A PORTFOLIO APPROACH TO DESIGN IN THE PRESENCE OF SCENARIO-BASED UNCERTAINTY

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A PORTFOLIO APPROACH TO DESIGN IN THE PRESENCE OF SCENARIO-BASED UNCERTAINTY

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

AHP	Analytical Hierarchy Process
ALCCA	Aircraft Life Cycle Cost Analysis
ANP	Analytical Network Process
CDF	Cumulative Distribution Functions
CO_2	Carbon Dioxide
EA	Evolutionary Algorithm
ECOSIS	Evolutionary Cooperative Optimization with Simultaneous Independent Sub-optimization.
FLOPS	Flight Optimization System
GA	Genetic Algorithm
HP	Horse Power
IPPD	Integrated Product and Process Development
JPDM	Joint Probabilistic Decision Making
MADM	Multi-Attribute Decision Making
MPG	Miles Per Gallon
MPT	Modern Portfolio Theory (MPT)
NASA	National Aeronautics and Space Administration
NPV	Net Present Value
OEC	Overall Evaluation Criterion
PDF	Probability Density Functions (PDFs)
PRISM-D	Portfolio Risk Mitigation for Design
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

SUMMARY

Current aircraft conceptual design practices result in the selection of a single (hopefully) Pareto optimal design to be carried forward into preliminary design. This paradigm is based on the assumption that carrying a significant number of concepts forward is too costly and thus early down-selection between competing concepts is necessary. However, this approach requires that key architectural design decisions which drive performance and market success are fixed very early in the design process, sometimes years before the aircraft actually goes to market. In the presence of uncertainty, if the design performance of alternative concepts is examined for individual scenarios as opposed to measuring the performance of the alternatives using aggregate statistics, the author finds that the single concept approach can lead to less than desirable design outcomes. This thesis proposes an alternate conceptual design paradigm which leverages principles from economics (specifically the Nobel prize-winning modern portfolio theory) to improve design outcomes by intelligently selecting a small well diversified portfolio of concepts to carry forward through preliminary design, thus reducing the risk from external events that are outside of the engineer's control. This alternate paradigm is expected to result in an increase in the overall profit by increasing the probability that the final design matches market needs at the time it goes to market.

This thesis first demonstrates the need for a better handling of scenario-based uncertainty in design through the use of a characterizing case study for automotive design. The case study demonstrates that while technical and design uncertainty reduction is desirable, this alone is insufficient to mitigate overall risk to a product's ultimate market success in situations where there is a high level of uncertainty in the scenario under which the product will go to market. In these circumstances, it is hypothesized that interaction between the optimum design and scenario reduce the traditional robust design methodology's effectiveness, and a fundamental shift in the philosophy of the design

process is required to improve outcomes when these interactions are present. Next, a set of mathematical examples and an informal mathematical proof is used to demonstrate how interaction between the design and scenario drive concept selection. Recognizing that the information required for a mathematical proof may not be available in modeling practice, a set of guidelines for practitioners is provided by specifying conditions where it is highly likely that a region of scenario based uncertainty will drive the concept selection. Finally, this thesis proposes the Portfolio Risk Mitigation for Design (PRISM-D) methodology for conceptual design in situations where scenario based uncertainties lead to reduced quality of design outcome.

This portfolio-based design approach, which leverages dynamic programming to enable a stochastic optimization of alternative portfolios of concepts to return an optimized development strategy for a new product that improves design outcomes in the presence of scenario-driven uncertainties. This is accomplished by changing the set of decision alternatives from a single best concept to a best portfolio of concepts. This change enables improved design outcomes through the use of a well-diversified portfolio better tailored to specific contingencies. Recognizing that the use of any contingency comes with an added cost, an approach to a cost-to-benefit analysis for contingency plans is detailed. While dynamic programming is identified as a means for doing a stochastic portfolio optimization that implicitly includes the cost-to-benefit tradeoff. Dynamic programming is an analytical optimization process which suffers heavily from the curse of dimensionality. As a result, a new stochastic optimization process is needed to reduce the effects of the curse of dimensionality.

Because current stochastic optimization algorithms are insufficient to optimize multifaceted problems, a significant contribution of this thesis is the development of a new optimization algorithm called the Evolutionary Cooperative Optimization with Simultaneous Independent Sub-optimization (ECOSIS) algorithm. The ECOSIS algorithm leverages a co-evolutionary algorithm to optimize a multifaceted problem under uncertainty. The proposed implementation for this co-evolutionary algorithm is described in detail and is verified and validated through the use of a sample problem. ECOSIS allows for a stochastic portfolio optimization including the desired benefit-to-cost tradeoff for a well-diversified portfolio at the size and scope required for use in design problems.

To demonstrate the applicability and value of a portfolio-based design approach, an example application of the approach to the selection of a new 300 passenger aircraft is presented. The portfolio-based design approach implemented using a co-evolutionary algorithm is able to shift the Pareto frontier defining the trade-off between acceptable risk and return in a favorable manner. This shift is accomplished through the use of a well-diversified portfolio of concepts, with the surprising result that added decision maker flexibility (so often lauded in literature) is significantly less important than the initial diversification of the concepts which make up the portfolio. As a result, this thesis is able to demonstrate improved design outcomes through the use of a portfolio-based design approach, implemented using a co-evolutionary algorithm, can improve design outcomes versus the traditional approaches.

CHAPTER I

INTRODUCTION

1.1 Design and the Role of Decision Making

This thesis examines design decision making under uncertainty. In particular, this thesis offers the hypothesis that design decision making can be improved by allowing for a portfolio of design concepts to progress beyond the conceptual design decision. As a result the next section describes the design process and the decisions that occur within different phases of the design process.

1.1.1 Design overview

Aircraft design is an iterative process that takes place at the early stages of the aircraft's lifecycle. Figure 1 shows a depiction of the aircraft lifecycle along with the engineering design elements [121]. This depiction describes how the design process begins with a requirements definition phase that leads to a design specification. From this point onwards, a series of iterative engineering analyses are conduced to select and refine a concept. Figure 2, taken from Fielding, is an example of the standard depiction of the design process as a spiral [40]. The first iterative loop is referred to as conceptual design, and its goals are to select an initial conceptual layout and define the basic geometries of the best design concept. It is important to note that the surveyed aircraft design literature uniformly assumes that a single best concept will be chosen at this decision point. The second iteration, called preliminary design, refines this best concept, and the third iteration, called detailed design, refines the concept to the point that each part is ready for manufacture. The following three sections will describe each of these elements in more detail.

Figure 3 shows the same design phases on a linear time axis [60]. Overlaid on the axis is a graph of cost and effort build-up. From Figure 3 it can be observed that the initial iterations of design are significantly less costly than the later iterations. The cost and effort increase is highly exponential, and as a result, most of the cost and effort is expended in the final stages of design. It is important to highlight the cost element because this thesis presents the hypothesis that bringing a portfolio of multiple concepts beyond the conceptual design decision, and an accurate accounting of the additional cost of carrying multiple designs beyond the conceptual design decision, will be necessary to improve design outcomes in the presence of uncertainty.

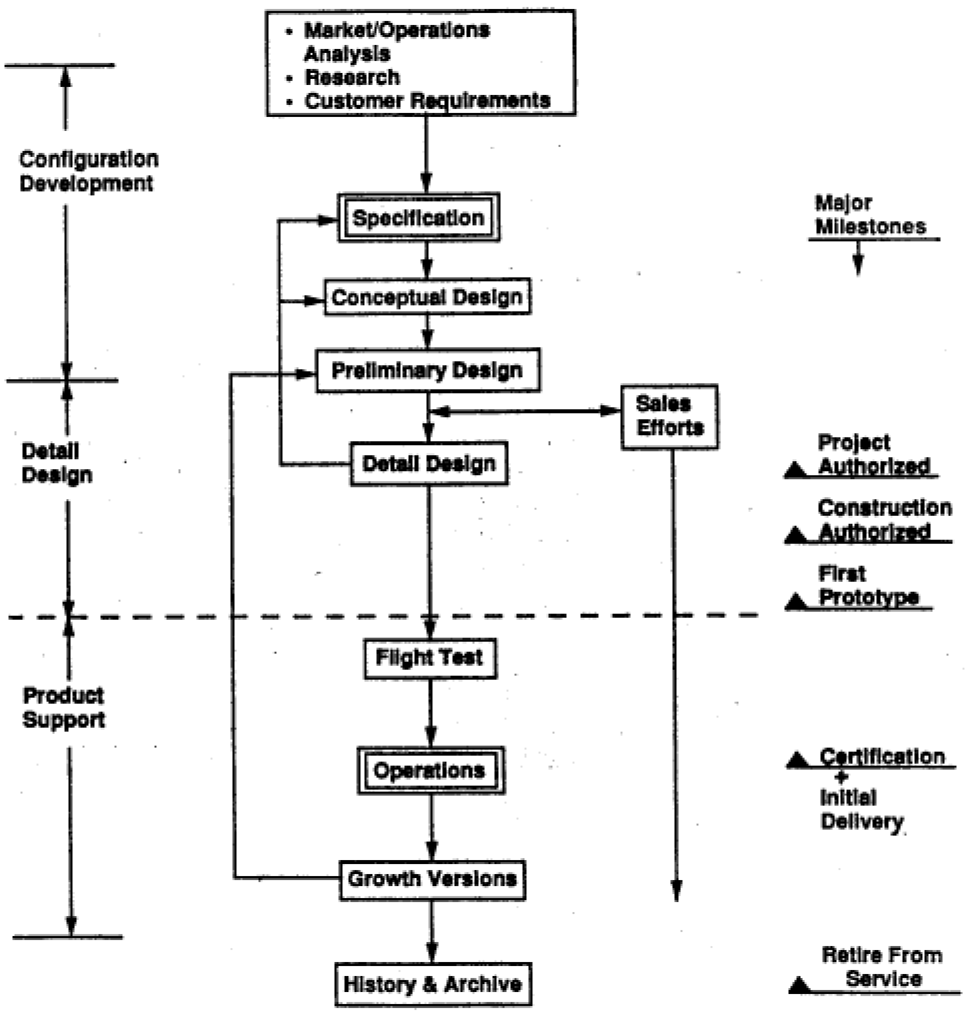


Figure 1: Critical Engineering Elements of the Aircraft Lifecycle

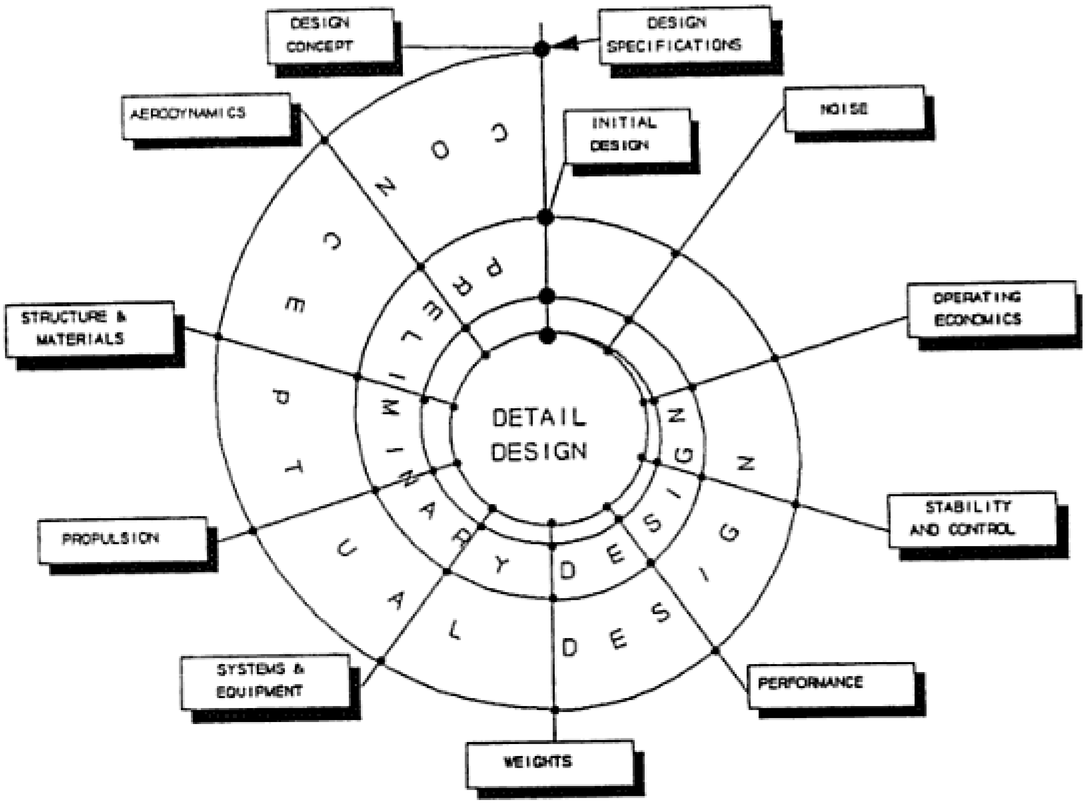


Figure 2: Aircraft Design as a Spiral

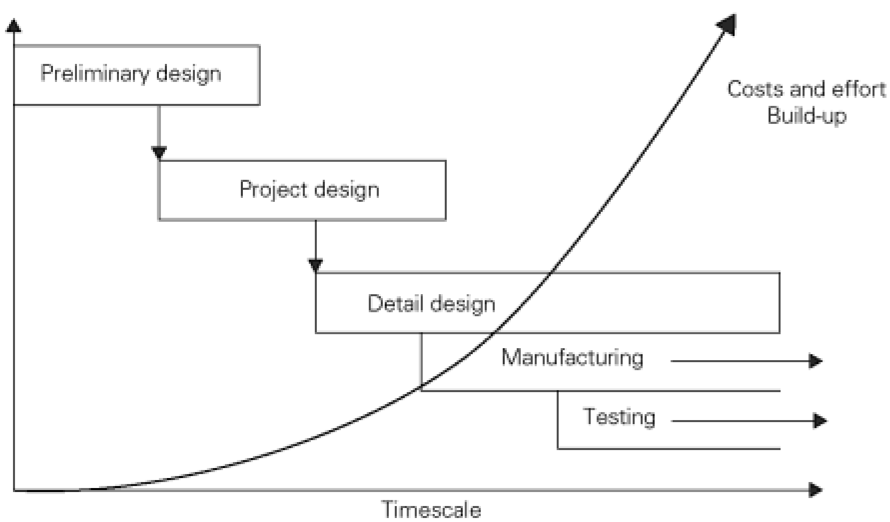


Figure 3: Design Phases and Effort

1.1.2 Requirements Definition

The requirements definition phase leads to a set of technical specifications that describe what the customer requires and desires in the future design. The requirements definition phase is often divided into two phases: the "stakeholder requirements definition" and "requirements analysis" [38, 58]. The first attempts to determine the stakeholder demands, values and preferences. The second translates these demand values and preferences into a set of technical specifications for the design to meet. This requirements definition phase prefaces the design process, and failures in the requirements definition can propagate throughout the rest of the process. The INCOSE handbook states that, "System requirements are the foundation of the system definition and form the basis for the architectural design, integration and verification… Changes in requirements later in the development cycle can have significant cost impact on the project, possibly resulting in cancelation [58]."

This requirement generation process establishes performance specification with thresholds of critical and/or desired levels of system performance. An emphasis is placed on the use of scenarios in requirement generation as this allows the design organization to "identify requirements that may otherwise be overlooked" [58]. However, little emphasis is provided in literature on how changes in scenario may change the demands and preferences encapsulated in the requirements. This thesis will focus on the effects of changes in scenario and how they propagate through the design process. As a result, this thesis uses a dynamic model of customer preference. This is done through the use of modeling of customer preference and accounts for how that preference changes in response to scenario changes.

1.1.3 Conceptual Design

In the literature, the stated goal of conceptual design is to select the best concept [127, 110]. John Anderson defines this selection with the question "is it [the selected design] the best design that meets the specifications? [5]" Multiple concepts are proposed and analyzed at this phase of design, and a number of trade studies are conducted to determine and select the best configuration for the air vehicle which will be introduced to fulfill the stated requirements. The question of best becomes more difficult when the designer is faced with uncertainty. When uncertainty is present, the goal of conceptual design is the same, but the definition of “best” often becomes more nuanced. Two commonly applied approaches are often observed in practice: 1) Uncertainty is largely ignored, and the design is simply done deterministically for a few representative scenarios; 2) The definition of best is determined using statistical values such as the mean, standard deviation, etc. These measures are then combined for each concept across a range of scenarios to justify the best concept [125, 86].

1.1.4 Preliminary Design

“Preliminary design can be said to begin when the major changes are over [110].” Preliminary design is the first of the design stages focused on the maturation of the design. This means the details of the selected concept are refined. The goal of the preliminary design is to determine the expected performance to a level of confidence such that the company can assuredly make the decision to take on the risk of future stages of design. Raymer [110] has described the decision at the end of preliminary design as “betting the company” and as such the goal of preliminary design is to ensure that the bet is an intelligent one. However, because the major design changes have been completed, the ability of the design organization to actively react to changing scenario is limited.

1.1.5 Detailed Design

The goal of detailed design is to design each of the parts as they will be manufactured. As a result, this design phase consists of a final refinement of the design as well as the set up for manufacture. This phase of design is drastically more expensive than the previous stages [60]. As a result, the ability to make changes to the design to react to changes in external uncertainties is also limited.

1.2 Integrated Process and Product Development

The quality and cost revolution introduced Integrated Product Teams and process engineering into design decision making. As a result the Integrated Process and Product Development Methodology (IPPD) developed by Schrage will be used as a current state of the art decision making process. The goal of the IPPD process displayed in Figure 4 is to provide a clear justification through analysis for the final design decision made. In Figure 4 the primary decision making process is shown as the center column, with the side columns demonstrating a set of methods which facilitate the accomplishment of the central process. The combination of a rigorous decision making process with a set of engineering methods for performing these elements leads to a well justified design.[117]

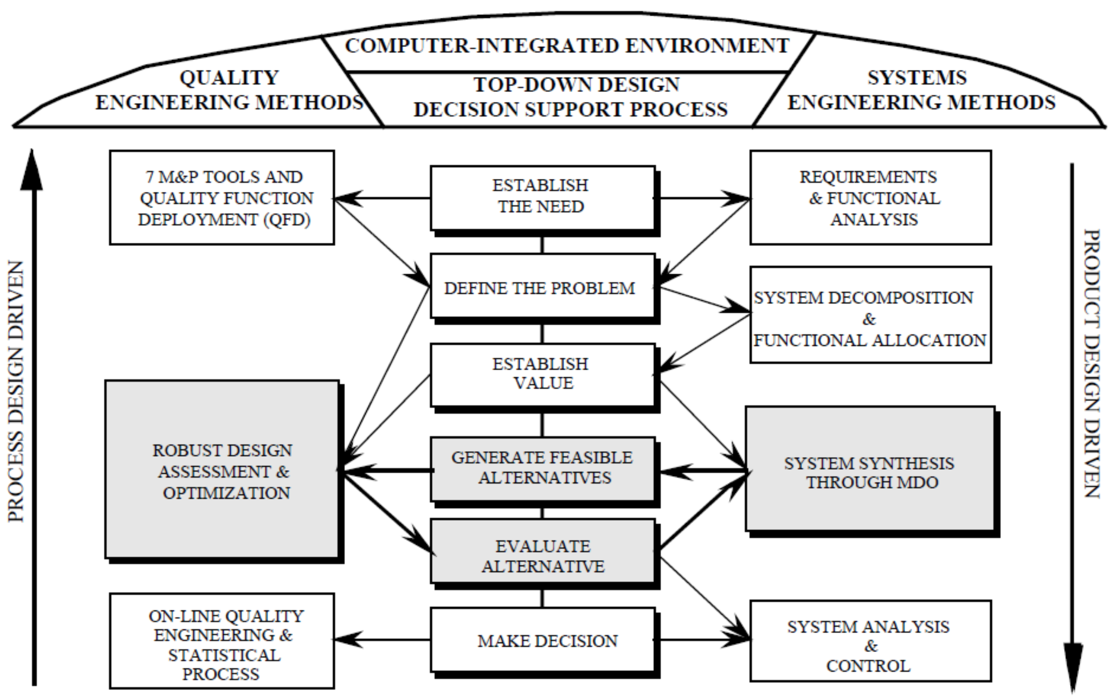


Figure 4: IPPD Process Proposed by Schrage

The figure is described by Schrage:

"The procedural approach illustrated in [Figure 4] has also been called a Design Justification approach. Design Justification is a term used to describe a design process where the economic ramifications of design decisions are considered concurrently with design development and are used to guide the design process so as to result in the most economical criteria satisfying design."

The goal of concurrent design processes can be clearly stated as a justification of the selection of the design concept that most economically satisfies the design requirements [98]. It is important to note that the analysis and iteration loops described in Section 1.1.1 occur within the center of the IPPD process shown in Figure 4. These design iterations are used to create the information necessary to quantify the value of each concept so that the most economical decision can be made.

In describing these elements Schrage states:

"The primary design/synthesis iteration illustrated is between the SE method; System Synthesis through Multidisciplinary Design Optimization (MDO), to "Generate Feasible Alternatives" and the QE method, Robust Design Assessment & Optimization, to "Evaluate Alternatives" and finally to update the System Synthesis." [117]

It is these central analysis elements, acting in conjunction to support the decision making process in the center column, that will be the focus of this thesis. The goal of these central elements is to provide the quantitative analysis necessary to support design decision making. It is important to note that these central element of design iteration and optimization as described by Schrage account for the effects of uncertainty through the use of robust design. Robust design, described in detail in Section 1.4, is a paradigm where statistical measures are used to determine a design that has high performance on the nominal conditions and maintains this performance at off nominal conditions. This thesis will examine an alternative to robust design for supporting design decision making under uncertainty. Section 2.1 will describe design decision making, and Section 1.3 will provide background on robust design.

1.3 Robust Design

Robust design is a paradigm for design that focuses on creating concepts that are insensitive to noise. This paradigm has seen wide scale adoption since the methods described by Taguchi were popularized in the late 1980s. Figure 5 shows a notional depiction of how the robust design paradigm operates [111]. In traditional optimization, the goal is to minimize Y as a function of X by finding the X which minimizes Y with no thought given to how this optimum point may change as a result of perturbations in the model or inputs. However, robust design recognizes that there may be some variability in the inputs or model itself. In this case a simple noise distribution has been applied around the X value. Mapping these distributions in X across the function provides a distribution for the output Y. Robust design considers the effects of uncertainty by considering the statistics of the output distributions and attempts to not only minimize the value but also the variability due to perturbations.

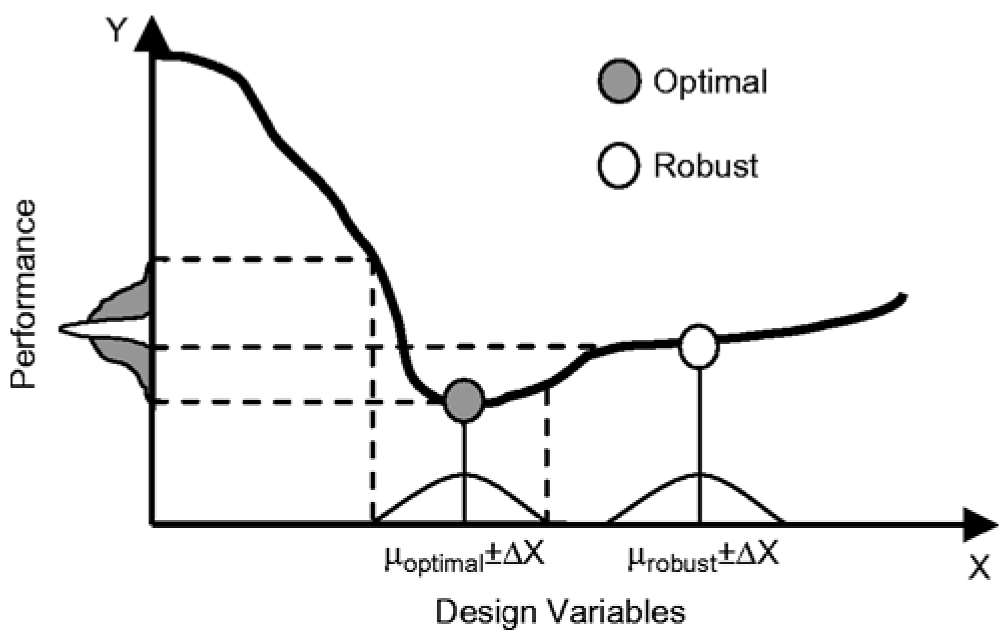


Figure 5: Robust Design Schematic

A number of techniques have been proposed for conducting robust design; a set brief descriptions and a history are presented here. A mathematical description of the techniques found in this paragraph can be found in Section 3.2.1 through Section 3.2.4

where these methods have been applied to a characteristic problem. The author recommends Daskilewicz et al. [31] for a more complete history.

The original robust design methods proposed by Taguchi in the late 1980s create a single aggregate measure called signal-to-noise that is used to determine the best robust design [122]. Born out of signal processing and intended for use in manufacturing process design, this aggregate measure uses a ratio of the mean to the variance to determine a design that has an acceptably low variance. Mistree [20][19] working with others extended the initial paradigm proposed by Taguchi to design decision problems. A host of other authors are continuously proposing various stochastic optimizers and statistical aggregations functions which take in the statistical measures mean and variance of the output and combine these measures into a means of measuring the best design [125] [3].

An alternative to the aggregation of statistical measures was born out of the uncertainty modeling techniques used in reliability engineering. These methods recognize the fact that often in design the goal is to maximize some value while ensuring that certain critical constraint conditions are met. These methods add a probabilistic constraint to the traditional design optimization objective. This constraint, representing reliability, operates on the output Cumulative Distribution Function (CDF) and states that the threshold of not meeting a specific constraint must not be less than some value [24]. This reliability can be stated mathematically as $P(g(\mathbf{x}) \leq c) \leq \alpha$. However, these methods suffer from the possibility that they will discard a large increase in reliability for a differentially small increase in the objective function, due to the use of the reliability measure as a constraint. Mavris et al. [87, 89, 86] proposed the use of the reliability directly as the objective function. This work culminated in the Joint Probabilistic Decision Making (JPDM) approach developed by Bandte et al. [11, 9, 10] in 2000 and allows for an increase in upside variance while penalizing downside variance below some critical threshold.

Robust design presented here will serve as the baseline from which an improvement in design decision making should be based. This thesis seeks to replace robust design with a portfolio-based design methodology in situations where robust design exhibits poor performance. Chapter III will demonstrate and diagnose this poor performance, and Chapter IV will propose an alternative to robust design.

1.4 Roadmap

The current design methods, discussed in chapter II, make the assumption that the design concepts are independent of each other. This assumption will be shown to be invalid for the design decision making context where the goal is to select a best design. The definition of the logic defining “best” creates a relationship that violates the independence assumption. The violation of this assumption can severely reduce the effectiveness of robust design in the presence of uncertainty. These principals will be demonstrated in Chapter III.

This thesis will address deficiencies in current design paradigms under uncertainty by removing the assumption that a single design should be carried through the design process. The remainder of this document will first provide background on current design practices and the challenges they face under certain conditions that will be demonstrated through the use of a motivating example. Chapter III will present an example problem as a means of demonstrating a particular failure mode within the robust design paradigm, as well as diagnose the causes of the failure mode. This will lead to the statement of research objective, which will then be answered through the development of hypothesis design to address several sub-research questions. The resulting methodology will be presented as well as a demonstration that is used to prove the hypothesis. Finally, observations will be made in order to draw conclusions about the success of this new process under the identified conditions. This thesis will show that this new portfolio-based approach to design can be used address the specified deficiencies for design under uncertainty.

CHAPTER II

BACKGROUND

2.1 Design Decision Making and Uncertainty

In the literature, the stated goal of conceptual design is to select the best concept [127, 110]. John Anderson [5] defines this selection with the question “is it [the selected design] the best design that meets the specifications?” It should be noted that design is a decision-making problem. Making the decision that best answers Anderson’s question becomes more nuanced under uncertainty. The following sections will address design under uncertainty. It is also important to recognize that design success is driven by outcome rather than statistics or likelihood. It is only the design outcome at the end of the design process that drives success in the market, not the statistics of which design concept was the most likely to succeed when selected in the conceptual design phase. As a result the following section offers a discussion examining how the quality of decision is being measured.

2.1.1 Defining Quality Decisions with Uncertainty

To measure the quality of any decision it is necessary to establish the difference between a good decision and a good outcome. This argument was first proposed by Herodotus around 500BC and referenced by Howard, the founder of modern decision analysis [52, 59]. In discussing the policies of Persian kings, Herodotus notes that,

“A decision was wise, even though it led to disastrous consequences, if the evidence at hand indicated it as the best one to make; and a decision was foolish even though it led to the happiest possible consequences, if it was unreasonable to expect those consequences.”[52]

To restate this argument, the quality of the decision should be judged on the basis of how likely it is that it will lead to a favorable consequence, rather than the actual realized consequence. This provides a measure of how good a decision is while disregarding the effects of luck. Decision goodness is classically measured as selecting the concept with the highest possible likelihood of outcome success. This logic originally translated to engineering design in the use of the most likely scenario in the requirements derivation. For this most likely scenario, a single concept with the highest value of success was chosen.

The robust design paradigm expanded this classical definition of the best decision by improving the way in which the best was measured. Instead of selecting the best design for the most likely scenario, the design is measured using the performance of that design across multiple scenarios. As a method of combining these multiple scenario based performances into a meaningful set of decision metrics, statistics such as the mean and standard deviation of the performance are used. The application of mathematical rigor to Herodotus's logic allows for a specific set of scenarios. However, Chapter III provides evidence of a failure mode in the conceptual design decision making process.

The goal of this thesis is to improve design outcomes as compared to those made by robust design, and as a result the logical argument presented for defining the best decision must be reexamined. This logical argument defining a good decision makes two unstated assumptions. The first is that the information available for decision-making is fixed. The second is that the set of alternatives from which a decision must be made is also fixed. A decision can be improved by improving either of these two elements. In these terms, a decision may be unwise *because* it was made with the evidence at hand. The decision should instead be made only when new evidence becomes available. This argument doesn't really invalidate Herodotus' logic. In terms of his logic, a specific decision alternative that should always be considered in the original decision is the one most often overlooked: Is this a correct time to make the decision, or should it wait until a future time?

2.1.2 Measures for Uncertain Design Decision Making

The following sections offer a brief overview of the metrics used in aggregating the scenario information for decision making purposes. Because it is impractical and often impossible for the decision maker to use the information about the design concepts performance from all of the scenarios in a simple mental construct, statistics for aggregating data about the performance have been developed. The next few sections detail some common metrics used in design and how they relate to this work.

Expected Value (Mean)

The expected value is the simplest and most common method for aggregating engineering data. In terms of design, this measure provides a centroid of the design performance across all of the scenarios. It is important to remember that the measure is called the expected value, but it is not the value that is most likely to occur. It is rather a probabilistically weighted centroid of performance. This expected value is the most commonly applied statistic for aggregating performance data across multiple scenarios in engineering design.

Standard Deviation (Variance)

The standard deviation is the second most commonly used metric in robust design and is defined as the square root of the variance. The variance is a probabilistically weighted moment of inertia of the design performance about the probabilistically weighted performance centroid. As a result, the standard deviation is a linearized moment of inertia about the mean of the probabilistically weighted centroid of performance. The standard deviation is typically used as a measure of how far off of the "expected" performance a design will be should an off nominal scenario occur. This measure is the second most commonly applied metric in robust design and the vast majority of robust design methods only apply the expected value and standard deviation as statistical measures. The standard deviation has been described in technical terms for this thesis so that the reader gets a feel for how far the actual measure strays from physical meaning in design.

One of the problems with the original robust design metric variance is that an increase in variance is not always a negative effect in conceptual design. As a thought experiment, take two designs with identical performance in every way with the exception that the second design has a very small chance of having extremely good performance in a particular situation. The second design in this thought experiment will simultaneously have an increased variance and yet be the better design due to this small likelihood.

Tail Conditional Expectation

The expected value and variance are the most common measures used in robust design. Bandte and a number of other authors [24, 9] have made the observation that the variance can, in certain situations, be an inappropriate decision metric in design because the desire is not to minimize the variance around a target but rather maximize some objective. As a result a number of other measures based on the cumulative distribution function (CDF) have been proposed that attempt to only penalize the downside variation but allow for upside variation.

This thesis will use the tail conditional expectation, sometimes referred to as the tail value at risk, as a measure which operates on the CDF but also accounts for the weight of the probability mass. This measure is commonly used to measure risk in the financial industry and is found in a few relatively unknown design publications. [116, 131]

The tail conditional expectation (TCE) is the expected value of the probability mass which lies below some specified quantile. Equation 1 shows the mathematical representation of the tail conditional expectation.

$$\text{TCE} = \mathbb{E}[X | X \leq x^{\propto}] \tag{1}$$

where

$$x^{\propto} = \inf\{x \in \mathbb{R}: \mathrm{P}(X \leq x) > \propto\} \tag{2}$$

The tail conditional expectation can also be displayed pictorially in a much simpler form than the mathematics imply. Figure 6 shows a pictorial depiction of the tail conditional expectation. From this depiction it becomes clear that the tail conditional expectation is simply the expected value of the tail for some specified quantile. For the purposes of this thesis the 5% quantile was chosen. The pictorial depiction also makes it clear the physical meaning of the measure. It is an expectation of the worst case scenarios.

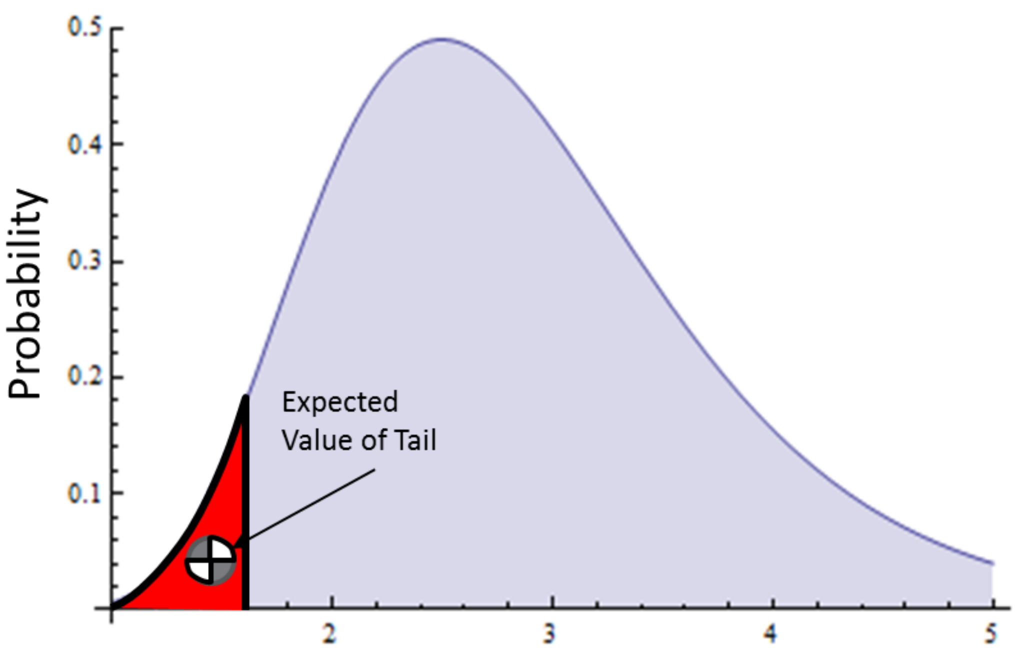


Figure 6: Tail Conditional Expectation

Regret

Regret is an alternative measure for determining the value of a decision. It takes a backwards looking approach and asks how much better could the outcome have been if different decision had been made [72]. The use of regret in design is particularly attractive because of the role of modeling and simulation in design. Modeling and simulation is used to provide justification for the decision made. However, this modeling and simulation is often used as a comparative analysis of the concepts, and is not considered to be a truly accurate depiction of a design's market success due to simplifying assumptions, such as the details of the physics or the specifics of the competitor's offerings, that must be made to implement a practical model. When being used in a strictly comparative analysis, it may be better to measure the design decision compared to the optimal decision rather than judge the design by the output of this comparative model directly. [123]

Typically a minimax approach is taken in determining the regret for any decision. In this approach, the decision made is compared to each decision that could have been made for every scenario. The initial element of the approach compares each decision to the optimum alternative decision for each scenario, providing a measure of the distance that a decision is from the optimum. This comparison of the decision made to the optimum decision is a measure of the maximum regret that decision will experience for each particular scenario. The second phase of the minimax approach looks across scenario and selects the design that minimizes the effects of the worst case scenario. This is done by examining each decision and determining its worst case scenario as measured by the distance from the optimum. The decision alternatives are then compared and the decision is selected with the best (maximum) worst case scenario performance. [15]

One of the benefits and detriments of the approach comes from the fact that the commonly applied minimax approach does not account for the probability of each scenario. This can be useful when the scenario's likelihood cannot be reasonably estimated, but can strongly skew the decision when a set of scenarios is used with long tails. Minimizing the downside of these tails which have a vanishingly small probability will drive the decision. As a result this thesis applies an average regret based approach. In this approach, the distance each decision alternative is from the optimum decision for every scenario is still calculated. However, the expectation of these distances is then taken. This approach allows for an accounting of the probability as well as the distance any decision is from the optimum decision for a particular scenario.

As a result of this backwards looking approach, regret analysis makes the assumption that two information elements are available for use in forward looking decision analysis: First, that a model which can be executed to determine the outcomes of the differing decision choices is available and can be used to simulate performance under varying evolutions of scenario (typically available in conceptual design); and second, that the optimum decision must be able to be found for each scenario. This second requirement can be very stringent for the design environment. It is often burdensome for the design organization to find an optimum for a single scenario, and the ability to find the optimum for each scenario examined can often be infeasible.

2.1.3 Uncertainty

The following section describes the differing efforts historically taken in the understanding and quantification of the effects of uncertainty. This thesis takes a probabilistic approach to the quantification of uncertainty, and a practical taxonomy is presented for describing the types of uncertainty captured in the proposed approach.

Uncertainty Classifications

A great deal of effort is expended in the literature on the determination of a useful taxonomy for uncertainty. In the 1660s, the terms probability and statistics were adopted to describe the modern notions of the mathematical study of uncertain systems. Probability was used to describe the reasonable degree of belief in a proposition, and statistics were devoted to the analysis of sample data from uncertain systems. However, the use of inductive and statistical probabilities blurred the lines between these two elements. Furthermore, it has been recognized from the earliest times that the models describing probability are based on some statistic and as a result it is difficult to separate the two. [46]

A famous anecdote attributed to mathematician Bertrand Russell in 1929 states, "Probability is the most important concept in modern science, especially as nobody has the slightest notion of what it means [64]." Due to this lack of clarity, Hacking notes in his book, <u>The Emergence of Probability: A Philosophical Study of Early Ideas about Probability</u> that "there have been many other words … 'propensity', 'proclivity' as well as a host of adjectival modifiers of the word 'probability', all used to indicate different kinds of probability. The duality of probability is not news."[46] The net result of this confusion is that the underlying mathematics has remained the same, but the philosophical implications of those mathematics have remained in debate. As a result, an alternative set of verbiage has been popularized over the last half century in an attempt to provide clarity.

Aleatory vs. Epistemic

In an attempt to clarify the notion of probability and statistics, the academic community has settled on the words aleatory and epistemic to describe uncertainties. Aleatory uncertainty is often defined as uncertainty that arises from natural variation. Epistemic uncertainty is defined as uncertainty that is the result of a lack of knowledge but is capable of being resolved through sufficient study or measurement. [51]

However, this classification of uncertainty falls into the same trap experienced by the previous definitions. With sufficient knowledge and measurement, a model capable of predicting outcomes rather than aggregate statistics, classified as aleatory, can be developed for the underlying uncertain elements. In this case, it is only a lack of knowledge about the inputs to that model that leads to uncertainty, and this would be classified as epistemic uncertainty. As a result authors have recognized that the line between these classifications is blurred as well and often dependent on the models available to the classifier or his/her purpose in studying the uncertain quantity [51, 64].

Working classification of uncertainties

A minority but growing opinion of the true nature of uncertainty is that it does not exist as some extrinsic property of nature but rather is a useful construct in describing the experimenter's own ignorance [59]. The author of this thesis has chosen to take this philosophical footing when developing a classification of uncertainty. As a result, the author has chosen to classify lack of knowledge into a) that which will be resolved before a decision is made; and b) that which will be resolved after a decision is taken. In the case of this thesis, the decisions will be the critical design decision made at the end of each phase of design.

For the purposes of this thesis uncertainty will simply be classified as scenario-based or experimental. This classification will provide a working set of definitions useful to the designer. Experimental uncertainty is the lack of knowledge that can be resolved through the use of experiments, modeling or any other means of gathering information for the design decision point located at the end of the current phase of design. Multiple methods are found in literature for bringing the largest possible amount of information to the current phase of design, typically through computer aided design and simulation thereby reducing the experimental uncertainty [94, 21, 65, 132]. At some point, it may become impractical, impossible or simply uneconomical to reduce the experimental uncertainty before critical design decisions are made, and this lack of knowledge then falls into the second class of uncertainties. Scenario-based uncertainties are those uncertain factors that are will be resolved after the design decision associated with this phase of the design process. Scenario-based uncertainties are those uncertain factors that will be resolved after the design decision associated with this phase of the design process has been made. Scenario uncertainties represent all of the lack of knowledge about the future state of the design and the environment in which it will be operated that cannot or will not be known before a design decision is made. This can either be elements external to the entire design organization, such as fuel price, or elements that are part of the design process but simply cannot be known due to the sequencing of the elements in a spiral design cycle. Two assumptions will be made about these uncertainties for practical use: First, that the current and future states of the uncertainty variables can be identified and estimated; and second, that the conditional probabilities of transitioning from one state to another can be estimated.

This classification system allows the designer to classify uncertainty into that which can be resolved before a design decision is made through experimental work, and that which cannot be resolved until after the design decision must be made. The author recommends that any lack of knowledge that can be practically resolved before critical design decisions must be made should be resolved, but also recognizes that a lack of knowledge will remain. This thesis focuses on the lack of knowledge that remains. Section 3.5 will demonstrate a need for a new design decision method that is focused on the scenario-based uncertainty rather than another method for reducing the experimental uncertainty at the current phase of design.

2.2 Introduction of Important Concepts

The following section details several key concepts which are referred to frequently in this thesis. The next four sections provide an overview of these key concepts.

2.2.1 Pareto Optimality and the Pareto Frontier

Pareto optimality, often called Pareto efficiency, is an economic concept adapted for use in engineering. For engineering problems, the Pareto frontier is a concept that applies to multi-dimensional problems. A Pareto optimal point is defined as one for which no improvement in any dimension can occur without a negative effect in another dimension. The Pareto frontier or is the set of Pareto optimal points. Figure 7 shows the concept of the Pareto frontier and Pareto optimality.

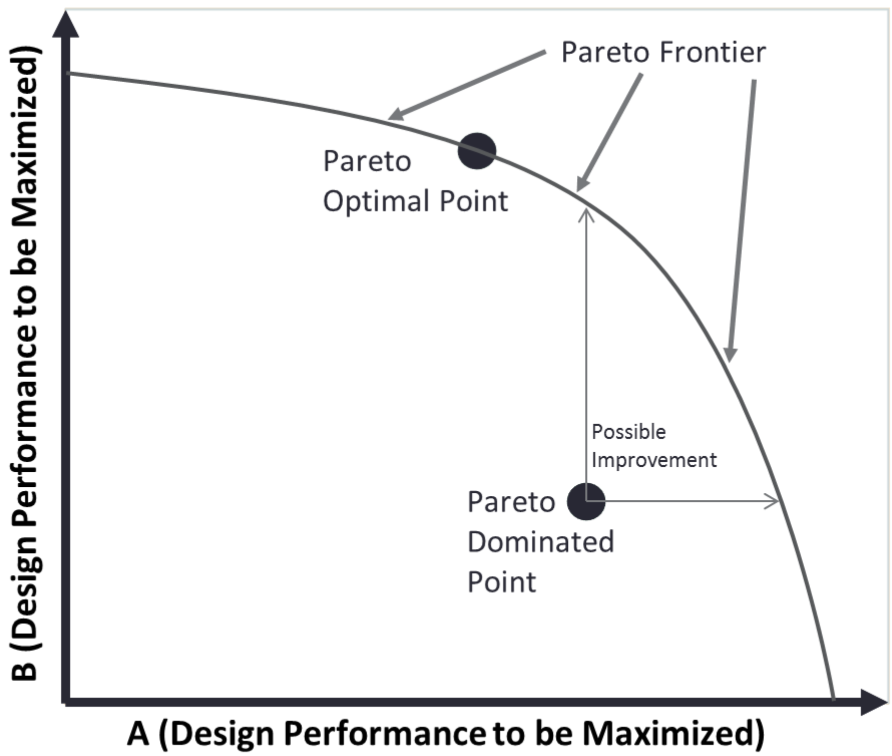


Figure 7: Pareto Optimality and Pareto Frontier

2.2.2 MADM/MODM

Multi-Attribute and Multi-Objective Decision Making (MADM / MODM) techniques are a set of mathematical procedures to rigorously make a decision in an environment where trades are required between multiple desirable traits. These techniques capture the logic used in selecting the one Pareto optimal point over another

Pareto optimal point. Since each point on the Pareto frontier is optimal for a particular set of preferences of one desirable trait over another, MADM / MODM techniques capture these preferences. It is important for the reader to note that these preferences are often driven by the scenario. As a tangible example, a Pareto frontier exists between the power of a car's engine and its efficiency assuming a fixed cost. Based on the current gasoline price, as well as, the decision maker's personal feelings, one engine on this Pareto frontier will be selected over another. Multi-Attribute and Multi-Objective Decision Making techniques are used to assist in selecting the Pareto optimal point that best matches the preference for fuel efficiency vs. power. The consequences of defining logic to select one design over another in the presence of a trade-off are shown in Chapter III. An excellent overview of MADM and MODM techniques can be found in reference [67] by Li [67, 87, 61, 11, 94].

2.2.3 Defining risk reduction

For the purpose of this thesis, risk mitigation will be defined as the following: *The outcome weighted reduction in the likelihood of unfavorable results, and the outcome weighted increase in the likelihood of favorable results.*

From this definition it can be seen there are two potential paths for risk reduction. The first path is based on improving the outcomes. The second path is based on improving the likelihoods. This section will examine the possibility for risk mitigation starting with an examination of the first path for risk reduction, improving outcome, and moving to the second, accounting for the likelihood of differing scenarios.

It has always been the goal conceptual design to produce the best outcome. This has traditionally translated to simply producing the best design for a specified scenario encapsulated in a set of requirements. John Anderson, describing the primary question conceptual design is attempting to answer, "is it [the selected design] the best design that meets the specifications?" provides a succinct description of the desire to have the best outcome for a specific set of requirements [5]. The introduction of robust design brought with it the recognition that the multiple future scenarios are possible. In this case, the goal is to create a design that is “best” for multiple scenarios. This means that best is now measured using statistical aggregate measures. Typically the mean and standard deviation of the objective are used. For the purpose of this thesis, it will be assumed that best practices are being used to improve the design outcome of any single concept. As a result, this path to risk reduction has already been maximized.

The second path to risk reduction is based on likelihood. The goal of risk reduction using this path is to reduce the multiple potential scenarios to a single known quantity. This path to risk reduction is typically only available for technical elements of the design. For any specific concept, the technical elements of the design are unknown, but within the designer’s control. For example, the uncertainty in the lift a wing will generate can be reduced through additional computational fluid dynamics modeling, or wind tunnel testing. Reducing the likelihood of negative technical outcomes by resolving the technical uncertainty is a valuable approach to risk reduction, and great deal of effort has been spent on achieving this aim [1, 31, 39, 7]. However, the example in Section 3.5 shows that under certain conditions, elimination of technical uncertainty cannot adequately reduce the likelihood of a negative outcome. In the example presented in Section 3.5, the technical uncertainty could be completely removed, and negative outcomes could still be possible. This is the direct result of the scenario uncertainty. Because the scenario uncertainties are by definition resolved after a decision has been made, for a competent design organization the set of future scenarios at the time of decision-making has already been reduced by the maximum amount that was sensible for that phase of design.

This seemingly lack of effective levers by which the risk can be reduced has led aircraft design organizations to pursue designs that are very similar to ones with past success.[139] A 2002 NASA technical report states, “A usual design strategy is to choose airframe designs for which one has sufficient experience to be able to assess risk.[139]" The belief here is that a design similar to one that has been successful in the past has low risk. Because of the knowledge contained in the organization about the previous design, this strategy does tend to reduce the technical uncertainty. However, it cannot reduce the external elements to scenario-based uncertainties. This strategy fails catastrophically if the future turns out not to be like the past, and any alternative choice is available that better matches this new future.

A better means of risk mitigation is still needed even if none is available at the conceptual level. The arguments in the past sections were looking at the risk of a single concept from the concept alternative space. For any alternative in the traditional conceptual design decision-making space, no lever existed for risk mitigation. Instead the only path for risk mitigation is to introduce new alternatives to the conceptual decision-making process with inherently different risks. This is a restatement of the second method for improving the decision-making process. As a result, the improved decision-making and risk mitigation are synonymous, as they must be achieved through the same mechanism.

2.2.4 Tipping point

Malcom Gladwell, a popular writer, coined the term "tipping point" to describe "the moment of critical mass, the threshold, the boiling point" [44]. He used the phrase to describe the point at which a system transitions from one stable equilibrium to a second stable equilibrium. The formulation he proposed is largely based on a network propagation model of the spread of information and ideas. The author of this thesis will build upon the concept of a tipping point, but finds the limitations of a network-centric formulation too confining. This thesis will show that design spaces are capable of exhibiting tipping points, but will not limit the term to continuously differentiable functions as implied by the ideas presented in the Malcom Gladwell's book Tipping

Point. For the purposes of this thesis the tipping point will refer to a rapid transition from one equilibrium to another equilibrium for both continuous and discrete transitions [44].

CHAPTER III

PROBLEM CHARACTERIZATION

In the aerospace industry, recent large-scale design results have been shown to be inadequate. *The Los Angeles Times* is quoted as saying, "The next-generation airliner [Boeing 787] is billions of dollars over budget and about three years late[49]" *CNN* reported that, "The A380 initially arrived three years overdue and billions of dollars over budget. Other setbacks during its first five years of service -- including cracks in the wing components discovered in January this year [2012][37]" The military side of aerospace is not performing any better. *The New York Times* reports, "The F-35 Joint Strike Fighter was supposed to prove that the Pentagon could build a technologically advanced weapon system within an affordable budget, without huge delays… The accountability office now estimates the total cost of acquisition at nearly $400 billion, up 42 percent from the estimate in 2007; the price per plane has doubled since project development began in 2001… the plane would not be in full production until 2019, a delay of six years. [97]" However, the complexity and length of the design process makes laboratory studies to determine the root cause of these failures infeasible. However, common themes published by the manufacturers often cite complexity and a need for new risk management methods. Boeing's 2010 financial report described a new risk management approach to help resolve these failures, stating, "This [new risk management process is a] back-to-basics approach includes a disciplined, 11-step technical review process now required for all new programs. This rigorous process for identifying and mitigating risks begins at the design concept stage and continues all the way through product delivery and support.[124]" Although it is likely that there are many contributing causes to these failures, this thesis asserts that insufficient attention to external, scenario-driven uncertainties when making key, early design decisions is a large contributor to these failures, and that better treatment of these uncertainties in early design will lead to better design outcomes.

In order to support this assertion, this chapter develops a series of established characteristics of engineering design problems, as well as a representative, simplified example problem containing these characteristics. Then, a case study is performed using this representative problem, which demonstrates the influence of scenario-based uncertainties on the success of the design. This representative problem is used to compare the outcomes from several standard design practices and demonstrate the likelihood of success across the spectrum of future market scenarios. In each case, it will be demonstrated that the likelihood of success is low, and that a paradigm shift in the design approach will be required to increase the likelihood of success. In order to further support this claim, a mathematical framework is presented that formally and rigorously describes the situations in which this scenario-driven failure mode will be present and should be accounted for during the design process. This framework can then be used to characterize situations in which a paradigm shift in design methodology is required. The remainder of this thesis will develop a methodology to improve design outcomes in the situations characterized in this chapter.

3.1 Characteristics of the Design Problem

In order to develop a simplified, representative problem on which to demonstrate the effect of external, scenario-driven uncertainties, it is necessary to first identify the characteristics that this problem must possess in order to accurately represent real-world aerospace design problems. Three particular characteristics of design will combine to create a set of conditions in which scenario uncertainties can create challenges for traditional engineering design paradigms.

The first established characteristic of engineering design is that design is multi-objective and involves trade-offs [119]. This means a design solution attempts to satisfy two or more desirable objectives, and a compromise is required in situations where improvement in one objective inherently leads to degradation in the other. A host of multi-attribute and multi-objective decision-making methods have been developed with the goal of helping designers perform these trade-offs, and the role of multi-attribute and multi-objective decision making is discussed in Section 2.2.2 [67]. An alternative approach to multi-attribute decision making is to include the modeling of preference directly in the modeling environment. This preference modeling is simply a more rigorous method for capturing the value of differing trade-offs between desirable design characteristics while directly accounting for the effects of a particular scenario.

The second characteristic of engineering design is that it occurs in the presence of uncertainty [138]. The robust design paradigm is the current state of the art in engineering design in the presence of uncertainty, and a discussion of this paradigm as well as an overview of methods is presented in Section 1.3.

The third characteristic of design is that a sequential set of decision are made concerning the best design and these decisions are difficult to revisit and impact the future success of the design. This set of decisions starts with the requirements and the resulting design is a product of the initial requirements defined for the design [36]. The conceptual design decision is based on the requirements and describes in broad terms the structure and architecture of the engineering design to satisfy these requirements. Based on the selected architecture and described concept, detailed decisions are made about the details of the design all the way to the part level in the preliminary and detailed design phases. Because of the sequential nature of design decision making and the added cost and time required to revisit decisions, it can be difficult for design organizations to react to changes in scenario.

These three characteristics are not independent. In order to develop requirements, assumptions must be made about the future state of the market, which is major source of uncertainty. Furthermore, design trade-offs must be performed against the requirements given the assumed scenario, leading to uncertainty in multi-objective decisions. Thus, the requirements set itself is subject to a high degree of uncertainty, and the outcomes of trade-offs made based on these requirements will have some associated degree of confidence. However, if this confidence level is not properly understood, it is possible to carry a design forward that has little real chance of success in the market. If, during the design process, the future shifts from the scenario assumed during the requirements process, some adjustment is required to make the product marketable in the new future scenario.

This resulting adjustment can be handled in one of two ways. Either the requirements can be changed, and many of the trade-offs must be revisited forcing new decisions to be made to match the new requirements. In this case, the design exhibits an increased chance of technical failure because of the difficulty in meeting the changed requirements on time and on budget in the face of changing requirements. This is a common practice in the DoD which has been identified by the Government Accountability Office (GAO) as a major source of cost and schedule overruns [128]. The logical alternative is that the requirements can be left fixed; resulting in requirements which are out of sync with the end user preference which leads to an increased chance of market failure.

3.1.1 Overview of the Automotive Characterizing Problem

In order to better understand the impacts of these interactions on design, a simplified problem is created which contains the characteristics described above. In this example, an automobile manufacturer is considering what new automobile concepts to pursue for the future. Uncertainty in the future scenario stems from the expected price of fuel in the future, and the impact of this fuel price on what characteristics consumers will desire in a future new car. A model is created that consists of two parts. The first part will represent the preference of the end user as value of a particular concept in the market. The second part will represent the technical design trade-offs stemming from the defined requirements.

Concept Value Modeling

The first model represents the net present value an automobile manufacturer can expect from different automobile concepts under uncertainty. The model takes in three inputs: vehicle horsepower, vehicle efficiency, and fuel price. The first two inputs are technical parameters defining the concept. The last input, fuel price, is an uncertainty beyond the vehicle manufacturer's control that has a large impact on the vehicle manufacturer's profitability for a given concept. The model has a single output: the net present value of a concept defined by its power and efficiency in a fuel price scenario. Equation 3 presented below shows the structure of the model.

$$Value = \frac{efficiency}{10(1+e^{2.75-fuelPrice})} + \frac{1}{100}\left(1 - \frac{power}{(1+e^{2.75-fuelPrice})}\right) \qquad (3)$$

This model represents the customer's preference and a translation of that preference into the value that is placed on a particular concept. The relative preference of power to efficiency for different future fuel prices is presented in Figure 8. This model is representative of the market analysis, and answers the question, "Given a future fuel price scenario, what net present value will be achieved by a particular concept with a given efficiency and power?"

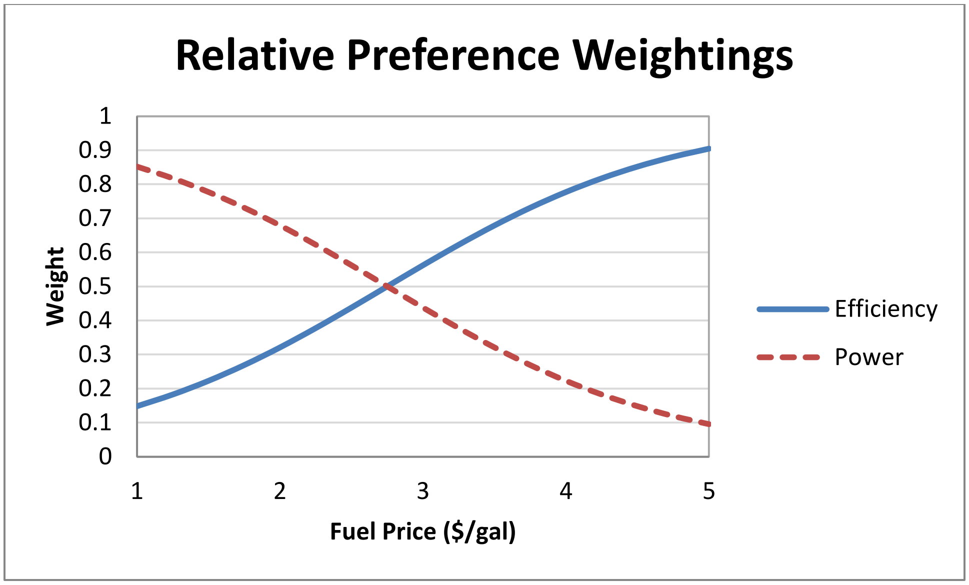


Figure 8: Relative Preference for Power and Efficiency

An image of the sensitivities of this model can be seen in Figure 9 through Figure 11. The inputs to the model are shown across the bottom of Figure 9, with the net present value (NPV) shown vertically on the side of Figure 9. In this depiction the slopes of the lines show the actual change in NPV for a deviation in that particular input variable while holding the other variables constant at the value shown in red on the horizontal axes. From this depiction, it is evident that an increase in either fuel efficiency or horsepower leads to an increase in NPV. However, the magnitude of the sensitivity of the NPV of a concept to an increase in power or efficiency is dependent on the fuel price. In Figure 9 the fuel price is $2.75 per gallon. In this case, power and efficiency are equally valued by the customer. This means that a 10% gain in efficiency would provide an equivalent increase in NPV to a 10% gain in power. Figure 10 shows the sensitivity of the NPV with the fuel price set to $1.5 per gallon. Under this fuel price scenario, the impact of a change in power or efficiency is drastically different. From Figure 10, it is evident that an increase in power has will increase the NPV of the design a great deal more than will an increase in efficiency. Figure 11 shows the same set of sensitivities with the fuel prices set to $4 per gallon. From this figure, it can be observed that an increase in efficiency is the best way to improve the value of the design. This model captures the impact of future scenario uncertainty on requirements and demonstrates the resulting impact to the success of the product on decisions made in a design trade-off.

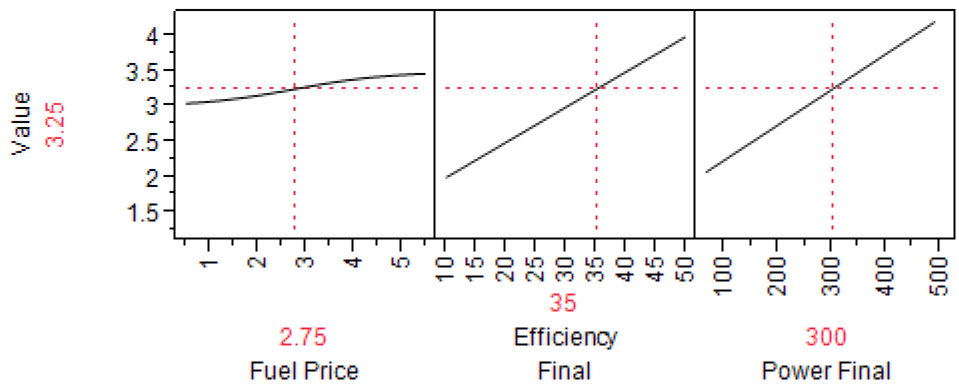


Figure 9: Sensitivities at a Fuel Price of $2.75

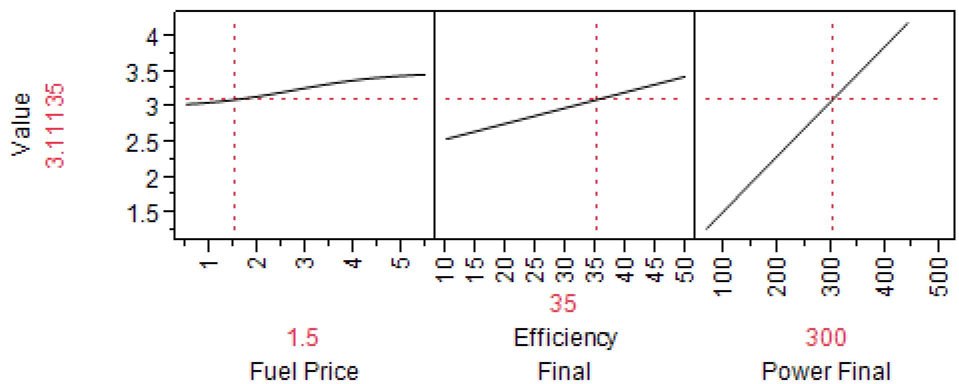


Figure 10: Sensitivities at a Fuel Price of $1.5

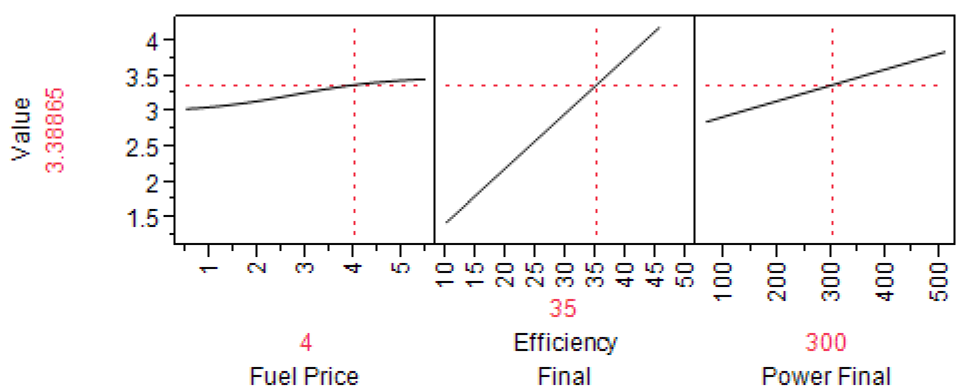


Figure 11: Sensitivities at a Fuel Price of $4

Concept Technical Model

External to the value model is a separate model representing the physical trade between power and efficiency. In a typical design process, the technical analysis environment is used to identify a set of Pareto optimal designs. A design is Pareto Optimal if an improvement in any one dimension leads to degradation in another dimension. The set of Pareto optimal designs is called the Pareto frontier, and its existence is the result of the technical limitations of the design imposed by the physics of the problem. For the characterizing problem, the Pareto frontier is a product of the fact that it is not physically possible to simultaneously increase both power and efficiency in a vehicle design. For the purposes of this problem, a simple function was used to represent the set of Pareto optimal points, which is shown in Equation 4. A pictorial depiction of the Pareto frontier can be seen in Figure 12.

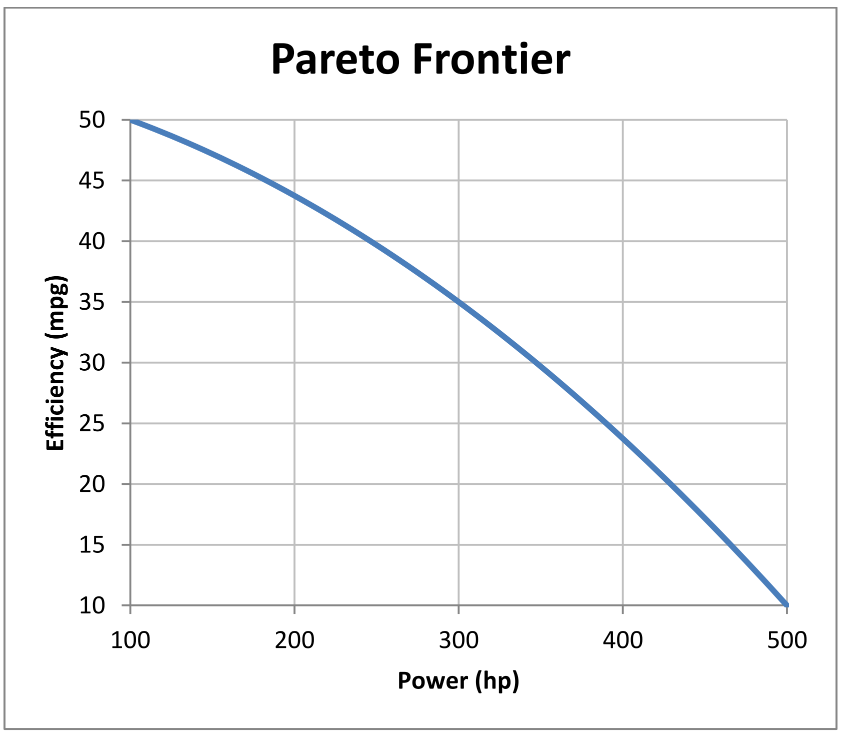


Figure 12: Pareto Frontier between the Vehicle Power (hp) and Fuel Efficiency (mpg)

$$Efficiency = 65 - 0.000125(-300 + Hp)^2 - 0.1Hp \tag{4}$$

Modeling Uncertainty

The NPV model described above is a deterministic model. It returns the value of a design given known values for fuel price, power and efficiency. However, the exact values for these inputs are not necessarily known in the early phases of design. Obviously, the future fuel price is unknown. The realized value of efficiency and power at the end of the design may also differ from the values initially estimated at the beginning of the design process. This is may be due to a number of factors, such as unforeseen technical challenges or inaccuracies in the modeling. Therefore, all of the inputs to this model are subject to uncertainty. It may be possible to determine a range of likely values for these inputs, but would be very difficult to know these values exactly.

In order to determine the feasible ranges for these values, it is first necessary to understand from where these values are obtained. The fuel price is a scenario variable and the potential range for this variable is estimated from a best guess of the possible future states of the economy. This can be done using any number of forecasting techniques, but for the purpose of this experiment, a lognormal distribution with parameters μ= 1.0116 and σ=.31015 was used to represent a range of reasonable future scenarios for fuel price.

The remaining two input variables to the NPV model, power and efficiency, are outputs of the physical model of the system itself. Examination of the physical model reveals a Pareto frontier between the power and efficiency. If it is assumed that the designer will always attempt to create a Pareto optimal design, then it follows that for a given power, it is possible to determine the corresponding Pareto optimal efficiency, and vice versa. Equation 4 defining the Pareto frontier is a direct statement of this fact. It defines the efficiency in terms of the power. In other words, by assuming that a chosen design will lie on the Pareto frontier, defining one of these variables will necessarily define the other. Thus, it is not necessary to explore the full range of combinations of power and efficiency, but only those that lie on the Pareto frontier. For the characterizing problem, a simple equation, Equation 4, is available to describe the Pareto optimal set. For more complex problems finding this Pareto frontier may itself be challenging and an alternative is a direct linking of the technical and value models into a single model.

Making use of this relationship allows the number of inputs considered to be reduced to two, design power and fuel price, with the design efficiency derived from the power. Equation 5 shows the model of the NPV with the efficiency removed by substituting in Equation 5 defining the Pareto frontier.

$$\begin{aligned} Value = {} & \frac{1}{100}\left(1 - \frac{1}{1 + e^{2.75 - Fuel\ Price}}\right) \\ & + \frac{1}{10}\left(1 - \frac{-.1 - .00025\,(-300 + HP)}{1 + e^{2.75 - Fuel\ Price}}\right) \end{aligned} \tag{5}$$

However, recognizing that it is early in the design process and that the models are not perfect, it is likely that the actual realized power of the design will not be equal to the design power specified at this stage of the design process, and likewise, that the realized efficiency will differ from the estimated design efficiency. To account for this uncertainty, two noise factors were added to the modeling: an efficiency noise factor and a power noise factor. Equation 6 shows the final modeling environment including both external scenario uncertainty and internal scenario-based uncertainty in the noise factors.

$$\begin{aligned} Value = {} & \frac{1}{100}\left(1 - \frac{1}{1 + e^{2.75 - Fuel\ Price}}\right)\left(HP + \frac{HP\ Noise}{100}\right) \\ & + \left(\frac{65 + \frac{Eff\ Noise}{10} - .000125\,(-300 + HP)^2 - .1HP}{1 + e^{2.75 - Fuel\ Price}}\right) \end{aligned} \tag{6}$$

Distributions were applied to the uncertain inputs: fuel price, power noise factor, and efficiency noise factor. Fuel prices were modeled with a lognormal distribution (as described above), and the noise factors were modeled with normal distributions with parameters N(0, 5) for fuel efficiency and N(0, 50) for power. Figure 13 summarizes the process used to create the model for uncertainty on the NPV inputs.

Next, a Monte Carlo algorithm, a commonly applied uncertainty modeling technique, was performed for nine specific design concepts spread along the Pareto frontier [32]. The Monte Carlo analysis was performed in the following manner. First 5,000 random cases were selected from the distribution for fuel price. For these 5,000 random fuel prices, each concept was evaluated 5,000 times under uncertainty, to provide an uncertain model for the NPV of these nine concepts. The reason for this two-step process is to ensure that the concepts are compared under the same set of future fuel price scenarios. An overview of the process is shown in Figure 13.

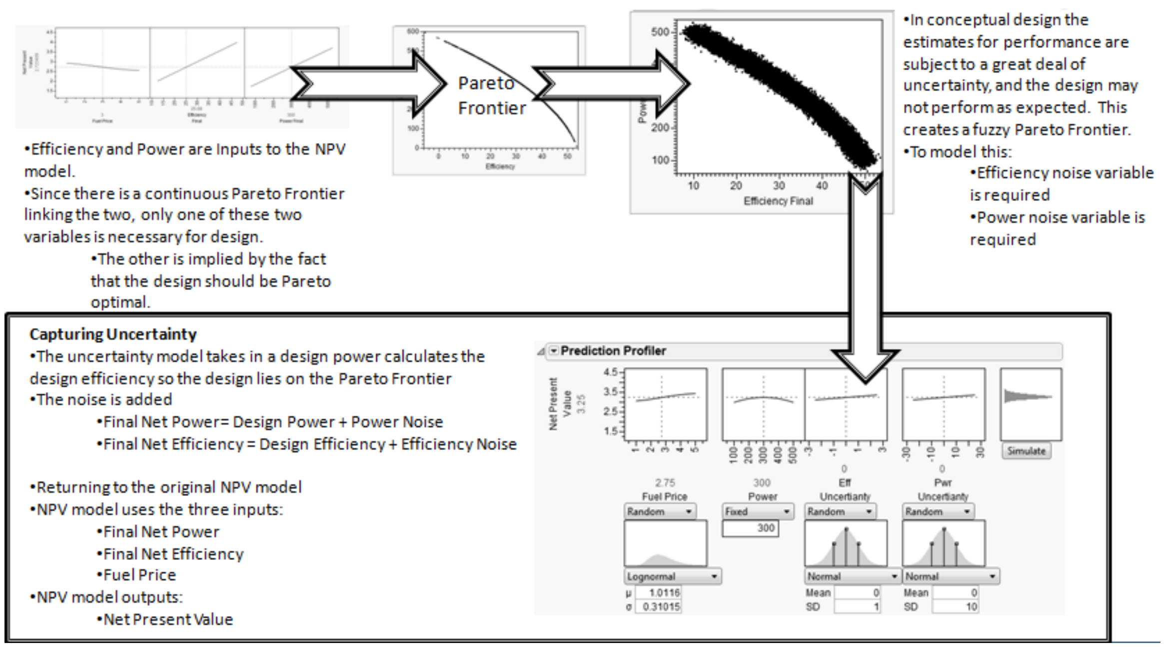


Figure 13: Uncertainty Modeling Process

Figure 14 shows the results of the model execution. The chart on the left shows the input and outputs for the NPV model under uncertainty. This visualization was created in the JMP® statistical analysis software package and is called a scatterplot matrix. Each box in the matrix represents one bivariate plot of one input or output variable against another input or output variable. All combinations of bivariate plot are represented in the grid, giving a multi-dimensional view of the space. Each of the points in each bivariate plot represents one single run of the NPV. All 45,000 cases of the Monte Carlo are shown in each box, with each color corresponding to one of the nine concepts. For each concept, all 5,000 Monte Carlo runs for that concept are shown in the same color. For example, all of the light purple dots correspond to the vehicle concept with a design power of 500 hp and a design efficiency of 10 mpg. Because of the uncertainty in the estimate of these parameters at conceptual design, the concept itself looks like a distribution of points around 500 hp and 10 mpg. For each of the concepts pictured, the 5,000 cases shown correspond to the same 5,000 fuel prices generated in the first step of the Monte Carlo process used here. It is also useful to note that these boxes are dynamically liked. Highlighting a set of points in any one box will cause the same points in all other boxes to become highlighted. In this way, it is possible for a user of this visualization to better understand the multi-disciplinary effects.

Figure 14 shows the Cumulative Distribution Functions (CDFs) and Probability Density Functions (PDFs) for each of the concepts based on the 5,000 Monte Carlo cases for that concept. Summary statistics with a color legend for each concept are presented in Table 1.

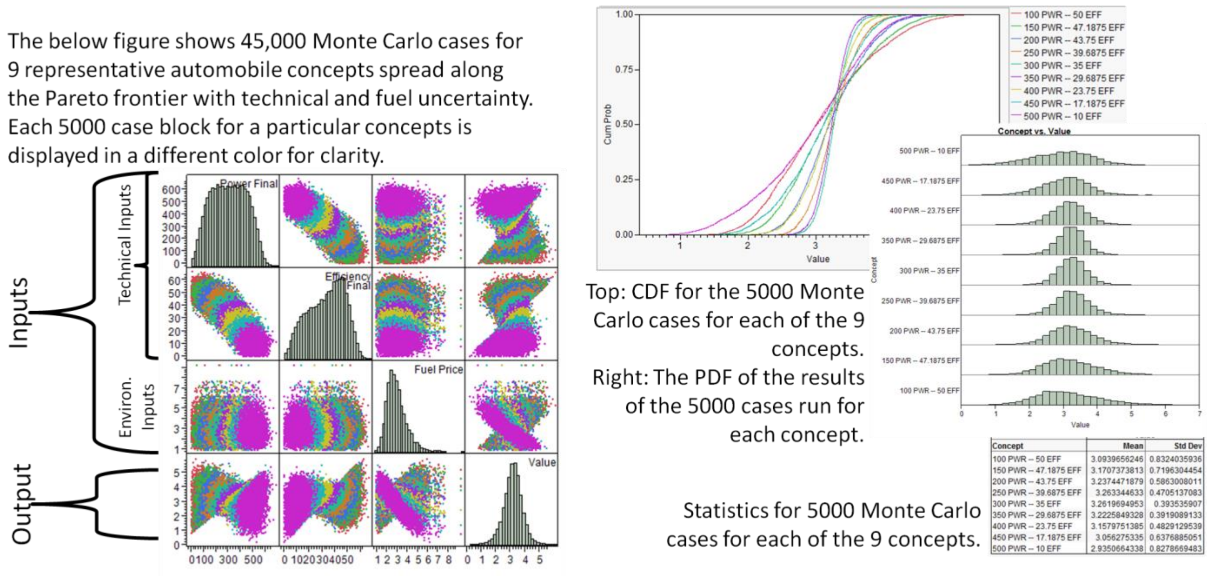


Figure 14: Outputs of Monte Carlo Simulation

Table 1: Summary Statistics for Vehicle Concepts

	Value	
Concept	Mean	Std Dev
100 PWR -- 50 EFF	3.0939656246	0.8324035936
150 PWR -- 47.1875 EFF	3.1707373813	0.7196304454
200 PWR -- 43.75 EFF	3.2374471879	0.5863008011
250 PWR -- 39.6875 EFF	3.263344633	0.4705137083
300 PWR -- 35 EFF	3.2619694953	0.393535907
350 PWR -- 29.6875 EFF	3.2225849328	0.3919089133
400 PWR -- 23.75 EFF	3.1579751385	0.4829129539
450 PWR -- 17.1875 EFF	3.056275335	0.6376885051
500 PWR -- 10 EFF	2.9350664338	0.8278669483

3.2 Discussion of Characterizing Problem Results

Making the decision under uncertainty requires the designer to look at multiple future scenario and determine the performance of the selected design under these differing scenarios. The following paragraphs describe a set of statistical depictions commonly used in describing the results of analyzing multiple scenarios. A discussion follows on the types of analysis typically done in the selection of a particular concept at the conceptual design decision.

3.2.1 Monte Carlo Output Statistics and the Eye Test

Figure 15 and Figure 16 show the PDF and CDF, respectively, of the different concepts under uncertainty. Figure 15 shows the PDF for each of the different concepts under uncertainty. The concepts are listed vertically down the side starting with the high-power low-efficiency concept and ending with the low-power high-efficiency concept. The potential realizations of NPV achieved for each concept for multiple scenarios is shown in the PDF. It can be immediately observed that there is a great deal of overlap in the distributions of NPV for each of the concepts. It is also observed that the concepts have different variances. This overlap provides the first indication that there is no single dominate concept. The differing variance indicates that the concepts have differing sensitivities to the uncertainties. This can further be seen in Table 1, which lists the mean and standard deviations for each of these concepts.

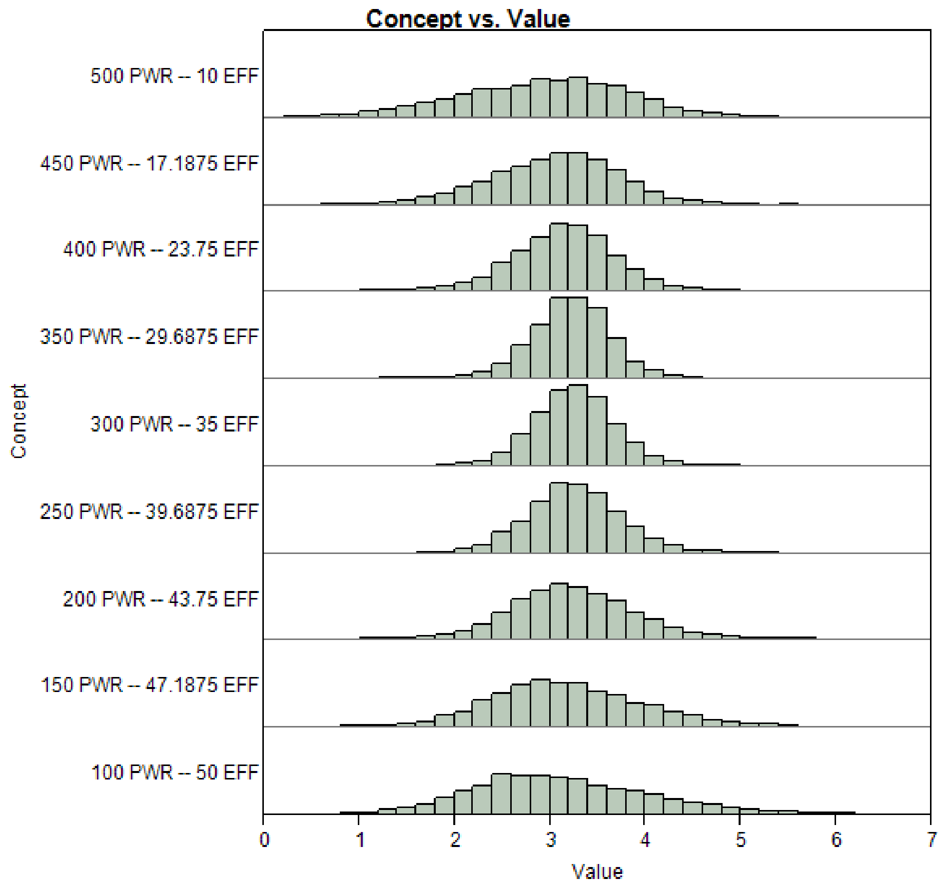


Figure 15: Vehicle Concept PDFs

Figure 16 shows the CDF for each of the concepts. Each concept's CDF is described by a different color line. The color used for each concept matches the color previously used in Figure 14. This CDF provides a quick visual means of understanding the likelihood that a particular concept will have an NPV less than or equal to a particular value of interest. The curves have been overlaid for ease of comparison. From this view it is straightforward to observe that the concepts at the extreme ends of the design space (100 hp – 50 mpg and 500 hp – 10 mpg) have both a higher likelihood of returning an NPV of less than two, but also a higher potential to return an NPV of greater than four. This indicates that the extreme concepts have the highest potential for profit should a more extreme scenario occur, but they also have the highest potential for failure.

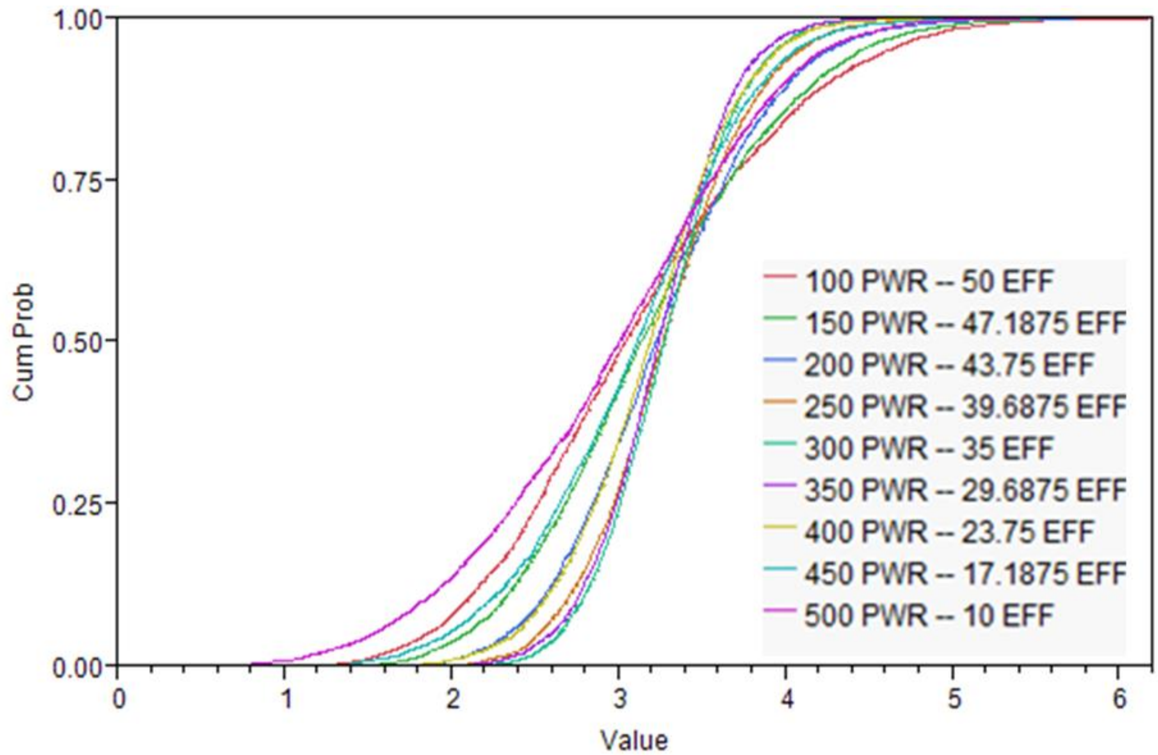


Figure 16: Cumulative Distribution Functions for NPV of Each of the Concepts

Examining Figure 14 and Figure 16 as well as Table 1, it is evident that there is no clearly dominant concept. To highlight this fact, the output statistics have been plotted in Figure 17. If faced with the question as to which concept should be selected, no definitive answer can be given. If the designer were to make the decision based on the statistics for the potential realizations of the different concepts under uncertainty, several different techniques are currently available in the literature and commonly applied to make these types of decisions. The following sections provide a brief summary of each technique and a discussion of what concept would be selected using each technique and why.

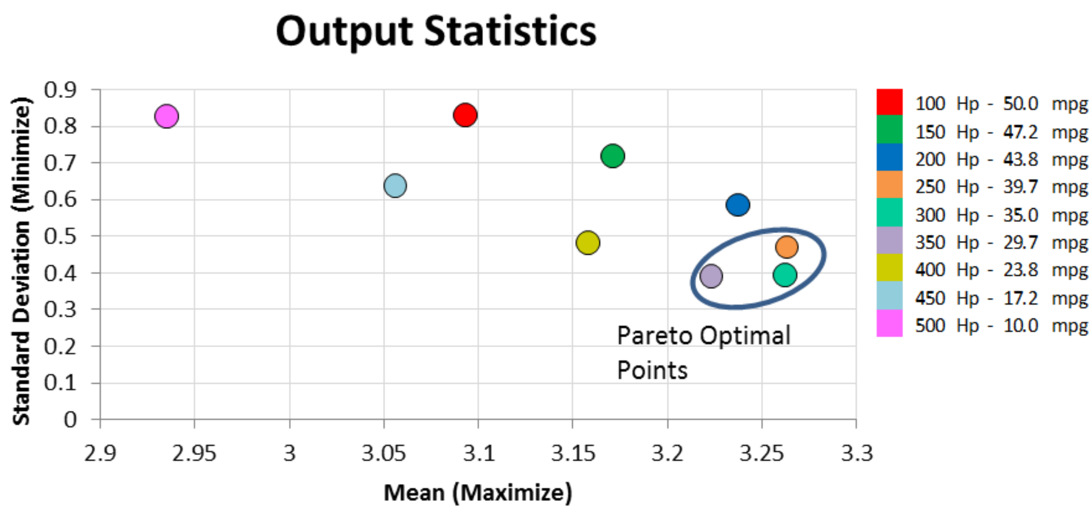


Figure 17: Standard Deviation and Mean of Concepts

Examining the results presented in Table 1 and plotted in Figure 17, the following can be observed: The 250 hp – 39.7 mpg concept has the highest mean of the NPV. The lowest standard deviation of NPV belongs to the 350 hp – 29.7 mpg concept. These two concepts bookend the 300 hp – 35 mpg concept, which has only a slightly lower mean and a slightly higher standard deviation than the aforementioned concepts. The eye test and examination of the output statistics would most likely lead to the selection of the 300 hp – 35 mpg concept. This selection is chosen because of its

3.2.2 Robust Design

Robust design is a paradigm where a concept with a low standard deviation and high mean is selected [92]. The traditional method for accomplishing robust design is performed using a set of experiments defined by an outer array for noise variables and an inner array for design variables as a means of obtaining the influence of the different variables. The experiments are mathematically selected to minimize the number of experiments required to understand the influences of variation across a range of each design and noise variable on the variation of the result. After completing the set of experimental runs identified in the arrays, a signal-to-noise ratio is calculated for the cases run. The formula for signal-to-noise ratio for a function in which maximal is desired is presented in Equation 7. This signal-to-noise ratio has been calculated using two commonly applied set of techniques. The first takes a sample set of data and uses it to calculate the signal-to-noise. The second uses extreme cases of the uncertain variables to calculate the signal-to-noise ratio. The extreme cases for the purposes of this example were a fuel price of 0.5 $/gal and a fuel price of 5 $/gal.

$$SignalToNoise = -10\log_{10}\frac{\sum_{i=1}^{n}\frac{1}{y^2}}{n} \tag{7}$$

Table 2: Taguchi Signal-to-Noise for Concepts

Concept	Random Sample	Extreme Cases (0.50 & 5.00 $/gal)
100 hp - 50 mpg	7.515	5.445
150 hp - 47.2 mpg	8.720	7.476
200 hp - 43.8 mpg	9.512	8.863
250 hp - 39.7 mpg	9.997	9.753
300 hp - 35 mpg	10.216	10.187
350 hp - 29.7 mpg	10.169	10.138
400 hp - 23.8 mpg	9.818	9.510
450 hp - 17.2 mpg	9.055	8.099
500 hp - 10 mpg	7.621	5.445

Table 2 shows the results of the signal-to-noise ratio for a random sample of 50 points and the extreme cases. This design paradigm would lead to the selection of the 300 hp – 35 mpg concept. [122]

3.2.3 MADM or MODM on Output Statistics

Application of Multi-Attribute Decision Making (MADM) techniques directly to the output statistics is a common and growing method for the selection of the best concept. The introduction of optimization methods such as Multi-Attribute Genetic Algorithms which operate directly on these parameters have led to growth for this technique. Application of these methods to this problem most often leads to the selection of the 300 hp – 35 mpg concept as well. This occurs because MADM techniques at their core are an objective function geared toward finding a compromise between several competing attributes, and unless extreme attributes weightings are used, these techniques will tend to select a middle-ground concept. Equation 8 shows an overall evaluation criterion (OEC), one of the simplest forms of MADM techniques. The OEC can be described as a weighted sum of a normalized set of dimensions. In this case, the 300 hp – 35 mpg baseline value has been chosen for ease of comparison. The OEC results are presented for a set of weightings in Table 3. It is important for the reader to note that the weightings varied across the table have not been varied linearly. The concept with the highest OEC value in Table 3 would be the one selected. From this table, it should be evident that the OEC selects the 300 hp – 35 mpg concept for over 50% of the preference values. This is compounded by the fact that the decision maker often chooses a weighting towards the center of the preference space.

$$Value = \gamma * \frac{\mu}{\mu_{Baseline}} + (1-\gamma) * \frac{\sigma_{Baseline}}{\sigma} \tag{8}$$

Table 3: Concept OEC Value for Differing Preferences

Preference for High Mean (γ)	**1**	**0.95**	**0.75**	**0.5**	**0.25**	**0.05**	**0**
Preference for Low Standard Deviation ($1-\gamma$)	**0**	**0.05**	**0.25**	**0.5**	**0.75**	**0.95**	**1**
100 hp - 50 mpg	0.473	0.497	0.592	0.711	0.829	0.924	0.948
150 hp - 47.2 mpg	0.547	0.568	0.653	0.759	0.866	0.951	0.972
200 hp - 43.8 mpg	0.672	0.688	0.752	0.832	0.912	0.976	0.992
250 hp - 39.7 mpg	0.835	0.844	0.877	0.918	0.959	0.992	1.000
300 hp - 35 mpg	1	1	1	1	1	1	1
350 hp - 29.7 mpg	1.004	1.003	1.000	0.996	0.992	0.989	0.988
400 hp - 23.8 mpg	0.815	0.822	0.853	0.891	0.930	0.960	0.968
450 hp - 17.2 mpg	0.617	0.633	0.697	0.777	0.857	0.921	0.937
500 hp - 10 mpg	0.475	0.496	0.581	0.687	0.794	0.879	0.900

MADM techniques allow for a preference among the attributes of interest. In this case, those attributes are a reduction in standard deviation and an increase in mean. Essentially, the MADM techniques provide a mathematically rigorous method of performing the same set of logical analysis presented in the “eye test”. However, an overwhelming preference for a decision based on either the mean or the standard deviation leads to some of these MADM techniques selecting either a 250 hp – 39.7 mpg or the 350 hp – 29.7 mpg concept because they also exhibit Pareto optimality. However, in most cases the application of MADM techniques leads to the selection of the 300 hp – 35 mpg concept.

3.2.4 Joint Probabilistic Decision Making

An alternative decision-making method has been proposed by Bandte et. al. [11] and is specifically designed for decision-making under uncertainty in conceptual design.]. His method, called joint probabilistic decision-making, provides slightly different results. His method takes in a “criterion value” or target value and selects the concept with the highest probability of meeting that target value [9]. For a situation such as this one, where the value can be quantified in a single dimension, this is the equivalent of finding the lowest curve on the CDF plot at a specific criterion value. The Joint Probabilistic Decision Making (JPDM) selection is consequently dependent on the criterion value. For criterion values greater than ~3.7 the best choice is the 100 hp – 50 mpg concept. For criterion values less than ~3.7, the majority of the probability weighted space, this method matches the MADM methods in selecting the 300 hp – 35 mpg concept. The reader can observe this directly in Figure 18.

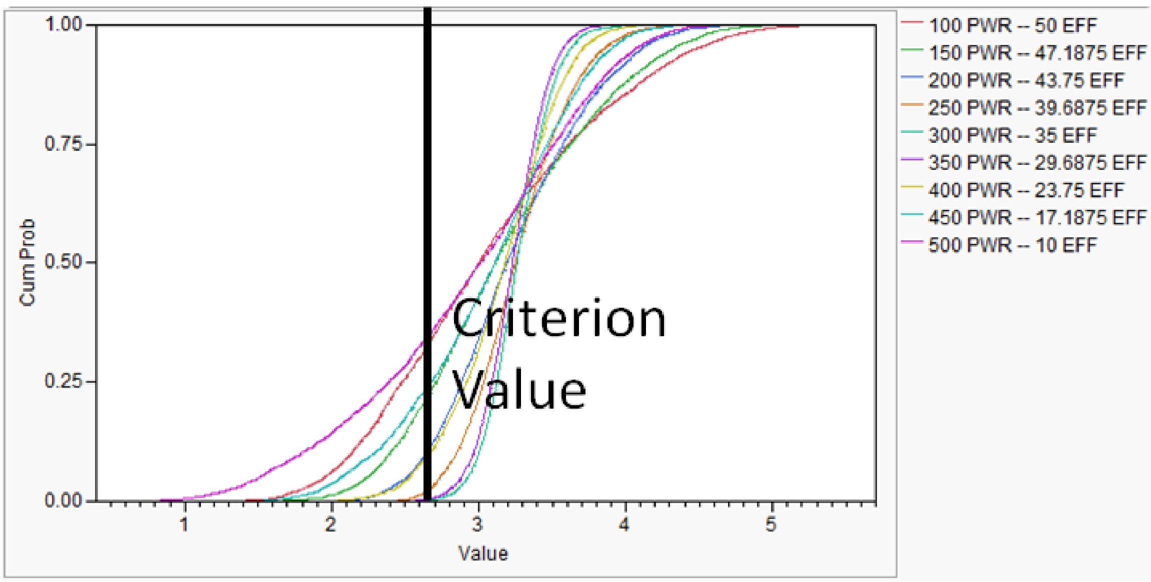


Figure 18: JPDM Example

3.3 Failure of Decision Making Processes Found in Literature

Recall that the purpose of the conceptual design phase is to select a single concept for refinement in future stages of design. The goal was to select the concept that returns the highest likelihood of being the most successful in the future market. Using the example problem, and implementing the conservative assumption that all of the uncertainties were characterized perfectly, it is possible to test which of the concepts was actually realized as the best concept across a range of scenarios. The testing procedure begins by performing a Monte Carlo simulation where 5000 random points were drawn from the distribution for fuel price. This fuel price represents the future "real" fuel price that occurs during production of the vehicle. Next, for each of the nine concepts, a Monte Carlo simulation was performed on the technical uncertainties around power and efficiency to create a set of "realized" designs. Each selection from the distribution represents one possibility of the actual performance of the concept at the end of design. Once this analysis was done for each scenario and each of the nine realized designed, the question was asked, "Which of the concepts would have been the best choice across this range of future scenarios?" The best choice is defined as the concept with the highest NPV for that scenario. Figure 19 presented below shows the results of this analysis. Across the horizontal axis is the percentage of fuel price scenarios for which a particular concept was the best choice. The vertical axis shows each of the concepts. From this plot it becomes evident that the concepts selected by the existing techniques found in literature (i.e. 300 hp – 35 mpg, 350 hp – 29.7 mpg or 250 hp – 39.7 mpg) are realized as the best concept the lowest percentage of the time. If the goal in conceptual design is to select the best design to meet the future market requirements, then the techniques outlined in literature actually chose the design with the lowest likelihood of matching market requirements, as reflected through NPV in this example. The next set of sections will detail why this result has occurred.

Figure 19: Likelihood of Each Concept Being Realized as the Best Concept

3.3.1 Effects of Changes in Distribution

The previous example showed the likelihood of success with the uncertainties modeled using the distributions described in Section 3.1.1. However, the shapes and parameters of these distributions can be difficult to estimate. The next section shows the effects of changes in the shape and parameters that define the distributions.

Figure 20 through 23 the effect of changes in distribution on the likelihood a particular concept ends up being the best design. Each of the figures consists of three separate charts. The two on the left represent the model and the input distribution. The top figure on the left shows the NPV of each of the nine concepts plotted against the input fuel price scenario. The bottom figure on the left half of Figure 20 through 23 show the distribution of fuel prices used as an input to the Monte Carlo simulation. This bottom figure has been aligned with the top figure so that the fuel price axis is identical for the top figure and the bottom figure. This allows relationship between the input distribution and performance can be directly observed. A Monte Carlo sample of 10,000 random fuel prices is selected from the green distribution shown in the bottom left part of Figure 20. For each of these the model is evaluated using the model in the top half of Figure 20 to determine the concept with the highest NPV. The percentage of times a particular concept had the highest NPV was recorded for all 10,000 cases and this information is plotted as a histogram on the right half of Figure 20 through 23.

Figure 20 through 23 show the effects of changes in the breadth of the distribution. To demonstrate this, the uncertainty was modeled as a simple normal distribution and the standard deviation was varied. The information about the parameters for the input distribution are shown below the green distribution on the bottom left part of Figure 20 through 23. In Figure 20 the standard deviation was set to 0.20 $/gal with a mean of 2.75 $/gal. This represents a very narrow change in the fuel price over the development and operational time frame. In Figure 20 it can be observed that the outputs for this input distribution shown that the robust design has the highest likelihood of being realized as the best design when the width of the distribution is narrow and distributed around the mean of 2.75 $/gal. This is the result of the fact that the robust design had the highest performance at the mean fuel price of 2.75 $/gal. However, as a significant proportion of the potential fuel prices shift away from the mean, the distribution begins of output likelihoods begins to resemble those shown in Figure 19. Figure 21 through 23 shows this transition with the standard deviation for each of the input distributions being 0.40 $/gal, 0.60 $/gal and 0.80 $/gal respectively. It can be observed from these figures that the likelihood of the robust design being realized as the best design choice reduces in value as the distribution spreads out. Furthermore, the extreme designs, those with very high efficiency or horse power, perform significantly better as the distribution of fuel price has a higher likelihood of producing a value farther from the mean.

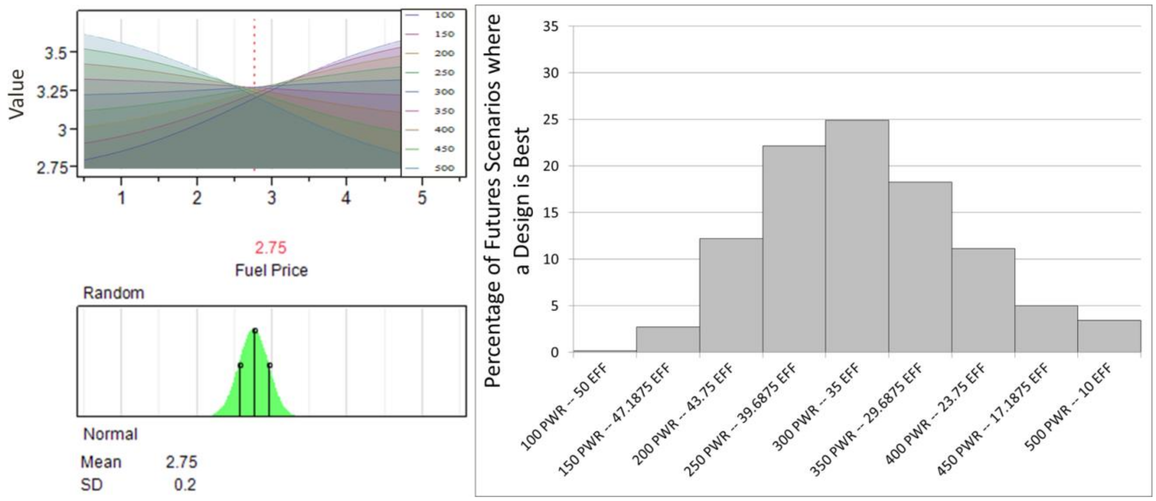


Figure 20: Best Concept Likelihoods for a Normally Distributed Variable (μ = 2.75, σ = .2)

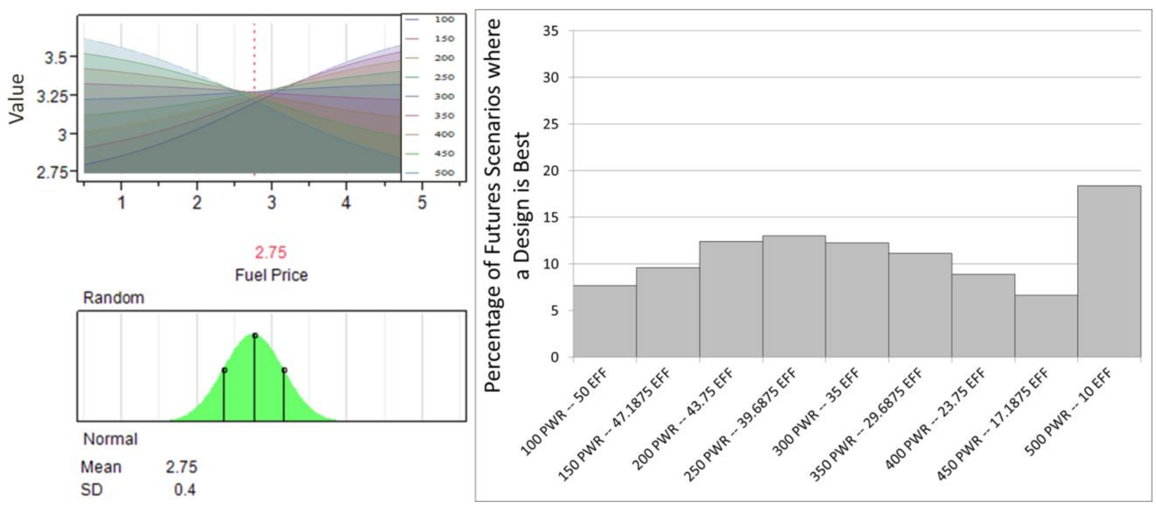


Figure 21: Best Concept Likelihoods for a Normally Distributed Variable (μ = 2.75, σ = .4)

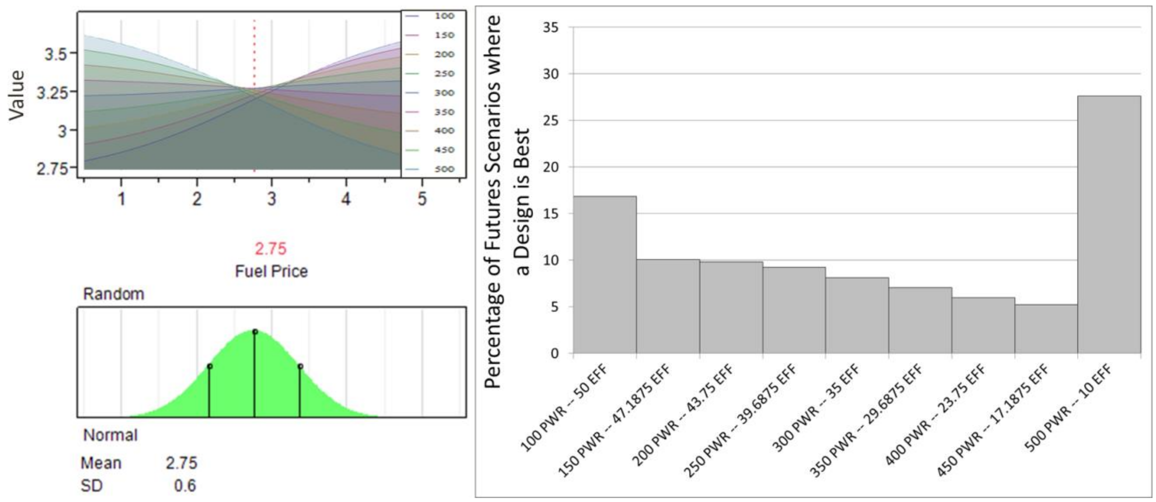


Figure 22: Best Concept Likelihoods for a Normally Distributed Variable (μ = 2.75, σ = .6)

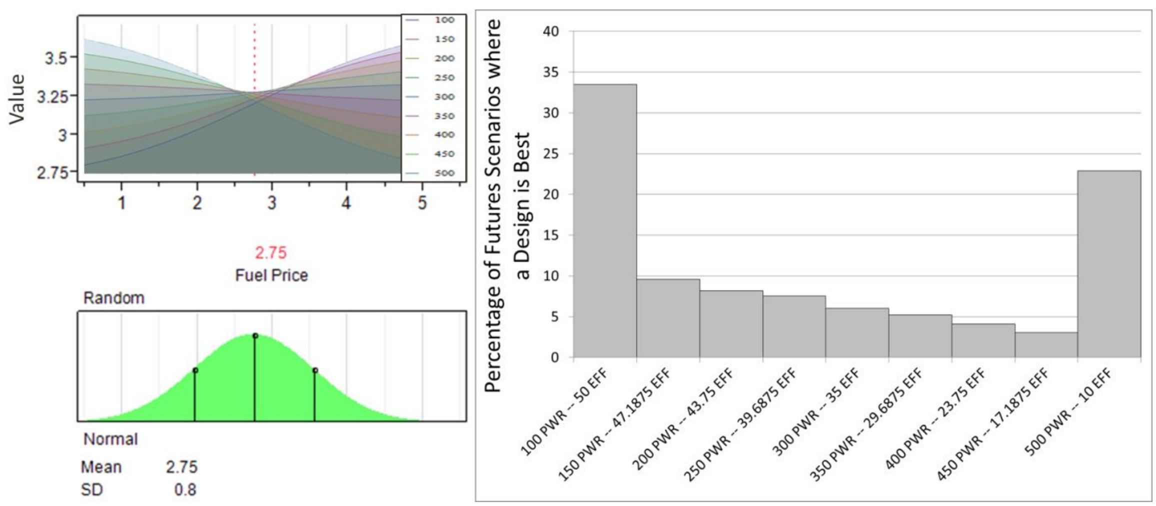


Figure 23: Best Concept Likelihoods for a Normally Distributed Variable (μ = 2.75, σ = .8)

Figure 20 through Figure 23 present the effects of an increase in standard deviation in the normal distribution on the likelihood that any particular design was realized as the best design. From these figures it can be observed that an increase in the breadth of the distribution leads to the robust design performing more poorly and the extreme designs on the edge of the design space performing better. This is a result of the structure of the design space itself. In particular a strong interaction existed between the preference for a particular design and the scenario. A detailed discussion of how the structure of the design space shapes the behavior is presented in Section 3.9.

Figure 24, shown below shows the same Monte Carlo analysis described in the preceding paragraphs applied for a uniform distribution with a range from 0.50 $/gal to 5.5 $/gal. More of the probability mass is shifted outward as compared to a normal distribution and as a result, the uniform distribution shows the extreme designs as by far and away the best choices if the desire is to maximize the chances of having a design that matches the scenario well.

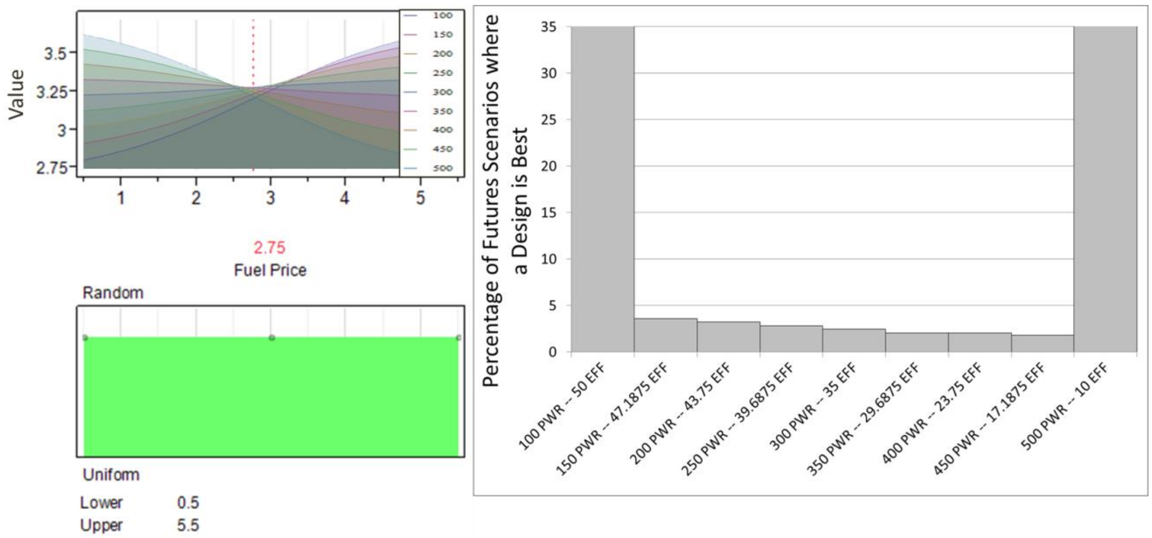


Figure 24: Best Concept Likelihoods for a Uniform Distributed Variable (Range = [.5, 5.5])

Figure 25, shown below shows the Monte Carlo analysis performed for a Cauchy distribution with a mode of 2.75 $/gal and a scale factor of .5 $/gal. The Cauchy distribution has both a strong centrally weighted behavior as well as heavily weighted tails. This results is a set of output likelihoods for each of the concepts which has both the improved performance for the robust design as well as a strong preference for the extreme designs to account for the heavily weighted tails.

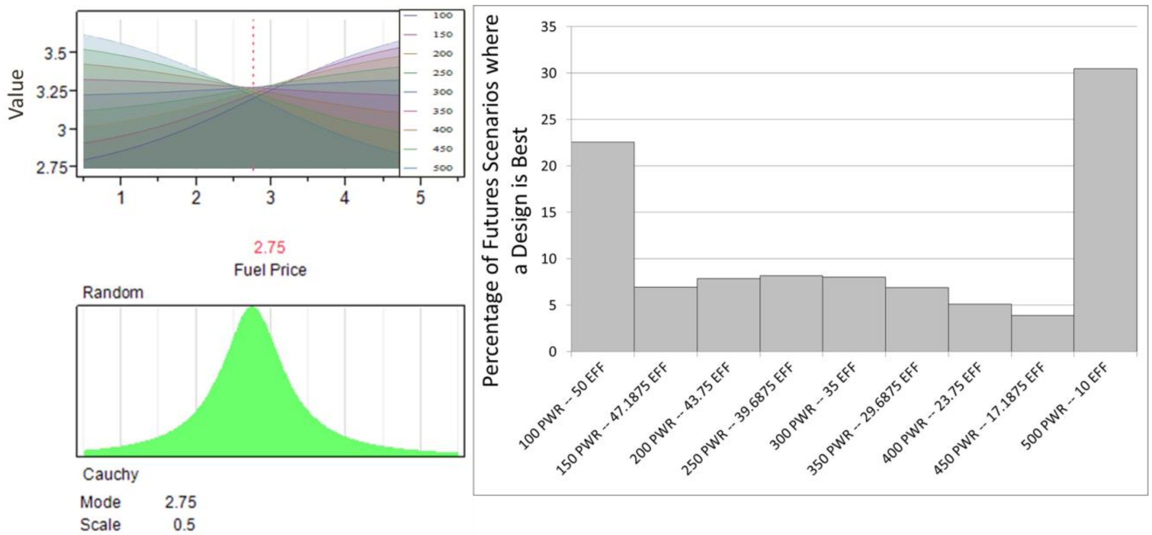


Figure 25: Best Concept Likelihoods for a Cauchy Distributed Variable (x_0 = 2.75, γ = .5)

3.4 Characterizing Problem Conclusions

The characterizing problem demonstrates a deficiency in the literature-based techniques by demonstrating that the design decisions made using the literature-based techniques led to selection of the design concepts that had the lowest probability of having the highest return. This deficiency occurs because the literature-based techniques focus on improving the aggregate statistical measures rather than the design outcomes. These techniques operate under the assumption that the aggregate statistical measures are a valid surrogate for a prediction of the design outcomes; however, it can be shown that in many situations this is not the case. The equivalence of aggregate statistical measures and design outcomes relies on an implicit assumption that the concepts are independent, which can be shown to often be an invalid assumption. When concepts are dependent, it can further be shown that the presence of a Pareto frontier will cause the literature-based techniques to select a design concept with a low probability of having the highest return. Hypothesis 1 offers a set of criteria for determining when improving design aggregate statistical measures will differ from improving design outcomes. The following sections will support the above claims and use the motivating problem to demonstrate why these are true. Once it has been shown that literature based methods are deficient, this thesis will explore the relationship between scenario-based uncertainty and experimental uncertainty and how this impacts the success of design concept selection.

3.4.1 Identification of scenario effects

In the example presented in Section 3.1.1, there was a clear relationship between the external scenario based uncertainty, fuel price, and the preference for the conflicting design traits fuel efficiency and horsepower. A strong preference existed for higher fuel efficiency when fuel price was low. However, it is very difficult, if not impossible, to discern these cause and effect type relationships using a Monte Carlo analysis approach. By definition, the Monte Carlo analysis takes in all potential uncertainties on input variables, and runs this randomly selected subset of scenarios. These uncertain outputs are used to find the total uncertainty distribution on the output. From this output distribution, it can be difficult to determine how the variability of any individual input variable by itself affects the variability of the output. This makes it difficult to understand the impact of the scenario uncertainty on the overall concept performance.

Similar difficulties arise when applying other literature-based techniques. These techniques often begin with the Monte Carlo analysis, and provide differing methods for operating on the resultant output distribution. The alternative concepts are then compared and a decision is made on the metrics specified by the robust design technique. All of the techniques including the baseline literature technique make a common assumption that the concept alternatives are independent. The following figure presented in Figure 26 is intended to present evidence that scenario based uncertainties can interact with the concept's desirability and violate the independence assumption.

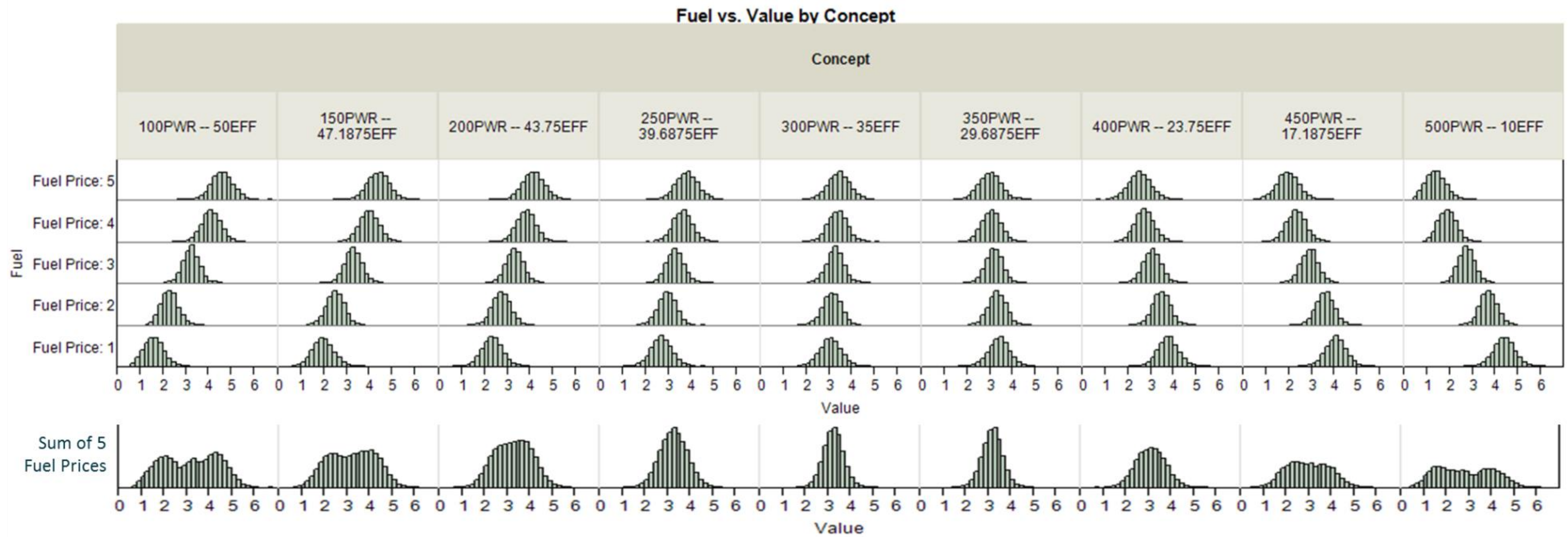


Figure 26: PDFs for Each Concept for Five Separate Fuel Prices

The relationship between scenario and concept leads to a violation of the independence of the concepts that was implicitly assumed by literature based techniques and the following discussion is intended to provide evidence of this fact. Figure 26 shows the distribution of value for each of the nine concepts and for each of five fuel price scenarios in the top set of charts. In this example, the fuel price was varied across five settings, shown vertically. This process was then repeated for each of the concepts. An individual Monte Carlo simulation was run for each of these fuel price settings for each of the concepts, creating a matrix of histograms where the row represents fuel price and the column represents the concept. This matrix provides the decision-maker an easy means of viewing the impact of changing uncertainty. Examining the matrix of plots vertically shows how each of the concepts changes with scenario. Examining Figure 26, the decision-maker can quickly see that the low-power high-efficiency concepts provide a much higher value when fuel prices are low and a much lower value when fuel prices are high. The opposite is true for the high-power low efficiency engines. Furthermore, it can be seen that the engine concepts with middling power and efficiency maintain a relatively constant net present value for all scenarios of fuel price. However, it is also evident that the robust design is outperformed by one of the more extreme concepts for most fuel price scenarios. This information was difficult to gather from the original set of histograms presented in Figure 15, but can be easily seen in Figure 26. The relationship between the concept's performance, which was driven by the uncertain variable, leads to a violation of the independence assumption.

To further illustrate this point, Figure 27shows a plot of the value of the two most extreme concepts. The technical uncertainties have been completely removed in the creation of Figure 27 to allow the reader a clear understanding of how the fuel price drives a failure of the independence of the concepts. The bottom axis of Figure 27 shows the fuel price. Across the bottom of Figure 27, the PDF for fuel price is shown in green. The vertical axis represents NPV. Five thousand random samples have been drawn from the distribution of fuel prices, and the NPV of the two extreme concepts has been calculated for each of these five thousand samples. These results are plotted as the points in Figure 27, with the points color-coded by which concept's value they represent. The red points are the NPV of the high power and low efficiency concept, and the blue points are the NPV of the low power high efficiency concept. From this depiction the relationship between concept and fuel price should be clear. As the efficient concept's value increases with an increase in fuel price, the high power concept's value decreases.

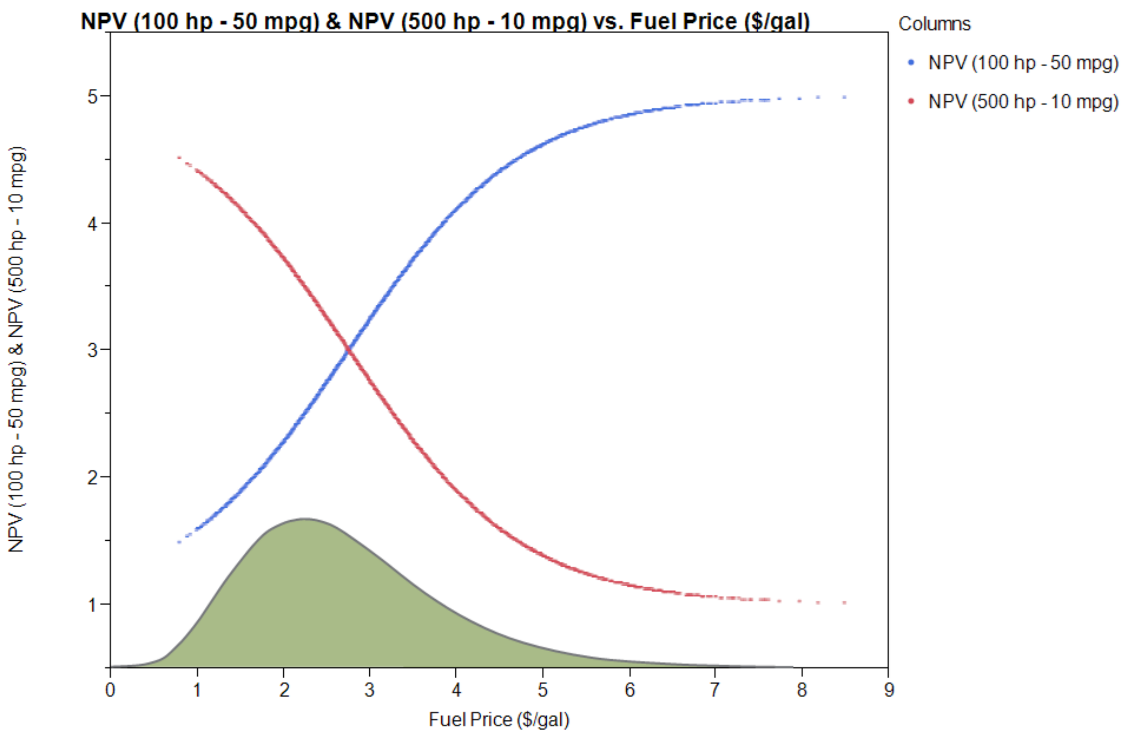


Figure 27: Performance of 100 hp - 50 mpg and 500 hp - 10 mpg Concept vs. Fuel Price

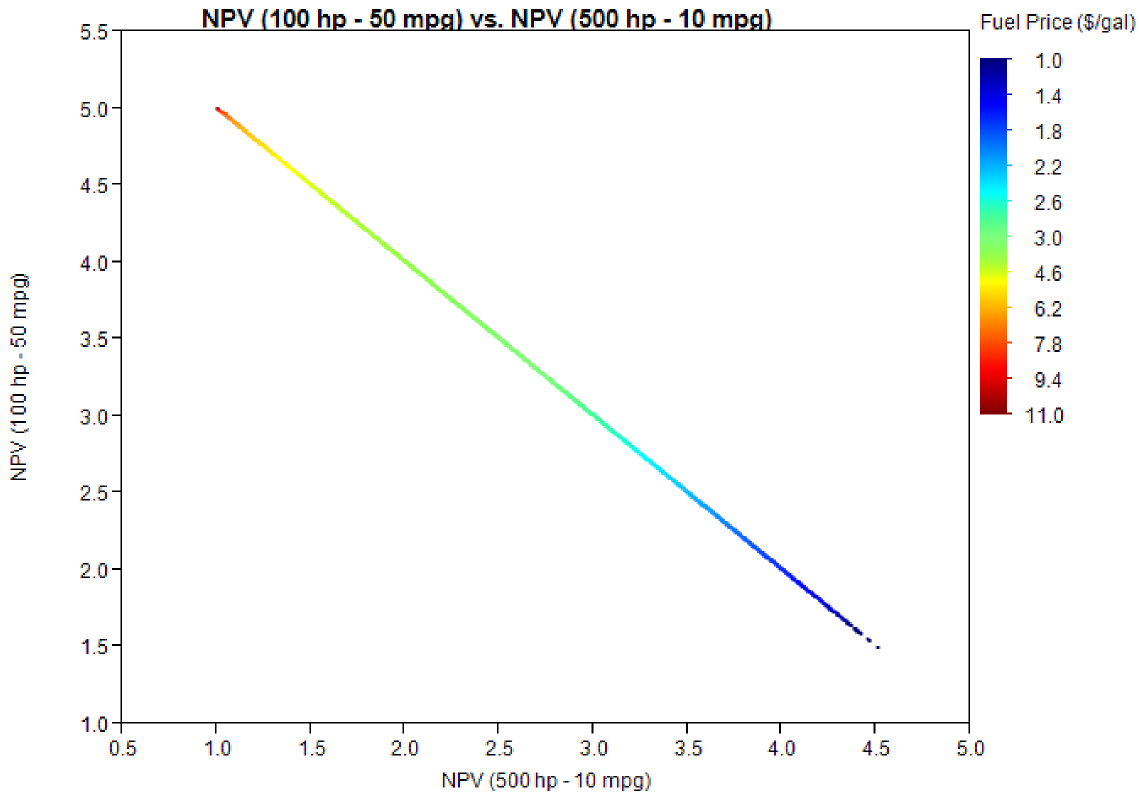


Figure 28: NPV of 500 hp - 10 mpg vs. NPV of 100hp - 50 mpg

To demonstrate the lack of independence of the concepts directly, the NPV of each of the concepts have been plotted against each other in Figure 28. This is the typical way of visually showing a relationship between two variables. The NPV of the high power concept is shown across the bottom axis, and the NPV of the high efficiency concept is shown across the vertical axis. A third variable is rarely depicted when showing a relationship between two variables, but in this case the fuel price has been shown by color-coding the points based on the underlying fuel price. From this depiction it should be evident that changes in fuel price lead to a violation of the independence assumption. For this example, the extreme concepts have a perfectly linear inverse relationship. In statistical terms, this amounts to a perfectly negative correlation, and a complete lack of independence.

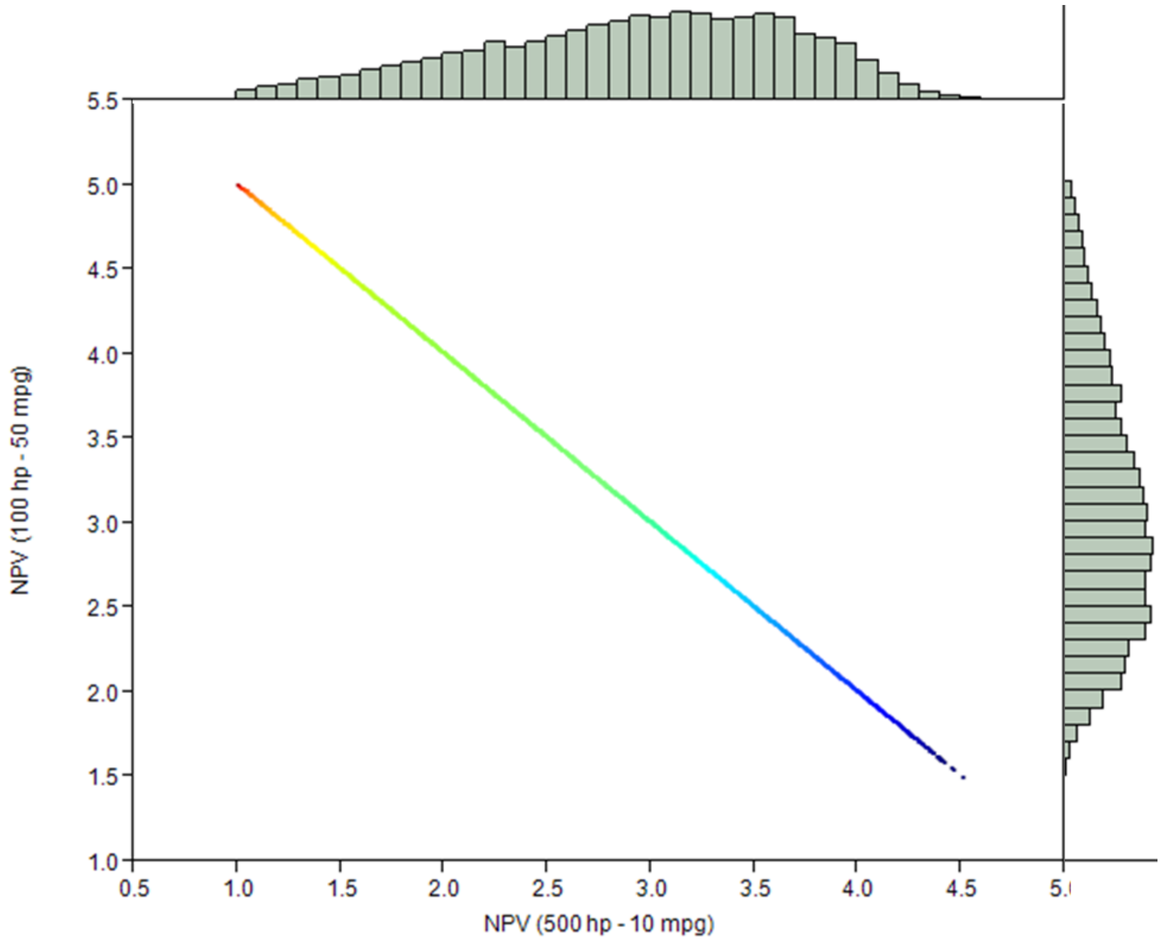


Figure 29: NPV of Two Concepts with Marginal Distributions

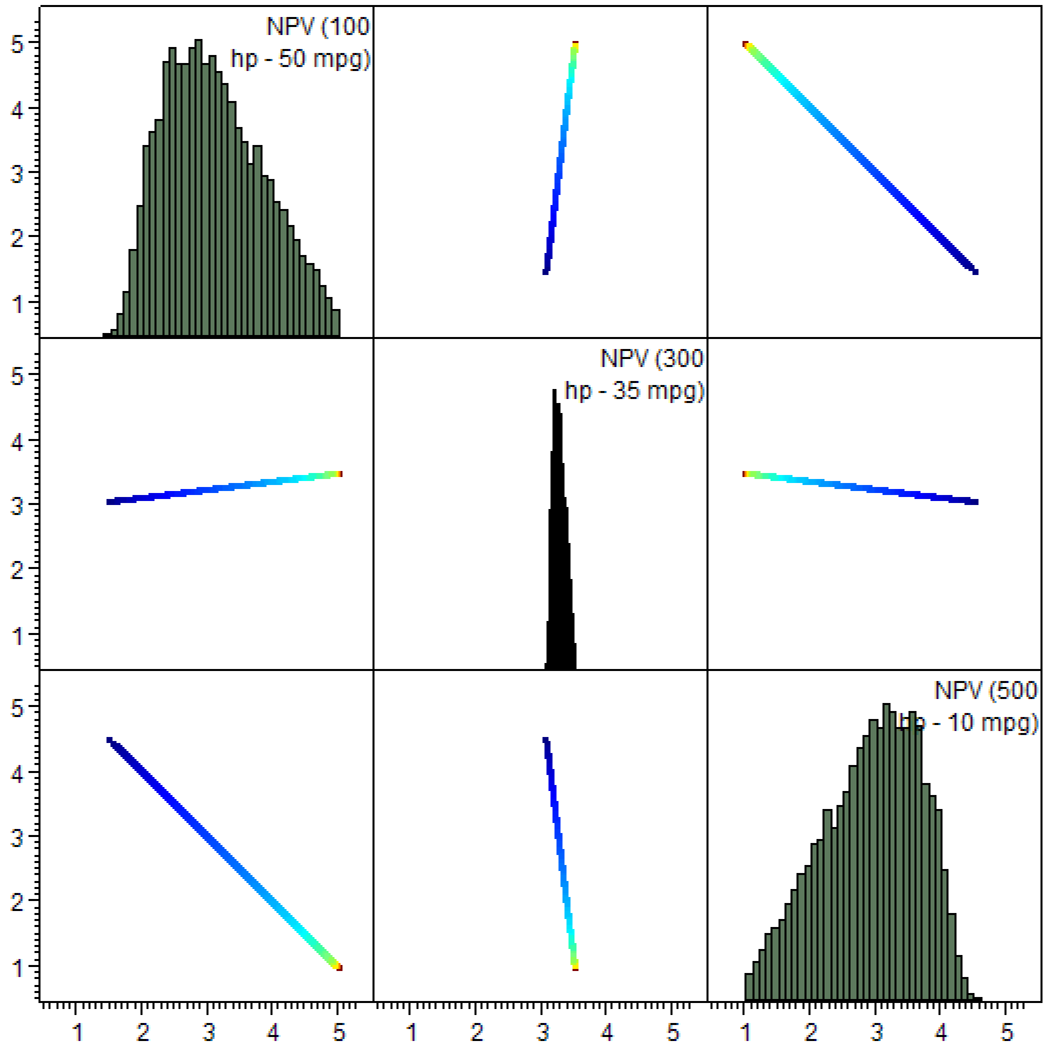


Figure 30: NPV of Three Concepts with Marginal Distributions

Figure 29 shows the plot of NPV with the marginal distributions of each of the concepts plotted along the vertical and horizontal axis. These marginal distributions are exactly the same as the distributions shown in Figure 15. From this final plot it is evident that the decision-making methods found in the literature operate on the marginal distributions for the design. These distributions are only mathematically valid if no relationship between the concepts exists. For many design situations with a common underlying uncertainty, this may not be true. However, a violation of the underlying mathematics may not necessarily lead to a failure in the robust design decision. For some situations in design, the robust design paradigm may mathematically misrepresent the design space, but not necessarily lead to an incorrect decision. The following sections will examine the role of the impact of reducing different types of uncertainties, and describe a set of mathematical examples to provide an intuitive understanding of the failure mode from the perspective of design.

3.5 Scenario Based Uncertainty vs. Experimental Uncertainty

The characterizing problem had two sets of uncertainties: the external uncertainty fuel price and technical uncertainty. These uncertainties were treated as scenario-based uncertainties, as they were considered to be resolved by which scenario occurred after the concept decision had been made. However, the technical uncertainties around the accuracy of the predication for future power and efficiency could potentially be reduced through the addition of better modeling, or more tests, or some other method prior to the concept decision. This would transition these uncertainties from the scenario to the experimental, and the next section will explore a direct comparison between reducing these uncertainties as experimental uncertainties vs. providing a better means of handling the scenario-based uncertainties. The following section is presented to provide justification for a focus on the scenario uncertainties rather than the experimental uncertainties.

3.5.1 Reduction in the Experimental Uncertainty

Because of the difficulty in design decision-making under uncertainty, a number of literature references have focused on means and methods for quantifying and reducing the uncertainty at the conceptual design phase [1, 31, 39, 7]. These typically involve the use of techniques and methods that allow information about future spirals to be brought into the current design phase without disrupting the sequencing of the design process. In terms of the uncertainty classification offered by this thesis, these techniques amount to a reduction in the experimental uncertainty. This thesis recognizes the value in doing so, but offers the following example for the justification of the focus on scenario-based uncertainties, rather than on the improvement in the information available at the current stage of design. The example will begin with a description of the uncertainties for the automobile problem and then proceed to a simple study in the reduction of the technical uncertainties through more experimentation.

The uncertainty represented in the fuel prices is beyond the design organization’s control. Better quantification of fuel price uncertainty can be done, but the uncertainty itself cannot be reduced. To state this differently, the model input distribution for fuel price can be made to more closely match the distribution that can be expected in the future, but the distribution’s shape cannot be changed, and the distribution’s variance cannot be reduced. The value each concept produces is highly dependent on this uncertainty. This uncertainty is classified as scenario-uncertainty and cannot be reduced.

In the automotive manufacture example, two of the uncertainties are within the organization's control. The uncertainty surrounding the technical parameters fuel efficiency and horsepower may be reduced through better modeling, testing or any other means of gaining information prior to the concept decision. This thesis recognizes the value in methods that reduce these biases and errors, and instead focuses on techniques for handling the fact that some of this error will remain. The element that remains is considered scenario uncertainty. The remainder of this section will focus on studying the impact of improving the information available at the current phase of design, thus reducing the amount of experimental uncertainty that remains as scenario uncertainty.

As a means of studying the effects of reduced technical uncertainty versus the effect of improving the decision process concerning scenario uncertainty the following study is offered. The variance of the distributions surrounding the concept power and efficiency at the decision of which concept to select will be reduced, and the effect on design outcome will be recorded.

To examine the impact of reducing technical uncertainty on the ability to mitigate risk and make correct design decisions, a study was done with the following assumptions.

- First, the external uncertainty fuel price is perfectly modeled but cannot be reduced. As a means of creating a highly conservative example, the fuel price input distribution will be assumed to be a perfect model of future fuel prices. This assumption is made to ensure the results are conservative.
- Second, the error in fuel efficiency and power that is predicted prior to the conceptual design decision is distributed about the true mean of the final realized value. Again, this is a highly conservative assumption corresponding to no bias in modeling or design.

For this study, the standard deviation of the technical noise factors has been reduced from 10% down to 2% with the mean perfectly distributed around final realized mean. The Monte Carlo analysis has been repeated, and the effect on the ability to mitigate risk and make informed decisions is examined. The results of this analysis are shown in Figure 31 below.

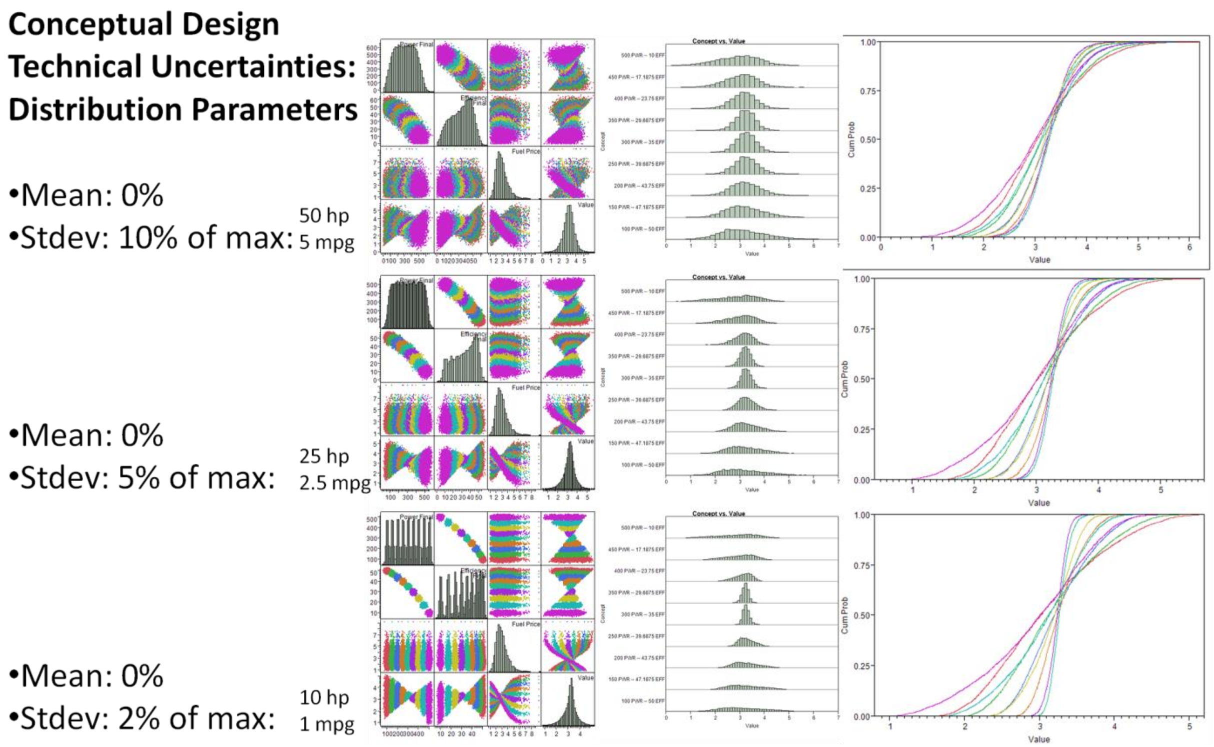


Figure 31: Effects of Reducing Technical Uncertainties

Examining the results of this study, the reader can see that reducing the technical uncertainties has the following effects: clarification of the location of the Pareto frontier, shrinking of the standard deviations of the output NPV distributions, and separating the CDF's. However, none of these effects provides clarity as to which decision is the best.

If the decision-making exercise is repeated, very little changes as to which concept is selected. Decisions based on the statistics alone lead to an identical set of decisions. The Joint Probabilistic Decision Making JPDM method selects an identical set of concepts as before with the exception of a very small range of criterion values around 3.2.

If we then returned to the study comparing the selected concepts and repeat the exercise comparing those selecting concepts' likelihood of being the correct selection once the design has been realized, we see the performance of the most selected concept (300 hp – 35 mpg) has in fact decreased. Figure 32 shows the percentage of times each particular concept ended up being realized as the best concept with the differing technical uncertainties shown in different colors.

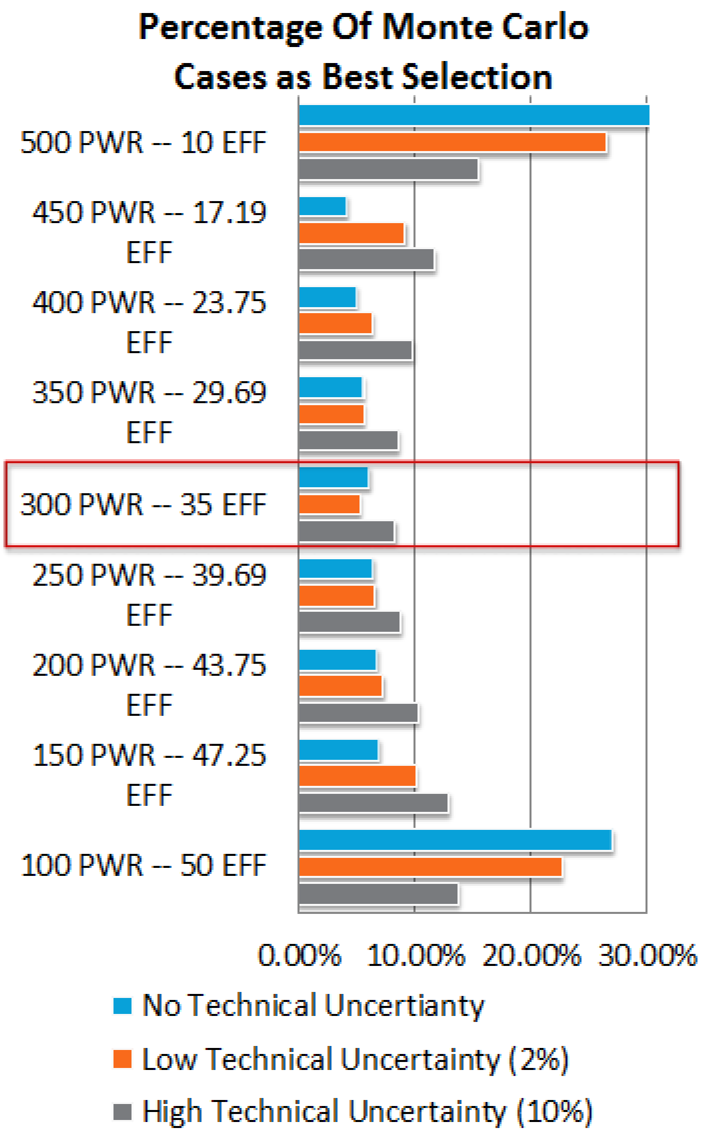


Figure 32: Effect of a Reduction in Technical Uncertainty on the Likelihood of Realization as the Best Concept

Examining this figure, two significant trends are apparent. First, the most often selected concept, the 300 hp – 35 mpg concept is one of the least likely to be realized as the best concept. Second, the reduction in the technical uncertainty actually leads to a less likely chance that the 300 hp – 35 mpg concept selected ends up being realized as the best concept. This is significant because it shows the decision process was so flawed that reducing technical uncertainty in the design process simply reduces the chance of happy accidents. Essentially, the reduction in technical uncertainty means that despite making the wrong decision, the likelihood that the realized concept was the correct one anyway has been reduced. As a result, one should first improve the decision-making process before focusing on the quality of information available at a particular stage of design.

3.6 Scope of this thesis

This thesis will focus on the effects of scenario-based uncertainty and what can be done to mitigate that uncertainty given that scenario-based uncertainties can be modeled with some accuracy. The thesis will not focus on the modeling itself, as that has been addressed in numerous works within literature [43, 120, 23]. It will be assumed that best practices in modeling both the scenario-based uncertainties and experimental uncertainties are being performed.

3.7 Summary of Results

The conclusion of this study is that current decision-making techniques under uncertainty fail to adequately provide a good decision. The approach of reducing the technical uncertainty and quantifying the external uncertainties does not necessarily provide a means for informed conceptual decision-making under uncertainty. Furthermore, it does not provide a means for risk mitigation given that the external uncertainties cannot be reduced.

The argument presented in Section 2.1 about how to define a good decision provides a measure by which we can describe the inefficiencies in the modeling and decision-making shown in the previously presented example. In this case, outcome success was measured as selecting the best concept relative to the other concepts. Decision “goodness” is then measured as selecting the concept with the highest possible likelihood of outcome success. It is only through this distinction that one is able specify the deficiency in the previously presented model and decision-making process. The example decision-making process selected the 300 hp – 35 mpg concept. This concept in fact had the lowest percentage of achieving an outcome success as defined by the measures stated. As a result, this could be considered a poor decision.

Each of the methods described above fail meet the definition of a good decision by discarding the information available about the relationship between the concepts and scenario. Each of the methods in literature uses statistical aggregate measures of outcome that can mask the relationships between the concepts. This can lead to the failure mode presented above.

3.8 Observations

The previous example demonstrated a particular set of problems decision-makers face when making decisions where scenario-based uncertainties have a significant impact on the value alternatives provide. In certain engineering situations:

- The most commonly applied means of uncertainty quantification, Monte Carlo analysis [32], combined with traditional means of conceptual design decision-making, can have poor performance.
- Technical uncertainty reduction cannot provide enough clarity relative to impact of external uncertainties to ensure the best decision is made.
- Technical uncertainty reduction does not provide adequate means to mitigate risk.

These problems are a result of the fact that the decision's quality may be driven by forces beyond the decision-maker's control. In the above example, the fuel price heavily influenced the relative value of the concepts along the Pareto frontier. To succinctly describe this phenomenon, this thesis will refer to a region of the design space where irreducible uncertainty drives the preference along the Pareto frontier as a "region of uncertainty driven preference".

It is not enough to simply recognize and name the problem. It is also important that the region of uncertainty-driven preference be described mathematically and bounded. This mathematical definition must then be extended to a practical description. Only after providing a formal definition of the region where uncertainty drives decision making can an approach to mitigating its negative effects be developed. This statement leads to the first research question.

Research question 1: *Can a definition be provided for the region of uncertainty-driven preference?*

3.8.1 Hypothesis 1

Examining the characteristics of the model shown in the previous section, the question arises, can a set of generalized characteristics be hypothesized that would define the regions of uncertainty driven preference?

It is hypothesized that if the following three conditions are met, there is a high likelihood that uncertainty-driven preference will occur.

1. A tradeoff must be made between desirable traits (Pareto frontier exists)

   Using the previous example as a demonstration, one can see that both fuel efficiency and horsepower were desirable traits should everything else be kept constant. However, the achievement of both of these traits simultaneously is limited by technical considerations. This information is shown in Figure 33 for reference.

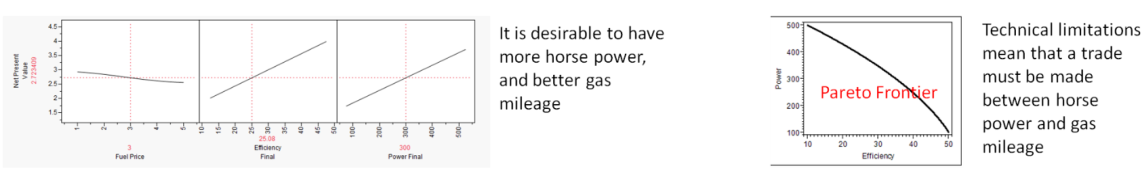


Figure 33: Depiction of the Interaction between Engineering Traits and Value in the Vehicle Problem

2. Preference for the desired traits may be uncertain, but is driven by scenario ("Best" location along the Pareto frontier is driven by scenario uncertainties)

Returning to the automobile manufacturer example, one can observe from Figure 34 that changing fuel price changes which point is most desirable. This related to the fact that better fuel efficiency is desired more than power when fuel is expensive. In general this trade between desirable outcomes is in a way that is most beneficial given a particular scenario. Because the future scenario is uncertain, the preference is uncertain. Figure 34 illustrates this principal visually for the example problem.

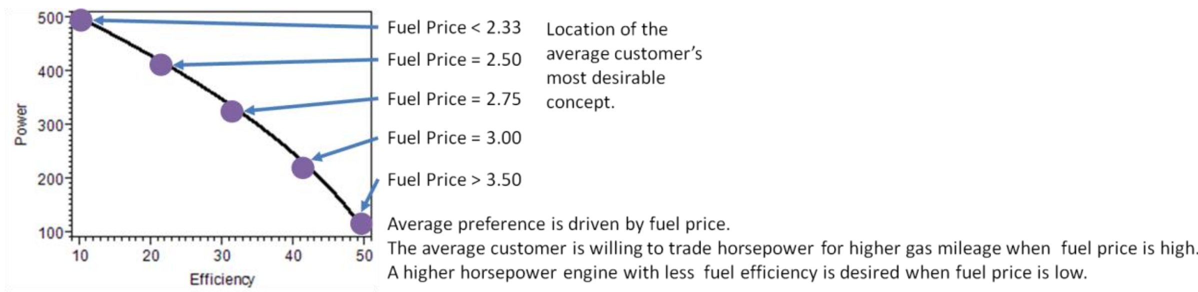


Figure 34: The Effect of Fuel Price on the Best Design Concept's Location along the Pareto Frontier

3. The best design is sensitive to changes in the uncertainties.

Returning to Figure 34, it can be observed that changes in the fuel price lead to a drastic change in which concept is the best. The best design moves across the entire design space dependent on which future fuel price is realized.

3.9 Testing Hypothesis 1

3.9.1 Simplified Mathematical Examples

In this section, the causes of the behavior demonstrated by the example problem will be examined in detail. This section takes a mathematical approach to understanding how the counterintuitive results presented in Figure 32 occur. This approach will use of a series of examples leading to a set of mathematical formulas. The approach has been chosen to provide the greatest amount of accessibility to the reader.

To begin to describe the underlying behavior that leads to the counterintuitive results presented in Figure 19, this thesis presents the simplest possible example. Figure 35 shows the most basic possible design space that includes both a design performance variable, as well as an uncertainty variable. Along the vertical axis the uncertainty variable γ is shown. Along the horizontal axis the design performance variable *A* is shown. In this case the assumption will be that the desire is to maximize the performance *A*. Three concepts are shown within this space. Each of the concepts has a specific performance in the dimension *A*. If the entire design space consisted of these two variables, it would make sense that the designer would most likely choose the concept numbered three because concept three has the greatest performance in dimension *A*.

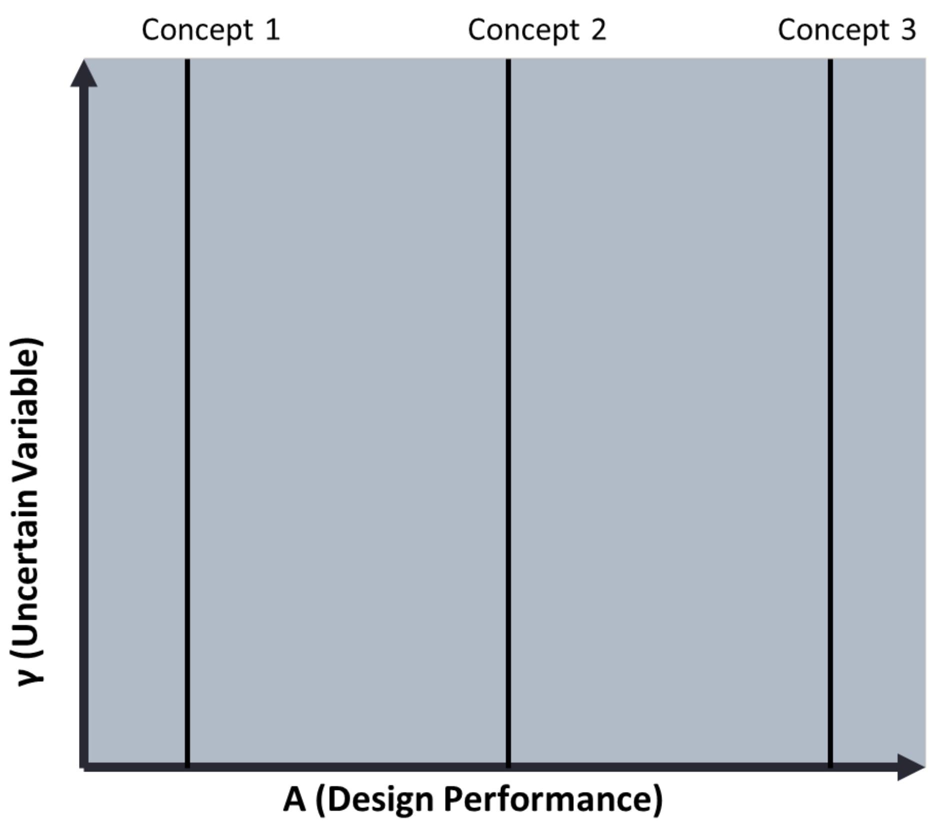


Figure 35: Simplest Design Space

The introduction of the second design performance variable *B* leads to a more realistic multi-attribute design space. The two performance variables, *A* and *B*, are linked through the simplest possible Pareto frontier. In this case, there is a simple inverse linear relationship between design variable *A* and design variable *B*. The Pareto front is plotted in Figure 36 and the equation is listed in Equation 11. Returning to the design space, it is no longer clear which concept is the best. The decision now depends on the relative value of performance in dimension *A* versus the performance in dimension *B*. To demonstrate the causes of the effects presented in Figure 19, we will introduce an interaction between the uncertain variable γ and the desired performance in dimensions *A* and *B*. Using the vehicle example again, *A* could be horsepower and *B* could be efficiency. As fuel price goes up, efficiency will be more desired relative to horsepower. In terms of our variables γ, *A* and *B*, this means that when γ is small, concept three with high performance in *A* and low performance in *B* is desired. However, when γ is large, concept one with low performance in *A* and high performance in *B* is desired. Figure 37 shows how this modifies the design space shown in Figure 35 creating a multi-attribute design space. The result of the interaction between relative preferences for the design attributes and scenario is a twist in the design space.

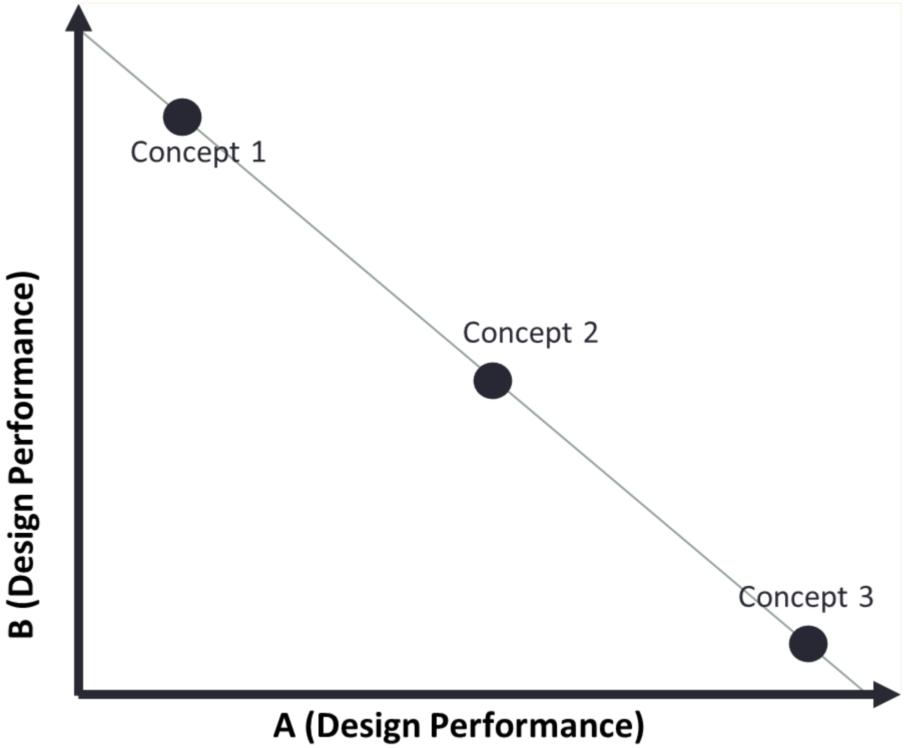


Figure 36: Simple Linear Pareto Frontier

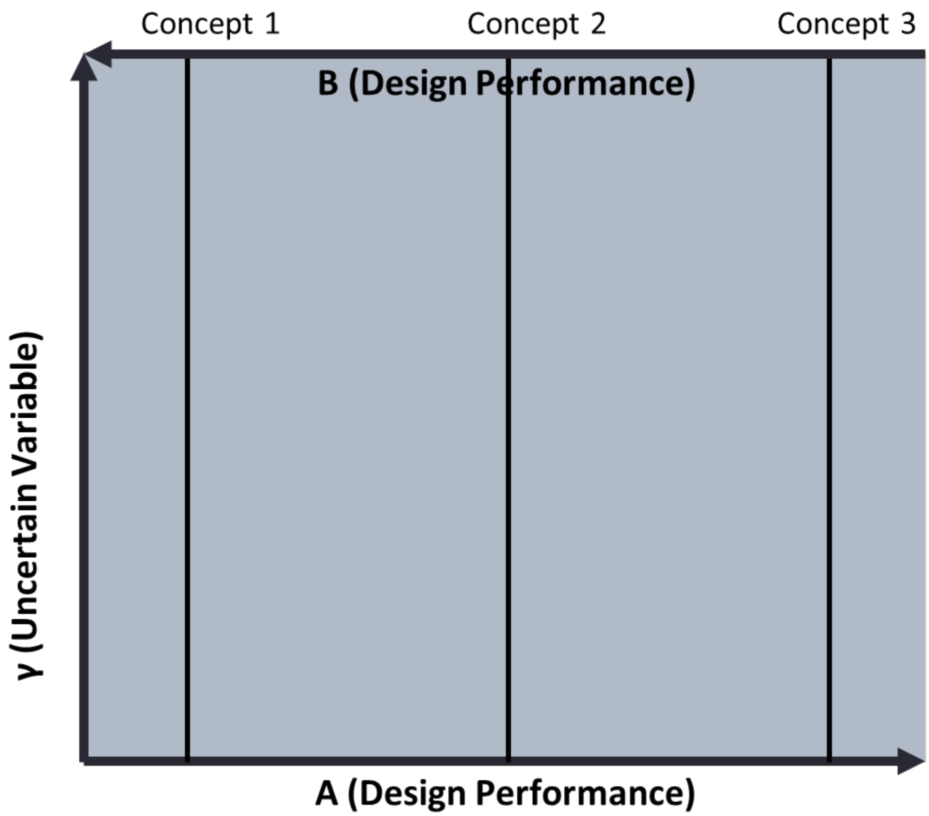


Figure 37: Multi-Attribute Design Space

In Figure 38, a new dimension to the design space has been introduced. The vertical dimension will be used to represent the value of a particular concept. Introducing this third dimension in value clearly shows the twist described in the previous section.

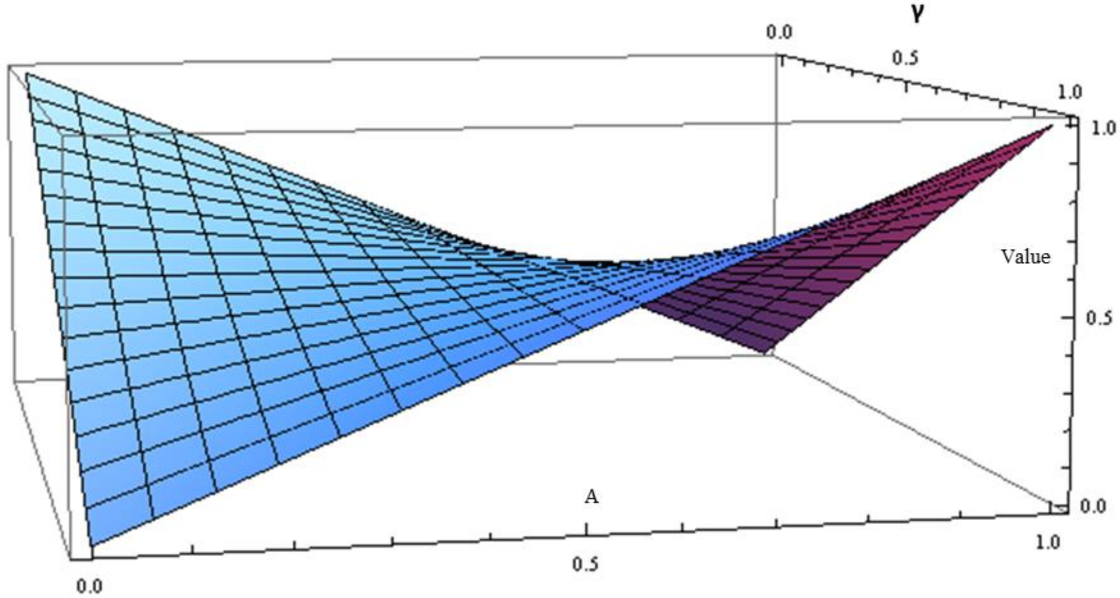


Figure 38: Value vs. Design vs. Uncertainty

Linear Value Space and Linear Pareto Frontier

To illustrate how this twist comes about, simple mathematical functional forms have been applied to our simplified design problem. The value of the concept is represented by Equation 9. Equation 9 states that the value of *A* is proportional to γ and the value of *B* is perfectly proportional to one minus γ. Essentially there is a linear weighting of preference between variable A and B based on the uncertain variable γ. Furthermore, the perfectly linear Pareto frontier has been maintained and is presented in Equation 10 and plotted in Figure 40.

Figure 39 shows this three-dimensional design space looking from the perspective of the uncertain variable γ. Each line moving across the space going from left to right in Figure 39 represents a particular concept. Examining this figure from the perspective of γ allows a simple graphical representation of the best concept at any point γ. Assuming the designer wants to maximize the value, shown on the vertical axis, the reader can see that the best concept is the one closest to the reader in Figure 39 until γ equals 0.5. At this point all of the concepts have equal value. From a γ of 0.5 to a γ of one of the concept farthest from the reader has the most value. It is also important to note that in this simple example, the robust concept is the concept directly in between the closest and the farthest concepts to the reader. This concept does not change at all with a change in γ. Returning to the counterintuitive result that motivated this thesis in Section 3.3, one can observe that the robust concept is only ideal when γ equals 0.5 and in this unique case any of the concepts can be considered ideal as they all provide equal value. The simplified example shows the most basic case where the robust design does not lead to the best-realized outcome. Next, this thesis examines what happens as changes are made to the design space. This is done to give the reader an intuitive feel for how the behavior that leads to robust design failure occurs.

$$\text{value} = \gamma A + (1 - \gamma)B \tag{9}$$

$$B = -A + 1 \tag{10}$$

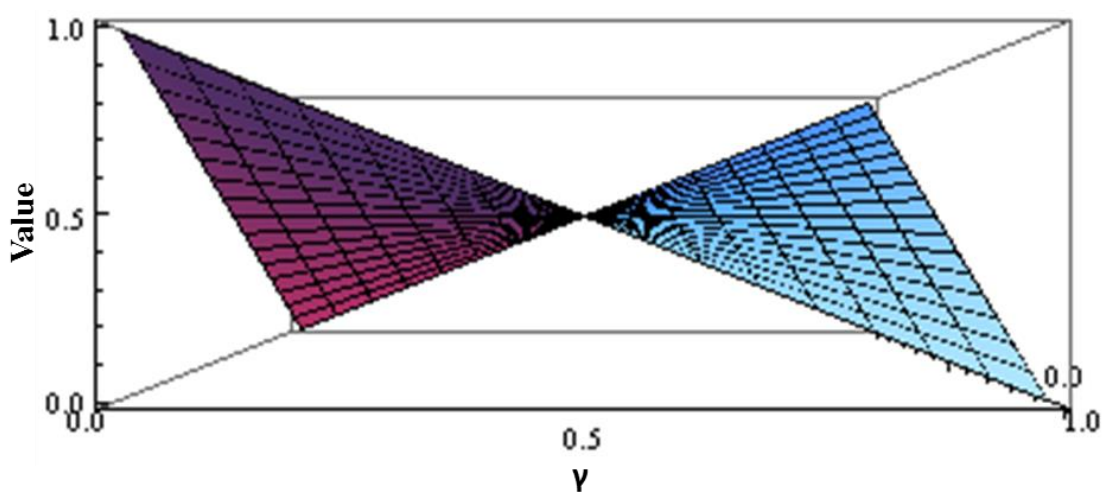


Figure 39: Value for a Linear Design Space with a Linear Pareto Frontier

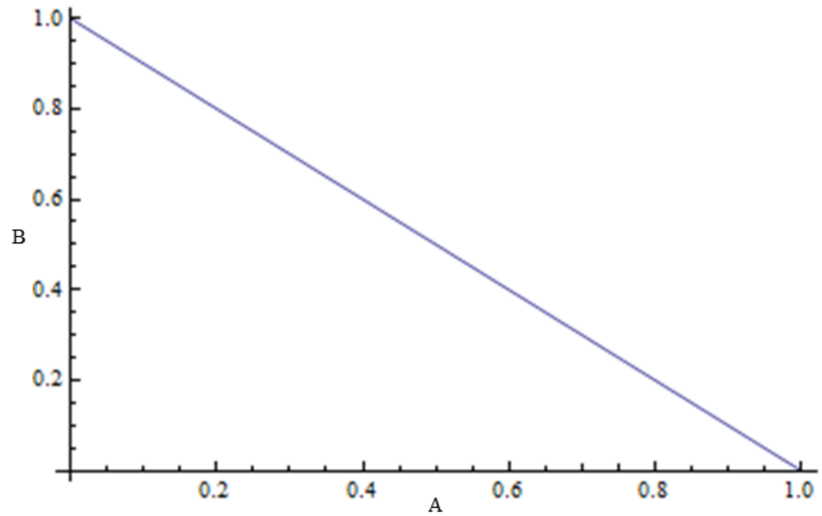


Figure 40: Inverse Linear Pareto Frontier

Linear Value Space and Concave Quadratic Pareto Frontier

It Figure 41 and Figure 42, the same results as in the previous section are shown for a slightly modified design space. In this case, the value function has been left the same and is identical to the one in the previous section. However, curvature has been added to the Pareto frontier. The equation for the Pareto frontier can be found in Equation 12. A concave curve has been used to represent the Pareto frontier. In this case a simple quadratic formula was used as the Pareto representation of the relationship between design variable *A* and design variable *B*. When this is translated to the value and uncertainty space shown in Figure 41, the reader can see that no longer is it only the concepts at the edges of the design space that are best. For the lowest range of γ, the edge closest to the reader is still the best. However, as we approach a middling value of γ, the best concept walks its way across the design space to the concept on the far side for a very high γ. In this case, the robust design is still the concept in between the furthest and closest concepts to the reader. When the design space is shaped as such, it may be possible for the robust design methodology to select the design that has the highest realized possibility of being the best design.

$$\text{value} = \gamma A + (1-\gamma)B \tag{11}$$

$$B = -\frac{5}{6}A^2 - \frac{1}{6}A + 1 \tag{12}$$

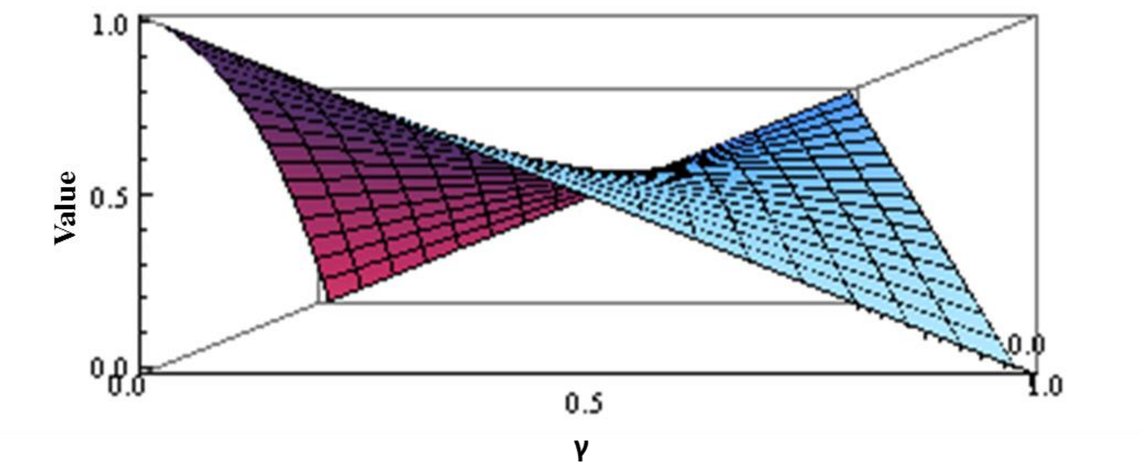


Figure 41: Value for a Linear Design Space with a Concave Pareto Frontier

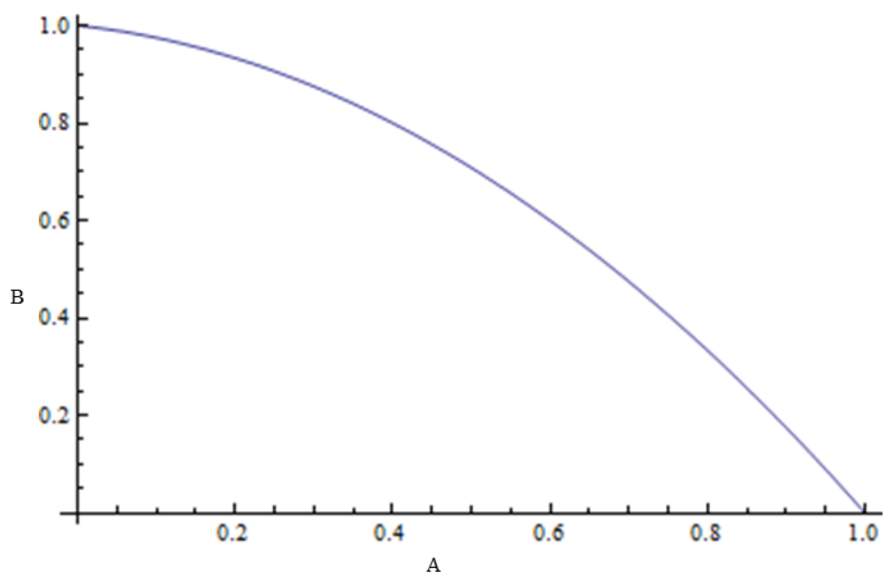


Figure 42: Concave Quadratic Pareto Frontier

Linear Value Space and Convex Pareto Frontier

Figure 43 and Figure 44 again show the same results as shown in the previous two sections. In this case, the Pareto frontier has been changed from a concave curve to a convex curve. This is translated into the uncertainty and value space in Figure 43. In this example, the reader should note that the best design is either always the concept closest to the reader or the concept farthest from the reader. At no value of γ is any design on the interior of the design space realized as the best concept. This includes the robust design. As γ changes, the best design will immediately move from the front edge to the back edge of the design space as γ passes 0.5. This is a situation where the design space contains tipping point behavior. Furthermore, the robust design will never be realized as the best design occurs when the design space has this shape. The results of the examples shown in Figure 39, Figure 41, and Figure 43 offer some insight into how the shape of the design space impacts the effectiveness of robust design as a paradigm. Since most Pareto frontiers are concave, the reader may be likely to believe that the applicability of this thesis is relatively limited. The next series of examples will show that the interaction between the value space and the Pareto frontier expands the region where the robust design paradigm may fail.

$$\text{value} = \gamma A + (1 - \gamma)B \tag{13}$$

$$B = \frac{5}{6}A^2 - \frac{11}{6}A + 1 \tag{14}$$

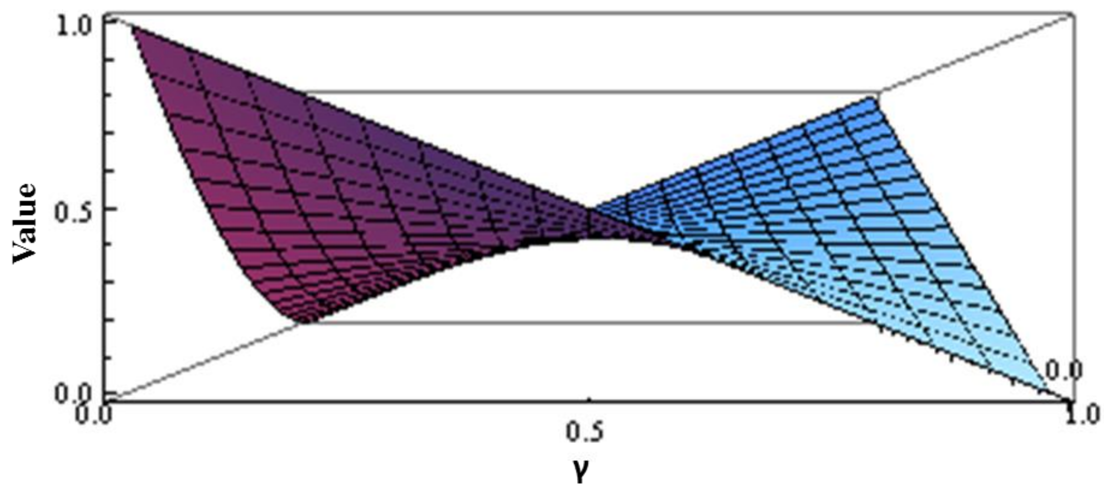


Figure 43: Value for a Linear Design Space with a Convex Pareto Frontier

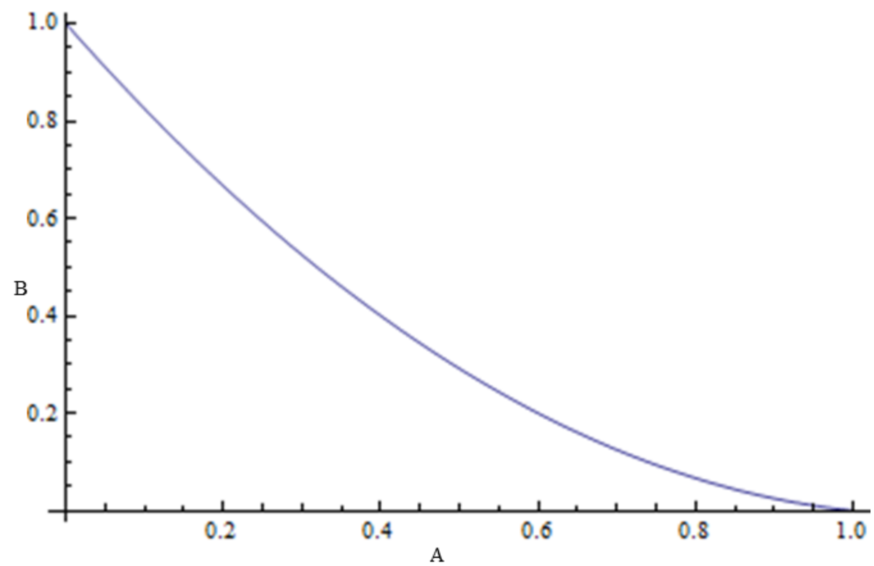


Figure 44: Convex Quadratic Pareto Frontier

Quadratic Value Space and Linear Pareto Frontier

In the examples shown previously, this thesis presented deviations to the function that define the Pareto frontier. In the following example, the Pareto frontier will be left as a simple proportional linear relationship. However, the value space will be changed to a quadratic space. Equation 15 and Equation 16 present the equations for the value space and the Pareto frontier. In this case, the interaction between the uncertainty variable γ and the design variables increases at a square rate. Examining Figure 45, the reader can see that this has a pronounced effect on the quality of the robust design paradigm. In this case the design space contains a severe tipping point behavior. The best design travels along the edge of the design space closest to the reader and jumps immediately to the design at the back edge furthest from the reader. Furthermore, the designs in between these two designs are drastically inferior to the edge designs for any given γ.

$$\text{value} = \gamma A^2 + (1-\gamma)B^2 \tag{15}$$

$$B = -A + 1 \tag{16}$$

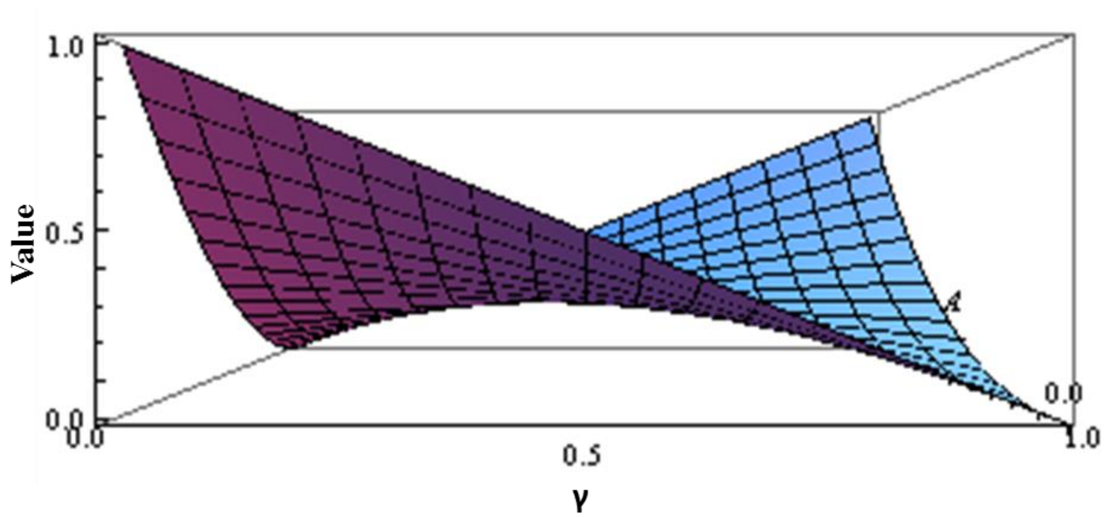


Figure 45: Value for a Quadratic Design Space with a Linear Pareto Frontier

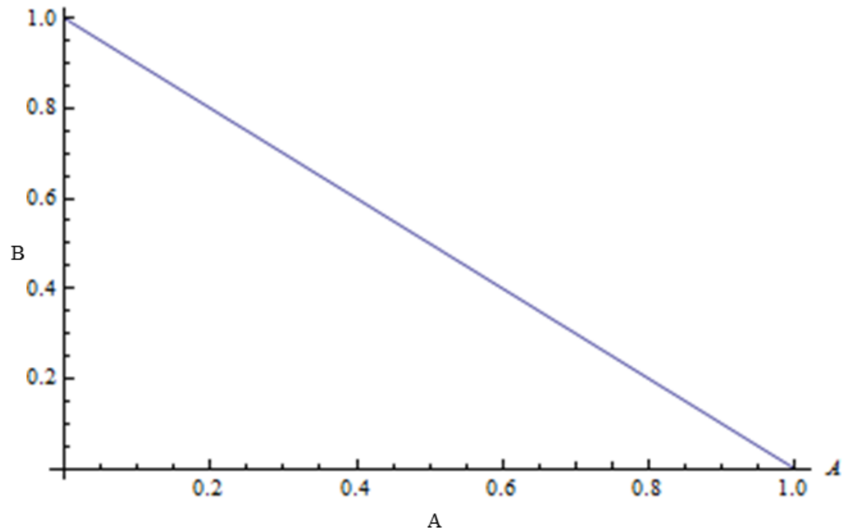


Figure 46: Linear Pareto Frontier

Quadratic Value Space and Concave Quadratic Pareto Frontier

Figure 47 and Figure 48, along with Equation 17 and Equation 18, describe a case where the value function is quadratic, and the Pareto frontier is concave quadratic as well. The Pareto frontier is shown in blue in Figure 48. In this case, the concavity of the Pareto frontier is not enough to make up for the quadratic nature of the value space. As a result, the design space still displays the tipping point behavior that led to the counterintuitive result shown in Figure 19.

Examining the value space in detail, it can be seen that the value space is circular. As a result, the concavity of the Pareto frontier is not enough to overcome the circular nature of the space. Figure 48 shows the Pareto frontier as a blue line, with a unit circle representing the value space as a purple line. In this depiction it is easy to see that the Pareto frontier's concavity does not match that of the value space.

$$\text{value} = \gamma A^2 + (1-\gamma)B^2 \tag{17}$$

$$B = -\frac{5}{6}A^2 - \frac{1}{6}A + 1 \tag{18}$$

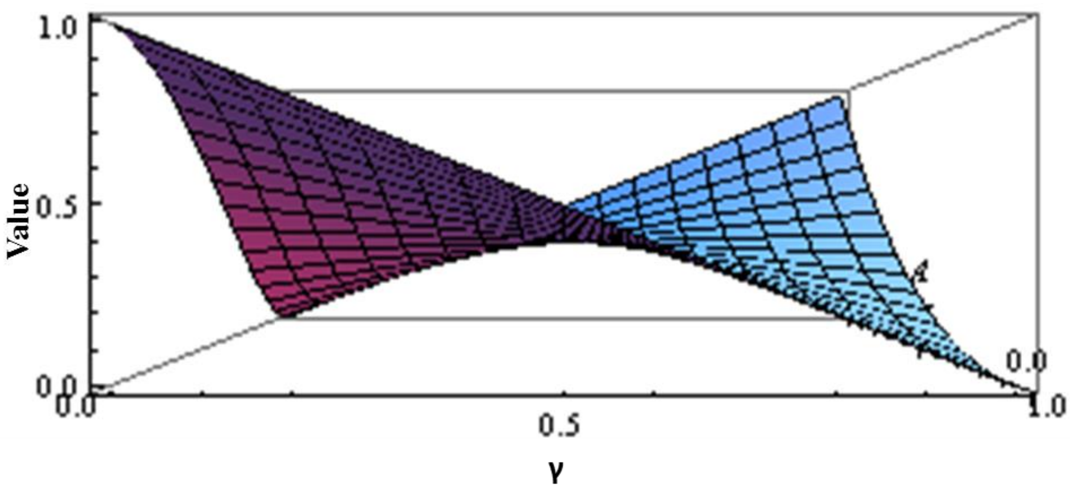


Figure 47: Value for a Quadratic Design Space with a Concave Pareto Frontier

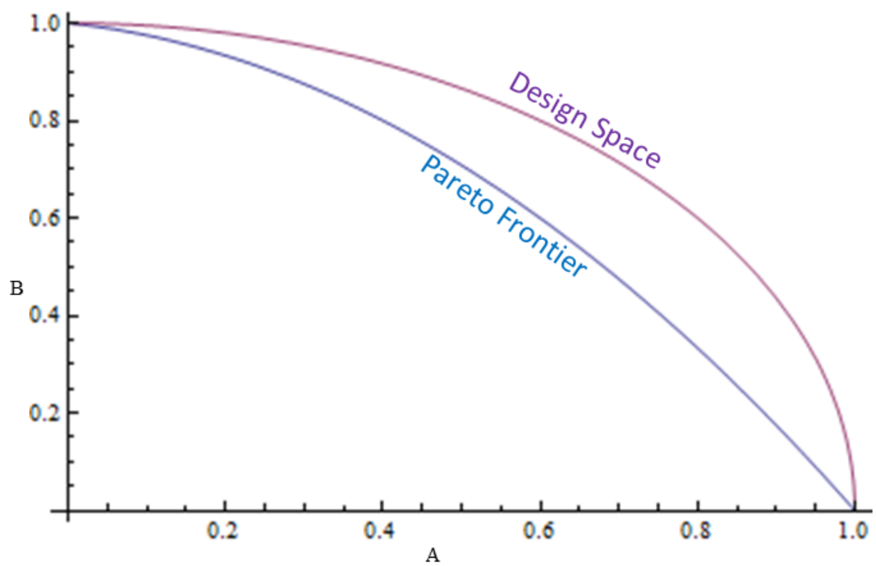


Figure 48: Concave Quadratic Pareto Frontier and Circular Design Space

Quadratic Value Space and Squircle Pareto Frontier

Figure 49 shows an example where the Pareto frontier has been replaced with a squircle. In Figure 50, the unit circle is still shown as a purple line, but the new Pareto frontier, shown in blue, has a much greater concavity than the circle. The equations for the quadratic design space and the squircle are presented in Equation 19 and Equation 20. As a result, the design space exhibits behavior that may lead to the appropriate usage of robust design.

$$\text{value} = \gamma A^2 + (1-\gamma)B^2 \tag{19}$$

$$B = \sqrt[4]{-A^4 + 1} \tag{20}$$

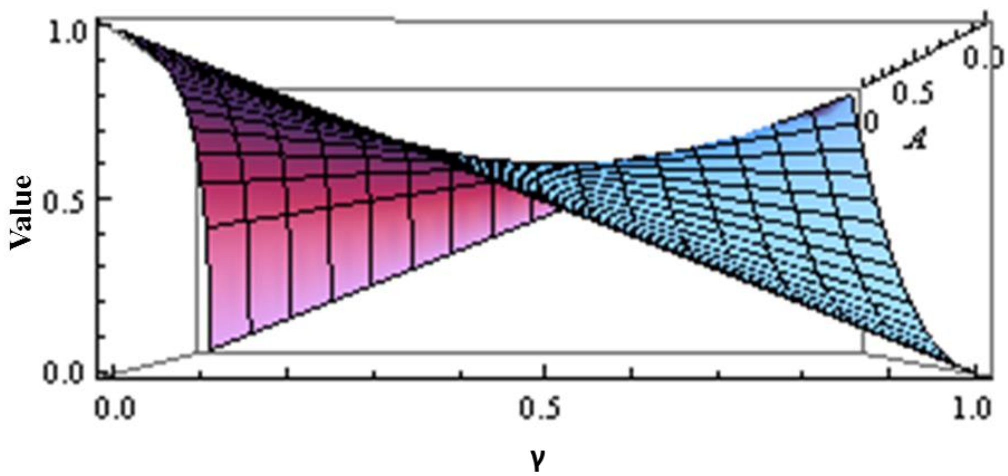


Figure 49: Value for a Quadratic Design Space with a Squircle Pareto Frontier

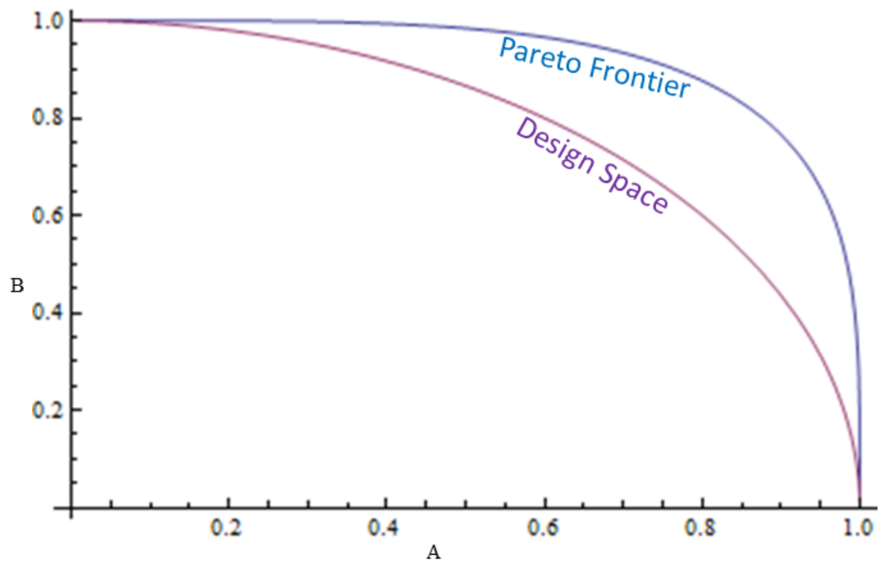


Figure 50: Squircle Pareto Frontier and Circular Design Space

3.10 Design and the Tipping Point

The previous section showed a number of example design spaces and the structures of these design spaces. These design spaces could be classified into two types of behavior: First, those with discrete jumps in the optimum design, depending on the setting for the uncertainty γ; and second, those with continuous changes in the optimum depending on the amount of the uncertainty γ. Table 4 divides the examples presented above into two categories for reference.

Table 4: Classifications of Examples

Discrete Changes in Optimum Design for Changes in Uncertainty	Continuous Changes in Optimum Design for Changes in Uncertainty
Linear Value Space and Linear Pareto Frontier	Linear Value Space and Concave Quadratic Pareto Frontier
Linear Value Space and Convex Pareto Frontier	Quadratic Value Space and Squircle Pareto Frontier
Quadratic Value Space and Linear Pareto Frontier	
Quadratic Value Space and Concave Quadratic Pareto Frontier	

The author would also like to point out that these examples had a limited number of design spaces variables and uncertain variables. In a more realistic design situation the designer can expect a much larger number of design variables and uncertain variables. The result of the expansion of the space is that most design spaces will exhibit mixed behavior, with some variables exhibiting continuous behavior in certain uncertainty scenarios and others exhibiting discrete behavior.

The implications of these two classifications are that those with discrete jumps in the optimum clearly display the behavior that meets the definition of a tipping point. In these cases, the optimum design will travel along one limit of the design variable (minimum for example) and at some point, the uncertainty will force a jump to the opposite limit of the design space (maximum for example). In this situation the robust design, which is the center of the design space, will never be the best choice even if it remains the statistically most robust choice. However, it is also important to recognize that it is possible for the continuous cases to exhibit a tipping point behavior. The next section will describe how this can take place.

3.11 Probability-Based Tipping Points

Returning to the automobile example will provide a platform for demonstrating the second possibility for tipping point-like behavior. This route for tipping point behavior arises from how quickly the optimum moves across the probability-weighted space as the uncertain variables change.

Figure 51 shows the three-dimensional plot of the value space including the information from the Pareto frontier described in Equation 3 and Equation 4. Figure 52 shows the same function from the perspective presented in the mathematical examples. In the characterizing problem, the uncertainty was the fuel price and this variable is plotted across the horizontal axis. The vertical axis represents the value for a particular design. The design variables are changing across the depth axis in Figure 52 from a value of 100 hp – 50 mpg closest to the reader to a value of 500 hp – 10 mpg furthest from the reader.

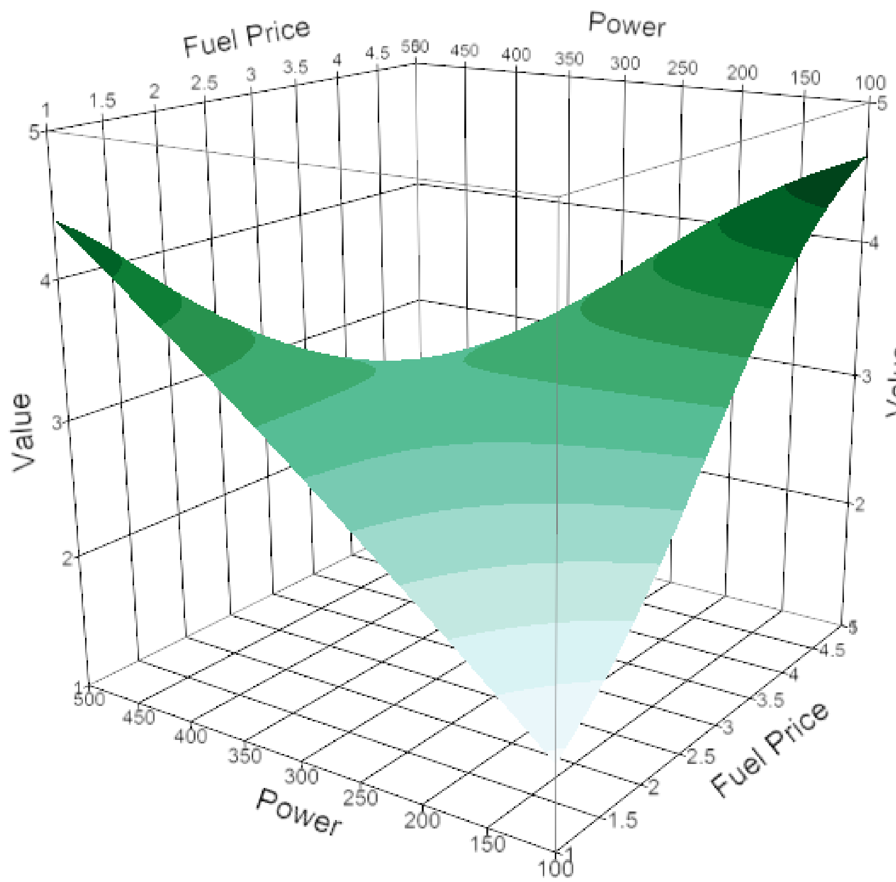


Figure 51: Characterizing Problem Value Space

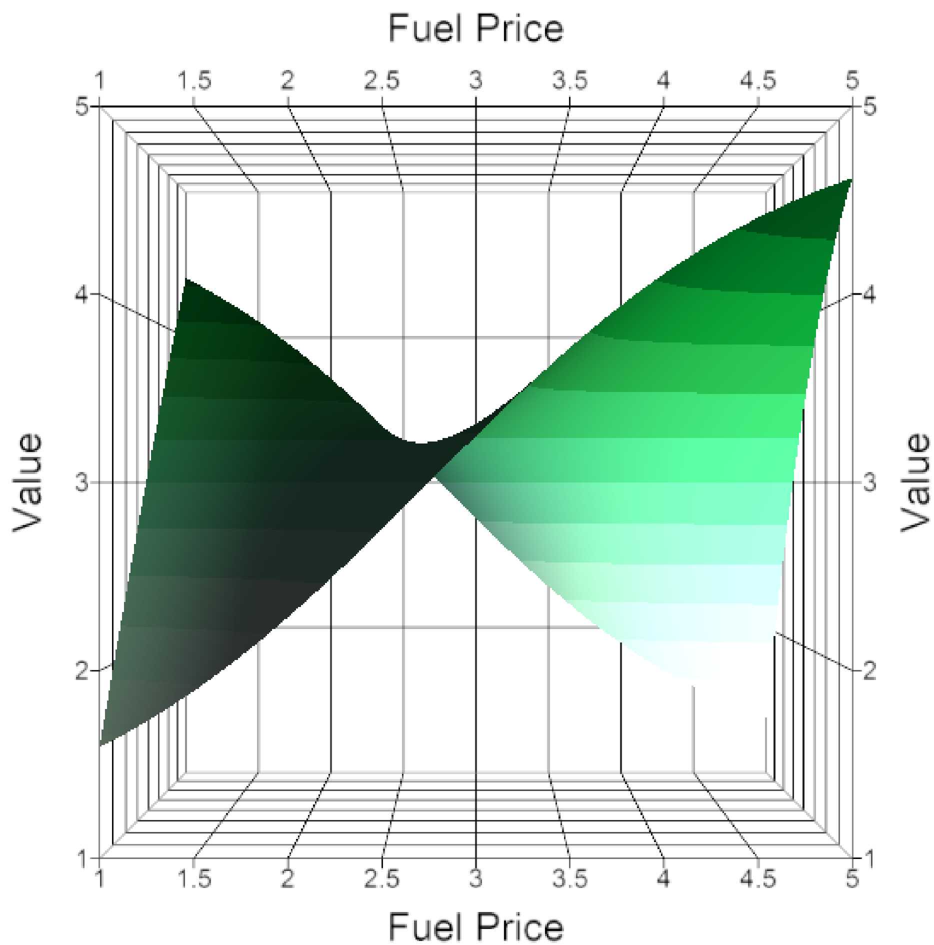


Figure 52: Design Space from the Perspective of the Uncertain Fuel Price

From Figure 52, it can be seen that the design space has a convex shape, and the optimum will in fact pass across the design space. However, the degree of twist is very high. As a result, the optimum passes very quickly across the design space. Examining Figure 52, the reader can approximately view the second case where the robust design paradigm can breakdown. Even in the cases where the design space is concave, a high degree of twist with respect to the uncertainty variables can strongly favor the boundaries of the design space. As a result, even a concave value space can have failures in robust design.

Since the functions describing this design space are simple mathematical equations, the function for the optimum power and efficiency as a function of fuel price could be explicitly solved for.

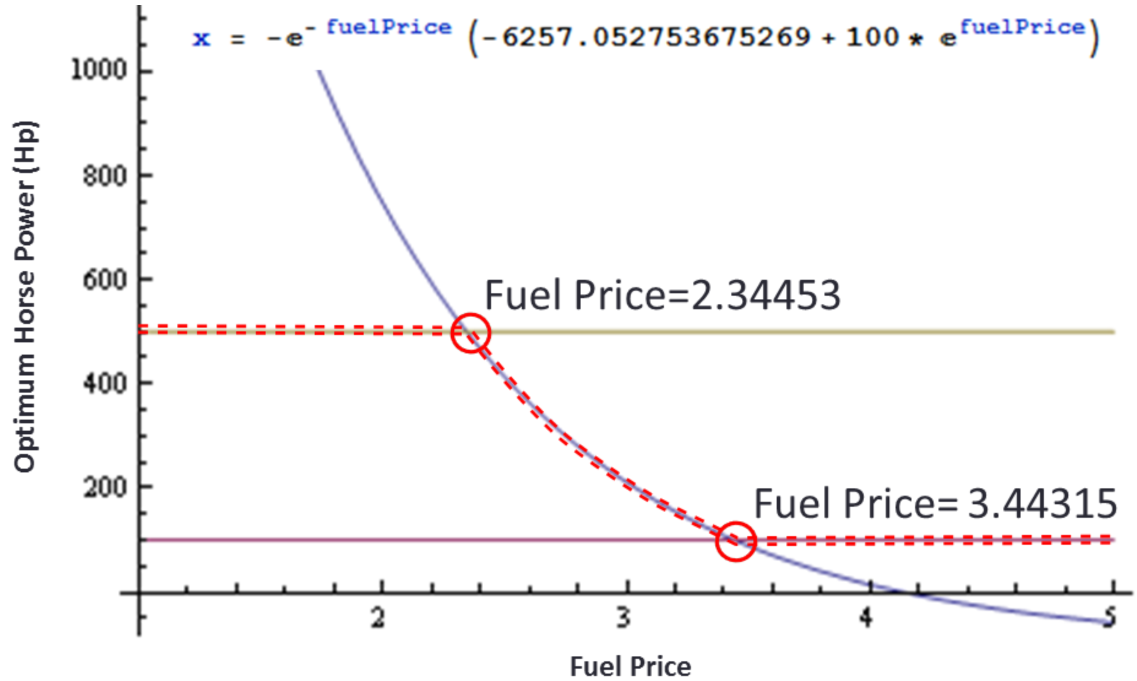


Figure 53: Optimum Design vs. Fuel Price

In Figure 53, the optimum concept as described for horse power and efficiency has been plotted against the fuel price scenario. Recall that the Pareto frontier implies a Pareto optimal efficiency for each horsepower. The equation in the top of Figure 53 shows the function for the unconstrained optimum horsepower for any particular fuel price. This equation is plotted in purple in Figure 53 and the equation was derived through simple calculus as explained in Section 3.12.1. Physical constraints have been placed on the design variables. In this case, the concepts have been limited to a 500 hp – 10 mpg concept in yellow, and a 100 hp – 50 mpg at the other extreme of the design space. The optimum concept for any fuel price has been highlighted with the dashed red line.

Because the function for the optimum is known for the characterizing problem, it is also possible to solve for the fuel price at which the designs hit their extreme cases. This information has then been overlaid on the value plot shown in Figure 53. In these specific cases, this information can be combined with the probability density function for the uncertainty variables to calculate the probability of lying along the edge of the design space. If the probability of lying along an edge of the design space is greater than being at some point within the design space, the development of a robust optimum may not be the best strategy.

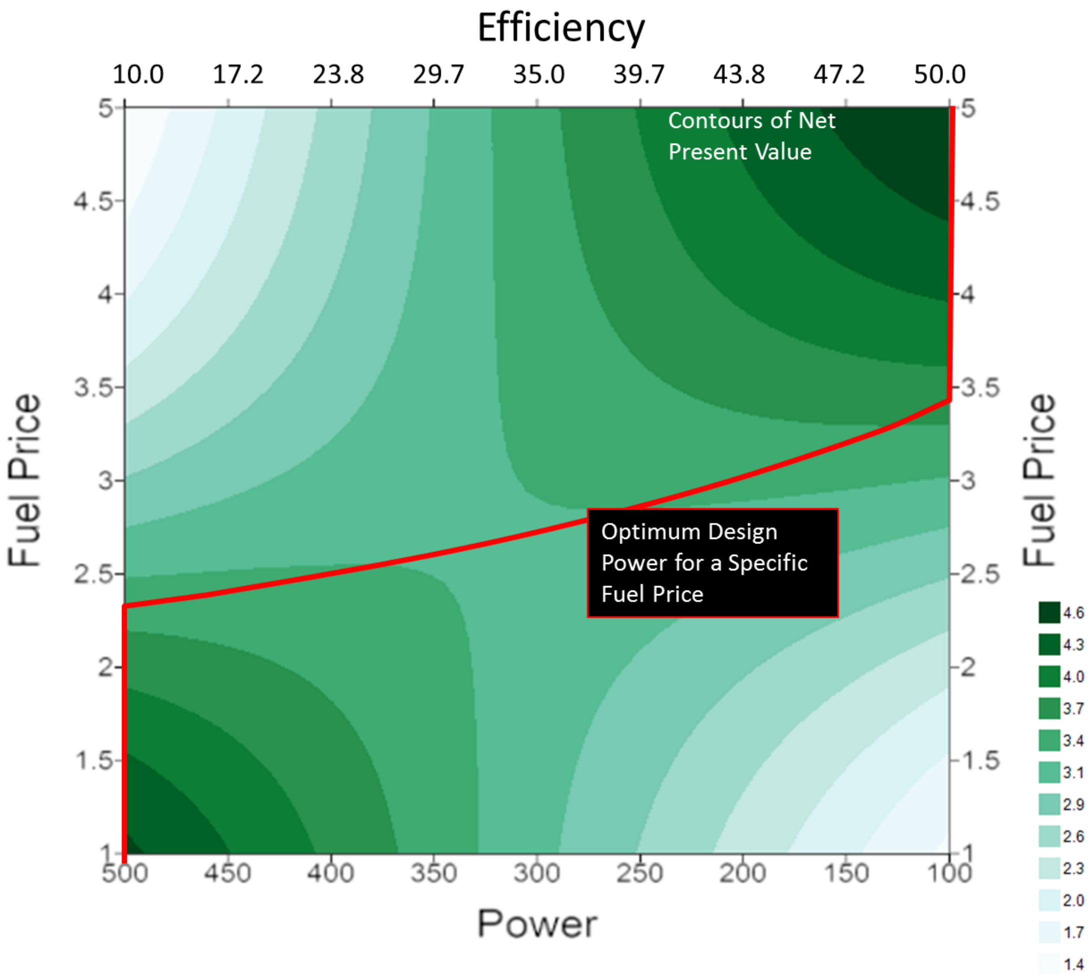


Figure 54: Optimum Design Overlaid with Design Space

Figure 54 shows the design space from the top. In this figure, the fuel price is varied along the vertical axis and the concepts run across a horizontal axis. Green contours of value are shown across the design space with the dark green being the highest value. The red line in Figure 54 takes the information from Figure 53 and provides a trace of optimum concept for a given fuel price.

Figure 55 shows the distribution of fuel prices beside Figure 54 for comparison. Recall that the fuel price was modeled as a lognormal random variable. The part of this distribution in which the optimum lies within the design space has been highlighted dark purple. From the left side of the design space, it is evident that the majority of the probabilistically-weighted design space actually lies along one of the edges, and a minority of the optimum designs will lie within the design space.

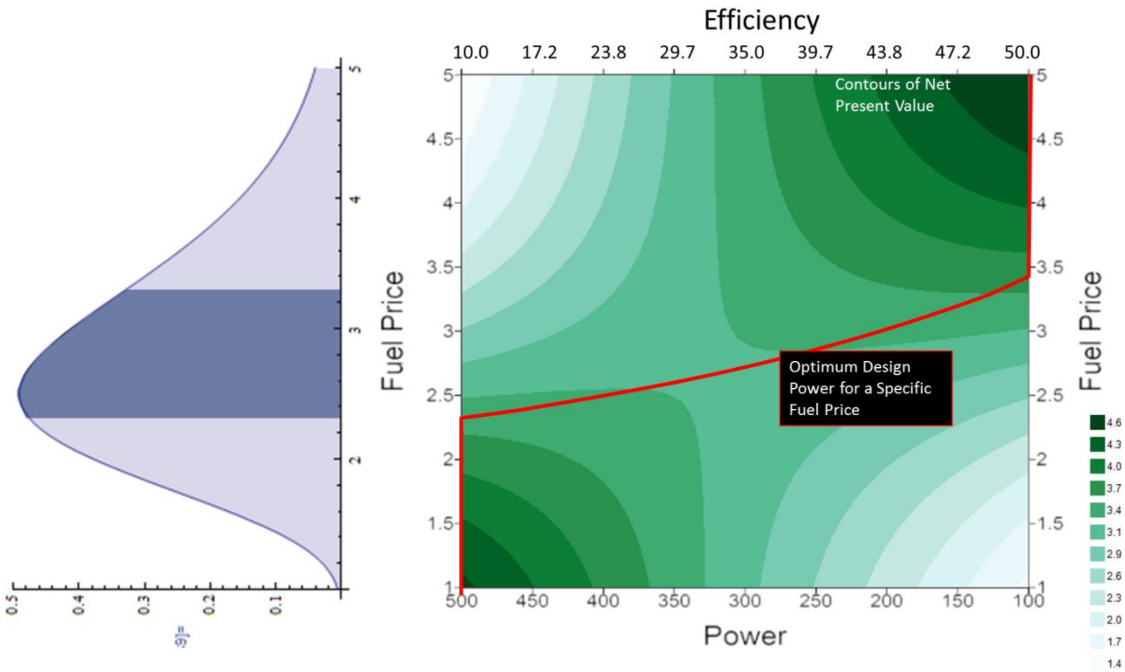


Figure 55: PDF of Fuel Price with Design Space and Optimum Function

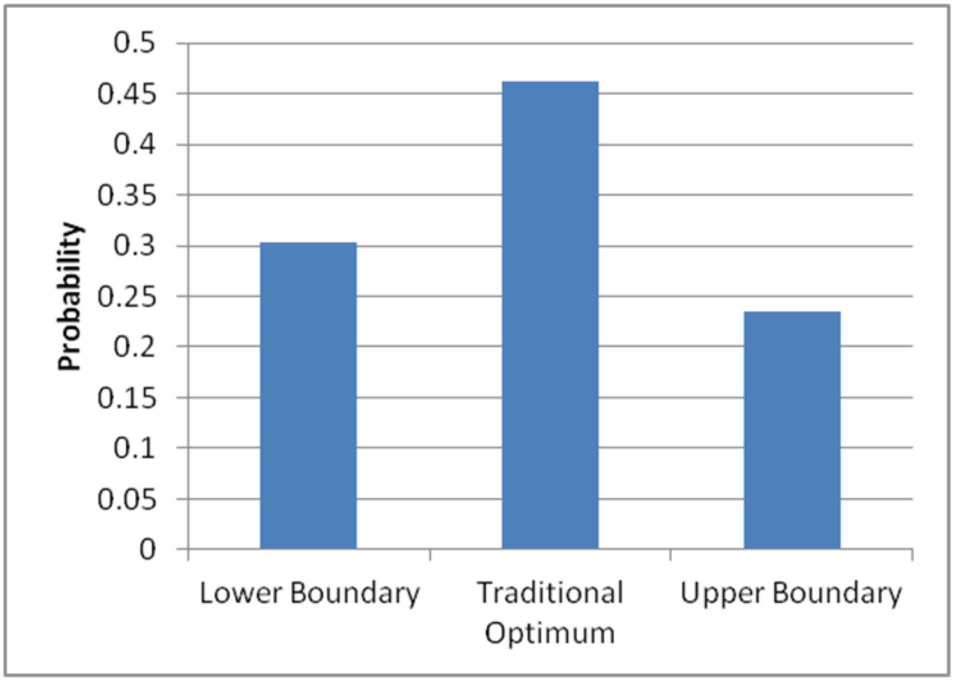


Figure 56: Probability of Optimum Lying on an Edge vs. the Interior of the Design Space

Figure 56 shows the calculated probabilities of the optimum design lying on one of the edges or the interior of the design space. From this figure it is clear that an unconstrained optimum will only be the best solution ~46% of the time. However, if we take a discrete set of concepts, in this case three concepts (one representing a concept on the lower edge of the design space, one representing the robust concept, and one representing the concept on the top edge of the design space), Figure 57 shows each of the concepts along with their respective performance for different fuel price scenarios.

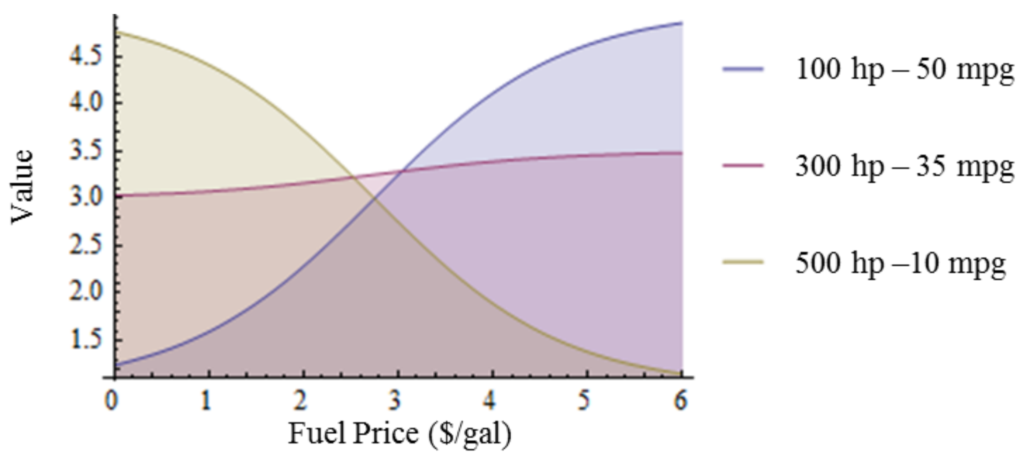


Figure 57: Three Concepts' Performance for Varying Fuel Prices

Examining Figure 57, it is evident that the robust concept will have the highest mean and the lowest variance. However, it is also evident that the robust concept is only the best concept for a very limited range of fuel prices. Solving for the intersections of these curves provides regions in which each concept is best. Using the CDF of the distribution along with intersections allows for an analytical determination of the likelihood that each of these concepts is the best concept. This likelihood is shown in Figure 58. It can be seen in Figure 58 that the robust concept has the lowest likelihood of being the best of these three concepts. This is because the concepts at the edges of the design space will outperform the robust concept for the outer edges of the central region as well. This result begins to mirror the counterintuitive results presented in section 3.3.

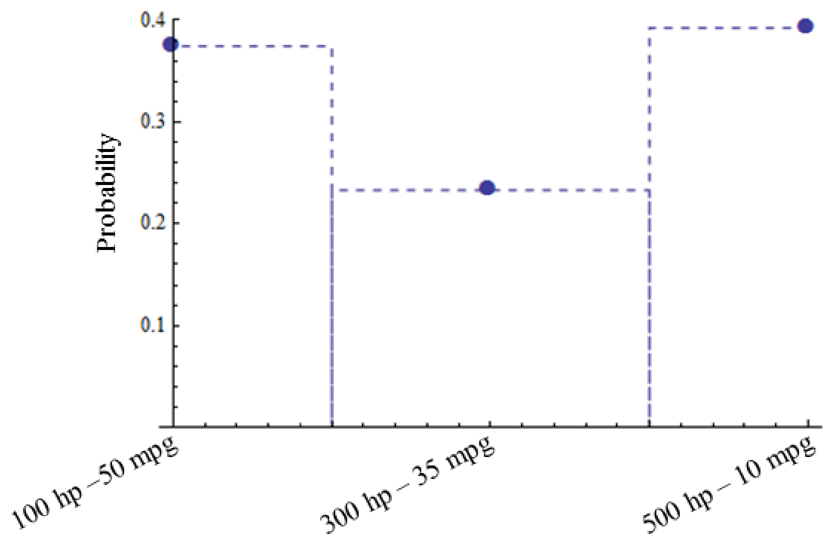


Figure 58: Probability Each Concept is Realized as Best Concept

Repeating the analysis show above for the nine concepts studied in section 3.5.1 yields an identical set of results to those shown in section 3.5.1. Figure 59 shows the value of each of the nine concepts along with the PDF of the fuel price. This allows the reader an indication of which concept is best and the likelihood of that fuel price scenario occurring. Combining this information allows calculation of the exact probability of each of the concepts being realized as best. These probabilities are shown in Figure 60 along with the numerical result from the Monte Carlo analysis done in Section 3.5.1.

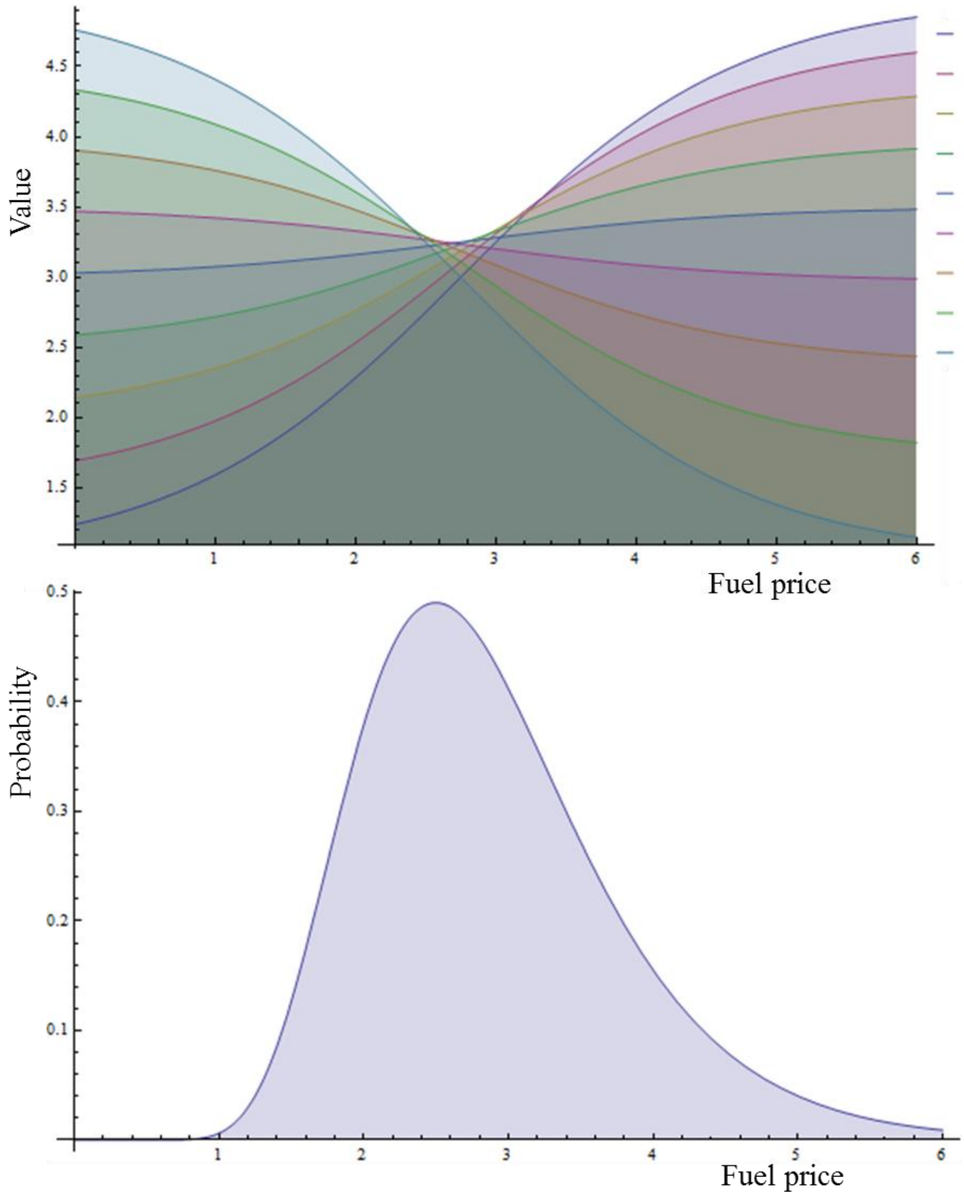


Figure 59: Value of Nine Concepts for Varying Fuel Price

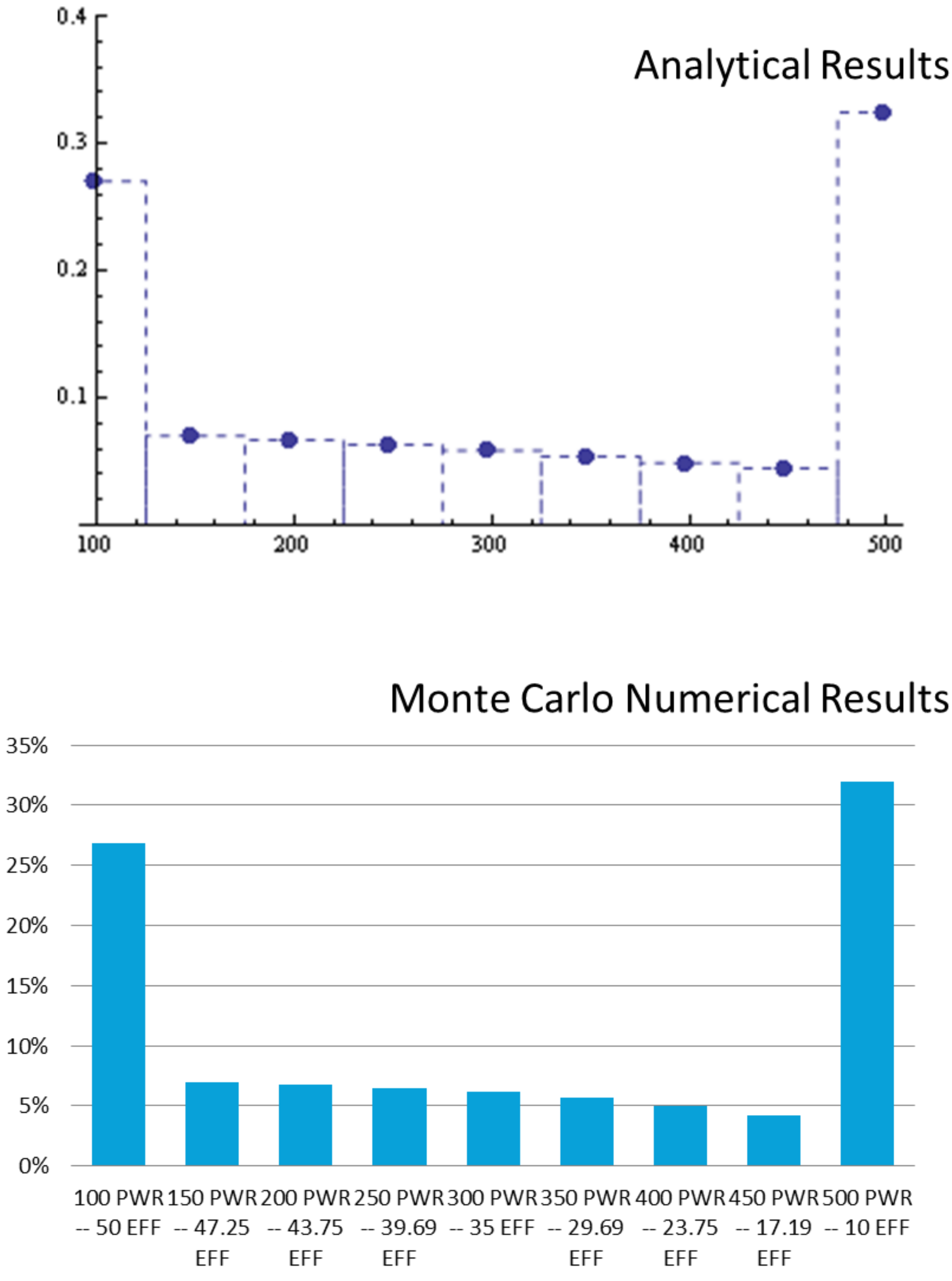


Figure 60: Analytical vs. Numerical Likelihood of Each Concept Being Best

3.12 Informal Mathematical Proof

The next sections will provide a set of informal mathematical proofs showing how the combination of a tradeoff between desirable traits and the preference for those traits as a function of the uncertainty can lead to the failure of robust design. These sections will simply show a few ways in which the failure mode can arise, but will not attempt to identify an inclusive set of ways in which robust design can fail. Because mathematical functions for the value model, the design space, and all the design tools and the Pareto frontiers are vanishingly rarely available for conceptual design, it was not necessary or feasible to mathematically prove an inclusive set of conditions in which robust design will fail. Furthermore, for the mathematical procedure outlined below to be applied to a real world design, the design problem itself must not be over- or under-determined. Instead, Hypothesis 1 can be used to offer a practical set of recommendations for identifying if the robust design will fail for a particular set of design tools and uncertainties.

3.12.1 Defining the Hypothesis Conditions Mathematically

The first step to a proof of the elements in hypothesis 1 is to frame the elements in hypothesis 1 in mathematical terms. The first element of hypothesis 1 states that there is a tradeoff between desirable traits for at least two traits. This will be an inverse relationship or some sort of negative correlation between the two desirable traits. Making the assumption that the designer will choose a Pareto optimal design means that one or more design variables can be defined in terms of the other design variables and the information will be contained in the Pareto frontier. This information can be used to eliminate one of the design variables in the function defining the value of the concept. The negative relationship between the variables reduces the likelihood that there will be a single optimum, and means the engineer will likely have to make trades. Equation 21 shows the generic form of the modeling environment for design. It contains a number of design variables represented by the X's as well as a vector of uncertain variables not within the designer's control represented by $\boldsymbol{\gamma}$. Equation 22 shows the solution of one of the design variables as a function of the remaining design variables using the information from the Pareto frontier. Equation 23 shows the use of Equation 22 in the value function to eliminate X_p. Equation 24 shows Equation 23 in the vector notion described in where $\boldsymbol{X}$ is the vector of design variables and $\boldsymbol{\gamma}$ is the vector of uncertain variables.

$$Value = \mathrm{F}\left(X_1, X_2, \dots X_n, X_p, \boldsymbol{\gamma}\right) \tag{21}$$

$$X_p = \mathrm{f}(X_1, X_2, \dots X_n) \tag{22}$$

$$Value = \mathrm{F}(X_1, X_2, \dots X_n, \boldsymbol{\gamma}) \tag{23}$$

$$Value = \mathrm{F}(\boldsymbol{X}, \boldsymbol{\gamma}) \tag{24}$$

The second element of hypothesis 1 is that the preference for the desired traits is driven by scenario. The introduction of preference leads to the introduction of an optimization. The optimization will proceed through the standard optimization with the goal of maximizing value. This process can be found in any calculus text, where the only notable exception is that the uncertainties will be treated as constants for the purposes of the proof. This process provides the optimum set of design variables $\boldsymbol{X}$ for any specific scenario represented by $\boldsymbol{\gamma}$.

$$\nabla \mathrm{F}(\boldsymbol{X}, \boldsymbol{\gamma}) = \begin{bmatrix} \frac{\partial}{\partial X_1} F(\boldsymbol{X}, \boldsymbol{\gamma}) \\ \frac{\partial}{\partial X_2} F(\boldsymbol{X}, \boldsymbol{\gamma}) \\ . \\ . \\ . \\ \frac{\partial}{\partial X_n} F(\boldsymbol{X}, \boldsymbol{\gamma}) \end{bmatrix} = 0 \tag{25}$$

$$\begin{gathered} X_1^{*0} = f(\boldsymbol{X}, \boldsymbol{\gamma}) \\ X_2^{*0} = f(\boldsymbol{X}, \boldsymbol{\gamma}) \\ \ldots \\ X_n^{*0} = f(\boldsymbol{X}, \boldsymbol{\gamma}) \end{gathered} \tag{26}$$

Solving for the critical points due to active constraints

$$\begin{gathered} X_1^{*1} = X_{1up} \\ X_2^{*1} = f\left(X_1 = X_{1up}, \boldsymbol{X}, \boldsymbol{\gamma}\right) \\ \ldots \\ X_n^{*1} = f\left(X_1 = X_{1up}, \boldsymbol{X}, \boldsymbol{\gamma}\right) \end{gathered} \tag{27}$$

…And

$$\begin{gathered} X_1^{*1} = X_{1low} \\ X_2^{*1} = f(X_1 = X_{1low}, \boldsymbol{X}, \boldsymbol{\gamma}) \\ \ldots \\ X_n^{*1} = f(X_1 = X_{1low}, \boldsymbol{X}, \boldsymbol{\gamma}) \end{gathered} \tag{28}$$

… All other potential combinations of active constraints

The extreme value theorem states that if a function F(x) is continuous on a closed interval [a,b] then f(x) has both a maximum and minimum value on [a,b]. This maximum can either lie at a stationary point or along one or more of the side constraints.

Equation 25 and Equation 26 represent the finding of the stationary points for the design variables $\boldsymbol{X}$ in terms of the uncertain variables $\boldsymbol{\gamma}$. Because the problem has side constraints, the mathematical analysis must test all combinations of active side constraints as well. Equation 27 shows this process done for a single constraint where X_1^{*1} is set to the maximum value and the optimum is resolved. This process must be completed for all combinations of active constraints, which is equivalent to LaGrange multiplier approach. In other words, variables on active constraints are set to the maximum or minimum, and then the problem is solved with these variables held constant. This procedure creates a set of potential optimum points $X_1^{*0} \dots X_n^{*0}$ to $X_1^{*m} \dots X_n^{*m}$, of which the one with maximum value is the optimum. This point will simply be referred to as $\boldsymbol{X}^*$. However, these points are dependent on the uncertain variables $\boldsymbol{\gamma}$.

To show that the preference for particular designs are dependent on the uncertainties $\boldsymbol{\gamma}$, a final set of concepts must be shown. First, it must be recognized that the previous paragraphs' procedure outlined the finding of an optimum for a single uncertainty scenario as represented by $\boldsymbol{\gamma}$. Next, it must be shown that the optimum point $\boldsymbol{X}^*$ is actually dependent on $\boldsymbol{\gamma}$. This can be done by examining the equations for $\boldsymbol{X}^*$ and observing that all the uncertainty terms were not removed when taking the gradient and finding the maximum. If the scenario variables $\boldsymbol{\gamma}$ are themselves bounded, then it is necessary to show that there are at least two states, γ_1 and γ_2, that change X*.

3.12.2 Discrete Tipping Point Behavior

If the design space meets the criteria specified in the previous section, and the value space is less concave than the Pareto frontier with respect to a particular variable, then the design space will exhibit the discrete tipping point behavior. If the design space is not concave at any optimum stationary point for any γ, then it will exhibit tipping point behavior in at least one dimension.

3.12.3 Probability-based Tipping Point

In specific cases where the problem is not over- or under-determined and the discrete tipping point behavior is not observed, it may be possible to solve for the point at which the uncertain variables forced the design to the edge of the design space. The author recognizes that these conditions are rare in design, and as a result an analytical solution to the design problem is not likely to exist. However, Section 4.5.1 provides some recommendations on how to examine the design toolset for this behavior. If it is possible to find the point at which a design is forced to the edge of the design space, this information can be combined with the probability density function for the uncertainty variables to calculate the probability of lying along the edge of the design space. This approach was taken in Section 3.11 to arrive at the analytical equivalency of the Monte Carlo results presented in Section 3.3.

The mathematical procedure for finding the probability that a particular design is on the interior of the design space as opposed to the edge is presented below. Beginning with the optimum design settings found in Equation 26, Equation 27, etc., a solution is found for the uncertainty that drives the optimum to the edge of the design space. This must be done for each constraint as shown in Equation 30 and Equation 31.

$$\text{Solving for } \gamma_1, \gamma_2, \dots, \gamma_n \tag{29}$$

$$\begin{aligned} \gamma_{1up} &= F\left(X_1 = X_{\boldsymbol{1up}}, \boldsymbol{X}, \boldsymbol{\gamma}\right) \\ \gamma_{2up} &= F\left(X_1 = X_{\boldsymbol{1up}}, \boldsymbol{X}, \boldsymbol{\gamma}\right) \\ &\dots \\ \gamma_{nup} &= F\left(X_1 = X_{\boldsymbol{1up}}, \boldsymbol{X}, \boldsymbol{\gamma}\right) \end{aligned} \tag{30}$$

And…

$$\begin{aligned} \gamma_{1low} &= F(X_1 = X_{\boldsymbol{1low}}, \boldsymbol{X}, \boldsymbol{\gamma}) \\ \gamma_{2low} &= F(X_1 = X_{\boldsymbol{1low}}, \boldsymbol{X}, \boldsymbol{\gamma}) \\ &\dots \\ \gamma_{nlow} &= F(X_1 = X_{\boldsymbol{1low}}, \boldsymbol{X}, \boldsymbol{\gamma}) \end{aligned} \tag{31}$$

Continuing for all constraints…

Once the $\boldsymbol{\gamma}$ for each constraint has been found, the CDF of the distributions of the uncertain variables can be used to determine the probability of being on a particular edge of the design space if the $\boldsymbol{\gamma}'$s are known and the structure of the uncertainties is simple enough for this possibility. Equation 32 through Equation 34 show an example of this process, where Γ_1 represents the intersection scenario. If the majority of the scenarios lie along one of the constraints, the robust design may not be the best design to maximize the chance of selecting the best design.

$$P_{Low\ Concept} = P(\Gamma_1 \leq \gamma_{1low}) \tag{32}$$

$$P_{Traditional\ Optimum\ Concept} = P\left(\Gamma_1 \leq \gamma_{1high}\right) - P(\Gamma_1 \leq \gamma_{1low}) \tag{33}$$

$$P_{High\ Concept} = 1 - P\left(\Gamma_1 \leq \gamma_{1high}\right) \tag{34}$$

3.13 Summary and Conclusions

The statistics-based methods fail because they focus on improving the statistics of a decision rather than the decision outcome. Literature-based methods equate better statistics to better outcomes by implicitly making an assumption about the independence of the performance of the designs. This assumption becomes incorrect when the designs' final performance is affected by a common scenario. Oftentimes, the less robust designs closer to the extremes of the design space are overlooked in the statistical-based decision-making paradigm. Although the extremes of the design space may have a large downside should the scenario go against what was expected, the upside can also be greater when the scenario goes as expected. Based on the scenario, one extreme of the design space fails horribly while the other extreme of the design space is a great success, and the robust center of the design space is always trumped regardless of which scenario occurs. This effect is masked by the statistics used in the literature-based approaches, and should be unmasked in future approaches to design decision-making. Basically if the conditions in Hypothesis 1 are met, one of the edges of the design space (or one of another equivalent set of equilibria within the design space) would have been the right choice.

However, it is impossible don't know a priori which edge or equalibria should have been selected. As a result robust design, which is based on aggregate statistics, determines that a central design should be selected. However, examining the scenarios individually it is possible that this central design is nearly always going to be the wrong choice.

In summary, it can be helpful to think of this situation in more common vernacular. Using automobile manufactures as an example, it often makes sense to design a Prius or a Porsche, even if it is impossible to know if the Prius or the Porsche is going to be the more successful design a priori. However, the robust design, the Pontiac, will always be overlooked by the customer. As a result, the designer must simply take the risk of selecting an extreme design, or a new design decision-making paradigm should be introduced.

3.14 Research Objective

The following bullets summarize the observations that can be taken from the previous elements of this thesis.

- Critical design decision must be made years prior to the deployment of the concept in the market.
- Scenario uncertainty can have a large impact on market success.
- Scenario uncertainty is typically handled through the use of a single or limited set of design scenarios or through the use of statistical methods found in literature.
- Literature based methods for handling scenario-based uncertainty fail if the following conditions are met: a Pareto frontier is present, and the ideal Pareto optimal concept is dependent on and sensitive to scenario.
- A method for design decision-making under uncertainty with dependencies between concepts is needed.

These observations have led to the following research objective.

Research Objective: *Create a methodology for better handling scenario-based uncertainty in aircraft design that improves decision outcomes.*

CHAPTER IV

METHODOLOGY DEVELOPMENT

The previous chapter presented a previously overlooked problem with current conceptual design modeling and decision-making when scenario-based uncertainty is present. It serves as motivation for the rest of this thesis. The goal of this chapter is to develop a methodology for addressing the problems demonstrated in the last chapter. This will require the methodology achieve two goals. First, it must improve design outcomes as compared to the methods presented in previous chapters of this thesis. Second, it must be formulated in a way that it is applicable to realistic design environments rather than the simplistic mathematical models shown in the previous chapter. If these two goals are accomplished the methodology will be considered a valuable contribution to design decision making when uncertainty is present in conceptual design.

Chapter III presented a deficiency in robust design and defined the conditions in which it would fail to select a design that would end up being a good fit for the scenario. However, Chapter III did not provide an alternative method for conducting design decision making in the presence of scenario-based uncertainty. An alternative to robust design will be built on addressing the faulty assumptions made by robust design.

Section 3.3 presented evidence that the statistically based methods for robust design found in the literature failed to select a design that would lead to the best possible outcome. This failure was due to the implicit assumption in the robust design about the independence of the concepts. A technique for making decisions when uncertainties are present and correlation exists between the alternatives is needed. This need leads to the following research question:

Research Question 2: What other techniques have been developed for optimization when alternatives are correlated through external uncertainties?

4.1 A Portfolio Based Approach

The example problem and the informal mathematical proof provided evidence that there are situations where scenario based uncertainty can create correlations between the concepts and drive the selection in the conceptual decision. This led to Research Question 2, and the purpose of the next section is to address this question.

In economics, investors are presented with a problem also containing irreducible statistically dependent uncertainties. This thesis will explore the principles of the Nobel prize-winning modern portfolio theory and how it addresses a similar problem. Management science also offers a set of product portfolio processes that claim to apply methods from quantitative finance. For completeness, this thesis will also address these techniques.

4.1.1 Modern Portfolio Theory

Modern portfolio theory (MPT) introduced by Markowitz in his seminal paper in 1952 provides a method for maximizing the expected return of the stock portfolio for a given level of risk or alternatively minimizing the level of risk for a desired level of expected returns[80][81]. This work has gained wide acceptance in finance and won the Nobel Prize for economics in 1990. His work is fundamentally based on Equation 35.

$$\sigma_{X+Y} = \sqrt{\sigma_X^2 + \sigma_Y^2 + 2\rho\sigma_X\sigma_X} \tag{35}$$

This equation represents the sum of the standard deviations of two correlated normal variables. The breakthrough introduced by Markowitz was the recognition that the sum of two correlated uncertain normal variables could be less than either of the variables alone. This is accomplished through the third term shown in Equation 35. By recognizing that the correlation (ρ) can take a negative value, Markowitz was able to build stock portfolios that have a lower variance and/or a higher return then the component parts. The key is to find negatively correlated distributions. Stated simply, modern portfolio theory quantifies the idea that two complementary things can be significantly better than one. This mirrors the effects seen in the example problem. Furthermore, design often has tradeoffs that lead to negatively correlated concepts. As a result, MPT offers a great insight into how design decision making can be improved.

There are two notable stated assumptions of MPT. The first is the assumption of the joint normal distribution. It is assumed that the uncertainty of each of the stocks in the portfolio follows this joint normal distribution. This, however. is the same assumption argued to be valid by Bandte et. al. in JPDM [11]. Even this valid assumption can be removed through the direct use of modeling.

The second assumption is that investments can be divided into parcels of any size. This assumption cannot be met in the design environment, because partial aircraft cannot be developed. Removal of this assumption will require that value be estimated through the modeling assuming a full development of the vehicle. The use of discrete aircraft concepts means that there will not be a smooth Pareto frontier trading risk and value. Instead the trade between risk and value will create a discontinuous curve that requires a more detailed cost-to-benefit analysis. The third sub-section within Section 4.1.1 discusses the effect of discrete costs on the use of portfolio theory in detail.

A third and unstated assumption in MPT is that the standard deviations are calculated from a time history of previous stock prices. The variability for design problems cannot be calculated from a historical data set, and a modeling environment that is capable of calculating the design outcome probabilistically is needed for understanding variability.

In relating MPT to design, it should be recognized that the design Pareto frontier is a semi-equivalent statement to negative correlation. However, the model that defines the Pareto frontier in conjunction with the rest of the modeling environment has a great deal more information than a simple correlation. The correlation is a measure of the linearity of the relationship between two variables as they change with respect to another dimension. The Pareto frontier and value model contain all of the nonlinear as well as linear effects of the related variables as they were captured by the modeling environment. The information in this frontier can allow the removal of the joint normal assumption as well as the use of correlation.

MPT uses a time history of previous stock prices to make an estimation of the likelihood of future scenarios. Similarly for design, a modification is needed in understanding the uncertainties. In many of the literature based processes the time element of the uncertainty was ignored. If a portfolio-based approach is to be used it is also requires the tracking of the uncertain variables as a scenario evolving in time.

The application of MPT to conceptual design requires some further modification of the conceptual design process. The decision set on which the conceptual design decision is made must be expanded from selecting the best single concept for continued development to selecting the best portfolio of concepts. Simply stated from a design perspective, MPT approaches risk mitigation through the use of two offsetting concepts.

In summary, MPT offers the potential to improve design outcomes through the selection of a well-diversified portfolio of concepts. This portfolio of concepts should be created as a diversified set of points located throughout the regions of the Pareto frontier that have an interaction with the scenario based uncertainty.

4.1.2 Product Portfolio Management

Product portfolio management is a discipline of management science that seeks to improve design outcomes through the use of product portfolios. After an extensive literature search, little commonality was found between product portfolio management and economic portfolio theory. The author of this thesis chooses to treat product portfolio management and MPT as independent and separate entities. This decision is due to the lack of mention in product portfolio theory of MPT's fundamental idea using negative correlation and dissimilarity to increase returns while minimizing risk.

The field of product portfolio management may not be directly linked to the mathematics of finance, but it does provide an alternative body of justification for the techniques it purports. Empirical evidence based on the company's earnings statements are typically provided as justification for the methods described in product portfolio management and have shown an increase in earnings for organizations that take a product portfolio-based approach [30].

Cooper and Edgett define product portfolio management as the following:

"We define [product] portfolio management as a decision process, whereby a business's list of active new product (and R&D) projects is constantly updated and revised. In this process, new projects are evaluated, selected and prioritized; existing projects may be accelerated, killed or de-prioritized; and resources are allocated and reallocated to the active projects." [29]

Product portfolio management is designed to achieve the following goals [57, 25]:

- Maximize the value of the portfolio within the bounds of the resource constraints
- Balance the portfolio to ensure an appropriate mix of projects and to diversify risks
- Align the portfolio with strategy
- Provide defensible reasoning for go/no-go decisions

If one were to replace the word portfolio in this list with the word concept, the previously stated list would closely match the goals of conceptual design decision-making. To achieve these goals product portfolio management generally follows the following process [26, 27, 22]:

- Identify and prioritize market opportunities

- Follow a disciplined process to assess the enterprise level costs, benefits, and risks of potential product alternatives
- Allocate resources in gated process

Again it is easy to see a remarkable similarity to the engineering design process. Product portfolio management differs from design decision-making in the way in which it makes down-selection decisions.

The product portfolio management process is most typically depicted as a funnel. An example depiction, shown in Figure 61, adapted from Reference [129] shows a notional example of a product portfolio approach to research and development [129]. The approach begins on the left and each product progresses through the funnel as it continues its development. Throughout the development process each product must pass a series of review gates. At each review gate the product is assessed in relation to the rest of the portfolio and a decision is made about the continuation of development. The gradual elimination of products from the portfolio gives rise to the funnel shape shown in Figure 61. Under this paradigm a large number of products pass the first few review gates but by the time the final review gate is reached, signifying an entry to market, only a few products remain. It is important to note that this notional depiction shows an elimination of concepts, but the literature does not specify methods for determining the rate of down-selection or a means of determining the correct number of products at each review gate. The literature does however apply the MADM techniques used in design decision-making to select the best set of products to continue on to the next decision gate. One of the key factors underlying this notional depiction is that information is gained as the products progress through the development process and review gates. This information can then be used to better select the right set of products for continued development.

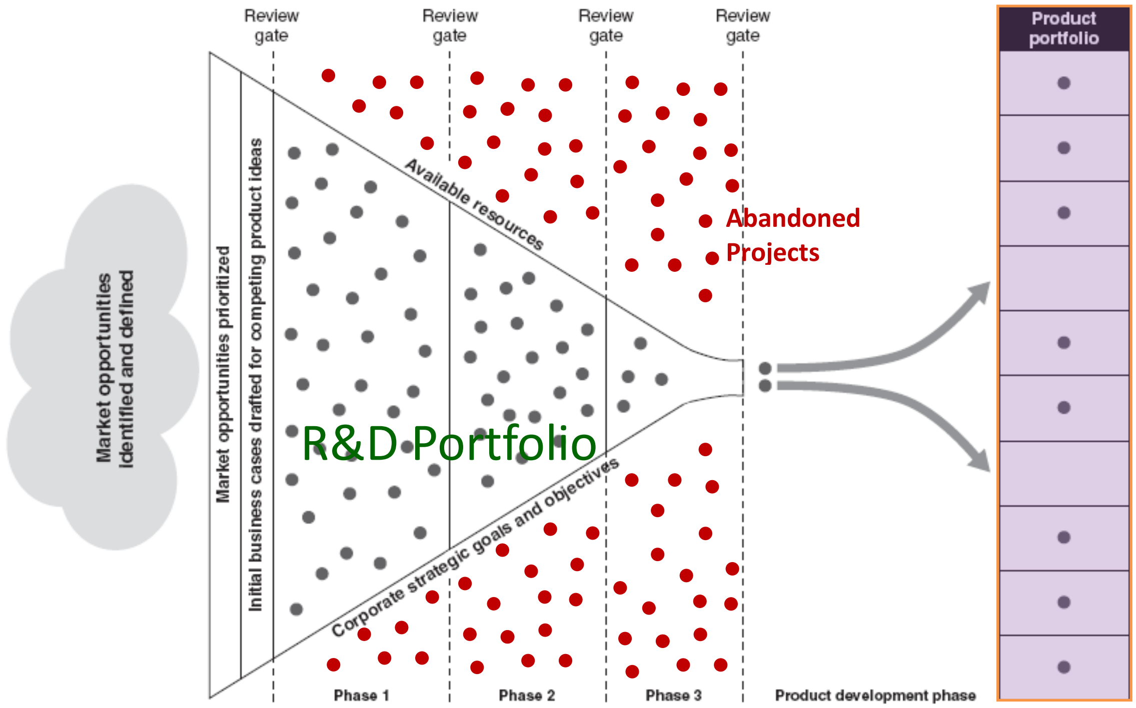


Figure 61: A notional depiction of the product portfolio management process [63]

Product portfolio management best practices are already typically applied in aerospace design [34]. The product portfolio management literature offers two structures for the review gates. One is a "gates dominate" approach and the other is a "portfolio reviews dominate" approach. In the gates dominate approach, the focus is on in-depth individual reviews of the particular product. In the "portfolio reviews dominate" approach the focus is on the value of one product relative to another. Edgett [28] states that "'portfolio reviews dominate'" is best suited for fast-paced companies… What was a great project several months ago suddenly is not so good anymore the whole market has changed! [28]"

Most aerospace design companies apply the "Gates dominate approach". This management approach was developed through observing successful engineering design. The conceptual, preliminary, and detailed design reviews are all examples of in-depth individual review gates. Product portfolio management offers no quantitative guidance on the best rate of down-selection of the funnel diagram shown in Figure 61. Without guidance on the number, the aerospace funnel starts very wide and collapses to one concept at the first review gate. From this point forward, the design continues through the product portfolio management process following a series of “gates dominate” reviews. Engineering, by definition, requires an in-depth look at the progress of the design on a fairly regular basis. This matches the “gates dominate” approach. However, all companies would like to be “fast-paced” and capable of agile reactions to changes in market conditions. The definition of “fast-paced” may be different for different organizations. In engineering design, the market may not change all that rapidly. However, it may still be necessary for the organization to the agile by maintaining a large set of options for responding to market changes if the development process itself is very slow. As a result, engineering organizations require the benefits of development under both types of review gates and a new method is needed for allowing both a regular review process and flexibility and agility.

Product portfolio management offers the idea that a portfolio of products should be pruned throughout a rigorous development process. Product portfolio management already occurs within a number of large aerospace companies, but no literature reference could be found where this information was linked directly to the engineering design. Furthermore, the literature focuses on the benefits of pruning a portfolio as a means of providing better decision alternatives to the decision maker, but does not include information on how to diversify a portfolio of engineering alternatives to maximize the benefits of a portfolio. As a result, product portfolio management offers the idea that successively pruning a portfolio leads to better returns for companies, but little specifics on what this would mean beyond what is already covered by engineering design literature.

4.1.3 A Portfolio Based Design Strategy and Implementation Challenges

The general strategy for addressing an uncertain decision where correlations exist is to carry forward a portfolio of alternatives. For this thesis the author will adapt portfolio-based methods from economics by creating a portfolio of concepts during conceptual design which are then iteratively refined and pruned in future design phases. The consequence of this adaptation is that the conceptual design decision will be to select multiple concepts to be used in a portfolio for further refinement. However, this portfolio will be iteratively pruned in reaction to changes in the scenario. As a result, a concept portfolio consists of two separate elements: the set of concepts that are to continue development as well as, the logic for removing a particular concept from the portfolio.

The use of a portfolio of concepts makes it possible to address the situations where robust design fails. In these situations, the design space exhibits strong movement with respect to changes in scenario or tipping point behavior. While Chapter III demonstrated that the robust design choice is not the correct choice, it is not possible to know a priori which of the more extreme scenario-tailored concepts will be the correct choice. The use of a portfolio allows design work to continue on multiple of these scenario-tailored concepts until a more informed choice can be made. As a result, the value of a portfolio-based approach comes from two separate elements. The first is the diversification of the portfolio in a way that mitigates the effects of changes in scenario. This has to do with initially selecting the right set of concepts. The second element that creates value is the ability to iteratively prune the portfolio to account for new information. This second element is dependent on the diversification step because the right concepts must be available to prune.

The knowledge that the use of a portfolio can increase the likelihood the best decision is made leads to research question:

Research Question 3: Which of the assumptions of modern portfolio theory are not directly applicable to the design problem?

4.1.4 Effect of Cost

It is been observed that engineering conceptual design literature focuses on the selection of a single best concept [42, 11, 61, 127, 110]. This single best concept is then further developed in preliminary and detailed design. If both MPT and product portfolio management provide a rationale for the continued design of multiple concepts, it would be expected use of these techniques would be widespread. This leads the one to question the applicability of the assumptions of MPT to the design problem, and this section will address the divisibility assumption of MPT that the design problem violates.

To examine the applicability of MPT to the design problem it is necessary that one of the most fundamental assumptions of MPT be revisited. MPT assumes that the investment resource can be divided in any proportion across multiple investments. This assumption is most definitely violated for engineering design. Returning to the vehicle example presented earlier this thesis, the simultaneous design of the high power and high fuel efficiency designs with only enough resources for one complete vehicle design leads to two half finished products. In this case, a half finished product returns no value, unlike a stock investment where half as much money still provides half the return. Because of this, the concurrent development of multiple concepts requires a great deal more resources than the development of a single concept.

Design is resource intensive and done in a resource-constrained environment. A limited set of resources is available, and this traditionally limits the organization to the development of a single concept at one time. Raymer [110] details the magnitude of resource intensity by stating “you bet the company” on whatever design is selected. The high-stakes of this game only serve to increase the desire for better risk reduction.

There are few reasons to revisit the assumption that only a single design concept can be developed at a time. The first is the recognition that design is an iterative process. As the design progresses through development, technical uncertainty is resolved. Furthermore, as the current date moves closer to the date of entry, the projections of external uncertainties are taking place over a shorter time horizon. This reduced horizon typically means higher confidence, and lower variance estimates. These statements about the time progression of the design can be combined with advances in modeling and simulation that allow an increased level of information available at each stage of the design [87]. They have reduced the cost and time required in acquiring higher fidelity information in the very early stages of design. The bottom of Figure 62 taken from Reference [87] shows the impact of recent developments in modeling and simulation on the aircraft design process. For comparison this has been overlaid with the product portfolio management process. While it still may be prohibitively expensive to take multiple designs through the manufacturing for a single market segment, the benefits of simultaneously developing multiple concepts merits a quantitative cost-to-benefit comparison. Rather than implicitly assuming a single design concept should be developed, it would be better to examine the cost-to-benefit comparison of concept portfolios where one of the alternative portfolios under consideration consists of a single concept.

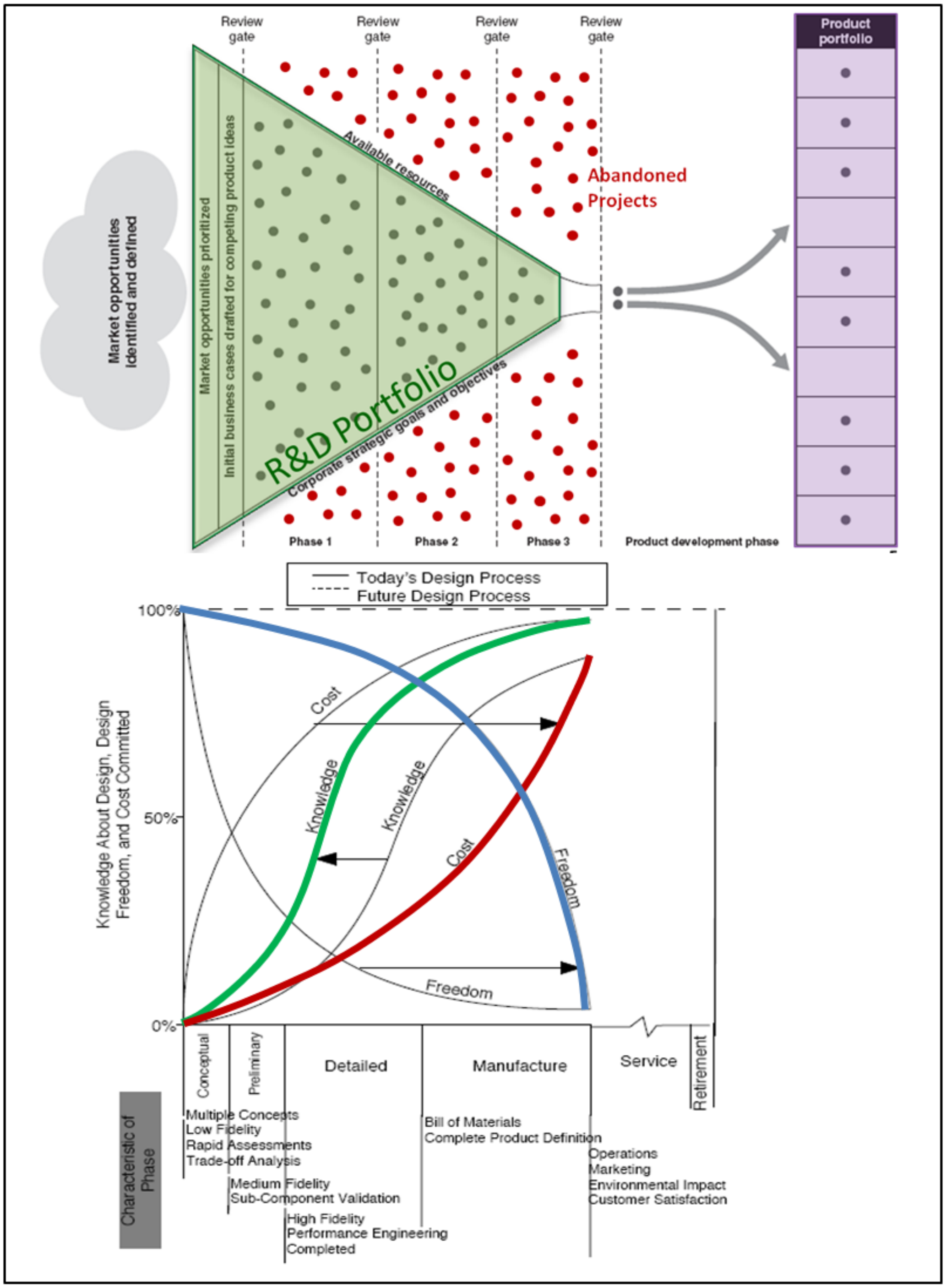


Figure 62: A comparison of the single system progression through design review gates and the product portfolio management gated depiction

In summary, the previous section provided the recognition that design is very resource intensive, and the organization has a limited set of resources. However, a portfolio-based approach should only be ruled out after a cost-benefit analysis has been performed to determine if the constraints actually rule out this approach. Any process for conceptual design decision-making should include this cost benefit analysis. Furthermore, any portfolio-based approach must ensure that it meets the organizational resource constraints. MPT suggests that a diversified portfolio can reduce risks and increase returns. Because the costs cannot be sub-divided for a design problem this implies a larger cost for a portfolio-based approach. The larger costs can be reduced through intelligent down-selection of the portfolio as implied by product portfolio management. If the benefits of this portfolio-based approach outweigh the added costs, then a portfolio-based approach should be pursued.

4.1.5 Portfolio Theory Conclusions

Both MPT and portfolio product management suggests the best means for improving conceptual design decision-making and mitigating risk is to change the decision alternatives from individual concepts to portfolios of concepts. Both MPT and product portfolio theory also emphasize the importance of including information about development through time.

Product portfolio theory offers some justification for the use of a portfolio in design and recommends a set of review gates at which the portfolio can be pruned to a single concept. Product portfolio management offers little insight into the correct number of concepts in a portfolio, how those concepts arrived in the portfolio, or at which review gates these portfolios should be pruned. Engineering design organizations are already applying the best product portfolio management practices with the assumption that down-selection to a single concept by the first review gate is ideal. The fact that aerospace corporations are already applying best practices from product portfolio theory and seeing poor results implies that it is not enough for product portfolio techniques be used to selectively prune an arbitrary portfolio, but rather that the mathematics from MPT be combined with a design optimization strategy to ensure that a well-diversified set of concepts are initially within the portfolio. Once this well-diversified portfolio has been selected, product portfolio theory highlights the fact that product development process is based around a set of decision gates, and these decisions can be used to iteratively prune the portfolio to reduce costs. Because of this “freezing” of design variables, product portfolio theory points out that the only method for retaining flexibility is to maintain a portfolio of designs to be developed in parallel.

MPT offers a set of mathematical tools for identifying how many and which assets should be included in a stock portfolio-based on their relative correlations. An opportunity for improving design decision-making and mitigating design risk exists in the potential to integrate these two separate portfolio management techniques.

The use of a portfolio-based approach requires the following changes: potential future scenarios must be defined, a benefit-to-cost analysis of the use of a portfolio must be performed, a method for creating alternative portfolios of concepts must be developed, and an iterative optimization strategy that allows for both the selection of the right concepts and an iterative downselection of those concepts must be developed.

In summary, the conclusion from MPT is that diversification of the portfolio towards changes in scenario-based uncertainty can improve the expected value while reducing risk. This improvement comes through the ability of MPT to create a well-diversified portfolio which is contains a number of concepts tailored to specific contingencies. However, this improvement comes at an additional cost. Product portfolio theory offers the conclusion that some of these costs can be recouped by intelligently down-selecting which concepts to continue as design progresses. The remainder of this chapter discusses methods for implementing a cost-to-benefit approach to determining if a portfolio-based approach can improve design outcomes. Chapter V will test the implementation on a realistic design problem.

4.2 Improving the IPPD Process through Resilient Design

The purpose of this chapter was to develop a implementable method for improving design outcomes when scenario-based uncertainty is present. This methodology will not be developed from scratch but will instead build on the IPPD process proposed by Schrage, and presented in Section 1.2 [117].

Figure 63 shows the central decision making process and analysis elements of the Integrated Process and Product Development method proposed by Schrage [117]. This section will provide the logic and rational for the changes necessary to allow the IPPD process to be modified for a portfolio-based approach. Based on the discussion of the portfolio-based approach four critical elements must be incorporated into the IPPD process to modify the current IPPD process to allow for a portfolio-based approach. These four elements are as follows:

- Define the potential future scenarios
- Conduct a benefit-to-cost analysis
- Create portfolio alternatives
- Develop an iterative portfolio optimization strategy

Addressing these four elements with a set of methodological changes will lead to the Portfolio Risk Mitigation for Design (PRISM-D) process presented in Section 4.10. The PRISM-D process will improve design outcomes in the situations described by Hypothesis 1 where robust design is not appropriate. The next few sections of this thesis will describe in detail the logic used in addressing these four elements and creating the PRISM-D process.

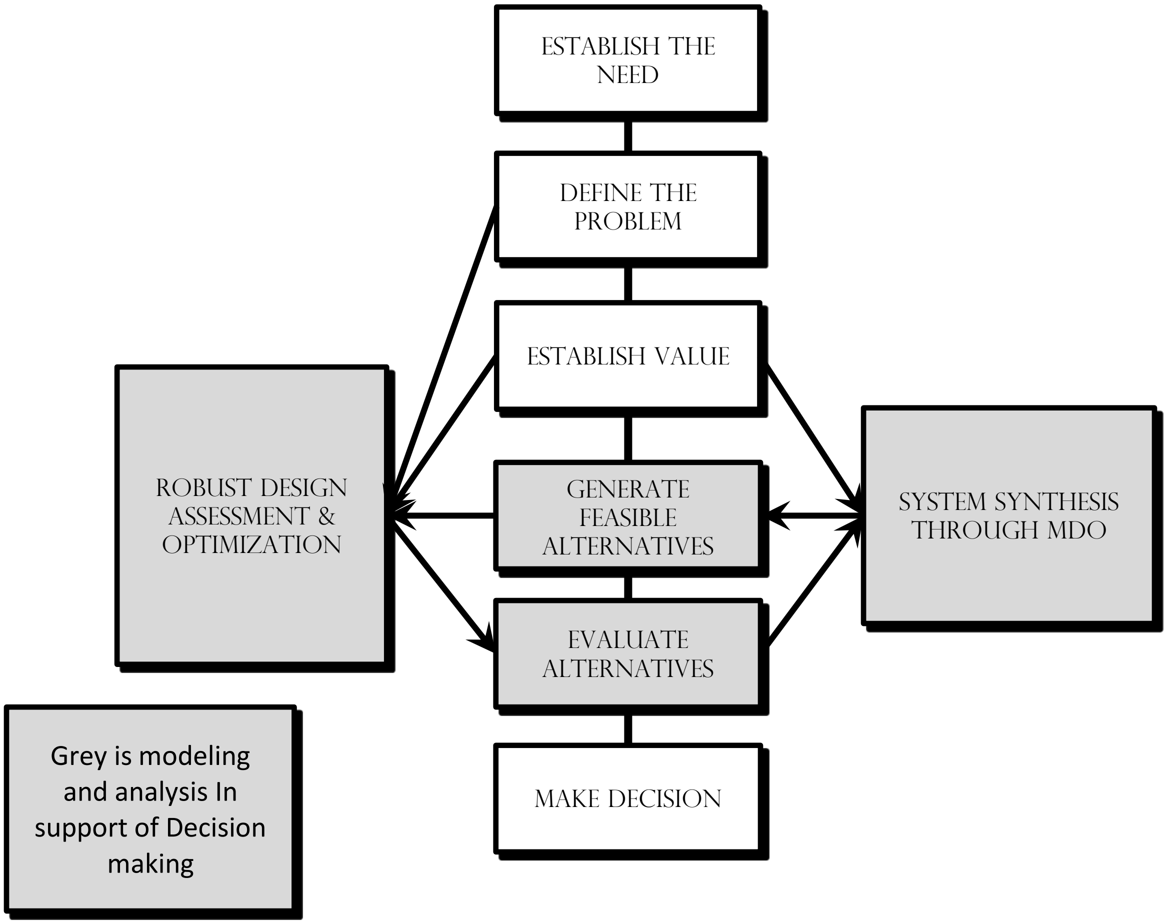


Figure 63: Decision making and modeling in the IPPD Process

4.2.1 Scenario Generation Techniques

This chapter focuses on providing a methodology for improving design outcomes in the presence of scenario-based uncertainty. For this to be possible, a definition and model of the potential future scenarios is necessary. This scenario model should include a description of the future scenarios to be expected along with the likelihood of each of those futures occurring.

Scenario modeling already occurs in the IPPD process as part of the problem definition. Typically in design literature this scenario modeling consists of nothing more than a distribution representing the potential variation in an uncertain input to the performance and business case models [32]. For example a distribution of potential fuel prices may be used to model the future scenarios. However, a distribution is insufficient for a time-based model of the scenario. Because the time evolution element is typically not considered in conceptual design, this thesis offers a brief overview of scenario generation techniques. The goal of this overview is not to be prescriptive, but rather to be descriptive allowing a particular user to select whatever method is best for his/her problem. For quantitative analysis, it is required that any method selected output a set of scenarios along with their respective likelihoods.

Scenario development and scenario planning constitute a field of study in their own right. The literature contains a very large number of methods and techniques for scenario generation. A good survey paper of scenario development techniques is presented by Bishop et al. in Reference [17]. This thesis will limit the number of scenario generation techniques to those that meet the following two conditions necessary for uncertainty analysis:

1. Uncertainty should be modeled as a stochastic process to allow the creation of "trigger" events that lead to downselection, or an adaptation of the method to include this information must be simple to implement.

2. The scenario generation technique must provide some means of quantifying the future likelihood of scenarios for decision making.

A summary of scenario generation techniques is presented in Figure 64 [17, 114, 45, 115]. The outline is programmed into three broad categories taken from Reference [17]. The three categories are event sequences and probability trees, dimensions of uncertainty and morphological analysis, and modeling. For each category, a number of named examples taken from literature are presented. In addition a set of pros and cons are presented to allow the user to identify a promising technique for his/her problem. The author of this thesis recognizes that not all of these techniques produce a set of probabilities along with the scenario. For those techniques that do not produce likelihoods of each scenario, it will be necessary to either assign a probability or in the case of modeling infer one from a Monte Carlo simulation [45]. It will be left up to the reader to select the best choice for his/her particular problem. An example problem is presented in Section 5.6.1 where, geometric Brownian motion and a Markov process have been used to model the uncertainty in conceptual design.

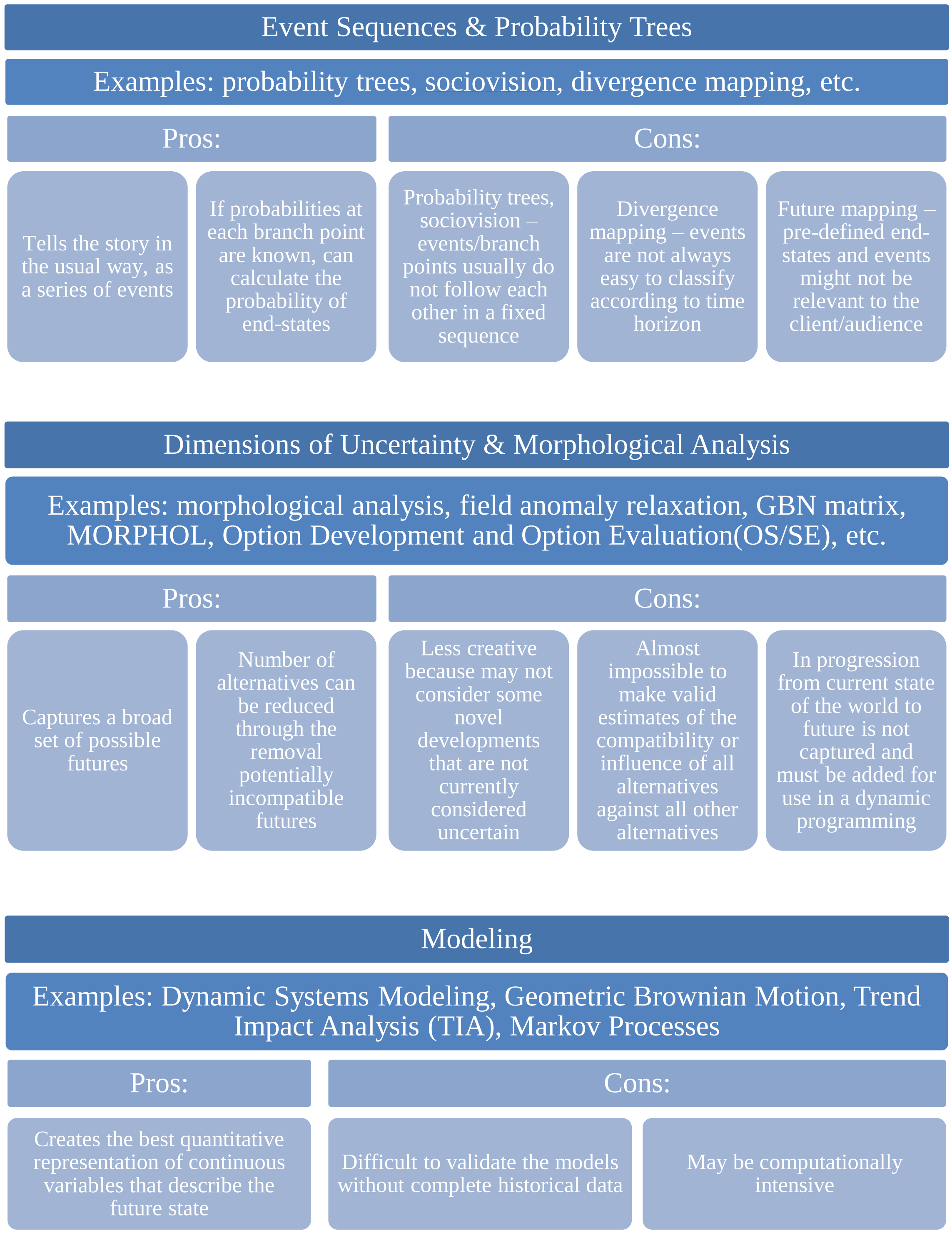


Figure 64: Scenario Generation Techniques

For each of the modifications required in Section 4.2, the author of this thesis has conducted a literature search of available tools and techniques and will make a methodological recommendation as to the best set of techniques for use in the PRISM-D process. For scenario generation, the established techniques were more than sufficient for defining the scenario in engineering design. Each of the techniques found in literature have a set of benefits and drawbacks. As a result the methodological recommendation is as follows:

Methodological Recommendation: It is recommended that the technique most appropriate for the specific problem and the uncertainties included that problem be implemented.

4.2.2 Quantitative Portfolio Value Measurement Methods

A portfolio-based approach has been selected as a means of improving design outcomes. Section 4.2 identified four elements of a portfolio-based approach that must be incorporated into the IPPD process to allow for a portfolio-based approach. The second element for incorporation into the IPPD process was "Conduct a benefit-to-cost analysis". This element will have direct impact on the second step in the IPPD process shown in Figure 63 labeled "Establish Value". The purpose of this section is to review the current quantitative portfolio optimization literature and make a methodological recommendation on the best way to incorporate a benefit-to-cost analysis into the "Establish Value" element of the IPPD process.

The following sections examine an overview of quantitative portfolio optimization techniques presented in Figure 65. This thesis is limited to only the quantitative techniques since quantitative information is desired in design. The quantitative techniques come from a broad variety of fields including management science, finance, mathematics, and systems engineering. The majority of the framework presented below has been taken from Heidenberger and Stummer. [48, 56]

The set of quantitative modeling techniques have been divided up into three separate categories for clarity based on their focus: value measurement methods, alternative comparison technique, and mathematical model / solution approach. It is not intended that in practice a mythology methodology selected will only draw from a single technique in a single category. Instead, it is expected that the methodology used in practice will most likely include at least one element from each of the categories. Furthermore, it is observed that selection of a technique from one category may imply the use of a technique from another category. For example, the use of Analytical Hierarchy Process (AHP) would imply that matrix manipulations will be used to determine a ranked list of alternatives.

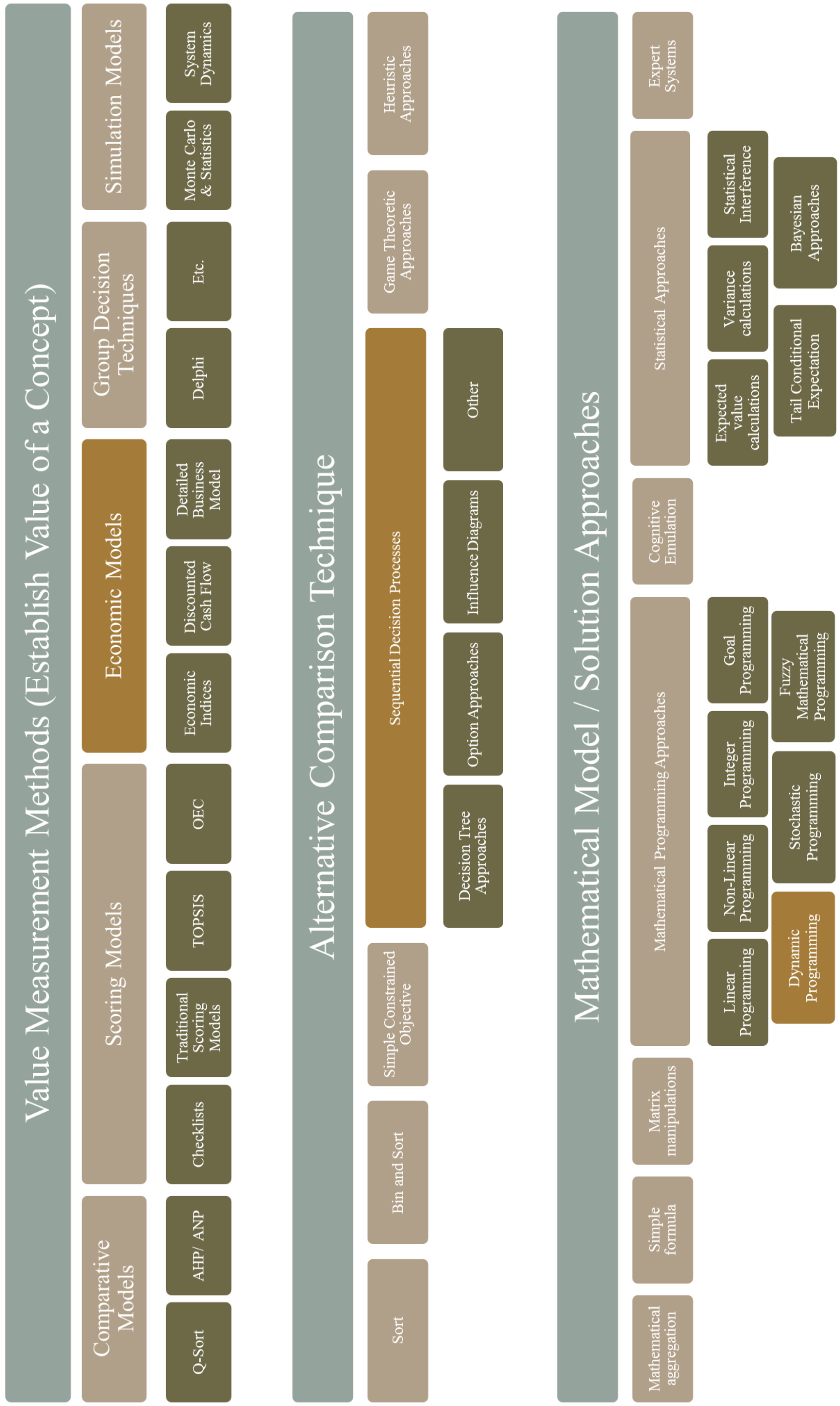


Figure 65: Existing Quantitative Portfolio Selection Techniques

The first category in Figure 65is value measurement methods and elements from this section will be used in modifying the step labeled “Establish Value” in Figure 65 This category is intended as a collection of ways in which the complex multi-attribute set of metrics can be collapsed into a single value that can be compared across all alternatives. From an optimization perspective, this provides the objective function on which an optimizer would operate. This category is largely made up of traditional MADM techniques. It is augmented with a number of techniques taken from finance such as the net present value and economic indices, as well as a generalized category representing complex business case modeling.

The requirement from the portfolio analysis was that the value measurement method be capable of measuring a benefit-to-cost analysis. This benefit-to-cost analysis allows the designer to measure if a portfolio-based approach, with its associated higher cost, outperforms a single robust design. Because of this requirement, the logic underlying a methodological recommendation for selecting a value measurement method from literature is straight forward.

The recommendation of a technique from the value measurement method category is that an economic model should be applied when conducting the PRISM-D process. Any of the techniques in this category can be used as our benefit measurement technique. However, some significantly simplify the process of cost-to-benefit evaluation at the portfolio level. The use of a portfolio rather than a single concept brings with it the need to demonstrate that the benefit of the portfolio exceeds the larger upfront cost required in developing a portfolio. Because of the desire to do this benefit-to-cost valuation at the portfolio level, the author recommends the use of economic techniques such as NPV or Internal Rate of Return (IRR). Alternatively, simulation models that outputs economic metrics often can offer higher fidelity modeling of the benefits and cost of a single concept as well as a portfolio-based approach. Dealing with economic terms directly simplifies the process of comparing the benefit as measured here to the cost of the portfolio measured in economic terms. As a result the methodological recommendation is as follows:

Methodological Recommendation: Because of the requirement for a cost-to-benefit analysis, it is recommended that an economic model that deals with both cost and benefit in terms of dollars is be used in the PRISM-D process.

4.2.3 Quantitative Methods for Creating and Evaluating Portfolio Alternatives

The following paragraph details the logic in incorporating the elements labeled "create portfolio alternatives" and "develop an iterative portfolio optimization strategy" into the IPPD process. The incorporation of these elements impacts the boxes in the IPPD decision making process labeled "Generate Feasible Alternatives" and "Evaluated Alternatives". Examining these boxes in Figure 63, the reader can observe that they are two of the four elements that make up the engineering analysis loop, shown in grey, which includes robust design.

The element "create portfolio alternatives" has been detailed in Section 4.1. However, section 4.1 defined the portfolio alternatives as both the set of concepts that make up a portfolio as well as the logic for the iterative pruning of those concepts. As a result this section will focus on examining the iterative portfolio optimization techniques which allow for the evaluation of such a portfolio. This means an iterative portfolio optimization strategy is needed which addresses the iterative analysis loop show in the grey boxes in Figure 63.

Returning to the literature techniques which have been categorized and sorted in Figure 65, the second category of is a set of constructs used in comparing the alternatives. Again it is assumed that some value measurement method will be combined with these comparison constructs. Furthermore, it is expected that in practice the constructs will most likely be combined in the actual decision making process. The most commonly used construct for selecting the best portfolio is simply to sort the portfolios based on the value, which was an outcome of the method selected from the first category, and choose the highest valued element in this sorted list. Other alternatives offer more sophisticated means of making the final decision that incorporate other aspects of the problem. Binning the alternatives allows comparison of alternative that meet some filtering requirements. The binning approach is the approach most often adapted by advocates of portfolio management science [30, 28]. Often constraints may be added to the decision process, or a time element may be added in the sequential decision processes. The game theoretic approaches attempt to model another entities reaction to the decision made, and heuristic approaches attempt to match past logic.

The third category in Figure 65 is a set of mathematical tools that are applied in evaluating a construct for decision making combined with a benefit measurement method. The techniques are often implied in the selection of a benefit measurement method or a mental model. However, the literature has often treated these mathematical tools as independent portfolio management techniques because in practice these are the fundamental basis for the quantitative evaluation of portfolios and are often documented by the academic community independent of the other two categories.

From this very large pool of techniques, only a few are ideally suited for an iterative process of decision-making under uncertainty. This section makes recommendations about which technique should be applied in conceptual design decision-making.

Examining the second category in Figure 65, the construct for comparing alternatives, the reader can observe that only the sequential decision processes best matches the iterative decision making found in a portfolio-based design. This category describes the logic of how the comparison between alternatives will be made. The simplest and most common method for comparing alternatives simply sorts the alternatives by value and selects the one with the greatest value. However, it should be noted that portfolio-based design is an iterative process where the portfolio is iteratively pruned, and as a result decisions are made and updated throughout this process. As a result, the construct for alternative comparison must mirror this iterative nature. Therefore, the only applicable subcategory presented in the outline is a sequential decision processes. This leads to the following methodological recommendation:

Methodological Recommendation: A sequential decision process should be implemented in the PRISM-D process because the iterative down-selection of a portfolio of concepts is a sequential decision process

Literature offers multiple applied approaches for portfolio management with a sequential decision process. The two most commonly applied methods are the decision tree approaches and options approaches. These two methods are not truly independent and it has been shown in literature that the options approach can be conducted with a decision tree [74]. Both of these techniques suffer from the following deficiencies: 1) they struggle with high dimensional problems, and 2) they offer no means for incorporating constraints. The options approaches further limit the decision-maker to a set of decisions that are capable of being made in stock options, and typically limit the uncertainty model to Brownian motion [95]. Both of these methods have the similar mathematical underpinning and the potential exists to create a similar method but removing the deficiencies using this underpinning.

Because none of the popularized sequential decision processes used in portfolio optimization techniques are ideal for the design problem, the mathematical underpinning of these popular techniques have been examined. This is shown in the final category in Figure 65 is “model solution approaches”. This category describes the underlying mathematical structure of the quantitative portfolio selection technique. From this category only mathematical approaches designed to handle uncertainty evolving in time are truly applicable. Two of the methods from literature have been specifically created for this type of problem. These mathematical tools are called stochastic programming and dynamic programming, and each incorporates an expected value calculation. Dynamic programming is a paradigm where the large top-level optimization problem is broken into sub-optimizations at the decision points, the uncertainty is typically discretized and a number of future scenarios are generated. From these scenarios, an expected value is calculated from the most future point, moving backwards through the programming to the current time. Dynamic programming is the classical method for handling sequential decision-making in the presence of uncertainty, and typically the mathematical underpinning for most of the literature-based methods for quantitatively determining the value of a set of sequential decisions [12]. Stochastic programming is a similar mathematical optimization that offers some efficiency gains over dynamic programming but requires that the decision choices not affect the probabilities of future events [118]. Because the selection or cancellation of a particular concept can affect the future set of possibilities, the classical approach, dynamic programming, offers a means for solving the portfolio cost-to-benefit optimization

Portfolio optimization techniques available from literature offer promising techniques for solving the design portfolio optimization. In particular dynamic programming offers a mathematical construct for solving portfolio-based problem with information updating over time [14]. Furthermore, this technique has been used successfully in the financial world particularly in the creation of options [93].

An existing approach implementing dynamic programming based on the use of financial instruments has been reintroduced into the product development world in the form of real options. The real options framework has received a great deal of attention recently, but this framework carries with it unnecessary limitations from its use in optimizing stock portfolios [54]. Real options are typically limited to basic yes or no type decisions with no constraints and an assumption of normality or log normality for the underlying uncertainty. Furthermore, these limitations mean real options approaches can only capture the cost savings from the intelligent down-selection of concepts. Even this is only possible in a limited set of situations. The majority of the value in a portfolio-based approach comes from the ability to quantify and select a well-diversified portfolio, and the benefits of a well-diversified portfolio cannot be captured by the traditional real options approaches [95]. This thesis will return to the mathematical underpinnings of dynamic programming to solve the stochastic optimization that is design decision-making in the presence of uncertainty [73].

Dynamic programming

Dynamic programming is the classical approach and an underlying mathematical framework for iterative decision-making under uncertainty. Developed by Richard Bellman in the early 1950s to solve multi-stage decision processes problems, dynamic programming is a mathematical optimization strategy [13]. The name dynamic programming originated as a means of disguising the mathematical nature of the work from the United States Department of Defense who was then funding the research but was at the time opposed to pure research [35]. However, it is important for the reader to note that despite the obfuscating name, dynamic programming is an analytical optimization which searches the entire design space and guarantees a discovery of the true optimum [13].

Equation 36 shows the Bellman equation, a mathematical representation of the dynamic programming problem. It breaks the decision problem into the current function determining the optimum $F(x_0, a_0)$, and a future function determining the optimum $V(x_1)$, which may be discounted by a factor β. The future function has a form similar to the current optimization function, but the future state is predicated by the fact that it must conform to the constraint that the future state x_1 is a function of the current state x_0 and the action currently being taken a_0 . As a result of this form, the decision problem is an iterative solution to Equation 36.

$$V(x_0) = \max_{a \in \Gamma(x)} [F(x_0, a_0) + \beta V(x_1)]$$
$$\text{such that} \tag{36}$$
$$a_0 \in \Gamma(x_0) \quad \text{And} \quad x_1 = T(a_0, x_0)$$

To translate this to the design decision making problem it is necessary to describe the elements of the design in the presence of uncertainty into the form used in Equation 36. To do this the decision problem will be displayed as a tree. The following paragraphs will relate dynamic programming to the design decision problem and walk through the logic used in solving this mathematical set of optimizations.

In representing the decision problem as a tree, it is common to represent uncertain scenarios evolving from the current state as a tree structure with each possible change in scenario represented as a set of branches with one symbol as the node connecting these branches. Typically, each potential decision to be made is represented as a set of branches of the potential actions to be taken with a differing symbol representing the node connecting these branches. Figure 66 shows a simple example of the scenario tree with three uncertainties fuel price and the success of two technologies. As decision alternatives, the tree contains two concepts, concept A and concept B. Each of these uncertainties has two discrete settings. If one was to examining the tree, starting at the left of the tree and moving to the right, it can be observed that the fuel price changes with time. In the time between now and the time of the second decision, shown as blue boxes, the fuel prices have the potential to move either up or down, and each of the technologies will demonstrate either a successful or failed development. The tree propagates the scenarios forward in this structure, with uncertain events occurring in-between decision points. It is assumed that an observation is made of what has occurred before the next decision is made.

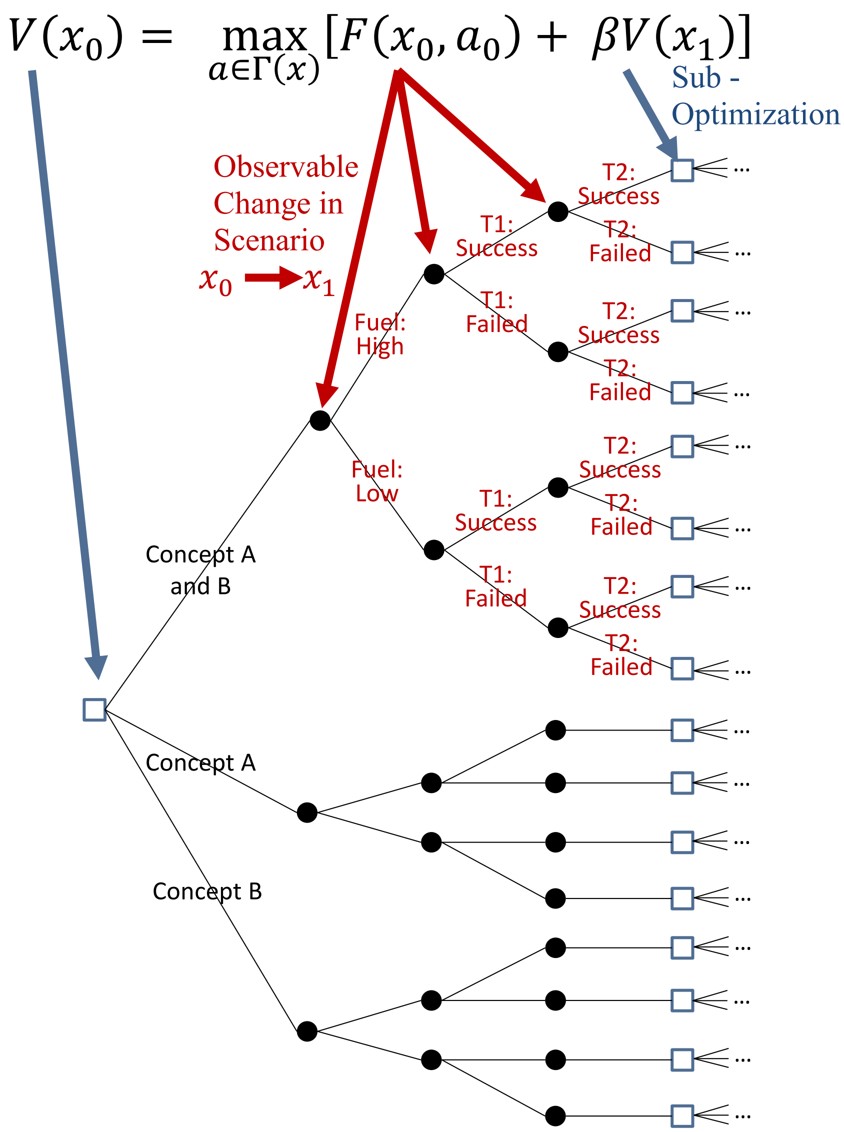


Figure 66: Uncertainty in stochastic programming represented as a tree structure

Solutions to the stochastic program come from the solution of a series of nested optimizations. The logic for solving the optimization problem is as follows:

At the current (first) decision point one should make the best decision available. However, because of the uncertainty, the best decision is dependent on the evolution of the scenario as well as the flexibility available through the parallel development of multiple concepts for reacting to changes in scenario. Because the development of multiple concepts is expensive, the best choice may include eliminating some of the concepts from the portfolio for development. At some time in the future the world will be observed, and the best decision should be made given the flexibility to choose from the concepts that remain in the portfolio. This logic is repeated iteratively throughout the decision process. The logic makes it difficult to state the best choice now because it is dependent on an uncertain future. What can be determined is that the best decision now is the one that satisfies some optimization statement that operates across all of the potential scenarios. So the best decision is something like "select the concept that maximize the expected value across all scenarios". However, the expected value of an iteratively updated decision is dependent upon the decisions made in the next iteration. For example, if originally an aircraft design had swept wings, but because of fuel price increases from the first decision point to the second decision point, we decided to remove the sweep for efficiency, then this new concept with no sweep has a different value. To help resolve this situation, I will assume now that in the future I will make the best decision available to me at that point. I will then assume that I do that for all future points. Because these decisions can be phrased in terms of an optimization problem (e.g. select the concept that maximizes profit) this decision logic represents a nested set of optimizations.

The solution to this set of nested optimizations by definition must work from the bottom of the tree upwards. Only at the end node in the tree can the final and deterministic scenario be observed and a direct calculation of the value of each alternative in that scenario can be determined. With this information it is easy to select the best alternative. The information about this scenario is then used to move backwards up the tree. This process can be repeated all the way back up the tree such that the optimal choice at the current time can be made.

By defining the initial choice for the concept portfolio as a selection of the best sub-set of all possible concepts from which the design can be selected, the designer can be assured that the selection of the optimum concept for the set of scenarios modeled has been found.

Dynamic Programming and Design

As the classical approach to iterative strategic making, a number of authors have recognized the relationship between the design process and dynamic programming [137, 99, 47]. The literature based work can be divided into two categories: Those which examine a broad set of alternatives with the engineering performance handled qualitatively; or those which examine a limited set of concepts with a quantitative model of the engineering performance.

The first category examines arbitrarily large numbers of potential products for the creation of portfolios, but these products are only described by a set of qualitative high level performance metrics. These performance metrics are numerical in value but only qualitative in their creation. They are often the result of expert opinion, or a very limited model for a specific set of scenario assumptions with an assumed engineering performance. The numerical value representing performance in the end can be viewed as a deterministic qualitative estimation of performance. As a result, the body of work within this category doesn't capture the effects of the engineered aspects of the problem, or how these aspects will relate to the scenario. While these techniques are capable of mathematically finding a well-diversified portfolio, this diversification cannot come via the engineering parameters and as a result they are not practical for engineering design [70, 69, 71, 126].

The second category describes techniques which perform quantitative modeling of the engineering performance, but limit the analysis to a limited number of concepts (no sources were found exploring more than seven concepts). Dynamic programming has been applied as a means of improving design outcomes in the aircraft design problem by Markish and Willcox [78, 77, 79]. In their work a quantitative modeling of performance, and costs was completed for three competing blended wing body concepts. The work was able to show that an increase in decision maker flexibility improved design outcomes, but diversification of the portfolio is limited to the three aircraft examined

[76]. Others have been able to show similar gains from decision maker flexibility as applied to the design problem, but have similarly limited the diversity to a small number of alternatives [82].

4.3 Literature Contributions to Methodology Development

Returning to the IPPD process shown in Figure 63, a portfolio-based approach allows for a replacement of the robust design assessment and optimization with a resilient portfolio optimization. This replacement involves a change in the alternatives to be considered from consideration of a single concept to the consideration of a portfolio of concepts. Finally, the evaluation of these concepts must be altered as well. This evaluation takes in the traditional modeling environment and places this within a dynamic program. This dynamic program is then used to value the portfolio of concepts and accounts for the iterative nature of design decision making.

In conclusion, dynamic programming offers the ability to account for the offsetting effects of a well-diversified portfolio as well as the beneficial effects iteratively pruning a portfolio and provides a measure of each portfolio's profitability. This allows for the alternatives to be transformed from a single concept to a portfolio of concepts, where the alternatives are evaluated by profitability. Finally the design process is transformed from selecting the best concept and iteratively refining that concept, to selecting the best portfolio of concepts and iteratively pruning which of those concepts will be further refined in future stages of design.

4.4 Hypothesis 2

To determine if a portfolio-based approach has merit, it is necessary to define the terms of success. For the purposes of this thesis, success will be defined by besting the optimum robust design in the two areas robust design attempted improve. Most of the robust design paradigms attempted to maximize expected value, or mean, while simultaneously attempting to minimize variance. To prove that a portfolio-based approach is an improvement, it will be necessary to first ensure the expected value of the outcome for the optimum portfolio is equal to or greater than the optimum robust concept. The second measure of robust deign, for most literature-based techniques is a reduction in variance. However, the use of variance is an oversimplification as discussed in Section 2.1. The proponents of robust design do not really care to limit the upside potential of the final outcome. It is actually desirable that the upside of the distribution stretch as far as possible. Rather, the reduction in variance comes from a need to limit the downside potential of the distribution. The symmetric measure variance was selected as a simplification, but will not be selected for the purposes of this thesis. Instead the reliability based approach selected in JPDM will be used which only attempts to minimize the probability that a specific threshold is not met. This accounts for the asymmetrical desires of the designer. The difficulty in this approach lies in defining the correct threshold. For the purposes of this thesis the most expansive test will be conducted, in that the portfolio-based approach must have a lower probability of not meeting a specified threshold than the robust design for the majority of any defined threshold. Hypothesis 2 is stated succinctly below, and described mathematically in Equation 37 and Equation 38.

Given that the conditions of Hypothesis 1 are met, there exists engineering situations in which a development of a family of concepts can have a higher expected value (as measured by the expected value) and a lower risk (probability of not meeting a specified threshold for any threshold) than the selection of a single concept while meeting all of the same organizational and design constraints.

$$\mathbb{E}[Optimum\ Porfolio] \geq \mathbb{E}[Robust\ Deisgn] \tag{37}$$

And

$$\mathbf{P}\left[\, \mathrm{P}_{Optimum\ Portfolio}(V \leq \alpha) \leq \ \mathrm{P}_{Robust\ Design}(V \leq \alpha)\right] \leq .5 \qquad (38)$$

$$\text{for all } \alpha \in \mathbb{R}$$

4.5 Implementation Challenges with Dynamic Programming

Figure 67 breaks the elements of a portfolio-based design problem into the elements as they are often handled in the literature. It shows four distinct but overlapping elements. Starting from the highest level and working down, there is the sequential portfolio optimization, the concept optimization, the technology optimization, and configuration optimization. Because of the scope of these elements they are each typically handled in a relatively independent manner. Each of these sub-problems is typically considered challenging independent of the rest of the problem. The approach proposed by this thesis takes a more holistic look at the problem and consequently allows an understanding of how the elements interact to create relationships that must be accounted for in design decision making. However, this holistic approach does lead to a number of implementation challenges.

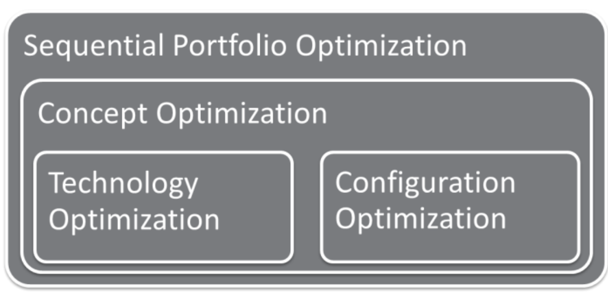


Figure 67: Decomposition of the Portfolio Optimization

The problem can best be described as a combinatorial problem. In simpler terms, combinatorial growth is a way of stating that the number of alternatives grows impossibly large very quickly as the problem experiences minor growth in scale. This has been referred to as the "curse of dimensionality"; a term coined by Richard Bellman the originator of dynamic programming to describe the rapid growth in the potential solutions in response to growth in the number of design and scenario dimensions. If our goal is to select the best alternative from this impossibly large set of potential solutions it becomes harder incredibly challenging. Numerically it is more difficult than finding a single atom, in all of the atoms in the visible universe.

The portfolio selection dynamic programming problem is itself a combinatorial problem that consists of nested sub-optimization problems at each decision point for each of the potential portfolio alternatives. These portfolio alternatives themselves grow at an exponential rate with respect to the number of concepts available to place in portfolios that are then compounded exponentially by the number of scenarios.

The number of concepts available to place into portfolios is dependent on the scale of the concept design problem. The concept design is itself made of two component parts, the best technology portfolio and the best configuration that defines a concept. This optimization should be done in a unified manner and environment, but no published and rigorous environment and methodology could be found for optimizing the technology portfolio as well as the configuration at the same time.

The technology portfolio sub-component of the design problem grows at an exponential rate of 2 raised to the number of technologies. This is because each portfolio can be included or not included in the portfolio.

The configuration sub-problem operates on both continuous and discrete variables. This means that the number of configurations that can be combined with the technology portfolios is technically infinite. However, it is often reasonable to discretize the dimensions of the continuous elements of the configuration. In this case, an estimate of the possible number of configurations is available. The numbers of possible configurations grows at an exponential rate of the number of discretizations raised to the power of the number of dimensions.

$$c = 2^T d^s$$

$$c = \text{number of concept alternatives}$$

$$T = \text{number of technologies} \tag{39}$$

$$d = \text{number of discritizations of each design variables}$$

$$s = \text{number of design variables}$$

$$a = \sum_{p=0}^{m} \binom{c}{p}$$

$$a = \text{number of alternative portfolios} \tag{40}$$

$$m = \text{maximum number of concepts in a portfolio}$$

$$\text{Final Search Nodes} = 2^a \prod_{\mathrm{i}=1}^{\mathrm{u}} \gamma_{\mathrm{i}} \left(\sum_{k=0}^{a} \left(\binom{a}{k} 2^k \prod_{\mathrm{i}=1}^{\mathrm{u}} \gamma_{\mathrm{i}} \right) \right)^{\mathrm{t}-1}$$

$$a = \text{number of alternative portfolios} \tag{41}$$

$$u = \text{number of uncertianties}$$

$$\gamma_{\mathrm{i}} = \text{number of levels of uncertianty } i$$

Equation 39, Equation 40 and Equation 41 show an estimate of the final number of optimizations and portfolio alternatives that must be examined. From these equations, it can be seen that the dimensionality of the design problem is raised to multiple powers in incorporating the concepts into portfolios, and these portfolios into a framework that allows searching for a best solution analytically in the presence of uncertainty. Consequently, design problems with large numbers of inputs become incredibly challenging to solve.

The final result of this nested set of decision problems is that the total number of decision alternatives contains a nested set of exponential growth terms where each exponential term is then raised to an exponent. This creates a situation where there is an impossibly large set of decision alternatives. This is typically handled organizationally by optimizing the individual elements in an independent manner and then integrated product teams of the relevant experts are used to create an integrated whole. Because this thesis attempts to improve design outcomes by quantitatively accounting for the lack of independence, an approach to handling the combinatorial alternative space is needed.

4.6 Addressing the combinatorial problem

The combinatorial problem space presents a new problem to be addressed by the thesis. This problem can be solved through a combination of three general ideas:

- Reduce the scope of the problem.
- Accelerate the analysis.
- Restrict the analysis to regions of interest.

4.6.1 Reduce the Scope of the Analysis

Combinatorial problems are often said to suffer from the "curse of dimensionality", which is a colloquial way of stating that as the number of dimensions grown the alternative space grows at an often greater than exponential rate. The simplest way to address this "curse of dimensionality" is to remove the dimensions from the decision problem.

Chapter III offered evidence that it was the interaction between the uncertainty and the concept that lead to the potential for improvement from a portfolio-based design. It is expected that only a limited number of uncertain scenario variables, and design variables share the interactions which would allow for a benefit from a portfolio-based approach. The purpose of the next section is to discuss a test for determining which variables must be carried to the holistic portfolio optimization, and which can be eliminated from the portfolio design space. If none of the variables in the design space meet the criteria for the following test it is highly unlikely that a portfolio-based approach will provide value.

Testing to determine which of the variables contain the interactions which would lead to a beneficial outcome from a portfolio-based approach begins with a standard system synthesis design optimization. In essence, the new part of this thesis, the portfolio optimization is being temporarily removed and a conceptual design optimization is being conducted which only includes the technology and configuration. The interaction between this standard optimization and the scenario will be examined.

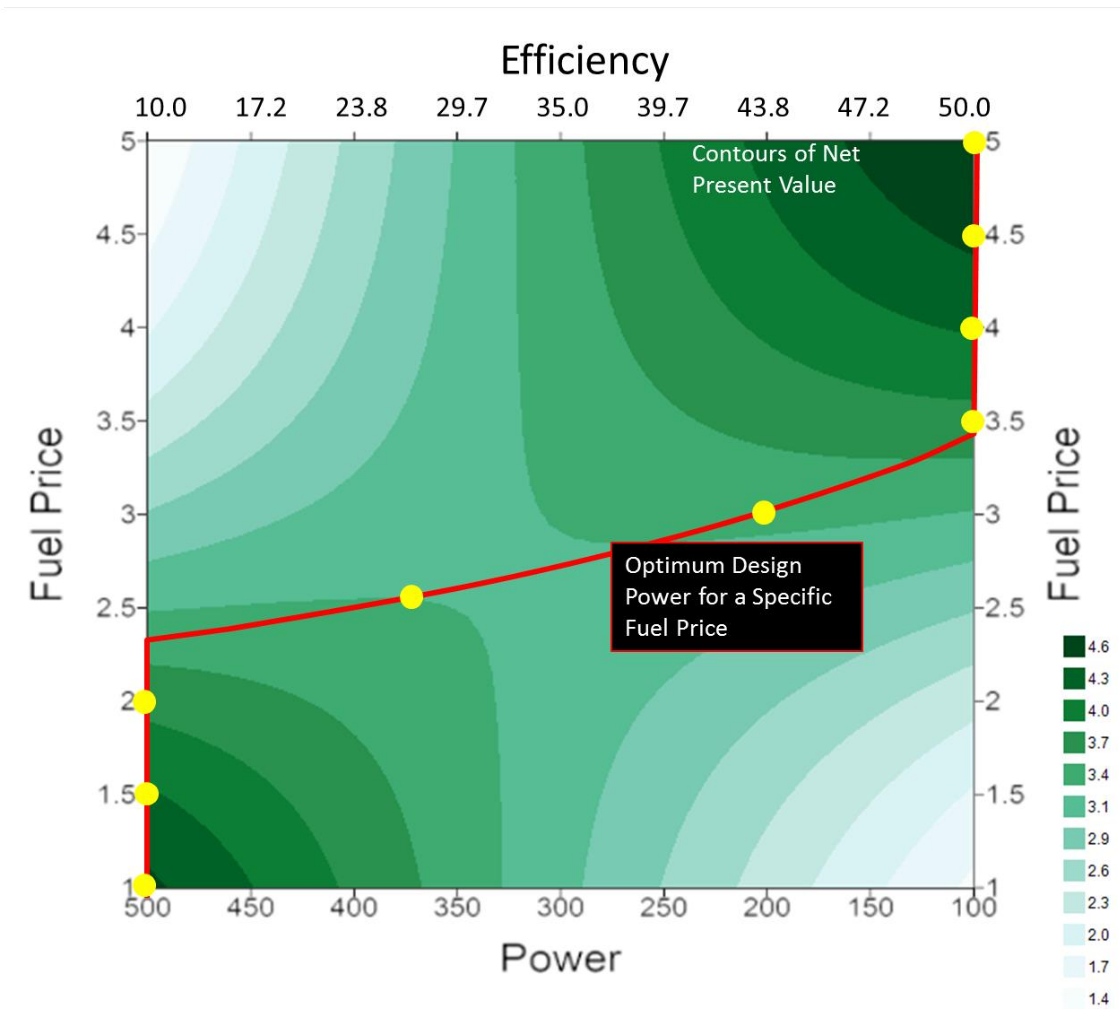


Figure 68: Analytical Optimum Design with Representative Sample Points

Recall that for the characterizing problem an optimum was found for each possible fuel price scenario. This optimum concept was analytically determined for each possible fuel price scenario was plotted in as a red line in Figure 54, and has been reproduced above in Figure 68. A strong twist in the design space leads to a result of this red line moving from one side of the design space rapidly to the opposite side of the design space. It is typically not possible for an analytical determination of the optimum to be found for realistic design problems. As a result, an approximation of this process is needed. The simplest approximation is to solve for the optimum design for a sampling of deterministic uncertain scenarios. Figure 68 shows 9 points in yellow that could be used to approximate the curve shown in red. If the points representing the design variables move rapidly from one equilibrium (typically the edge constraint) to another equilibrium at these sample points, there is a high likelihood that the design will experience tipping point behavior. In this situation, there is a reasonable chance that a portfolio-based approach can improve design outcomes, and a portfolio-based analysis should be pursued. Furthermore, the example shown in Figure 68 only has one degree of freedom which represents the design. This degree of freedom (power or efficiency depending which one was framed in terms of the other using the Pareto frontier) has an interaction with the uncertainty. As a result, it is necessary to include this single dimension in the portfolio optimization. However, with realistic design problems there are typically multiple degrees of freedom. Only a limited number of the variables associated with these degrees of freedom may exhibit the interaction the uncertainties.

For a realistic design problem, this approximation approach can be taken, and only the variables which show a transit in their respective dimension are necessary in the portfolio optimization. The rest of the variables, while important to the optimum design, are not used in creating the negative relationship between concepts that allows for a better handling of uncertainty, and these variables can simply be set to their respective optimum value. The remaining variables are sufficient to describe the changes in the best design with respect to changes in scenario, and these are the variables which will be used to create a set of concepts for the final optimum portfolio. Section 5.5 demonstrates this approach for a realistic aircraft design problem.

The use of this simple test to which allows for an initial estimation of how the optimized design changes with scenario allows for a rapid reduction in the number of dimensions. Only the design dimensions which show an interaction with a scenario dimension are required in the portfolio-based design.

4.6.2 Accelerating the analysis

A common method for accelerating the analysis is to use surrogates in place of the actual design code. Surrogate modeling is a method where a complex design code is represented as a simple mathematical function. This is done by running a specified set of cases though modeling environment and performing a statistical regression on those cases. The regression is then checked for accuracy and used as a representation of the modeling environment for the region of the specified set of cases. The use of surrogate modeling is applied in this thesis. [96, 41]

A second common method for accelerating the analysis is to run the analysis in parallel on multiple machines. This implies that the analysis can be broken into semi-independent sub segments and then combined at a later point. This is not a specific technique but rather a criterion on which the any technique used in optimization considered should be judged.

4.6.3 Restrict the analysis to the minimum needed

The challenge in restricting the analysis to regions of interest is that these regions are not known until analysis has been completed. There are two general paradigms for gaining an understanding a design space and defining the regions of interest. The first is design space exploration. In this case the goal is to do a broad sweep across the design space to provide and understating of the shape of the space, so an informed decision can be made. The second approach involves the use of optimization. In this case, logic is used to encode the designer's preferences and an algorithm is applied to iteratively search for the location that best meets those preferences. This second method reduces the decision-maker's insight into the global space, but drastically reduces the computational effort involved in finding an answer that best meets the decision-maker's preference. An optimization based approach is required for this problem, due to the vast size of the alternative space. [130, 108, 66, 102]

The second way of restricting the analysis to regions of interest is to perform a breadth first exploration of the design space, and use the information gained from this exploration to target the in depth exploration of regions of interest. This is the goal of most numerical optimizations. Again, this particular idea does not specify a particular method for use but adds a second criterion to any method chosen. [130, 108, 66, 102]

The last way the analysis can be restricted to the areas of interest, is to recognize the diminishing returns that can be expected from continuing analysis once a very good solution has been found. Even if the solution can to be verified to be the best, a continued search to prove that this is the best may not be of value. The inverse of this statement is that a better solution may be found through a continued search, but the solution will not be that much better. This last means is not a method or a criterion, but rather a statement of fact for numerical optimization on most real problems. [130, 108, 66, 102]

4.6.4 Conclusions on handling this combinatorial design space

In conclusion, the combinatorial space will be approached through the use of three independent methods. First the dimensions considered in the portfolio optimization will be limited to only those dimension of design which show and interaction with the scenario uncertainties. Secondly, surrogate modeling will be used to accelerate the analysis, and optimization will be used to reduce the analysis needed. Finally the use of optimization will be applied to the portfolio section problem. The optimization selected should perform well in a number of criteria. The criteria include: the ability to be parallelized, the ability to explore the total space and the quickly find a local best in regions of interest (breadth first search), the ability for early stopping of the optimizer once a “good enough” design has been found.

4.7 Reexamining Dynamic Programming from an Implementation Standpoint

When searching for an optimization capable of efficiently handling the combinatorial design space, the search should begin with the identified quantitative mathematical model dynamic programming. Dynamic programming is a mathematical procedure for optimization. Specifically, dynamic programming is a set of nested analytical optimizations used to determine the global optimum. Before examining other more complicated methods for optimizing the space, dynamic programming as defined by the mathematics must be compared to the criteria identified for the optimizer in Section 4.5. Table 5 shows a simple graphical representation of the criteria compared to the baseline method, dynamic programming.

Table 5: Stochastic Programming Compliance with Optimization Requirements

Optimization Criteria	Compliance
Maintain Solution Diversity	✓
Parallel Computation	✓
Breadth First Exploration	☒
Potential for Early Stopping	☒

The first requirement for any optimization method selected is that it must be capable of maintaining diversity in the solution space. This is necessary because it is diversity in the concepts, in particular contrasting behavior, which allows for improved outcomes. This requirement is met by dynamic programming since the technique test all potential solutions to determine the optimum. However, for many numerical optimizations which are design to rapidly converge on the best design do not maintain diversity well. The second requirement is that it be able to be run in parallel. This criterion can be met as the mathematical procedure involves dividing up the optimization problem into sub-optimization problems. The third criterion is that the optimization takes advantage of a breadth first search to target the in-depth search of specified regions. Examining Equation 36 which shows a generic representation of dynamic programming, on can see that it begins with a depth first approach. This is because the only location where the scenario can be known with certainty is at the end of evolution of the scenario throughout time. Stochastic programming fails to meet this criterion. The algorithm must simultaneously deal with the fact that certainty is only available at the end state, but a breadth first type search is needed for computational efficiency. The final criterion is the idea that the analysis can be stopped once a "good enough" solution has been found. Dynamic programming offers the guarantee of finding the exact optimum, but does so at the expense of early stopping once some criteria has been met. This particular criterion demands that a numerical optimizer to be integrated into the analysis.

4.8 Challenges of Integrating Numerical Optimization

The following section details the challenges faced in selecting and integrating a numerical optimization with uncertainty evolving in time. The section details why the structure has been used in dynamic and offers a strategy for creating a hybrid analytical and numerical optimizer.

Dynamic programming introduced an idea of nested analytical optimizations where the goal was to solve the highest level optimization. The lowest (most nested) optimization was solved first, and then the information gained from this optimization was used to solve the next level up. This process is repeated for the entirety of the program, allowing the highest level optimization, representing the decision that should be made at the current time period, to be solved. This structure was driven the fact that only the end state after all decisions have been made and uncertainty has been specified through the use of a specific scenario is enough certainty available for the modeling environment to determine the performance of the design concept.

The challenge in integrating numerical optimization, as desired for computational efficiency, is that this lack of information at the top level cannot be overcome. Enough certainty for modeling of concept performance still only exists at the lowest level of the nested structure. In contrast, the strategy employed by non-gradient based numerical optimizations typically begin with a breadth first exploration of the design space and a rapid in depth exploitation of regions of better value once they have been found. This is a desirable trait of numerical optimization and one of the key elements in its ability to limit the analysis. However, the stochastic nature of the problem requires the optimizer to start at the most detailed level. This means the breath first element of numerical is incompatible with the structure of dynamic programming. A hybrid approach is examined in this thesis.

Solving the mismatch between the structure of dynamic programming and the structure of numerical optimization is done by recognizing that the dynamic program is a set of nested analytical optimizations. It is not necessary to replace the analytical optimization at all levels with a numerical optimization. Instead only selected levels can be replaced. The solution proposed by this thesis is that only the highest level of analytical optimization is replaced by the numerical optimization, the rest of the optimizations will remain analytical. Figure 69 shows a simple schematic of this idea for clarity. This single optimization replacement has little impact on the solution time, unless it is combined with another idea. Each top level numerical optimization operates on a small subset of the concepts. This limits number of portfolios significantly since the creation of portfolios from concepts is itself a combinatorial problem, and grew at a greater than exponential rate. These top level numerical optimizations select the best concepts from the limited number that were examined. The concepts are then compared creating a pseudo-breadth first search. The top level numerical optimizations share information about the performance of their respective portfolios, and concepts, and a decision is made about a second iteration of portfolios based on this initial information. This solution allows for a pseudo-breadth first search as desired for computational efficiency, but still accommodates the nature of the stochastic problem.

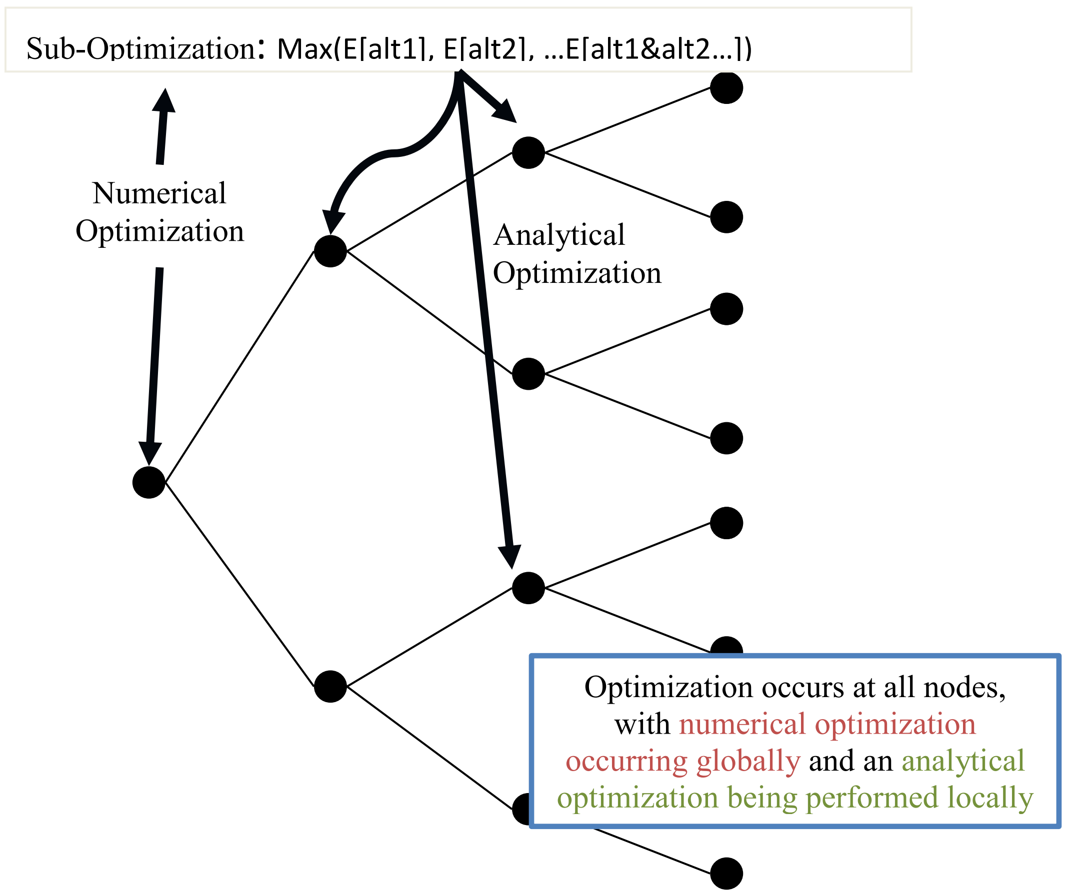


Figure 69: A Partial Implementation of Numerical Optimization Allowing for a Pseudo-Breadth First Search

4.9 Selecting a numerical optimizer

A range of numerical optimizers are available for use as the top level numerical optimization in the hybrid approach proposed. The following section details the logic used in selecting a strategy for numerical optimization.

4.9.1 No free lunch theorem

The selection of a numerical optimizer best suited to our problem must begin with a discussion of the no free lunch theorem. The no free lunch theorem, introduced by Wolpert and Macready in 1996[134] and expanded in 1997[135], states:

There cannot exist any algorithm for solving all problems [including optimization] that is on average superior to any alternative. Any benefit in the solution to one class of problem must be compensated for by a deficiency in another class of problem. [134, 135, 50]

The theorem is a statement, and corresponding mathematical proof of Pareto optimality for algorithms. The consequence of this theorem is that there is no ideal algorithm when solving multiple different problems.

The statement is generally not an issue to practitioners. For anyone looking to use a particular algorithm is not interested in solving all problems but rather their specific problem.[8] However, for the problem this thesis addressing the no free lunch theorem describes a significant issue. The conceptual design decision-making problem consists of three very distinct sub-problems which are integrated into a whole by a fourth problem. As would be indicated by the no free lunch theorem, each of the sub-problems has been proven to be solved effectively by an algorithm. However, no algorithm currently exists that can simultaneously solve the set of problems effectively. The no free lunch theorem indicates that that none will exist.

4.9.2 Free Lunch Anyway

Because this thesis has defined a need of an optimization algorithm that can solve the entire space at once, it is required that a method be found that violates the free lunch theorem. This thesis is based around an argument that Pareto optimality can be violated by applying a portfolio approach. The approach can also be applied to Pareto optimality in algorithms. Here the algorithm is replace by multiple algorithms each tailored to solve a specific part of the design space. Information is passed between these separate algorithms and the results of this algorithm will then be integrated in an intelligent way to solve the whole problem. This technique should allow for a version of free lunch.

Independently, the idea of co-evolution has been observed to enable free lunches when a goal exists (e.g. maximize a performance measure)[136]. Co-evolution is a specific type of evolutionary algorithm that is based on the biological idea of co-evolution.

An evolutionary algorithm is an algorithm based on the idea of evolutionary improvement. In these algorithms a population of alternative solutions to the problems exists. At every iteration, each individual/alternative in the population has its fitness measured by determining how well that alternative solved the problem. Individuals with better fitness reproduce to create similar children, and alternatives with worse fitness are discarded. By this mechanism the algorithm proceeds towards an optimum solution [75].

Co-evolution is a continuation of the biological logic by recognizing that biological populations interact. Examples of biological co-evolution include evolutionary "arms" races, and symbiotic relationships. In terms of biology the cheetah gets faster because the gazelle is fast. As a result, the gazelle gets faster and so on. Co-evolution separates individuals into "species" that do not directly breed but interact through their fitness function [133]. The methodology is particular appealing because it offers the potential to maintain diversity while improving the overall result. There are two general classes of co-evolution that mirror biology: competitive co-evolution and cooperative co-evolution.

Cooperative co-evolution has been successfully applied to large monolithic problems that can be broken into sub-problems [104, 55, 100]. All sources found in literature use same underlying EA for separate populations [106, 103]. The problem specified by this thesis requires not only separated populations, but entirely separate algorithms. The architecture proposed by Potter is flexible enough for specifically targeted EA's, provided the fitness functions can be combined [104, 105]. As a result, co-evolution with a portfolio of specifically targeted evolutionary algorithms will be used to solve the portfolio-based conceptual design optimization.

4.10 Development of the ECOSIS Algorithm

The use of multiple combining evolutionary algorithms allows for a computational free lunch, but associated with this violation of the Pareto principle for optimizers is a hidden cost. The effort has been shifted from the algorithm to the algorithm's designer. It is necessary for the following two elements to be defined for the algorithm to be successfully implemented:

- Provide a decomposition of the problem that allows for the algorithmic solution to specific sub-problems
- Identify evolutionary algorithms specifically targeted towards each of the sub-problems

4.10.1 Decomposition into sub-problems

A decomposition has been provide for the problem that contains a set of sub-problems in Section 4.4. A pictorial representation of the sub-problems can be seen in Figure 67. This decomposition will also provide the structure for the individual evolutionary algorithms which will be combined to create the environment for running the co-evolutionary algorithm

4.10.2 Criteria for Selecting Evolutionary Algorithms for Sub-Problems

A set of evolutionary algorithms capable of solving each of the specific sub-problems must also be specified. For each sub-problem multiple algorithms exist. However, no algorithm existed to solve any of the sub-problems in exactly the way needed by the integrated conceptual design decision making framework. The no free lunch theorem means that a comparative evaluation of the alternative evolutionary algorithms for the sub-problems will have little meaning once the algorithms are implemented for a new problem. As a result the decision criteria used in selecting EA's for the sub problems were the following:

- Must have demonstrated successful use in a similar problem
- Must in meet the criteria specified in Table 5
- Must be similar enough to other sub-optimizers so that integration is possible

The following sections detail the type of optimizer chosen for each of the sub-optimizations. An evolutionary algorithm has been selected for each of the sub-optimizations for ease of use in integration with the top level co-evolutionary algorithm.

4.10.3 Concept Optimization Problem

The concept optimization is the fundamental element of the evolutionary algorithms discussed throughout this thesis. While the concept optimization problem is made of two sub-problems, it is the performance of the concept operating in a specified scenario which can be simulated through the use of modeling and simulation. As a result, this is the lowest unit of decomposition for which the performance can be measured. This performance becomes the simplest form of fitness function applied in the evolutionary algorithms used in this body of work.

The concept description consists of two separate elements. The first is the technology portfolio, and the second is the concept specification. These two elements are combined together to create a concept for which the performance can be measured in a specified scenario. The performance is combined in differing ways to specify the fitness of a particular concept based on the goal of optimization. For example, when optimizing for a robust portfolio a concept is evaluated using a Monte Carlo selection of scenarios and it is the mean and standard deviation of performance that becomes the fitness function. These different fitness functions will be used throughout this thesis to explore differing design strategies. For all of the differing fitness functions a tournament selection method is used in selecting the concepts for crossover.

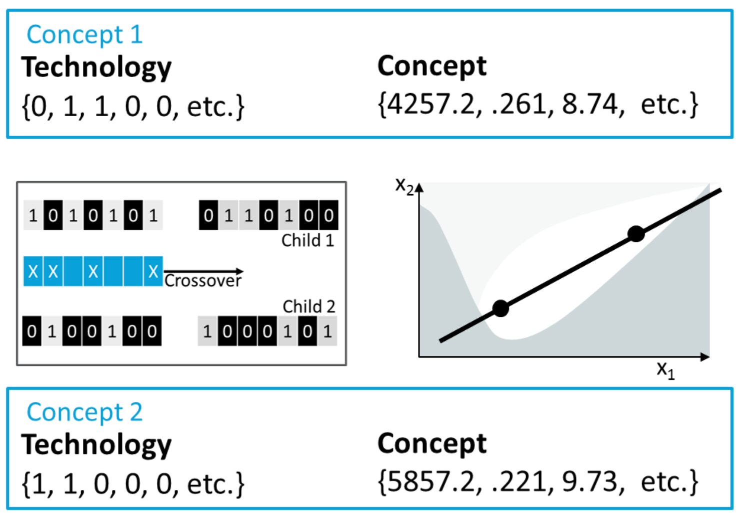


Figure 70: Concept EA and Crossover

Figure 70 shows a notional depiction of two concepts and the crossover techniques used for the two elements. The technology element of a concept contains a binary description of the technologies, and a continuous depiction of the concept design specification. The following two sections will describe the detailed mechanics of how crossover and mutation work for these two sub-elements, which will provide enough information for the creation of a GA which can simultaneously optimize both the concept and the technology portfolio for a single specified scenario.

4.10.4 A technology selection sub-problem evolutionary algorithm

The technology selection problem most closely resembles the type of problem for which the genetic algorithm (GA) was developed. The use of a GA for technology selection has been detailed and document by Raczynski in reference [107]. His work presents a standard binary representation of the technology problem in a GA which was adapted for this thesis. For this thesis, a binary representation of technology portfolio as a series of on or off bits where each bit corresponds to a single technology being either included or removed from the technology portfolio.

The mechanics of the portfolio optimization are completed using the following mechanisms. Uniform crossover, a method which randomly selects genes for crossover, was used for crossover, and a simple binary mutation was applied when mutation was needed. A good overview of the mechanics of binary genetic algorithms including uniform crossover can be found in Reference [68].

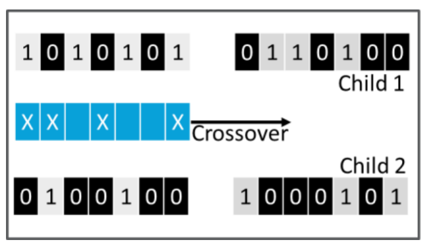


Figure 71: Uniform Crossover

Figure 71 shows a pictorial depiction of how uniform crossover works for a binary technology selection problem. Two concepts are selected (in this case using the tournament selection at the concept level) and these two concept's technology portfolios are crossed using uniform crossover. This involves creating a "mask" which is a binary string of the same length as the technology portfolio represented as a binary string. This "mask" is a randomly generated set of binary bits. Where the "mask" has a positive bit the corresponding genes at that location are crossed. This procedure is used in creating the binary elements of child concepts.

4.10.5 A concept optimization sub-problem evolutionary algorithm

In designing the algorithm for crossover for the continuous specification of the concept, it was necessary for the selected GA to be able to handle both the side constraints as well as the various internal physical constraints in the modeling. A genetic algorithm developed by Rasheed et. al. for the search of a continuous design space is adapted for use in this element of the thesis [109]. Rasheed et. al. proposes a line crossover method as a generalization of the linear crossover method introduce by Wright [109]. This method is tailored towards the search of "slab" spaces common in aircraft design due to the internal physical constraints, and was demonstrated on an aircraft design problem by Rasheed et. al.

The left half of Figure 72 shows a representation of a "slab" design space adapted from reference [109] along with a pictorial depiction of the line crossover method. In this crossover technique, the line is drawn in-between the two designs selected for crossover. A random number is generated that defines the distance along this line from the better of the two concepts and selects a new point up to but not stepping over the side constraints. This procedure is repeated twice to create the two new children from the original pair of continuous specifications. These new continuous specifications are combined with the two children of the discrete crossover, to create two new children concepts.

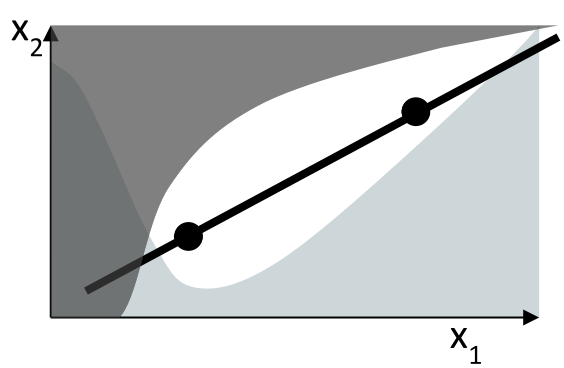


Figure 72: Line Crossover

Mutation for the continuous specification element of the concept is done by on a dimension by dimension basis. If a dimension is randomly selected for mutation, then the line crossover is used on that singular dimension with the newly mutated concept having traversed a random distance along a line which travels in the direction of the dimension of mutation.

4.10.6 Robust Design Concept Optimization

The purpose of this paragraph is to detail the changes needed to modify the previously described algorithm for a robust design approach. The previous sections described the mechanics and elements for creating an evolutionary algorithm capable of determining the optimum concept for single input scenario. This evolutionary algorithm was modified to conduct an internal Monte Carlo simulation. This modification requires that the inputs for the scenario be changed to a description of the distribution from which the Monte Carlo samples could be taken. Once this Monte Carlo sample is taken, the performance for a particular concept is evaluated multiple times using the modeling environment for each of the scenarios within the Monte Carlo sample. The mean and standard deviation of performance for the concept can then be calculated from these multiple simulations. Finally the mean and standard deviation can be transformed into a single fitness function using either the OEC described in Equation 42 or the Taguchi signal-to-noise described in Equation 7.

$$Value = \gamma * \mu - (1 - \gamma) * \sigma \tag{42}$$

4.10.7 An Iterative Portfolio Optimization Algorithm

Modifications to the base evolutionary algorithm for optimizing a single concept for a single scenario are needed to allow for portfolio-based optimization. This section focuses on the modifications necessary for iterative portfolio optimization. The modifications are shown pictorially in Figure 73. The following three sections will describe how dynamic programing is used as the fitness function for evaluating a particular portfolio, the crossover method for refining portfolios, and the Co-Evolutionary Algorithm which allows for the simultaneous refinement of concepts and diversification of the portfolio.

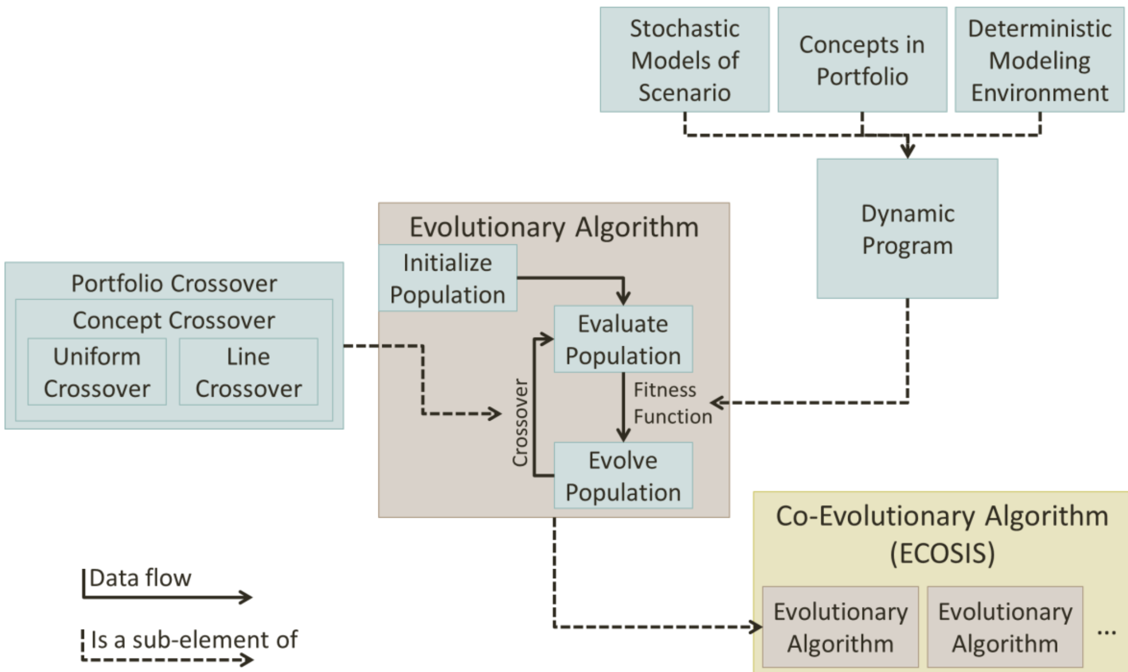


Figure 73: Modifications to a Typical EA for Portfolio Optimization

Dynamic Programming as a Fitness Function

The value of a portfolio comes from the solution to the analytical dynamic programming problem for that portfolio. This means that Equation 36 is solved for the limited number of concepts within the portfolio. To accomplish this, all possible strategies for concept downselection must be tested and the modeling environment must be run for multiple scenario evolutions. This allows the extra costs of continuing the portfolio development throughout the design phases to be carefully weighed against the reduction of the portfolio to a single concept based on the scenario evolution in time. The value of the optimum strategy including the developing or canceling concepts within the portfolio in response to changes in scenario is used as the portfolio value / fitness. It is this fitness which is used in the generic framework of an evolutionary algorithm. The following paragraphs will describe the mechanics of the specific co-evolutionary algorithm developed to solve the combinatorial portfolio-based design optimization problem

Portfolio Crossover Method

Figure 74 shows a pictorial description of a concept portfolio to provide the reader a visual indication of the fact that the portfolio has been defined as a collection of concepts. The portfolio shown in Figure 74 consists of two individual concepts, but any number of concepts could be chosen. The maximum number of concepts in the portfolio is typically limited within the algorithm by the extra cost of a large portfolio but it can also be limited to some pre-specified amount to account for organizational capacity constraints, such as limitations in workforce.

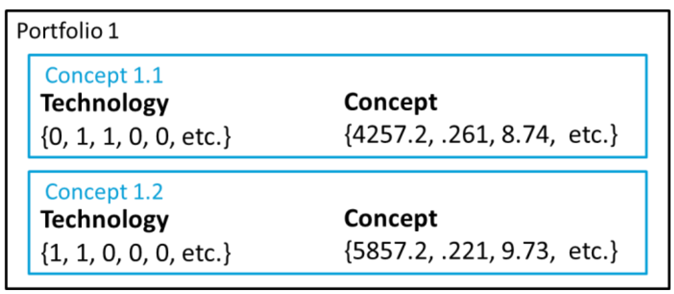


Figure 74: Example Concept Portfolio

Figure 75 shows the procedure for crossover for two portfolios. The procedure for crossover for portfolios is slightly more complicated than that for individual concepts, because it was desirable to keep diversity in the crossover procedure and the portfolios themselves can have differing lengths.

Figure 75 shows the notional crossover of two portfolios labeled 1 and 2 which have differing lengths. The first portfolio consists of two concepts and the second one consists of only a single concept. The procedure for crossover has multiple steps and begins by randomly selecting a number which represents the length of the child portfolio. The length of the child is randomly selected from a range going from the length of the shortest input portfolio to the length of the longest input portfolio. For this example, the length of the child portfolio would be either 1 or 2.

Once a length of the child portfolio has been selected, the next step is to determine the type of crossover that will occur. Two types of crossover are possible, and the one used is randomly chosen based on a specified probability for the selection of one verses the other.

The first type of crossover is shown on the left half of Figure 75 and randomly selects concepts from each of the input portfolios. These concepts are then combined into a single child portfolio. If the number of concepts in the child portfolio is less than the randomly selected length of the child portfolio, this process is repeated until enough concepts have been randomly selected from each of the parent portfolios to create a child of the desired length.

The second type of cross over is shown on the right half of Figure 75. In this type of crossover a concept is randomly selected from each of the two parent portfolios. Crossover is then done with these concepts using the crossover procedure described in Sections 4.9.3 through 4.9.5. The two new concepts are placed in the child portfolio and the process is repeated until the child portfolio is of the appropriate length. Since this crossover procedure produces two new concepts each time it is performed, a modification must be made for portfolios with odd numbers of concepts. For creating portfolios with odd numbers of concepts, on the last crossover, only one of the new concepts is placed into the new child portfolio. This procedure allows for a second method of crossover for portfolios.

The use of two crossover techniques allows for diversity to be maintained within the concept portfolios when the first crossover technique is used, but also allows for a pseudo-gradient following optimizer when searching for an improvement in the concepts themselves.

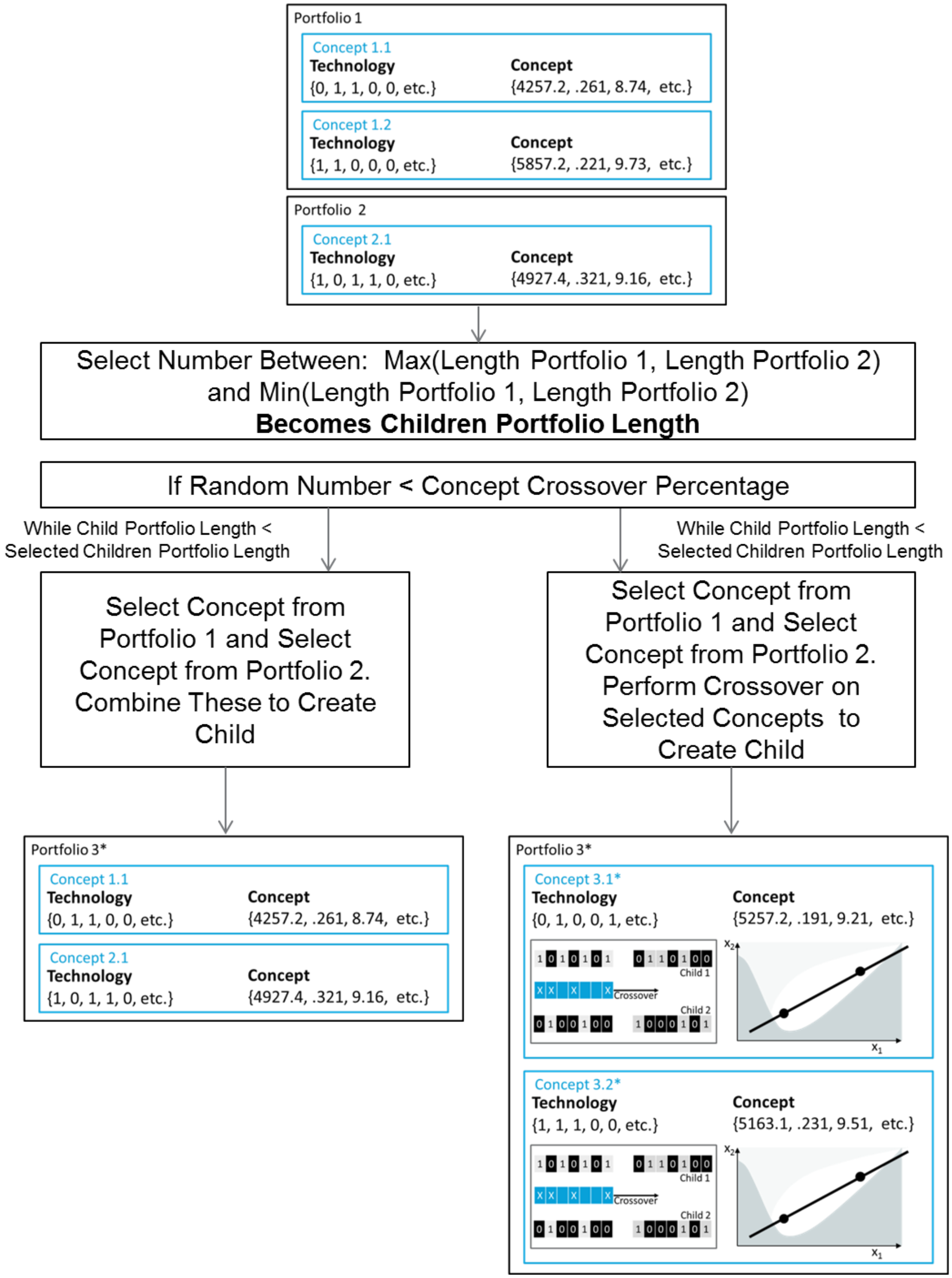


Figure 75: Portfolio Crossover Procedure

Co-Evolutionary Optimization

Figure 76 shows a depiction of the algorithm developed for co-evolutionary optimization of the concept portfolio space. This optimization strategy meets all of the criteria for a numerical optimizer as specified in Table 5.

In keeping with the idea of a co-evolutionary algorithm, the algorithm described in Figure 76 breaks the optimization into separate populations. Each of these populations contains a specified number of concept portfolios as described in Section 4.9.7 which act as the population members. For the remainder of this section the words "concept portfolio" and "population member" will be considered to be synonymous since each member of the population is simply a single concept portfolio.

These separate populations will be asked to optimize individual areas of the scenario/design space without interacting. The first population is asked to optimize the global space, while a series of other populations are asked to optimize random sub-optimization within the dynamic programming framework. This can be seen as the set of individual paths extending from the top of Figure 76. This separation serves an important purpose in portfolio optimization. By design, traditionally optimizers do a poor job of maintaining diversity within the set of points currently being maintained in memory for further evaluation. They are designed to quickly explore the design space and rapidly converge on the best area of the design space. For this problem however, optimization is occurring simultaneously at multiple levels. Not only is the diversity of the concepts in the portfolio being refined, but the concepts themselves are being refined. As a result, it is necessary to maintain some diversity at the portfolio level while the concepts are being refined. Otherwise the optimizer rapidly settles on a robust design rather than finding a diverse set of scenario optimized designs. The use of individual populations each optimizing to a randomly selected scenario allows the portfolio level optimizer to find a diverse portfolio of the best possible concepts, because the concepts can be refined to randomly selected scenarios. However, a second step is needed to ensure the best well-diversified portfolio is found for the global set of possible scenarios. Before discussing the combining of the populations in the second step, it is necessary to discuss the evaluation of fitness and execution of the evolutionary algorithm for that sub-population as shown in the middle of Figure 76.

For the divided populations, each concept portfolio's fitness is determined by solving the dynamic programming sub-optimization for the set of concepts contained within its own concept portfolio. Recall that dynamic programming broke the global optimization into sub-optimizations based on the evolution of scenario and the decisions made throughout the time evolution of the numerical optimization. So each concept portfolio's fitness is the solution of a random sub-optimization from within the dynamic programming global optimization which corresponds to the following:

- A randomly selected future time.
- A randomly scenario evolution has occurred up to the randomly selected future time.
- A set of decisions have been made in the past such that the particular portfolio being evaluated is available to the decision maker at the randomly selected future time.

For each of the divided individual populations the fitness of all of the members (concept portfolios) is evaluated (for the randomly selected dynamic programming sub-optimization). Once all of the individual members have been evaluated, the individual populations are allowed to evolve using tournament selection and the crossover method described in Section 4.9.3. This means that each individual population will evolve to find the portfolio that best matches the randomly selected dynamic programming sub-optimization. Because this dynamic programming sub-optimization corresponds to a particular uncertainty scenario occurring, the populations are evolving to find the best portfolio to match the randomly selected scenario. However, these individual scenario specific optimizations are not allowed to run to their completion. Instead the best members of the populations will be selected after a specified number of iterations and sent to represent their scenario in a global optimization. However, the performance in a particular scenario is not indicative of the global performance, so a second step is needed to combine the sub-populations.

The global population for the global optimizer consists of the best *n* members from each of the scenario specific optimizations. For the global optimum, an individual's fitness is determined by solving the entire dynamic programming problem for the limited number of concepts contained in that individual's portfolio. The concept portfolios for this global population are evaluated, and an evolution is allowed to occur in this global space which was seeded by the scenario specific optimization. To ensure diversity, early stopping is again performed after a limited number of iterations on the global population, and the best *m* members are selected and sent to a new randomly selected set of scenarios. However, to ensure diversity, these globally best scenario seed portfolios are combined with a set of randomly generated portfolios to create the populations for a repeat of the scenario optimizations. This process is repeated until convergence.

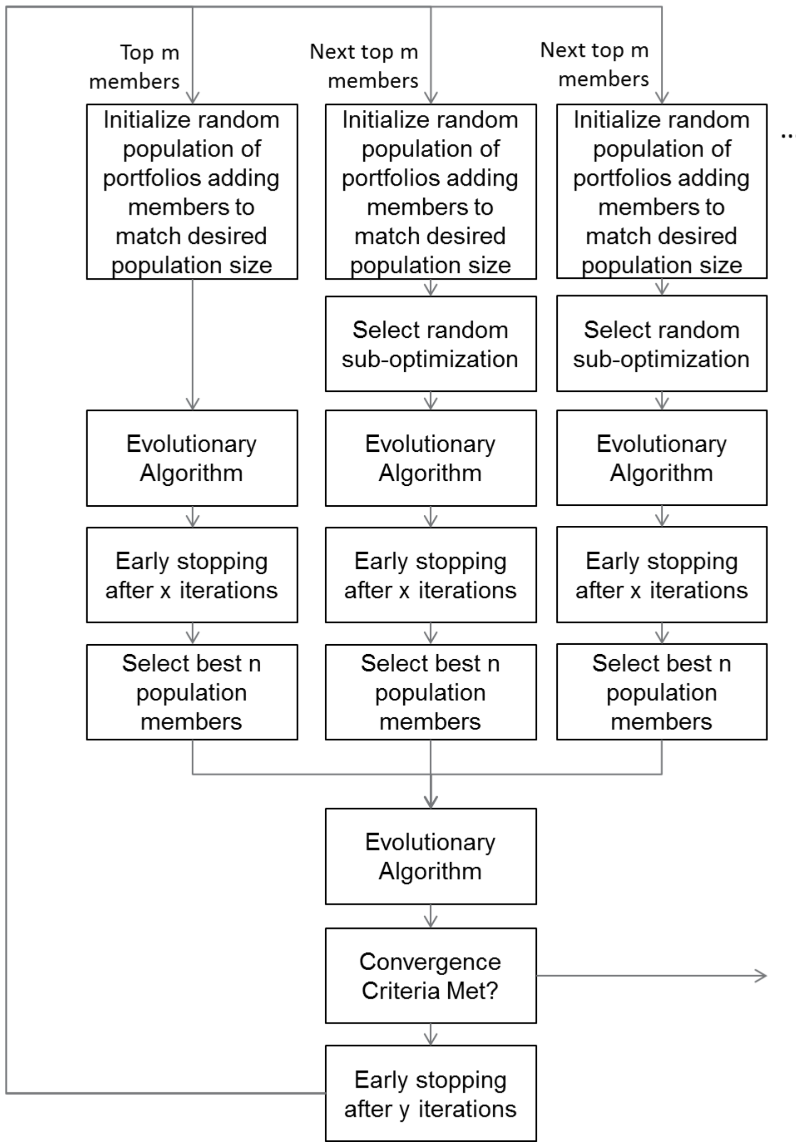


Figure 76: ECOSIS Co-Evolutionary Algorithm

4.11 PRISM-D Methodology

PRISM-D methodology modified IPPD approach presented in this thesis is shown in Figure 77. The core steps from the original methodology are maintained, including define the problem, establish value, generate alternatives (which has been recast as ‘generate concepts’), evaluate alternatives, and make decision. In addition, the optimization and synthesis iterative loop is also maintained. However, there are several key differences between the proposed approach and the original IPPD approach. The key modification to the IPPD process is the addition of the ability to consider a portfolio of alternatives rather than down selecting to a single concept. In order to enable this modification, it is first necessary to explicitly include the generation of multiple potential future scenarios during the problem definition phase. Next, there is a step added prior to the generation of alternatives which test whether a portfolio-based approach is needed according to the test described in Section 4.6.1. If it determined that a portfolio-based approach is not required, the traditional IPPD process leveraging robust design is followed, as shown on the right hand side of the figure. If a portfolio-based approach is determined to be required, then the alternate paradigm proposed in this thesis is followed, which is shown in the left hand side of Figure 77 and begins by generating alternative concepts and grouping these alternatives concepts into portfolios. Next the portfolio-based optimizer described in Section 4.9 is used to evaluate and select the best alternative portfolio. This process is iterated upon as needed until a decision is finally reached. The ECOSIS Algorithm presented in this thesis is used to automate the execution of this section of the methodology. The following section will summarize each step of the PRISM-D process, which was developed in detail previously in this chapter.

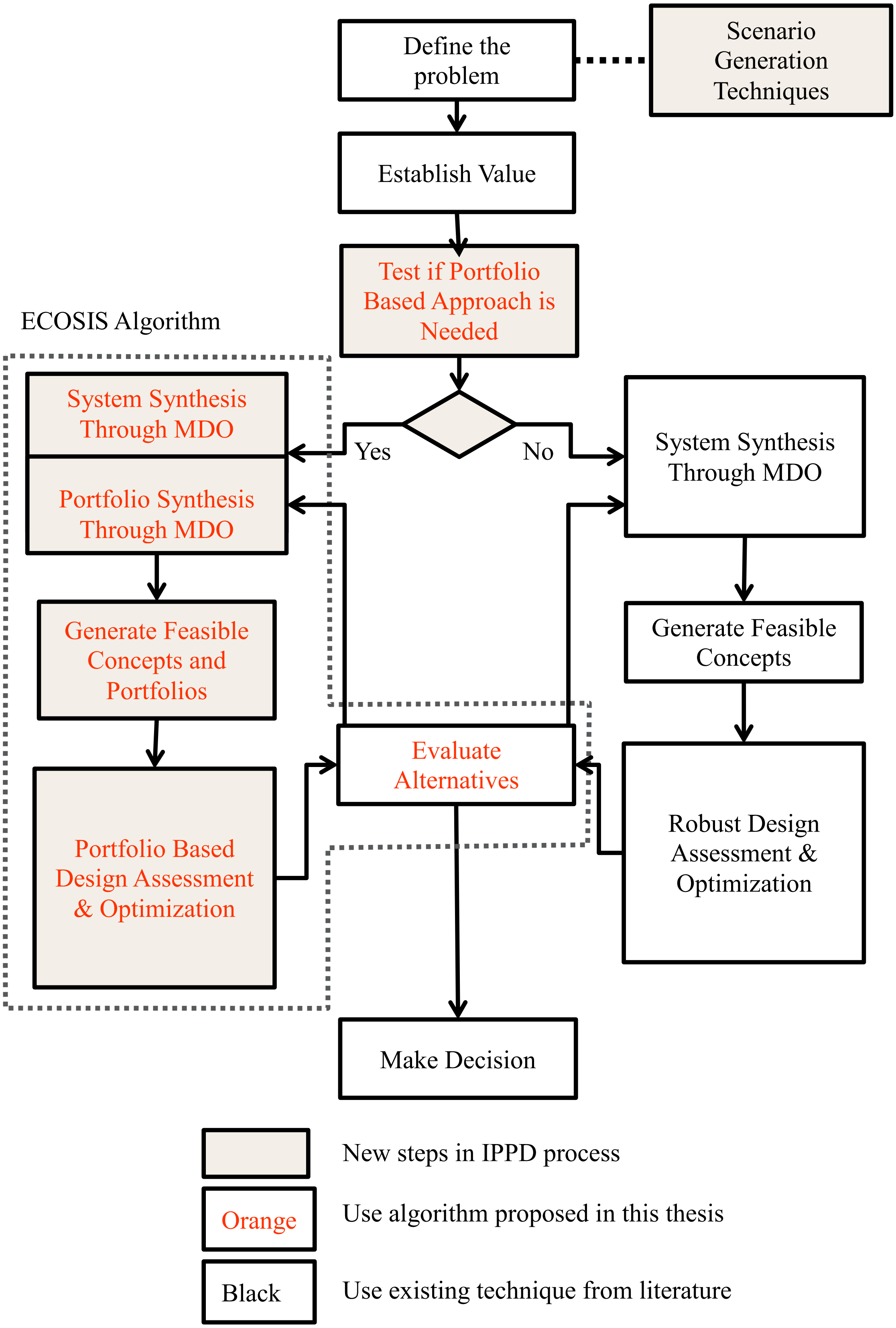


Figure 77: PRISM-D: a modified IPPD process

4.11.1 Problem Definition and Scenario Generation

Defining the problem is a step where the assumptions about future scenarios are developed and requirements definition/generation takes place. The scenario assumptions are not typically an emphasis for engineering design, but this is a necessary and critical step that takes place any time requirement definition is performed. Because this thesis focuses on the reducing the negative effects uncertainty in the scenario can have on engineering design outcomes, a thorough definition and description of the expected scenarios is required. A number of techniques are available in literature for scenario generation for engineering design. Details of these techniques are described in section 4.1.3. However, because literature techniques are sufficient for scenario definition, this step is included but not directly addressed by this thesis. It is recommended that the scenario generation technique from literature that bests matches the particular problem being solved be applied at this step.

4.11.2 Establishing Value

In the step labeled "establish value", the method and metrics by which the value of differing solutions marketed to solve the defined problem are created. A number of tools are available for measuring value and the systems engineering community has provided ample techniques. For this thesis, it will be necessary to do a cost-to-benefit analysis on the use of a portfolio vs. single design concept. As a result, it is recommended that the methods for measuring value be limited to those where both benefit and cost are measured in the same units. This requirement leads to the strong recommendation that an economic model be used as the value measurement method. Both cost and benefit are measured in a monetary unit and can be directly related in economic models.

4.11.3 Testing for a Portfolio Based Approach

The step labeled "test if a portfolio-based approach is needed" is the first new element introduced by this thesis. This test consists of determining which design variables display a significant interaction with the scenario. This determination contains three steps. The first is to perform a traditional design optimization using the selected modeling and simulation environment for a range of scenarios. The second step is to determine if a design interaction with scenario is present. This can be done by examining the design parameters for the scenario optimized designs. Design dimensions which change in response to changes in scenario are exhibiting an interaction with the scenario. The final step is to remove all of those design dimensions which do not exhibit an interaction with scenario. The practitioner should examine the interaction terms to determine if any of the interactions between scenarios and design variables have a significant impact on the variability of the value metric. If no design dimension exhibit a significant interaction then a portfolio-based approach is not needed. If the effect of the interaction is found to be significant then the portfolio-based approach should be used. This test is described in detail in Section 4.5.1 and an example implementation is shown in Section 5.4.

4.11.4 ECOSIS Algorithm and the IPPD Process

After a determination that a portfolio-based approach is needed, this thesis introduces an alternative approach to the four grey boxes in the IPPD process which represented the analysis and optimization in support of decision making. This analysis is divided into four steps. In the IPPD process, the two steps, labeled "generate feasible alternatives" and "evaluate alternatives" are generalized to the decision making process, and the two labeled "system synthesis through MDO" and "robust design and optimization" are descriptions of specific techniques for achieving the more generic steps. These four steps create an iterative loop where feasible concepts are created though system synthesis, and then these concepts are evaluated through a robust design assessment and optimization. The results of this optimization are often used to refine a set of new feasible concept. This process continues until a well refined concept which achieves the required level of value is found. This thesis replaces the single concept paradigm with a portfolio-based approach.

The ECOSIS algorithm has been introduced as an optimization strategy that accomplishes the same four basic analysis steps for a portfolio-based approach. However, these steps must be modified for the use of portfolios. Describing these modifications begins by understanding how the decision which the analysis must support changes. The final decision that these boxes changes from a selecting a single best concept to iteratively pruning a portfolio, and as a result a sequential decision process is needed. A number of literature based methods exist for solving sequential decision processes. Each of these methods contain a number of assumptions relevant to the problems they were intended to solve, but not necessarily relevant to the engineering design problem. A more detailed discussion of the literature based methods for decision making can be found in Section 4.1.1. As a result of these assumptions, a literature based decision making method will not be used directly in evaluating the portfolio alternatives, but rather the more generic mathematical formulation of these methods will be examined as potential methods for evaluating portfolio alternatives while retaining a sequential decision process.

A number of mathematical tools and techniques for evaluating the value of a sequential decision process are available, and these are described in Section 4.1.1. Dynamic programming, the classical method for solving sequential decision problems, was selected for use in evaluating the alternatives. This selection was made because of its prevalence in literature and the well understood behavior of the mathematical optimization.

However, dynamic programming is a mathematical optimizer which searches the entire design space. To accelerate the analysis a hybrid approach using both the analytical and numerical optimization was introduced in the ECOSIS algorithm. This hybrid approach allows for a portfolio-based assessment, thought the use of dynamic programming, but is still faced with challenges in the synthesis of concepts and portfolios. In synthesis and refinement of concepts it is desirable to rapidly narrow the design space to a concept which best meets the objective. However, in the synthesis and refinement of the portfolio, the desire is to maintain the diversity. These two conflicting objectives lead to the introduction of a co-evolutionary algorithm for the numerical part of the hybrid optimization. ECOSIS is the culmination of these elements and is described in Section 4.10 with an implemented example found in Section 5.6.

4.11.5 Impact of PRISM-D Process

The PRISM-D method described above results in a decision which better accounts for the uncertain and iterative nature of design. It allows for the selection of a well-diversified portfolio of concepts where the strengths and weakness of each of the concepts within the portfolio offset each other. This combined with the added flexibility a portfolio provides to the decision maker allows for improved design outcomes.

4.12 Methodological Hypothesis

The combinations of the elements within this chapter lead to the development of the PRISM-D method for improving design outcomes. The value of this method will be tested through the following hypothesis:

Methodological Hypothesis: The application of the PRISM-D methodology will determine if interaction between scenario and design requires a portfolio-based approach through the application of Hypothesis 1, and will produce design outcomes that will match or exceed the quality of robust design, as measured by Hypothesis 2.

CHAPTER V

HYPOTHESIS TESTING

The purpose of this chapter is to present the results of hypothesis testing. The hypothesis testing begins with the characterizing problem and continues for a realistic design problem.

5.1 Results for Characterizing Problem

Returning to the example problem, this section exists to provide evidence for the value of a portfolio-based approach. However, before the use of a portfolio-based approach can be implemented, an additional modeling step must be completed that models the decision making, cost expenditure and scenario development as a time series.

The modeling of the decision making as a time series requires little change. It simply requires the specification of the time at which future decisions will be made. Since these decisions correspond to the progression from one phase of the design process to the next and this progression has already been scheduled, this information should be available.

A model of the cost of progressing from one decision point to the next must also be created. Since this progression from one design phase to the next corresponds to a particular stage of the design process, this information most likely exists in the budgeting information for the project. For the example problem, a profit margin of 10% was assumed. The cost was assumed to be fixed for the different vehicle concepts, and was 2.925. One quarter of this total cost was assumed to be related to R&D. This R&D cost was then divided across three design phases. The cost of the conceptual design phase was varied from 0 to 35% and the remaining costs were divided across preliminary and detailed design, with 33.3% allocated to preliminary design and 66.6% allocated to detailed design.

5.1.1 Time Series Modeling

A model is also necessary for the scenario and the potential ways it can evolve in time. For the purposes of this thesis, the models for the scenario were limited to Markov processes. Any that which allows for both the determination of the probability of a particular scenario as well as the path taken in reaching that scenario can suffice. The reasons for selecting Markov modeling as a means of capturing the changes in scenario stems from the need to compare the portfolio-based results, using dynamic programming to the traditional Monte Carlo baseline. Markov models were chosen because of the fact that the distribution at any future time can be easily determined. This allows for a simple and direct comparison between the Monte Carlo-based methods and the dynamic programming result.

Modeling of fuel prices was done using geometric Brownian motion. This simplified model is the underlying structure for the Black Scholes equation often used in the financial community[18]. A multi-nominal lattice approach, detailed by Hsu, was used for numerically modeling the Brownian motion[53]. This approach discretizes the continuous distribution using the binomial distribution into a discrete set of scenarios that can be run through the design modeling environment.

Geometric Brownian Motion

Geometric Brownian motion is a commonly used model for representing the time history of market traded quantities. Figure 78 shows a simple pictorial depiction of two paths that follow geometric Brownian motion[6]. Each of these paths was created using the stochastic differential displayed in Equation 43.

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{43}$$

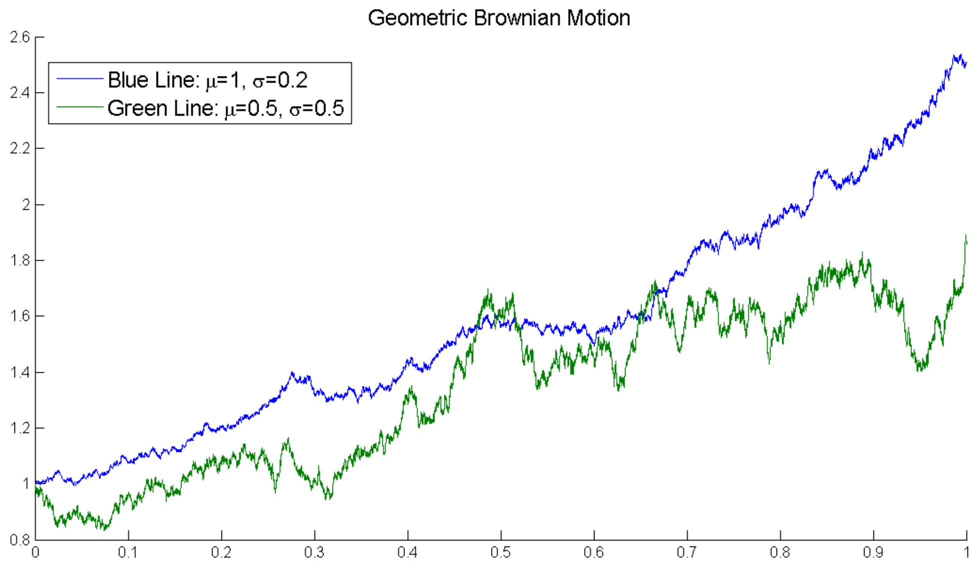


Figure 78: Two Paths Created With Geometric Brownian Motion

While Figure 78 shows two individual paths, it is often more useful from a decision making stand point to examine the cumulative effects of all possible paths. One of the useful features of geometric Brownian motion is that the set of all possible paths at some future time is lognormal distributed with parameters $\ln x_0 + \mu$ and $\sigma\sqrt{t}$. Figure 79 shows a notional representation of the distribution evolving through time. The feature that the set of future states can be determined and follows a standard distribution is not necessary for the portfolio optimization proposed but is necessary for a direct comparison of the time varying stochastic approach with the Monte Carlo based approaches found in literature.

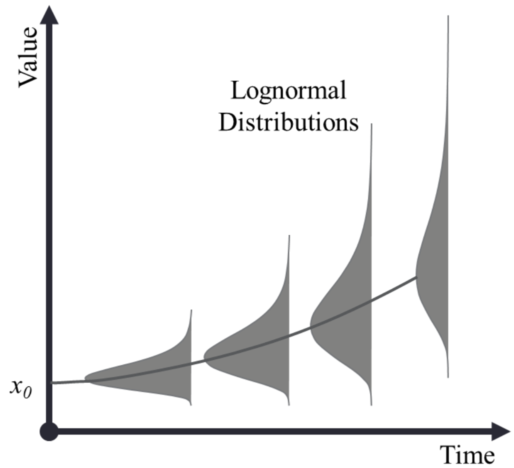


Figure 79: Time Evolution of Geometric Brownian Motion

For computational purposes, it is common to approximate geometric Brownian motion using a binomial lattice such as the one shown in Figure 80[4]. Instead of dealing with an infinite set of possibilities for future states, these states are discretized and the lognormal distribution is approximated using a binomial approximation. In this approximation, the geometric Brownian motion is limited to random movement along the lattice. As long as the elements in the lattice are small enough, this approximation returns very good results with the limiting of an infinitely small lattice exactly matching geometric Brownian motion.

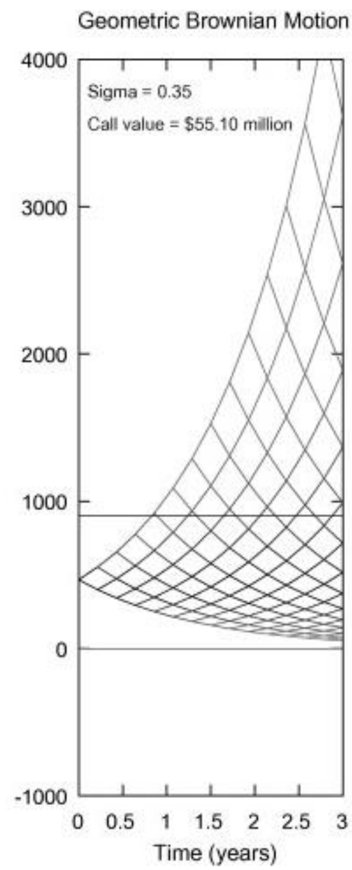
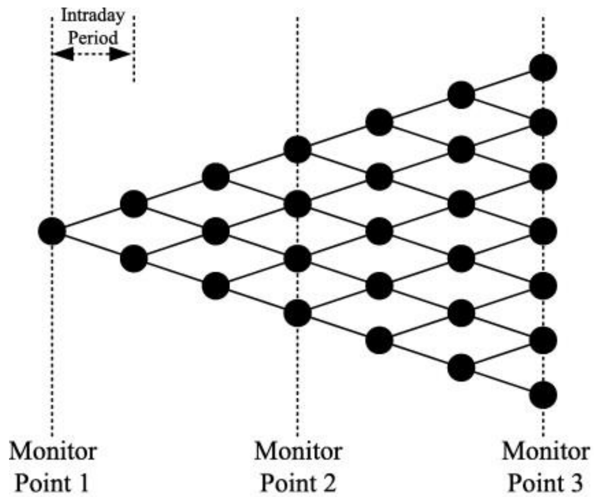
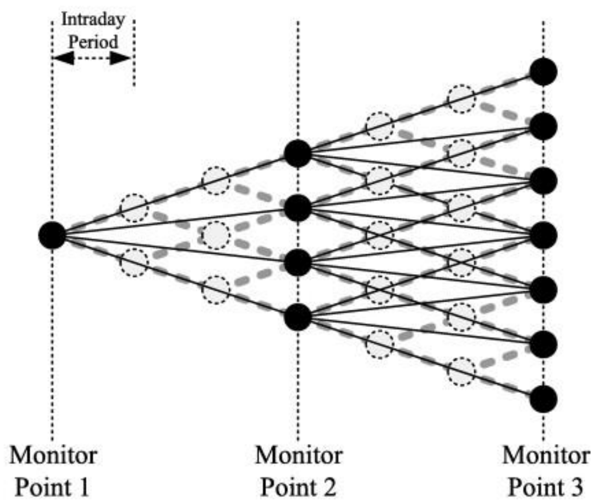


Figure 80: Binomial Lattice

However, for the purposes of this thesis, a multi-nomial approach developed by Hsu was adopted to better match the decision problem[53]. This multi-nomial approach shown in Figure 81 allows for the fact that critical go/no-go decisions are only made at specific points in time within the design process[53].



(a) A binomial lattice.



(b) A multinomial lattice.

Figure 81: Multi-Nomial Approach As Developed by Hsu

5.1.2 Testing Hypothesis 2

Hypothesis 2 stated that the portfolio must outperform the robust design to be considered a better approach. Two measures were developed for testing this hypothesis, and they can be found in Section 4.3. The first measure states that the expected value of the portfolio must outperform that of the robust design. The second measure states that the portfolio must have a higher chance of meeting an arbitrary threshold for any selected threshold. The following paragraphs detail the performance in these two measures.

Hypothesis 2: Expected Value Comparison

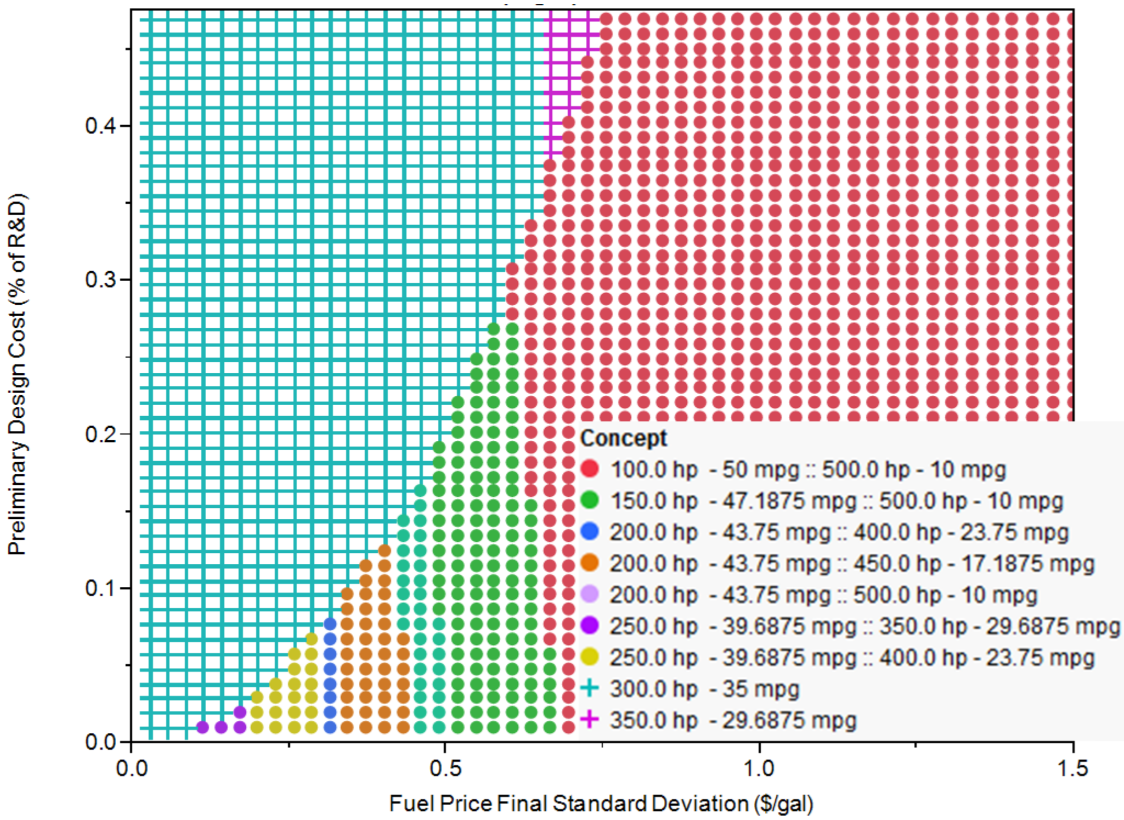


Figure 82: Optimum Portfolios for Characterizing Problem

Figure 82 shows the results of the expected value calculations for the portfolio-based approach as compared to the single concept. The graph is intended to provide a visual means of showing the regions in which a portfolio-based approach is used. The vertical axis of the plot show the percentage of the R&D costs spent on conceptual design. The horizontal axis shows the annual standard deviation (volatility) of the fuel price in $/gal. The body of the plot shows a set of discrete points at which the portfolio-based design environment was evaluated. At each of these points the design portfolio with the highest expected value is shown using a combination of symbol and color. The cross symbols represent the cases where a single concept has more value than a portfolio-based approach. The dots represent the cases where the portfolio has the greatest value. The points in the chart have been color coded by concept.

The interpretation of the results for this simplified model is fairly straight forward. There is a roughly quadratic curve separating the two regions in Figure 82. This is the result of the fact that both the volatility of fuel and the conceptual design cost affect the value of using a portfolio-based approach. When the conceptual design cost is inexpensive, multiple concepts can be explored for little cost. Information about the scenario is gained in the time that the design is progressing through conceptual and preliminary design, and the concept that is best aligned with this new information can be kept and the others can be discarded. As the cost of design increases, this approach is no longer beneficial because the cost of designing multiple concepts outweighs the benefits of better matching the scenario. This is the effect that leads to the threshold that the portfolio-based approach faces when moving vertically through the plot.

The impact of changes in the volatility of the scenario is shown moving horizontally across the chart. As the fuel price becomes more volatile, the chance of a large and rapid deviation from the current expected fuel price increases. The portfolio-based approach gains value from two mechanisms. First, a rapid deviation from the current scenario during the early phases of design drastically shifts the expected final scenario, and the portfolio-based approach provides flexibility to react to this information. Secondly, as the volatility of the fuel price increases the distribution of the scenarios spreads out. Since geometric Brownian motion was used as model of fuel price, the final lognormal distribution's standard deviation increases at a rate of $\sigma\sqrt{t}$. Returning to Figure 55, one could see that as the standard deviation of the purple distribution increases, the number of scenarios in which the optimum will lie on the edge of the design space will increase as well. This effect can be observed in both the shape of the two regions as well as the concepts that have the highest expected value. Moving across the bottom of Figure 82, one can see that the portfolio that is selected as best initially narrowly straddles the robust design. As the volatility increases the portfolio spreads outward towards the concepts at the extremes of the design space. The net result of these effects is the trends shown in Figure 82. For each of the modeling setups on the bottom right half of Figure 82 shown as dots, the expected value for the portfolio-based approach exceeds that of the robust design despite the added costs. This means all of the points in this region meet the first criteria specified in Hypothesis 2.

Hypothesis 2: Likelihood of Meeting an Arbitrary Threshold Comparison

The hypothesis stated in Section 4.3 had two parts. The first is that a portfolio would have a higher expected value, and the second stated that the portfolio-based approach would outperform the robust design for greater than 50% of the potential future scenarios. Figure 83 highlights the results of a single modeling setup from the entire space of modeling setups shown in Figure 82. This single setup was arbitrarily selected as a representative example of the behavior of all of the setups that are shown in Figure 82. This representative setup has a final standard deviation of 0.572 $/gal and a cost of 20.5% of total R&D expenditure. Starting with the table at the top of the highlighted box shown in Figure 83, one can immediately see that the portfolio-based approach meets the criteria specified in Hypothesis 2.

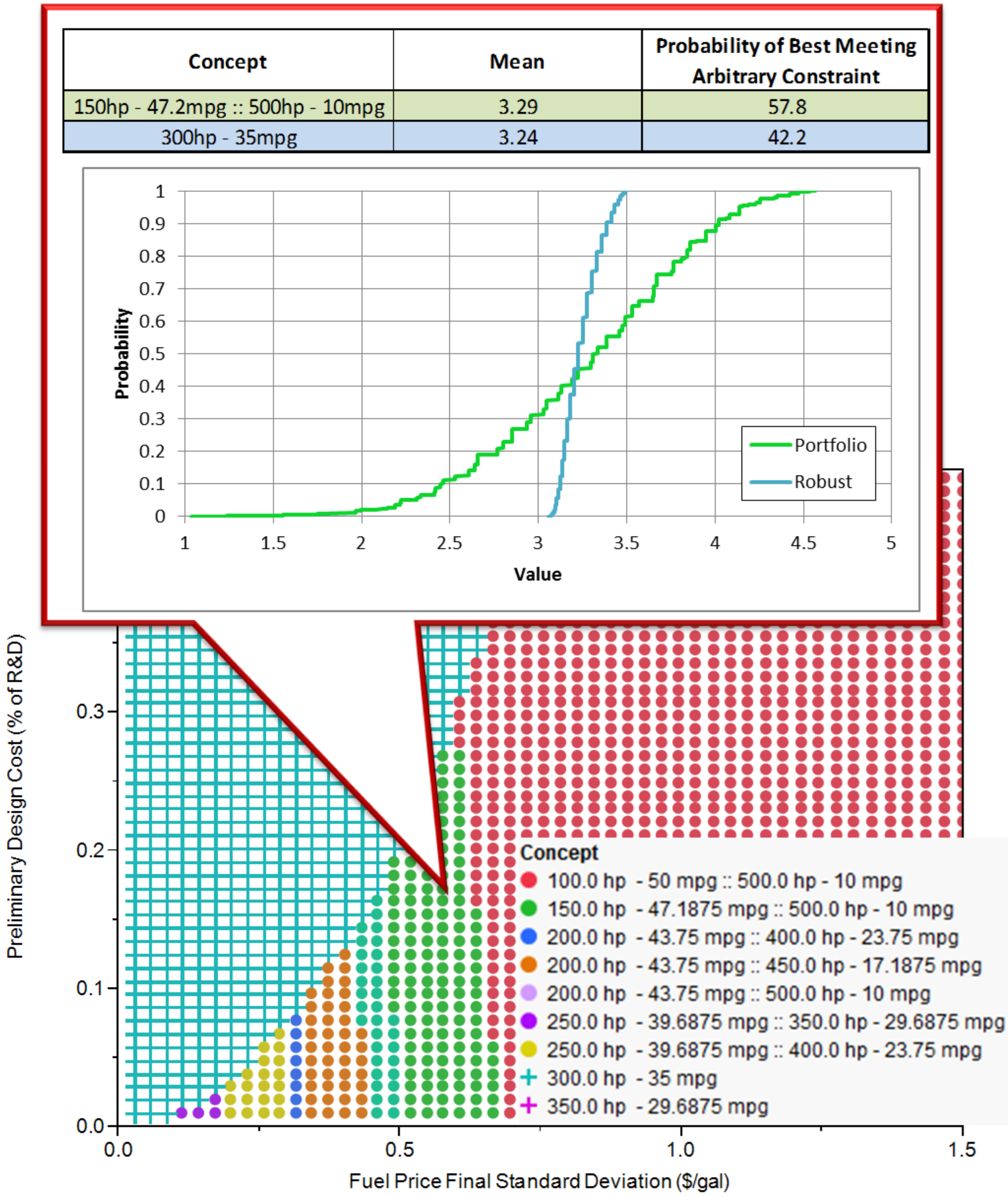


Figure 83: Testing Hypothesis 2 for a Single Modeling Environment

Figure 83 shows the CDFs for the robust design and the best portfolio for a single point, which corresponds to a single modeling setup, within the space shown in Figure 82. Examining the CDFs one can see that for over 50% of the scenarios the portfolio outperforms the robust design. A single representative case had been shown, but this fact is true for all of the cases where a portfolio is used. This meets the second criteria imposed by the hypothesis. However, it can also be immediately observed that there are a set of cases where the portfolio-based approach performs significantly worse than the robust design. These cases are the ones where it initially appeared that the scenario was evolving in one direction. For this example, fuel price had increased to a point where it appeared that it was likely to stay high. Then the scenario proceeded to move rapidly in the other direction after the decision to eliminate the low fuel price optimized alternatives from the portfolio was made and the design organization was left with a severe mismatch between design and scenario. As a result, the use of the portfolio-based approach introduces a higher risk (as measured by the performance of the worst case scenarios) for this particular example. The following section below will discuss an additional set of metrics which show that the portfolio-based design does introduce risk in the worst case scenario, but also mitigates risk as measured by other metrics.

However, it is important to note that this characterizing example was specifically chosen as an extremely stringent test for the portfolio-based approach. The stringency of this test comes from the fact that the robust design could be achieved without having to compromise the design in any way. Figure 5 commonly used in describing the robust design methodology shows that the robust design often compromises on nominal performance for a better off-nominal performance. The characteristic problem did not contain this trade and as a result was a highly stringent test for the portfolio-based design methodology. However, even for this stringent test, the portfolio-based design methodology still had merit depending on the decision maker's preference for certainty vs. return.

Hypothesis 2: Discussion and Other Metrics

Figure 84 shows the outputs of the characterization problem with each of the metrics discussed in Section 2.1.2 plotted against each other. A notional Pareto frontier has been drawn on each of these measures. From this chart, it becomes clear that in this situation there are essentially two best designs based on the designer's risk preference and the role of the modeling within the design phase. The highest expected value and lowest average regret comes from the optimum portfolio. The lowest standard deviation and highest tail conditional deviation is achieved with the robust design. This indicates that the robust design will have a performance with the minimum losses should things go wrong. However, the portfolio-based design has a much higher potential for things to go right. Furthermore, the portfolio-based design has a lower average regret. This indicates that the portfolio-based design will likely achieve a design closer to the optimum design than the robust design.

Since the modeling did not account for competition in the market place, this indicates that even if a competitor manages to select the absolute optimum design for the scenario, the selected design will not differ as much from that optimum design. This has implications for the decision maker based on the role of the modeling. If the model is not a perfectly accurate prediction of economic performance but is rather being used to simply compare designs so that the optimum design inputs can be found, then the distance from the optimum design inputs given the scenario evolution is a better measure of success than the model outputs themselves. However, this calculation requires that the optimum be known, and so it is not often used as a decision metric. However, it is important to note that the process used in selecting an optimum portfolio naturally improves this metric because it uses the portfolio to select a design that is better matched to the end scenario.

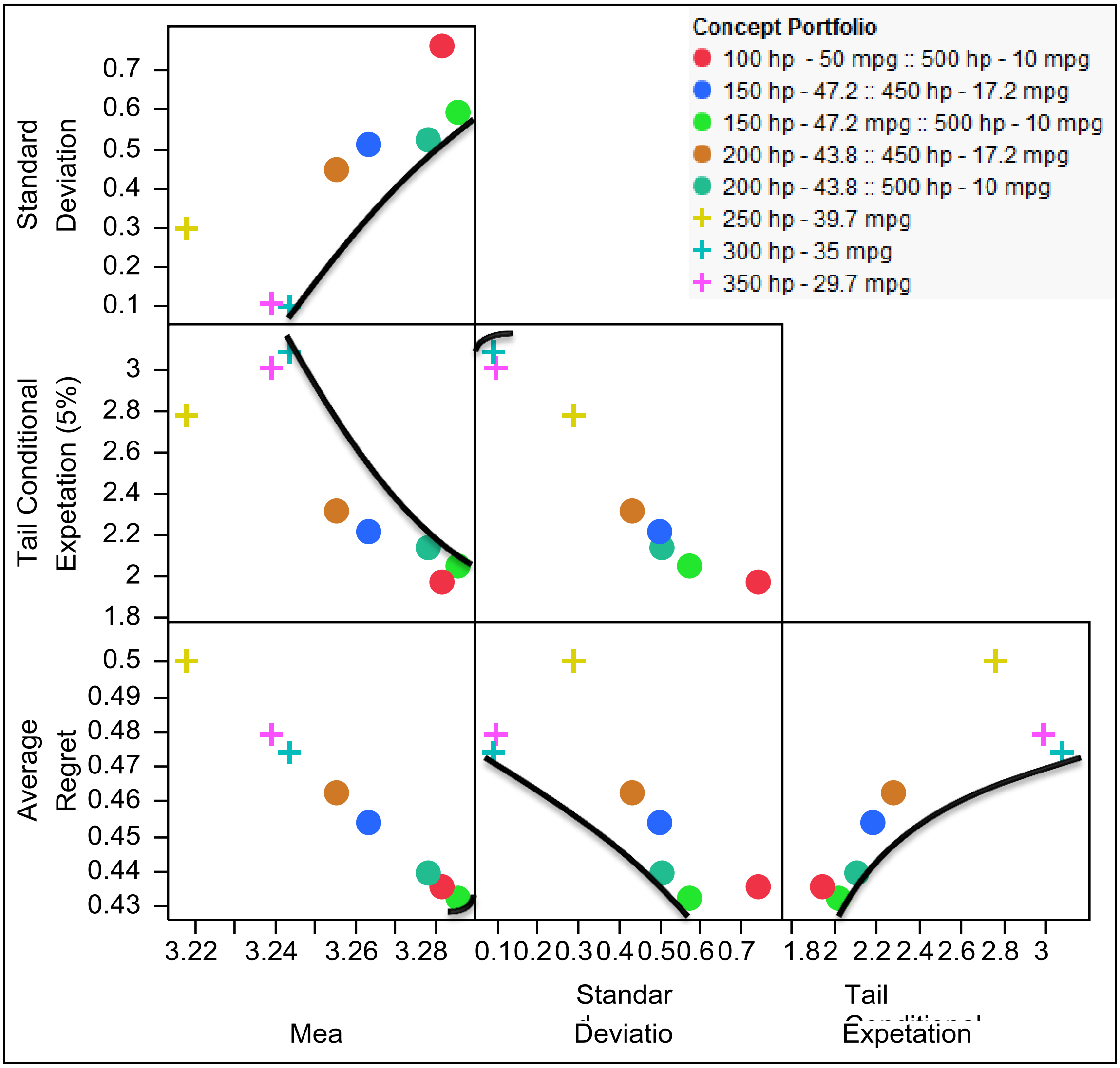


Figure 84: Characterizing Problem Aggregate Statistics

5.2 Applying PRISM-D to a 300 Passenger Civil Aircraft Design

To further test the methodological hypothesis described in section 4.12, the PRISM-D process has been applied to a notional design of a 300 passenger commercial aircraft. The remainder of this chapter will focus on the comparison of the two identified baseline design processes design to the PRISM-D process. This chapter will describe the common elements of the IPPD processes for only once, but will describe the variations in the IPPD design analysis and decision making steps for each of the baselines and the PRISM-D process independently.

5.2.1 Problem Definition

The design problem studied will include the study of the optimum aircraft configuration with a fixed rubberized engine choice, as well as, a technology study for the best technologies to apply to this new aircraft. In addition to the traditional engineering design analysis, an aircraft lifecycle cost and business case analysis is included for both the airframe and the airline. The combination of the engineering technical analysis and the economic analysis allows for the use of a top level economic metric (profit) as the objective function that captures both the benefit of differing levels of technical performance and the effect of the scenario. As advocated previously in this thesis, the use of the economic measure as the optimization objective simplifies the cost/benefit analysis required to determine if a portfolio-based approach is necessary and beneficial. This integrated modeling environment allows the decision maker to evaluate potential design concepts and to understand how future scenarios will affect the different design concept's performance in the market. This information will then be used to demonstrate the use of a portfolio-based approach in engineering design.

Notional 300 Passenger Aircraft Design

The design of a notional 300 passenger aircraft has been used as a test of the methodology under realistic design conditions. This section describes the design problem. Figure 85 shows a simplified overview of the elements included in modeling the design problem.

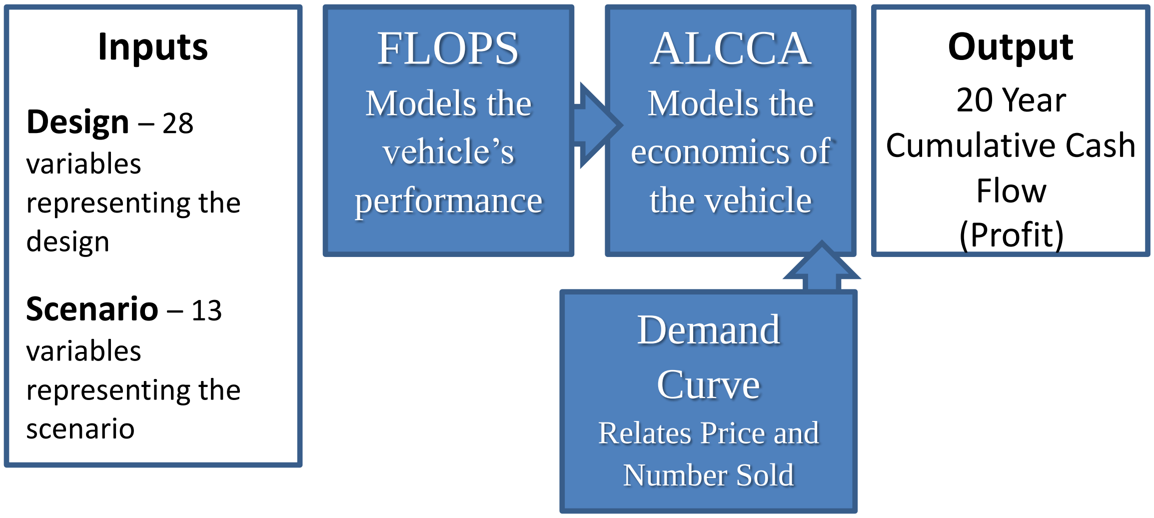


Figure 85: Overview of Problem Modeling

The goal of the design problem was to create the most profitable 300 passenger commercial aircraft with a design range of 7500 nautical miles. The vehicle was assumed to be a twin engine civil transport. Table 6 shows the inputs varied in the optimization of the design. Table 7 shows the design inputs ranges that bound the design space. The remaining design variables necessary for the conceptual description of the full aircraft were either set using historical trends or solved for analytically using NASA's FLight Optimization Program (FLOPS) described in Section 5.2.2.

Table 6: Design Inputs Varied for Optimization

Design Inputs	
Wing area	HT area
Thrust to weight ratio	VT aspect ratio
Wing aspect ratio	VT taper ratio
Wing taper ratio	VT thickness-to-chord ratio
Wing thickness-to-chord ratio at root	VT area
Wing thickness-to-chord ratio at tip	Sticker Price / Sales Price
Wing quarter-chord sweep	Technology 1 (on/off)
HT aspect ratio	Technology 2 (on/off)
HT taper ratio	...
HT thickness-to-chord ratio	Technology 12 (on/off)
Scenario Inputs	
Jet Fuel Price	
Development Success of Technology 1	
Development Success of Technology 2	
...	
Development Success of Technology 12	

Table 7: Design Input Ranges

Parameter	Low	High
Wing Area	4500	6500
Thrust To Weight	0.26	0.31
Aspect Ratio (wing)	8	10
Taper Ratio (wing)	0.19	0.25
Thickness to Chord at Root (wing)	0.1	0.13
Thickness to Chord at Tip (wing)	0.09	0.12
Sweep (wing)	27	37
Horizontal Tail Taper Ratio	3	5
Horizontal Tail Thickness to Chord	0.34	0.38
Horizontal Tail Area	0.07	0.105
Horizontal Tail Aspect Ratio	900	1100
Vertical Tail Taper Ratio	1.15	2.3
Vertical Tail Thickness to Chord	0.02	0.5
Vertical Tail Area	0.08	0.11
Vertical Tail	550	700
Sales Price	125	350

In addition to the size and layout of the concept configuration, twelve representative technologies were provided to the designer as options for inclusion in the concept. A technology can either be included in the concept, or omitted from the design concept. Table 8 provides a list of the representative technology names. Since the specific name of the technology is not critical to this work, for the remainder of this document the representative technologies will simply be referred to by their number for brevity.

The effects of these technologies on the design concept have been represented using the k-factor technique borrowed from Kirby [62]. Further details of the use of k-factors for modeling technology impact can be found in [33] and [63]. The representative technology k-factors were taken from Reference [85]. In Table 9, the technology is listed across the top and the types of effect these technologies have on the design of the vehicle are listed vertically in the first column. The interior of the table contains the effect each of the technologies would have on that particular aspect of the design. For example, Technology 5 decreases the vertical tail area by 5%. For the purposes of this thesis, the impact of multiple technologies applied to the same concept was modeled by summing the impact. The specific variable that is manipulated in FLOPS is listed in the second column of Table 9 for reference.

Table 8: Representative Technologies

Technology Number	Technology Name
T1	Stitched RFI Composite on Tail and Wing
T2	Wing-Tip Engines
T3	Low Cost Composite Manufacturing on Tail and Wing Structure
T4	Propulsion System Health Management
T5	Engines Buried in Fuselage Base/boundary layer inlets and Goldschmied Shrouds
T6	Emerging Alloy Tech & Forming on Tail and Wing
T7	Superplastic Forming on Fuselage, Tail and Wing Skin
T8	Russian Aluminum Lithium Fuselage Skin
T9	Adaptive Engine Control System
T10	Active Load Alleviation on Tail and Wing
T11	Chutes and Automatic Landing System
T12	Adaptive Wing Shaping

Table 9: Technology Impact Matrix

Technology Impact	Acronym	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Wing Wt	FRWI	-0.06	0.1	0.03	0	-0.07	-0.08	-0.03	0	0	-0.05	0	0
Fuselage Wt	FRFU	0	0.02	0	0	0.05	0	-0.07	-0.07	0	0	0.02	0
HT Wt	FRHT	-0.16	0.05		0	0	-0.1	-0.03	0	0	-0.05	0	0
VT Wt	FRVT	-0.16	0.1		0	-0.05	-0.1	-0.03	0	0	-0.05	0	0
Induced Drag	FCDI	0	-0.2	-0.02	0	0	0	0	0	0	0	0	-0.091
Profile Drag	FCDO	0	0	-0.01	0	-0.02	0	0	0	0	0	0	-0.091
Landing Gear Wt	FRLG	0	0	0	0	0	0	0	0	0	0	-0.3	0
Hydraulics Wt	WHYD	0	0	0.02	0	0	0	0	0	0	0	-0.01	0
VT Area	SVT	0	0.1	0.3	0	-0.05	0	0	0	0	0	0	0
HT Area	HVT	0	0.05	0	0	0	0	0	0	0	0	0	0
Engine Wt	WENG	0	-0.02	0.05	0.05	0	0	0	0	0.05	0	0	0
Fuel Consumption	FACT	0	0	0	0	-0.1	0	0	0	-0.1	0	0	0
RDT&E Cost	AKRDTE	0.025	0.03	0.03	0.01	0.03	0.03	0.03	0.01	0.005	0.015	0.01	0.03
O&S Cost	AKOANDS	0.03	0.015	0.015	-0.03	0.02	-0.04	-0.03	-0.02	-0.02	-0.01	0.01	-0.02
Production Cost	AKPRICE	0.03	0.02	-0.03	0.01	0.02	0.026	0.035	-0.03	0.005	0.02	-0.005	0.025
Utilization	U	-0.05	0	-0.05	0.03	-0.01	0.06	0.04	0.01	0.02	0.02	0	0.01

Since some of the technologies may not be possible to fit to the same aircraft, a compatibility matrix was introduced to list which technologies could be fitted and which ones could not. This matrix represents the reality that certain technologies such as Technology 2 (Wing-Tip Engines) cannot occur on an aircraft also employing Technology 5 (Engines Buried in Fuselage Base / Boundary Layer Inlets and Goldschmied Shrouds). Table 10 shows the technology compatibility matrix for these technologies. A 1 in Table 9 indicates that two technologies are compatible, and the 0 represents two technologies that are incompatible. Further details of the technology impact matrix formulation can be found in Reference [90] and [2].

Table 10: Technology Impact Matrix

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
TRL	6	3	8	7	2	7	4	4	4	4	5	3
TRL=9 Date	2010	2015	2010	2010	2015	2010	2011	2013	2011	2013	2012	2014
T1		1	0	1	1	0	0	1	1	1	1	1
T2			1	1	0	1	1	1	0	1	1	0
T3				1	1	0	1	1	1	1	1	1
T4					1	1	1	1	1	1	1	1
T5						1	1	1	0	1	0	1
T6							0	1	1	1	1	1
T7								0	1	1	1	1
T8									1	1	1	1
T9										1	1	1
T10											1	1
T11												1
T12												

Since

Furthermore, the scenario was modeled with two classes of uncertain variables. The first class consists of the future price of jet fuel, and the second class consisted of the variables used to represent the level of success each of the individual twelve technologies. These variables represent the percentage of the maximum gain listed in the technology impact matrix shown in Table 9 that are achieved in the final design.

These elements are combined to study the design of a notional 300 passenger aircraft. The design goal is to find the concept or concept portfolio that maximizes the profits for the air framer given a particular jet fuel price and technology development scenario. The modeling of this situation is described in the following sections.

NASA's FLight Optimization System

The technical modeling for the following problem was done using NASA's Flight Optimization System (FLOPS). This modeling environment takes in an extensive description of the vehicle concept. It runs a mission analysis, based on a described design mission profile to see if the description describes a technically feasible aircraft that meets a set of design constraints (landing field length, etc.). It repeats this process varying elements of the design left unspecified to determine an optimum aircraft matching the input configuration. The analysis is based on the physics of aircraft performance as well as an extensive set of historical regressions for elements of the design that have not yet been defined (such as element weights). The optimizer internal to FLOPS uses the classical design metric weight to define the "optimum" aircraft and it seeks to minimize gross take-off weight for the required input payload. The optimizer then returns this optimized aircraft and its performance as the model output[91].

Furthermore, the analysis environment allows for the study of new technologies applied to the concept through the use of k-factors. Described succinctly, k-factors are a set of multipliers internal elements of the design to represent the effects of a technology.

For a more detailed description of the use of k-factors to study the inclusion of technologies on an aircraft designed in FLOPS, please see Kirby's work[62].

Using this environment the designer can vary the input parameters describing the aircraft to determine the optimum aircraft configuration for any objective function the designer desires. This varying of the design input parameters can be automated, for 1)the optimization or exploration of the design space, and 2) the performance the designer can expect from different aircraft configurations that meet the specified mission and constraints[91].

Aircraft Life Cycle Cost Analysis

The second piece of the modeling environment described in the characterizing problem is the value modeling. The modeling of value is done in NASA's Aircraft Life Cycle Cost Analysis (ALCCA) software. This software does a complete lifecycle cost analysis of the vehicle from the perspective of the airframer and the airline. Furthermore, it allows the designer to input a market price for the aircraft and calculates a twenty year cashflow for the both the airframer and the airliner based on the lifecycle cost of the aircraft and the operational expenses of the airframer or airline. It is important to note that the operational expenses of the airline and the airframer are driven by scenario based uncertainties such as fuel price, the cost of aluminum, etc. The lifecycle cost analysis uses typical financial methods coupled with a database of historical cost regressions to determine the lifecycle cost, operational costs, and cashflows for the airframer and the airline. The cumulative cashflow at the end of the twenty year horizon provides a good estimation of the value to either the airframer or the airline for a particular aircraft configuration sold at a particular market price. The focus of this thesis will be on the cumulative cashflow of the airframer, and the design objective of the conceptual design study will be to maximize the airframer's cumulative cashflow [88].

An Integrated Model

The purpose of the integrated modeling environment should be to return the value of a concept given a scenario. The value model and technical model have been linked so that the entire modeling environment includes ALCCA inputs directly linked with FLOPS outputs to create a model capable of taking a detailed description of the aircraft concept and turning that into an aircraft performance and economic value. This description and performance from FLOPS is then fed forward to ALCCA to estimate the lifecycle cost, including elements such as R&D cost. An operational analysis is conducted based on the performance of the aircraft and is combined with the operational expenses of the organization to determine the economic value of the concept to the airframer. A separate analysis is done using the same aircraft performance and the airline's operational expenses (based on scenario) to determine the airline's cashflow sharing only a common sales price and number produced with the airframer's economic analysis. This integrated modeling environment allows the designer to calculate the value of a particular set of technologies on a design configuration for the airframer or the airline given a sales price and the number sold.

A slight addition is needed to the modeling to allow the designer to understand how the scenario-based uncertainties affect the cumulative cashflow of the airframer. The model as it stands has two deficiencies. First, the sales price and the number of aircraft sold are two of the most sensitive inputs to the model for the airframer's cumulative cashflow. The most basic law of economics, the law of supply and demand tells us that these inputs are not independent [101]. This means that a relationship, that of how pricing affects demand for the vehicle, has not been captured by the modeling environment and this relationship must be added.

Secondly, because the lifecycle analysis for the airframer and the airliner are separate, it is not possible to understand how changes in uncertainties that affect the airline's profitability propagate to affect the profitability of the airframer. If a certain scenario occurs, such as high fuel price, and the airframer produces an aircraft that burns significantly less fuel, then it stands to reason that the demand from the airline's for that vehicle will increase.

This deficiency appears from the literature remaining about the development of the FLOPS and ALCCA environments to have been intentionally left in the modeling to allow for a separate analysis of requirements for the airframer and the airline operator, and to accelerate the analysis on what at the time were significantly slower computers. Figure 86 reproduced from reference [83] shows how the two separate lifecycle analysis are related. In this case only the aircraft price was passed from the aircraft lifecycle analysis to the airline lifecycle analysis. However, at the bottom of Figure 86 on can see that the effects of the performance as measured by the required yield per passenger mile and the production quantity were also known to be drivers of the price and the ROI (which is an analog of profit).

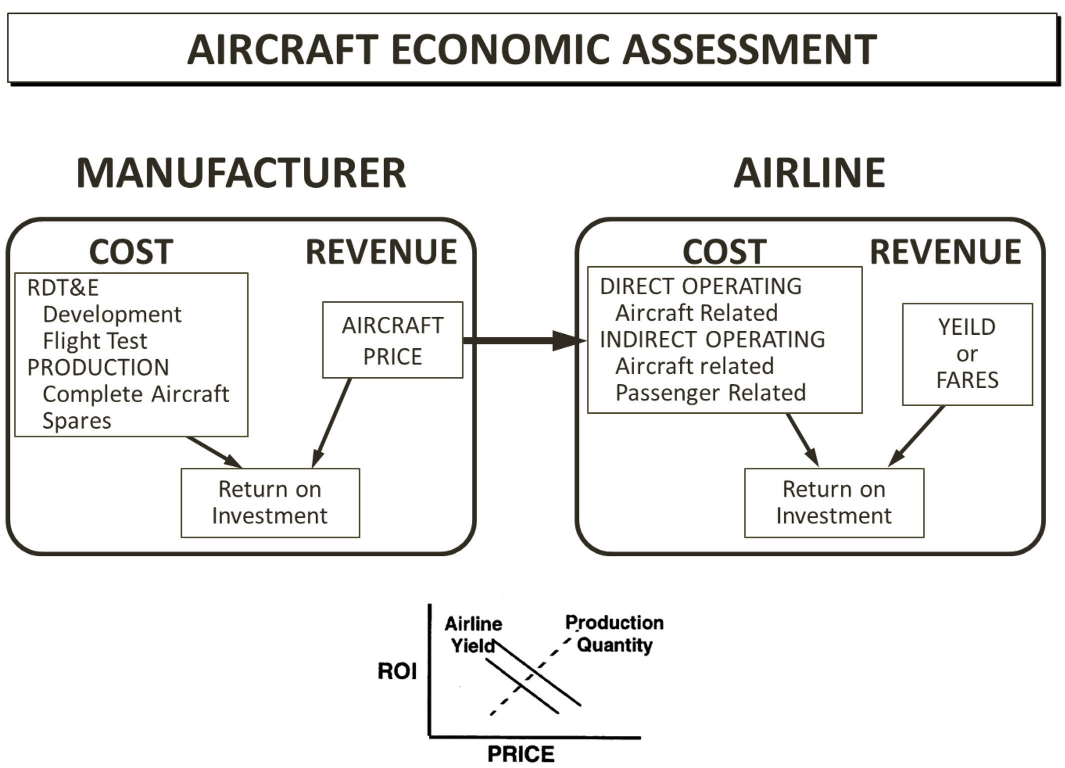


Figure 86: Aircraft Economic Assessment in ALCCA

Figure 87, adapted from Reference [83], shows a detailed picture of the small graph at the bottom of Figure 86. A second manufacturing curve has been overlaid on the Figure 87 for clarity. Figure 87 shows a four dimensional carpet plot where the axis dimensions are ROI and Price, and the carpet dimensions are units manufactured (production quantity in Figure 86) and airline yield. It is also important to note that the demand curve described in the following section operates on a more commonly applied measure, required $/RPM which is equivalent to the required yield but normalized in a different manner. The author acknowledges the inconsistencies in the terminology used in the documentation of the development of the ALCCA model can be conceptually confusing, but has verified that the logic and implementation within the program are correct. More details on the creation of Figure 87 can be found in References [83, 84]. Careful examination reveals that Figure 87 is capturing the most basic laws of economics, the supply and demand curves. The supply side of the Figure 87 has been rearranged with the production quantity in the bottom of Figure 88 to conform to the way this information is typically presented in economics.

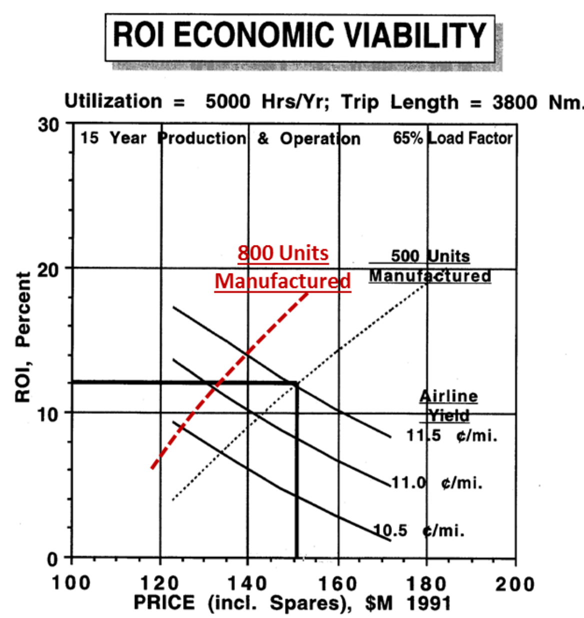


Figure 87: Price vs. ROI vs. Required Yeild vs. Units Manufactured

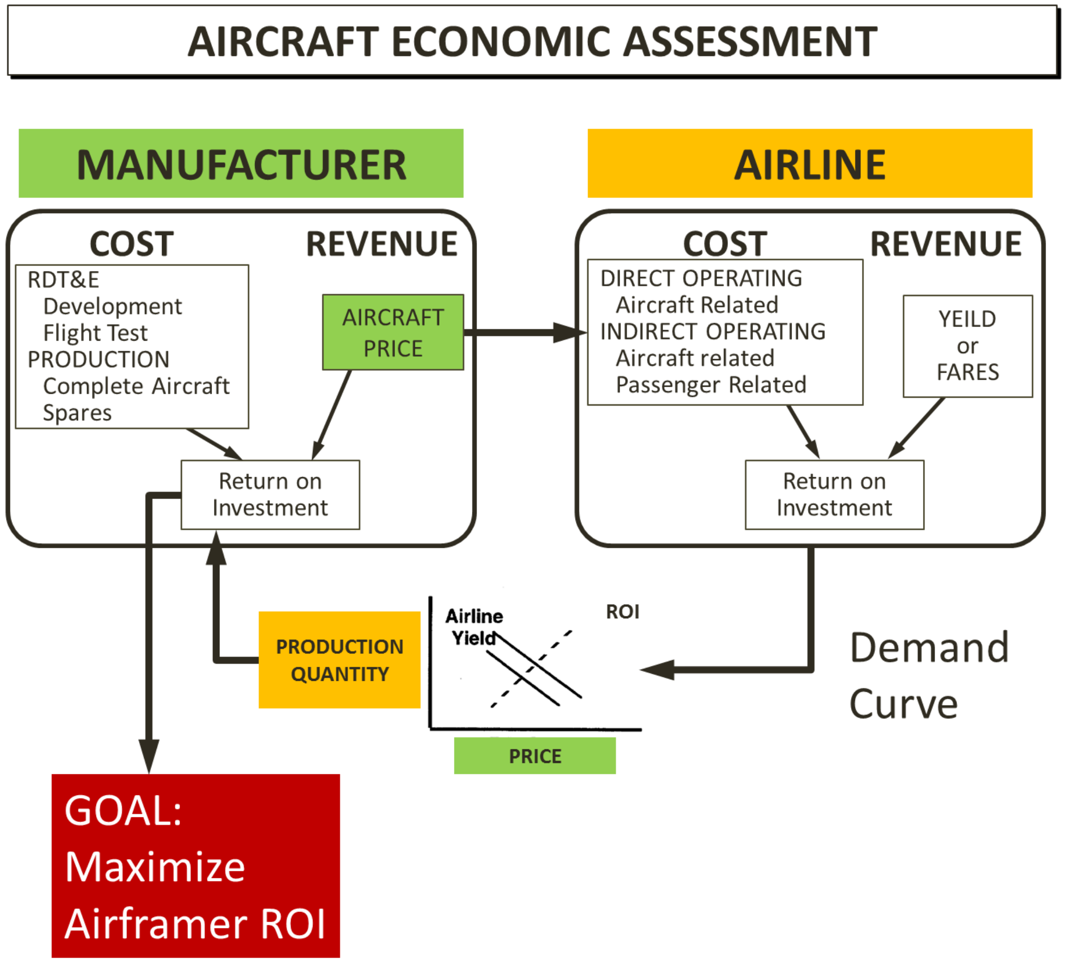


Figure 88: Demand Curve Linked Aircraft Economic Assessment in ALCCA

Figure 88 shows the framework for linking the manufacture and airline lifecycle analysis. This link comes from the introduction of a demand curve, which states that the manufacture sets the aircraft price, and the airlines will purchase a specific number of aircraft and by definition set the production quantity. However, referring to Figure 88 one can see that the demand curve is actually a multidimensional curve which is not only dependent on the price the airframer offers the aircraft but also the economic performance of the aircraft being offered. The introduction of this demand curve creates an iterative loop for which an equilibrium price and quantity can be found by introducing a goal. In this case, the stated goal of the 300 passenger aircraft is for it to maximize the airframer’s profit (ROI). The use of the demand curve means that the maximization of the airframer's profit is dependent on the profitability of the airline operators and the demand curve is the economists' method for representing the compromise that these two entities make in determining the price and production quantity. The next section will discuss the details of the demand curve adapted from Besanko implemented in the modeling process [16].

Aircraft Demand Curve

Both of the deficiencies described in Section 5.2.4 can be solved through the addition of a demand curve linking the number sold to the price at which the vehicle is operated. The demand curve will be made to shift based on the effect it has on the airline's profitability. Figure 89 shows how this takes place. Looking at Figure 89, one can see a number of curves representing different demand curves for differing levels of technical performance. Each curve represents a demand curve for a particular change in required yield per passenger revenue mile versus a baseline concept. This measure captures the required profitability of the seat sales to the airline for an investment in a particular aircraft concept at a particular aircraft sales price. A lower required yield per passenger revenue mile indicates that a particular concept requires less profit from the seat sales to become profitable to the airline. As a result of this, the demand curve shifts towards the right. This shift accounts for the fact that a more profitable aircraft to the airline will sell a larger number of vehicles if priced the same as a less profitable aircraft to the airline. This mirrors the approach taken by Marx [84].

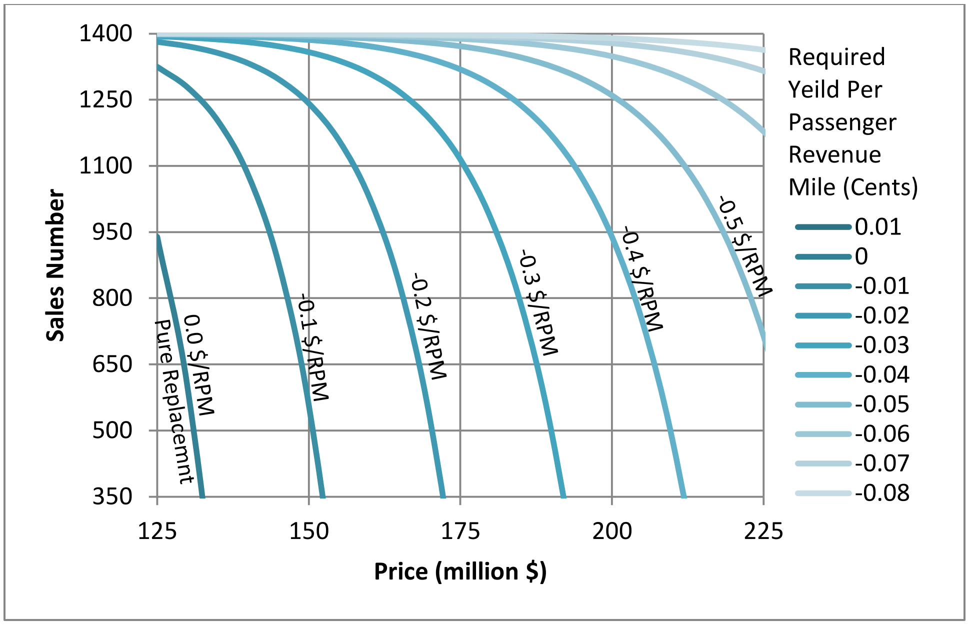


Figure 89: Demand Curves with Required Yield

The structure of the demand curve was chosen to match market behavior. Commercial aircraft are typically the textbook example of an item that has differing short-term and long-term demand curves [16]. The short-term demand curve is typically very flat and the long-term behavior of the demand curve is very steep. It is possible to extend the life span of a typical commercial airliner over some short period and as a result a change in aircraft price will lead to a delay in purchases of new aircraft. As a result, the short-term demand curve is highly elastic. However, the long-term behavior is the opposite. This is because the item itself is critical to the airline industry and the global economy as a whole. As a result, the long-term demand is highly inelastic and a change in aircraft price has little impact on the future number sold [16]. However, a steep linear slope is not enough to define the demand curve. There is only a fixed number of commercial aircraft needed in any market segment, even if the price were reduced a great deal. As a result, the market for commercial aircraft can be saturated, and the demand curve must be flattened to account for this saturation. The combination of these two ideas into a mathematical function led to the shape of the curve shown in Figure 89.

$$SalesNumber = N - N * \mathrm{e}^{-C*\left(1-\frac{Price}{P\,(1-S*\$RPM)}\right)}$$

$$N = \text{Number of Aircraft for Market Saturation}$$

$$P = \text{Maximum Price at Replacement} \qquad (44)$$

$$C = \text{Curvature Calibration}$$

$$S = \text{Stretch Calibration}$$

$$SalesNumber = 1400 - 1400 * \mathrm{e}^{-15*\left(1-\frac{Price}{135(1-15*\$RPM)}\right)} \qquad (45)$$

Equation 44 shows the functional form of the demand curve used for this thesis. The equation has four calibration factors, and these were adjusted for a market saturation point of 1400 vehicles with a maximum price for a pure replacement vehicle (no performance improvement) set at \$135,000,000. The other two factors were used to calibrate the profit per aircraft to the levels shown in Figure 100. Equation 45 shows the calibrated demand curve. A brief sensitivity study was conducted to determine the impact of using a different functional form for calibration of the demand curve on the entire environment. The net result of this sensitivity study was to show that the functional form of demand curve affects the magnitude of the final results of the modeling environment but not the trends. The magnitude of the response must be calibrated to appropriate profit margins and, as a result, any functional form of the demand curve and as a result any curve that mathematically describes the logic of the section above can be used with marginal impact on the design results. The functional form shown above was found to be sufficient, and the introduction of a demand curve provided the necessary complement to finalize the modeling environment.

Testing Setup

The total of this integrated modeling environment consisting of the three separate elements, FLOPS, ALCCA and the demand curve, provides a deterministic environment that can link a concept described by its geometric inputs directly to the profitability that the airframer can expect from this concept give a specific scenario. This integrated modeling environment can then be used to optimize the concept geometry to maximize the profit the airframer can expect. This environment provides a realistic testing environment for comparing the quality of decision which is made using the robust design methodologies presented above to a portfolio-based approach. The following sections will use the described environment that represents the 300 passenger aircraft design problem being studied for analysis using the two baselines and the PRISM-D methodology.

Portfolio Based Design Modeling

The use of a robust design methodology or a portfolio-based design process requires a few additional elements be included in the modeling of the design scenario. First, modeling must be available for the evolution of the scenario throughout the design process. Since the portfolio-based design allows the decision maker flexibility in reacting to changes in the evolution of the scenario, it is necessary to model this evolution. Secondly, the cost of the portfolio must be captured accurately including any savings or additional expense due to synergies or conflicts in developing multiple designs. These costs must also be modeled in a manner that includes a time series so that the savings that results from canceling the development of a particular concept in response to changes in scenario can be captured.

Modeling Scenario Evolution

The modeling of the evolution consisted of two separate types of models. The first model represented the potential evolutions of fuel price, and the second model was used to model each of the technologies.

Modeling Fuel Price Evolution

The fuel price was modeled using geometric Brownian motion as described in Section 5.1.1. Data for historical jet fuel prices was gathered from references [113, 112]. Figure 90 plots these historical jet fuel prices. Figure 91 shows the logarithmic change in the historical jet fuel prices used in modeling the fuel price as geometric Brownian motion. Table 11 shows the volatility of the historical data as well as the drift. The drift term was assumed to be negligible based on its small magnitude. Using the volatility in Table 11 with no drift, a multi-nominal lattice approach was applied to model future fuel price scenarios as described in Section 5.5.1.

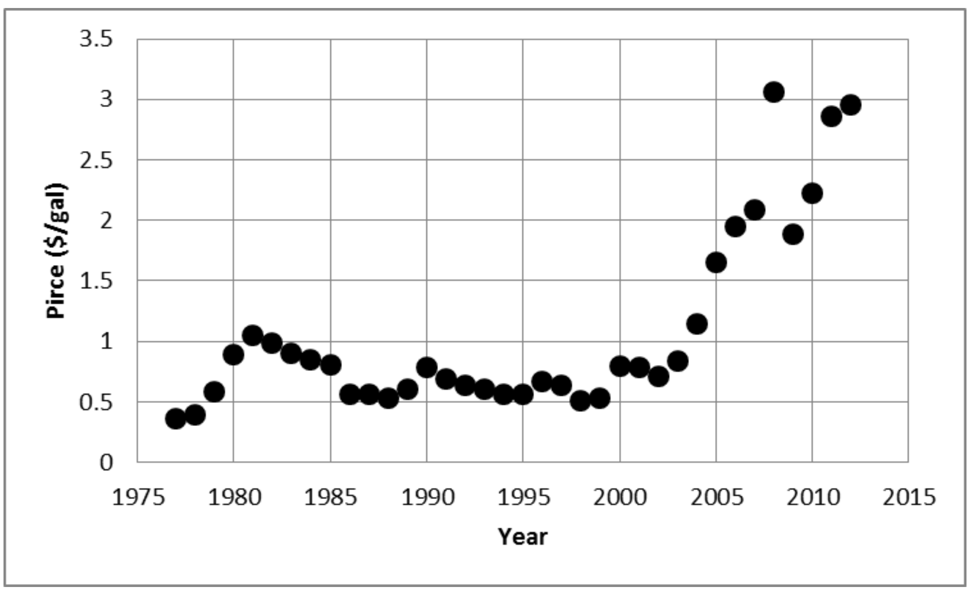


Figure 90: Historical Jet Fuel Prices

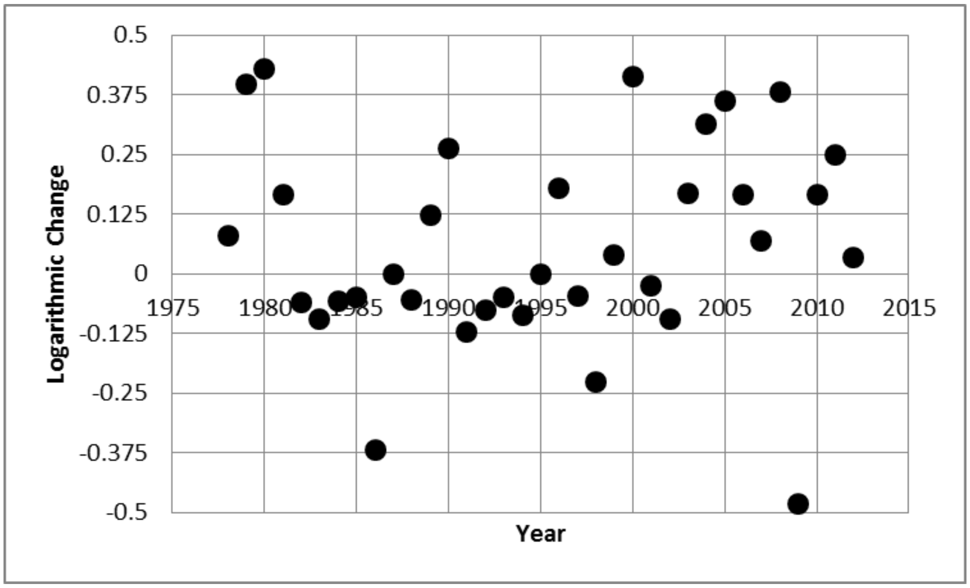


Figure 91: Logarithmic Change in Historical Jet Fuel Prices

Table 11: Historic Jet Fuel Statistics

Volatility	0.2131
Drift	0.0016

Modeling Technology Development

The technology development was modeled as a Markov process. Figure 92 shows the Markov model used in modeling the technological development. The model has four discrete states. These four states are "above nominal", "nominal", "below nominal" and "failed". Each of these states in Figure 92 contains a number representing the degradation or improvement to the technology impact found in Table 9 for the specified technology. The probabilities of transition from one state to another for a single time period are shown along the arrows in Figure 92. The discrete time step has been assumed to be a single year to match the budgeting information within ALCCA. The technological uncertainty is assumed to be resolved within the first 2 years of the 6-year development program.

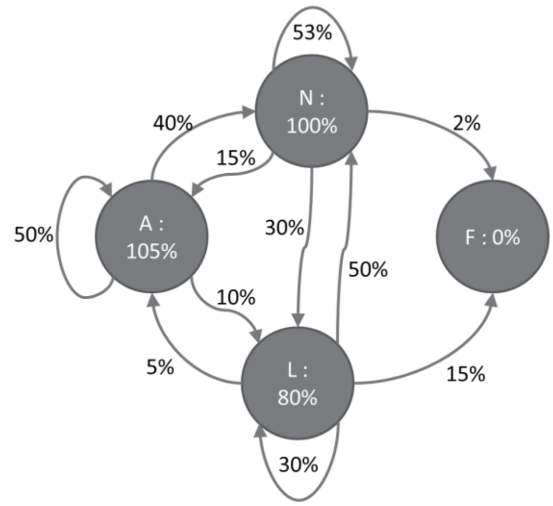


Figure 92: A Markov Model for Uncertain Technology Development

Modeling Portfolio Cost

ALCCA models the development cost of a single concept over the six-year development program by assuming that the development cost ramp up in the first year is evenly distributed over the next four years, and ramps down in the final year. A series of modifications were made to this baseline cost profile as a method for modeling the cost of a portfolio. Figure 93 shows a set of examples of the cost modeling that will be used to explain the modifications made to the cost profile for portfolio modeling. The author recognizes that the expenditure profile differs from the exponential profile described in literature and detailed in Section 1.1, and has accepted this limitation of ALCCA as the cost modeling environment as it provides a more stringent test for the proposed methodology.

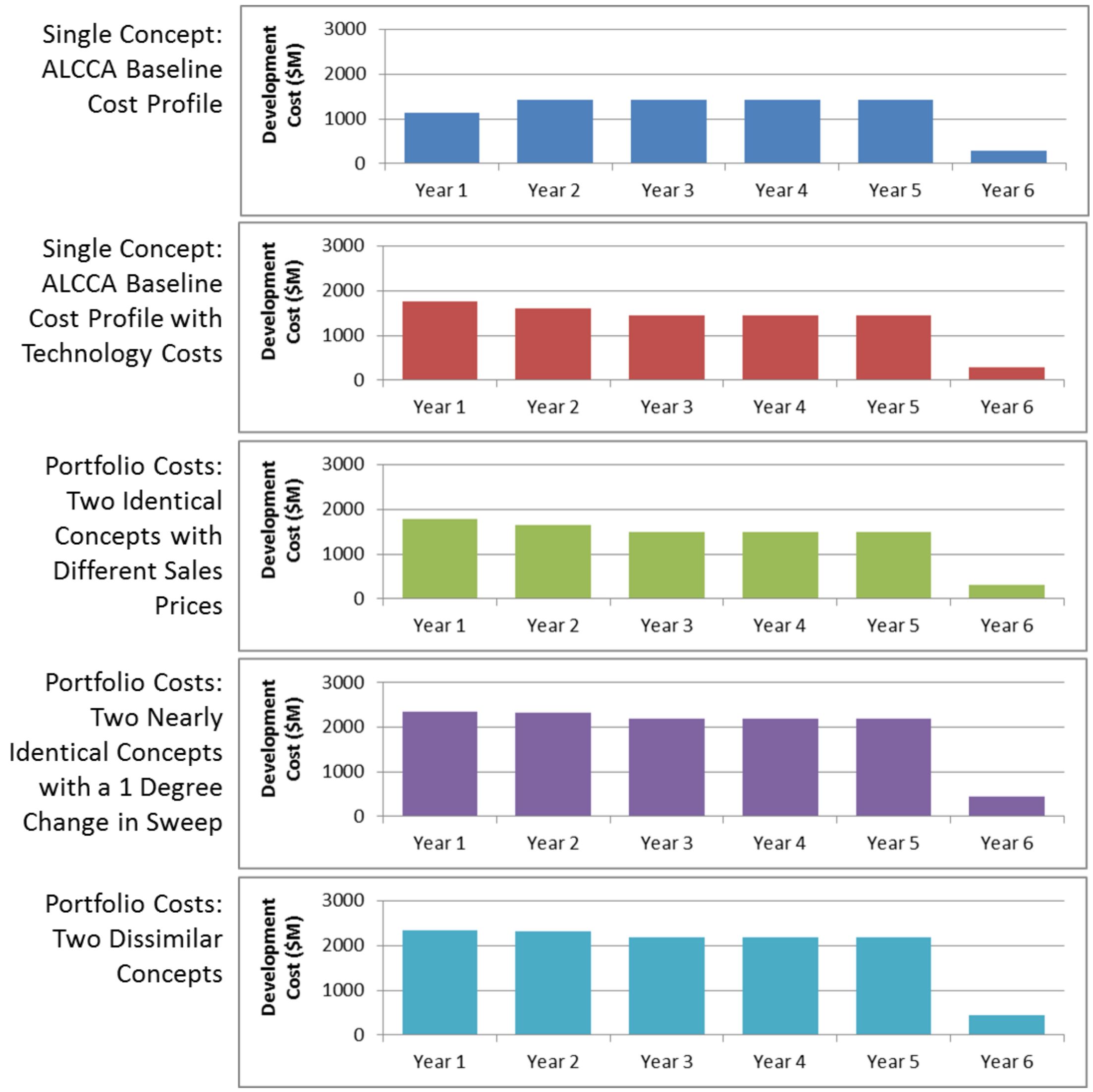


Figure 93: Example Portfolio Costs

The top chart in Figure 93, shown in dark blue, presents the costs for the development of a single concept as modeled by ALCCA. The general profile for cost expenditures for design can be seen in the dark blue chart in Figure 93 with a ramp up year, four level years, and a ramp down year. The cost at each of these years is dependent on the configuration of the design as well as on the technologies chosen. ALCCA uses a weight-based estimation approach, where the cost for components of the design are determined by using the calculated weight for the component and matching that to a regression of historical costs where cost has been regressed against weight[88].

The second chart in Figure 93, shown in red, presents the cost profile for the development of a single concept including the technology development costs. ALCCA does not explicitly model the technology development costs, so this has been added to the modeling environment as an input. For the purposes of this thesis, each technology was assumed to cost $250 million for development. The assumption was made that the cost for technology development was expended in the first two years of development, with 80% of the costs expended in the first year, and 20% in the second year. As a result the year 1 and year 2 costs are higher when modeling the cost of a concept that includes technology development.

The final three charts in Figure 93 each show the cost of development for portfolios consisting of two individual concepts and these three charts provides a series of examples for describing the logic used in determining the cost of portfolio development.

The first assumption made in determining the cost of a portfolio is that technology development only occurs once for a specific technology regardless of how many differing concepts it has been applied. This is a reasonable assumption since ALCCA accounts for the integration cost for technologies in its internal model, but not the cost of developing a technology to the point at which it can be integrated.

The second major assumption in determining the cost of a portfolio of concepts comes from synergies in the concepts within the portfolio. The effort to design two highly similar aircraft may not be as great as that expended to design two vastly different aircraft. A simple cost reduction function was implemented which reduces the cost of the second of any pair of similar concepts. This cost reduction function is shown in Figure 94 and has been made highly conservative to provide a stringent test for the portfolio-based approach.

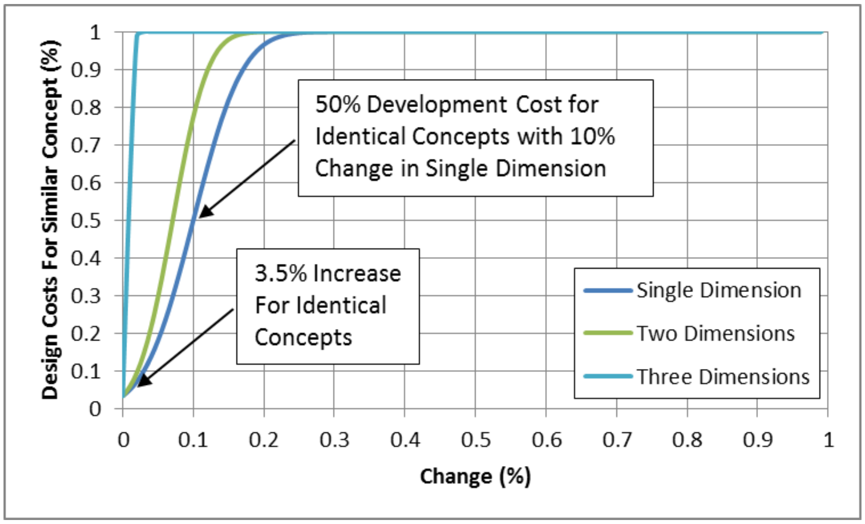


Figure 94: Cost Reduction Function

Recall that of the 28 design variables, the 12 technology variables are assumed to be developed only once. Furthermore, out of the 16 variables defining the continuous specification of a design concept, only 4 of these variables were found to interact with the scenario. The rest of the design variables will be identical. The four variables that remain for creating diversified concepts are the wing aspect ratio, the wing sweep at the quarter chord, the wing thickness at the root, and the sales price. The first three variables are technical descriptions of the vehicle's wing's size and shape. Changes in these variables imply a different design process and added cost. The fourth variable listed, the sales price, does not require additional design effort to change. The cost of producing two identical concepts with separate sales price was assumed to be 3.5% of the total R&D costs, which is a flat rate marketing fee. The green cost profile in Figure 93 shows an example of a portfolio of concepts where diversification has occurred only through changes in the cost. The green cost profile is identical to the red cost profile with the exception of the described 3.5% cost increase.

Figure 94 contains three curves that plot the cost reduction function assuming changes in these variables. The curve shown in dark blues represents the cost of developing a second similar vehicle with a change in a single design dimension. For example, the development of two concepts that are identical in every respect with the exception of a 1 degree change in the single variable, wing sweep, will not cost the full development cost of two concepts but will instead cost the development cost of one and a half concepts. This cost is a result of the fact that the second similar concept has a 10% change in wing sweep relative to the range specified in Table 7. Following the blue curve in Figure 94 limiting design changes to a 10% change in a single variable leads to a 50% reduction in development cost for the second concept. This situation corresponds to the purple cost profile in Figure 93.

The other curves in Figure 94 represent the effects of changed in more than one design dimension. If there are multiple changes in the wing design, it was assumed that the development costs would rise very quickly to the cost of developing two concepts independently. The light blue cost profile shown in Figure 93 corresponds to multiple changes in the three design dimensions where variation has been found beneficial. The net result of this variation is a cost profile that is identical to the cost profile for developing the two concepts independently.

The addition of the model for the development cost for a portfolio of designs along with the addition of a time varying model of the uncertainties provides enough information for the evaluation of the merits of a portfolio-based design process. The following section will detail the results of applying the co-evolutionary algorithm described in Section 4.9.8.

5.2.2 Establish Value

Chapter IV described the need for a benefit-to-cost analysis in determining the applicability of a portfolio-based method. The problem definition presented ALCCA a business case model capable of doing a benefit-to-cost analysis as well as representing a number of the other aspects of the business case for a new aircraft. The value function which will serve as the optimization objective for the test problem will be the present value of the aircraft program over a 20 year lifespan. The objective will be to maximize this present value.

5.2.3 Testing for a Portfolio Need

The PRISM-D method includes a step testing to determine if a portfolio-based approach is needed. Because a portfolio-based approach is only required in the conditions specified by Hypothesis 1, this amounts to a test to determine if the modeling environment meets the conditions of Hypothesis 1. This test is built on the data obtained by doing a traditional analysis for a series of deterministic scenarios. The use of a deterministic analysis is the first analysis baseline for the IPPD process, and as a result the discussion about the determination if a portfolio-based approach is required will be left till Section 5.5 after the results of the first baseline are presented.

5.2.4 Deterministic Design Analysis and Decision Making

While not necessarily state of the art, a commonly applied design method and the first baseline demonstrated in this thesis is the optimization of the aircraft design to a single deterministic "likely" scenario. This scenario can be selected because numerical methods have shown it has the highest probability of occurring or in many cases simply because it is what the decision makers believe will occur. The following section will go through the process of selecting a concept based on a deterministic scenario. For completeness the following section will show the effects of selection a number of different scenarios as the "likely" scenario.

Deterministic Scenario Optimization Setup

As stated before the goal of the experimental setup was to provide an environment that represents the start of the design process and the initial decision that take place in the conceptual phase of design. As part of this, a decision must be made about the best design for future consideration. This decision is typically supported through the use of an optimizer to optimize the configuration that will be refined in future stages of design.

An evolutionary algorithm was used for optimizing the concept to a single deterministic scenario. A description of the algorithm can be found in Section 4.9.6. A pictorial depiction of the optimization for the realistic design problem can be seen in Figure 95. The inputs to this genetic algorithm consist of two elements, the scenario and the concept inputs. The scenario consists of a fuel price and the developmental status of each of the technologies. The concept inputs consist of the variable bounding ranges for the design variables to be used in the creation of a random population of concepts. The bounding ranges for the technology design variable inputs are simply a binary 1 or 0, and the bounding ranges for the continuous variables can be found in Table 7. The output of the evolutionary algorithm is the best design inputs and the present value for the particular input scenario.

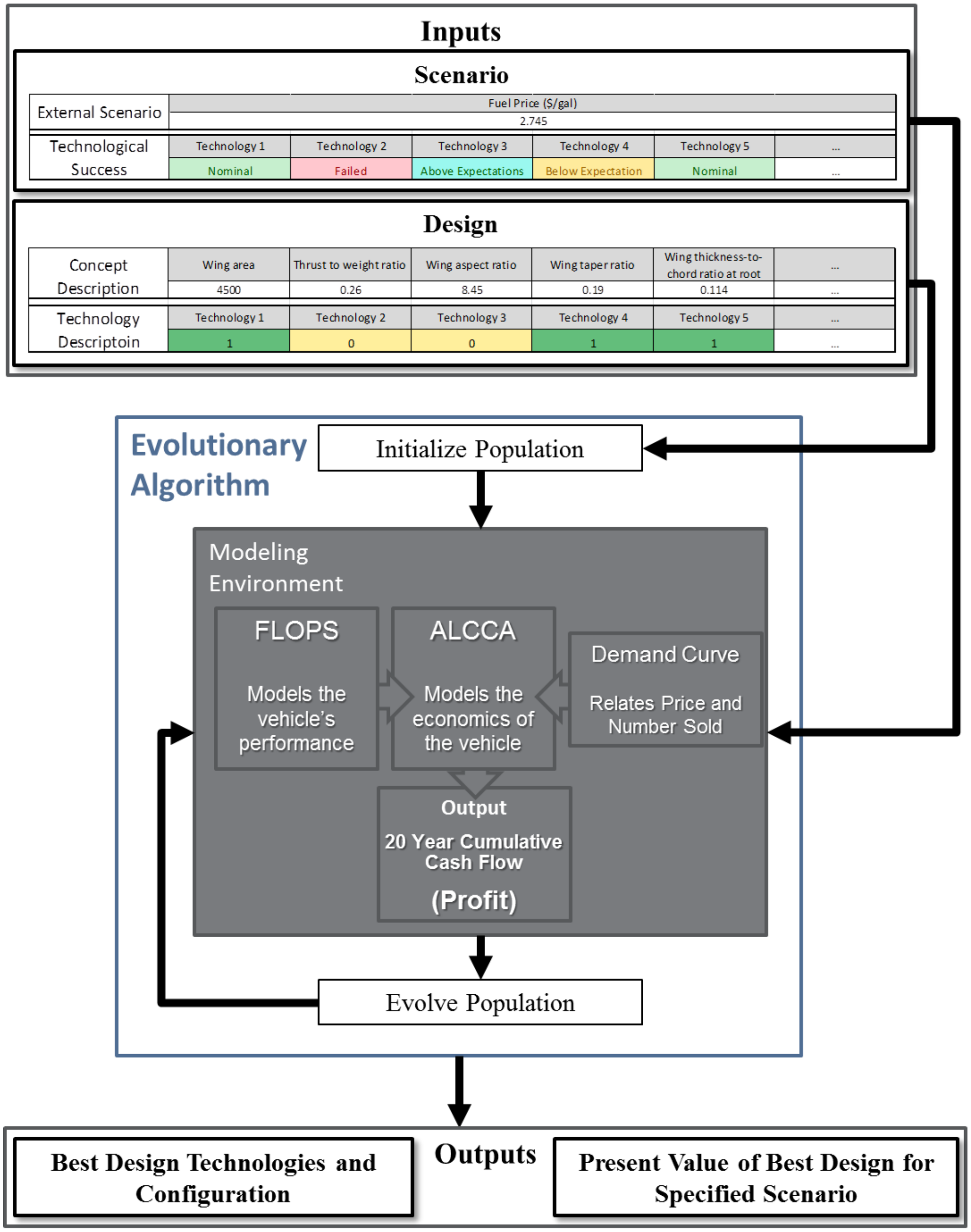


Figure 95: Deterministic Optimization

Uncertainty and Design Space Interaction

In Section 4.5.1 a procedure was outlined for testing to determine if a portfolio-based approach was required. This included optimizing the design for an extreme set of scenarios, and examining the design variables to see which of the inputs interacted with the change in scenario. If twist was present in the extreme scenarios, a richer sampling of the optimum design with respect to scenarios was recommended. The following section details the recommended series of tests that allow for a drastic reduction in the necessary variables for portfolio optimization. The section ends by highlighting an initial set of conclusions about the design space from the design information gained in running the test.

Optimizing for Extreme Scenarios

Table 12 shows a tabular and graphical form of representing the optimum configuration for four extreme deterministic scenarios. These four extreme scenarios are used to determine how the optimum design concept is affected by changes in scenario. In particular, the table represents the minimal sampling of the scenario space that can provide some information about whether interaction effects exist between the scenario and the optimum design configuration. This information is used as an initial test as to whether or not a portfolio-based approach has potential to provide value.

The continuous design variables run across the top of Table 12 and the scenario runs down the side of Table 12. The top row of Table 12 represents a scenario with a jet fuel price of 4.5 $/gal and nominal technology development success for all technologies. The second row represents a scenario with a jet fuel price of 0.5 $/gal and nominal technology development success for all technologies. The third row represents a jet fuel price of 4.5 $/gal and failed technology development for all technologies. The final row represents a jet fuel price of 0.5 $/gal and failed technological development for all technologies. The internal portion of the table is filled with a set of symbols and numbers. An arrow pointing to a line on the left half of the cell in the table indicates that the optimum value for a particular variable for the specified scenario lies on the lower edge of the design space. A symbol pointing to the right indicates that the variable lies on the upper constraint for the design space. A number indicates that the optimum value for that design variable lies at some point internal to the design space.

The purpose of running the extreme cases is to obtain an initial estimation of which, if any, design inputs have an interaction with the uncertain scenario variables. The four columns highlighted in blue show an interaction between the scenario and optimum value. The “wing aspect ratio” and the “wing thickness to chord at the root” each move from one extreme end of the design space to the opposite extreme of the design space in response to a change in fuel price. The “wing sweep measured at the quarter chord” and the “sales price” also show an interaction with the uncertainty but remain within the design range. While tipping point behavior may not be observed in these variables, they still offer the potential for an improvement in design outcome due to a portfolio-based approach.

Table 12: Extreme Scenario Optimized Design Inputs

Design Scenario	Tech Package	Sticker / Market Price	VT area	VT thickness to chord ratio	VT taper ratio	VT aspect ratio	HT area	HT thickness to chord ratio	HT taper ratio	HT aspect ratio	Wing quarter chord sweep	Wing thickness to chord ratio at tip	Wing thickness to chord ratio at root	Wing taper ratio	Wing aspect ratio	Thrust to weight ratio	Wing area
High Fuel - Successful Tech Development	A	213	↓	↓	↓	↓	↓	↓	↓	↓	28.8	↓	↓	↑	↑	↓	↓
Low Fuel - Successful Tech Development	A	158	↓	↓	↓	↓	↓	↓	↓	↓	29.3	↓	↑	↑	↓	↓	↓
High Fuel - Failed Tech Development	n/a	176	↓	↓	↓	↓	↓	↓	↓	↓	29.1	↓	↓	↑	↑	↓	↓
Low Fuel - Failed Tech Development	n/a	156	↓	↓	↓	↓	↓	↓	↓	↓	30.3	↓	↑	↑	↓	↓	↓

Table 13: Extreme Scenario Optimized Inputs (Numerical)

Design Scenario	Wing area	Thrust to weight ratio	Wing aspect ratio	Wing taper ratio	Wing thickness to chord ratio at root	Wing thickness to chord ratio at tip	Wing quarter chord sweep	HT aspect ratio	HT taper ratio	HT thickness to chord ratio	HT area	VT aspect ratio	VT taper ratio	VT thickness to chord ratio	VT area	Sticker / Market Price	Tech Package
High Fuel - Successful Tech Development	4500	0.26	10	0.25	0.1	0.09	28.8	3	0.34	0.07	900	1.15	0.2	0.08	550	213	A
Low Fuel - Successful Tech Development	4500	0.26	8	0.25	0.13	0.09	29.3	3	0.34	0.07	900	1.15	0.2	0.08	550	158	A
High Fuel - Failed Tech Development	4500	0.26	10	0.25	0.1	0.09	29.1	3	0.34	0.07	900	1.15	0.2	0.08	550	176	n/a
Low Fuel - Failed Tech Development	4500	0.26	8	0.25	0.13	0.09	30.3	3	0.34	0.07	900	1.15	0.2	0.08	550	156	n/a

Optimizing for a Range of Scenarios

With the information that some interaction did exist between the optimum design and the uncertainty, a further sampling of scenarios was completed. This set of scenarios focused on fuel price since the previous table indicated that the change in technological success had little effect on the optimum concept with the notable exception of the price. Figure 96 shows the optimum concept vs. differing fuel price scenarios with nominal technological development for all technologies. In Figure 96, fuel price runs across the horizontal axis and a series of four separate plots are shown vertically. The bottom plot is the final optimized present value of the optimized concept. The other four plots correspond to the four design dimensions identified in Table 12 to have an interaction with fuel price. The following sections will detail the procedure for making the plots and discuss the results individually.

The procedure for creating the plots shown in Figure 96 is as follows: a set of deterministic optimizations using the genetic algorithm described in Section 5.4.1 were conducted with for fuel prices ranging from 0.5 $/gal to 5 $/gal with an increment of 0.25 $/gal. Across the range from 2.00 $/gal to 4.50 $/gal, a smaller sampling increment of 0.125 $/gal was used to better explore the interesting behavior in this region. The optimized design for each of these fuel prices was then plotted in Figure 96 with the optimization objective, present value, shown in the bottom plot and the four interacting design variables plotted above. The next paragraphs discuss the results.

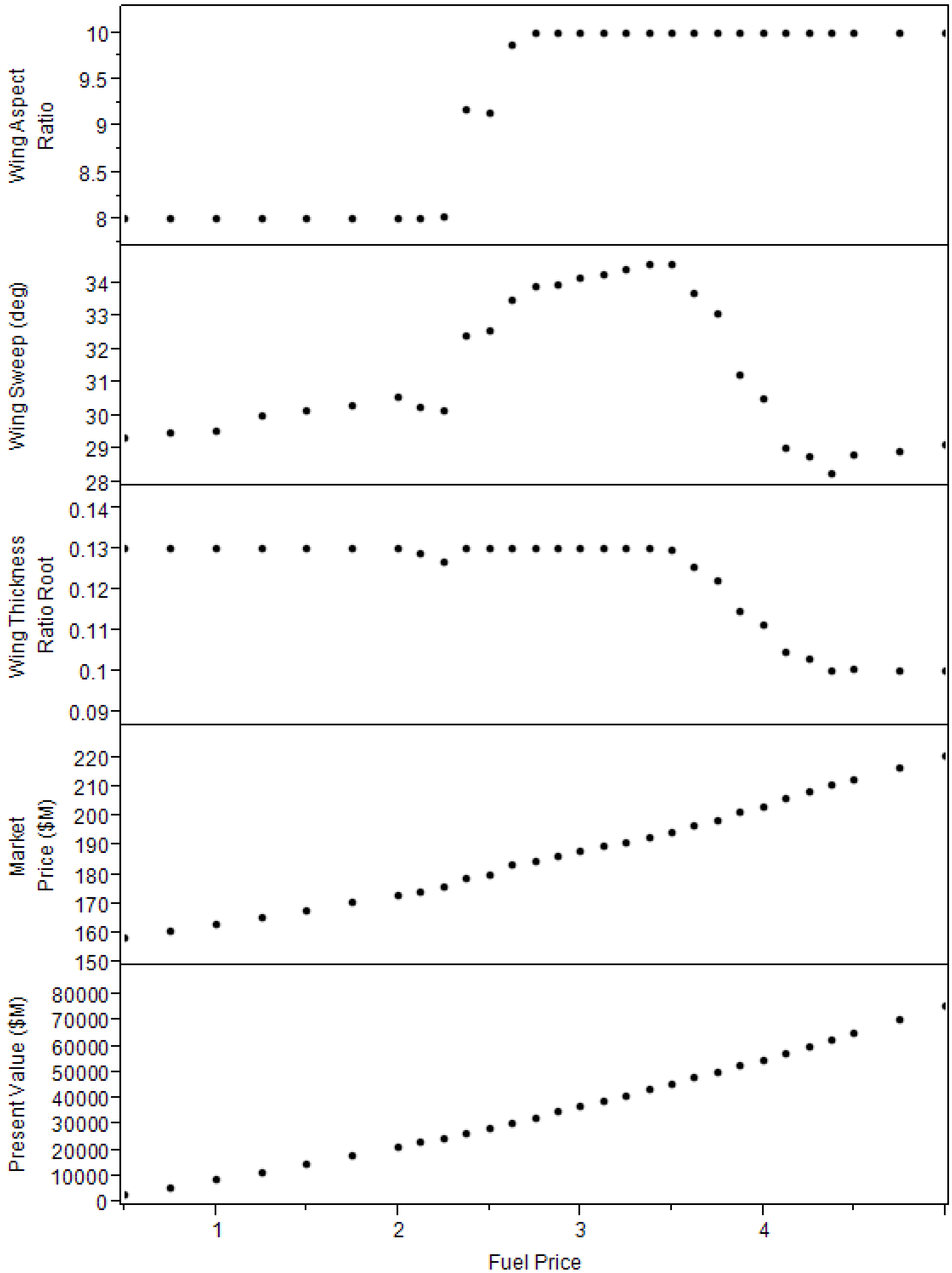


Figure 96: Interacting Scenario Optimized Design Inputs

The optimized present value vs. fuel price chart shows a trend that the present value for the airframer increases at a slightly greater than linear rate as the fuel price increases. This result arises from two primary sources: the concept market price at sale, and the concept costs to bring to market.

The market price at sale will be discussed first. Examining the optimum market price vs. fuel price, shown in the fourth plot in Figure 96, a trend emerges that shows the optimum price rises at a slightly larger than linear rate with respect to a change fuel price. This trend is a result of the fact that the cost of a technologically less advanced aircraft, with higher fuel burn, increases as the cost of fuel increases. As a result, the economics analysis captured in ALCCA determines that it becomes more desirable to replace these aircraft with new more efficient aircraft when fuel price is higher. Rather than continue to sell aircraft at the same price, the optimum price for the airframer to offer the aircraft to the airlines is adjusted upwards as fuel price increases. Because the demand curve was relatively inelastic for aircraft demand, the airframer has a decent amount of freedom to extract the value of a more technologically advanced aircraft from the airlines in this situation and can expect to sell aircraft at a higher price when fuel prices increase (provided the assumption that financing is available to the airlines holds true).

The other half of the profit equation for the airframer comes from the cost to bring the aircraft to market. This cost is driven by the technical aspects of the design. Beginning by examining the top chart in Figure 96, the aspect ratio vs. fuel price, the reader can see that the design exhibits tipping point behavior. The optimum aspect ratio is at the bottom constraint on the design space for any fuel price approximately less than 2.30 $/gal and rapidly traverses the range of possible aspect ratios to reach the top constraint by a fuel price of 2.65 $/gal. This particular result is driven by the fact that a shorter wing with a lower aspect ratio is structurally simpler, and as a result lighter and less costly for the airframer. These benefits come with a penalty of increased drag. The increase in drag results in an increased required thrust and ultimately increases fuel burn. At a fuel price around 2.5 $/gal the benefits of reduced cost and weight are rapidly obscured by the costs of increased fuel burn, and a high aspect ratio wing is desired. This has immense implications for the latter stages of engineering design. Since the aspect ratio of the wing is a measure of its most basic shape, the best wing, and the expenditure of all the future effort to refine and design this wing, is heavily driven by the fuel price.

The wing thickness ratio at the root, show in the third chart of Figure 96, follows a similar but mirrored trend to the aspect ratio. In this case the transition from the high end of the design space to the low end takes place within fuel prices ranging from around 3.50 $/gal to 4.25 $/gal. These two variables together represent one of the fundamental trade-offs in wing design: the trade between structural simplicity and aerodynamic efficiency. A wing with a low aspect ratio and a thick root is structurally simpler. This structural simplicity is the result of a lower bending moment from a shorter wing (lower aspect ratio) as well as a thicker wing root with which to support that moment. The net result, is that the wing can be made simpler, lighter, and as a consequence, more cheaply. When fuel price is low, this simplicity and the cost savings associated with it are desirable. However, a lower aspect ratio wing will produce more induced drag, and a thick root will have a higher profile drag. Increased drag leads to increased fuel burn, and as a result the transition to a lower drag optimum design occurs as fuel price increases.

The final design variable that exhibited an interaction with the uncertain fuel price was the wing sweep. The second chart down in Figure 96 shows the wing sweep vs. the fuel price. The final present value is relatively insensitive to the wing sweep, and this variable's behavior is largely a reaction to the changes in the aspect ratio and the wing thickness ratio at the root. There is an underlying behavior in the sweep that acts as a secondary effect which mimics the effect of aspect ratio and root thickness and also trades an aerodynamic efficiency of a higher sweep for slightly increased weight. However, this is a secondary effect to matching the sweep to the aspect ratio and thickness.

A Cost Cutting Perspective on Hypothesis 1

Hypothesis 1 provided and proved a set of conditions for defining the design dimensions where a change in scenarios leads to a desired design change in that dimension. The inverse of this statement is that Hypothesis 1 provided and proved a set of conditions for defining the design dimensions where a change in scenarios has no impact on the desired value for that dimension. This inverse statement is useful from a cost cutting perspective. If an organization already believes that its products are well diversified against changes in uncertainties, the use of Hypothesis 1 can be used to test this belief. If the belief is mathematically true, then the knowledge of which design dimensions are mathematically determined to be insensitive to changes in scenario can be used to create a set of common parts for those design elements. As a result, Hypothesis 1 can also be viewed as a cost cutting tool.

Application of this idea to the 300 passenger civil aircraft problem is straight forward. Table 12 highlights the dimensions which the optimum design choice changes in response to a change in scenario. Of the 15 continuous dimensions studied, only four demonstrated this change. The other 11 dimensions indicated no change. The dimensions that demonstrated change were those related to the wing and the marketing strategy. All of the other dimensions remained unchanged. If the company was currently selling multiple designs tailored to different customers, the use of Hypothesis 1 allows for those designs to be collapsed to a family of designs based on a common platform where only the wing and marketing strategy are varied. This commonality can lead to cost savings provided the uncertainties and customer's values have been modeled accurately.

Examining Design Space Uncertainty Interaction (Twist)

Figure 96 was able to show that there was tipping point behavior within the design space. It did not directly show twist in the design space relative to the uncertainty, or the magnitude of that twist. To directly show the effect of the interaction between the design variables and the uncertain variables, or twist, it is necessary to show the performance of the scenario optimized designs away from their respective design scenarios. Figure 97 presents a uniform sampling of the optimum designs color coded by the fuel price for which each design is optimum. These nine optimum designs are evaluated for a random Monte Carlo sample of 1000 scenarios. In these scenarios, both the fuel price and the technological development were randomly selected to provide an accurate representation of the uncertainty space. The performance of each of these designs in scenarios other than the ones in which they were optimized is plotted in the three-dimensional chart shown in Figure 98.

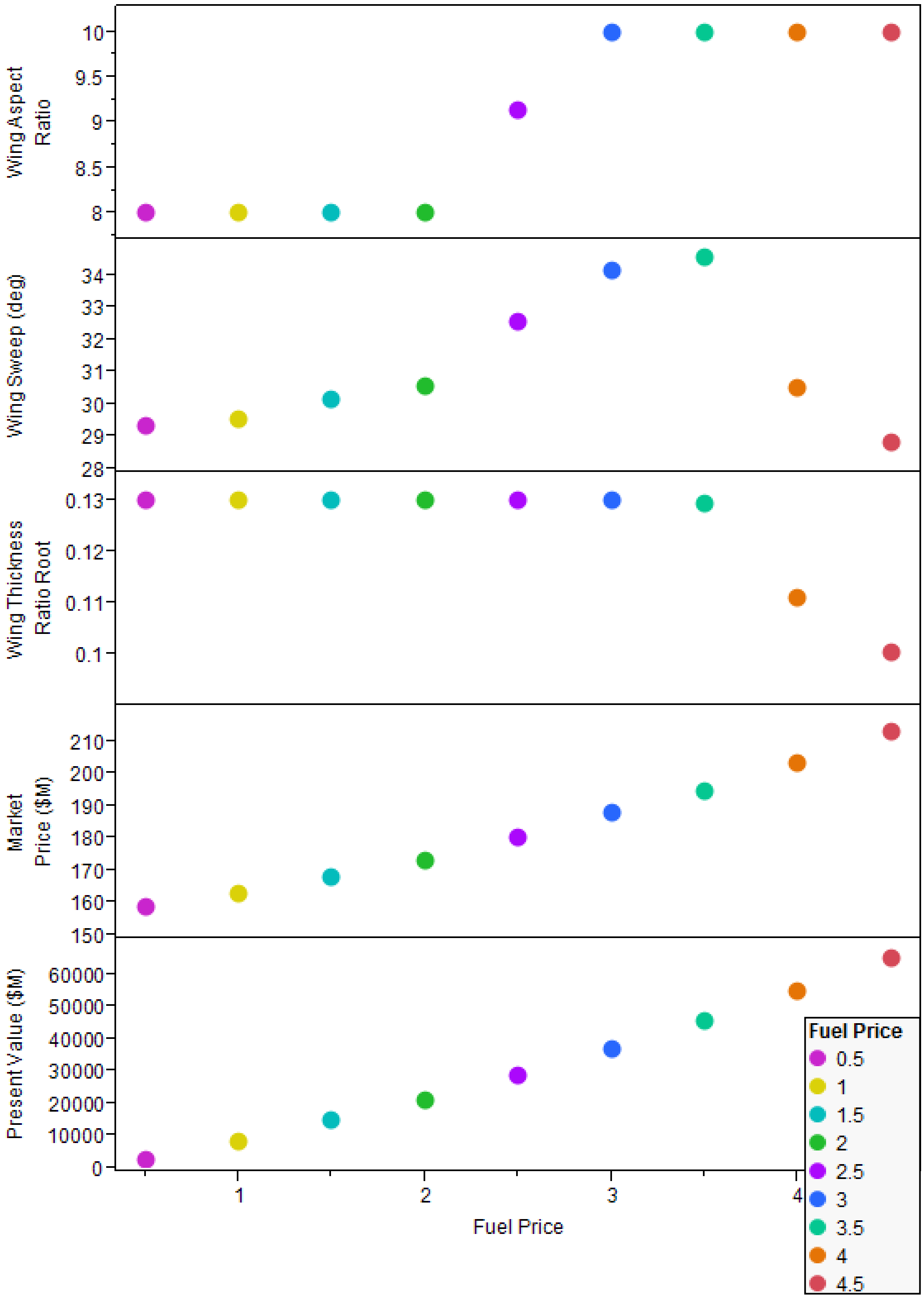


Figure 97: Color Coded Scenario Optimized Design Inputs

Figure 98 shows three 3D charts from different perspectives. Each chart shows a different view of the nine concepts shown in Figure 97 evaluated 1000 times for a common set of 1000 randomly sampled uncertain scenarios. These scenarios included randomness in both the fuel price and the technological development. The purpose of this chart is to provide evidence that the value space of the realistic design problem is twisted as required by Hypothesis 1. The three axes on each of the charts are as follows:

- The present value runs vertically on each of the charts.
- The randomly selected scenario fuel cost runs into the first chart on the right and the perspective has been rotated so that it runs across the horizontal axis by the bottom chart.
- On the remaining axis each concept has been plotted on an axis representing the fuel prices scenario for which the concept was optimized. The concepts have been charted against the optimized fuel price since it was not possible to represent all of the differing dimensions of a concept on a single axis. However, the full list of inputs defining the concepts can be found in Table 13.

As the chart is rotated, the reader can observe that for randomly generated scenarios with a very low fuel price, the concept optimized to a low fuel price performs the best. For extremely low fuel prices, the concepts optimized for higher fuel prices are unprofitable to the point that the value extends below the negative range of both the vertical axis and the modeling environment. As the fuel price rises, the optimum design moves as expected from the concepts optimized for low fuel prices to those optimized for higher fuel prices. As a result, the present value is twisted with respect to the uncertainty fuel costs meeting the conditions specified by Hypothesis 1.

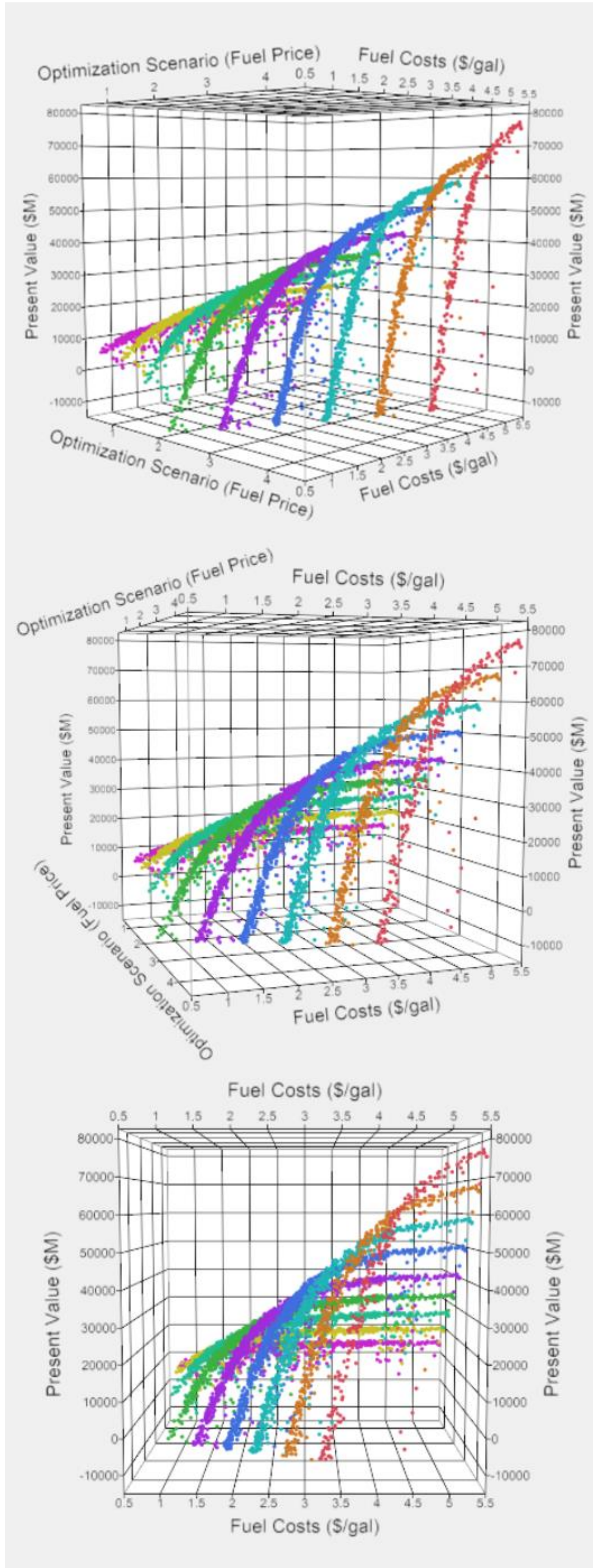


Figure 98: Monte Carlo Performance from Three Perspectives

Exploring the Effects of Uncertainty on the Design

Figure 99 shows a two dimensional projection of the information shown in bottom plot in Figure 98. In this figure two effects can be observed. The first arises from uncertainty in the fuel costs, and the second effect is the result of the uncertainty in the technological development. The following paragraphs discuss these effects.

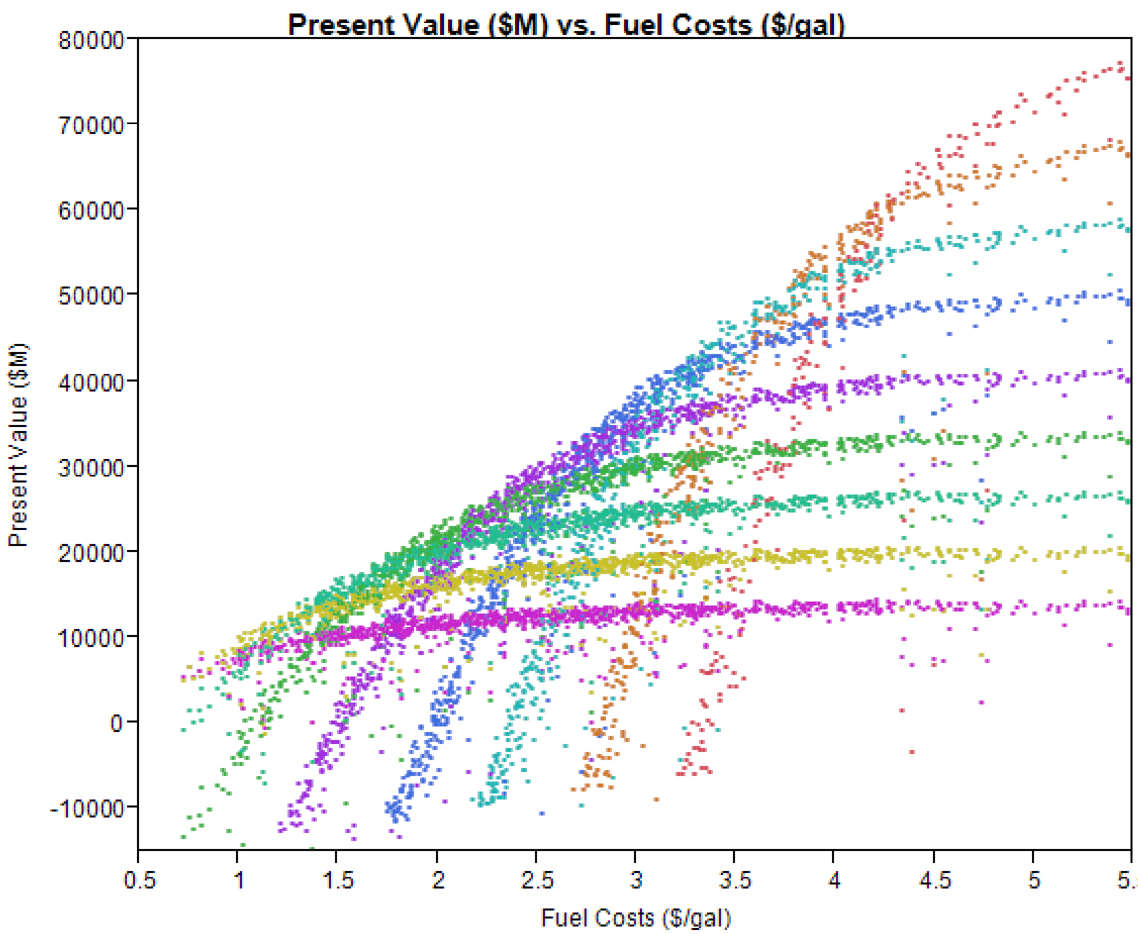


Figure 99: Fuel Scenario Optimized Designs

Examining the effects of fuel cost uncertainty first, the optimum performance for any fuel price corresponds to the concept that was optimized for a particular fuel price. Furthermore, the performance of the concept away from its optimum fuel price has two distinct behaviors. For fuel prices above the price at which a particular concept was optimized, that concept will have a relatively flat performance. However, for fuel prices below a concept's optimum fuel price, the performance reduces drastically. This behavior is largely driven by the price at which the aircraft has been offered. If the airframer develops a low cost aircraft and markets it for less money, then they will ensure that they can sell a large number of them at a lower profit margin regardless of the fuel price. However, if they choose to develop a technologically advanced aircraft and market it at a higher price, the airframer can squeeze all of the profit out of the airlines when fuel prices go up. This is because those airlines cannot afford to fly older less efficient aircraft, and they cannot afford to fly no aircraft, so they are forced to take out loans to purchase new aircraft at a higher price. However, if the fuel price remains low and the airframer has pursued an expensive technologically advanced aircraft. The airlines can afford to continue operating less efficient aircraft rather than pay a large amount for a new aircraft. The net result of this is that the number of sales of an expensive aircraft rapidly declines as the fuel price decreases, and the cost of development cannot be recouped. This leads to large losses. For concepts optimized to a higher fuel price, the losses become negative to the point that the model no longer is capable of accurately calculating the losses expected. In reality, a design organization would likely cancel a program that is expected to make huge losses, and as a result, the losses expected in this situation have been capped at the development cost for that concept plus a penalty. For simplicity's sake, these failure dimensions are not shown on the plot in Figure 99, but the trends should still be easily observable. The low cost and price concepts are a more certain bet, but will not return a high value, and the opposite is true of high technology concepts.

The second effect of uncertainty that can be observed in Figure 99 is the effect of the uncertainty in technological development. While not plotted as an individual axis, this manifests itself in the fuzziness of the lines. Each concept contains 5 technologies. Each of these technologies is subject to uncertainty as described in Section 5.6.1. As a result the technological uncertainty represents 12 uncertain variables. The fuzziness of the lines in Figure 99 results from differing levels of performance in the 5 included technologies. As more technologies experience a higher level of failure, the present value is reduced from the nominal value for that optimum concept, and the line appears fuzzy. Since each of the concepts in Figure 99 contains the same technologies and has been evaluated under the same technological development scenario, the effects of failures in technology are fairly uniform across the differing concepts. The higher cost concepts experience a slightly greater sensitivity to a scenario where multiple technologies fail, since the higher price is more dependent on improved performance, but the overall trend for each of the concepts to changes in technology development scenarios is the same.

Figure 100 presents the same results as Figure 99 with the exception that the present value axis has been transformed to a profit percentage per aircraft sold. From Figure 100, it can be observed that the profit percentage varies widely between concepts as well as with fuel price. The concept optimized to a low fuel price guarantees a fairly level profit percentage of slightly less than 5%, while the high priced concepts offer a percentage of up to 25% with the risk that they will be completely unprofitable should the fuel price drop. This view and these numbers are easier to relate to from a design perspective, but because the profit percentage per aircraft translates the output away from a pure dollar amount, it cannot be directly compared to the additional cost expected in a portfolio-based approach. As a result, the present value will be used as the measure of value for the remainder of this thesis, with the recognition that there is a 1-to-1 translation between the two representations.

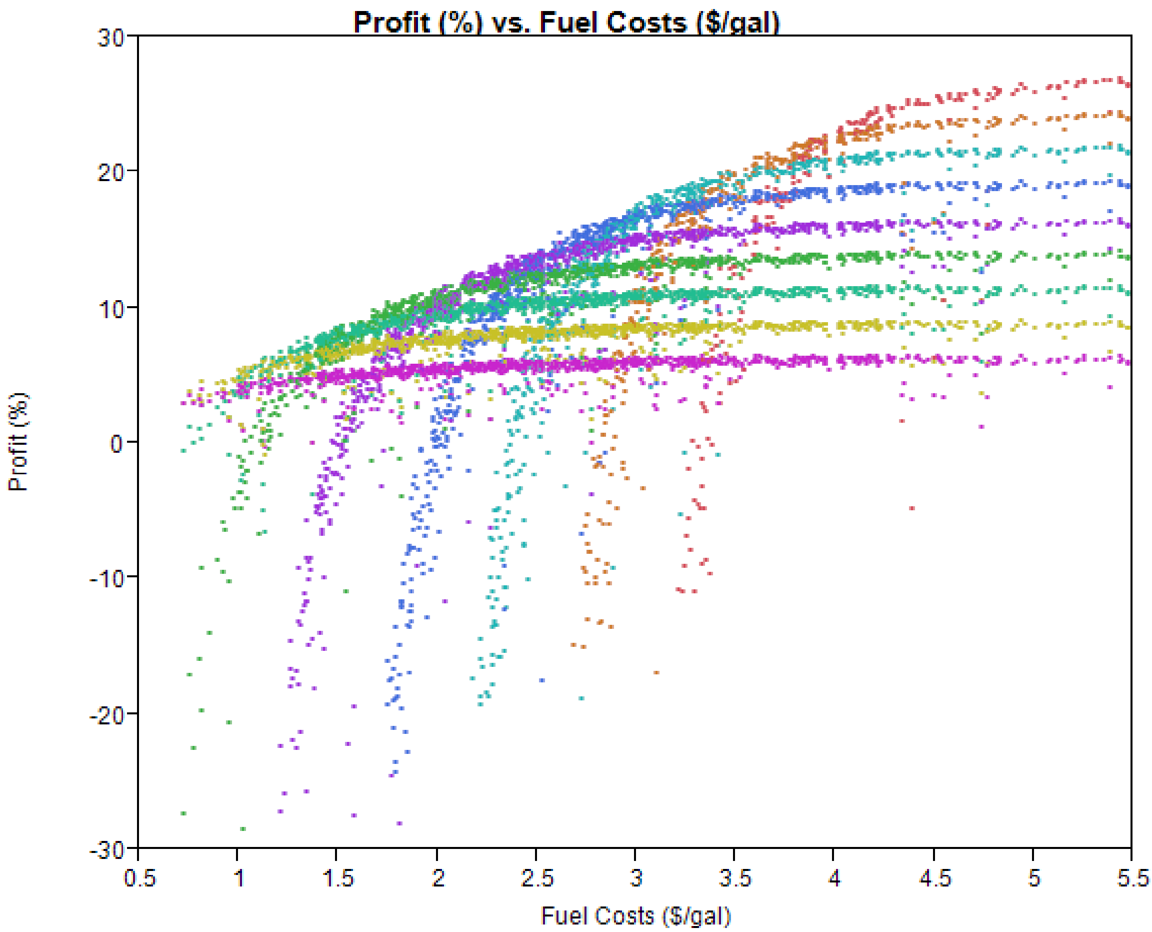


Figure 100: Fuel Scenario Optimized Designs vs. Per Aircraft Profit Percenage

5.2.5 Testing Hypothesis 1 for the 300 Passenger Design Problem

Recall that the methodology shown in Figure 66 required a test to determine if a portfolio-based approach is needed. This test revolves around determining if the conditions defined by Hypothesis 1 have been met. Recall that Hypothesis 1 had three conditions and Chapter III demonstrated how these conditions translated to the geometric structure of the model outputs. To confirm that the modeling environment meets the conditions specified by Hypothesis 1, the results presented in the previous section from the will be presented as a test of the conditions in Hypothesis 1.

Hypothesis 1

1. A tradeoff must be made between desirable traits (Pareto frontier exists)
2. Preference for the desired traits may be uncertain, but is driven by scenario ("Best" location along the Pareto frontier is driven by scenario uncertainties)
3. The best design is sensitive to changes in the uncertainties.

Chapter III offered a number of mathematical examples that demonstrated that the first two conditions listed in Hypothesis 1 translated to a geometrical twist in the design space when the concepts were plotted with the uncertainty along one axis and the objective plotted against another axis. This twist then leads to an edge along which differing concepts are optimum. Figure 101 shows a reproduction of Figure 99 with the optimum edge highlighted and the twist can be seen in the roughly 45 degree bend in the structure of the space.

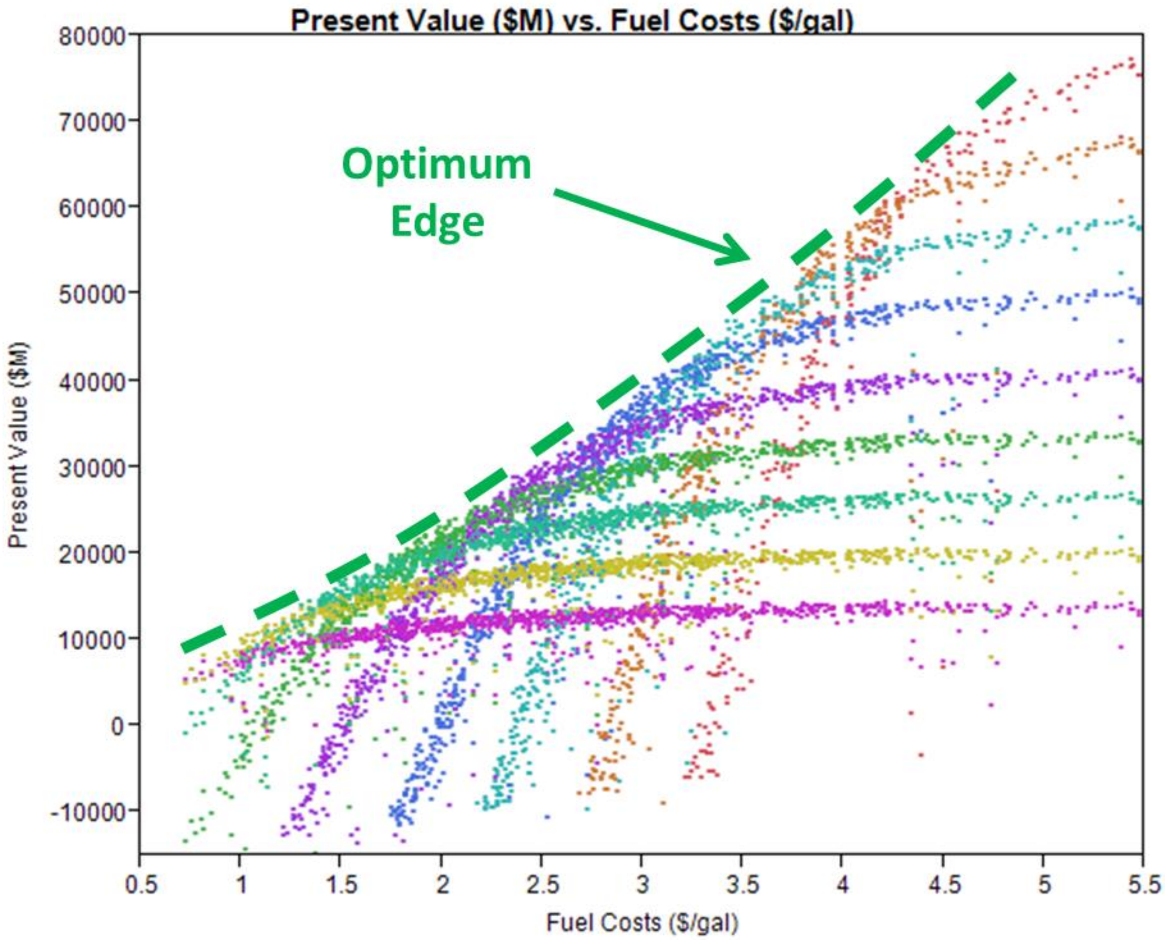


Figure 101: Twist and Optimum Edge in 300 Passenger Design Space

The third condition in Hypothesis 1 states that the optimum design inputs must change with respect to the scenario. Figure 102, shown below, is a reproduction of Figure 96 where the fact that large changes in the optimum design have occurred in response to changes in scenario is highlighted. From Figure 101 and Figure 102 it should be evident that for four of the design dimension and one of the scenario uncertainties the conditions of Hypothesis 1 have been met. Because the conditions of Hypothesis 1 are met, the problem as represented by the modeling environment falls within the bounds of applicability of a portfolio-based approach and the model is a valid test of a portfolio-based approach.

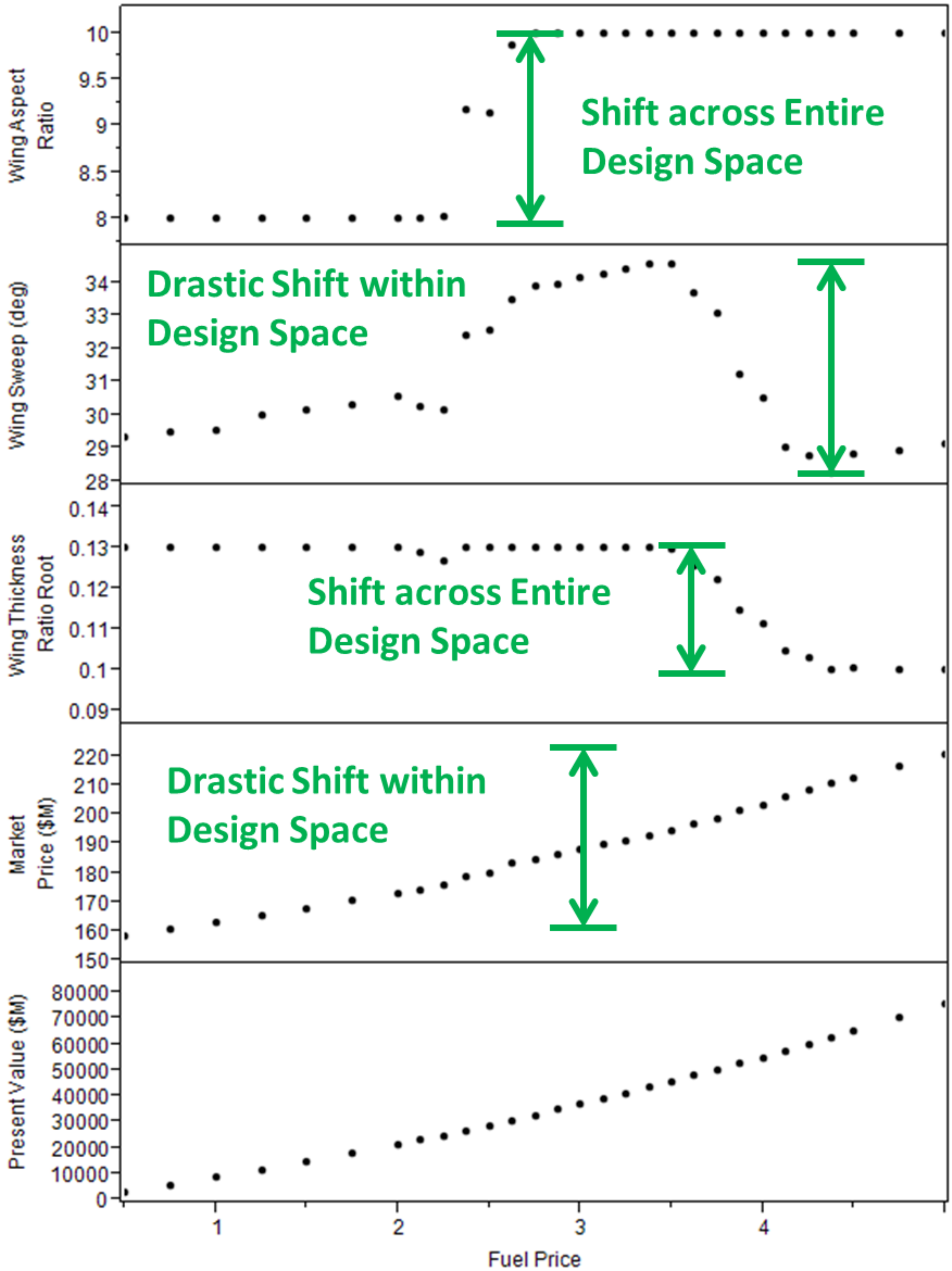


Figure 102: Sensitivity of Best Design Inputs to Changes in Scenario

5.2.6 Robust Design Analysis and Decision Making

The following section completes a robust design process for the aircraft design problem as a second baseline for comparison to the portfolio-based optimization. This section describes the optimization setup, the results of the robust design and draws conclusions on the differences between the robust design output and the scenario based design.

Robust Design Optimization

Robust design optimization was performed by adding an internal Monte Carlo sampling to the optimizer used in Section 5.4. A description of this process can be found in Section 4.9.6.

Figure 103 shows the modified inputs for the robust design evolutionary algorithm. The fuel price was modeled as a lognormal distribution with a mean of 0.9163 and a standard deviation of 0.426, which corresponds to the geometric Brownian stochastic process described in Section 5.6.1. The technological success was modeled as a discrete Markov Chain, and each technology was allowed one of four states as described in Section 5.6.1. Assuming the uncertainty in the technological development was resolved within the first two years led to the probabilities shown in Table 14 for each of the states. From this discrete set, a random selection was made with the probabilities listed in Table 14 for each of the technologies. This selection, combined with the randomly selected fuel price, created a single Monte Carlo case. An internal sample of 500 scenarios was done for each evaluation of any particular concept.

Table 14: Technology Uncertainty Modeling

State	Probability	Technology Impact Multiplier
Failed Development	0.02	0%
Below Nominal Development	0.3	90%
Nominal Development	0.53	100%
Above Nominal Development	0.15	105%

As a result, the output is modified to 500 potential cash flows for the concept based on the 500 randomly selected scenarios. The present value, which is the final cumulative value at the end of the lifecycle of 20 years, contains 500 data points. The mean and standard deviation was calculated for these data points. A simple OEC shown in Equation 44 and described in Section 4.9.6, was used to determine the robust design. The weights of the OEC in Equation 44 were varied to create a Pareto frontier of robust designs for varying preference for higher expected value vs. reduced variance.

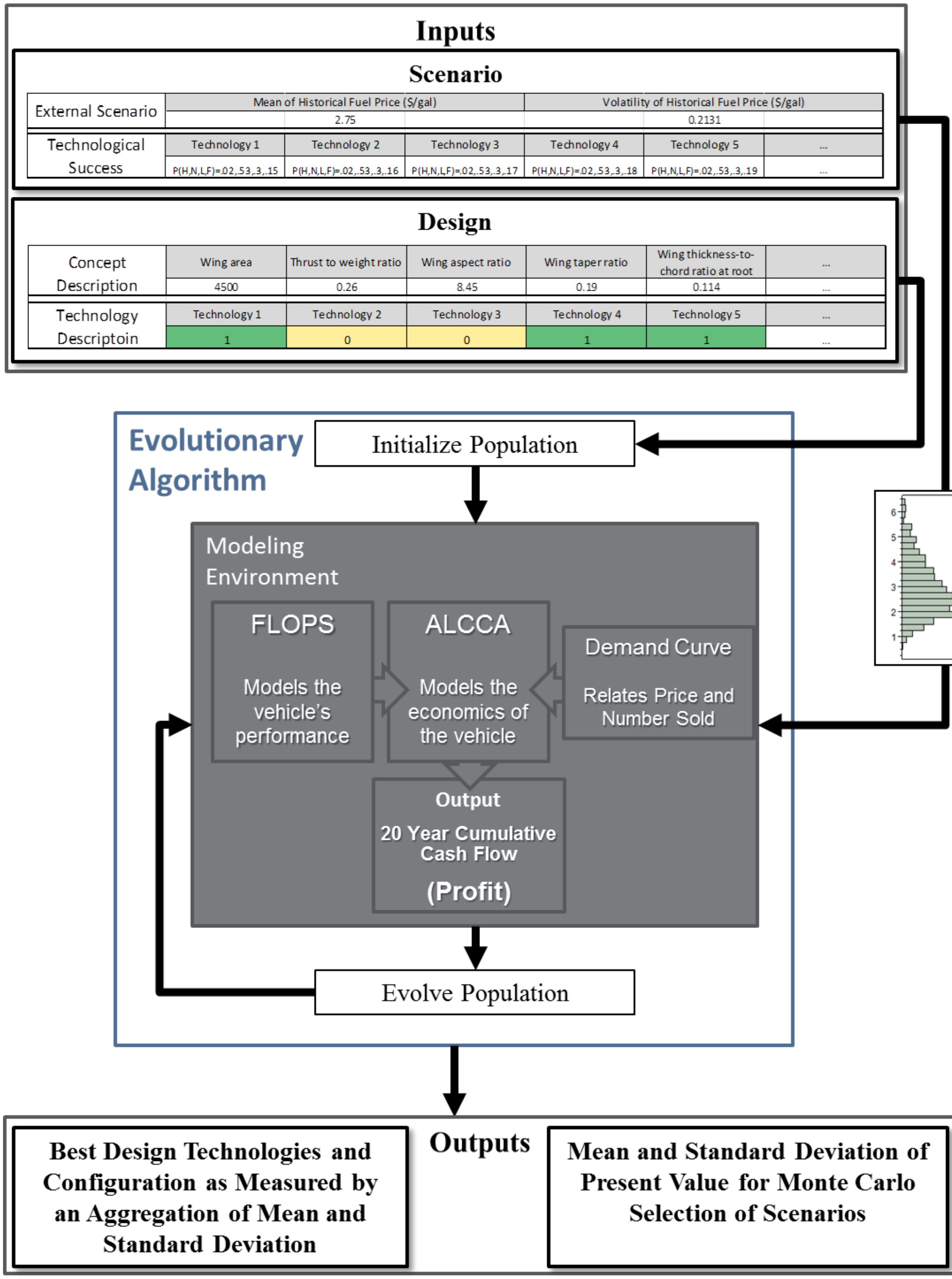


Figure 103: Robust Design Optimization Setup

Robust Design Optimization Output

Figure 104 shows the Pareto frontier along the dimensions of expected value and standard deviation for both the robust design and the scenario-optimized design. The scenario-optimized design is shown in blue while the robust design is shown in Figure 104 as a set of red points. However, after a limited number of robust optimizations for differing preference for higher expected value or lower standard deviation, it was observed that the robust designs were simply fuel price scenario optimized designs with a differing technology portfolio. Table 15 shows a comparison of the scenario-optimized technology portfolio to the robust technology portfolio. Since the robust design is nearly identical to the scenario-optimized designs, for ease of comparison, the results of the robust design optimization are shown in terms of the fuel price scenario for which that particular concept would have been optimum, with the recognition that determining an optimum for a specific scenario was not the objective function.

Table 15: Comparison of Technology Portfolios

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Scenario Optimized	0	0	0	0	1	1	0	1	0	1	0	1
Robust	0	0	0	1	0	1	0	1	1	1	1	1

Each pair of points in Figure 104 has been labeled by the fuel price scenario for which that concept is optimum. In these pairs, the red point is the robust design optimum for that scenario and the blue is the purely scenario-based optimized design. In essence the optimizer created “robust” designs by adding a larger but roughly equivalent set of technologies to the technology portfolio, and then optimizing a design with this portfolio to the more stringent fuel price scenarios. This has the net effect of reducing the effective rate of catastrophic technological failure since multiple technologies must have poor developmental progress for this situation to occur. The robustness to fuel price changes has come from the fact that the design is optimized to a more stringent fuel price requirement.

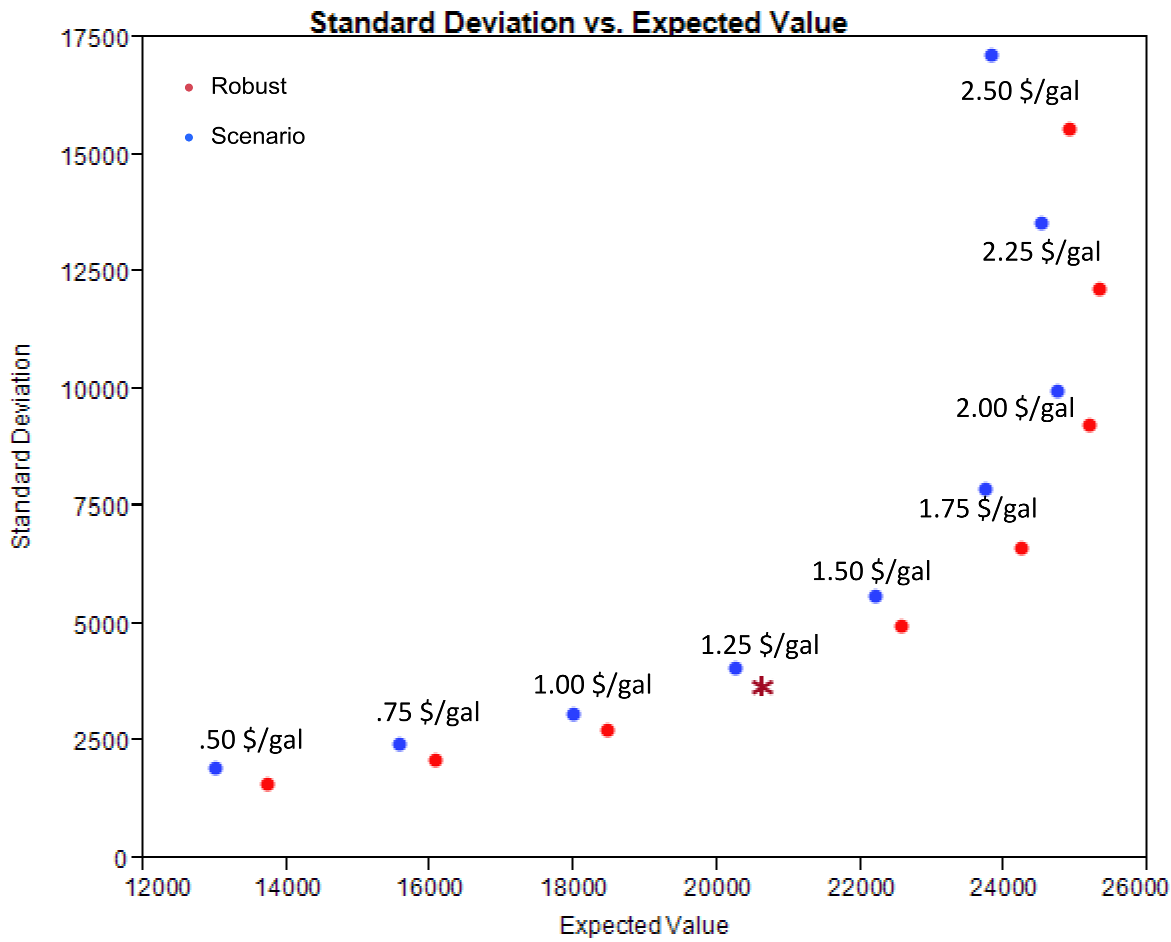


Figure 104: Pareto Frontier for Robust Design Candidates

From Figure 104 it is evident that the robust design paradigm improved the performance of the design process when uncertainty is present. The robust designs have a higher expected value and lower variance than their corresponding scenario-optimized designs, and the net result is robust design shifts the Pareto front in a positive manner and each of the scenario-optimized designs are now Pareto dominated. It is this perspective that has led robust design to be treated as a separate technology for improving design outcomes by many in literature [89].

It is also important to note that in the modeled representative design problem both the robust design and the scenario-optimized design trade value for robustness. This fact can be seen in Figure 104 through the broad sweeping Pareto Frontier. Recall that in the characterizing problem, where a similar chart was shown in Figure 17, there was not a broad sweeping Pareto frontier. This indicated that the characterizing problem was a much more stringent test for the portfolio-based design process than a more representative design problem.

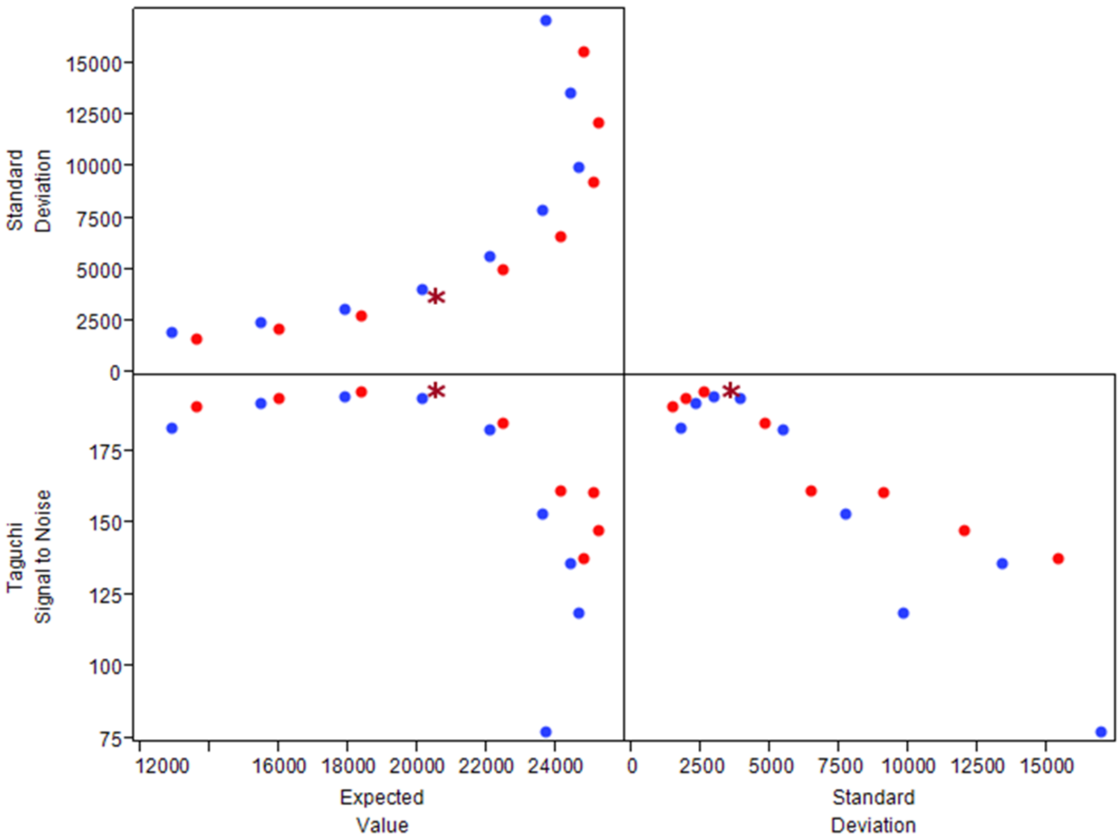


Figure 105: Expected Value vs. Taguchi Signal to Noise vs. Standard Deviation

Figure 105 shows the plots of three dimensions of measurement for robust design, the standard deviation, the expected value, as well as Taguchi's aggregation function, the signal-to-noise ratio. The top right chart is identical to Figure 104. The bottom two charts show the expected value and standard deviation plotted against the signal-to-noise ratio. The signal-to-noise ratio equation is shown in Equation 7. If the goal is to maximize the signal-to-noise ratio, as stated by Taguchi's methods, then the optimum robust design is shown as a slightly darker red star in Figure 104 as well as in Figure 105 and corresponds to a design optimized to a fuel price of 1.25 $/gal.

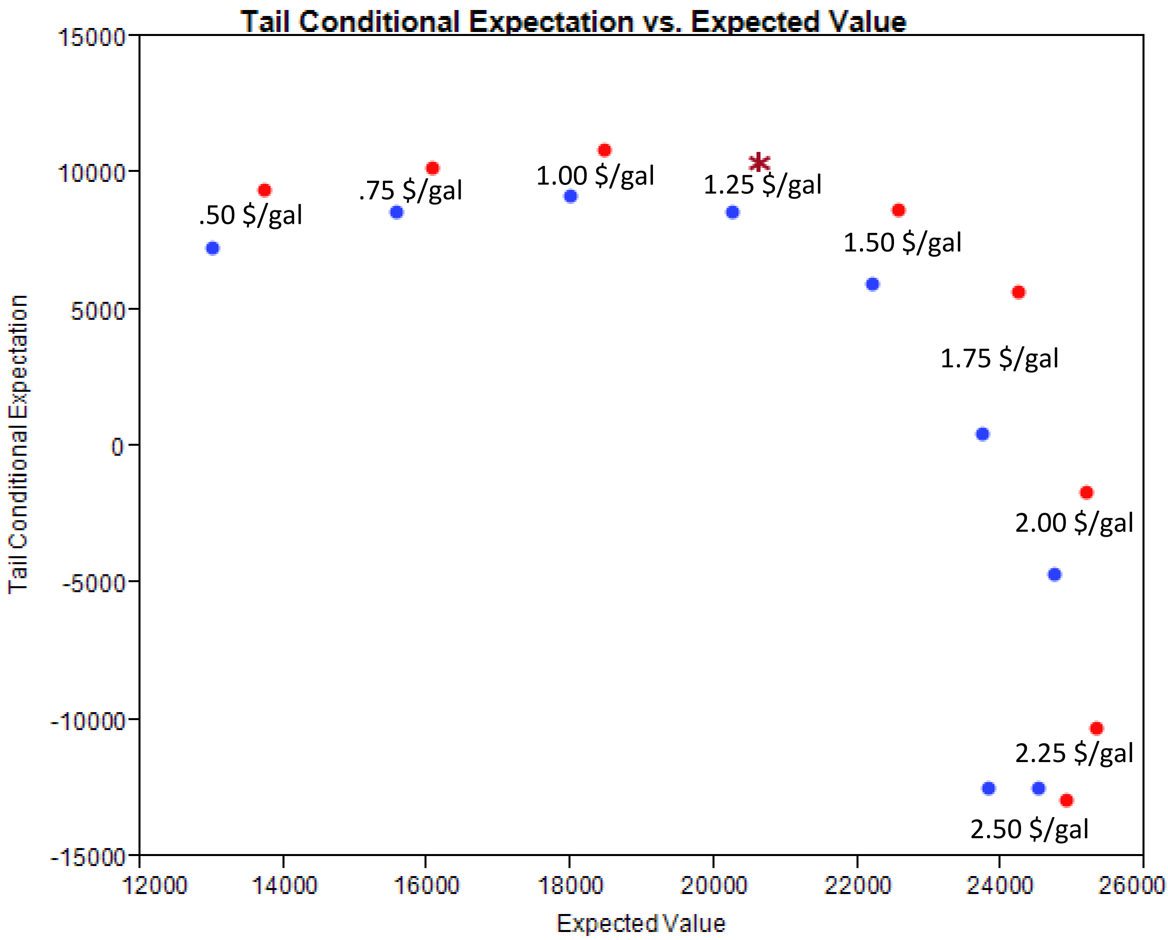


Figure 106: Expected Value vs. Tail Conditional Expectation for Robust Design

Section 2.1.2 detailed problems that may occur with the use of the standard deviation as a decision metric for design. Section 2.1.2 recommended the use of the tail conditional expectation as an alternative measure to the use of standard deviation. Figure 106 shows the expected value of the robust designs plotted against the tail conditional expectation. Comparing Figure 105 to Figure 106, one can observe that Figure 106 closely mirrors the results of Figure 105. The largest difference between the two figures results from the fact the goal is to minimize the standard deviation but maximize the tail conditional expectation. It is important to note that the Pareto optimal points are the same for the two charts even though the direction of Pareto optimality has changed. While the standard deviation doesn't exhibit problems when the robust concepts are the decision alternatives, the use of tail conditional expectation will be necessary for comparison of the robust designs to the portfolio-based designs.

Robust Designs vs. Scenario-Optimized Designs

Figure 107 shows a comparison between the robust design and the fuel price scenario optimized design configuration. Only the four variables that change with respect to the uncertainty are shown. The rest of the variables are set to the value shown in Table 13 in the white columns. Only those points from the range 0.50 $/gal to 2.50 $/gal would lie on the Pareto frontier between maximum expected value and standard deviation. As a result, only these designs are considered robust. The points representing these robust designs have been enlarged in Figure 107. However, for visualization purposes, the entire set of optimized concepts for specified fuel prices is shown with the robust technology portfolio selected to examine the impact of the change in technology on the rest of the aircraft. The robust designs consist of the set of designs optimized to lower fuel price scenarios that have an aspect ratio of 8. This indicates that the robustness is achieved by creating a simple aircraft. Furthermore, the robust design for any fuel price is nearly identical in terms of the general configuration of the aircraft. The market price is slightly higher for the robust design due to the larger technology portfolio; however, this increase is outweighed by the cost of these added technologies should the technological development go according to the initial estimates. However, when technological development uncertainty is included, the robust designs have a better expected performance as shown in Figure 105.

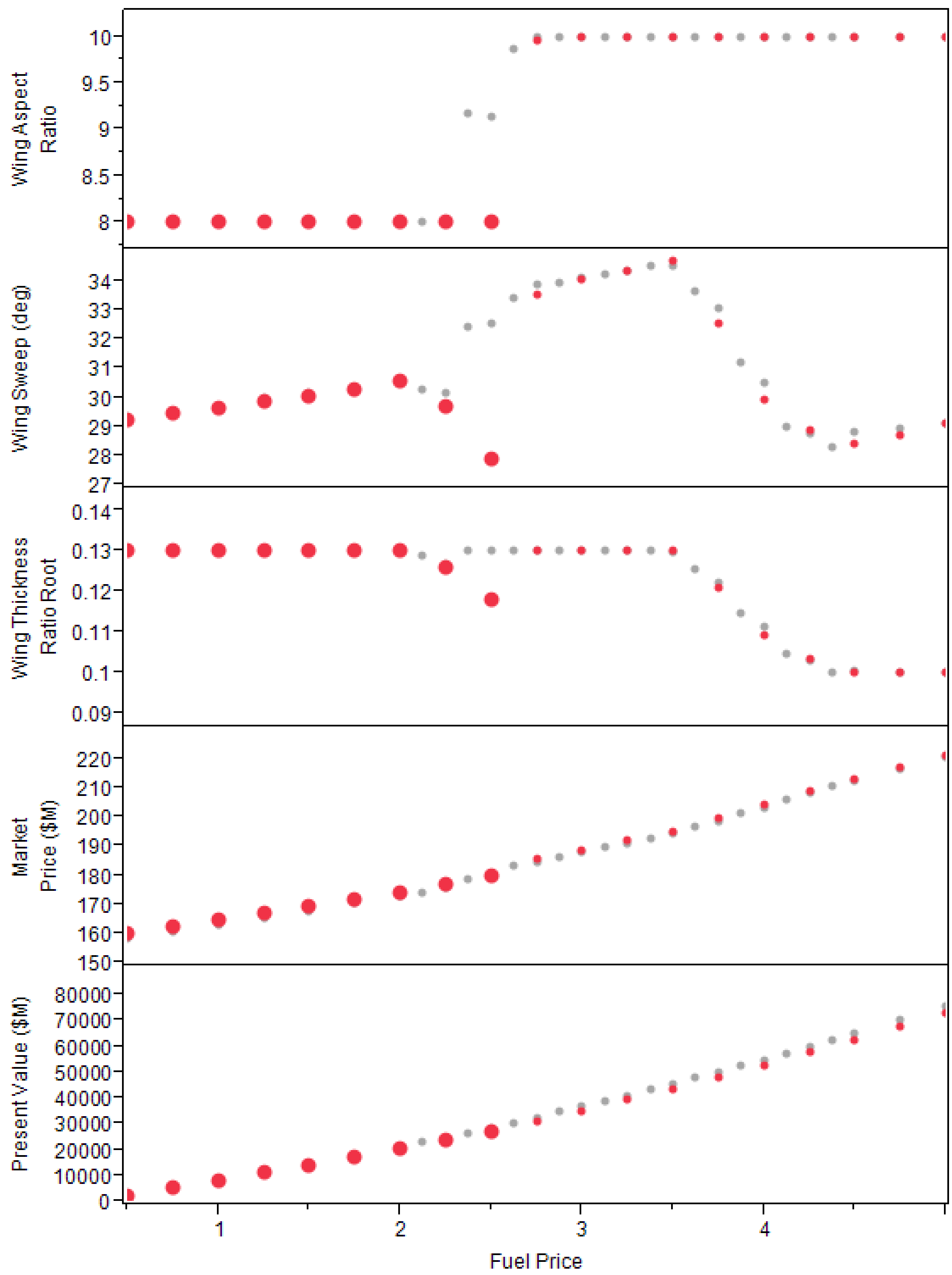


Figure 107: Design Inputs for Robust Designs

In conclusion, the robust design paradigm provides a way of improving the design outcomes of expected value and standard deviation by better accounting for uncertainty.

However, for the design problem modeled, this methodology requires that a great deal of performance be sacrificed to achieve robustness to uncertainty. Figure 108 is offered as a visual confirmation of this conclusion. The robust designs are highlighted in Figure 108 with the other "semi-robust" fuel price optimized designs shown slightly greyed out. Each of the robust design's performance has been evaluated for 1000 random off nominal scenarios and the results show a trend similar to those in Figure 99 with a significant reduction in the fuzziness. In this picture, the reader can readily observe that for the majority of the future scenarios, another design will outperform the robust design. This is a consequence of the fact that the robust design is has been chosen to minimize the negative impact of the worst case scenarios.

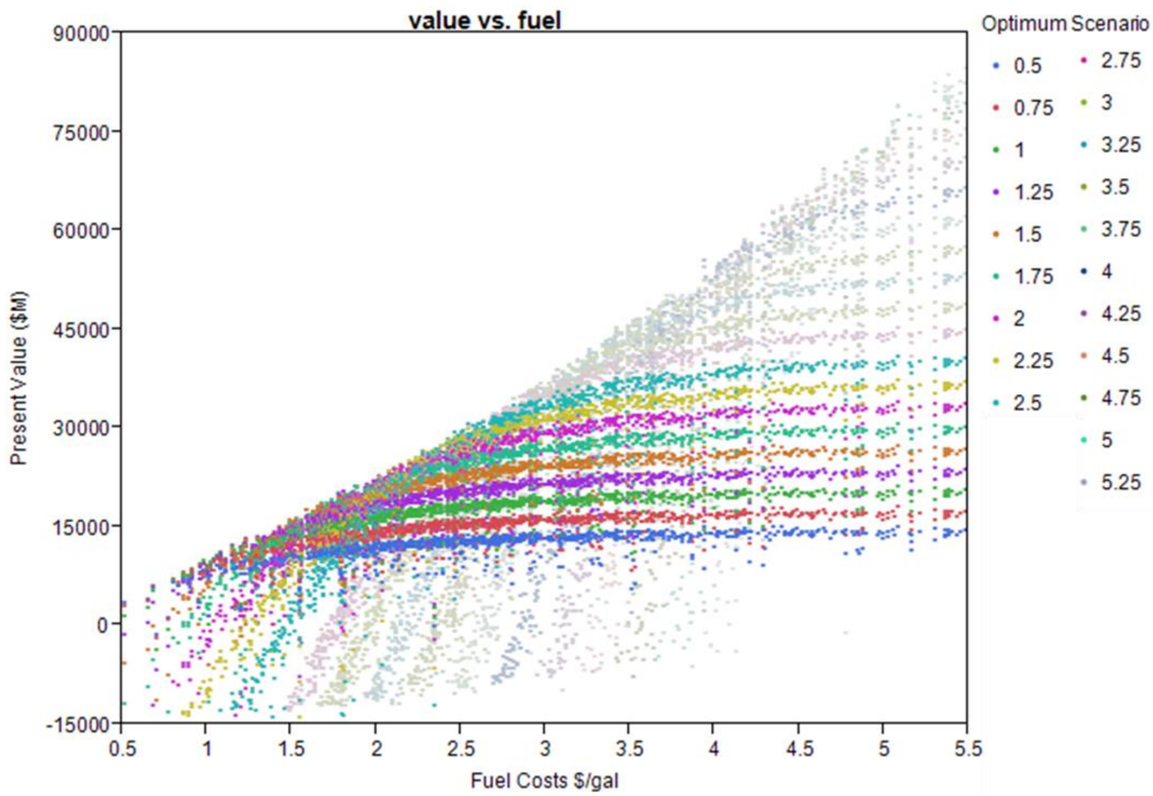


Figure 108: Monte Carlo Showing Off Nominal Robust Design Performance

5.2.7 Portfolio-Based Design Analysis and Decision Making

The following section demonstrates the outputs of the use of the ECOSIS algorithm to complete a portfolio-based design analysis for a 300 passenger aircraft design problem. This section will generate the data use in section 5.3 to prove that the PRISM-D process outperforms the best robust design, and meets the conditions specified by Hypothesis 2.

Portfolio Based Optimization

The following sections details the portfolio-based optimization results. This section describes the results of the modeling and describes the logic used in performing the optimization.

Portfolio-based optimization consisted of selecting the best portfolio up to and including a specified number of concepts. The number of concepts in the portfolio can be limited by two possible mechanisms. The first mechanism naturally arises in the course of the optimization since the optimizer itself has a tendency towards smaller portfolio sizes due to the extra cost in developing multiple concepts. The second mechanism is a result of the fact that any design organization has a number of limited resources not directly accounted for in this analysis. The following examples are offered as a demonstration of the types of resource limitations design organizations face: the number of design engineers specializing in wing root structures is limited to a small team, as is the number of wind tunnels, etc. These capacity constraints are not directly accounted for in the formulation presented, so they have been added as a constraint on the number of concepts allowable in the portfolio. Because portfolio-based design is a proposed methodology, and not the current method used in practice, the capacity of current design organizations are optimized for the single concept design process. This results in a series of very limiting capacity constraints. As a result, often even the parallel design of two concepts can stress a design organization. However, if the costs of adding new capacity are known, the method presented can easily provide the cost-to-benefit justification for expanding design capacity by simply adding these costs to the portfolio development cost. Since the cost of hiring more engineers, doubling test facilities, more effective scheduling, etc. is something often known to the business departments of the design organization, this information could be added to the engineering analysis.

Aggregate Measures of Performance

The following analysis presents the results for a portfolio with a maximum number of concepts initially limited to two per portfolio due to the capacity constraints described above. Figure 109 shows the results of a portfolio-based optimization, and plots the statistics for the present value from a Monte Carlo sampling for a portfolio of two concepts as compared to the other design strategies. The results have been presented using the two metrics, expected value and tail conditional expectation. The expected value is plotted along the horizontal axis, and the tail conditional expectation is plotted along the vertical axis. As a result, the optimal point lies in the top left corner, and the Pareto Frontier is oriented towards the top left. Three sets of points are shown in Figure 109. The blue points represent the scenario-optimized designs. The red points represent the robust designs with the starred red point representing the Taguchi robust design. These two series of points represent an identical set of points to those shown in Figure 106 with the exception that the Monte Carlo process allows for some variation through statistical randomness. The final set of green points provides an estimation of the Pareto frontier that can be achieved using a portfolio-based design process. Due to the randomness inherent in the use of a co-evolutionary algorithm along with the randomness in a Monte Carlo sampling, the green points do not form a crisp curve in the same way as the other two series. However, the general trend is observable form the green series: The use of a well-diversified portfolio of concepts allows the Pareto frontier to be extended in a positive direction allowing for better design outcomes.

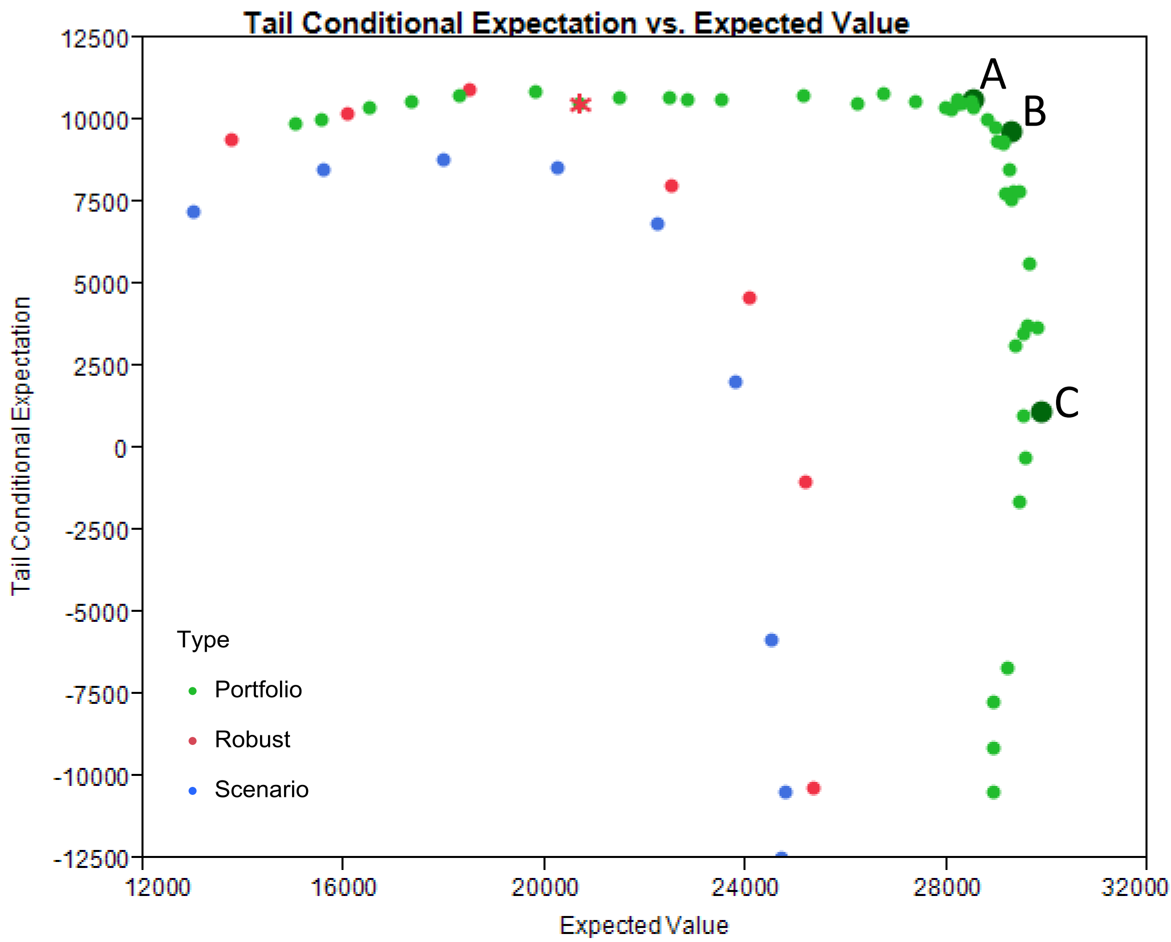


Figure 109: Expected Value vs. Tail Conditional Expectation for Portfolio Based Design

Three optimized portfolios were selected as representative portfolios from those shown in Figure 109 and will be used to demonstrate the behavior of the portfolio-based design process in more detail than the use of aggregate measures such as the expected value and tail conditional variation allow. The point labeled A represents a portfolio optimization with a strong emphasis on the ability to reduce the impact of the worst case scenarios. This point corresponds to a low risk portfolio, while allowing a reasonable increase in expected value. The other two portfolios trade this low risk for slightly higher risk and slightly higher expected value. The point labeled B represents a medium level of risk and the point labeled C represents a higher level of risk. While each of these points has an increased level of risk relative to point A, their risk levels are relatively low as compared to the many of the scenario and robust optimized designs.

Figure 110 shows the traditional statistical measures used in robust design in addition to the two measures shown in Figure 109. From Figure 110, it can be seen that the portfolio-based design extends the Pareto Frontier for the traditional measures as well as the tail conditional expectation used in this thesis. Figure 111 and Figure 112 show larger versions of selected charts from Figure 110 as a means of demonstrating the pitfalls of using traditional statistical measures in portfolio-based design.

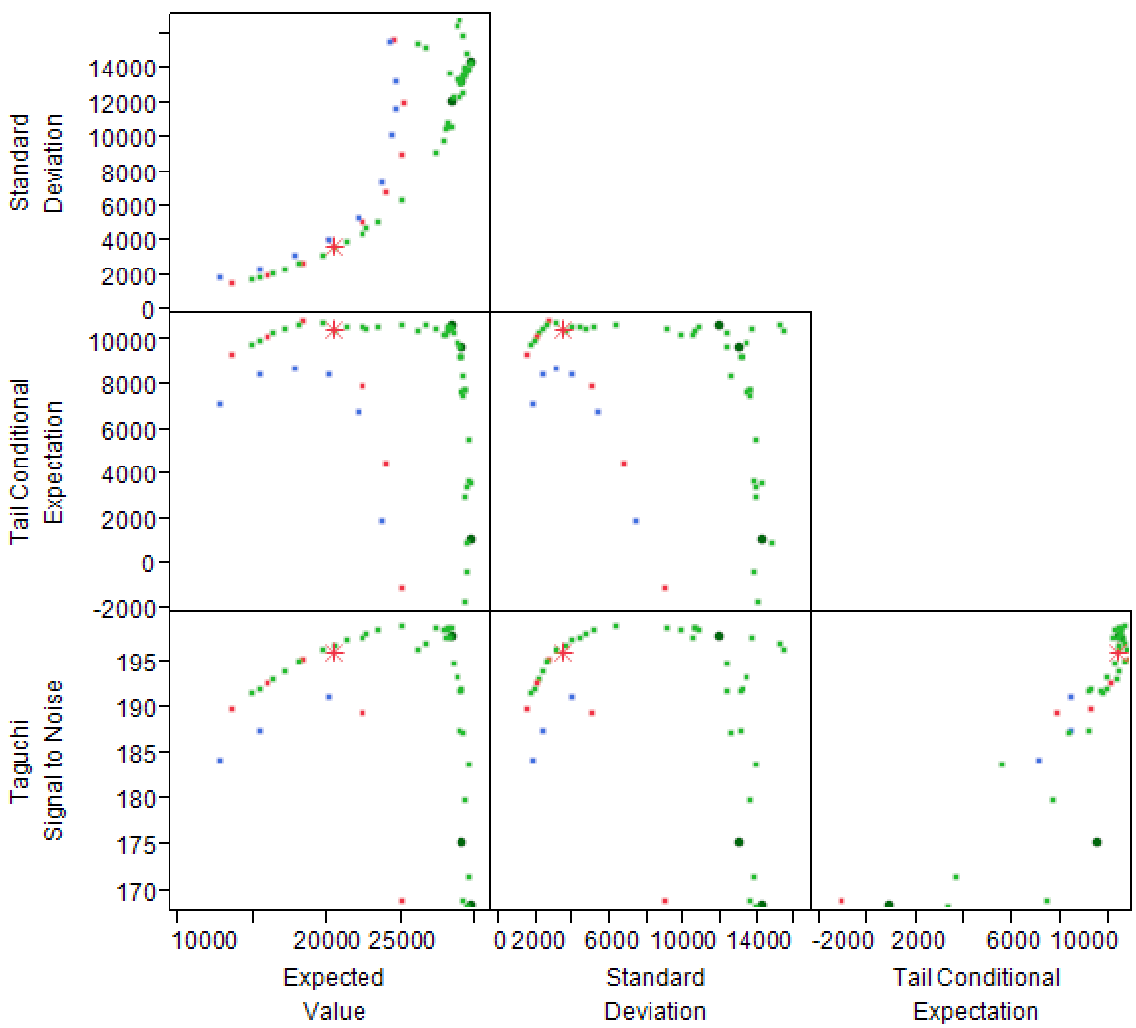


Figure 110: Multiple Statistical Measures for Portfolio Based Design

Figure 111 shows the standard deviation versus the expected value for the 1000 Monte Carlo scenarios. The Pareto frontier has been overlaid on Figure 111 as a grey dashed line. From this Pareto frontier it can be observed that the use of a portfolio-based design process extends the Pareto frontier as measured by the traditional robust design measures. However, the use of the standard deviation would imply that the portfolio-based approach has the potential to increase the expected value of the outcome, but indicates that this would come with an increased risk as measured by the standard deviation. Figure 109 shows that this impression is false, and a further examination demonstrated in the next section will show how this arises.

Figure 112 shows the plot of Taguchi signal-to-noise versus the standard deviation. Again, the Pareto frontier has been overlaid on the figure, and the reader can observe that the Pareto frontier has been extended upwards increasing the Taguchi signal-to-noise. However, the reader can also observe that the portfolios labeled A, B, and C in Figure 112 appear to be Pareto dominated. This is a result of the inappropriateness of the standard measures of variance with a portfolio-based design optimization.

While the standard deviation of the portfolio-based designs does increase, this increase is the result of the ability for the portfolio to contain a design with a greater upside potential. This upside increases the standard deviation, but does not have to come at a penalty of higher risk. The following section details this behavior. This effect cannot be captured by the use of standard deviation and as a result it should not be used as the risk metric in a portfolio-based design process. The analysis of the individual cases as opposed to the aggregate measures described in this section will demonstrate how the tail conditional expectation has a more direct physical meaning and allows for better decision-making in design.

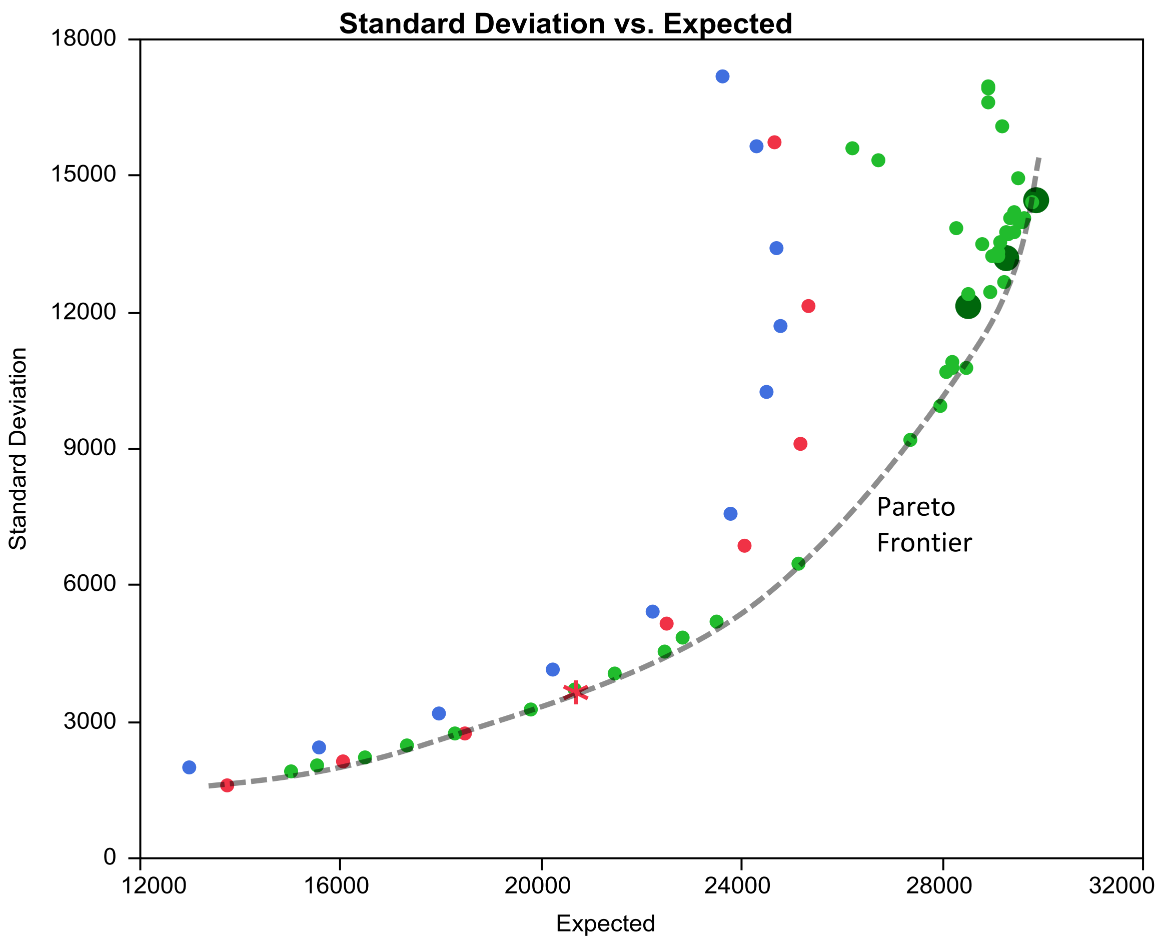


Figure 111: Expected Value vs. Standard Deviation for Portfolio Based Design

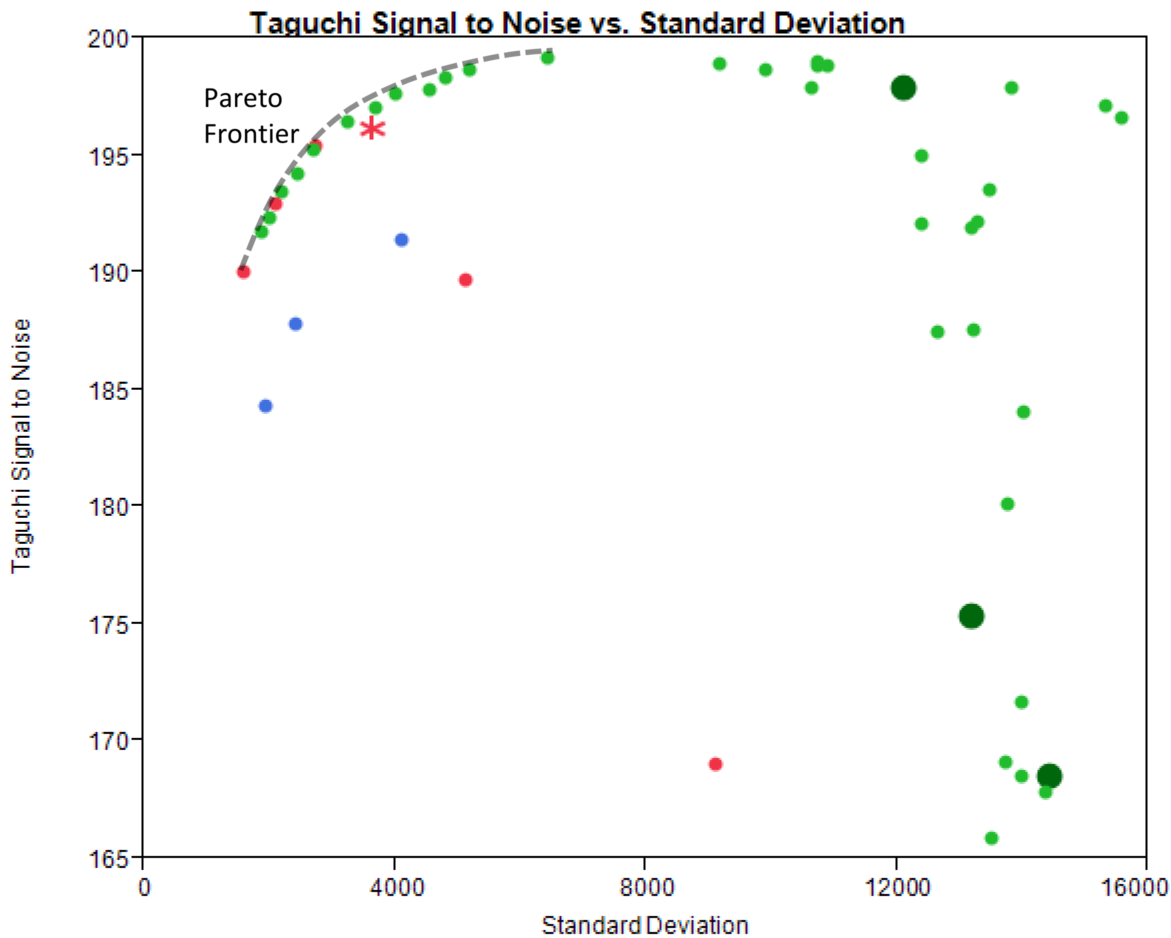


Figure 112: Standard Deviation vs. Taguchi Signal to Noise for Portfolio Based Design

Analysis of Scenario Performance

The previous sections demonstrated that at an aggregated level the portfolio-based design process improved outcome. However, Chapter III demonstrated that a deeper understanding of the interaction between the concept's behavior and the scenario can be obtained by examining the performance at a number of specific scenarios.

Table 16 shows the optimized design inputs for the three concepts labeled A, B, and C in Figure 109. It is important to note that the portfolio-based optimization has selected portfolios with changes made largely to the price of the vehicle rather than the concept specification. This minimizes the cost of the portfolio while diversifying the portfolio along the price dimension, which has the strongest influence on the profit.

Table 16: Optimum Portfolio Design Inputs

Name		T4	T5	T9	T11	AR	Sweep	ToC Root	Price
Robust		1	0	1	1	8	29.83	0.13	166.7
Portfolio A	*Con 1*	1	0	1	1	8.002	28.99	0.13	166.4
	Con 2	0	0	1	1	8.002	28.99	0.13	184.8
Portfolio B	*Con 1*	1	0	1	1	8	30.72	0.129	168.2
	Con 2	1	0	1	1	8	30.72	0.129	188.8
Portfolio C	*Con 1*	1	0	1	1	8	29.70	0.126	172.9
	Con 2	1	0	1	1	8	29.70	0.126	190.7

Figure 113 shows a 5000 case Monte Carlo simulation of the performance of the portfolios listed in Table 16. The horizontal axis in Figure 113 is the fuel price and the vertical axis is the Present Value of the portfolio. The red points show the performance of the Taguchi robust design, while the green/yellow points show the performance of three portfolios for the 5000 randomly selected scenarios. The shape of each curve is the result of the portfolio's interaction with fuel price, while the fuzziness of the curve is a result of the level of success in technology development for that particular scenario. Figure 114 through Figure 116 shows the same plot with one concept portfolio highlighted and the other two portfolios greyed out for clarity.

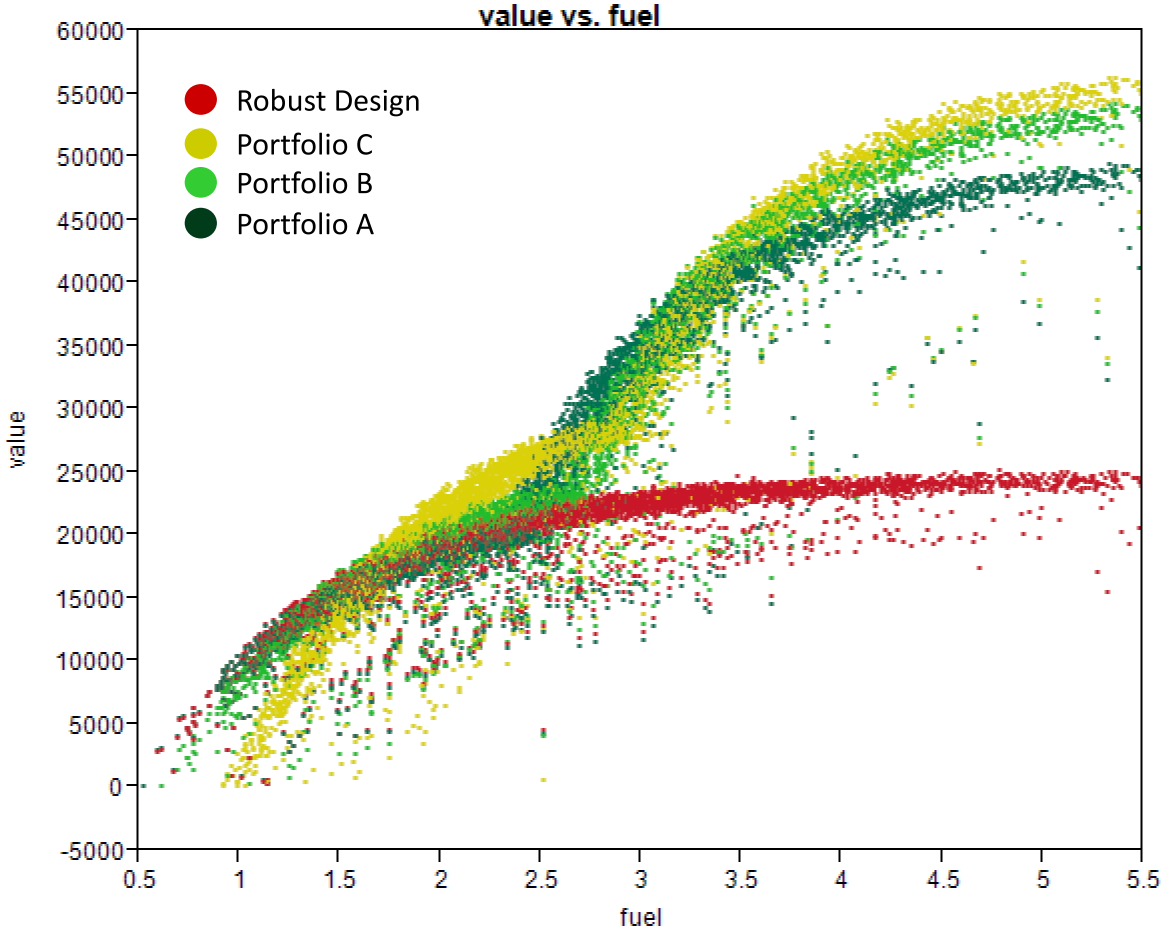


Figure 113: Monte Carlo Simulation Results for Selected Portfolios

Figure 114 shows a comparison between the Taguchi robust design and concept portfolio A. Recalling from Figure 109 that Portfolio A was the concept portfolio with the emphasis placed on the tail conditional expectation and a limited emphasis on increasing the expected value. From this figure, the reader can observe that the increase in expected value with virtually zero increase in the risk is accomplished by essentially having a second marketing plan with an increased price for the same concept, should the fuel price increase and the market accepts this higher price. This can be observed from the discrete bend in the curve around a fuel price of 2.5 $/gal.

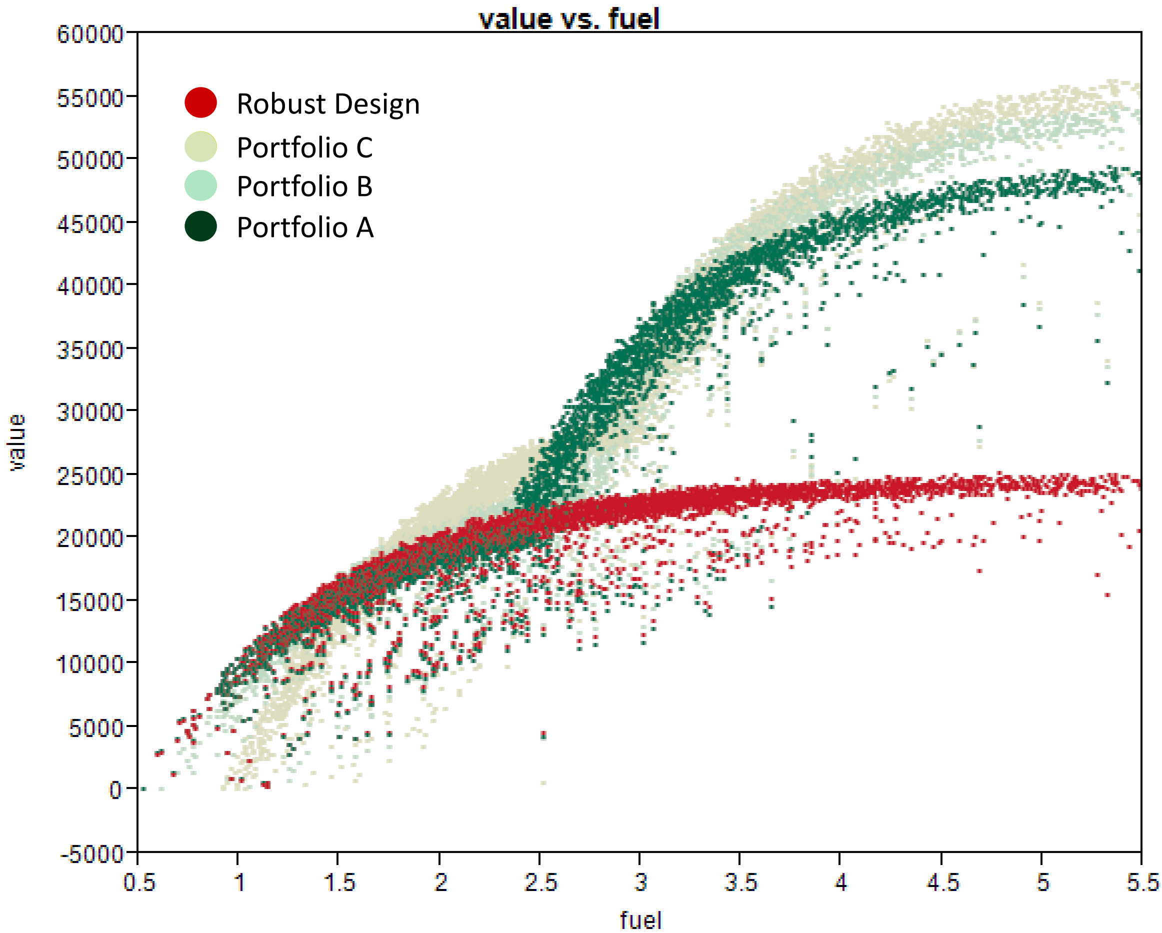


Figure 114: A Comparison of Portfolio A and Robust Design

Figure 115 shows a comparison of the Taguchi robust design and the portfolio labeled B in Figure 109. This portfolio was representative of portfolios optimized with a relatively even preference for a high tail conditional expectation and an increased expected value. This portfolio demonstrates similar behavior to the one in Figure 114, with the exception that concept selected is optimized to a slightly less stringent scenario.

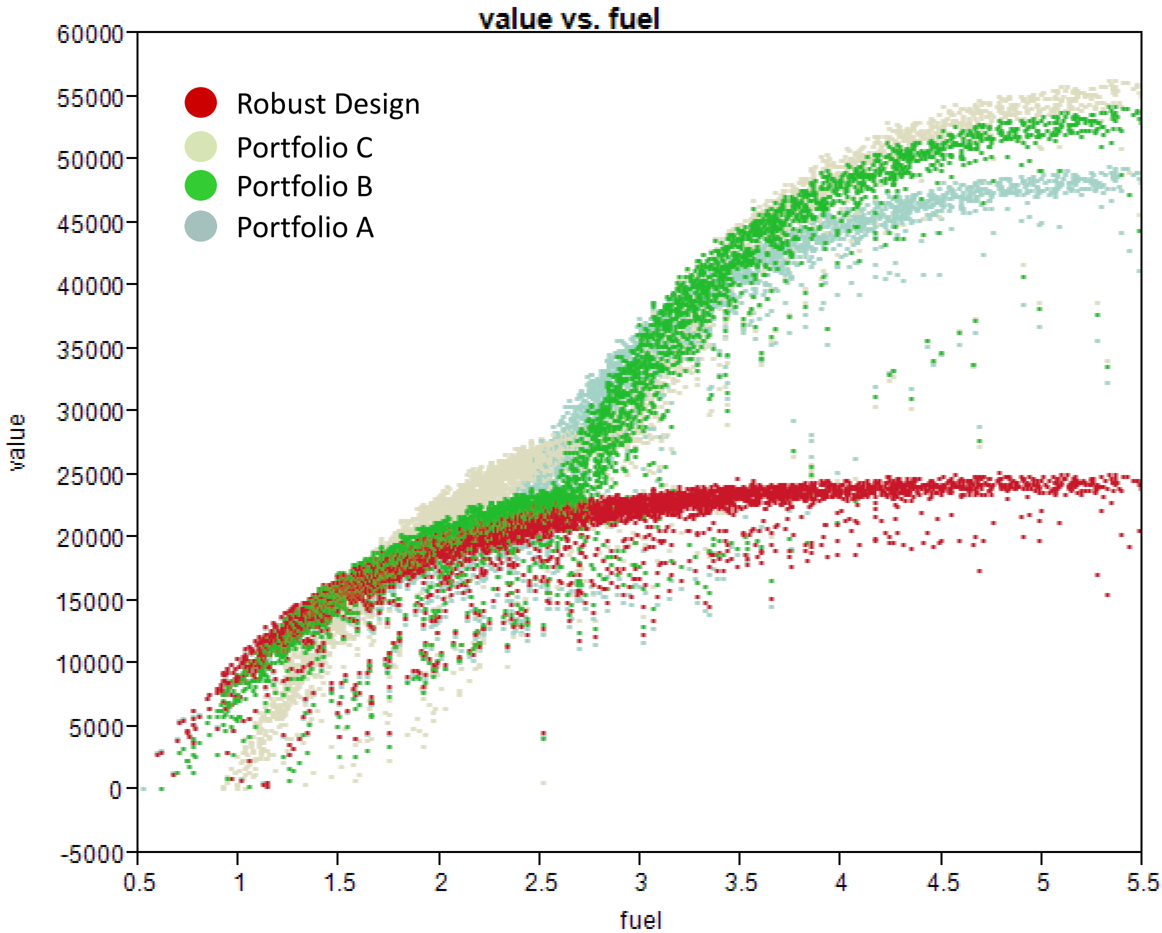


Figure 115: A Comparison of Portfolio B and Robust Design

Figure 116 shows the third concept portfolio, labeled C in Figure 109. This concept portfolio has an emphasis on an increase in the expected value. From Figure 116 and Table 16 it can be observed that this increase has been accomplished by selecting two prices that are ideal for slightly higher fuel prices.

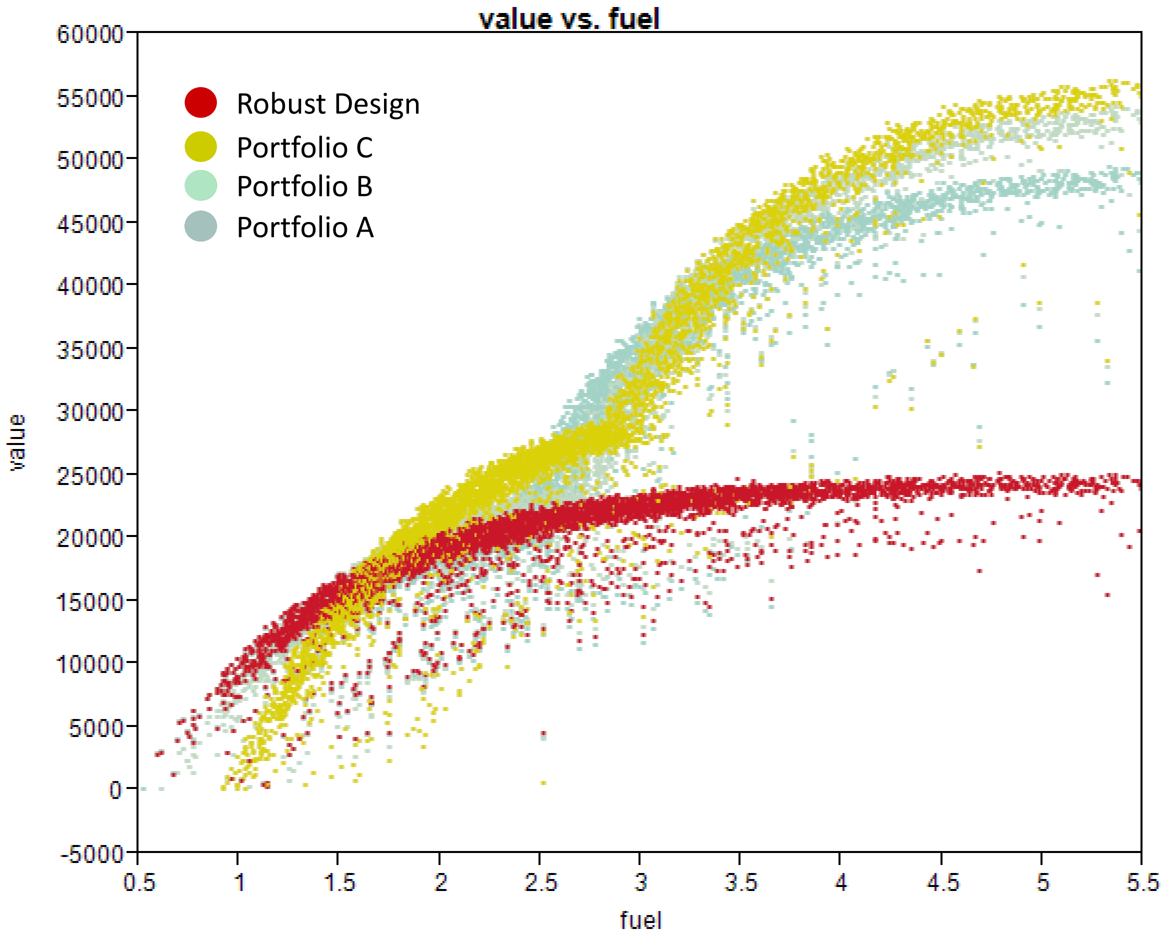


Figure 116: A Comparison of Portfolio C and Robust Design

The Effects of Hypothesis 1 on Diversification

Recall that Hypothesis 1 contained a set of conditions that can be used to determine where diversification through the use of a portfolio can be beneficial. Section 5.3 showed that the modeling environment met the conditions of Hypothesis 1. The interaction with the uncertainty, fuel price, was present for four of the 15 design variables and displayed in Figure 102. This limits the dimensions along with diversification will occur to the four shown in Figure 102.

The three concept portfolios, displayed in Table 16, demonstrate an interesting trend in that each of them has chosen to diversify the portfolio of concepts through the use of changes in price. This is because a portfolio with multiple prices brings a great deal of diversification along the most influential dimension, the price. This diversification allows for a large increase in the profit with little or no increase in the risk to the design organization.

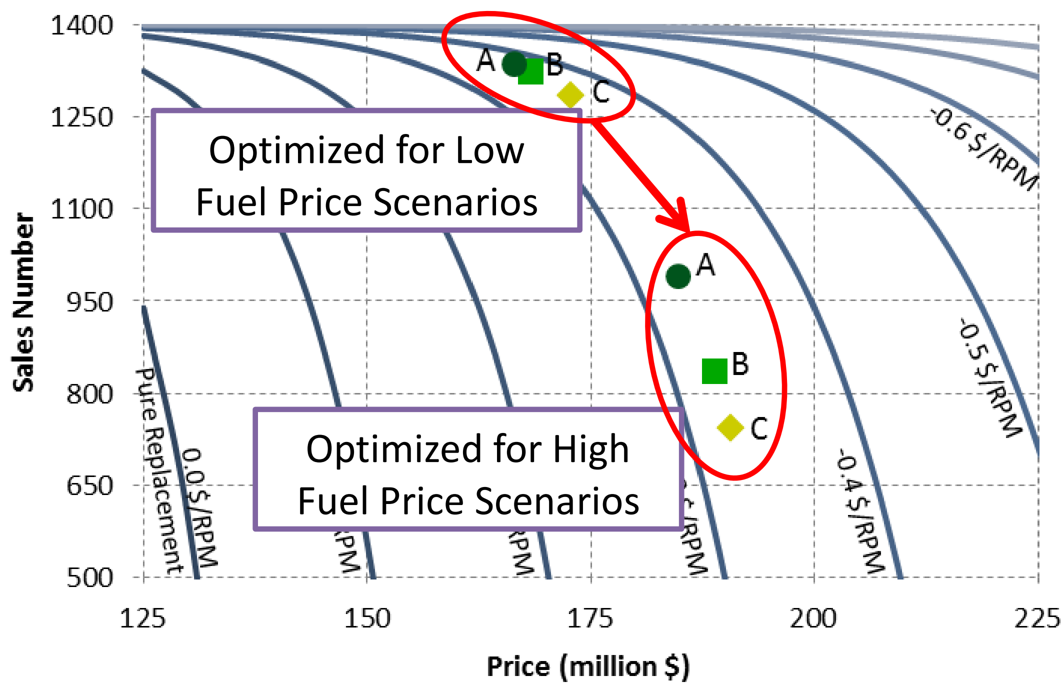


Figure 117: Diversification Mechanism

Figure 117 shows how diversification was achieved for the three portfolios shown in Table 16. These three portfolios show the influence of Hypothesis 1 directly. For each portfolio two concepts with differing marketing strategies have been selected. These concepts are distributed along the multi-dimensional demand curve, which accounts for the trade between the sales price, the sales number, and the economic performance of the vehicle. The existence of this Pareto frontier corresponds to the first condition in Hypothesis 1. The fact that the concepts are distributed along this Pareto frontier corresponds to the second condition in Hypothesis 1, and the fact that the movement is significant corresponds to the third condition in Hypothesis 1.

It is also important to realize that the distance along the Pareto frontier of the diversification is relatively constant. Figure 118 shows the distribution of the percentage change in fuel price for the concepts along the Pareto frontier in Figure 109. Table 17 shows the mean and standard deviation of these differences in price. The optimizer has determined that the optimum portfolio where the portfolio has been limited to two concepts is to select a portfolio with a single design marketed at two prices with a roughly 10% difference between them. Based on the designer's risk preference, these prices will shift to lower prices corresponding to less risk or higher prices if more return is desired. Furthermore, the optimum design will evolve slightly in wing sweep based on risk preference but will maintain a low aspect ratio and thick wing root.

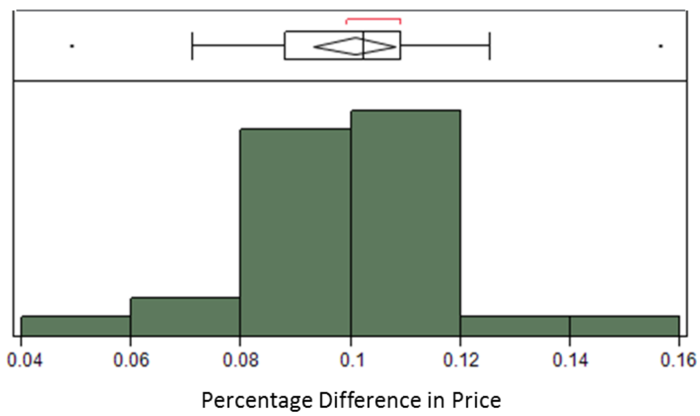


Figure 118: Distribution of Percentage Difference in Price

Table 17: Statistics for Price Differences

Mean	***Standard Deviation***
0.1006	0.0189

Figure 119 shows the mechanism for diversification. The figure shows the trade-off between sales price and number sold as represented by the demand curve. The two prices for each of the three highlighted portfolios in Figure 109 have been overlaid on this demand curve. This plot provides an intuitive understanding of the mechanism through which the optimizer has achieved a well-diversified portfolio.

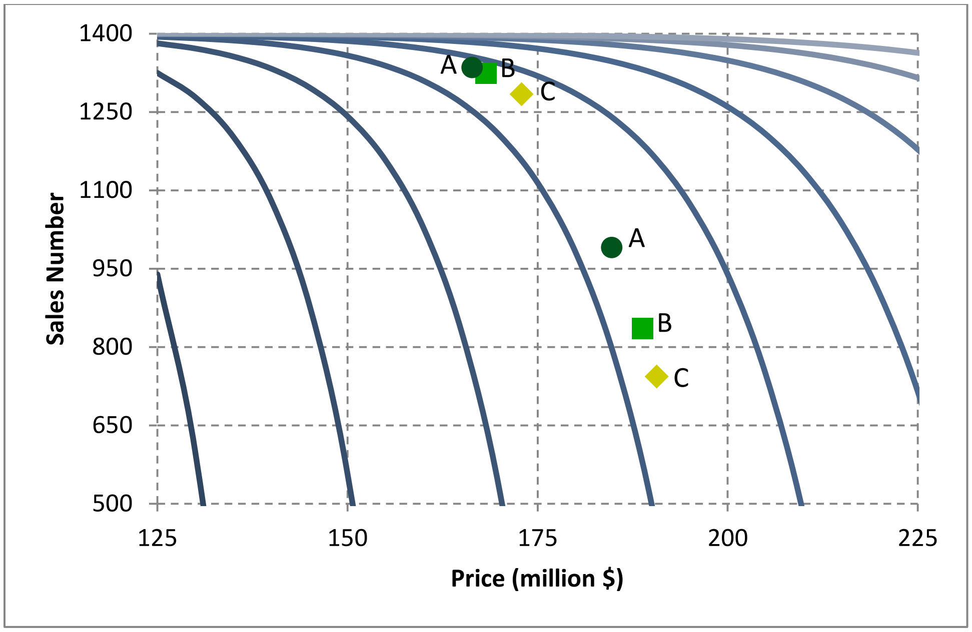


Figure 119: Diversification along the Demand Curve

5.3 Testing Hypothesis 2

Figure 120 shows the CDF for the 5000 case Monte Carlo sample shown in Figure 113. The CDF shows the Taguchi Robust design as well as the three concepts labeled A, B, and C. From this CDF a few features should be noted. The first is that the portfolios essentially have two separate curves. The first consists of a fairly conservative design sold at a conservative price, and the second sells the same design at a higher price and as a result shifts the CDF outward and the gain experienced by the portfolio-based approach comes from this second curve. The second important trend is that the portfolios perform slightly less well that the robust design in the worst case scenarios, but only marginally. However, the upside potential of the portfolio-based approach easily makes up for the slight reduction in performance.

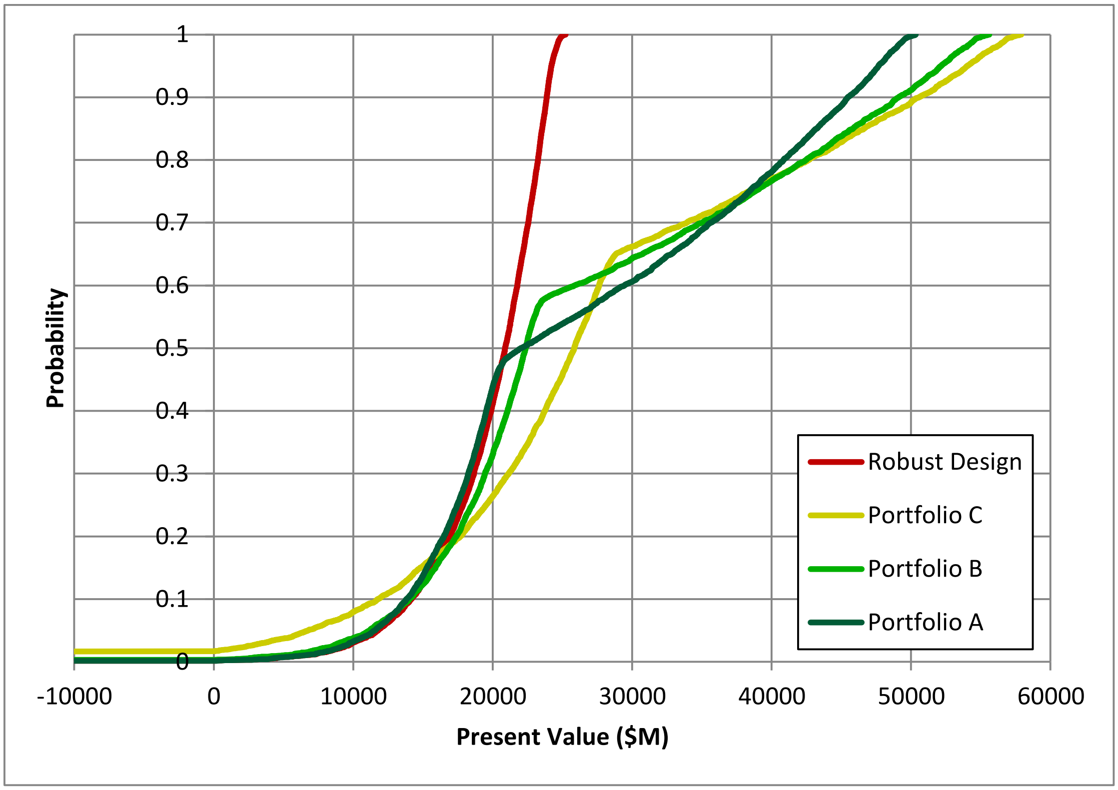


Figure 120: CDFs for Selected Portfolios and Robust Design

Recalling that Hypothesis 2 consisted of two separate conditions, it is necessary to verify that each of these conditions has been meet for the portfolio-based approach. Table 1 shows the mean of the probability of meeting an arbitrary constraint better than the robust design. From this table, it can be observed that each of the portfolios easily exceeds the expected value of the robust design. It can also be seen that each of the portfolios has a greater than 50% chance of outperforming the robust design at meeting an arbitrary constraint. It is also important to note, that while Portfolio A only slightly performs better than the robust design at meeting an arbitrary reliability constraint, the performance is only marginally worse than the robust design. This means that for most decision makers, the upside potential will easily outweigh the marginal reduction in performance for the 42.12% of the time that the robust design has a slightly improved performance.

Table 18: Hypothesis 2 Statistics for Portfolio Based Design

Name	**Mean ($M)**	**Probability of Meeting Arbitrary Constraint Better than Robust Design**
Robust	19792.7	N/A
Portfolio A	27015.9	53.28%
Portfolio B	27667.1	87.90%
Portfolio C	28106.0	82.50%

5.4 300 Passenger Aircraft Portfolio Based Optimization Conclusions

This example demonstrates two interesting points from the perspective of the portfolio-based optimization. The first is that the portfolio-based design decision making increased the profit the design organization could expect without impacting the level of risk the design organization faced, if risk is measured as only the worst case scenarios. However, if risk is defined more broadly as missed opportunity, then the portfolio-based approach offers a method for reducing risk and increasing the expended profit simultaneously. Adding a second marketing strategy had the effect of increasing the expected profit by more than 21.3% for a portfolio of two concepts that maintained similar levels of risk to the robust design.

The second interesting element of the application to a realistic design problem comes from the nature of the way in which the increase in value was obtained. The majority of the design literature discussing the use of portfolios focuses on the value of flexibility. For the realistic design problem, all of the added value came from the ability of the designer to accurately measure diversity and create a well-diversified portfolio. The literature's focus on the flexibility that a portfolio provides to the decision maker in iteratively removing concepts from the portfolio is only applicable after a well-diversified portfolio has been created. For the design problem, the added costs of continuing the development of the portfolio were easily made up for by the value of the continued development throughout the design cycle, and as a result the portfolio was not pruned until the start of production. This came from the fact that the diversification came through a relatively inexpensive mechanism, changes in the sales price. However, for a portfolio where the diversification across the Pareto frontier occurred as a result of changes in the physical parameters of the concept, the effects of the decision maker iteratively pruning the portfolio would be more pronounced. However, these effects will still be predicated by selecting a well-diversified portfolio.

5.5 A Portfolio of Physical Changes

The above analysis described the creation of a concept portfolio that consisted of what would typically be considered a single concept with multiple marketing strategies. However, because sales price was treated as an independent input variable, the portfolio-based optimization diversified the portfolios along the Pareto frontier between sales price and number sold as shown in Figure 119. This section details the effects of removing the sales price from the modeling environment.

The sales price can be eliminated from the modeling environment by making the assumption that the aircraft will be sold at the optimal value at the point of sale. This makes the assumption that the salesperson has the freedom and skill to obtain the most money the airline is willing to pay for a vehicle at the point of sales. For aircraft design, this assumption is not necessarily realistic as the vehicles are sold years in advance of their production, but making this assumption allows for the removal of the sales price from the engineering optimization. This has been accomplished within the modeling environment by adding a gradient-based optimizer that optimizes the sales price for the scenario. Figure 121 shows a reproduction of the optimization setup described in Section 5.3, with the gradient-based optimization occurring before the evolutionary optimization.

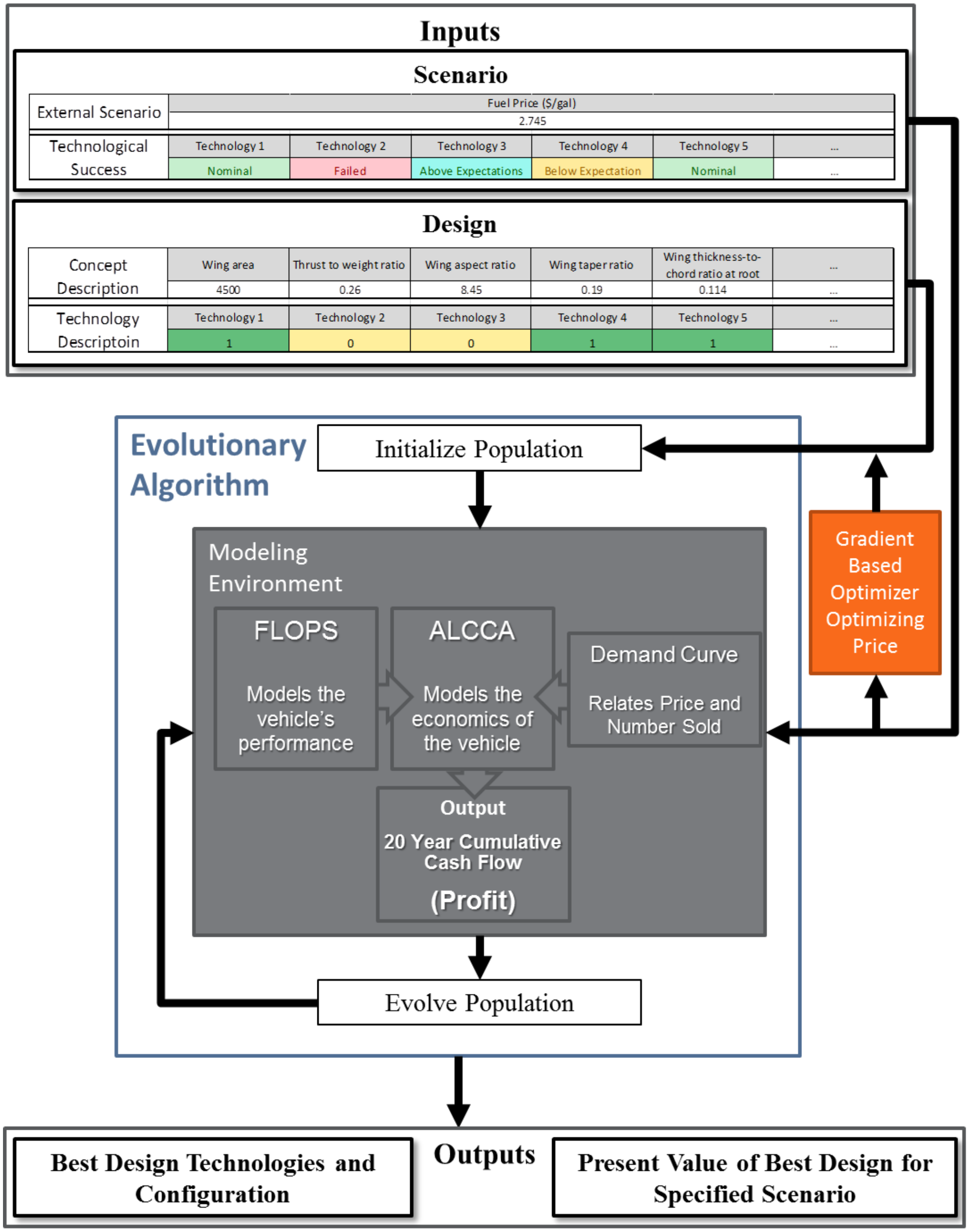


Figure 121: Optimization without Sales

Returning to the process described in Section 4.11, the first element in performing a portfolio-based approach is to determine if the approach is needed at all. This requires a determination if there is an interaction between the design inputs and the scenario.

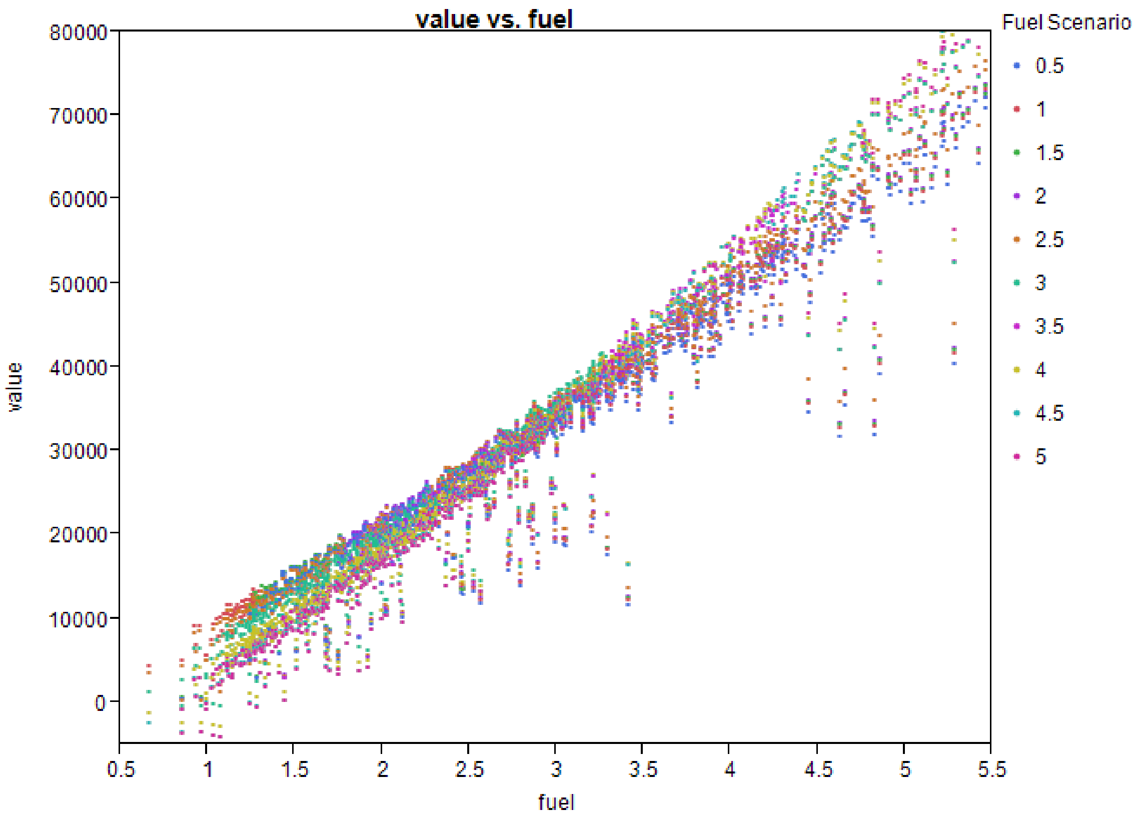


Figure 122: Performance of Robust Designs without Sales

Figure 122 shows a plot of the present value plotted against the fuel price. The points in the plot correspond to the present value of a single case from a 1000-case Monte Carlo simulation for each of the nine robust design concepts leading to 9000 points. The points have been colored by concept. For each of these 1000 randomly selected scenarios and the nine robust concepts the sales price has been removed through the gradient based optimization. However, this removal of the sales price has largely removed the twist that indicates an interaction between the scenario and design. Although a small amount of twist remains, it is significantly less important than the noise in the technology space. As a result, the modeling environment without the sales variable does not exhibit an interaction with enough sensitivity to the scenario to justify a portfolio-based approach. Since this was the condition necessary for the use of a portfolio-based optimization, a portfolio-based approach will fail to yield a result different from the robust design in this situation. This counterintuitive result indicates that there is not a strong set of Pareto optimality trades within the technical portion of the aircraft design problem. The following paragraph details a limitation in the modeling environment that leads to this counterintuitive result.

A top level overview of the modeling environment is shown in Figure 123. This depiction shows the optimization objective, profit, broken into two halves, the sales price and manufactur's cost. These two elements are combined together to create a model of the manufacture's profit.

Examining the marketing half of the profit equation on the right side of Figure 123, one can observer that a trade-off exists between the price and the number sold. This trade-off is so prevalent that it has been given a name by economists and is represented in the demand curve. The portfolio optimization shown in Section 5.6 created diversity by selecting multiple concepts along this statement of Pareto optimality.

To examine the engineering half of the profit optimization from a portfolio-based approach the sales price is removed as described above. This leaves only the left half of the profit equation as captured by two separate elements: the price to bring a concept to market and the performance, as measured by required average yield per passenger mile. Typically a trade exists between the performance and the sales price of an aircraft, and the design lies somewhere along the Pareto frontier for these two variables.

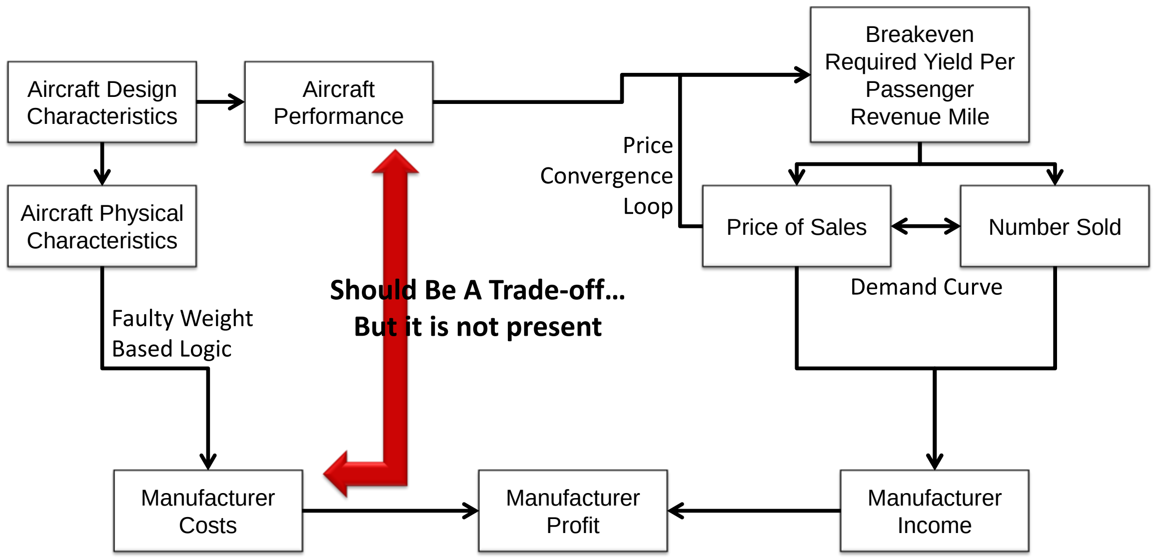


Figure 123: Simplified View of Modeling Environment

A careful examination of the methodology used in ALCCA for modeling the costs reveals that the model is not well suited to make these trade-offs. ALCCA uses a set of weight-based regressions to determine the aircraft costs. Figure 124 shows an example of the weight-based regressions used in determining the wing labor and material costs based on the wing weight. The component weights sum to create the entire airframe weight. Figure 125 shows the relationship between the engineering hours, a key component of R&D costs, and the airframe weight. Both of these figures show a decrease in cost for a decrease in weight. For a given class of vehicle, a lower weight typically corresponds to a better performing vehicle. This in turn corresponds to lower costs. This means there is no trade-off between better performance and lower cost. Typically it is this trade-off between better performance and lower cost that provides interaction of the engineered characteristics with the scenario. The trade-off is not present, and as a result a measurable interaction is not present. The modeling environment available thus does not capture the engineering trade-offs in a way that allows for a portfolio-based approach to diversify along the Pareto frontier that represents that trade-off.

While author believes the application of the PRISM-D method to an activity based aircraft costing model may yield additional interesting results for aircraft design, the modeling environment as it stands has provided a useful test of the PRISM-D method. Furthermore, the demonstration of a test case where the portfolio-based approach is appropriate in Section 5.6.2, as well as, the demonstration of a test case where a portfolio-based approach is not appropriate provides a useful demonstration of how Hypothesis 1 provides a test of the applicability of a portfolio-based approach.

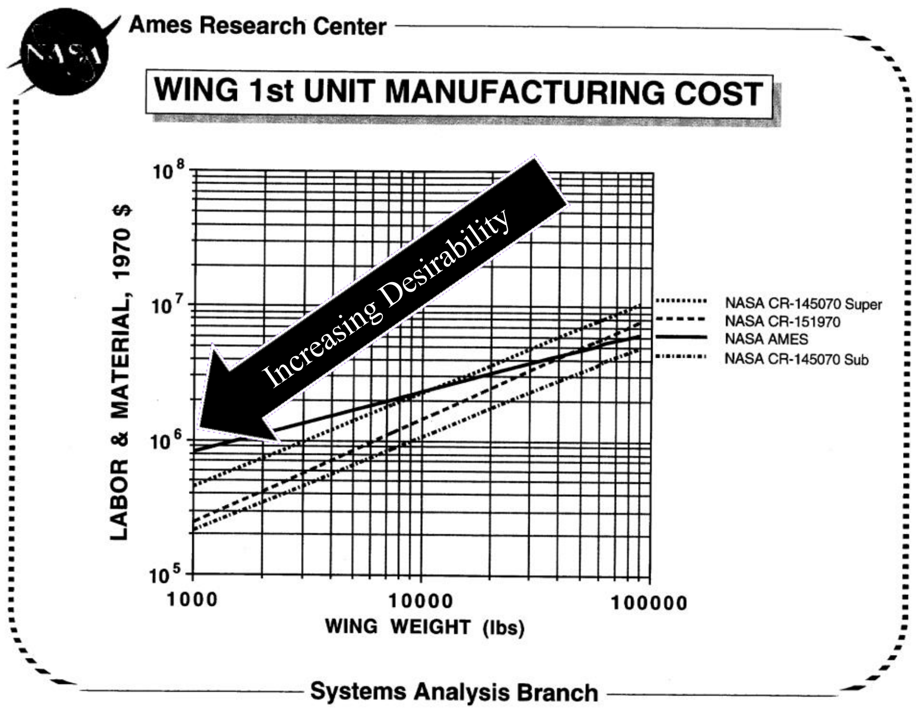


Figure 124: Wing Costs

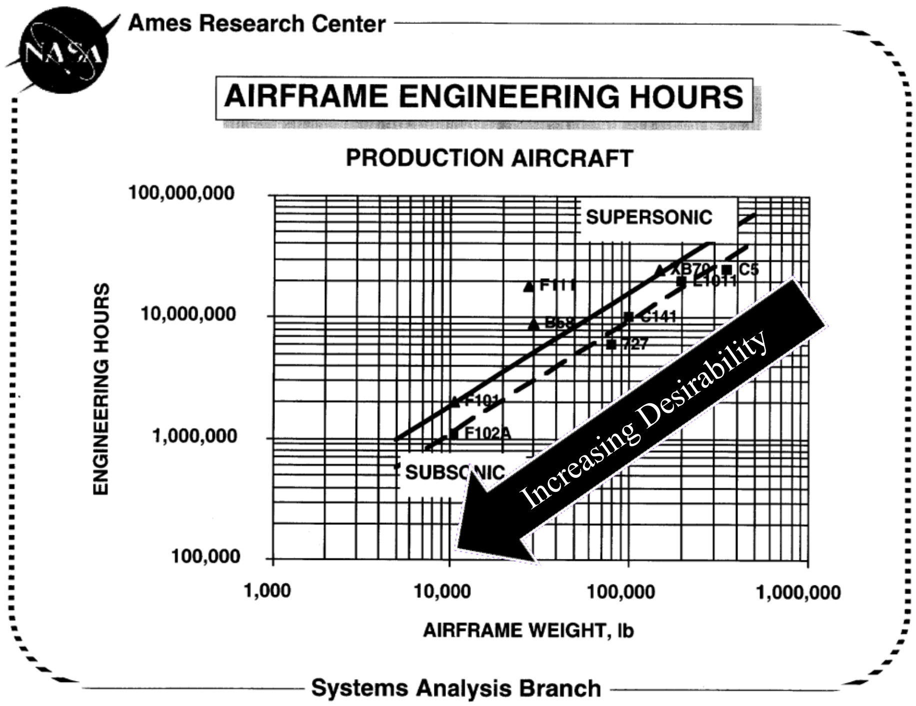


Figure 125: Engineering Hours

5.6 Sensitivity of Design Outcomes to Changes in Portfolio

Section 5.6 demonstrated that a well-diversified portfolio of concepts could improve design outcomes by creating a set of concepts spread along the dimension of design trade-off (Pareto frontier) which interacted with the scenario. The purpose of this section is to examine the sensitivity of the portfolio to changes in concept. The reason for examining this sensitivity is that there is potential that once the generalized strategy of creating a portfolio is known, if the sensitivity to changes in the portfolio is low, it may not be necessary to do a detailed analysis. Instead, the generalized strategy can be applied without the complex modeling environment.

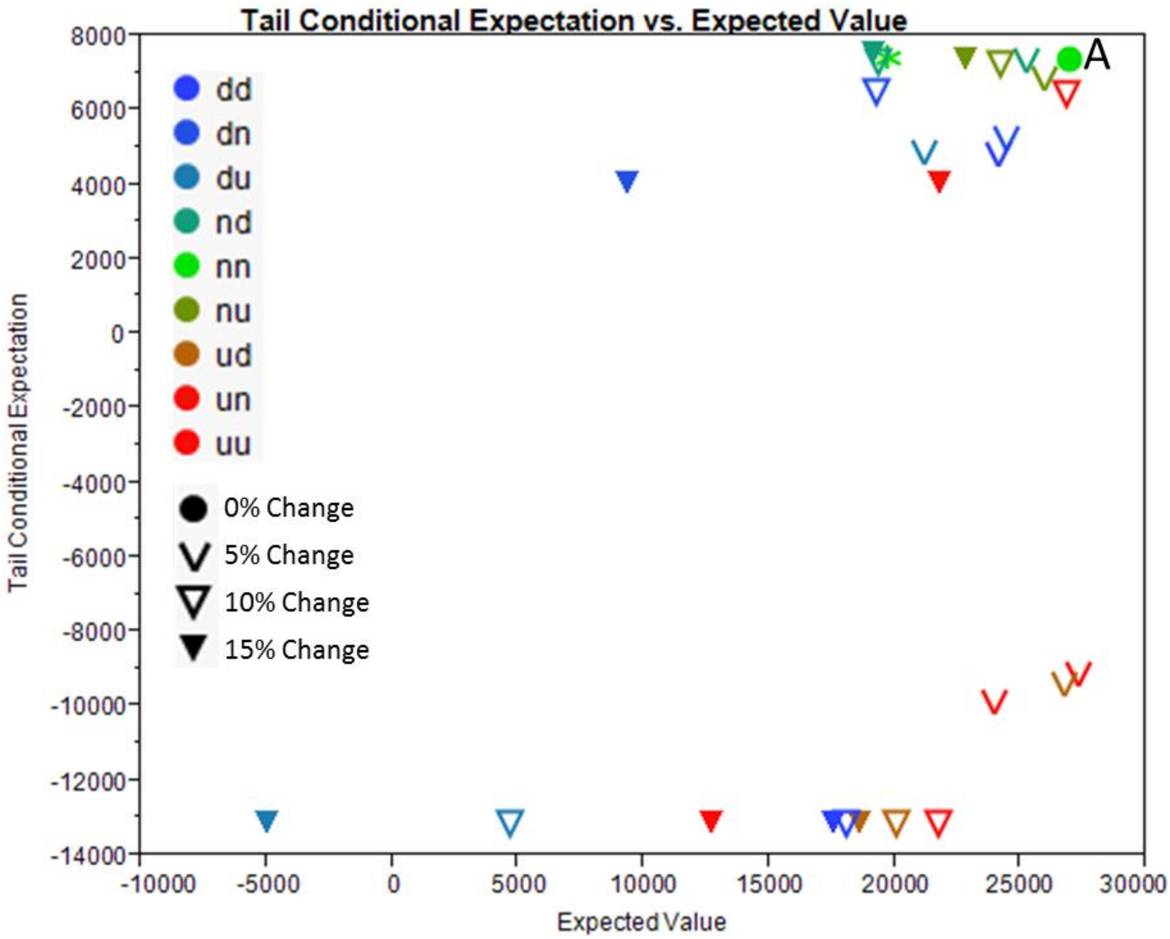


Figure 126: Portfolio Sensitivity

Figure 126 shows a set of changes from the portfolio labeled A in Figure 109 and shown in Table 16. The green circle labeled A in Figure 126 represents the baseline portfolio. From this baseline portfolio deviations have been made in the sales price of each of the two concepts that constitute the portfolio. For these modified portfolios, a Monte Carlo simulation has been conducted and the aggregate statistics, as well as, expected value vs. tail conditional expectation, are show for these new modified portfolios.

Because the portfolio has been diversified along the design dimension sales price, deviations in sales price give an indication of the sensitivity of the portfolio to changes in the diversification. Eight possible changes can be made to the two sales prices in the portfolio. Color has been used to indicate the change made, with “dd” representing a downward change in both prices, “dn” representing a downward change in the first price with no change in the first price, “du” representing a downward change in the first price with an upward change in the second price, etc. Four symbols have been used to indicate the magnitude of the change. For example, the orange “v” is representative of a modified portfolio with the first concept’s sales price raised by 5% and the second concept’s sales price lowered by 5%. For that particular case, the expected value has been moderately reduced, but the tail conditional expectation has been dramatically reduced indicating a reasonable percentage of scenarios with complete market failure.

Examining Figure 126 holistically, the reader can see that the benefits of diversification degrade rapidly with changes in portfolio. A number of cases with only 5% or 10% changes see significant increases in the level of risk. As a result, it seems unlikely that the strategy of diversification along the design dimensions with a trade-off and interaction with uncertainty can be done qualitatively, and the modeling based approach will need to be retained.

5.7 Summary of Hypothesis Tests

This section provides a brief summary of the hypotheses and the results of their respective tests. This thesis contained four hypotheses; a methodological hypothesis supported by three numbered hypothesis.

The methodological hypothesis stated that the PRISM-D process would find, if present, and exploit interaction between the design variables and the uncertain scenario to improve the design outcomes as compared to robust design. The PRISM-D process was successfully applied to the notional design of a 300 passenger commercial airliner, and through the use of the hypotheses described in the next few paragraphs, it was shown that the PRISM-D process improves design outcomes as compared to robust design.

Hypothesis 1 described three conditions that would lead to a situation where the uncertain scenario would drive the most desirable design. This in turn leads to a situation where a portfolio-based approach should be evaluated for merit. These three conditions were confirmed through a series of mathematical examples and an informal proof with the characterizing problem offered as an example to help relate the more abstract concepts to a more realistic example.

Hypothesis 2 stated that a portfolio-based approach could provide better design results compared to robust design as measured by the expectation and a reliability-based measure (best likelihood of meeting an arbitrary constraint). This was confirmed through the use of the characterizing problem and a notional 300 passenger civil aircraft design problem. The characterizing problem demonstrated that this hypothesis could be proven true even under stringent conditions. However, under these conditions, the use of a portfolio implied the willingness to accept increased risk as measured by the expected value of the 5% of worst case scenarios. The 300 passenger civil aircraft design demonstrated the use of the portfolio-based design process in more realistic conditions. In this example, the portfolio-based design also allowed better design outcomes as compared to robust design, but these improved outcomes did not require an appreciable increase in the risk required. The conclusion of these two tests was that Hypothesis 2 had been confirmed.

Hypothesis 3 differed in structure from the first two hypotheses in that it simply stated that the use of a set of techniques and a particular optimization algorithm would allow for the optimization of a portfolio in conceptual design. The results presented in Chapter V provide proof that this hypothesis has been confirmed.

CHAPTER VI

CONCLUSIONS

This thesis began by offering an overview of the current state of the art within engineering design known as robust design. In Chapter III, a problem containing a number of the characteristics of engineering design was used to demonstrate that the state-of-the-art, robust design, can be insufficient in producing quality design decisions as measured by design outcomes in the presentence of scenario-based uncertainty. Poor design decision performance was shown to be related to the non-independence of the concepts. A series of mathematical examples were used to demonstrate that the non-independence was a result of the interaction between preference, scenario and the design itself. Hypothesis 1 stated that a conceptual design space could exhibit "tipping point" behavior that was likely to reduce the quality of design outcomes expected from robust design if the following three conditions were met: a Pareto frontier existed, preference for the design's location along that Pareto frontier was driven by scenario, and these two effects were sensitive to changes in scenario. This hypothesis was then confirmed using a set of simplified mathematical examples, an informal poof and a final set of analyses on the characterizing problem.

While the information in Chapter III provided enough evidence to accurately describe a problem with robust design, the ultimate goal of the thesis was to improve design outcomes. To improve design outcomes, improvements to the Robust design step within the IPPD process were needed.

This thesis then presented a process for improving design outcomes in Chapter IV. This improvement was assumed to take place within the traditional design IPPD process. A philosophical argument put forth by Herodotus stating, that any decision in the presence of uncertainty is wise if the choice made maximized the likelihood of a good outcome was used as a defense of robust design. The logic of this argument in defending the robust design methodology could not be directly overcome, and as a result improvements in design decision-making were achieved not by improving robust design directly, but rather by changing the alternative choices. A portfolio-based approach was presented as a new set of choices ideally suited to improving design outcomes. Modern portfolio theory demonstrated the ability of a well-diversified portfolio to reduce risk through offsetting behavior of the elements within the portfolio. A decision was made to translate this portfolio-based approach to the design problem.

An examination of portfolio-based approaches in literature lead to the selection of the classical methodology for solving iterative strategic decision problems, dynamic programming, as the mathematical method for implementing a portfolio-based design process. However, the design problem suffers from the curse of dimensionality, and as a result dynamic programming could not be implemented directly. To solve this problem, a hybrid method using the analytical optimization proposed by dynamic programming was combined with a global numerical optimizer. This hybrid approach was then implemented using a purpose built global numerical optimization strategy based on a co-evolutionary algorithm.

This co-evolutionary algorithm was then used in Chapter V to test the hypothesis that a portfolio-based approach could improve design outcomes as compared to robust design. This hypothesis test was performed on both the characterizing problem and a notional 300 passenger aircraft design problem. The characterizing problem demonstrated that the use of a portfolio as opposed to a single concept in design could improve design outcomes as measured by the conditions described in Hypothesis 2. However, in this particular problem the use of a portfolio also implied the willingness to accept a higher level of risk as measured by the tail conditional expectation. The application of a portfolio-based design process to a notional 300 passenger civil aircraft design also demonstrated the value of a portfolio-based approach. However, in this more realistic design problem, design outcomes could be improved without an increase in risk.

These two examples led to the conclusion that in cases where there is a strong interaction between the optimum design and the scenario, a well-diversified portfolio can improve design outcomes. The most significant finding of this thesis, is not a statement that a well-diversified portfolio can improved design outcomes (as this particular idea has been stated many times in literature), but rather it defines the ability to describe the conditions under which a portfolio-based approach has value and definitively defines what it means for a portfolio to be well-diversified in an actionable buzzword-free manner. As a result a well-diversified portfolio can be defined as follows.

Well-diversified portfolio: *A portfolio that has a number of concepts spread along those dimensions of design trade-off (Pareto frontiers) that exhibit a strong interaction with the uncertain scenario.*

6.1 Contributions

Within this work, this thesis offers a number of unique contributions detailed in the following list.

- This work demonstrated that the interaction between the scenario and the concept alternatives can reduce the quality of conceptual design decisions.
- Poor design decision performance was shown to be related to the non-independence of the concepts, which is present in the cases where a trade-off (Pareto frontier) interacts with the scenario.
- A portfolio-based approach was proposed and demonstrated to improve the design decision making performance.
    - Provided a comparison between the two baseline methodologies, scenario optimized & robust design.
    - Provided a comparison of these baselines to portfolio-based design.
- Algorithmic Contributions

    - Demonstrated a EA capable of simultaneously optimizing technology selection and concept specification
    - Demonstrated a co-EA capable of simultaneously optimizing the concept and the portfolio in response to scenario.
- Provided a strategy for improving design outcomes.
    - Demonstrated that the value from a portfolio-based approach largely comes from the diversification of the portfolio, not the decision maker flexibility lauded in literature.
    - Defined diversification in an actionable manner: *A well-diversified portfolio has a number of concepts spread along those dimensions of design trade-off (Pareto frontiers) that exhibit a strong interaction with the uncertain scenario.*
    - The inverse of the definition of diversification can also provide a useful tool. By defining the dimensions which must change to diversify against changes in scenario, those dimensions which remain unchanged have also been determined. As a result, these dimensions may be used to create a base platform on which a family of vehicles with changes only in the identified dimensions occurs. This commonality has the potential to reduce cost.

6.2 Future Work

This thesis also leaves open a number of interesting modifications and applications of the work presented. These have been divided into three broad categories.

The simplest addition to the work presented would be to re-conduct the analysis presented with an activity or process-based cost modeling environment. The modeling environment, ALCCA, used in this thesis allowed a set of interesting trades to be made when the sales price was included in the model, but it did not allow for the examination of the engineering benefits of this approach due to the weight-based cost estimation method this tool uses. As a result, ALCCA could not capture the trade between technology, concept performance, and additional costs. The use of an activity or process based cost model would allow for a direct examination of the engineering portion of the design problem from a portfolio viewpoint. Furthermore, it would allow the experimenter to answer the question, “Given fixed funding, do I spend money on multiple concepts or more technology?” It is the answer to this question, and the opportunity costs that a portfolio-based approach implies, that will allow for the wide spread acceptance of a portfolio-based design process.

The second element of future work would revisit the implementation methodology used in evaluating a portfolio. The classical approach, dynamic programming, was selected to initially test portfolio-based design. This selection was made in large part due to the fact that it allowed a testing of the portfolio-based approach with a well-known set of mathematical techniques. However, the use of dynamic programming required the discretization of the scenario space. For computational purposes, this discretization was required to be fairly coarse. While this has little impact on the evaluation of the portfolio-based approach or the ability to select one concept alternative over another, it makes it difficult for the decision maker to precisely know what combination of uncertain events should trigger a change in strategy. As a result, the author of this thesis would recommend replacing the decision tree in the algorithms presented with a Bayesian approach. A Bayesian approach would allow for a more precise estimation of the scenarios that require a change in strategy and could potentially help accelerate the analysis as the focus would be on the elements important to the design organization.

The final and most important modification to this work would be to introduce scheduling into the portfolio optimization. The current optimization and set of tests assumed that all technologies and concepts are developed in parallel and they are assumed to progress at the same rate. It would be much more interesting to examine the question "Which concepts should be invested in now, and which should be scheduled for the future?" This would allow the option of creating portfolios with a primary design; and a secondary contingency design that is developed in slack time and answers a question about how much design capacity should be carried by the design organization.

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