNU Millennium Project, Futures Research Methodology. 1994. <http://www.futurovenezuela.org/_curso/9-trend.pdf>, retrieved November 2005.

[37] Gordon, T.J., H.S. Becker. "The use of Cross-Impact Matrix Approaches in Technology Assessment" *A Methodology of Technology Assessment*. Gordon and Breach Science Publishers, New York, 1972.

[38] Gordon, T.J., J.C. Glenn (Eds.), Futures Research Methodology, Version 2.0Millennium Project of the American Council for the United Nations University, July, 2003.

[39] Gordon, T.J., J.C. Glenn. "Integration, Comparisons, and Frontier of Futures Research Methods". Presented at the EU-US Seminar: New Technology Foresight, Forecasting & Assessment Methods. Seville, May 13-14, 2004.

[40] Grupp, H., H.A. Linstone. "National Technology Foresight Activities Around the Globe: Resurrection and New Paradigms" *Technology Forecasting and Social Change* Volume 60, Issue 1, 2 January 1999, Pages 85-94.

[41] Hileman, B. "An Urgent Plea On Global Warming" *Chemical and Engineering News*. June 28, 2004 Volume 82, Number 26, p 44.

[42] Hollingsworth P., D. Mavris. "Determination of Revolutionary Requirements Boundaries for a High-Speed, Airbreathing Propulsion System" Presented at the AIAA's Aircraft Technology, Integration, and Operations (ATIO) 2002 Technical Forum, Los Angeles, California, October 1-3, 2002. Paper Number: AIAA-2002-3916.

[43] Huaidong, Xu, *A 'Bayesian' Theory of Cross-Impact Analysis for Technology Forecasting and Impact Assessment*. Ms Thesis, Georgia Institute of Technology, October 1990.

[44] Hwang, C.-L., K. Yoon, Multiple Attribute Decision Making: Methods and Applications : A State-of-the-Art Survey, Springer-Verlag, Berlin, 1981.

[45] Johnson, J. "Putting A Lid On Carbon Dioxide" *Chemical and Engineering News* December 20, 2004 Volume 82, Number 51, p 36-42.

[46] Johnson, D. S.; C. R. Aragon, L.A. Mcgeoch, C. Schevon, "Optimization by Simulated Annealing: An Experimental Evaluation; Part I, Graph Partitioning", *Operations Research*, Nov/Dec 1989, Vol. 37 Issue 6, p865-893. <http://search.epnet.com/login.aspx?direct=true&db=buh&an=4493714>, Retreived January 2006.

[47] Jablunovsky, G., C. Dorman, and P.Yaworsky., "A Neural Network Sub-model as an Abstraction tool: Relating Network Performance to Combat Outcome", Presented at the Proceedings of SPIE, Orlando, Florida, 2000.

[48] Khoury, G.J. Gillett. *Airship Technology*. Cambridge Aerospace Series 10. Cambridge University Press 1999.

[49] Kirby, M. R., *A Methodology for Technology Identification, Evaluation, and Selection in Conceptual and Preliminary Aircraft Design*. Ph.D. thesis, Georgia Institute of Technology, 2001.

[50] Kirby, M.R., D.N. Mavris, "An Approach for the Intelligent Assessment of Future Technology Portfolios," Presented at the 40th AIAA Aerospace Sciences Meeting, Reno, NV, January 14-17, 2002.

[51] Kirby, M.R., D.N. Mavris, "Forecasting Technology Uncertainty in Preliminary Aircraft Design", Presented at the World Aviation Conference, San Francisco, CA, October 19-21, 1999.

[52] Kirkpatrick, S., C.D. Gelatt Jr., M.P. Vecchi, "Optimization by Simulated Annealing", *Science*, New Series, Vol. 220, May 13, 1983, pages. 671-680. <http://links.jstor.org/sici?sici=0036-8075%2819830513%293%3A220%3A4598%3C671%3AOBSA%3E2.0.CO%3B2-8>, Retrieved January 2006.

[53] Kohout, L., P. Schmitz. "Fuel Cell Propulsion Systems for an All-Electric Personal Air Vehicle" Presented at the AIAA International Air and Space Symposium and Exposition: The Next 100 Years, Dayton, OH , July 14-17, 2003. Paper Number: AIAA-2003-2867.

[54] Kulak, O., C. Kahraman. "Fuzzy Multi-attribute Selection Among Transportation Companies Using Axiomatic Design and Analytic Hierarchy Process" *Information Sciences—Informatics and Computer Science: An International Journal* February 2005, Volume 170, Issue 2-4.

[55] Lewis, A.V., G. Cosier, P.M. Hughes, "Dimensions of change - A Better Picture of Disruption" *British Telecom Technology Journal*, Volume 19, Number 4, October, 2001, p 15-23.

[56] M. Chamberlain, C. Williams, J. Allen, F. Mistree, "Strategic Design: Leveraging Market Forecasts and Emerging Technologies in Engineering Design Applications" Presented at the 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Albany, New York, August 30-1, 2004. Paper Number: AIAA-2004-4652.

[57] Mattingly, J.D, W.H.Heiser, D.T. Pratt. *Aircraft Engine Design, 2nd Edition*. AIAA Eductaion Series. 2002.

[58] Mavris, D., A. Baker, D. Schrage, "Implementation of a Technology Impact Forecast Technique on a Civil Tiltrotor", Presented at the American Helicopter Society 55th Annual Forum, Montreal, Quebec, Canada, May 25 - 27, 1999.

[59] Mavris, D., O. Bandte, D.P. Schrage, “Application of Probabilistic Methods for the Determination of an Economically Robust HSCT Configuration”, AIAA-96-4090.

[60] Mavris, D., T. Danner, E. McClure, J. de Luis. *Analysis Methods for Revolutionary/Unconventional Aeropropulsion Concepts*. Prepared for: NASA Glenn Research Center. September 10, 2005.

[61] Mavris, D., M.R. Kirby, "Preliminary Assessment of the Economic Viability of a Family of Very Large Transport Configurations," Presented at the 1st World Aviation Congress and Exposition, Los Angeles, CA, October 21-24, 1996. AIAA-96-5516

[62] Mavris, D., G. Mantis, M. Kirby, 1997, “Demonstration of a Probabilistic Technique for the Determination of Aircraft Economic Viability”, AIAA-97-5585.

[63] Mazur, G. “Theory of Inventive Problem Solving (TRIZ)” February 26, 1996, <http://www.mazur.net/triz/>, Retrieved January 2005.

[64] Mendivii, F., R. Shonkwiler, M. C. Spruill. *Optimization by Stochastic Methods*, Georgia Institute of Technology, Atlanta, GA 30332, December 16, 1999. <http://www.math.gatech.edu/~shenk/>, Retrieved December 2004.

[65] Mietzner, D., G. Reger. “Paper 3: Scenario Approaches – History, Differences, Advantages and Disadvantages” Presented at the EU-US Seminar: New Technology Foresight, Forecasting & Assessment Methods. Seville, May 13-14, 2004.

[66] Millett, S.M, E.J. Honton. *A Manager’s Guide to Technology Forecasting and Strategy Analysis Methods* Columbus: Battelle Press. 1991.

[67] Murray, Williamson, HARD CHOICES: Fighter Procurement in the Next Century, Automic Energy Commission, and Department of Defense, Report to Congress, February 26, 1999.

[68] Montgomery, D.C., *Design and Analysis of Experiments, 3rd Edition*, Wiley & Sons, New York, 1991.

[69] NASA – Flight Research R&R Base Program - Goals,<http://www.nasa.gov/centers/dryden/research/RT/goals.html>, Retrieved February 2005.

[70] NASA, “Fact Sheet: Helios Prototype” <http://www.nasa.gov/centers/dryden/news/FactSheets/FS-068-DFRC.html>, Retrieved December 2005.

[71] National Hurricane Center, NOAA, “2005 Hurricane Tracks” <http://www.nhc.noaa.gov/tracks/2005atl.gif>, Retrieved March 2006.

[72] Newman, D., *Interactive Aerospace Engineering and Design,* McGraw-Hill Science/Engineering/Math. 2001.

[73] National Oceanic and Atmospheric Administration, "2005 Atlantic Hurricane Season Outlook", Press Release, May 16, 2005 <http://www.noaanews.noaa.gov/stories2005/s2438.htm>, Retrieved February 2005.

[74] National Oceanic and Atmospheric Administration, "NOAA Predicts Very Active 2006 North Atlantic Hurricane Season", Press Release, May 22, 2006, <http://www.noaanews.noaa.gov/stories2006/s2634.htm>, Retrieved May 2006.

[75] National Oceanic and Atmospheric Administration, ":NOAA Reports Warmer 2005 for the United States, Near-Record Warmth Globally Hurricanes, Floods, Snow and Wildfires All Notable", Press Release, December 15, 2005, http://www.noaanews.noaa.gov/stories2005/s2548.htm>, Retrieved February 2005.

[76] Osman, M.S., M.A. Abo-Sinna, A.A. Mousa. "An Effective Genetic Algorithm Approach To Multiobjective Resource Allocation Problems" *Applied Mathematics and Computation,* Volume 163, Number 2, April 15, 2005, p 755-768.

[77] Porter, A.L., "Technology Futures Analysis: Toward Integrationof the Field and New Methods" *Technology Forecasting and Social Change*. November 7, 2003.

[78] Porter, A.L., A.T. Rober, T.W. Mason, F.A. Rossini, J. Banks. *Forecasting and Management of Technology* New York: Wiley & Sons, Inc. 1991.

[79] Rasky D., P. Kolodziej, S. Farkas, "The Phased Development Approach: for Advanced Technology and Complex Systems" Presented at the 41st Aerospace Sciences Meeting and Exhibit, Reno, Nevada, January 6-9, 2003. Paper Number: AIAA-2003-1180.

[80] Reynolds J., M. Nesman, Brijendra, F. Torres "Process-based Development Cost Model for Ramjet-Scramjet Engines" Presented at the AIAA Space 2003 Conference and Exposition, Long Beach, California, September 23-25, 2003 Paper Number: AIAA-2003-6344.

[81] Roskam, J., Creighton, T., et. al., Advanced Propfan Analysis for the Family of Commuter Airplanes. NASA Grant NGT-80001, May 1987. <ntrs.nasa.gov/archive/nasa/casi. ntrs.nasa.gov/19880010084_1988010084.pdf >, Retrieved January 2006.

[82] Roth, B., B.J. German, D.N. Mavris, N. Macsotai, "Adaptive Selection of Engine Technology Solution Sets from a Large Combinatorial Space," Presented at the 37th Joint Propulsion Conference and Exhibit, Salt Lake City, UT, July 2001.

[83] Roth, B., D.N. Mavris. "Commercial Engine Architecture Selection in the Presence of Uncertainty and Evolving Requirements," Presented at the 15th International Society of Air Breathing Engines, Bangalore, India, September 2-7, 2001.

[84] Roth, B., Patel, C.," Application of Genetic Algorithms to the Engine Technology Selection Process," Presented at the 2003 Turbo Expo, June 16-19, Atlanta, GA.

[85] Roth, B.A., D.N. Mavris,"A Stochastic Approach to Designing Affordable, Environmentally Acceptable Systems," Presented at the 2002 NSF DMII Grantees Conference, San Juan, January 2002.

[86] Saaty, T.L., *The Analytic Hierarchy Process: Planning Setting Priorities, Resource Allocation*, Mcgraw-Hill, April 1980.

[87] Sackman, H., *Delphi Assessment: Exert Opinion, Forecasting and Group Process*, Prepared for United States Air Force Project, Rand, April, 1974.

[88] Sahal, D. *Patterns of Technological Innovation*. Addison-Wesley Publishing Company, Inc. 1981.

[89] Scharl, J., D.N. Mavris, "Building Parametric and Probabilistic Dynamic Vehicle Models Using Neural Networks," Presented at the AIAA Modeling and Simulation Conference and Exhibit, Montreal, Canada, August 6-9, 2001.

[90] Schlueter, M. “QFD by TRIZ”, Presented at Altshuller Institute TRIZ Conference, June, 2001.

[91] Shuylak, L. “Introduction to TRIZ”, Exerted from *40 Principles, TRIZ Keys to Technical Innovation*, Technical Innovation Center Inc., 1998, <2001.http://www.aitriz.org/ai/index.php?page=triz&article=about>, Retrieved January, 2006.

[92] Sipple, V., White, E., Greiner, M., “Surveying Cost Growth”, Defense Acquisition Review Journal, January–April 2004.

[93] Smith C., P. Snyder, C. Emmerson and M. Nalim “Impacts of the Constant Volume Combustor on a Supersonic Turbofan Engine” Presented at the 38th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, Indianapolis, Indiana, July 7-10, 2002. Paper Number: AIAA-2002-3916.

[94] Stoffel, J. “Dreams of Nuclear Flight, the NEPA and ANP programs” NEEP 602, University of Wisconsin-Madison May 10, 2000. Available at

[http://fti.neep.wisc.edu/neep602/SPRING00/TERMPAPERS/stoffel.pdf] *Information Sciences*, Volume 170, Number 2-4, February 25, 2005, p 191-210.

[95] Szakony, R., “So Many Projects, So Little Time: Improving the Selection of R&D Projects”, Technology Management: Case Studies of Innovation, Edited by R. Szakony, Auerbach, Boston, 1992.

[96] Type Certificate Data Sheet, Number 183, Airbus A340 Airplanes, December 2002, <www.content.airbusworld.com/SITES/Certification_Register/ PDF-tcds/A330-A340/A340_DGAC_183.pdf>, Retreived February 2006.

[97] United States General Accounting Office, Review of Manned Aircraft Nuclear Propulsion Program, Automic Energy Commission, and Department of Defense, Report to Congress, February 1963.

[98] Viswanathan, S. “A Giant Leap for Civil Aviation…”. *Industrial Economist*. February 15, 2005, <http://www.indeconomist.com/150205_aviation.html>, Retrieved March 2005.

[99] *Wikipedia* “Artificial Neural Network”. Last updated on January 26, 2006. <http://en.wikipedia.org/wiki/Artificial_Neural_Network>, Retrieved January, 2006.

VITA

Erin Kathleen McClure was born in Harrisburg, PA in 1979. In 1997, she graduated from Vestal High School, in Vestal, New York. After high school, she attended Duke University in Durham, North Carolina, where she received her B.S. in Engineering. After graduating from Duke, she attended Georgia Institute of Technology to pursue her Ph.D. in Aerospace Engineering. She received her M.S. in Engineering there in May of 2003.