RISK-INFORMED SCENARIO-BASED TECHNOLOGY AND MANUFACTURING EVALUATION OF AIRCRAFT SYSTEMS

A Thesis
Presented to
The Academic Faculty

by

Robert Vincent Combier

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

Georgia Institute of Technology
August 2013

RISK-INFORMED SCENARIO-BASED TECHNOLOGY AND MANUFACTURING EVALUATION OF AIRCRAFT SYSTEMS

Approved by:

Professor Dimitri Mavris, Advisor
School of Aerospace Engineering
Georgia Institute of Technology

Professor Daniel Schrage
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Zhimin Liu
School of Aerospace Engineering
Georgia Institute of Technology

Mr. Charles Saff
Boeing Research and Technology
The Boeing Company

Professor Vitali Volovoi
School of Aerospace Engineering
Georgia Institute of Technology

Date Approved: 17 May 2013

To my mother,

the first Dr. Combier

ACKNOWLEDGEMENTS

I can only begin to express my gratitude to the individuals who have made this dissertation and academic journey possible, let alone give them sufficient credit. This has been an incredible experience.

I must first acknowledge my parents and brothers who have tirelessly persevered above and beyond the call of duty to make me achieve (and become) more than I ever thought possible. I thank my father Philippe, a fellow 'Tech alumnus, and my grandfather Charles for cultivating my insatiable curiosity for engineering and technology. To my mother, Professor Combier, I owe thanks to the unconditional encouragement and guidance by example. You are and were an inspiration in every single step along the way, and I am honored to dedicate this dissertation to you.

Secondly, my family at the Aerospace Systems Design Laboratory deserves recognition. My sincerest thanks go to Drs. Cyril de Tenorio, Olivia Pinon, Michael Ellis, William Engler, Stephanie Mma and the Manufacturing-Influenced Design team. Your innumerable hours of support and friendship extended beyond expectation, and it will always be remembered. I would also like to thank Joseph Murad for growing my fascination with risk and reward.

I must also give a heartfelt thank you to my wonderful friends and fellow students at Georgia Tech, especially those of the *Lair*, the *Technique*, and BuzzStudios. You brought balance, perspective and sanity countless times. On the note of friendship, I cannot thank my best friends enough: Dr. Ghislain Retaureau, Dr. Adam Maser, Karl Janus and Rachel Caldas. This experience has made us lifelong friends. Your daily humor, advice and encouragement were integral to the success of this thesis and have been unquestionably invaluable.

I also owe a sincere debt of gratitude to my thesis committee: Professor Daniel Schrage, Professor Vitali Volovoi, Dr. Zhimin Liu, and Mr. Charles Saff. Your contributions have been exemplary, and I thank you for your infinite patience and wisdom during the thesis process.

Most importantly, I must thank my thesis advisor, mentor and friend Professor Dimitri Mavris. *Doc, you have given me a gift that will never be forgotten*, and I will honor you and your teaching for the rest of my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

In the last half century, the aerospace industry has seen a dramatic paradigm shift from a focus on performance-at-any-cost to product economics and value. The steady increase in product requirements, complexity and global competition has driven aircraft manufacturers to seek broad portfolios of advanced technologies. The development costs and cycle times of these technologies vary widely, and the resulting design environment is one where decisions must be made under substantial uncertainty. Major sources of frustration, capital loss, and schedule slippage in aerospace development projects can be traced back to the understanding or handling of uncertainty and the consequences of the decisions made under that uncertainty.

Modeling and simulation have recently become the standard practice for addressing these issues; detailed simulations and explorations of candidate future states of these systems help reduce a complex design problem into a comprehensible, manageable form where decision factors are prioritized. There have been several important advancements in system design methods that have leveraged modeling and simulation to carry out structured analyses. Nevertheless, the field is still growing quickly–especially in the domain of probabilistic methods that treat uncertainty quantification and mitigation. These analyses attempt to reduce overall uncertainty in cost, performance and schedule by delivering holistic analyses with the ability to examine the key engineering and programmatic trades: *Should I risk making the product in-house or outsource the manufacturing? What is the best technology portfolio and how do I optimize and adapt it to my risk tolerance constraints?* While there are still fundamental criticisms about using modeling and simulation approaches (pertaining to fidelity, model form, applicability of assumptions and scalability, etc.), the emerging challenge becomes *How do you best configure uncertainty analyses and the information they produce to address real world problems?*

One such analysis methodology was developed in this thesis by structuring the input,

models, and output to answer questions about the risk and economic impact of technology decisions in future aircraft programs. Unlike other methods, this method placed emphasis on the uncertainty in the cumulative cashflow space as the integrator of economic viability. From this perspective, it then focused on exploration of the design and technology space to tailor the *business case* and its associated risk in the cash flow dimension. The methodology is called CASSANDRA and is intended to be executed by a program manager (or executive) of a manufacturer working of the development of future concepts. The program manager has the ability to control design elements as well as the new technology allocation on that aircraft. She is also responsible for the elicitation of the uncertainty in those dimensions within control as well as the external scenarios (that are out of program control).

The methodology was applied on a future single-aisle 150-passenger aircraft design so as to evaluate the cost and schedule implications of a composite materials technology. The problem was scoped away from searching for highly improbable or unforeseeable failure modes and focused on a broader impact of design, technology and scenario uncertainty.

The research contributions resulting from the proposed methodology may be considered at two levels. The overall methodology is compared to existing approaches and is shown to identify more economically robust design decisions under a set of at-risk program scenarios. Additionally, a set of metrics in the uncertain cumulative cashflow space were developed to assist the methodology user in the identification, evaluation, and selection of design and technology. These metrics are compared to alternate approaches and are shown to better identify risk efficient design and technology selections.

At the modeling level, an approach is given to estimate the production quantity based on an enhanced Overall Evaluation Criterion method that captures the competitive advantage of the aircraft design. This model was needed as the assumption of production quantity is highly influential to the business case risk.

Finally, the research explored the capacity to generate risk mitigation strategies into two analysis configurations: when available data and simulation capacity are abundant, and when they are sparse or incomplete. The first configuration leverages structured filtration of Monte Carlo simulation results. The allocation of design and technology risk is then identified on the Pareto Frontier. The second configuration identifies the direction of robust risk mitigation based on the available data and limited simulation ability. It leverages a linearized approximation of the cashflow metrics and identifies the direction of allocation using the Jacobian matrix and its inversion.

The result of the dissertation was a methodology that enabled early design and technology awareness of the multidisciplinary risk of the economic viability of an aircraft program in conceptual development.

CHAPTER I

MOTIVATION

Take calculated risks. That is quite different from being rash.

General George S. Patton

As modern aircraft systems continuously grow in complexity and development cost, the burden on product development managers to develop successful aircraft programs is increased. Consequently, there is a clear and present need for the continuous development of formalized methods to augment the decision information available during the design of aerospace vehicles [107]. Unfortunately, with the rise in system complexity comes a rise in net uncertainty of the system itself, particularly when the implementation of new technologies, materials and processes are critical to the expected product success. In new aircraft development programs, the decisions regarding the investment of billions of dollars in research, development, manufacturing and assembly infrastructure must be made very early on and in the presence of sparse data and abundant uncertainty. In the lack of competition, this may not pose a significant challenge, but modern commercial and military aircraft industries experience aggressive competition between a small number of key players. Failure in this context is unacceptable, and as the adage goes for aircraft developers, '*every new aircraft bets the company*' [35].

The ultimate decision to launch the project will depend on a judgment about the quality of the assumptions and the treatment of the uncertainty in the analysis presented. Shareholders in the project are likely to ask *How sure are you about the results presented?*

As the decision to include technologies is often made before they are fully mature, the resulting uncertainty and risk must therefore be managed. From the technical perspective, this typically translates into managing the cost and time line of the technology development, its application on the aircraft, and the manufacturing setup. From the programmatic perspective, the investment and profitability aspects must also exhibit favorable qualities of risk and reward. The fundamental need for its management stems from this simple perspective: *If I do nothing, there are consequences; but if I do something, the consequences may be improved*. The risk management problem can then be reduced to the four questions:

1. *What happens if I do nothing?* - answered through risk analysis and other technical studies

2. *What happens if I do something?* - answered through assessment of alternatives and their integration in the system

3. *What is the penalty/payoff for trying to reduce/confirm a given risk level?* - answered through exploration of the risk mitigation power and the costs of the identified mitigation strategies

4. *What should I do?* - answered through alignment of the decision to core program or enterprise strategy and selection

Forecasting the effects of uncertainty on complex systems follows a similar logical sequence: uncertainty *elicitation* (or identification and description of uncertain parameters), *propagation* of that uncertainty through a system to achieve distributed responses (via modeling and simulation), and uncertainty *mitigation* (alternative selection and execution). The end result of risk management is an explorative measurement of the implications of uncertainty entry and their combined effect on the decisions and trade-offs between alternatives.

Many authors believe that risk is an integral part of successful product development management [50]. The challenge lies in how uncertainty information is developed and treated in complex system design environments such that the quality of the risky decision is maximized by the specific, in-depth information about the risk. Decision-making in this context is often considered as much an art as it is a science: a blend of the *objective* and physical with the *subjective* and psychological. In its most basic form, design activities and the body of decision making processes can be viewed as the ongoing balance between risk and reward.

1.1 Forecasting and Risk

An appreciation of the feasible scope of research is pertinent here–before delving deeper into the topic. A technical decision has the following attributes: an uncertainty about the result, the consequential effects of such result and a lead time before those effects are realized. As methods and processes improve the ability to deal with the uncertainty and risk, Twiss states that with forecasting technology there are:

> ...too many unknowns surrounding the future for us to ever hope to forecast it with certainty. These forecasts will inevitably contain errors, but this cannot be avoided. Our decisions must be made in the present using the best information available at the time, but it behooves us to use it in the most effective way... although [forecasting] cannot eliminate uncertainty, it can assist in reducing it; thereby a better view of the future and its evolution can be obtained, leading to better decisions. More than this cannot be expected [132].

Risk is manifested in many forms, most often described in the performance, schedule, and cost risk of the proposed product. At the enterprise level, a new product risks are correlated with the market, the competitive position, and the short term to long term investment balance of the company strategy.

C.W. Miller produced a cartoon illustration showing the differences in disciplinary perspectives of aircraft design. In the drawing shown in Figure 1, it depicts each of the candidate aircraft concepts if that discipline were not required to compromise and could design the rest of the aircraft in isolation. While exaggerated and amusing, it begs the question to the author as to what that aircraft might look like to the *Risk* discipline. Following the earlier quotation by Twiss, it is estimated that risk-in-isolation aircraft design might look like what already exists, as the uncertainty in that configuration is essentially zero. However, when additional dimensions of risk are introduced in the problem, such as the risk of more stringent requirements, new competitors, and continuously developing technology, the risk in isolation design now begins to evolve.

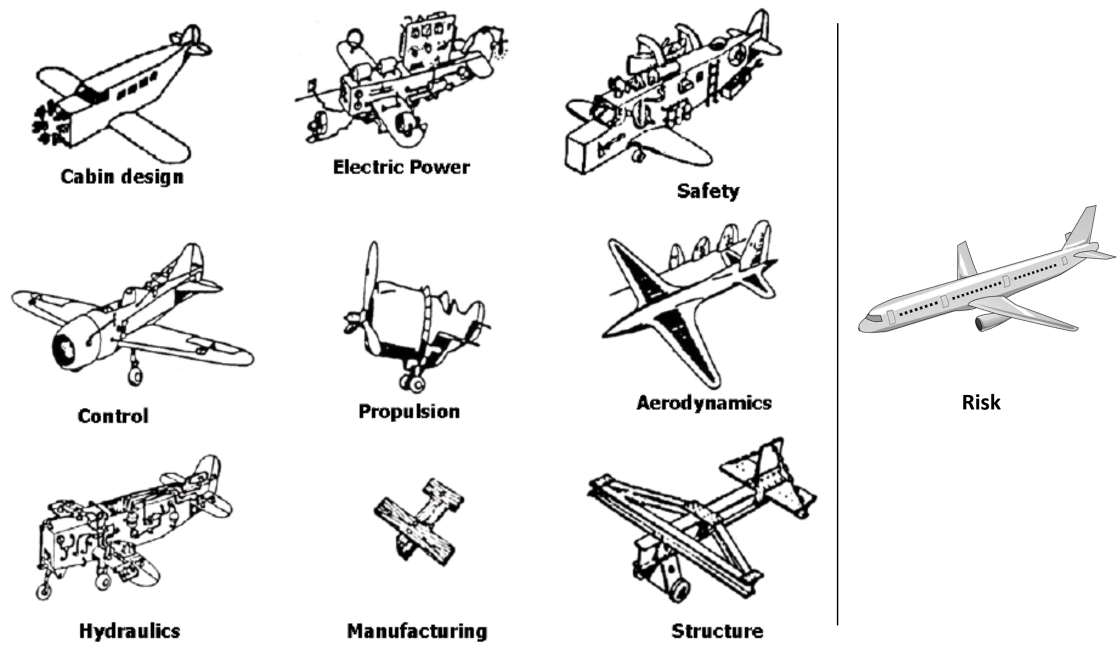


Figure 1: Cartoons illustrating the *design in isolation* effect of contributing disciplinary perspectives of the airplane by C.W. Miller [93]. Note that the likely risk averse design would be as little deviation from the existing paradigm as possible.

1.2 Changing Times

The civil air transportation industry is arguably one of the largest and most economically sensitive industries today. In recent events, a volcanic crisis over Europe hampered air traffic for weeks, causing billions of dollars of damages and loss to both airlines and the businesses that rely on commercial air travel and transport.

The emergence of a fierce duopoly in major commercial aircraft developers between Airbus and Boeing has changed the face the market and the way the game is played [128]. In the presence of competition, new social and political pressures have tightened requirements and the manufacturers are driven to seek higher risk technologies to gain market share and competitive edge. In this modern business, the voice of the customer is tied to sales performance, and recently that voice has shifted to an acute awareness of the total life-cycle cost. Simply put, airlines demand new aircraft that can achieve the same performance at a lower operational, maintenance and disposal cost.

In response to this customer demand, Boeing, Airbus and others continuously seek new technology to improve performance and decrease operating cost while maintaining a profitable business for their shareholders. An important contributing technology is the use of new materials such as carbon-epoxy composites for aircraft structure; however, this has not come without difficulties, as several major programs have gone over cost, under performance and past schedule as the the inherent risks to the industry have been realized.

1.3 Why is Risk on the Rise?

The information revolution has enabled widespread dissemination of knowledge across the world, and the aerospace industry is no different. The continual globalization of the design and production of commercial aircraft has slowly transformed what was once a privately guarded industry into an *economy of learning.* This learning poses long term competitive risk. A lucid report on commercial aircraft cycle time by NASA in 2001 describes the implications to aircraft developers of incremental business risk due to learning economies:

> The new economics literature on learning economies suggests that the risk inherent in new aircraft development may be even larger than originally posited. While commercial aircraft production is subject to significant learning economies, companies can benefit from these economies to a much greater extent if they are able to maintain or increase their annual production rates. When there are wide variations in production rates, there will be a significant depreciation in learning benefits, and the realized economics of the program may be disappointing.[118]

The major driving reasons for increased risk to aircraft developers are summarized in the following:

1. *Rise in development or acquisition costs* driven by technology and process investment needed

2. *Rise in development cycle time (program launch to first delivery)* - interrelated disciplines must converge on synthesized solutions taking time as the underlying technology

development network is mixed mode (serial and parallel development)

3. *Rise in aircraft systems and subsystems complexity* - supply network, disciplinarian interactions, produce and service expansion

4. *Rise in stakeholder expectations and societal usage* - development of a duopoly raises customer (airline) leverage

Aircraft development cost and cycle times have steadily increased in the last 40 years. Table 1 displays a selection of the major commercial aircraft, showing a steady increase in the development time and inflation-adjusted development costs of the program. This rise in costs places increasingly heavy reliance on program success.

1.4 Industries of Risk

There has been substantial research risk management methods that try to bring results about risk analyses of various systems and subsystems development analyses to the decision-maker's attention. However, a comprehensive review of program risk management by the Rand Corporation report in 2004 [40] describes:

> "a striking lack of literature on the use of the (risk management) techniques"
> (and) "that virtually all of the evidence for its utility was anecdotal."

In addition, there is a lack of consensus on how those risk analyses are combined, weighed, evaluated, and translated into a holistic view of the net risk-reward of competing alternatives.

This is a challenging task because the different disciplines involved with aircraft design view uncertainty (and thus risk) in different ways. Some of the uncertainty is purely subjective (qualitative), others are data-driven and bear quantitative uncertainty that is not always explicitly expressed in the design environment. Another part of the net uncertainty lies in the unidentified possible system states not considered (or "*unknown unknowns*"). For these reasons and others, a defensible, traceable, rigorous approach to combining the information sources into traceable knowledge structure is difficult and therefore challenging (not to mention stressful) to the decision maker. The decision process begins as technically-driven (where the decision maker examines a large partially disconnected set of data and analyses from the contributing areas) and these results feed an internal, human and judgment-based process. It is for this reason high-level decision making is traditionally left to experienced people within the field; they draw on a large wealth of human knowledge and experienced-based perception to crystallize the ultimate decision. The growing complexity of aircraft systems, in addition to the increasing societal implications of making design mistakes, threaten this classical decision model. It is clear that given the stakes involved in today's projects, such intuitive measures, based solely on experience, are no longer sufficient [47].

Of all aerospace-related organizations, NASA is one of the most risk-aware and prolific on the subject of technical risk management. Their missions continually present new and unique technical and safety risks; much of their research has been to minimize risk. Studies conducted on low-volume, high cost missions have laid the ground work for aerospace systems risk research. Their focus has covered areas such as risk and uncertainty analysis, reliability, decision-based design, and robust design [130].

> There is a conspicuous need for more advanced risk-informed methods to characterize, balance and minimize risk in the uncertain and ambiguous stages of conceptual design. Such methods will treat risk as a trade-able resource that can be used to make robust and reliable design decisions [130].

NASA has also used the term *risk-informed* design instead of *risk-based design*, emphasizing that risk analysis tools and methods cannot be the sole basis for decision making in design processes [28]. This thesis adopts a similarly balanced view of incorporating risk into existing design paradigms.

1.4.1 Rise in Aircraft System Complexity

Browning gives a detailed description of the ramifications of schedule risk as a function of complexity rise, stating that *complex system product development inevitably involves risk*

Table 1: Duration of major commercial transport aircraft development programs.

Launch Year	Aircraft	Development Time	Development Cost ($*B 2010*)
1965	Boeing 747	9 years	11.8
1986	Airbus A330/340	11 years	11
1990	Boeing 777	11 years	7.3
1994	Airbus A380	13 years	15
2003	Boeing 787	14+ years	17

[17]. As systems grow in complexity, the possible risk entry points grow in kind, given that the integration risk is also a function of system interactions.

Masten provides a detailed description of the business-economic effects arising from the increase in overall aircraft complexity, stating:

> The greater the complexity of the transaction and the level of uncertainty associated with it, the greater the likelihood of being bound to an inappropriate action, and hence the greater the implicit costs of contractual organization [83].

The long-term risks associated with an extended supply chain, design out-sourcing, and particularly outsourcing the design of *key components* (such as the wing) is described in great detail in Pritchard's critique of Boeing and Airbus's risk-sharing enterprise strategy [104]. These risks are complex to quantify and are considered outside the scope of this thesis.

The rising stakeholder and airline operator impact is described in the 2011 Federal Aviation Administration (FAA) air traffic forecast, projecting a steady increase in commercial airline traffic for the next 30 years [36], shown in Figure 2 and in Boeing's 2012 forecast shown in Figure 3.

These elements contribute to a increased culture of awareness and detailed, knowledge-driven risk management techniques among managers at many levels of the new aircraft development process. The next section will focus on the influence advanced materials on

[1] In billions of USD, corrected to Fiscal Year 2010. Amounts are approximates, as development aid and subsidies shroud actual development cost.

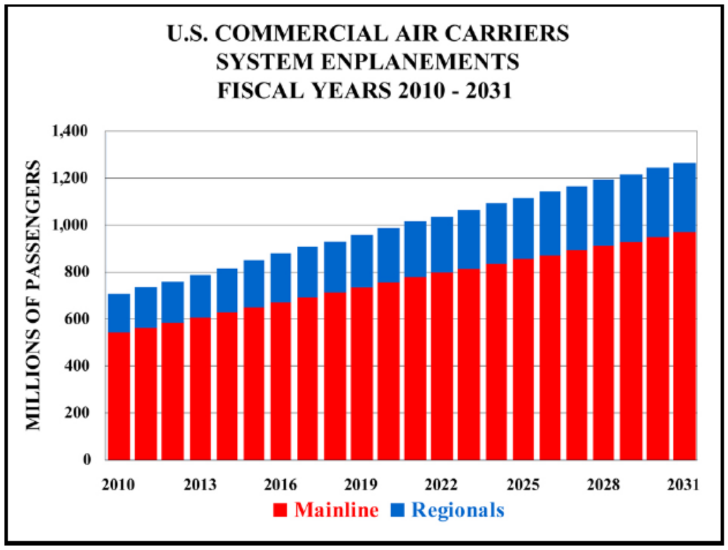


Figure 2: The FAA's projected increase in U.S. Commercial Traffic for 2010-2031 [36].

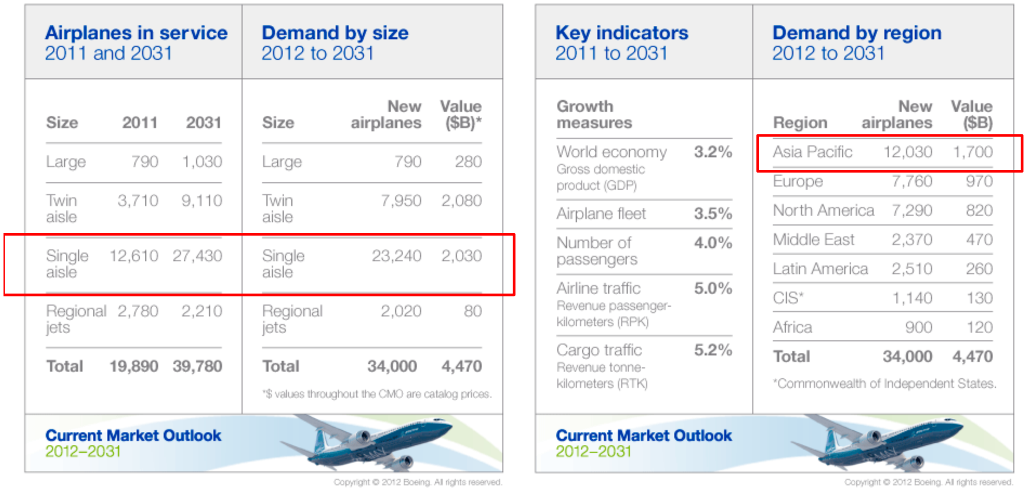
the risk temperature of development programs.

Research Observation I

New aircraft development programs are increasingly challenged by the rise in advanced technology, multidisciplinary complexity growth and implications of program failure. These changes open new, never before seen opportunities for risk entry and therefore, the risk assessment methods used by program managers must advance in kind which incorporate the increased merging of these aspects.

1.5 Aerospace Perspectives of Risk

The aerospace industry has long been claimed as a technology development leader. This is partly due to the fact that it takes a substantial degree of technology working together in harmony to fly (the combination of the gravity of Earth and the viscosity of air have



Airplanes in service 2011 and 2031

Size	2011	2031
Large	790	1,030
Twin aisle	3,710	9,110
Single aisle	12,610	27,430
Regional jets	2,780	2,210
Total	**19,890**	**39,780**

Demand by size 2012 to 2031

Size	New airplanes	Value ($B)*
Large	790	280
Twin aisle	7,950	2,080
Single aisle	23,240	2,030
Regional jets	2,020	80
Total	**34,000**	**4,470**

*$ values throughout the CMO are catalog prices.

Key indicators 2011 to 2031

Growth measures	
World economy Gross domestic product (GDP)	3.2%
Airplane fleet	3.5%
Number of passengers	4.0%
Airline traffic Revenue passenger-kilometers (RPK)	5.0%
Cargo traffic Revenue tonne-kilometers (RTK)	5.2%

Demand by region 2012 to 2031

Region	New airplanes	Value ($B)
Asia Pacific	12,030	1,700
Europe	7,760	970
North America	7,290	820
Middle East	2,370	470
Latin America	2,510	260
CIS*	1,140	130
Africa	900	120
Total	**34,000**	**4,470**

*Commonwealth of Independent States.

Figure 3: Boeing's 2012 30-year market outlook, broken down by aircraft type, growth factor, and region [13].

contributed to the technical challenge). The safety of hundreds of passengers per flight depends on the continual performance of these technologies. It therefore demands considerable investment, time, attention to detail and effort to design and build a safe airplane.

Fifty years ago, the technical know-how and immediate market was held within small, distributed business groups, often clustered in the United States and Western Europe. Today, most developed nations manufacture aircraft elements and the list of countries producing their own aircraft has grown to include Brazil, China, Japan, Korea, Canada, and many more.

Aerospace risks have fluctuated amidst the Industrial Revolution and Modern Era. In early human aviation history, the physics of flight were poorly understood, leading to a high probability of failure and this risk. For example, before the Wright Brothers' success at Kitty Hawk, countless extreme-risk level and often catastrophic attempts at flight are fully documented in the history books. However as knowledge and technology about flight developed, the aggregate risk of manned flight was reduced.

Over time though, the net risk began to be transform into programmatic challenges. New prototype designs in the early part of the 20th century were characterized by dramatic entrepreneurial exuberance, success and disaster. As war became an accelerator for technology development, or rather, as the impact associated with failing at war grew wildly, the concept of balancing risk, whether programmatically or of human life, was barely a consideration. Gradually, as the Cold War subsided and economic belts tightened, both commercial and military aviation corporations were forced to evaluate and carefully balance the impact decision quality. Eventually enough competition was created and programmatic considerations and product alignment to enterprise strategic vision took hold.

In the military maritime sector, high development costs and low production quantities caused program managers to develop some of the first product risk management methods. Among them was PERT, a schedule risk management tool which arranged anticipated project tasks into a linked network and assigned probabilities: most optimistic, most likely (often interpreted as the average) and most pessimistic duration for each of the activities. According to Lionel Galway's review in 2004,

> PERT was a great success from a public relations point of view, although only a relatively small portion of the [Navy's] Polaris program was ever managed using the technique. And this success led to adaptations of PERT such as PERT/cost that attempted to address cost issues as well. While PERT was widely acclaimed by the business and defense communities in the 1960's, later studies raised doubts about whether PERT contributed much to the management success of the Polaris project [40].

As life becomes driven by increasingly intelligent systems, the uncertainty about even the nearest moment in the future still remains constant. It is a simple fact: we cannot predict the future with perfect certainty. Risk versus reward is a boiled-down decision device that combines the utility of a reward (for example, we really want to go to the moon), with the associated risk in life (astronauts might die), money (costs too much), time (takes too long). This is a core metric in any investor's mind: *what is my exposure to bad events, and* *is it worth the perceived benefit I will receive?*

1.5.1 The Rise of Composites in Aircraft Structures

Composite materials have become crucial to the development of new aircraft designs for their increasingly important role in aircraft design, cost estimation, and manufacturing. Including more composite materials in an aircraft design generally reduces the weight and occasionally maintenance costs. There is an uncertainty caused by the rapid technological development of the use of the material, as well as the continuously changing design and manufacturing processes. Therefore, much of the cost data either does not exist, or it is difficult to obtain accurately. There is also a continuing improvement in the manufacturing process that will be challenging to include within the scope of this project.

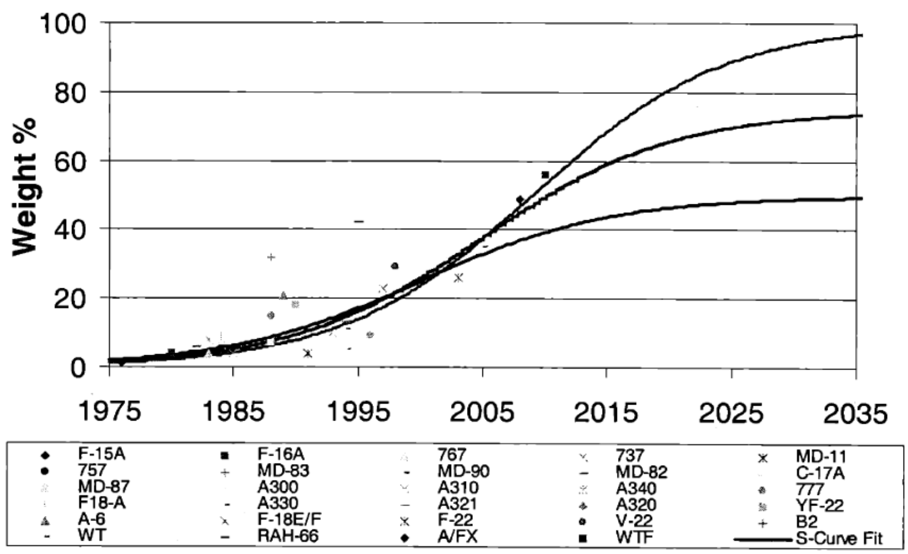


Figure 4: Use of composite structures in aircraft components and regressed forecasts [51].

Structural design and loads analyses, among other disciplines, are continuously burdened with uncertainty quantification and mitigation during design. Engineers face this challenge at every point of the design process, especially during the conceptual and preliminary phases where the trade studies between the performance of alternative designs rely on heavy assumptions. However, uncertainty quantification of the data substantiating the analyses for design alternatives is often simply estimated after the fact by subjective experience-based expert input. Automating these qualitative processes so as to develop rigorous and evaluative studies of the existing uncertainty is clearly valuable to a decision maker, specifically the uncertainty in the requirements, inputs and potential interactions within the system model. This is true for new technology insertion across disciplines within the aircraft architecture.

1.5.2 Examples of Realized Risks with Composite Aircraft

Recent major aircraft development programs such as the Boeing 787 Dreamliner and the Airbus A380 have experienced a variety of delays and technical setbacks in the development process. It is not the aim of this thesis to criticize these programs, or their management of the difficulties presented. Rather, it is to illustrate that the risks associated with new, high technology complex systems are indeed real, and to present a candidate approach to exploring the exposure specific to each new product. Looking at the schedule risks realized by the 787 Dreamliner program, there have been an assortment of manifestations. Most are associated with the risk-sharing approach Boeing has taken in the the use of a global supply network, as shown in Figure 2. Several authors have criticized the approach of exchanging unit cost risk for program schedule risk, and a complete view of this risk trade space will be discussed later through the use of *Risk Interrelationship Matrices* in Section 2.3.2. The result of these delays is the potential for cancellation of pre-orders from airlines as well as several billion dollars in customer contract penalties.

One example of recent schedule risk was related to a new materials technology applied in the 787 Dreamliner, and contributed to the motivation for this thesis. The unprecedented proliferation of the use of composites in this all-new aircraft experienced growing pains, particularly in the joint between the wing and the fuselage. During a ground test late in the development cycle, it was found that the upper skin and stringers had slight delamination from locally exceeding limit load (operating limit) in upward bending.

The damage occurred below the required load level needed for certification. It was expected that this type of failure would occur at ultimate load, and not limit load, thus causing the need for a repair or re-design. The resulting re-design called for installing

Table 2: History of change in the Estimated dates for the First Flight and First Delivery of the Boeing 787 program. Data collected from [46]

.

Date	First Flight	First Delivery	Reason Given at Announcement
Launch	8/1/2007	5/1/2008	
10/1/2007	3/1/2008	12/1/2008	Gap where the left side of the nose-and-cockpit section is out of alignment with the fuselage, shortage of fasteners
1/1/2008	6/1/2008		Program Manager replaced, supply chain problems
4/1/2008	12/1/2008	9/1/2009	Labor dispute, machinist strike. Union members maintain that if more of the key production had been in-house instead of by subcontractors, the 787 would have been completed on time.
12/1/2008	6/1/2009	3/1/2010	The design and installation of reinforcements along the upper part of the place where the wings join the fuselage
12/1/2009	(*completed*)		First flight completed
7/1/2010	(*completed*)	2/1/2011	Explosion of engine during testbed
11/1/2010	(*completed*)	9/1/2011	Electrical fire in cockpit

additional fasteners and a re-shaping of the stringers at the wing box. Figure 5 illustrates the cross section of the wing box and location of stress point.

Another example of the complexities of realizing returns with plastic-composite materials in aircraft is explained by McLellan [90], describing the loss of performance margin by adapting the new material extensively in their design of the new Adams A500 aircraft:

> Adam Aircraft is another worrisome example of composites gone wrong. The center-line thrust piston twin A500 also came out heavier than expected and was more costly to build. It was eventually certified but its payload and performance restrictions dried up what had been a promising market [90].

The next section will address the core perspective of business case risk measurement by assessment of the cumulative cashflow.

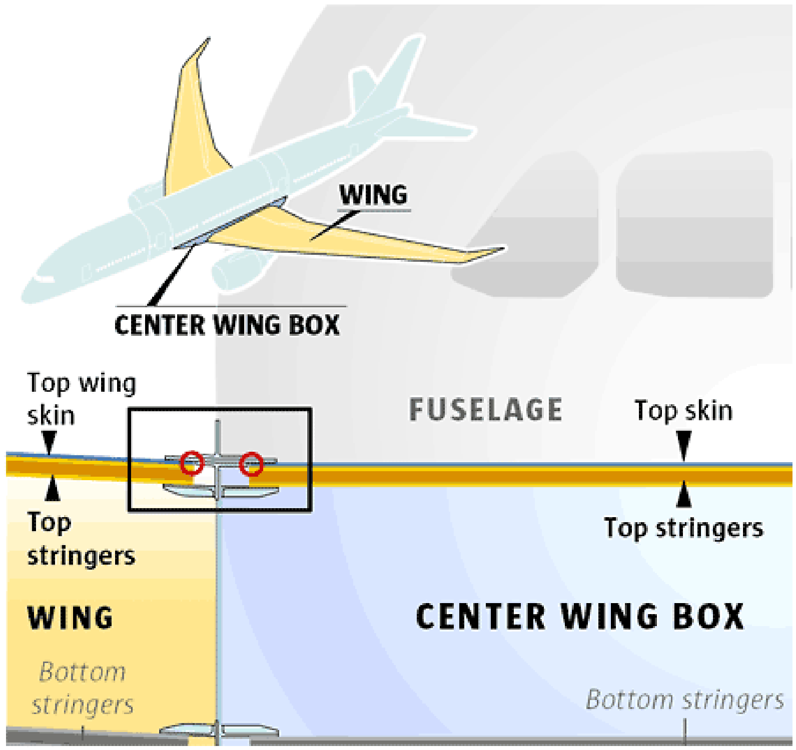
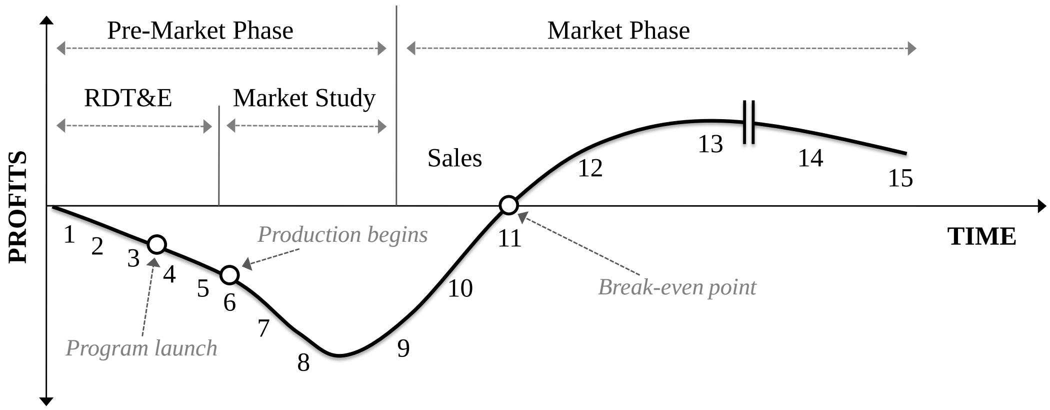


Figure 5: Location of the stress point arising from joining advanced composites on the Boeing 787 [46].

1.5.3 Break Even Analysis of Aircraft Programs

Cost models have been applied to generate forecasting models for cash flows as a treatment and abatement of cashflow risk concerns [100]. From a high-level business perspective, these risks can be transformed directly into measures of uncertainty on a manufacturer's Cash Flow chart given in Figure 6.

Products with a positive expected return on investment (or positive Net Present Value) are green-lighted, but the assumptions substantiating the product performance, cost, market availability and future presence of competition are subject to sizable uncertainty. This uncertainty ultimately translates to a possible shift in the expected cash flow chart, shown with the dashed lines above and below the mean expected return in Figure 79. Note that the uncertainty around the expected line increases with time, following general assumptions



Premarket Phase
1. Idea generation
2. Idea evaluation
3. Feasibility analysis
4. Technical RDT&E
5. Product (market) RDT&E
6. Preliminary production
7. Market testing
8. Commercial production

Market Phase
9. Product introduction
10. Market development
11. Rapid growth
12. Competitive Market
13. Maturity
14. Decline
15. Abandonment

Figure 6: New product development profits and their key product life cycle milestones [110].
.

of stochastic diffusion processes.

Figure 7 shows the estimated annual cash flows for a modern commercial transport aircraft program. Note the sharp ramp up in magnitude of both costs and revenues as production begins, as well as the exponential decrease in production costs over time. Also note that there are typically some payments early in the development phase. These inflows are typically a result of purchase agreements with customers, as many sales incorporate a down-payment of approximately 10-50 percent of the aircraft. This down-payment varies between customers as a function of the other purchase agreement details. In this example a discount rate (similar to inflation rate adjustment) of 10 percent was used. The effect of this is that as the value of money now is greater than money in the future, the large capital returns in the future may not balance with large expenditures in early phases of the program [91].

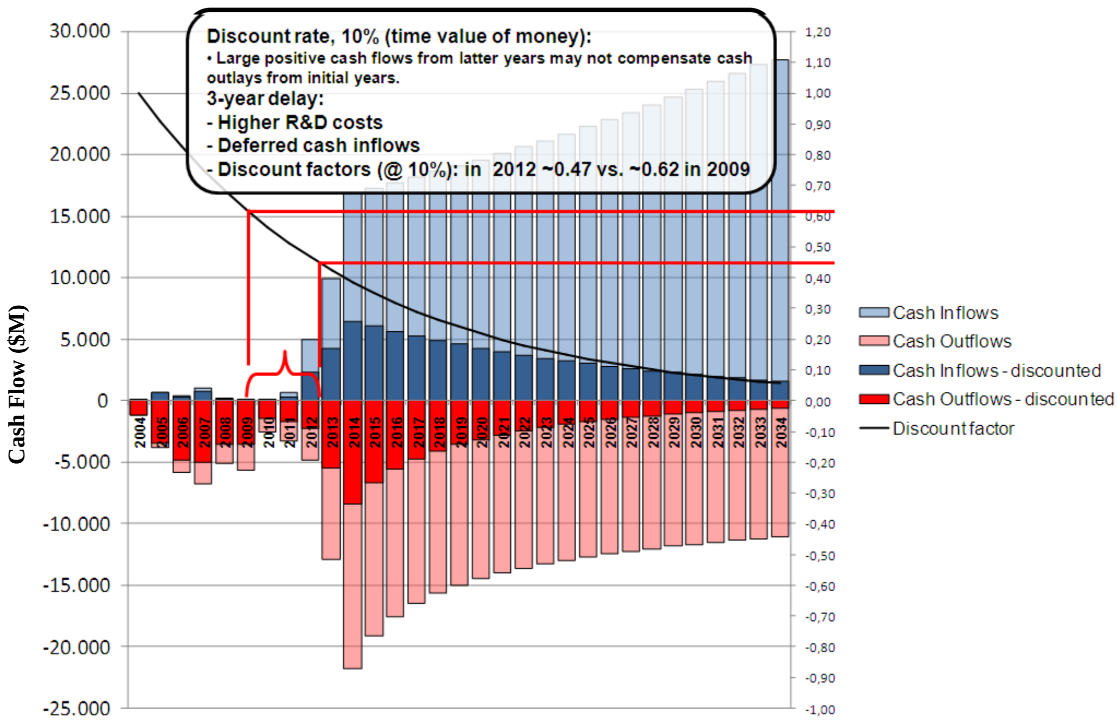


Figure 7: Cash flow diagram, showing the annual and cumulative cash flows for a typical commercial transport aircraft. Also note the discount factor and its effect on the present value of future payments (in the darker shading) [91]. .

1.6 The Uncertain Cumulative Cashflow Concept

Literature review of the uncertainty described in the cumulative cashflow of aerospace vehicle programs has separated two fundamental contributing areas: Technical Uncertainty (related to costs and schedule in research, development, testing and evaluation (RDT&E), and Market Uncertainty (related to the manufacturing rate/costs, sales price and market capacity). Provided that the product, vehicle, or technology is valuable, these two uncertainty projections combine to form the programmatic uncertainty, or uncertain cumulative cash flow (as referred to in this thesis). This is shown in Figure 8. This dissertation research views this projection of uncertainty as a potential approach for forecasting business case dimensions, and ultimately, success and profitability.

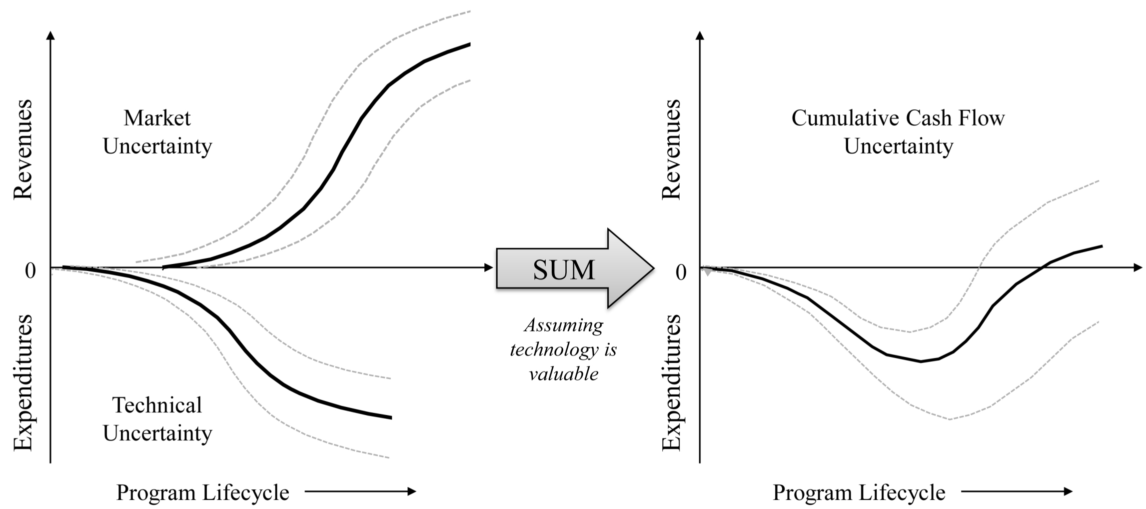


Figure 8: Cumulative cash flow for complex engineered systems is highly dependent on technical and market uncertainty [110]. .

1.7 Envisioning the strategic mitigation effect on the business case

The uncertain cash flow diagrams give insight into the business case in terms of both risk and reward (or more specifically: break even year, sunk cost, ROI and their associated risk dimensions) in an aggregated way. Understanding the impact of a strategic mitigation plan on a perturbed scenario then becomes clear: design and strategy alternatives can be compared simultaneously.

Figure 9 shows a notional example of two alternatives possible. The first example has a much steeper capital expenditure curve, but also has a larger expected overall return on investment. The potential for upside is also lower, however it comes at the expense of the possibility that the program may never break even (note the lower dashed line bound). The lower diagram has less total sunk cost, a longer expected break-even date, and a low return on investment, yet the uncertainty around those dimensions is much lower. Note that both of these aircraft design alternatives have the approximately same *risk-to-reward* ratio, so it follows that evaluating this ratio alone is *insufficient* in positioning the program manager's strategy.

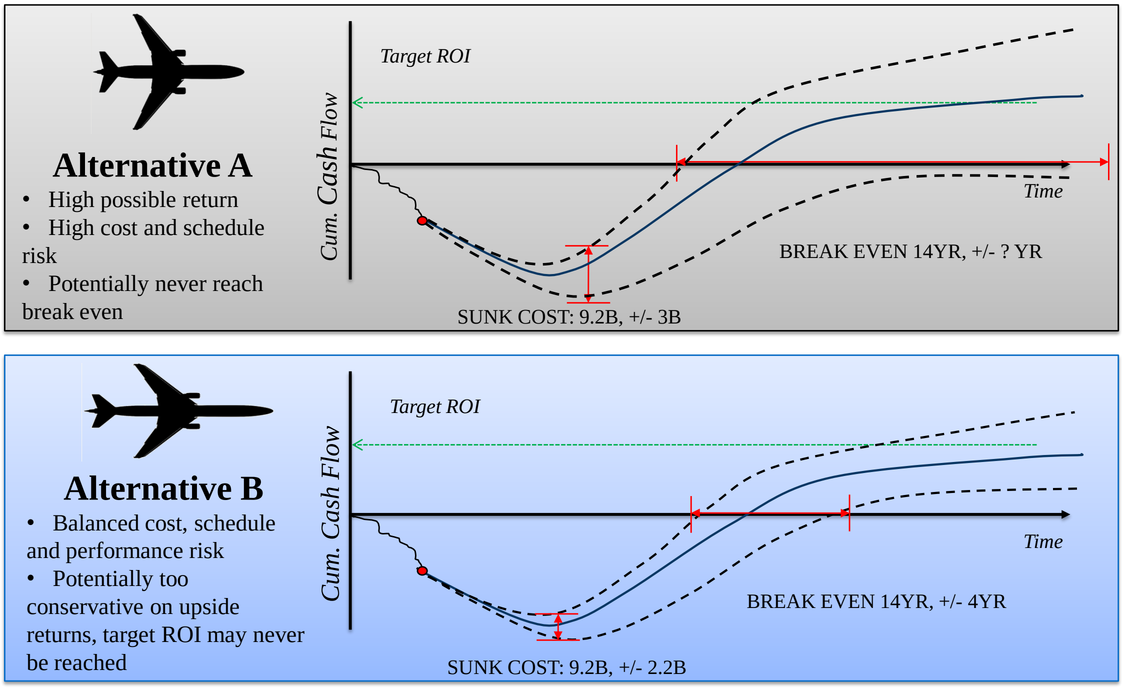


Figure 9: Alternatives compared by uncertainty and risk propagated to the cash flow chart, allowing balance between cost schedule and performance trades to be evaluated holistically.

The program manager's attitude towards risk (as well as the higher level manufacturer's economic situation and product placement) then come into play to the already crowded decision space. By being able to reduce these decisions to the single business perspective gives an increasingly transparent feedback to the program manager, and ultimately enable better, more informed decisions. This is the CASSANDRA methodologies core deliverable.

The methodology also enables studies to be made in evaluating the robustness of the business case. By introducing scenario perturbations to the uncertain cash flow curve and then examining the program manager's control power to return the program back to the desired state, an assessment of the business robustness can be made.

This aspect is the *risk mitigation and strategy development* section which is the final step of the methodology. Not only is the program manager able to evaluate the total business case of design and technology decisions, but she is also able to examine what control power is available at that specific design point. Ideally the program manager should be able to find a design that meets the cash flow and risk perspectives desired, and also meet the robustness requirement of that business case. When the modeling and simulation environments are setup, the business case can be torture-tested by various scenario, economic, and technological perturbations. In this thesis, three case studies are evaluated and carried out, and are found in the Results chapter.

1.8 Research Objective

The end goal for fusing the paradigms of financial risk management, psychological perception of risk, and modern preliminary aircraft design is summarized in the following research objective:

Research Objective

In order to contribute to the present techniques for integrating risk management practices into the design process, the objective of this research is to deliver three things:

1. A methodology that a program manager can use to measure and allocate the risk arising from technology and manufacturing uncertainty onto the business case of a new aircraft development project.
2. Development of metrics in the uncertain cumulative cashflow space which better express the extent and usefulness of the risk being assumed.
3. A process for identifying robust risk mitigation strategies in the presence of either large or small available data sets.

The goal of this research is to propose and evaluate a method designed to alleviate the process between information collection and decision execution by providing a risk-integrated framework in the context of preliminary level aircraft design. It is hoped that aircraft development decision makers can then simultaneously view and interpret competing alternatives and their associated aggregated risk and make the best documented, risk-aware decision possible.

This methodology produces a strategic recommendation to program manager of such an aircraft program facing simultaneous risks in multiple dimensions and disciplines. If successful, it will improve the quality of decision making at the preliminary level in technology of commercial aircraft structures by developing traceable, interrelated and knowledge-driven aggregated risk formulations that are translated directly into the modern aircraft design environment.

1.8.1 Summary of the Problem Motivation

In this chapter, the fundamental motivation for incorporating risk analyses within the aircraft design program agenda has been explored. Three primary reasons illustrate why the proposed research is valuable.

1. The informed handling of risk, regardless of the form in which it is manifested, is vital to program success and therefore is a core responsibility and concern of aircraft product development programs
2. Risk is steadily increasing with the rise in cycle time, development costs, advanced technology (specifically materials), and globalization of supply and competition.
3. Critical review and publication of the successes and failures of the risk management methods executed by development programs is limited or non-existent, either due to the uniqueness of their approach or by proprietary protection.
4. Decision making methods in design must incorporate risk information to improve decision quality and program success robustness.

1.8.2 Key Research Questions and Hypothesis

The basic themes of risk measurement, risk mitigation, and robust strategy selection of this dissertation are captured by the following driving Research Questions:

Research Question I

How can the present design methods be improved to *measure* the multidisciplinary risk presented when using advanced technologies in vehicle development?

Research Question II

How can risk analysis and mitigation methods be improved to *generate* mitigation strategies amid the multidisciplinary risk presented when using advanced technologies in vehicle development?

Research Question III

How can risk analysis and mitigation methods be improved to *select* the robust mitigation strategies for addressing multidisciplinary risk presented when using advanced technologies in vehicle development?

These questions led to the development of a methdology called CASSANDRA which structures an analysis that answers the Research Questions. *CASSANDRA* stands for **C**omputational **A**ircraft **S**ub-**S**ystem **AN**alysis of **D**esign **R**isk **A**lternatives. The fundamental hypothesis of the methodology is:

Methodology Hypothesis

The CASSANDRA methodology improved design awareness by forecasting the cost and time risks caused by uncertainty in the technology and manufacturing decisions during the conceptual design phase.

1.8.3 Declaration of the Research Scope

Risk management in aerospace vehicle design is a broad and complex field, with many technical, quantitative and qualitative methods. Many, if not most of the methods focus on flight safety and technical performance risks. This research has instead scoped the motivating problem away from safety and performance aspects, and assumes those are addressed separately and held constant. This research focuses only on the cost and schedule impacts and their risks to an aircraft manufacturer/integrator who is incorporating still-developing technologies into its design.

There exist several fields of research on the flexibility of program control as well as the adaptability and timing of design decisions (such as the fields of Real Options and agile manufacturing). The design phase in consideration of this research does not encompass those, and focuses a fixed time of the program during the conceptual design phase.

With these research constraints in place, the problem and methodology may be structured to evaluate the Research Questions in sufficient depth.

1.9 Organization of Thesis

In the following chapters, a comprehensive review of risk concepts, risk-informed decision methods, and aircraft-specific design processes are presented. Its purpose is to examine existing methods to explore how those approaches may be combined and adapted to form a new way of addressing the problem presented in this chapter.

Chapter 2 covers the fundamentals in risk literature and measurement methods applicable to aircraft programs, beginning with the definitions and existing taxonomies of risk and uncertainty. Risk is a commonly misunderstood and mis-communicated term, and a key anchor of this thesis is the selection and formalization of a risk definition and vocabulary. The industry standards for risk measurement and mitigation are given, and the concept of cumulative cashflow is introduced in detail.

Chapter 3 evaluates the experimental apparatus used to build and test the CASSANDRA methodology. Here, the thought processes are given leading to the high-speed sizing, synthesis, and cost estimation modeling framework (called BASUCA). An evaluation of the relationship between experimental run count and risk bounds are also addressed.

Chapters 4 and 5 break apart and address the two aspects of the uncertain cumulative cashflow given in Figure 8. Chapter 4 addresses the *Technical Uncertainty* aspect pertaining to managing cost and schedule of design processes and specifically technology development. The elicitation and propagation of uncertainty is addressed in this Chapter and the approaches for modeling and simulation of Technology Readiness are explored. The research contributes a networked approach to mixing Technology Readiness Levels with Manufacturing Readiness Levels to give a combined cost and schedule distribution.

Chapter 5 addresses the second aspect of the uncertain cumulative cashflow diagram: the market (and manufacturing) uncertainty. Here the economics of manufacturing and selling aircraft are addressed. This research contributes an approach to modeling the market capacity or likely program production quantity, which is shown to have a strong affect on both aircraft price and overall profitability. The total program risk and profitability is addressed by contributing a set of metrics that measure the risk-to-reward and risk efficiency aspects. These metrics are called the Risk Aversion angle and Risk-Benefit ratio.

Chapter 6 reviews the ability to use the uncertain cumulative cashflows of individual designs and their metrics to generate risk reduction or mitigation strategies. Two approaches are addressed, one with the availability of large data sets and inexpensive models, and one with small data sets or expensive models. The first uses a filtered Monte-Carlo approach, and the second uses a first order linearization of the modeling framework using the Jacobian matrix.

Chapter 7 reviews the problem formulation and details the individual steps of the CASSANDRA methodology. An in-depth look is taken to the objective function of the methodology user, and a case study is given where the manufacturing assumptions in costs are perturbed.

Chapter 8 reviews the thesis contributions, Research Objectives, and offers suggestions for future work.

CHAPTER II

AIRCRAFT PROGRAM RISK ESTIMATION

> There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns: the ones we don't know that we don't know.
>
> Donald Rumsfeld, Former Secretary of Defense

Many aspects of life have changed dramatically, even exponentially in the last 50 years. The list is long and familiar: population, communication, transportation, information, globalization, cultural balances, etc. There are certain things which have not changed in this time such as human need for survival, safety and quest for success and happiness. So, with the static traits of human life amidst an ever-changing world comes the inevitable pressure to keep up and moving forward so as to better ensure our survival, safety and happiness.

2.1 Definitions of Risk

2.1.1 Classical Definition of Risk

Frank Knight, in his seminal paper of 1921, distinguished risk and uncertainty in the following way:

> The essential fact is that *risk* means a quantity susceptible of measurement [...] It will appear that a measurable uncertainty, or *risk* proper [...] is so far different from an immeasurable one that it is not in effect an uncertainty at all. We [...] accordingly restrict the term *uncertainty* to cases of the non-quantitative type [68].

This perspective implies a measurement criterion to the likely state. If the measurement of the probability is known, or even measurable, then the term risk describes such a state. However, if no measurement or distribution of the state is known, then uncertainty fully describes the knowledge about the state.

This definition has been greatly contested over the course of the century; the main criticisms are that the implication of measurement is independent of concepts of risk and uncertainty alone.

2.1.2 Hubbardian Definitions of Risk and Uncertainty

Hubbard, among other authors, did not taken the same perspective of the measurement criterion. Rather, Hubbard separates the measurement of risk and uncertainty and defines them individually, as follows: [58]

Uncertainty: The lack of complete certainty, that is, the existence of more than one possibility. The *true* outcome/state/result/value is not known.

Measurement of uncertainty: A set of probabilities assigned to a set of candidate future states.

This approach to defining uncertainty is precise and originates from Probability Theory. It is also time independent, as there could potentially be uncertainty about the future, present and past. The measurement of uncertainty, in a strict mathematical sense, is a value or set of values ranging from 0 to 1, with 0 representing impossibility and 1 representing total certainty about a state. For example, there is a 60% chance this market will increase this year.

Risk: A state of uncertainty where some of the possibilities involve a loss, catastrophe, or other undesirable outcome.

Measurement of Risk: A set of possibilities each with quantified probabilities and quantified losses.

In the Hubbardian perspective, risk is derived from uncertainty, or rather is a superset to uncertainty, as a natural development of the implication of consequence to the associated future uncertain states. However it makes no specification on what defines the boundary between loss and gain. This definition is widely accepted for general use (especially in safety and hazard risk assessment), but it often lacks completeness when implemented in formal programmatic risk methods.

2.1.3 Risk Definition Standards

As the definition of risk is easily misunderstood and often the source of communication difficulties, several major organizations have sought to develop standards formalizing the definition and management processes. The first standard presented here is that of the United States Department of Defense (DoD), which publishes and maintains a Risk Management guide for the DoD Acquisition processes. This definition is especially relevant to aircraft design programs, as many of the aircraft developers synchronize their communication standards for the ease of integrating their products in government acquisition processes. The latest revision of this document describes the definitions and component of risk in the following way:

Risk is a measure of future uncertainties in achieving program performance goals and objectives within defined cost, schedule and performance constraints. Risk can be associated with all aspects of a program (e.g., threat, technology maturity, supplier capability, design maturation, performance against plan,) as these aspects relate across the Work Breakdown Structure (WBS) and Integrated Master Schedule (IMS). Risk addresses the potential variation in the planned approach and its expected outcome.

Risks have three components:

1. A future root cause (yet to happen), which, if eliminated or corrected, would prevent a potential consequence from occurring,
2. A probability (or likelihood) assessed at the present time of that future root cause occurring, and
3. The consequence (or effect) of that future occurrence.

A future root cause is the most basic reason for the presence of a risk. Accordingly, risks should be tied to future root causes and their effects [22].

Figure 10 illustrates the separation between risk and uncertainty that will be taken in this research. Risk is considered in the presence of uncertain system responses (results or metrics) given by the probability density function shown, in conjunction with the presence of a *target* or *objective*. These objectives may be defined at the system (aircraft) level or at the subsystem level (wing, propulsion, flight controls, etc).

A number of non-military organizations have sought to standardize a modern, functional definition of risk. The general form is not unlike the Hubbardian and DoD definitions; there is a description of the uncertain element and some form of impact or consequence on objectives. The most recent and widely accepted definitions though still debated [55]) is that of the ISO31000:2009, which describes risk as simply *the effect of uncertainty on objectives*.

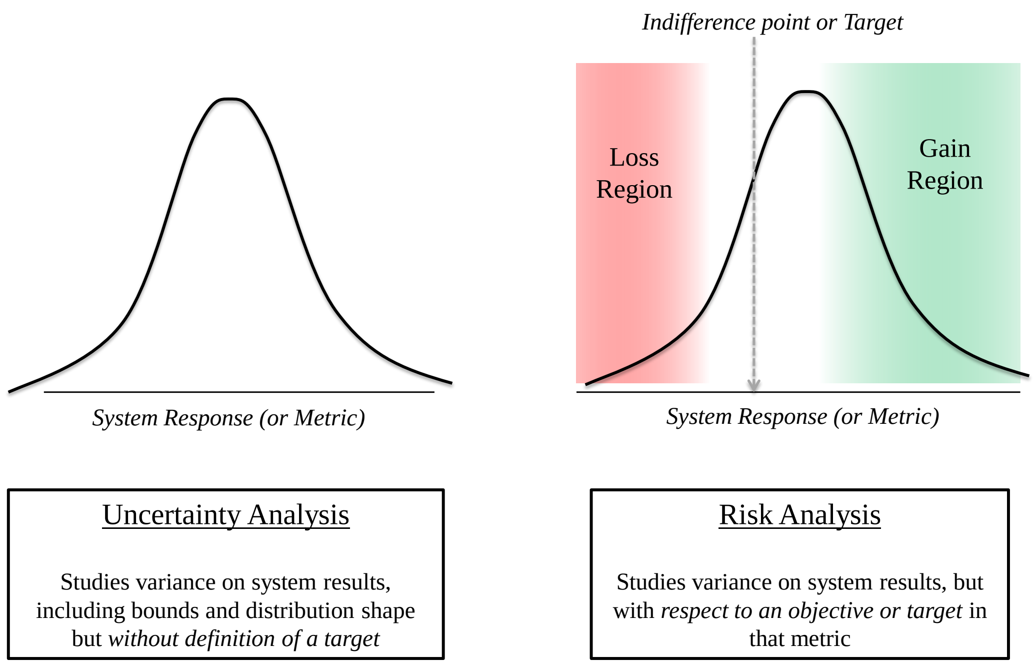


Figure 10: Distinction between risk and uncertainty on system results due to the existence of a target and associated loss and gain regions.

Note the range of definitions and how certain risk definition standards describe the *impact* portion of the definition. In most, an objective is described, and in others a *consequence* is alluded to. This consequence aspect is of particular relevance to real-world business prospects, as the consequence of a failed objective may range from negligible reduction in schedule, cost or performance all the way to permanent failure of the business enterprise. New commercial or military aircraft programs are not immune to this effect; recall the adage, *every new airplane bets the entire company.* On a smaller scale, the consequence may manifest itself in an incremental delay or cost to a program element, which then propagates to the other program elements and ultimately contributes to the overall economic and business outlook. A key problem this dissertation aims to address is the discovery and quantification of the incremental cost and performance risks from adjustment of either the internal aspects of the program (such as design or technology selection) and external aspects (such as market changes or supply chain disruption).

Standard	Description of Uncertainty	Description of Impact
British Standard BS6079-3:2000 (2000)	"Uncertainty inherent in plans and the possibility of something happening (i.e. a contingency) ..."	"... that can affect the prospects of achieving business or project goals."
British Standard BS IEC 62198:2001 (2001)	"Combination of the probability of an event occurring ..."	"... and its consequences on project objectives."
A Risk Management Standard (Institute of Risk Management et al, 2002)	"The combination of the probability of an event ..."	"... and its consequences."
Australian/New Zealand Standard AS/NZS 4360:2004 (2004)	"The chance of something happening ..."	"... that will have an impact on objectives."
Risk Analysis & Management for Projects [RAMP] (Institution of Civil Engineers et al, 2005)	"A possible occurrence ..."	"... which could affect (positively or negatively) the achievement of the objectives for the investment."
APM Body of Knowledge (Association for Project Management, 2006)	"An uncertain event or set of circumstances ..."	"... that should it or they occur would have an effect on achievement of one or more project objectives."
Management of Risk [M_o_R]: Guidance for Practitioners (Office of Government Commerce, 2007)	"An uncertain event or set of events ..."	"... that should it occur will have an effect on the achievement of objectives."
A Guide to the Project Management Body of Knowledge [PMBoK® Guide] (Project Management Institute, 2008)	"An uncertain event or condition ..."	"... that if it occurs has a positive or negative effect on a project's objectives."
British Standard BS31100:2008 (2008)	"Effect of uncertainty ..."	"... on objectives."
ISO31000:2009 (2009)	"Effect of uncertainty ..."	"... on objectives."

Figure 11: A summary of standardized risk definitions, organized by descriptor of uncertain element and impact.

It is then appropriate to select the definition relevant to aircraft design programs, and hold this definition constant in the language describing risk within this research. Common practices for new development aircraft programs include very specific design goals (or objectives), and the consequence of failure in meeting those objectives has quantifiable impact. The existence of an *objective* and a *consequence* is a fundamental departure point for the approach to handle risk in this thesis. This thesis will hereforth use this definition of risk as *the effect of uncertainty on objectives and its consequence* in its vocabulary.

2.1.4 Epistemic and Aleatory Uncertainty

Helton [53] distinguishes an important separation between two views of uncertainty, aleatory and epistemic, in the following way: ‘ *aleatory* uncertainty derives from an inherent randomness in the behavior of the system under study and *epistemic* uncertainty derives from a lack of knowledge about the appropriate values to use for quantities that are assumed to have fixed but–poorly known–values in the context of a specific study. Aleatory uncertainty is usually represented with probability and leads to cumulative distribution functions (CDFs) or complementary CDFs (CCDFs) for analysis results of interest. In the presence of epistemic uncertainty, there is not a single CDF or CCDF for a given analysis result. Rather, there is a family of CDFs and a corresponding family of CCDFs that derive from epistemic uncertainty and have an uncertainty structure that derives from the particular uncertainty structure (e.g. interval analysis, possibility theory, evidence theory or probability theory) used to represent epistemic uncertainty [53].

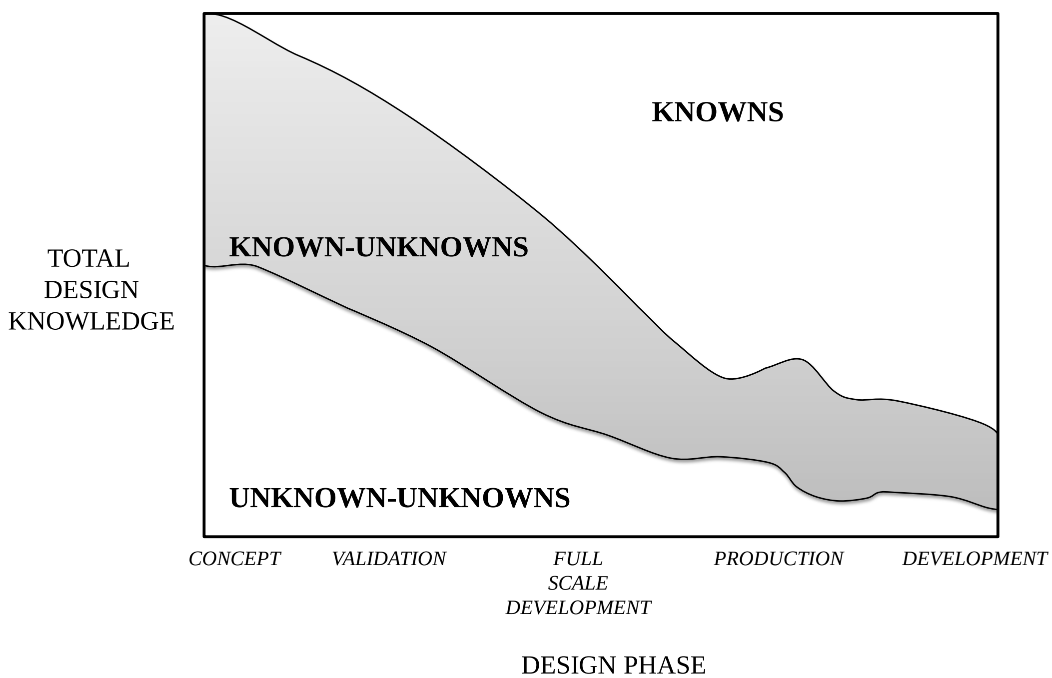


Figure 12: Progression between knowns, known unknowns, and unknown unknowns through a new product development [110]/

Figure 12 illustrates the programmatic shift in the three categories of variables throughout a new product development program. In the beginning of the program, there is maximum uncertainty, of which is split between known unknowns (such as the physical shape or weight of the final product) and unknown unknowns, which are the uncertain variables and factors of which the program management is not even aware. An example of unknown unknowns are unforeseen, damaging system behaviors arising from the complexity of the undeveloped system. As the program moves forward through the design phases, the unknowns (both known and unknown) decrease, typically monotonically as the product becomes almost completely understood. The unknown unknowns are never eliminated completely in practice and in theory. The program may experience non-monotonic decrease in unknowns as external factors or conditions change the system requirements or possible uses of the product. An example here is a transport aircraft program that acquires a launch customer who plans on using the aircraft in Antarctica, where the new flight and landing conditions suddenly increase the manufacturer's uncertainty in how the product will perform in that environment. That new uncertainty is reduced in this example with testing or re-design, and the program returns to its steady path towards complete certainty.

2.2 Theoretical Approaches to Risk Measurement

2.2.1 Frequentist Risk Estimation

The frequentist inference approach is a mathematical perspective on risk measurement. It is what is meant when simplistic explanations of risk are given (risk is probability of failure times the cost of that failure). Its formulation:

$$R(\theta, \phi) = E_\theta L(\theta, \phi(X)) = \int_X L(\theta, \phi(X)) dP_\theta(X) \tag{1}$$

Where

- θ is a fixed possible state
- X is the vector of observations drawn from the population
- E_θ is the expectation for all X

- $dP_\theta(X)$ is the probability measure of the event space X

While brutally objective in its formulation, the frequentist approach has limited use in novel risk management approaches, as the risk rarely is perceived linearly in real projects. That is, a \$1,000,000 potential loss, occurring at a rate of 1 in a million, has the same expected loss in the frequentist approach as a 100% probability of losing a single dollar. The Expected Utility and Prospect Theory (described in subsequent sections) approaches correct for this effect by creating adjusted payoff functions that are sensitive to risk attitude.

2.2.2 Robust Design Methods

Taguchi introduced a quality improvement process that was an important contribution in the way of system variance (and thus risk) minimization. He argued that any decrease in the quality of a system leads to customer dissatisfaction, which he represents as a *loss* [122]. Originally applied to the automotive industry, the principle concept is that it is possible to set the parameters of a system to be insensitive to uncontrollable noise effects, while still retaining proximity to an optimum. This process was called *robust design.* An excerpt from SAS Institute documentation gives a succinct overview of the Taguchi method:

> The Taguchi method defines two types of factors: **control** factors and **noise** factors. An inner design constructed over the control factors finds optimum settings. An outer design over the noise factors looks at how the response behaves for a wide range of noise conditions. The experiment is performed on all combinations of the inner and outer design runs. A performance statistic is calculated across the outer runs for each inner run. This becomes the response for a fit across the inner design runs [108].

Figure 13 shows the relationship between transmission of variance. On the section of the curve where the slope is large, there is a great sensitivity on the output to the input variables. Further towards the right, the curves becomes more insensitive to changes in the inputs, and more *robust.* This effect, carried out across several simultaneous dimensions, is the core goal of the robust design approach.

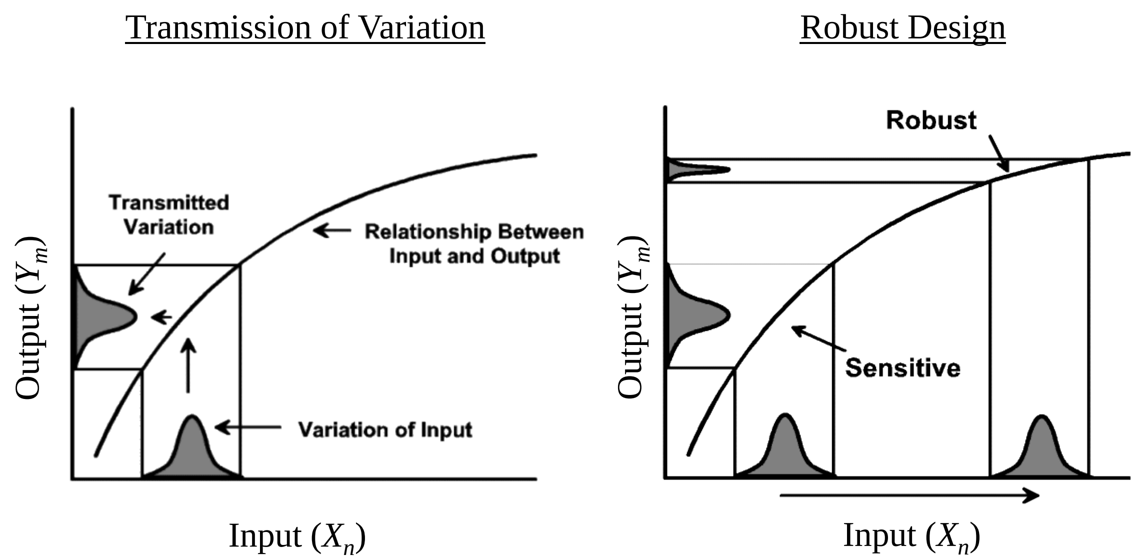


Figure 13: The relationship between input and output variables for sensitive design and insensitive design, Robust design approaches try to shift design variables (X) towards settings where there is less sensitivity to the input variables, especially if some of those variables are outside of control [124].

Chen gives a description of Taguchi's famous quality and process improvement work, citing two broad categories for minimization of performance variations and bringing the mean to a target: [21]

1. *Type I* - minimizing variations in performance caused by variations in noise factors (*uncontrollable parameters*).

2. *Type II* - minimizing variations in performance caused by variations in control factor(*design variables*).

Taguchi's quality methods and robust design approaches have been applied to many non-automotive applications in aerospace. A particularly good example is from a study in 2009, where Dodson and Parks applied a robust design approach combined with polynomial chaos theory to reduce sensitivity of the lift to drag ratio to leading edge thickness [29].

The results demonstrated that the robust designs were significantly less sensitive to input variation in leading edge thickness, compared with non-robustly optimized airfoils. The non-robust, optimal design degraded 20 percent from slight variation in the inputs. One drawback of robust design is that it can be computationally expensive to carry out the variance study on large multidisciplinary systems; several approaches have been taken to reduce computational time by creating efficient variance estimation algorithms that improve the rate of convergence when compared to Monte Carlo [33].

2.2.3 The Loss Function and Signal to Noise Ratios

Taguchi advocated understanding the cost of quality in a variety of manufacturing and business scenarios. Instead of limiting the cost estimation to the cost of products that were outside of specification, he introduced the concept that there were costs associated with the larger perspective of the society, and that those costs would eventually return to impact the corporation itself. Other statisticians, such as Donald Wheeler, claimed that variance within the specification caused no loss to the corporation or society [137], [136]. As the specification limit is somewhat arbitrarily drawn, Taguchi instead argued for an approach that minimized the societal cost or *loss*. The minimization of this measure improved quality for the corporation and reduced loss for society at large.

The formulation of the loss function L for minimization in terms of probability is:

$$\min \int_{\theta \in \Theta} L(\theta, \delta) p(\theta) d\theta \qquad (2)$$

where θ is the index or parameter over probability space Θ.

He identified three types of situations [122]:

1. Larger the better (for example, agricultural yield);
2. Smaller the better (for example, carbon dioxide emissions); and
3. On-target, minimum-variation (for example, a mating part in an assembly).

For practicioners, Taguchi suggested a direct approach for maximizing quality. The relationship to a target or utility space could be aggregated in the formation of a signal-to-noise (S/N) ratio which was to be *maximized*. Taguchi offered these formulations of the S/N ratio for each of the situations given in Equations 3 to 5.

Smaller the better:

$$SN_{smaller} = -10 \log \frac{\sum_{i=1}^{n} y_i^2}{n} \tag{3}$$

Larger the better:

$$SN_{larger} = -10 \log \frac{\sum_{i=1}^{n} \frac{1}{y_i^2}}{n} \tag{4}$$

Nominal the best:

$$SN_{nominal} = 10 \log \frac{y^{-2}}{\sigma_{n-1}^2} \tag{5}$$

where y_i are the n data points and σ is the variance of the set.

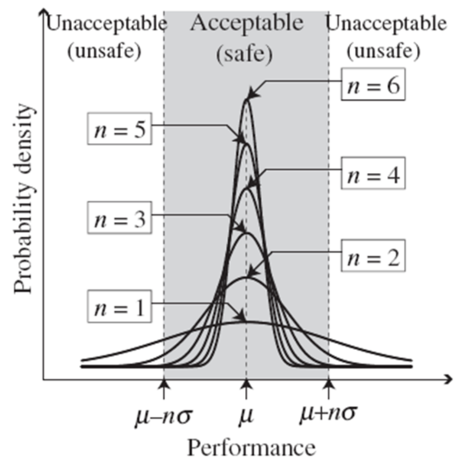
These formulations were part of the foundation of what became the 6-Sigma quality movement.

2.2.4 Design for 6-Sigma

A noteworthy variance minimization design process is *Design for 6-Sigma* (DFSS) which is a business management approach for the development of process guidelines so as to produce fewer than 6σ 'rejected' products as possible [114]. Rejection is determined by deviation outside the lower and upper specification limits, for which 6-Sigma processes are si standard deviations, accounting for a shift in the mean, or 3.4 rejections per million. DFSS is an excellent quality improvement guideline, especially for products produced in substantial quantities.

2.2.5 Expected Utility Theory

Expected utility is a method of evaluating decision alternatives that present risky or uncertain outcomes by comparing the product of the utility values and their respective probability of occurrence. It was first proposed by Nicholas and Daniel Bernoulli as a method to solve



Sigma level n	Acceptable (safety) probability, %
1	68.25
2	95.46
3	99.73
4	99.9937
5	99.999943
6	99.9999998

Figure 14: Six-Sigma approach to minimization of process variance [114].

the Saint Petersburg Paradox. This paradox deals with naive decision criterion that only takes into account expected value [3]. The solution to the paradox, published in 1738, was to create a parallel concept to the outcome called *utility* which describes a subject-relevant measure of value. Bernoulli states:

> The determination of the value of an item must not be based on the price, but rather on the utility it yields. There is no doubt that a gain of one thousand ducats is more significant to the pauper than to a rich man though both gain the same amount.

The suggested model of the utility function was a logarithmic S-curve, known as *log utility*. Figure 15 illustrates a normalized, notional utility for risk adverse, risk neutral, and risk seeking functions.

2.2.6 Application of Expected Utility Theory to Choice

Expected utility theory states that the overall utility is the statistical expectation of the outcomes [63]. This is given as

$$U(x_1, p_1; ...; x_n, p_n) = p_1 u(x_1) + ... + p_n u(x_n) \tag{6}$$

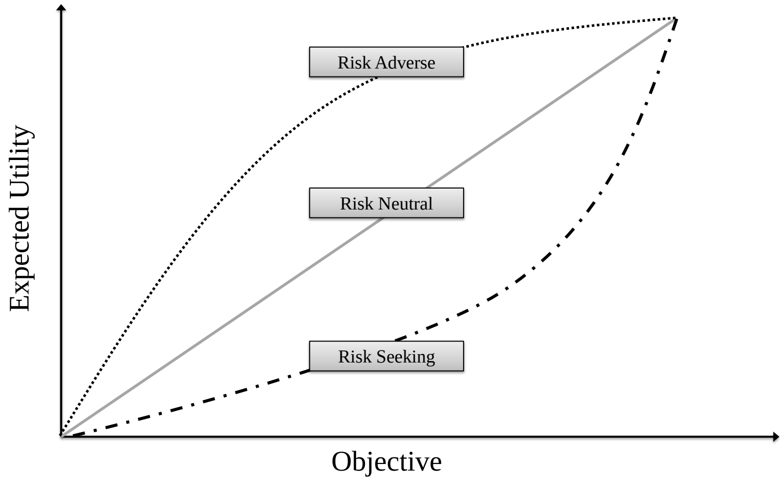


Figure 15: Notional utility functions for various risk attitudes.

Where U is the utility of a prospect, x_n is the value of the nth outcome, and p its respective probability. One can easily see the resemblance to the expected value of a set of probabilities and outcomes.

The choice model describes as favorable if the utility of the prospect, when integrated with one's existing assets, exceeds the utility of those assets alone [63]. The context of the utility function is then given as the final state of one's assets instead of as a gain or a loss. If w is the asset position, then

$$U(w + x_1, p_1; \ldots; w + x_n, p_n) > u(w) \tag{7}$$

> Expected utility theory reigned for several decades as the dominant normative and descriptive model of decision making under uncertainty, but it has come under serious question in recent years. There is now general agreement that the theory does not provide an adequate description of individual choice: a substantial body of evidence shows that decision makers systematically violate its basic tenets [131].

2.2.7 Prospect Theory

In the late 1970's, two psychologists named Daniel Kahneman and Amos Tversky observed that individuals make decisions involving risk differently than that prescribed by the widely-accepted model called Expected Utility theory [63] . They published an alternative to Expected Utility Theory in a paper published in 1979 that became the most cited paper in Econometrica [112]. Subsequent research and refinement created an entire field of study called Behavioral Economics, for which ultimately Kahneman was awarded the Nobel Prize in Economics.

> Kahneman and Tversky (1979) "Prospect Theory: An analysis of decision under risk" is the second most cited paper in economics during the period, 1975-2000 [112].

The revised descriptive model of decision making under risk was called Prospect Theory (prospect in reference to a lottery) that improved the empirically observed discrepancy. The new model bears the fundamental differences with Expected Utility Theory that the value function is non-linear with the probabilities, and value is relative to a *reference point*. Below the reference point, the value is perceived as a loss, and above which is considered a gain. In addition, the functions for value are asymmetric, meaning that the value is steeper for losses than gains.

> Prospect theory deals with the way we frame decisions, the different ways we label (or code) outcomes, and how they affect our attitude toward risk [7].

These changes, while seemingly minute, have made a profound impact on the decision making models involving uncertainty. The body of literature on this topic and the subsequent ideas are vast:

> Rather, in assessing such gambles, people look not at the levels of final wealth they can attain but at gains and losses relative to some reference point, which may vary from situation to situation, and display loss aversion – a loss function that is steeper than a gain function [115].

Hasite and Dawes [52] give a summary of the major contributions of Prospect Theory has enabled, stating three key characteristics:

Prospect Theory Characteristics

1. **Reference level dependence**: An individual views consequences (monetary or other) in terms of changes from the reference level, which is usually that individual's status quo.

2. **Gain and loss satiation**: The values of the outcomes for both positive and negative consequences of the choice have the diminishing returns characteristic. The α term in the value function equation captures the marginally decreasing aspect of the function. Empirical studies estimate that α is typically equal to approximately .88 and always less than 1.00. When the exponent $\alpha < 1.00$, the curve will accelerate negatively (if $\alpha = 1.00$, the function would be linear; and if $\alpha > 1.00$, it would accelerate positively).

3. **Loss aversion**: The resulting value function is steeper for losses than for gains; losing 100 dollars produces more pain than gaining 100 dollars produces pleasure. The coefficient λ indexes the difference in slopes of the positive and negative arms of the value function. A typical estimate of λ is 2.25, indicating that losses are approximately twice as painful and gains are pleasurable. (If $\lambda = 1.00$, the gains and losses would have equal slopes; if $\lambda < 1.00$, gains would weigh more heavily than losses) [52].

2.2.7.1 Mathematical Formulation

The decision weight scale is denoted as $\pi(p)$ which reflects the impact of p on the overall value of the prospect [63]. Note that π is not a probability measure, and it is generally found that $\pi(p)+\pi(1-p) \leq 1$. The subjective value of the each outcome x is given as $v(x)$.

In simple prospects of the form $(x, p; y, q)$, one earns x with probability p and y with probability q, and nothing with the probability $1-p-q$ where $p+q \geq 1$. The overall prospect value is given as:

$$V(x, p; y, q) = \pi(p)v(x) + \pi(q)v(y) \tag{8}$$

The value function reduces to Equation (6) when the $\pi(p) = p$ and $v(x) = U(x)$. A typical value function is given in Figure 16, showing the asymmetrical value functions $v^-(x)$ and $v^+(x)$.

X_o is defined as the reference point (the boundary between gains and losses), empirical studies have shown that the value function $v(x)$ is uniquely defined as $v^+(x)$ over the range $x > x_0$ and $v^-(x)$ over the range $x < x_0$.

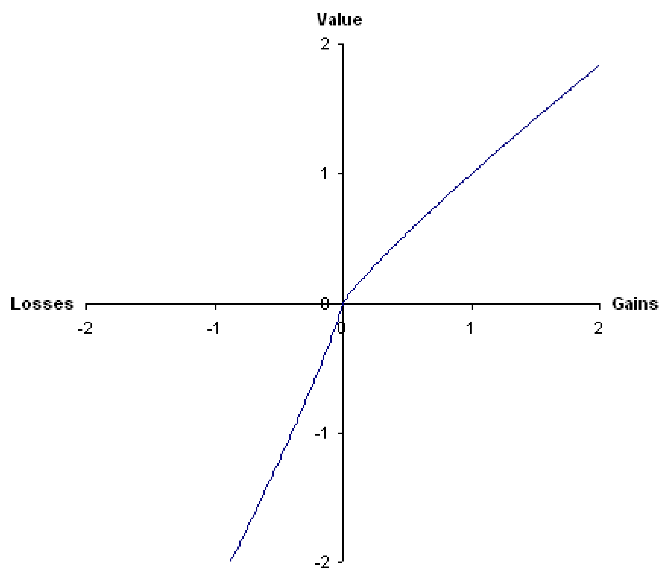


Figure 16: Notional value function curve for Prospect Theory, showing the asymmetry around the reference point (origin) [112].

The model form of Prospect theory is a generalized version of expected utility. The probability and value curves can be permuted (and calibrated) to suit the descriptive or prescriptive approach. When the probability curves are linear, the value curve reduces to that of expected utility. Ultimately, prospect theory gives a mathematical formulation for calibrating the probability and value scales, and a concrete measure of a risky prospect.

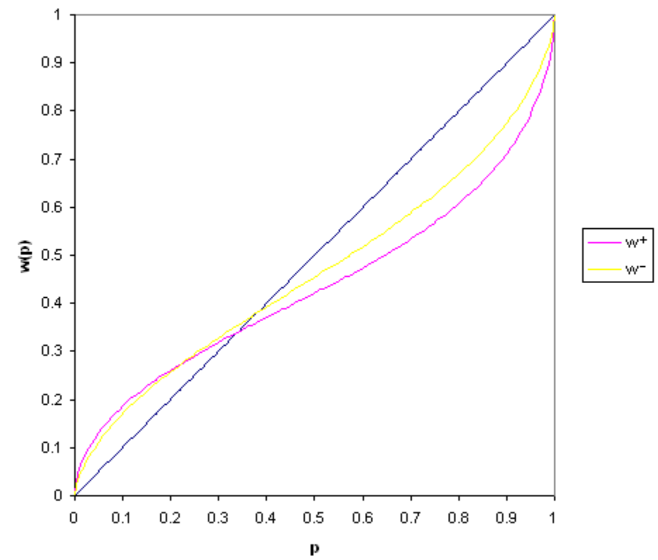


Figure 17: Weighting functions for gains (w+) and losses (w-) based on median estimates of parameters [112].

2.2.7.2 Cumulative Prospect Theory

After the initial release of the theory in 1979, several economists criticized prospect theory and presented improvements. In the original version of the theory the cumulative probabilities were transformed by $\pi(p)$, leading to a dominance of extreme events occurring with small probability [131] [70]. One of the main criticisms was in regard to continuously distributed risky propositions. That is, the available options were not individual and discrete, but instead infinitely distributed along some dimension. It is given as Equation 9:

$$U(p) = \int_{-\infty}^{0} v(x)\frac{d}{dx}(w(F(x)))\,dx + \int_{0}^{+\infty} v(x)\frac{d}{dx}(-w(1-F(x)))\,dx, \tag{9}$$

where the cumulative probability is given as

$$F(x) = \int_{-\infty}^{x} dp \tag{10}$$

2.2.7.3 *Prospect Theory as a Prescriptive Model*

Prospect theory was developed as a *descriptive* model for empirically observed phenomena. Its model form was created to be immediately useful for gaining insight into psychological decision-making routines and other studies on human systems. It was not initially developed as a prescriptive model for a basis upon which to make future decisions. Expected utility does not distort the probability curves, and presents a more readily suitable prescriptive tool. The difficulty with expected utility theory is that there is no principled way of measuring risk [111].

In 2009 Sewell took a hybrid approach to Prospect Theory and Expected Utility theory. He used the linear probability scales of Expected Utility functions and the grounded (reference point) approach for establishing value functions in terms of gains and losses from Prospect Theory. The resulting methodology was a general prescriptive model for decision-making under risk.

2.3 Business Perspectives of Risk

The most general measure of risk within an operational business is cost uncertainty. However, although cost is today recognized as the ultimate discriminator of risk [139], it is notoriously difficult and labor-intensive to estimate accurately in aircraft design, even with an extensive cost database [107].

Manufacturing-based businesses such as commercial aircraft manufacturers, have advanced uncertainty and risk approaches, but typically in regards to product quality. Recently methods have emerged that integrate both the design and manufacturing related risks into the design team analyses [127].

2.3.1 Insurance Methods and the Law of Large Numbers

However, the insurance and finance communities have much to offer in the way of sheer business experience, methods/tools, and profit-oriented perspective of risk. For an insurance company, risk is a transferable commodity to be collected from consumers, adjusting premiums to outweigh aggregated risk exposure on a daily basis. Therefore it is appropriate for our review risk methodology to investigate how their paradigms might be applicable to aircraft design processes. It was found that these communities leverage the following key concepts:

1. *The Law of Large Numbers* - Enough data exists to accurately fit high fidelity models.

2. *Access to near real-time data* - The data is continuously generated and updated.

3. *Liquid and/or readily convertible expressions of risk* - All forms of risk are expressed in few dimensions: money and time.

The first is likely the most important: the bulk of insurance organizations use finely correlated information from vast claims databases to build models of similarly-exposed individuals, relying on the Law of Large numbers as shown in Figure 18 to generate precise calculations of the risk they assume. For an insurance company, it does not matter if the first fifty clients file expensive insurance claims, because the Law of Large Numbers asserts that eventually there is convergence to a mean. More detail on the particularly mathematical approach taken by these companies is given in this dissertation's review of *Expected Utility Theory*.

In contrast, modern *advanced* design methodologies considered in this thesis develop their analytical foundation from physics-based models and other high fidelity codes instead of from large sets of empirical data. This is done out of necessity in advanced design projects as data substantiating the analyses needed do not usually exist. However, many aircraft programs are evolutionary, not revolutionary, and the argument can be made to use past similar data. Still, even with aircraft with a long history of derivatives such as the Boeing 747, the total design count is on the order of a dozen, and certainly less than 100. The law of Large numbers and the risk mitigation methods that leverage it tend to be more applicable to lower-level (and high quantity) aspects of aircraft design and manufacturing. This generally precludes the application of The Law of Large Numbers, where thousands of cases are often needed to obtain sufficient model resolution.

Research Observation II

New aircraft development programs are increasingly challenged by the rise in advanced technology, multidisciplinary complexity growth and implications of program failure. Unlike financial and insurance industries that leverage the Law of Large numbers, the aircraft design and manufacturing business must seek program risk assessment and mitigation methods using small or non-existent empirical data sets.

The second advantage of an insurance business is related to the validity of the first. The regressed premium calculation models have access to a continually updated claims, loss and additional other databases (for example: a driving record in the context of automotive insurance) which is often shared across insurance companies. This allows a rapid reaction time to changes in exposure, situation and environmental effects. This luxury is rarely enjoyed by aircraft manufacturers, where technology, market, and other environmental effects are matched at discordant and delayed rates.

Thirdly, insurance and other financial risk institutions monitor and exchange directly in a small set of units, generally money and time. Risk exposure is calculated and sold over a period. While this shares some similarities to the perspective of the function an aircraft provides over its service life, the aircraft manufacturer is faced with risk across several fronts in addition to money and time. Performance, market and competition risks must be estimated and managed throughout a product development cycle and the conversion between each of the dimensions is specific to the particular exchange of concern. This issue is discussed and presented in greater detail in the form of risk interrelationship matrices.

Businesses place bets, staking everything (including the well-being of their employees, and to an larger extent society) investing considerable sums of money and time, when the outcomes are largely dependent on factors sensitive to random events or variables. So why do some businesses continually succeed as if immune to this risk, and some fail? Part of the answer lies in their ability to correctly manage a risky future, or more precisely, correctly

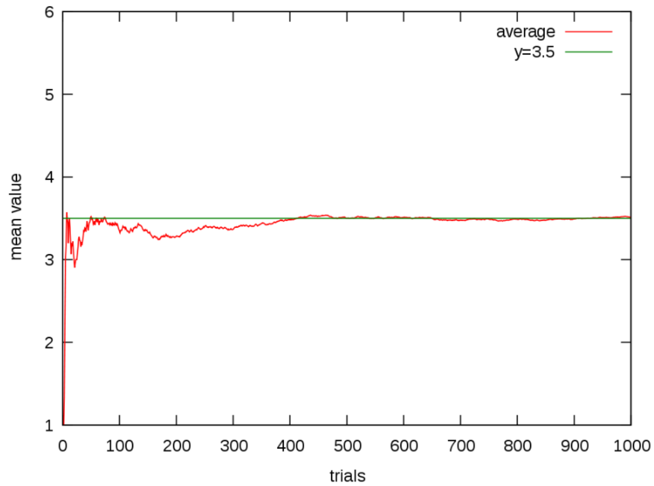


Figure 18: The Law of Large Numbers indicates gradual and certain stabilization towards the mean as the number of samples approaches the net population.

assess and prepare for the possible future states, likelihood and their consequence.

In the project management and financial management communities, a variety of specific methods for assessing investment opportunities are used. In general, the decision methods can be categorized into two groups, organized by fundamental architecture:

1. *Technical Analysis:* those that are empirical and employ rigorous analysis of past data sets, searching for patterns and indicators of likely future states.

2. *Judgmental:* which rely on personal selection of core parameters, and rely on the law of averages to carry the portfolio success.

Indeed, both approaches include elements of the other; judgmental processes emphasize intuition, personal compass and weighting assignment of influential attributes. Technical processes focus only on the mathematical effect of the factors considered and patterns recognized therein, and bear little influence on factors not explicitly and quantitatively defined.

2.3.2 Risk Taxonomy and Trades

Consider an aircraft manufacturer whose CEO is faced with the decision to launch a new aircraft program. Like any other CEO, she must weigh risk versus the potential for gain. From the aircraft sales strategy, the supply network, the marketing forecasting, the technology investments, the international political lobbying, the partnerships, alliances, and the development of the product itself, the concept of developing a strategy and executing it is performed in a risk versus reward mindset. Risk management processes are fundamental to design activities. This thesis will stay within the realm of the latter, focusing on the product development/definition and more specifically the preliminary design of aircraft as a central bet-placing environment.

The goal of any product development program is essentially the same: produce a product or service that sustains a profit or value beyond which it took to build. This is no different for commercial transport aircraft; like any other product, they must be economically viable, competitive, revenue-generating endeavors. The fact of life is that there are clearly certain aircraft that fail, and others that succeed. The causes of failure to meet objectives are diverse and program-specific, but they generally fall into one of the following 6 categories:

Program Level

1. *Performance* - ability to meet the technical performance objectives
2. *Cost* - ability to meet the cost objectives
3. *Schedule* - ability to meet deadlines and pre-determined milestones

Enterprise Level

4. *Time* - The balance between long-term and short-term enterprise level objectives
5. *Market* - The ability to meet the voice of the customer and realize sales targets
6. *Competition* – The ability to maintain market share or competitive edge

These categories for failure to meet objectives outline a multidimensional space in which the aircraft program must manage consistently during the program. Based on the previously described definition of risk (that risk is the effect of uncertainty on target objectives), these 6 categories translate directly into Performance Risk, Cost Risk, Schedule Risk, Time Risk, Market Risk and Competitive Risk.

Not all are at the forefront of concern during each phase life cycle of the aircraft or at each level of the design hierarchy. For example, the development group in charge of the landing gear may bear no competitive risk because they do not compete externally to the aircraft manufacturer. Browning states that:

> Without a systems view, however, many risk management actions serve only to push schedule risk into another category – such as cost or performance risk – rather than truly reducing overall risk [17].

This overarching perspective of system-level risk can be represented in a Risk Interrelationship Matrix (RIM) to demonstrate the risk trade space between the six previously identified high level dimensions. A notional example is given under each block of risk exchange in Figure 19.

		PROGRAMMATIC			ENTERPRISE		
	Defined	**Performance**	**Cost**	**Schedule**	**Time**	**Market**	**Competition**
Performance	*Ability to meet target efficiency, etc*		When a prototype component is under target efficiency, higher cost materials may be selected to help meet performance target	Under-efficient components require redesign or re-supply, increasing schedule risk	Rushed tech. insertion in order to meet performance targets can increase the risk of being leap-fogged by a competitor who develops the tech more carefully	The more aggressive the performance target, the lower the market risk. Inversely, the lower the performance target, the higher the market risk.	The higher the performance targets, the lower the competitive risk, given that the target exceeds the competitor's offerings (or their performance targets)
Cost	*Ability to meet target unit cost or program cost*			Time is money. Cash can be allocated to accelerate lagging critical-path projects or penalties can be assessed by late product delivery	Investing aggressively in the short term may delay break-even point.	If the cost risk is too high, the market risk increases as the profit margin narrows.	Increased cost risk can decrease the competitive edge. Also, selecting lower cost (risk sharing) partners may increase long term competitive risk
Schedule	*Ability to meet target delivery date*				Consistently late deliverables can hurt long term sales and global reputation	If the product is too late in the market, there is increased risk that the developed capacity will either not meet or exceed market need	Late deliverables increases the risk that a competitor will react and win market share
Time	*Balancing long-term and short term exposure*		(the lower triangle is intentionally left blank. No directional relationship is meant by this arrangement)			Short term investments can better handle changing markets, but not enough long term investments can erode or prevent stable market share	Seeking too many short term rewards can cause a competitive disadvantage when some cutting-edge technologies require long term development
Market	*Ability to meet market need*						High volatility markets can pose competitive risk for larger companies who are not as agile as smaller and more adaptable enterprises
Competition	*Ability to compete & prevent market entry*						

Figure 19: Risk Interrelationship Matrix demonstrating trades between program and enterprise level risks.

What is critically important is that these risk areas are interrelated: time is money (Schedule versus Cost), Market is related to competition, etc. Inherently, the decisions made during the course of the development program make trades within this space so as to minimize the exposure to the failure modes. The risk interrelationship matrix provides a complete view of these relationships. This perspective is appropriate for defining the program strategy and weighing the high-level preferences and aversion to risks. Figure 20 shows the the relationship between the c*ost impact* per decision made and the time at which the decision is made. It also describes notional aircraft product milestones and regions specific to design-to-cost and manufacturing-to-cost activities.

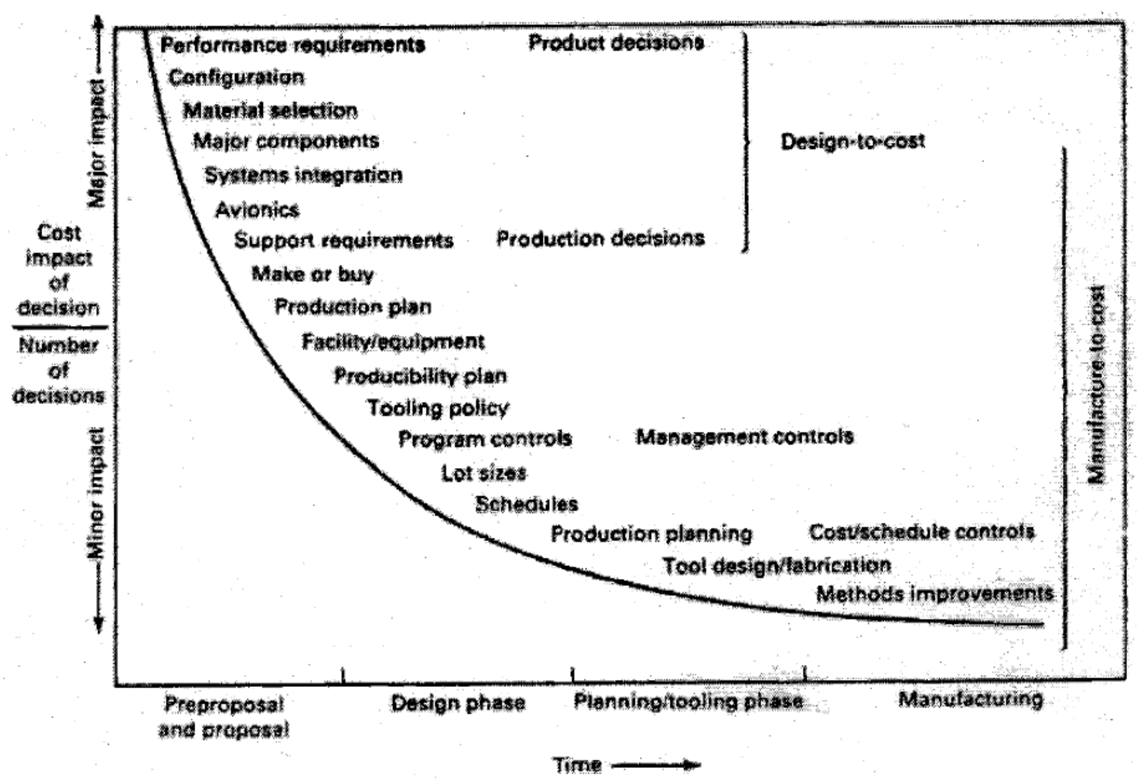


Figure 20: Cost impact per decision during product development, with relative milestones and design-to-cost and manufacture-to-cost considerations [31].

For example, it has been well documented that the risk-sharing strategy of Boeing's 787 program with its supply partners is an effort to reduce the cost risk of the program by distributing its advanced design and composite manufacturing to foreign suppliers (notably Japan) [104]. This in turn presents an exchange of cost-risk with both competitive and time risk, as the distribution of traditional core-competencies of Boeing to first and second tier suppliers potentially enables them to compete as an airframe manufacturer or supplier to their existing competition [113, 37].

2.3.3 Handling of Uncertainty with Safety Factors

The use of safety factors has been the traditional approach to designing for the uncertainty in the load experienced by systems. Safety factors are most often employed in directly measurable load-bearing systems, such as aerodynamic loads (structural load such as wing or fuselage design), or aircraft electrical loads (power and thermal load management). The safety factor approach is a practical and rudimentary approach that captures the cumulative uncertainty in the system, accounting for factors such as the future vehicle loads experienced by the structure, errors in the load and stress calculation, accumulated structural damage, and variation in material properties and standards. Safety factors also mitigate potential errors or quality issues arising from manufacturing variance. This functional approach is historically successful at capturing risk where margin is allowed for the known unknowns and a degree of unknown unknowns. There are two categorized approaches to handling the uncertainty in design with safety factors:

Explicit: The safety factor is 1.5 times the maximum design load.

Implicit: Design decisions, at every scale, are made conservatively, with the implication that the system on the whole will exhibit tolerance to states exceeding original design specification.

There exist difficulties with each approach. The explicit safety factor approach, while precisely defined, leaves little or no room to adjust for particularities of subsystem interactions and is often therefore over designed (excessively expensive, heavy or powerful). The implicit approach, however allows the safety factor to be distributed as needed, yet suffers from imprecise and unknown metrics and a lack of a formalized method.

2.4 Chapter Summary

In this chapter, an overview of the concepts, definitions, and perspectives of risk and uncertainty is presented. Of the many definitions reviewed across industries, the definition of risk as the *effect of uncertainty on objectives* was selected as the most relevant and pertinent. The concept of the objective is later exploited to assign a reference point on the value function of system responses.

A distinction between financial risk-transferring (insurance) industries and aircraft developers is argued: the majority of financial methods of risk assessment leverage the Law of Large Numbers to develop precise risk exposure estimations. This information is typically unavailable to new, technology-driven, competitive aircraft development programs that instead must rely on technical, exploratory forecasting methods for risk analysis.

CHAPTER III

EXPERIMENTAL APPARATUS AND INVESTIGATION

This Chapter evaluates the two experimental apparatuses used to build and test the CASSANDRA methodology. An evaluation of the relationship between experimental run count and risk bounds are also addressed.

The two apparatuses evaluated are as follows:

1. Apparatus 1 - A ModelCenter-based execution and parsing of the lifecycle cost code network. This apparatus was used to first explore the cumulative cashflow space with few samples and few factors of interest as the execution time was relatively lengthy.

2. Apparatus 2 - A high speed queuing, execution, and parsing tool for the lifecycle cost code called BASUCA. This apparatus was used to explore the need for resolution and breadth of contributing factors to the risk measurement and mitigation frontier.

3.1 Initial Investigation of Cumulative Cash Flow Drivers

The MInD study and previous publication by the author [23] of the experimentation concluded with the observation that uncertainty alone provided value to the program manager, but that the conversion of uncertainty into risk required additional mapping onto a utility space. Since then, the author reviewed several candidate approaches and selected the cashflow diagram as a potential aggregate measure of the business case risk of a new aircraft development program.

3.1.1 Selection of the Life Cycle Cost Estimating Code

On the surface, the calculation of cumulative cashflow diagrams alone is simple, however the level of fidelity in the constituent cost estimations must be sufficiently high to develop a worthwhile trade space [121]. For this reason, it was selected to use and existing cost estimation and aggregation code (or software). There were several candidate codes evaluated (such as SEER-MFG, a CLIPS knowledge-based code, or process and activity based cost estimation codes) , but the author selected the code set FLOPS and ALCCA as the core lifecycle cost code for three reasons: 1) it was readily available and open for use in the disseration, 2) the software has been updated continuously over the last twenty-five years and is of acceptable fidelity for commercial transports, and 2) it incorporates the cost estimates directly with aircraft sizing and synthesis processes.

Annual and cumulative cash flows are direct outputs from ALCCA in the form of tables, broken down by RDTE (Research, development, testing and evaluation) costs, manufacturing costs, sustaining costs, and income. This level of resolution was not captured int he MInD study framework on a cash flow basis, so it was decided to use FLOPS and ALCCA directly, instead of within the MInD framework.

3.1.2 Experimental Setup

FLOPS and ALCCA were setup as an independent executable within a ModelCenter code-stitching environment. This was done to facilitate varying the input parameters and capturing the output parameters from the text-based output files. Figure 21 shows the setup of FLOPS and ALCCA from within the ModelCenter environment.

Experimental Apparatus
FLOPS / ALCCA simulations were executed from Model center to capture cumulative cashflow results.

3.1.3 Initial results with the the ModelCenter apparatus

The background documentation on ALCCA [43] indicated that the main drivers of the cost estimation results were learning curves (LC), annual percentage inflation (API) and production quantity.

Therefore, the initial experiment sought to evaluate the resulting uncertainty introduced

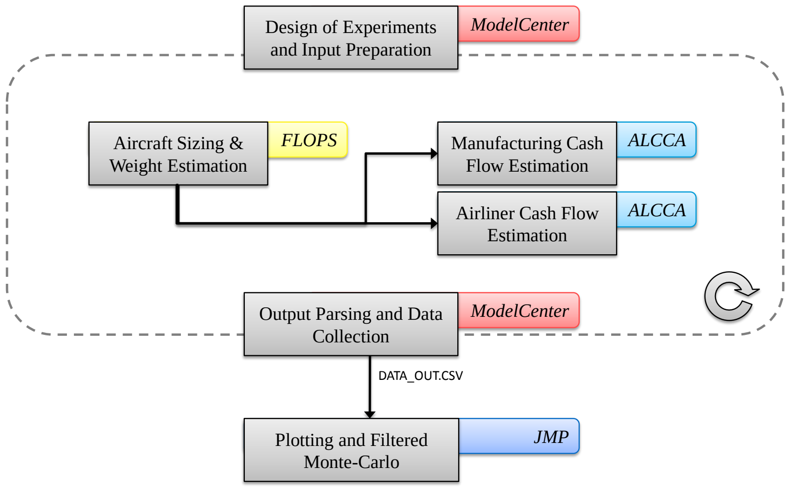


Figure 21: Flowpath of ModelCenter, FLOPS ALCCA, and JMP codes used for cashflow analysis of design alternatives.

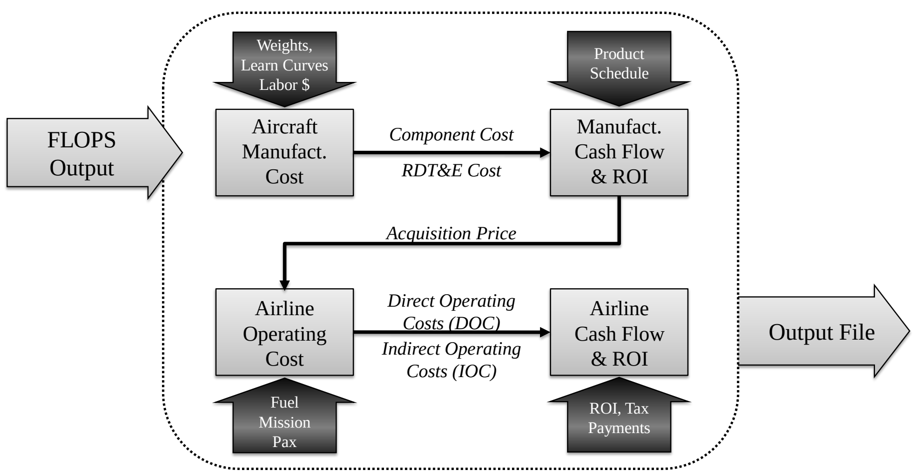


Figure 22: ALCCA modeling methodology illustrating the main modules and examples of their inputs [41].

Table 3: Input variables and their ranges for Experiment 1 of the ModelCenter FLOPS and ALCCA apparatus.

Description	FLOPS Variable	Mean	Minimum	Maximum
Manufacturer's Rate of Return	RTRTN	10	8	12
Learning Curve (Block 1)	LEARN1	80	70	90
Learning Curve (Block 1)	LEARN2	80	70	90
Learning Curve, Assembly (Block 1)	LEARNAS1	80	70	90
Learning Curve, Assembly (Block 1)	LEARNAS2	80	70	90

by varying those parameters as well as a small set of basic design variables. The complete list of variables, and their ranges in this experiment are given in Table 3:

Figure 23 shows a cumulative cash flow of an initial study from the FLOPS and ALCCA Model center example. In this study there were X input variables that were varied according to a design of experiments with n runs. This was done to gain an initial appreciation of the overall scale of the output and magnitude of the impact these input variables caused. It was also to investigate the presupposition about their impact on the cash flow diagram. The study revealed several subtleties about the inputs of the model that were not previously understood, such as the manufacturer's target return on investment and the aircraft price. It was found that FLOPS and ALCCA treat these calculations separately; the code will solve for either the aircraft price required to meet the return on investment, or evaluate several different aircraft pricing strategies and subsequently calculate the return on investment.

For the purposes of this dissertation, the latter approach was found to be most useful. This is because the sales price of the aircraft varies in practice due to market forces and unique negotiations with customers. Secondly, aircraft price is a strategically controlled variable that strongly affects the dynamics of the business case of the manufacturer. It was selected to keep it independent rather than the return on investment.

A few observations should be noted looking at this figure: first is the sheer magnitude of the sunk cost maximum, and the variance in the cumulative cash flow at the end of the program. Of the sunk cost and the peak profitability of the program or in excess of \$200 billion. Figures of these magnitudes were initially unexpected, but it became apparent why

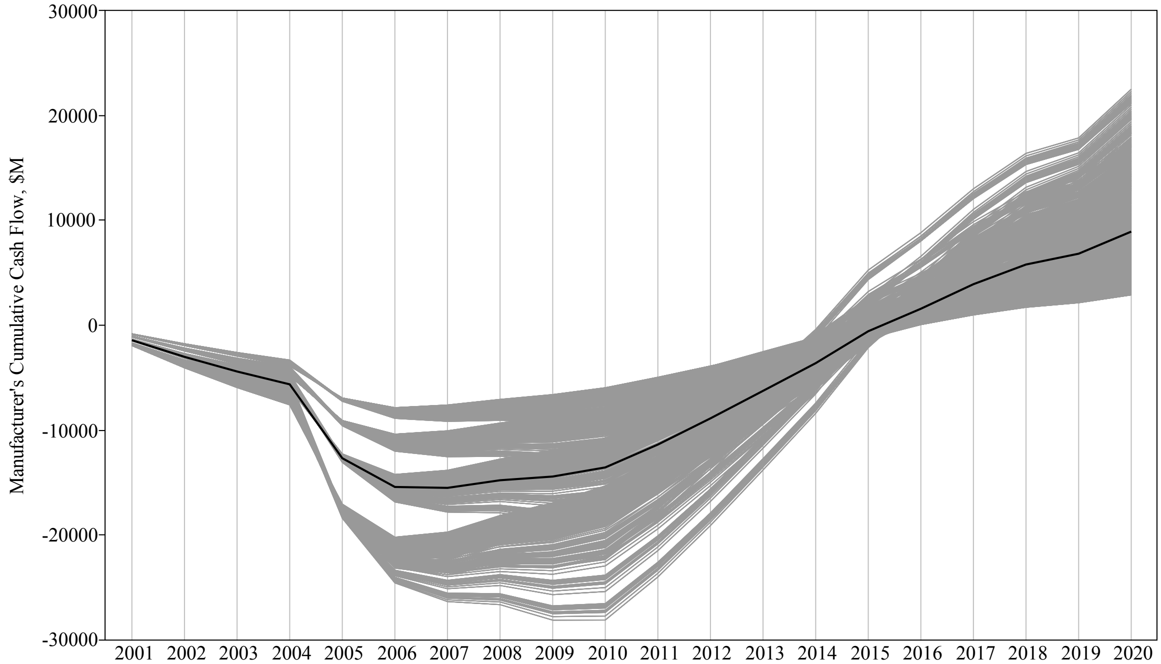


Figure 23: Manufacturer's cumulative cashflow from FLOPS/ALCCA output, showing all cases from the design of experiment.

they reached such heights when filtering the results by inflation rate.

Figure 24 shows the same data colored by inflation rate and it shows the effect of vertically stretching the cumulative cashflow results. Near break even (when the cumulative cashflow reaches zero), the variance in the overall set of cash flows is very tight relative to the rest of the plots. This is because the inflation stretching factor decreases linearly towards zero as the program reached break-even.

3.1.4 Statistical Methods and Prediction from Sparse Data Sets

Following the observation from the previous Chapter regarding the applicability of the *Law of Large Numbers* to aircraft design problems, it is of utility to provide a brief overview of the statistical methods available for small data sets. Fundamentally, the challenges of small data sets is that the sample of available data provides an unclear view of the underlying drivers for variance. Data may be missing and it becomes difficult to assume how the missing data may affect the conclusions drawn from the sparse set. Little states that *a common concern when faced with multivariate data with missing values is whether the missing data*

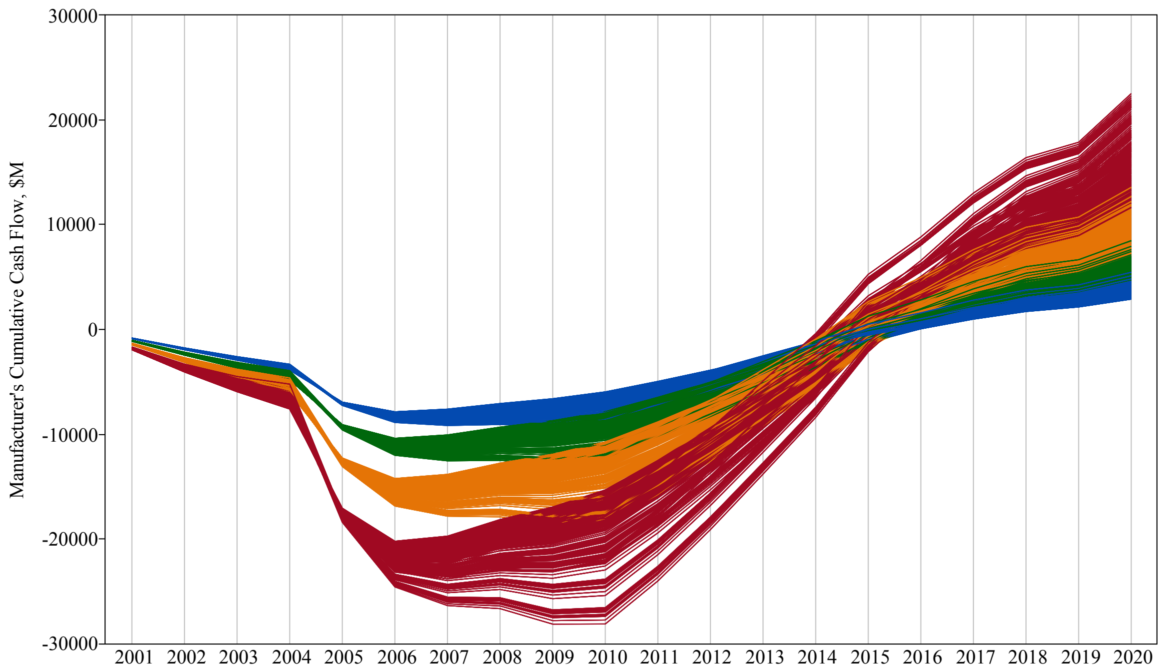


Figure 24: Manufacturer's cumulative cashflow grouping based on average inflation rate throughout the program. Red indicates an inflation rate of 12 percent, blue a rate of 4 percent .

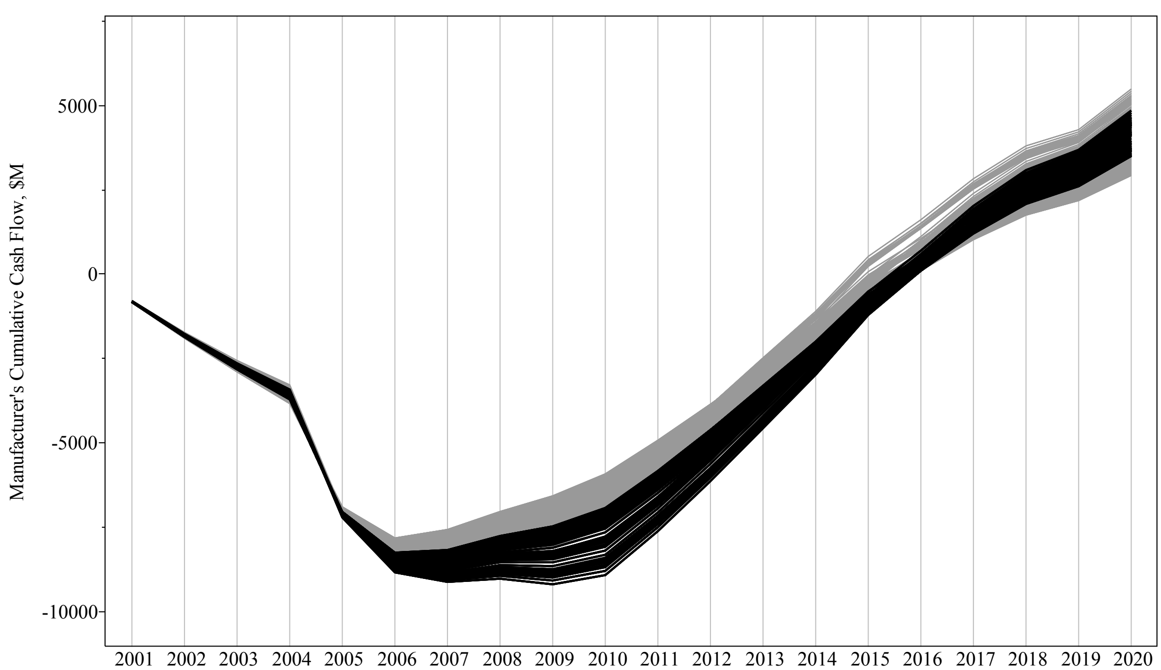


Figure 25: Manufacturer's cumulative cashflow from FLOPS/ALCCA output, for a single inflation rate, showing the effect of split learning rates .

are missing completely at random (MCAR); that is, whether missingness *depends on the variables in the data set* [74]. Anscombe gives an example of the errors possible from summary statistics, showing graphs from four sets of data with identical summary statistics in Figure 26 [2].

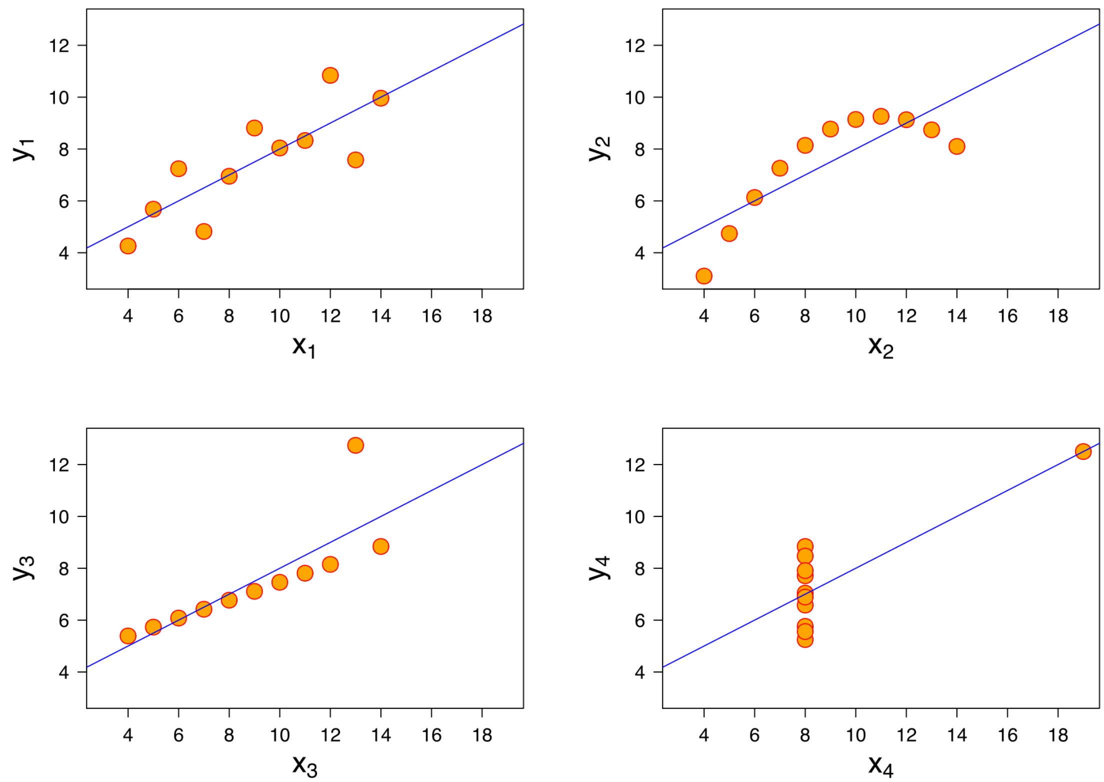


Figure 26: Each of the above data sets exhibit identical summary statistics, showing the importance of graphing results when dealing with sparse or missing data [2].

Here, it is evident that the summary statistics alone do not provide a complete picture of the underlying population. Or, if indeed the statistical summary is valid, there appears to be a substantial segment of data missing. In many circumstances, an aircraft design decision involving new materials, processes, and technologies has never been done before (at least not under the particular circumstances and conditions) and the data with which to build an empirical model is either sparse or nonexistent. The typical solution to addressing the lack or sparse data is to develop regression models, as detailed in the next section.

3.1.5 Creating Models for Cumulative Cashflow Uncertainty

The need for creating a surrogate model for the cumulative cashflow diagrams arose from a desire by the author to explore uncertain cumulative cash flows instantaneously, thus enabling parametrized exploration of the business case space without having to execute the experiment repeatedly. This additional understanding and clarity can be developed using models. This approach was taken in developing the knowledge-based framework by Marx in 1996 [81].

There are two approaches evaluated in this thesis; the direct and the indirect. In the direct approach, the simulation results are analyzed with statistical analysis software such as JMP or MINItab. These are referred to as direct in this thesis because the uncertainty is represented by statistical metrics that are directly measured from the data, and nothing else. Metrics such as the moments of the data set (mean, variance, skew and kurtosis), as well as the quantiles from the cumulative distribution function can be used to describe the resultant uncertainty.

The first approach is to model the statistical moments of the distributions in cash flows by year. There were three indirect approaches considered in developing models for the year-wise uncertainty, and they are listed below:

1. **Neural Networks** - Originally considered to be the most suitable approach, Neural networks offer a great deal of capability in addressing non-linear effects found in review of uncertain cumulative cash flows, yet must be trained and can introduce spurious side effects.

2. **Year-wise fitment of continuous distributions** - This approach applies a continuous distribution that is regressed in by the Least Squares Method. A variety of models can be tested, but they should generally be applied on a year-wise basis for uncertain cumulative cash flows.

3. **Response surface methodology** - Using a second order RSE approach is better suited for smoother surfaces with less compound curvatures. The cumulative cashflow model generally has two inflection points (one positive one at the maximum sunk cost

point, and one negative one after break-even is reach and production rate begins to decline), therefore it was considered to be less suitable than other approaches. An alternate approach would be to use RSM on a year-wise basis, but this approach is much more complicated and less effective than year-wise continuous distribution.

Neural networks were found to have generally acceptable fit when modeled for the cashflow means, but not the associated surrounding uncertainty. Moreover, the effects of technology and scenario factors were evident on the cashflow curve, but they did not predict the uncertainty in those effects nearly as well. The R-Squared parameter for the means occasionally was 0.9 or better for the means, but rarely was it better than 0.4 for the associated uncertainty.

Figure 27 gives an example of the model fit and associated drivers from the initial results.

The second approach is to introduce an additional modeling layer to represent the continuous probability density function underlying the simulation results. This allows the knowledge of the relationship between the design resulting uncertainty to be estimated with a single function. When analytical continuous distribution functions (like the Normal or Weibull) are fit to the data, that knowledge may be called upon without executing new simulations and in any of the density function moments.

Table 4: Comparison of the available continuous distribution surrogate models in JMP and their applicability for modeling uncertain cashflows.

Distribution	Number of Parameters	Suitability for Cash flows
Normal	2	Poor, no asymmetry
Normal 2 Mixture	5	Fair, requires dispersion
Normal 3 Mixture	8	Good, but too many parameters
Johnson Su	4	Excellent, both fit and bounds
Johnson SI	3	Good but under-damped
Beta	4	Fair, too thin in tails, thick elsewhere
Weibull	3	Fair, requires threshold term

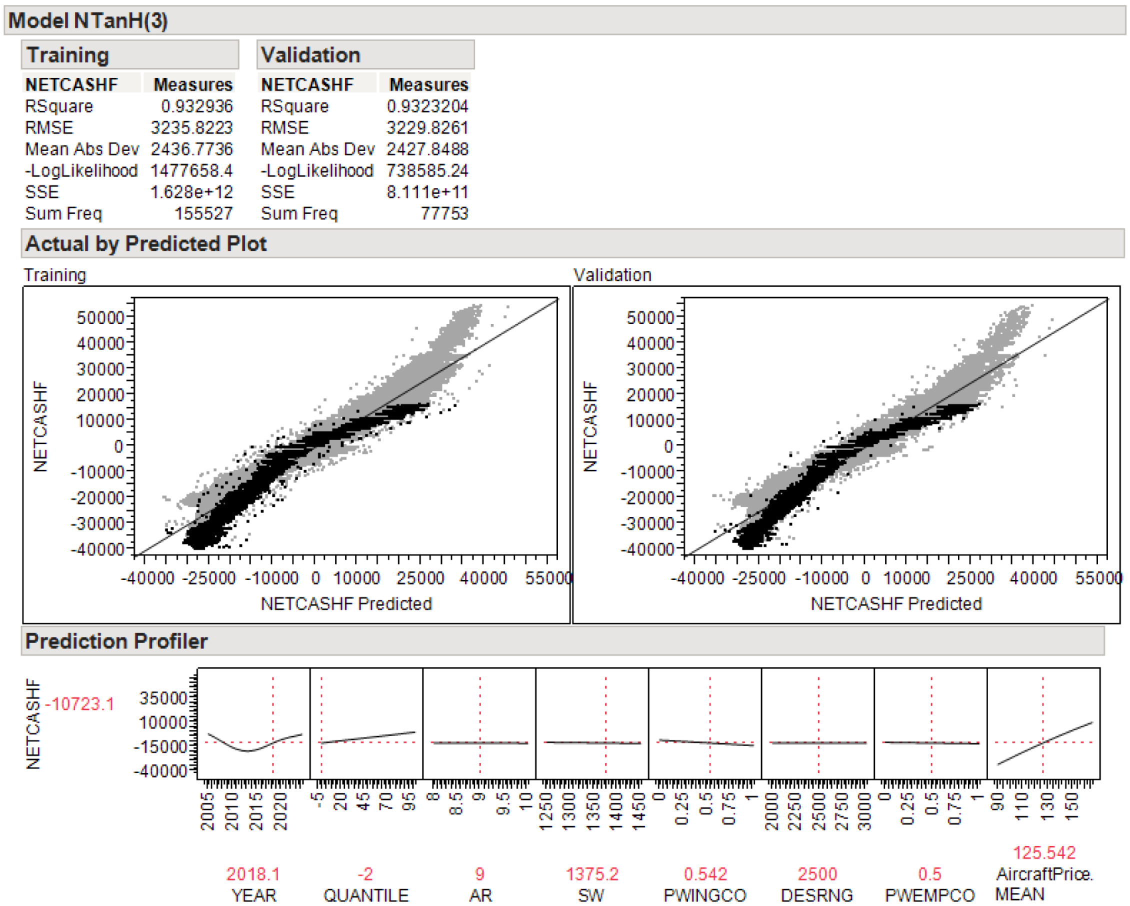


Figure 27: Neural network model demonstrating fit for an uncertain cumulative cashflow. Shown here is the fit for the Net Cash Flow Mean.

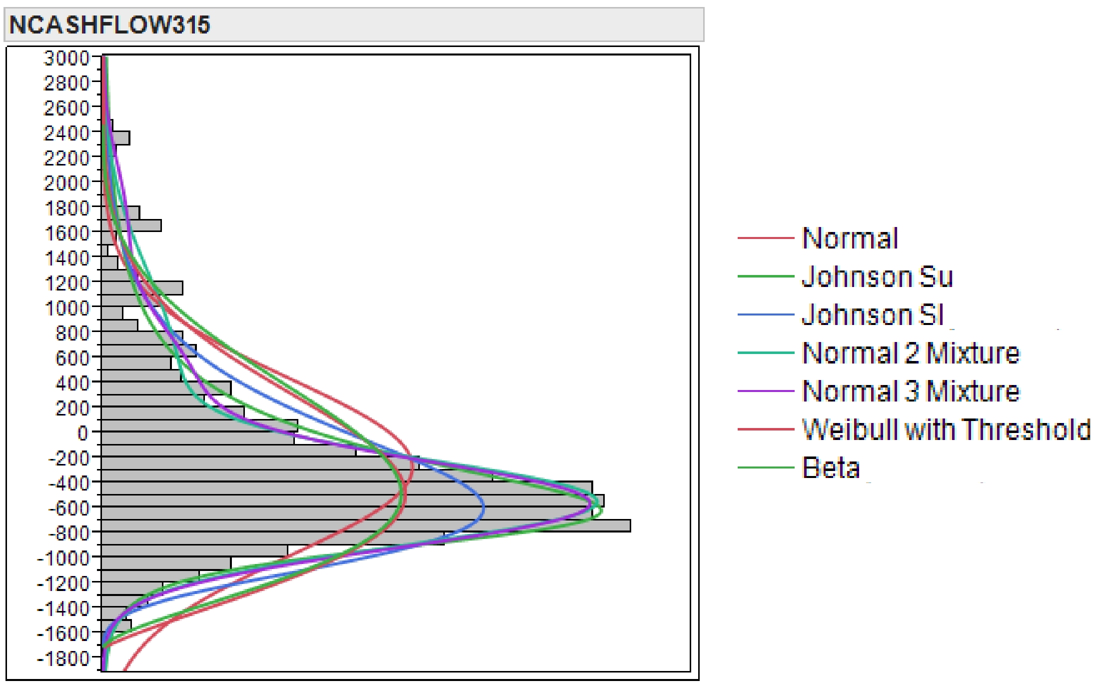


Figure 28: Comparison of the different fits reviewed of continuous distributions to typical cumulative cashflow probability distribution function, (in this case year 15 of the program).

3.1.6 Formulation of the Cost Estimating Relationships in ALCCA

FLOPS and ALCCA use cost estimating relationships for the most of the constituent cost breakdown structure. These are calculated on a per-component basis [42], and then summed appropriately based on the cost structure. The n component cost estimating relationships (CERs) are given generally as:

$$Cost(x_1, x_2)_{n,estimated} = Ax_1^{B_n} * x_2^{C_n} \tag{11}$$

where A,B,and C are solutions from a linear regression of the component cost against empirical data. The x_1 and x_2 variables are traditionally weight-based cost predictors. In this dissertation based on FLOPS and ALCCA output, the B and C regression coefficients are denoted as complexity and efficiency factors. Using weights as the independent variables have traditionally been the best available predictors for aluminum aircraft structures. Aircraft manufacturers have thus become keenly aware of the relationship between weight of the aircraft structure and the business case and economic viability of the aircraft program. Several manufacturers have even reportedly offered cash bonuses to engineers as a function of the pounds of weight saved from an engineering or system configuration improvement [64].

However, the emergence of new composite materials has challenged the historical validity of the weight-based estimator. These materials tend to be both lighter and more expensive (in raw material and tooling costs). Therefore, the traditional CER model form relationship has suffered poorer fit error as composites become a more prevalent structural material. The MInD study was launched in part because of this observation.

Experimental Result

Cumulative cashflows indeed provide an aggregated wealth of programmatic insight, showing wild swings as a function of scenario and design variables.

3.1.7 Dimensionality, Risk and the Need for Speed

The CASSANDRA methodology, like other uncertainty propagation approaches, is based around exhaustive sampling of a multidisciplinary sizing and cost estimation code. For the selected design problem with dozens of control and noise variables, thousands of executions of the design code are necessary for basic risk analysis and millions of executions are desired. This leads to the observation that a key challenge in this thesis is therefore to establish a balance between analytical fidelity and computational speed. This issue has been addressed in various ways and in multiple publications and theses, and is covered in great detail by Stults in 2009 [121]. His work focused on the selection of appropriate modeling fidelity in the context of the problem being solved under finite available resources. His approach included a methodology for unifying the level of uncertainty expressed in the system in order to achieve minimized computational time. This is a characteristic inherent to the baseline problem of aircraft design, as the multidisciplinary nature forces the number of factors required for holistic analysis.

3.1.8 Exhaustive Nature of Risk Analyses

As with almost any analysis, the adage of *garbage in, garbage out* applies with risk analyses as well. In most analyses though, this applies in two ways: primarily to the quality of the data and model/analysis structure, and secondarily to the number of analyses performed. The probabilistic nature of risk analyses suggests that the number of simulations or cases evaluated plays a larger role. To illustrate this with an analogy, consider again the thought experiment of asking the question, *Is it warm outside?* The quality of the data from a single temperature and humidity measurement will likely matter more than how many of those measurements were made outside. The temperature is not likely to vary with position, direction, or within the near future. Now consider the question, *Is it safe outside?* In this case, the associated measurements of safety are exhaustive in nature. Safety, or danger, would need to be measured in all directions, or along an entire perimeter. A small breach in a perimeter may be enough for safety to be compromised, and so the analysis measures at a resolution finer than the smallest expected danger.

This effect is recognized in many standardized risk analysis approaches, typically in steps such as Enumerate the Risk Factors / Danger Modes. The weakness of these approaches is that they rely on the analyst to identify all of the adverse states. In a deterministic or discretized space this is possible; but in an aleatory, continuous space (such as the real world), this is essentially impossible. Guassian approaches are often satisfied with the 95 percent solution, however the highly unlikely can have great impact. This notion was studied at great length by Nassim Taleb [123] in *The Black Swan*. In his research, he illustrated several examples where the most improbable events caused dramatic shifts in systems *not bounded by gravity* such as markets, ideas, monetary value, policy, sales volume, etc.

There is also little to suggest that safety is stable over the near future, as threats could appear suddenly. The system has no mass or momentum effect, as in the case of temperature and humidity. Thus the combinatorial aspect of the problem is also introduced: if safety is measured to be true in all directions, does it hold true over time? As more and more dimensions are included in the analysis, the number of runs required to reach the same statistical clarity increases exponentially (see equation 57 for a two-level experiment). Therefore, the quality of a risk analysis is typically more dependent on the exhaustive nature of exploring possibilities than the quality of a single measurement. In the probabilistic domain, this results in a high number of simulations as the bulk addresses both resolution and the combinatorial aspects of the problem.

In the case of financial (or cashflow) risk analysis of aircraft programs, the problem resembles that of *Is it safe outside?*, rather than *Is it warm outside?*. The main reason for this is that the danger from a cashflow perspective may come from any number of variables or settings and cause sudden economic infeasibility states. This fragility is analogous to the dimensional problem of safety in which all directions, at all times, must be measured.

Appendix A addresses this exhaustive risk simulation and risk factor dimensionality by examining the growth of the boundary extrema as a function of the number of simulations. Here it the width of the simulation maximum and minimum grows by approximately 1-σ with every additional order of magnitude of simulation trials.

New Research Observation III

Execution time in ModelCenter was slow and limited the number and resolution of factors in the uncertainty analysis.

This examines the effect of boundary analysis and the likely effect of risk resolution under the central limit theorem. For the purpose of the CASSANDRA methodology, it is also worthwhile to examine how many executions are needed to resolve the same design and strategy mitigation results? This subsequent question leads to the following Research Question:

Research Question IV

How many executions are enough to propagate the uncertainty to the cumulative cash flow space and draw the same design conclusions?

To answer this question, a high-speed apparatus was developed so that this question could be explored without experimental constraints.

3.2 Development of the High-Speed Apparatus

As described in the previous section, it was observed that tens of thousands if not hundreds of thousands of executions were possibly required to capture multi-dimensional risk analysis problems in sufficient detail to draw design conclusions. This causes the total experimental time to be unacceptably large for slow experiments, reaching tens of several hours or possibly days per experiment. The new experimental apparatus could improve the speed concern by an order of magnitude, and thus enable key trades arising from the fidelity and capability of multi-disciplinary risk analysis.

With this in mind, the author considered several approaches to solving the speed and fidelity issue:

1. **Develop an additional surrogate model layer around the FLOPS/ALCCA Environment.** This solves the speed problem easily as response surface equations and neural networks enable near-instantaneous rates; however the additional layer of modeling may introduce artifacts and force the user to make even more assumptions regarding the drivers for risk and uncertainty. The FLOPS and ALCCA cost models are already a layer of modeling which introduce loss of fidelity, as they are developed from empirical data from heterogeneous sources.

2. **Develop a queuing, executing, and parsing tool that could leverage advancements in multi-core processors.** This approach suffers no loss of fidelity from the FLOPS and ALCCA outputs, yet it may not be able to accelerate the analyses sufficiently as it was initially unclear how much of the execution time was processor-based, software-based, and read+write-based.

3. **Execute experiments over a distributed or cloud-computing. environment** This approach also suffers no loss of fidelity from the FLOPS and ALCCA cost models, and the execution time for the analyses increases with the number of computers available. However, the setup and reliability, and availability of a distributed network may prove to be challenging.

4. **Develop an all-new cost model (process or activity-based).** This alternative was considered as well since it has been done previously by Marx [81], Lee [72], Madachy [76] and many others studying cost model research. However the resulting speed is not necessarily guaranteed, and the fidelity of the resulting models, the availability of cost information and the programming time needed to be taken into consideration.

In order to select which apparatus would be used to capture the program economics, the following criteria were identified and are given in order of importance to the CASSANDRA methodology:

1. **Fidelity**: The cash flow model must be at an industry-accepted level of cost estimation fidelity and incorporate aircraft design trades, technology trades, scenario trades. Additionally, the risk sensitivities to fidelity are preferred to be taken as late as possible, if at all in the methodology. This gives less opportunity for spurious artifacts to enter the decision space.

2. **Speed**: As argued previously, the speed is directly proportional to the fidelity given a fixed experimental period.

3. **Availability of experimentation**: Due to the iterative nature of the methodology, it is preferred that the apparatus be as available as possible to the author.

4. **Ease of setup**: While ease was the least of the concerns to the author for the methodology development, programming experience and software development were also considered in the apparatus decision.

From the above concerns to the author, it was clear that Approaches 1 and 4 were to be eliminated. The fidelity issue is a principle concern to risk analyses and an additional modeling layer may mask those effects. For Approach 4, the ground-up development of a new cost model suffers from fidelity issues as well due to the availability of cost data. It should be noted that SEER-MFG, the industry approved cost and labor estimation tool used in the MInD project, was considered as a source of information for Approach 4. However, this tool provides excellent detailed cost information for part and assembly manufacturing, and much less detailed information on non-structure-related costs that are present and substantial in aircraft development (such as avionics, programming, and research and development).

This leaves approaches 2 and 3: the development of a queuing, executing, and parsing tool or evaluating the experiments in a distributed or cloud computing environment. In considering approach three, the reliability and availability of a distributed network was a major concern. The author looked into several approaches for doing this, such as acquiring a cloud computing account with a large Internet cloud computing retailer; but, it was found to be unnecessarily complicated and expensive. The other alternatives were distributed computing over the Aerospace Systems Design Laboratory (ASDL) computing network, or on a clustered array. The availability of this network and computing array was found to be unsatisfactory to the author, as it imposed experimental setup constraints and scheduling difficulties with other researchers.

In evaluating Approach 2, it was necessary to review how much improvement could be achieved using multiple core processing. As mentioned above it was unclear how much execution time was devoted during the FLOPS and ALCCA cycle towards core processing, hard drive access, and software constraints within ModelCenter.

Hypothesis

Queuing, executing and parsing FLOPS / ALCCA data would be substantially faster on a stand-alone software that enables multiple CPU core technology.

A single execution of FLOPS / ALCCA from within ModelCenter was metered using performance measuring software in Windows. The results are plotted and shown in Figure 29 and demonstrate the excessive time spent not operating FLOPS.exe. The hard drive read and write time was negligible, yet the ModelCenter time was substantial. There was also an unexpected segment of time where nothing was happening. It was discovered that ModelCenter was waiting for read+write access from the input and output files. It was later found that FLOPS.exe requires that the input and output files be locked during a single execution. This process slows down the batch execution because ModelCenter must wait for FLOPS.exe to release the files.

After observing these CPU effects and their relation to time management of ModelCenter, it became clear that there were gains to be had by writing a customized multi-core batch software. Before committing to writing about software, further investigation was done in how Model Center could be adapted to use multiple cores. Certain versions of ModelCenter are multi-core enabled, however when this feature was activated there were marginal to no

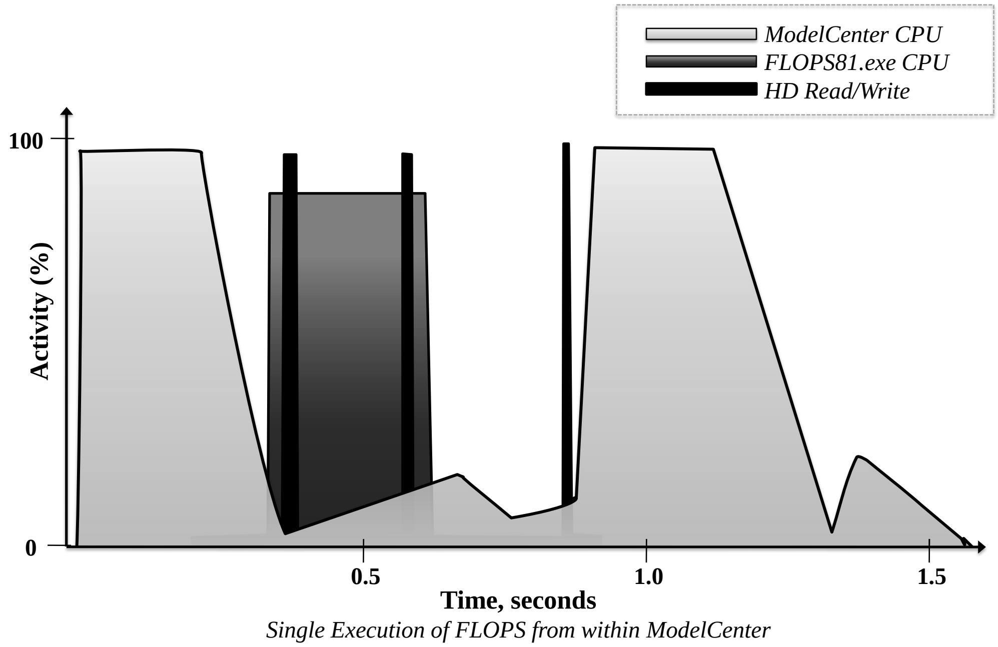


Figure 29: Activity log for a single execution of FLOPS / ALCCA from within ModelCenter, showing the hard drive read+write access, FLOPS.exe and ModelCenter process loads.

gains observed. This is potentially due to the fact that Flops.exe was preventing read or write to the input and output files.

With these considerations in mind the Batch Accelerated Sequencer of Uncertain Cash Flow Alternatives was written in C++ to accelerate parsing execution, and queuing of FLOPS and ALCCA.

3.2.1 FLOPS/ALCCA accelerated sequencer and parsing method

The batch accelerated sequencer uncertain cash flow alternatives, or BASUCA was written to automate and sequence the vertical simulations of sizing synthesis and cost estimation tool. It was found that running these cost and sizing tools in an integrated environment (such as Model Center) the total execution time was approximately 0.5 to 1.5 seconds per execution. This included the preparation of the input file and parsing of the output file.

Table 5: Improvement to FLOPS/ALCCA execution rate by the BASUCA queuing/executing/parsing code which leverages multi-core processing of experiments.

Metric	Model Center	BASUCA	Change
Straight executions per second (eps)	1.25	150	120X
Converged executions per second	0.5	55	110X
Time to 1 million runs	277 hours (11 days)	2hr 15min	120X

Experimental Apparatus

BASUCA (Batch Accelerated Sequencing of Uncertain Cashflow Analyses) was written in C++ to reduce the total experimental time by accelerating the preparation, execution, and parsing of data.

BASUCA was coded in C++ by Karl Janus, using modern libraries that enable and make the most use of multiple core processors available and most computers today. The software also addresses the problematic file lock on the input and output files. It achieves this by creating all of the input files for the entire experiment before executing a single instance of FLOPS. It also creates copies of all of the supporting files needed for each execution, such as the engine deck. Then, BASUCA is able to queue jobs (whether executing flops, or parsing output files) for all of the processor cores such that no core remains idle during the experiment. This approach proved to be successful in reducing the overall experimental run time. It was found that on certain computers, typically with more recent processors, BASUCA was able to reduce the run time to approximately 100th of a second. A table of results is given in Table 5 comparing the execution speed (for both converged solutions in FLOPS / ALCCA and straight through), showing the approximate 2 orders of magnitude improvement.

Experimental Result

One to ten orders of magnitude reduction in total execution time, enabling exhaustive analysis of candidate factors and their contribution to the uncertain cumulative cashflow.

Note that there was a slight decrease in the factor of improvement when converged cases of FLOPS were executed instead of straight-through cases. This reduction in benefit of BASUCA over ModelCenter is likely due to the fact that in the converged cases the duration of FLOPS.exe is longer in proportion to the total execution time because of the time devoted towards converging the cruise fuel segment. As BASUCA increases the efficiency of execution by minimizing waste CPU idle time, this effect was not unexpected.

Similar to the Taguchi method of using an *inner* and an *outer* array within a design of experiments for quality improvement, BASUCA allows inputs in the form of two separate comma separated value (CSV) spreadsheets: a control file and a noise file. This input format that allows for independent runs over a set of designs within the control space, where each of the designs are exposed to the possible instances described by the noise set. This same approach was used in the MInD study. The goal is to analyze the design-specific reaction to the set of possible future instances (given as distributions of variables out of the user's control).

This inner and outer array format is flexible for screening tests as well as uncertainty analysis. When no noise states are identified, BASUCA functions as simply a batch queuing tool, and can execute screening tests with many control variables. Similarly, reverse noise and control experiments can be executed to observe what impact the control space has when the noise space becomes the independent set.

To further facilitate the uncertainty analysis, BASUCA calculates statistics from the noise set on each of the outputs, for each of the control runs. The statistics include the four fundamental statistical moments of sets: mean, variance, kurtosis, and skew. BASUCA also calculates the values at a given set of quantiles in the cumulative distribution function.

Typically, the author specified 0^{th}, 5^{th}, 95^{th} and 100^{th} quantiles. These statistical results are given in the output file which is arranged by row for the control runs, and by column for the parsed outputs and their statistical results. This process is shown in Figure 30.

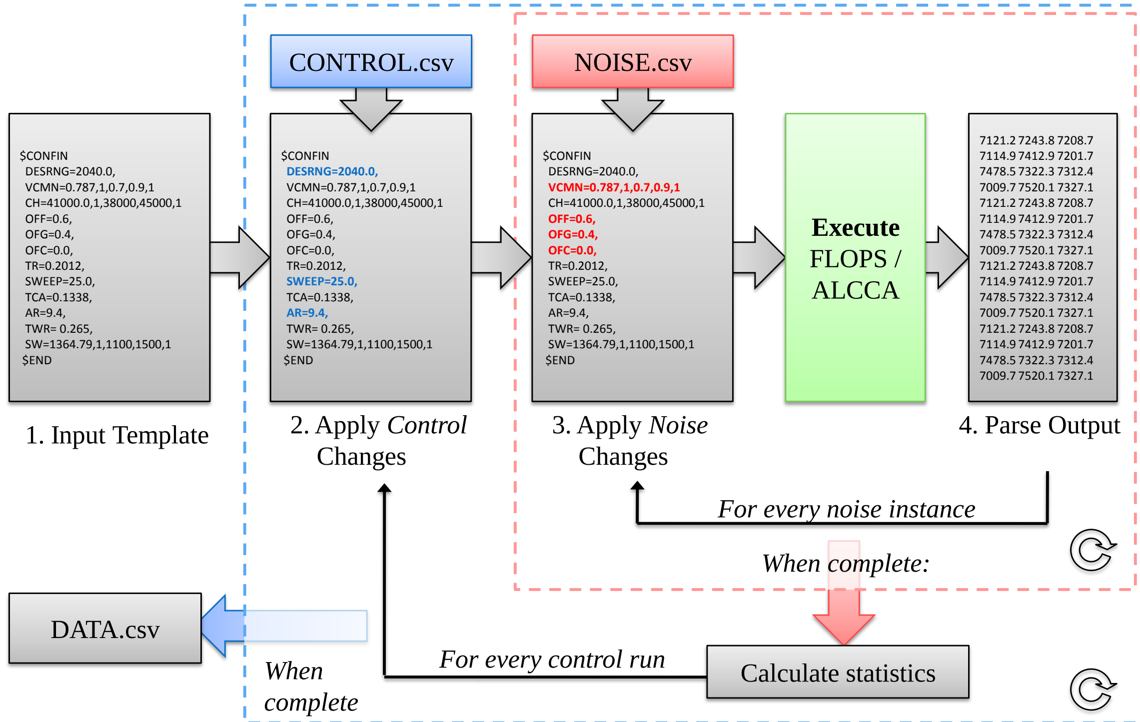


Figure 30: Process flowchart of BASUCA showing the application of control and noise parameter changes to the template. Note that statistics on the total noise set is calculated *per control run* as the method used for evaluating design-specific risk.

3.2.2 Results with the BASUCA apparatus

After verifying that the BASUCA apparatus was functioning properly, the first step in addressing the cash flow risk problem with BASUCA was to identify the factors most likely to affect the cash flow in greater detail than before. Recall that it was hypothesized that there may be a substantial number of variables that affect the risk of the aircraft program. With BASUCA, thorough exploration of these variables is now possible. This was done by a large screening test similar to other experimental methodologies with large degrees of freedom.

3.2.2.1 *Effect of Aircraft Price on Cashflow Uncertainty*

ALCCA computes cumulative cashflows two separate ways and both approaches are evaluated in the CASSANDRA methodology. The aircraft price, the return on investment are co-dependent variables; one may fix one and solve for the other. The following bullets segment the rationale behind each pricing and return-on-investment approach.

- **Price fixed, solve for ROI** - in this approach, ALCCA takes a target aircraft price and computes the return on investment over a input production quantity. This approach is useful when the market is extremely price sensitive and known a priori.

- **ROI fixed, solve for Price** - This approach actually computes the ROI for 5 different aircraft prices, then linearly interpolates to solve for the price that meets the target ROI. This approach is useful when considering that the manufacturer has a fixed internal rate of return that must be guaranteed by its creditors.

This dissertation takes a neutral perspective to price versus ROI fixation. This is because the reality of pricing and sales of aircraft exhibits the fixation of neither specifically [66], rather that the price of the aircraft is driven by the market and what the customer is willing to pay. Forces such as private negotiations, governmental and manufacturing agreements, order size and program maturity affect the actual sales prices substantially [48] [125].

Similarly, the manufacturer's return on investment is not held constant. They may enjoy handsome return on investment when the products continue to sell past their accounting life or when the demand exceeds supply, typically from lengthy competitive advantage [4].

The approach taken in this thesis then is to consider both simultaneously. The execution of ALCCA occurred in the second approach where a Desired ROI was specified; then five candidate aircraft prices were explored, with the sixth being the price which meets the ROI requirement. This allows a healthy variance in the uncertain cumulative cashflow space and gives the program manager (and associated marketing and sales forces of the aircraft manufacturer) further insight on the pricing and ROI effects.

Figure 31 illustrates the view of the cash flow uncertainty broken down by expectation (represented as quantiles). Note the mean of the distribution is represented as numerically as the Quantile -2. Looking at the quartiles from zero to 100, it is evident that there is a shift in the variance of the cashflows toward the end of the program. This is likely due to the compounding effect of the reduction in manufacturing costs due to learning, the steady 3% increase in aircraft price per year, and the growth of inflation. On a lighter note, the quantile perspective of the uncertain cumulative cashflow clouds resembles a bird landing, with the developmental and investment phases representing the head, and the wings and feathers of the cashflows the different aircraft prices used by ALCAA.

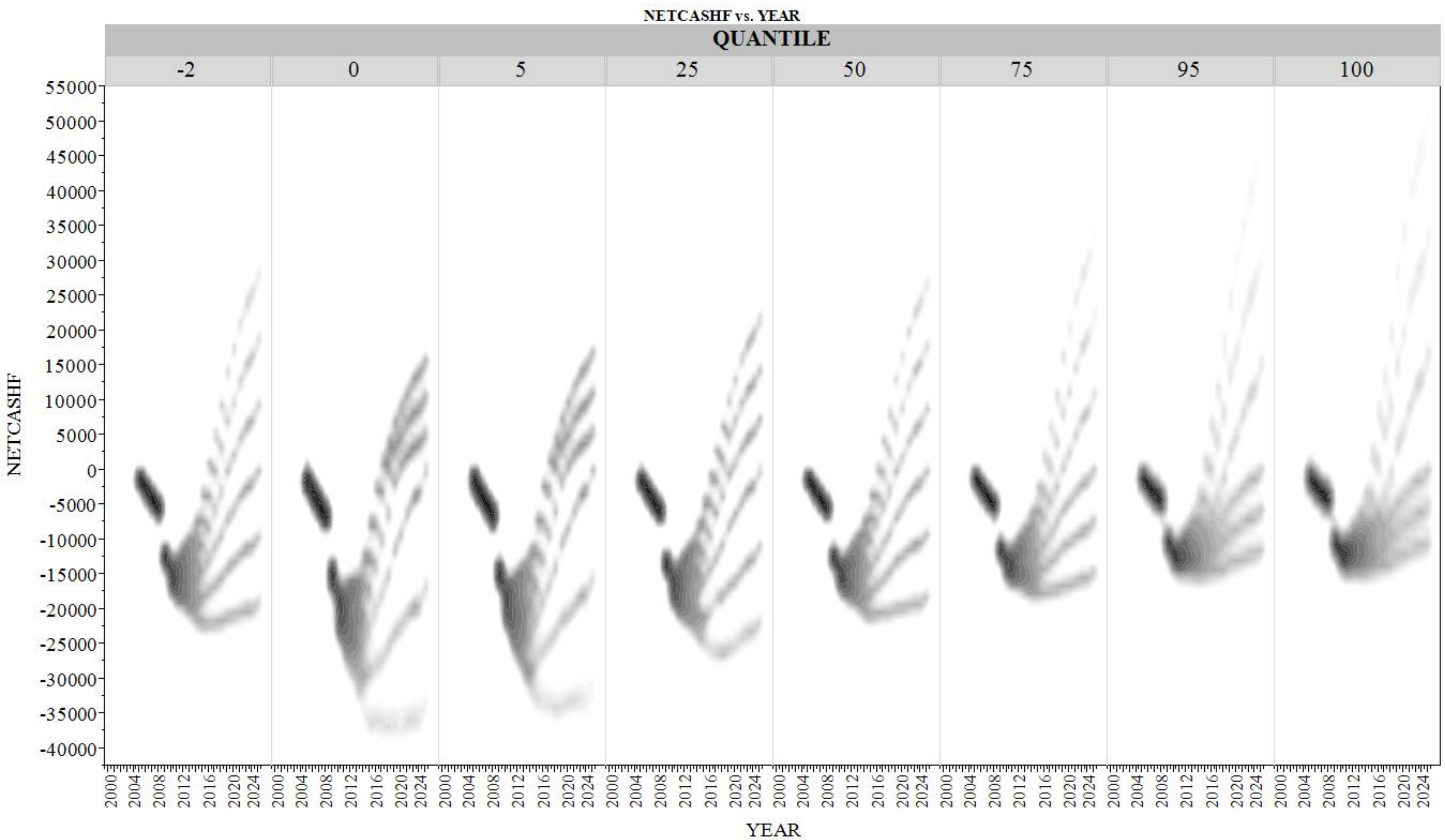


Figure 31: Aggregation of cumulative cashflow diagrams, arranged by quantile (Note: -2 refers to the mean).

In addition to exploring the aircraft pricing effects on cashflow, a full factorial design of experiments was executed, permuting the allocation of composites materials to the wing, body, empennage and engine nacelles. All other variables were held constant. The resulting variance is shown in Figure 32. It was observed that the composites perturbation exhibited substantial uncertainty in the cashflow space, especially on the cost side where Aircraft Prices 1 and 2 were extremely negative and never broke even.

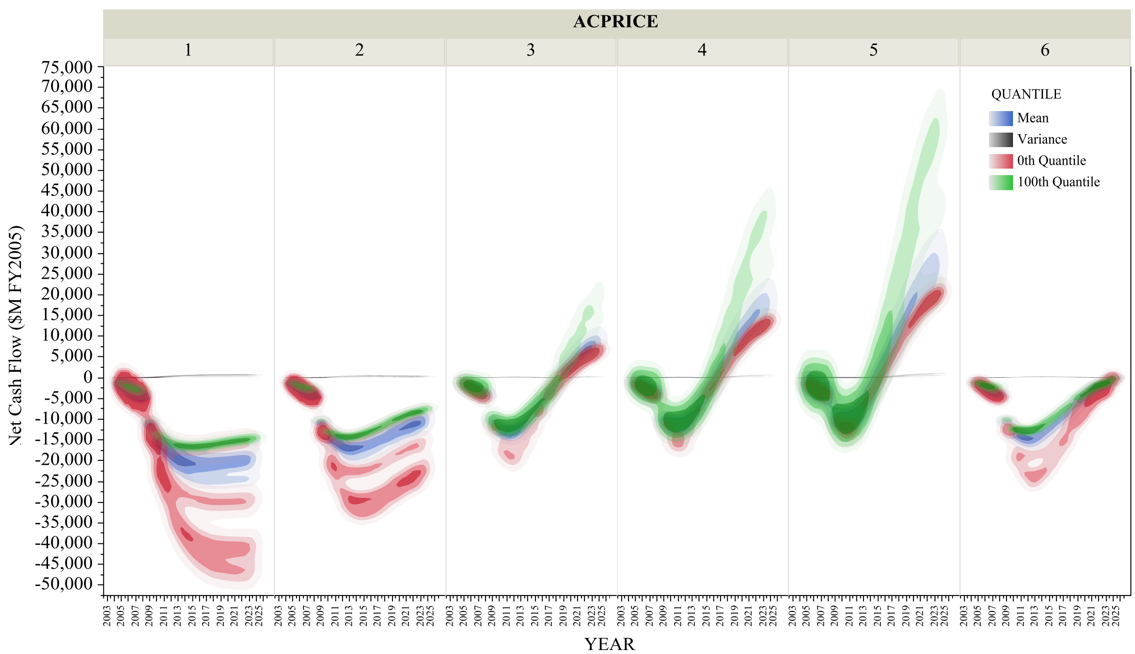


Figure 32: Experimental results showing the mean, variance, 0^{th} and 100^{th} quantiles from an experiment where only variables related to composites manufacturing were evaluated.

The effect of aircraft price was also evaluated against the break-even date. Figure 33 illustrates the strong trend and the range of breakeven dates possible. Note that for prices 1,2 and 6, the aircraft never broke even.

3.2.2.2 Screening tests

For the screening test, 73 variables were identified within the design, technology, and scenario variables sets available within FLOPS and ALCCA. These were selected largely based on prior experience with FLOPS and ALCCA and the software's documentation on the

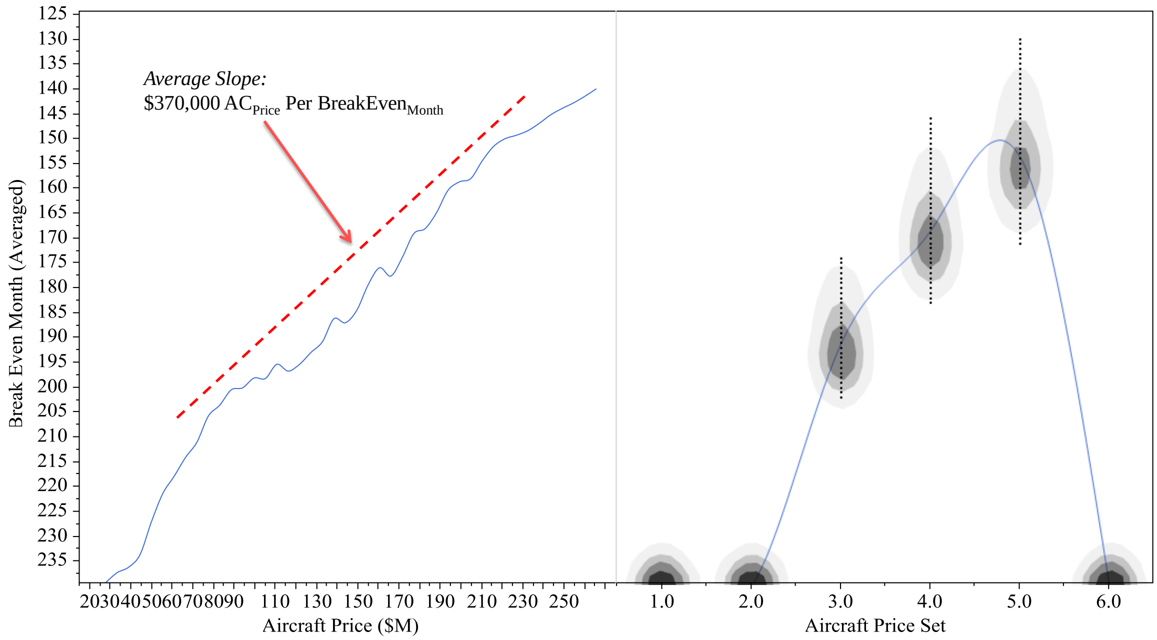


Figure 33: Average break-even month versus price, showing overall trend as well as aircraft price bucket deviation.

drivers of cash flow economics. For each of the variables identified, it was necessary to estimate ranges of experimentation that were likely possible in the single aisle 150-passenger aircraft design problem identified in Chapter 7. The variables, their taxonomy type, and their associated ranges are given in Tables 6, 7 and 8.

Table 6: Control variables and their associated ranges used in the Screening Test.

Design Type	Taxonomy Category	Description	Variable Handle	Min	Max	Units
Control	Design	Aspect Ratio (Wing)	AR	7	9	-
Control	Design	Aspect Ratio (Horizontal Tail)	ARHT	5.13	6.33	-
Control	Design	Aspect Ratio (Horizontal Tail)	ARVT	1.12	1.38	-
Control	Design	Design Range	DESRNG	2200	2800	Miles
Control	Technology	Percentage of Composites (Body)	PWBODYCO	0	1	Percent
Control	Technology	Percentage of Titanium (Body)	PWBODYTI	0	0.5	Percent
Control	Technology	Percentage of Composites (Empennage)	PWEMPCO	0	1	Percent
Control	Technology	Percentage of Titanium (Empennage)	PWEMPTI	0	0.5	Percent
Control	Technology	Percentage of Composites (Wing)	PWINGCO	0	1	Percent
Control	Technology	Percentage of Titanium (Wing)	PWINGTI	0	0.5	Percent
Control	Technology	Percentage of Composites (Nacelle)	PWNACCO	0	1	Percent
Control	Technology	Percentage of Titanium (Nacelle)	PWNACTI	0	0.5	Percent
Control	Design	Area (Horizontal Tail)	SHT	300	400	ft^2
Control	Design	Area (Vertical Tail)	SVT	270	300	ft^2
Control	Design	Area (Wing)	SW	1250	1350	ft^2
Control	Design	Sweep (Wing)	SWEEP	22	30	Degrees
Control	Design	Thickness at Chord	TCA	0.12	0.14	-
Control	Design	Taper Ratio	TR	0.18	0.22	-
Control	Design	Taper Ratio (Horizontal Tail)	TRHT	0.25	0.31	-
Control	Design	Taper Ratio (Vertical Tail)	TRVT	0.35	0.43	-
Control	Design	Thrust to weight Ratio	TWR	0.24	0.29	-
Control + Noise	Scenario	Number of Vehicles Produced/Sold	NV	600	1000	Aircraft

The complexity factors and efficiency factors were selected near their default values. It was found that if these complexity and efficiency factors deviated too much from the default values, then FLOPS and ALCCA returned failed values for aircraft weight and subsequently aircraft cost.

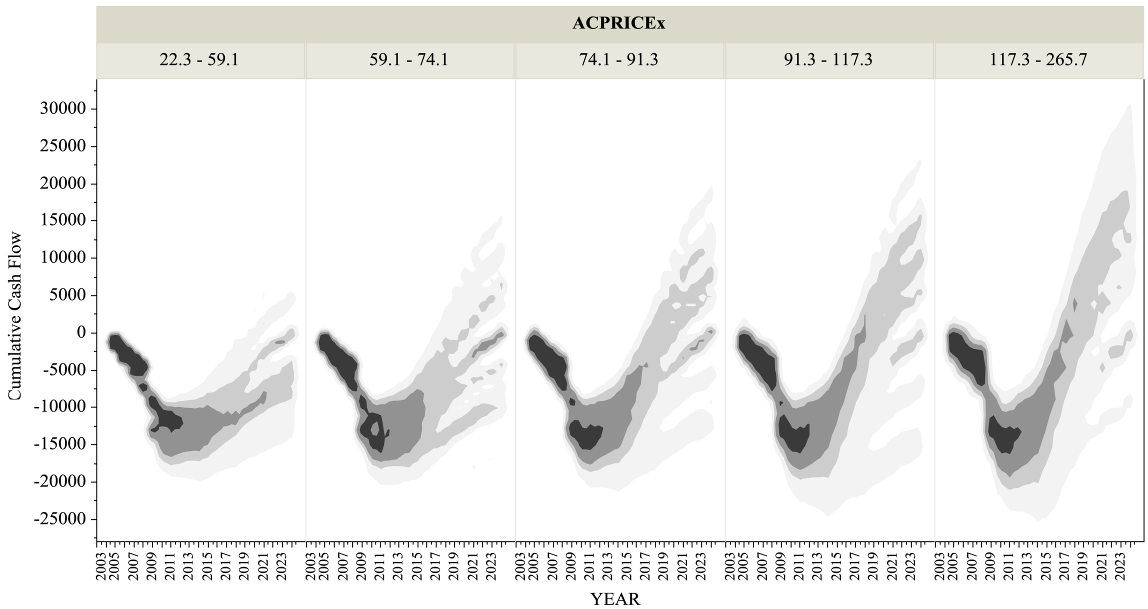


Figure 34: Aggregate cumulative cash flow diagram for the effects screening set, divided by aircraft price range.

3.2.2.3 Visualizing Uncertain Cumulative Cashflows

Figure 36 shows the year-wise approach to dissection of the drivers for cumulative cashflow uncertainty. The distributions were then fitted to the Johnson-Su continuous distribution function, then the 4 distribution parameters were modeled using the control, scenario, and technology variables. The result is a parametric uncertain cumulative cashflow trade environment, allowing the program manager to explore risk trades to tailor the business case and risk-aversion profile of the program.

Table 7: Scenario (Noise) variables and their associated ranges used in the Screening Test. (1 of 2)

Description	Variable Handle	Min	Max	Units
Complexity Factor	CFBODYAL	0.9	1.11	-
Complexity Factor	CFBODYCO	0.31356	0.39	-
Complexity Factor	CFBODYTI	1.2744	1.57	-
Complexity Factor	CFEMPAL	0.9	1.11	-
Complexity Factor	CFEMPCO	0.4518	0.56	-
Complexity Factor	CFEMPTI	1.3617	1.68	-
Complexity Factor	CFLGAL	0.9	1.11	-
Complexity Factor	CFLGCO	0.9	1.11	-
Complexity Factor	CFLGTI	0.9	1.11	-
Complexity Factor	CFNACAL	0.9	1.11	-
Complexity Factor	CFNACCO	0.9	1.11	-
Complexity Factor	CFNACTI	0.9	1.11	-
Complexity Factor	CFWINGAL	0.9	1.11	-
Complexity Factor	CFWINGCO	0.4518	0.56	-
Complexity Factor	CFWINGTI	1.3617	1.68	-
Efficiency Factor	EFBODYAL	0.9	1.11	-
Efficiency Factor	EFBODYCO	1.17945	1.46	-
Efficiency Factor	EFBODYTI	0.90315	1.12	-
Efficiency Factor	EFEMPAL	0.9	1.11	-
Efficiency Factor	EFEMPCO	1.1034	1.36	-
Efficiency Factor	EFEMPTI	0.89604	1.11	-
Efficiency Factor	EFLGAL	0.9	1.11	-
Efficiency Factor	EFLGCO	0.9	1.11	-
Efficiency Factor	EFLGTI	0.9	1.11	-
Efficiency Factor	EFNACAL	0.9	1.11	-
Efficiency Factor	EFNACCO	0.9	1.11	-
Efficiency Factor	EFNACTI	0.9	1.11	-
Efficiency Factor	EFWINGAL	0.9	1.11	-
Efficiency Factor	EFWINGCO	1.1034	1.36	-
Efficiency Factor	EFWINGTI	0.89604	1.11	-
High-Value Material Cost (Buy-to-fly)	HIMAT	0.7875	1.40	Percent
Learning Curve (Block 1)	LEARN1	75	85.00	Percent
Learning Curve (Block 2)	LEARN2	75	85.00	Percent
Learning Curve, Avionics (Block 1)	LEARNA1	75	85.00	Percent
Learning Curve, Avionics (Block 2)	LEARNA2	75	85.00	Percent
Learning Curve, Assembly (Block 1)	LEARNAS1	75	85.00	Percent
Learning Curve, Assembly (Block 2)	LEARNAS2	75	85.00	Percent
Learning Curve, Fixed-Equipment (Block 1)	LEARNFE1	75	85.00	Percent
Learning Curve, Fixed-Equipment (Block 2)	LEARNFE2	75	85.00	Percent
Learning Curve, Engine (Block 1)	LEARNP1	75	85.00	Percent
Learning Curve, Engine (Block 2)	LEARNP2	75	85.00	Percent
Other Direct Cost Factor	ODC	0.03	0.05	Percent

Table 8: Scenario (Noise) variables and their associated ranges used in the Screening Test. (2 of 2)

Description	Variable Handle	Min	Max	Units
RDTE Labor Rate	RDEVPMHR	38	68	Dollars
Engineering Labor Rate	RE	60	80	Dollars
Markup for Other Direct Cost	RGA	0.82	1.45	Dollars
Manufacturing Support Labor Rate	RMANSUP	41	73	Dollars
Manufacturing Labor Rate	RMANUMHR	38	68	Dollars
Rate for Manufacturing Material Cost	RMFGMAT	0.78	1.39	Percent
Quality Assurance Labor Rate	RQA	43	77	Dollars
Tooling Labor Rate	RT	35	55	Dollars
Test Engineering Labor Rate	RTENGMHR	65	115	Dollars

New Research Observation IVa

Price and volume produced trends emerge, and seem uncorrelated to the performance and likely value to the end customer.

New Research Observation IVb

Quantity produced is equal to the quantity consumed and is treated as an input in the FLOPS/ALCCA model. There was no consideration for the level of value to the customer in a competitive environment.

3.2.3 Input Variance and Simulation Count Study

Essential to providing insight into the use of the CASSANDRA methodology is an awareness of what affect the inputs and operational setting have on the dispersion of the results. The width of the input ranges on the noise variables is of particular concern, as the resulting cumulative cashflows are capable of enormous variance. Similarly, there exists the possibility that the simulation exhaustiveness itself interacts with the estimates, particularly when evaluating the *bounds* as discussed in the previous section.

Table 9: Effects screening study on Cumulative Cash Flow (Year 2024) showing the average factor rank from two experiments. Tabulated are the top 25 of 73 factors evaluated. Number of Runs=5,000., Experimental configuration: Experiment 1: Monte Carlo, Experiment 2: D-Optimal Design

Factor	Rank in Exp. 1	Rank in Exp. 2	Average Rank	Rank Difference
RE	6	4	5	2
ARHT	9	1	5	8
RT	1	10	5.5	-9
CFWINGTI	8	11	9.5	-3
SVT	10	14	12	-4
EFLGAL	12	15	13.5	-3
LEARN2	25	5	15	20
EFNACAL	5	26	15.5	-21
ARVT	26	7	16.5	19
RMANUMHR	4	33	18.5	-29
RGA	7	30	18.5	-23
PWINGTI	15	22	18.5	-7
LEARNA2	35	3	19	32
PWNACTI	17	24	20.5	-7
TRHT	16	28	22	-12
HIMAT	3	46	24.5	-43
LEARNAS1	30	20	25	10
CFNACAL	51	2	26.5	49
EFNACTI	37	23	30	14
CFBODYTI	46	16	31	30
PWNACCO	2	61	31.5	-59
PWEMPCO	29	34	31.5	-5
EFEMPTI	32	31	31.5	1
EFBODYTI	20	45	32.5	-25
RMANSUP	61	6	33.5	55

Table 10: Effects screening study on Break Even Month showing the average factor rank from two experiments. Tabulated are the top 25 of 73 factors evaluated. Number of Runs=5,000., Experimental configuration: Experiment 1: Monte Carlo, Experiment 2: D-Optimal Design

Factor	Rank in Exp. 1	Rank in Exp. 2	Average Rank	Rank Difference
RT	5	3	4	-2
HIMAT	6	9	7.5	3
EFNACAL	10	6	8	-4
ARHT	13	4	8.5	-9
RMANSUP	17	2	9.5	-15
ARVT	20	1	10.5	-19
PWEMPTI	21	7	14	-14
EFLGCO	19	15	17	-4
CFBODYTI	25	10	17.5	-15
LEARNA2	24	13	18.5	-11
EFWINGAL	30	8	19	-22
PWINGTI	4	35	19.5	31
RQA	23	18	20.5	-5
CFNACTI	14	31	22.5	17
EFLGAL	16	33	24.5	17
CFLGAL	22	28	25	6
DESRNG	12	40	26	28
EFEMPTI	8	47	27.5	39
RMANUMHR	9	48	28.5	39
EFLGTI	7	50	28.5	43
CFWINGTI	39	21	30	-18
LEARNAS1	46	16	31	-30
RDEVPMHR	40	22	31	-18
CFWINGAL	2	61	31.5	59
RE	1	62	31.5	61

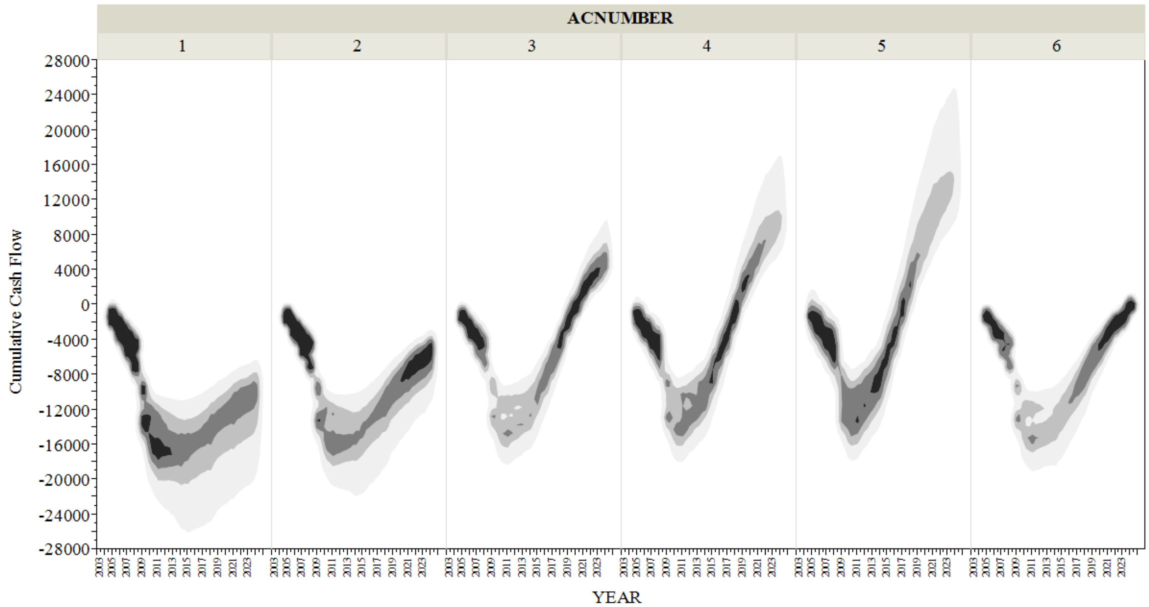


Figure 35: Aggregate cumulative cash flow diagram for the effects screening set, divided by the FLOPS / ALCCA aircraft price number (not aircraft price). Note that aircraft price number 6 refers to the converged aircraft price to reach a manufacturer's return on investment goal.

To capture this effect, a 4-level, full factorial experiment was executed on a single control setting for the design. The baseline setting was that of the Screening Test, as given by the centerpoints of the distributions given in Table 6.

The noise variable ranges were expanded by setting the input distribution types to Normal/Gaussian and setting the variance to be a fixed percentage of the mean. This percentage ranged from 3% to 12%.

The simulation run count was varied from 10 to 1000 runs in the noise array. As mentioned previously, the BASUCA apparatus was designed to handle millions of total executions of FLOPS and ALCCA. Setting the noise (outer) array length to 1000 would result in 1 million total executions if the control array were of the same length.

The results described the mean, variance, skew, and bounds are given in Table 11.

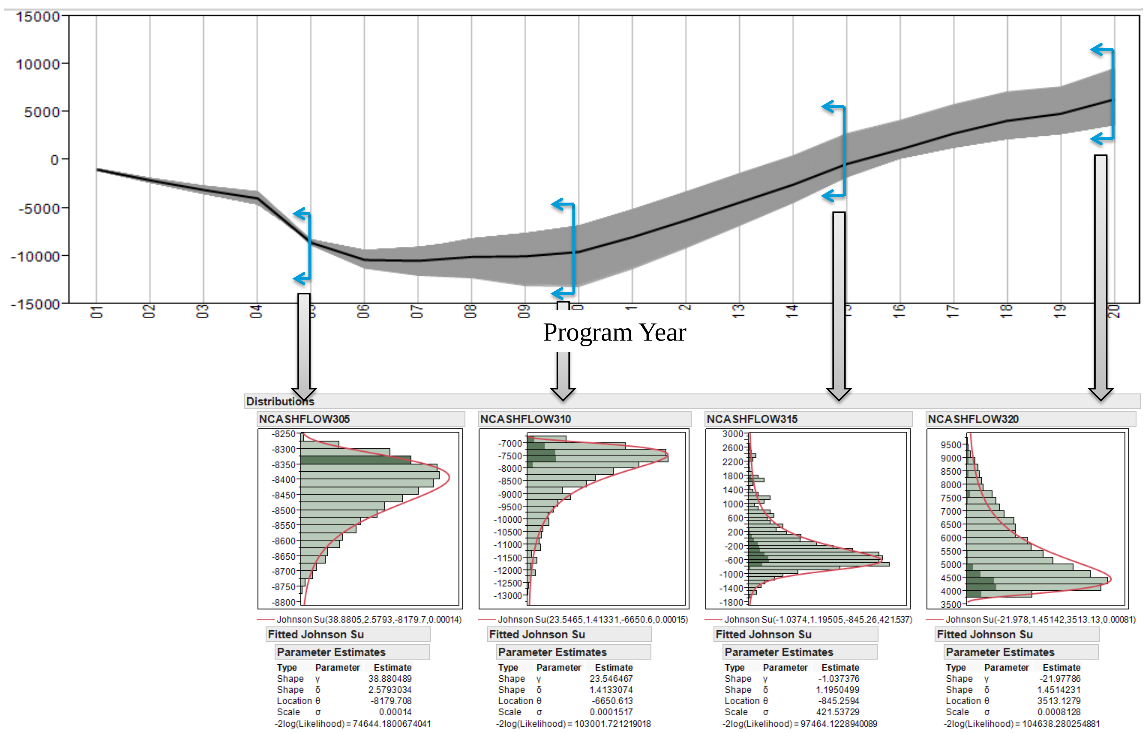


Figure 36: Continuous distributions fitted to cumulative cashflow drivers, then regressed as a function of design, scenario and technology variables.

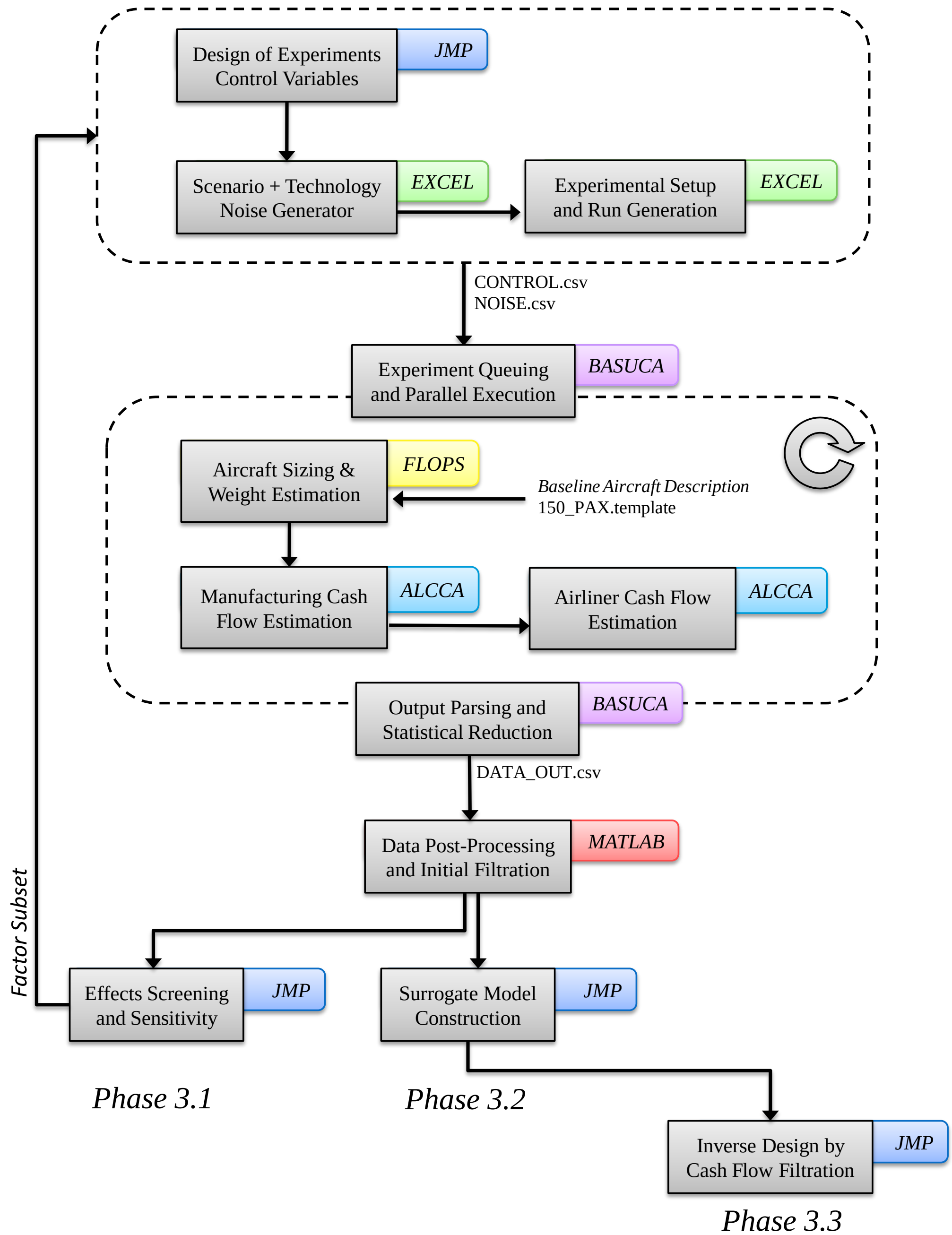


Figure 37: Overview of the information and data flow of the experimental apparatus (BASUCA) that used to accelerate FLOPS and ALCCA cumulative cashflow analysis. Note the three steps : the Effects screening, the Surrogate Model construction, and the Inverse Design.

Table 11: Results from the BASUCA noise array variance and simulation run count study.

Input Variance (%)	Simulation Run Count	Mean	Variance	0^th Quantile	100^th Quantile	Skew
3	10	20084	150	19765	20508	-0.49
3	25	20311	164	19233	21430	0.37
3	100	20043	104	18456	22399	0.52
3	250	20043	63	17938	22399	0.28
3	1000	20055	32	17439	22991	0.16
7	10	22386	1090	19451	23475	0.57
7	25	20722	589	17421	23475	0.92
7	100	20751	273	16366	27230	0.58
7	250	20867	169	16203	28487	0.66
7	1000	20675	84	15148	29973	0.64
10	10	20657	1897	16614	21804	1.63
10	25	21242	1213	16120	26676	1.98
10	100	21323	508	14115	34967	1.30
10	250	21143	283	13862	36407	1.14
10	1000	21218	162	11935	47381	1.74
12	10	23750	1973	18986	27675	0.84
12	25	21995	1068	16466	30208	0.96
12	100	21964	584	14235	37836	1.16
12	250	22005	401	12806	44254	1.54
12	1000	21834	198	12280	58812	2.14

Figure 38 shows the effect of stabilizing mean estimate in the cumulative cash flow as a function of increasing run count and input variance. For each of the input variances, this effect is evident. Of particular interest is noting that between 50 and 100 executions, the mean has already stabilized. This effect was expected. As the input variance grew from 3 to 12%, a steady but slight increase in the cumulative cash flow was observed. This was likely due to the slight asymmetry of the learning curve effect input distribution.

Figure 39 shows the effect of the output variance in the cumulative cash flow as a function of increasing run count and input variance. Here, two trends are evident. The first was that as the simulation count was increased, the variance estimate decreased substantially in each case. At first glance this was surprising, however examining the other results made this effect more clear. As the number runs increased in the noise array, the estimate of the variance in the output decreased exponentially. More specifically, the estimate for variance on the set decreased with increasing simulation run count as the peakedness of the distribution, or kurtosis, was found to decrease with simulation run count. The second trend was expected: increasing the input variance also increased the output variance, and this effect was approximately linear.

Figure 40 shows the effect of simulation run count and input variance on output kurtosis in the cumulative cash flow. Recall that the kurtosis describes the *peakedness* of a distribution. Here the sample *excess kurtosis* K (kurtosis value minus 3) was largely invariant with the input variance, and like the mean estimate tended to settle down as the simulation count increased towards a slightly less kurtotic distribution than the perfect normal distribution (in which excess kurtosis = 3). For reference, the sample kurtosis of a set of n samples follows Equation 12:

$$K = \frac{m_4}{m_2^2} - 3 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} - 3 \tag{12}$$

where m_4 is the fourth sample moment about the mean, m_2 is the second sample moment about the mean (that is, the sample variance), x_i is the i^{th} value, and $\overline{x}$ is the sample mean.

Figure 41 shows the effect of the increasing run count and input variance on output *skew* in the cumulative cash flow. It was found that the skew increased as both the input variance

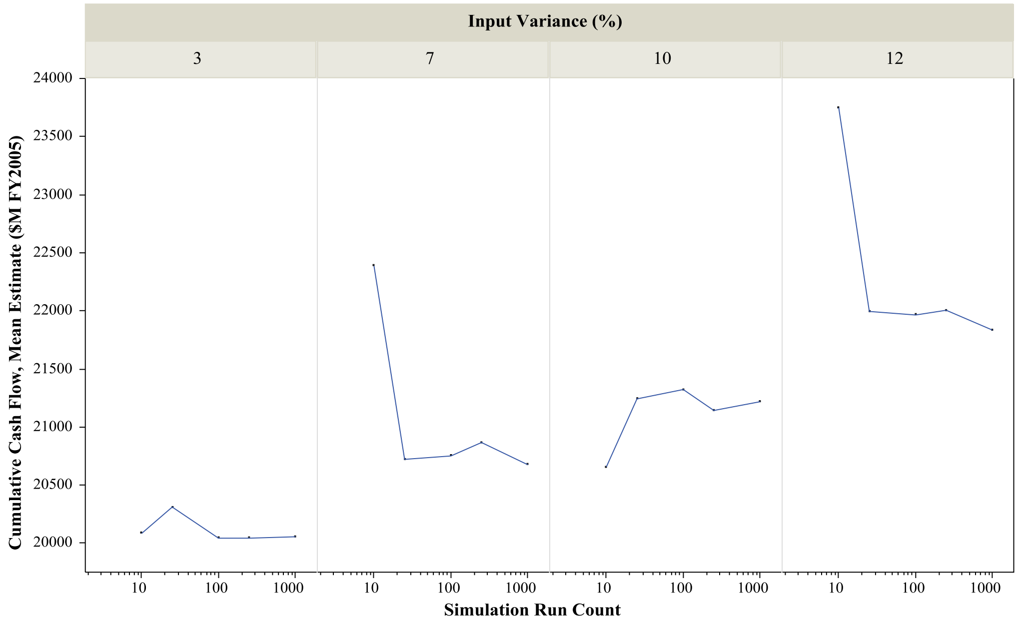


Figure 38: The relationship of noise array input variance and simulation results on the **mean** of the cumulative cashflow space.

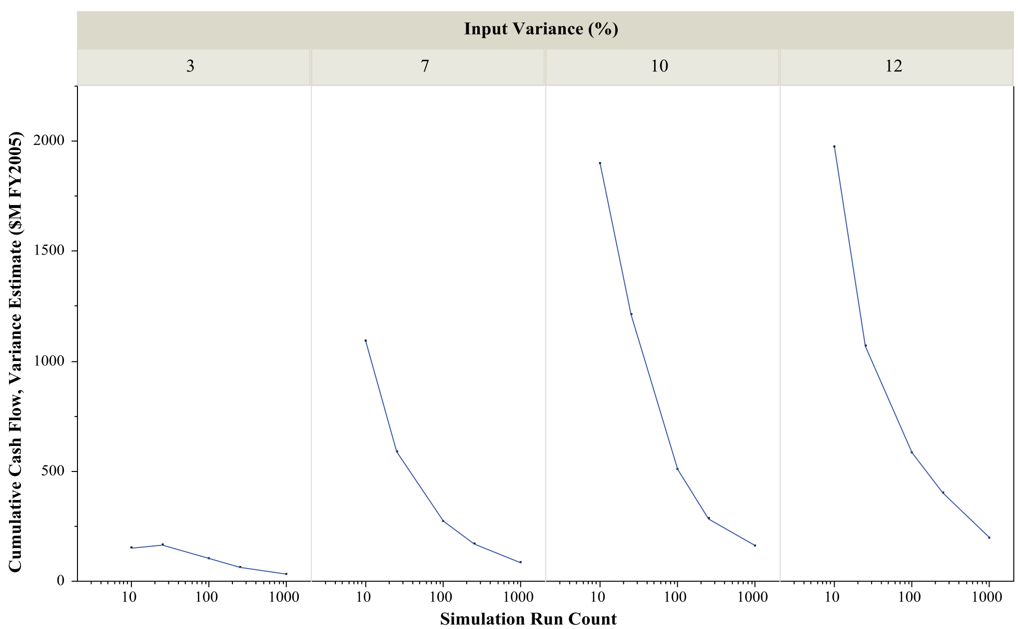


Figure 39: The relationship of noise array input variance and simulation results on the **variance** of the cumulative cashflow space.

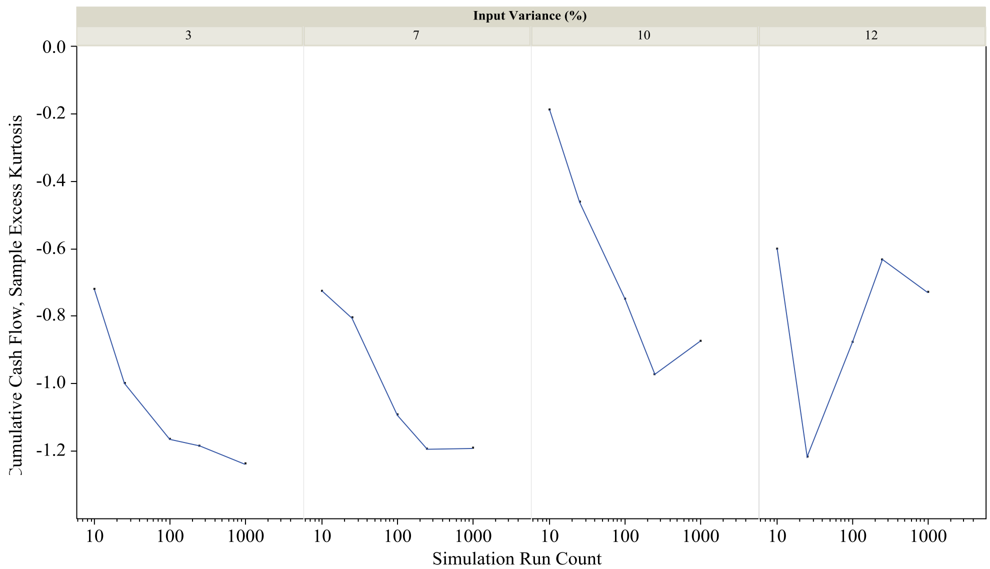


Figure 40: The relationship of noise array input variance and simulation results on the **excess kurtosis** of the cumulative cashflow space.

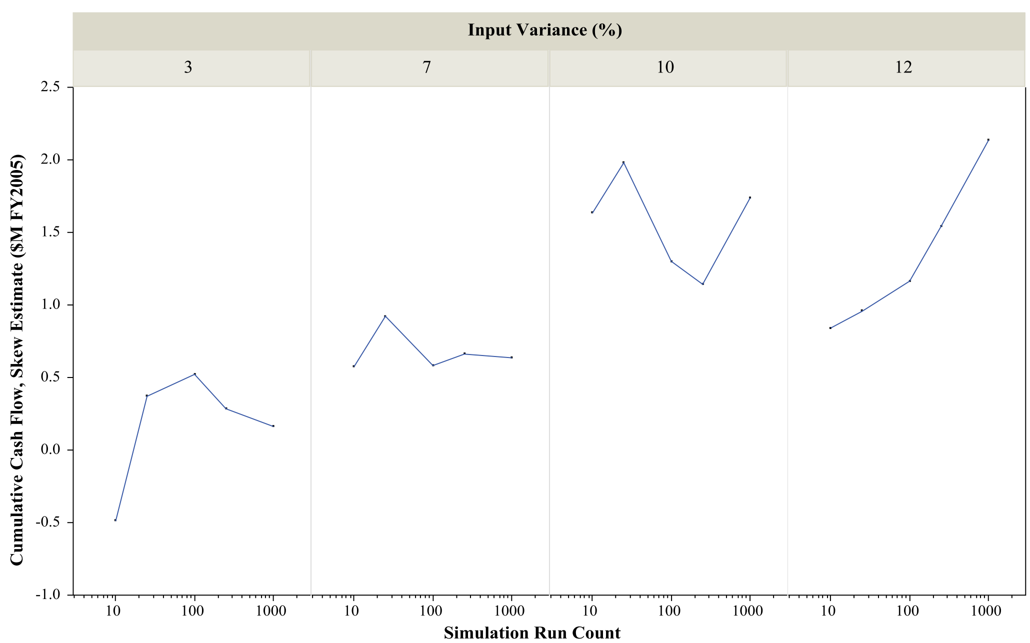


Figure 41: The relationship of noise array input variance and simulation results on the **skew** of the cumulative cashflow space.

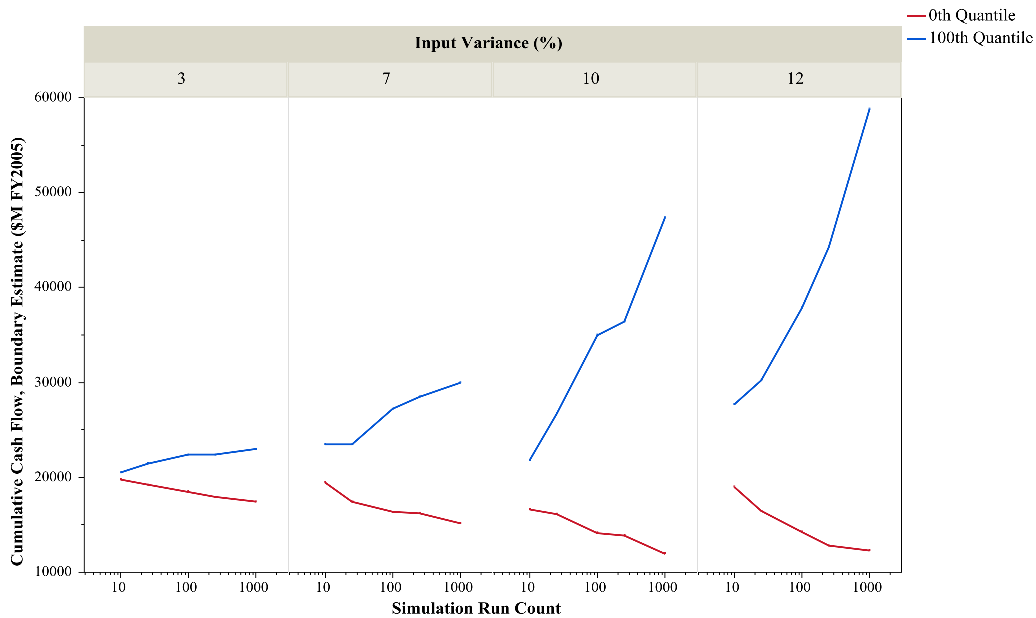


Figure 42: The relationship of noise array input variance and simulation results on the 0^{th} and 100^{th} **Quantiles** of the cumulative cashflow space.

increased and settled slightly as the simulation run count increased. The simulation run count had a weaker impact on skew and was found to settle to usable value by approximately 100 runs. The input variance showed a strong impact on skew, likely due to the inflation rate distortion effect by cumulative cashflow values that were further and further from zero. Here, as the input variance increased, the ending program cash flow skew was increased. This effect is also shown in Figure 42, demonstrates the effect of the increasing run count and input variance on *output bounds* in the cumulative cash flow.

Here the results from the Monte Carlo simulation evaluating growth in normal distribution bounds as a function of samples is repeated. The spread between the 0^{th} and 100^{th} Quantiles increases dramatically with input variance, as well as simulation count. The effect is stronger with input variance than with simulation run count.

3.3 Chapter Summary

This chapter reviewed the experimental apparatus and explored two different setups for evaluation. The first apparatus evaluated the sizing and simulation software from an embedded code stitching environment. This gave the initial exploration and sensitivity confirmation of the uncertain cumulative cashflow concept. The execution time was approximately 1.5 seconds per run, and it was originally assumed that a million executions might be necessary when using the control-by-noise array structure. The reason for this assumption was due to the desire to capture all of the interactions possible for generating design risk. A full-factorial experiment of the control and noise variables to the risk space led to an unacceptable total experiment time of approximately 11 days. Note that the full factorial design of experiments could be reduced to a fractional factorial or Latin Hypersquare design, but both of these approaches concede interactions which were not desired to be assumed.

Therefore, a high-speed apparatus was built called BASUCA to reduce the CPU idle time of the experimental process. From here, it was then possible to evaluate the validity of the full factorial assumption, which was found to be false. The initial hypothesis of needing 1000 executions in the noise array turned out to be invalid: approximately 75-150 executions captured the majority of the cumulative cashflow statistical estimates sufficiently.

CHAPTER IV

ALLOCATING RISK TO MANAGE SCHEDULE AND COST

4.1 Introductory Remarks

As described in the previous chapter, the aircraft designer's management problem is to balance the consequences of design decisions in the dimensions of performance, cost, and schedule to higher-level goals of generating sustainable, profitable products. The program manager's values place risk constraints on the level of acceptable risk in each of those dimensions. To meet those constraints, only a few parameters can be controlled: capital allocation and investment, technology selection, and time resources.

This allocation problem poses a unique challenge to the designer or program manager, and in order to succeed in the aircraft program, measures are needed to identify the gaps and the excesses in risk allocation.

Developing a methodology that identifies the relationship between technology risk and overall economic impact could meet this challenge, however it must address the investment variations as well of the production variations in order to make the recommendations useful.

The goal of this chapter is to address the allocation problem of technology risk and identify methods in which the consequence to program schedule and cost may be measured. In addition, it will present a brief summary of the literature relevant to identifying, measuring, and interpreting uncertainty and risk in the context of aircraft development programs.

4.2 Literature Review of Relevant Background

The literature review begins with the assessment of uncertainty methods into the aircraft product development process, and it begins on the ground floor with an engineer. One of the first publications revealing the use of engineer-level uncertainty elicitation was given by Batson, et al. in 1988 in their report of uncertainty analysis of new aircraft development at Lockheed Martin [5]. This is illustrated in Figure 43. They used a Monte Carlo process to map the input uncertainty to payload-range outputs of various conceptual design alternatives. The risk was identified by the overlap of the maximum payload at critical range and the frequency of loads carried [5]. This approach to calculating risk by load-stress probability overlap is common in reliability and structural safety analyses [6, 26, 129, 138]. This is illustrated in Figure 44.

Risk assessment in aircraft design is a broad, comprehensive field, and there have been several trends and methods to address system design risk. In 2009, Curran used stochastic modeling to capture uncertainty and sensitivity analysis for the minimization of operating costs by permuting structural design variables. They found that the minimum weight system did not correspond to the lowest direct operating cost [26].

Real Options is another trend for studying the variance and managerial adaptability of large, complex system design. *Real options* uses financial valuation models to capture 'payoffs' of possible future states of real-world problems, then uses the stochastic Black-Scholes options pricing model to evaluate and compare the value of non-permanent alternatives [32, 20].

Peoples and Wilcox looked at an alternative design technique by comparing performance-optimized and value-optimized designs. They showed that there existed a trade off between aerodynamic efficiency and manufacturing costs when value was used as a design metric, and that the stochastic methodology indicated an advantage in strategy of spending up-front capital to improve long term profitability [101].

Lessard [73] provides a broad distinction between risk management approaches that is appropriate at this time:

1. *Type I*: Decision theoretic approaches that by and large assume that risks are exogenous.
2. *Type II*: Managerial approaches that recognize that risk depends on the interaction among exogenous risk drivers, managerial choices during the front end, and the shaping of risk drivers throughout the process.

A relevant example of an exogenous variable is manufacturing labor rate. In Lessard's

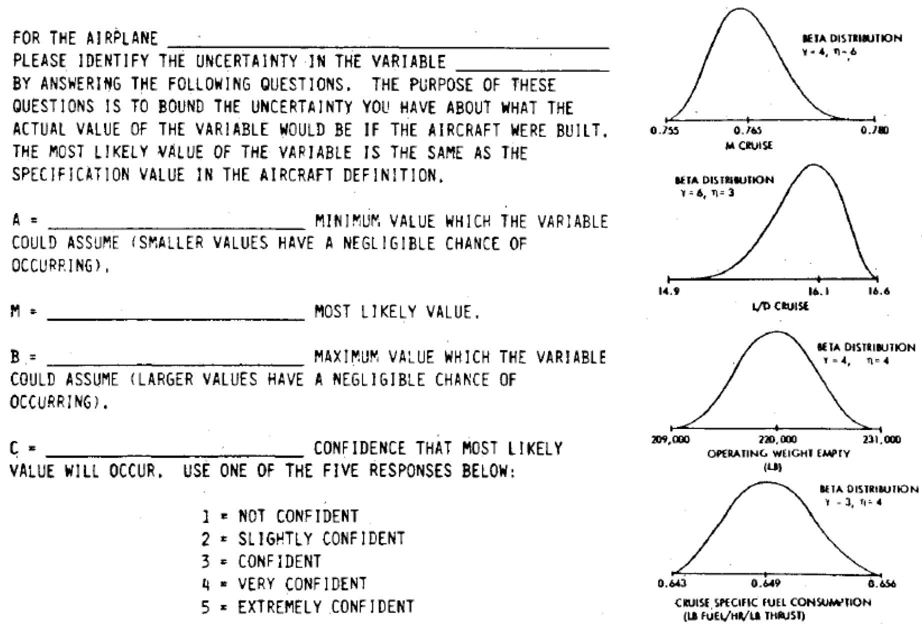


Figure 43: Uncertainty elicitation questionnaire released in 1988 [75].

Type 1 approach to risk management, the risk on cost and schedule objectives arising from labor rate is considered as something that comes from outside the model and is unexplained by the model. Risk management approaches in this case are static: the labor rate is assumed to be fixed, and the risk mitigation process aims to reduce sensitivity to the exogenous variable. In the Type II approach, there is an active interaction between the fluctuating labor rate and the subsequent development processes: the risk can be continuously managed assuming sufficient managerial flexibility. The field of Real Options has emerged to model the time-variant strategic adaptability of decision alternatives in the same way as financial options pricing mechanisms [14].

For the sake of simplicity, the scope of the proposed research is kept to time-invariant analyses (similar to Lessard's Type I approach), although Real Options is certainly a promising area of research.

Classical venture valuations methods apply the Discounted Cash Flow method, where a decision maker makes future cash flow estimates and discounts them to present day, then considers the investment cost associated with creating the cash flows. Typical research and development efforts display a high amount of uncertainty, rendering the deterministic

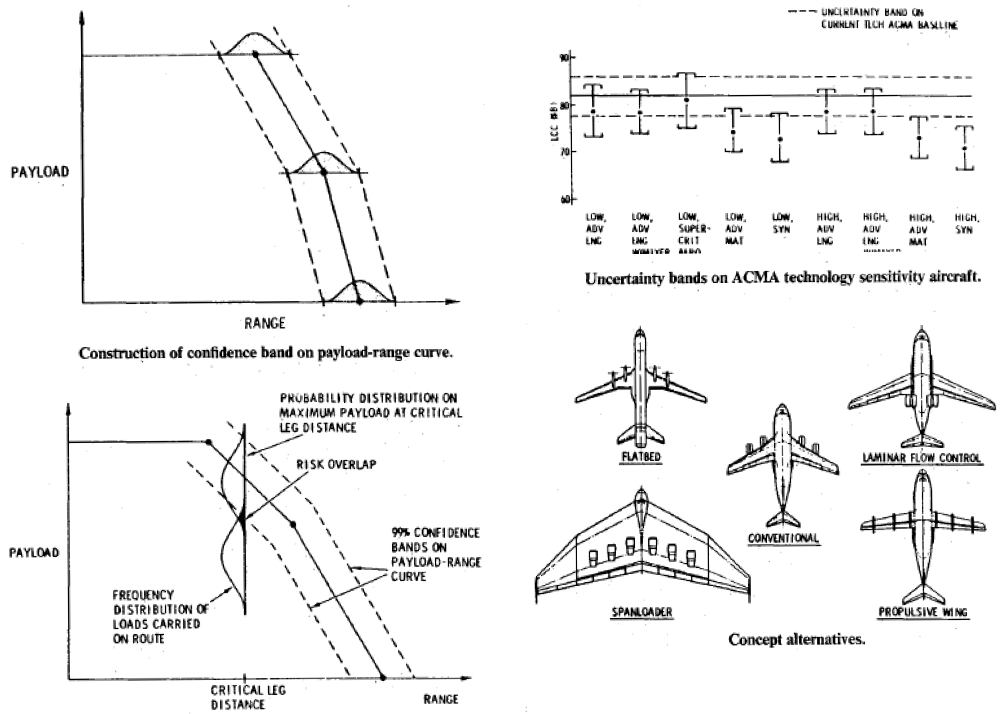


Figure 44: Uncertainty propagation to Payload-Range diagrams, illustrating the probabilistic load and ultimate stress overlapping perspective of structural risk [5].

discounted cash flow method difficult to apply [92].

4.2.1 Uncertainty Elicitation and Mitigation Processes

Risk management processes are as diverse as definitions and interpretations of risk. A simple literature search will reveal hundreds upon hundreds of various risk management processes, of varying degrees of fidelity and utility. There is an evident trend that appears, as with the definition of risk, and the generalized steps are summarized below.

1. *Step I*: Identification of uncertainty
2. *Step II*: Representation or elicitation of uncertainty
3. *Step III*: Propagation of the uncertainty through the system
4. *Step IV*: Analysis and interpretation
5. *Step V*: Mitigation of resulting risk

There has been extensive research in each of these broad steps. A more detailed, refereed example from the ISO31000:2009 [60] is given.

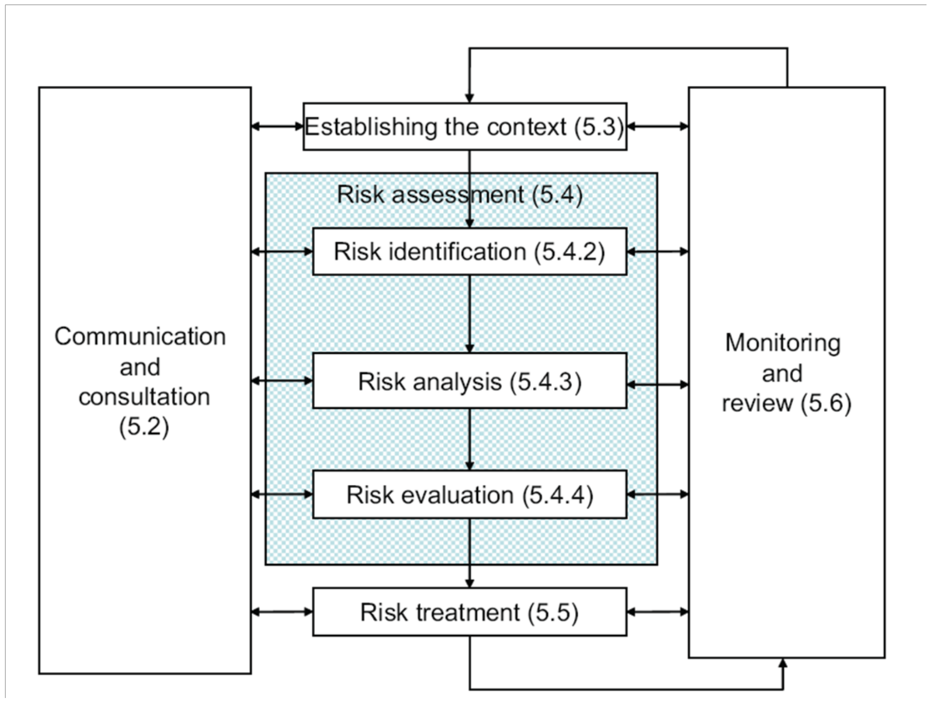


Figure 45: The ISO31000 risk management process [60].

Long and Narciso [75] used probabilistic design methods to evaluate sensitivities of design variables to evaluate risk of composite systems for the Federal Aviation Administration (FAA). NASA published an iterative risk management process [97] that identifies a system hierarchy as well as a risk management processes executor. This identification is given in the form of a pyramid, with the hierarchy broken down into agency, directorate, program, project, and element in Figure 46. The risk management process itself is similar to that given in ISO31000:2009 shown before.

4.2.2 Identification of Uncertainty

As with any transfer analysis, the quality of the results is only as good as the quality of the inputs and model itself. Risk analysis is particularly sensitive to this effect as measurement of the error, variance and bounds of the results is the primary goal. Because of this effect, careful attention must be paid as to how uncertainty about the system is described. Without

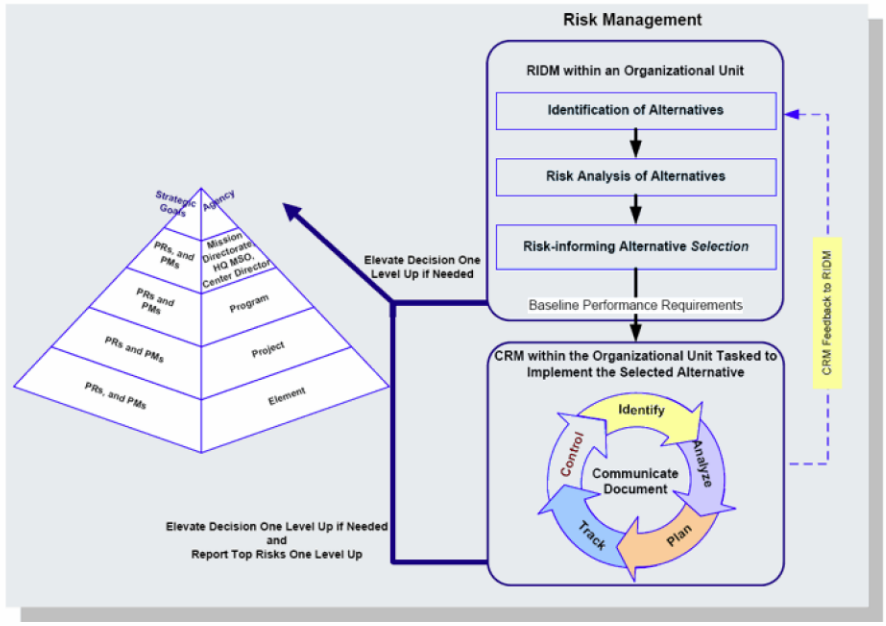


Figure 46: NASA Agency Risk Management approach, breaking down the user and system level iterative processes [97].

a clear understanding of the assumptions going in to the elicitation, the resulting analysis is either difficult or meaningless to interpret.

As described in Section 2.1.4 aleatory and epistemic uncertainty are used to describe uncertainty in fundamentally different ways. For risk analyses measuring the inherent variability of the system, such as the price of oil in future states, or the dimensions of manufactured parts, aleatory uncertainty elicitations and subsequent treatment theory are appropriate. Probability Theory is widely accepted in the reliability engineering community as the most suitable approach [121].

In contrast, epistemic uncertainty exists when there is a cognitive lack of knowledge about the system. Several representations and model theories exist for capturing epistemic uncertainty, such as Bayesian Theory, Possibility Theory, and Dempster-Shafer's Evidence Theory. Discussion of the various advantages and relative performances for aerospace problems is well documented in Stult's thesis [121].

When surrogate models are used, a new source of epistemic uncertainty may exist related to the Model Fit Error (MFE) and Model Representation Error (MRE). Delaurentis describes uncertainty in regards to modeling and simulation as the "...the incompleteness in knowledge (either in information or context), that causes model-based predictions to differ from reality in a manner described by some distribution function." [27].

For the scope of this thesis, epistemic uncertainty is considered in Probability theory and Bayesian theory alone.

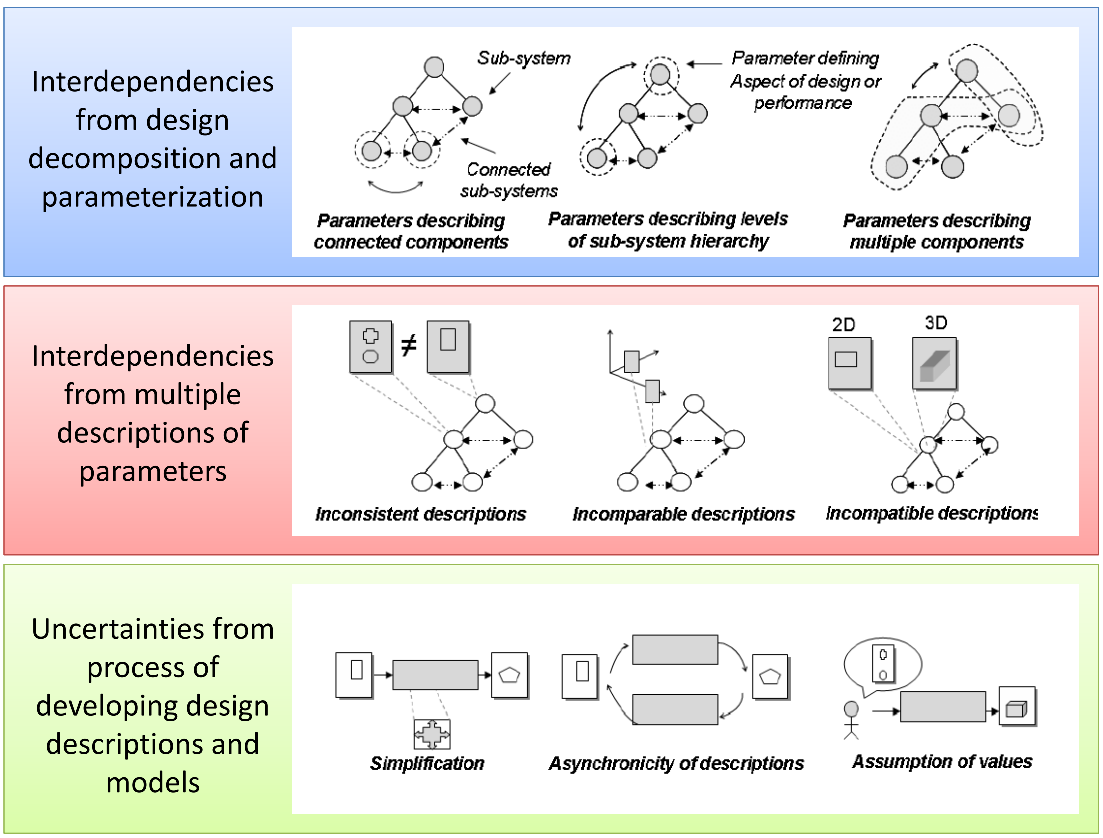


Figure 47: Three-level decomposition of the entry points and interdependencies of uncertainty during the design process [49].

4.3 Uncertainty Propagation

There are two general approaches to propagating uncertainty throughout a system: Approximation and Sampling Method. In the approximation approach to propagating uncertainty, the uncertainty of the output is directly computed through the linearized function describing the system using statistical propagation theory, and provides limited information on the resulting output: mean and variance. This is useful when the mathematical representation of the system is linear and when the propagated uncertainty is sufficiently described by the variance alone. This approach is rare in aircraft design methods as the restrictions imposed on the function are often undesirable and additional information is needed regarding the shape of the output distribution. There have been notable improvements in central dispersion approximation methods, including Quadratic Combination and Perturbation, but discussion on those methods is out of the scope of the research.

The second method to propagating uncertainty is sampling. In sampling, no linearization or preparation of the system functions is needed. Instead, the propagated uncertainty arises simply from mass collection of independent samples from the function. Monte Carlo Sampling is an example of such a technique and is widely used in system design problems.

4.3.1 Monte Carlo Sampling

A standard technique for the exploration of a design space as well as analyzing uncertainty through a system is Monte Carlo (MC) simulation [10]. In this technique, the subjects (often deterministic analysis codes or surrogate models) are stochastically sampled to produce correctly scaled dispersion of results. Depending on which variables are selected in the sampling set, the Monte Carlo process can be used for *design space exploration* (from a Design of Experiments on the design variables) or a *uncertainty propagation*, or both simultaneously. This subtle distinction is often the source of confusion in interpretation of the results. Design space exploration by itself is a *deterministic activity*; the assumptions and scenario variables are held constant and the resulting variance in responses is due to static design permutation. When the distributions are instead applied to scenario variables (or as future-path influences on design variables), the resulting distributions describe possible outcomes of frozen design due to variance in the assumptions. Both approaches are useful in the Risk Management process.

Monte Carlo Sampling may require a substantial number of samples in order to populate and resolve output probability density distributions (PDFs); sample set sizes in the thousands and millions are not uncommon [121]. If the individual clock time of the subject is lengthy, this computational expense can quickly exceed reasonable limits. It is for this reason that surrogate models are used to accelerate net analysis time. Though there are a variety of Monte Carlo (MC) sampling algorithms such as Stratified Monte Carlo sampling, Importance Sampling and Quasi Monte Carlo sampling, this thesis aims to default the uncertainty propagation method to Monte Carlo sampling of surrogate models.

4.3.2 Fast Probability Integration

An alternative approach in uncertainty propagation to full sampling techniques was developed by Southwest Research Institute for NASA. In this method the cumulative probability functions (CDFs) are approximated by creating a linearized form of the system response, then calibrated the CDF with additional samples [138] [86].

The three approaches to propagating uncertainty through a system are illustrated in Figure 48.

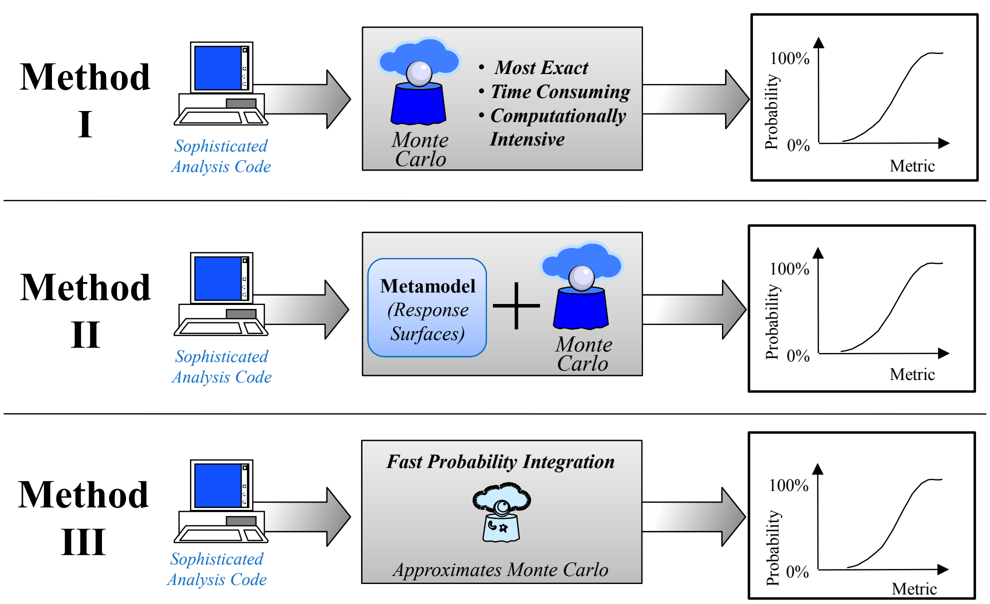


Figure 48: Illustration of various probabilistic design methods [67].

4.3.3 Response Surface Methodology

The Response Surface Methodology (RSM) is one of the multi-variate reduced-form modeling approaches used in this study. The acceleration enabled Monte Carlo simulations with high run count, and thus thorough explorations of the uncertain permutations. The formulation of response surface methodology is given below in Equation 13.

$$R = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \epsilon \tag{13}$$

The b coefficients result from linear regression of the empirical outputs (R) with respect to the inputs (x_i and x_j). The response surface equation is suitable for smooth outputs with few non-linearities within the range of interest. It was found that the majority of the responses in the MInD could be modeled with response surfaces of an acceptable R^2 fit.

4.3.4 Multi-disciplinary System Interactions

In multi-disciplinary design of systems, the individual components (or sub-systems) must be designed to work in concert to serve the greater system. This simple fact introduces an opportunity for risk entry in the *integration* of the hierarchical linkages between the systems. A common measure of systemic risk is the maximization of the component hierarchy; that is to say, the risk of the entire system is equal to that of the component with the greatest risk. In this *squeaky wheel* approach, managerial resources are then allocated to mitigating risks of that particular component– whether in reduction of uncertainty contributing to the risk or in hedging the consequential impact.

This hierarchy also provides a structure with which to *exchange* risk parameters, specifically in regards to objectives. During the Preliminary design and Detailed Design phases, contributing disciplines are exchanging information in cycles as the design is refined. The system level design is also re-evaluated using the latest estimates, and component level objectives are re-distributed to the various disciplines. A prime example of this is the structural load sizing. As the aircraft control systems, propulsion systems and various other systems are designed in greater detail, the weight estimate of the overall aircraft evolves. This weight

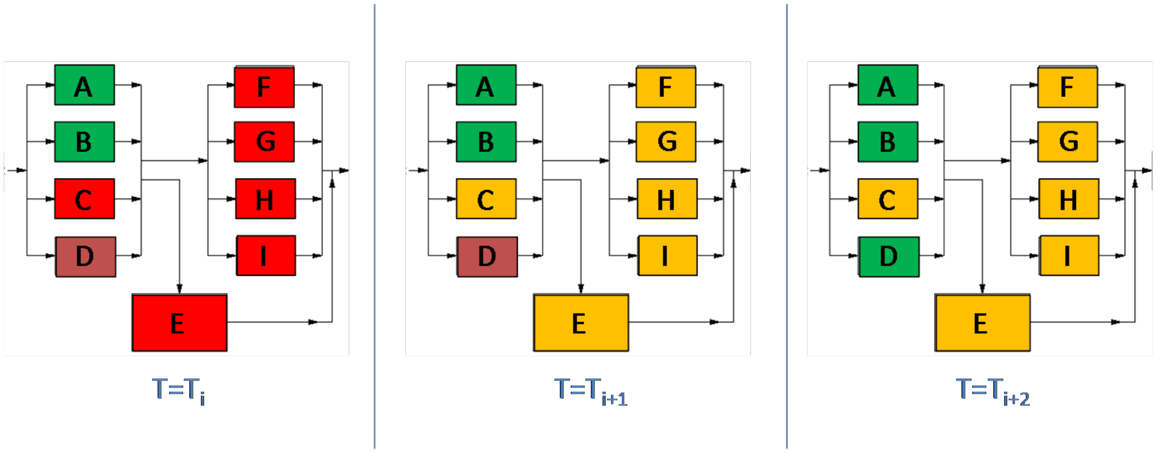


Figure 49: Hierarchal system risk evolution over time as a function of maximum risk

estimate (often Empty Weight) is redistributed to the wing aerodynamics and structural design disciplines–which may then need to be re-sized. Following the definition of risk selected in Section 2.1.3 of *effect of uncertainty on objectives*, this shifting in the component-level objective causes a subsequent possible shift in that discipline's component-level risk.

4.4 Risk Matrices

Risk matrices are a common approach to mapping likelihood and impact in one visual matrix, usually color according to the product of the axes. Several private organizations and governmental standards have adopted the use of risk matrices as a generalized method of evaluation and visualization of risk thresholds.

However, much like overall validation of risk methods mentioned earlier by Galway [40]. Cox argues that there has been little research that risk matrices validates the performance in actually improving risk management decisions [24]. The criticism of their use was broken into four reasons:

1. *Poor resolution* - Unambiguous differentiation between hazards can only be done for a small fraction of the alternatives.

2. *Errors* - Risk matrices can mistakenly assign higher qualitative ratings to quantitatively smaller risks. For risks with negatively correlated frequencies and severity, they

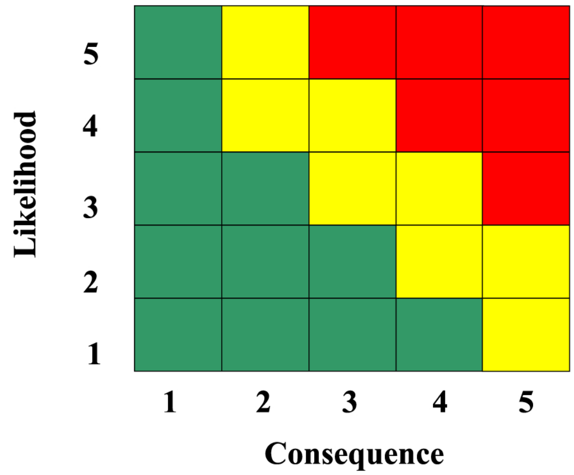


Figure 50: Risk reporting diagram [22].

can be worse than useless, leading to worse-than-random decisions.

3. *Sub-optimal Resource Allocation* - Effective allocation of resources to risk-reducing countermeasures cannot be based on the categories provided by risk matrices.

4. *Ambiguous inputs and outputs* - Categorizations of severity cannot be made objectively for uncertain consequences.

4.4.0.1 Example Uncertainty Analysis using FLOPS

NASA Langley and the National Institute of Aerospace conducted an uncertainty study on a multi-disciplinary, multi-objective subsonic mission using FLOPS design analyses to determine the reduction in design space due to uncertainty [25]. They varied the take-off weights, aerodynamic coefficients, technology readiness levels, and uncertain future fuel prices for cost analysis. Their research illustrated the difference between the probabilistic design space boundary and the deterministic design space boundary. Figure 51 illustrates the relative shift in the boundaries in two response dimensions.

4.4.1 Value-Based Aircraft Risk Management

Markish and Wilcox evaluated a method that augments the net present value method to include considerations of market uncertainty and managerial decision flexibility using three

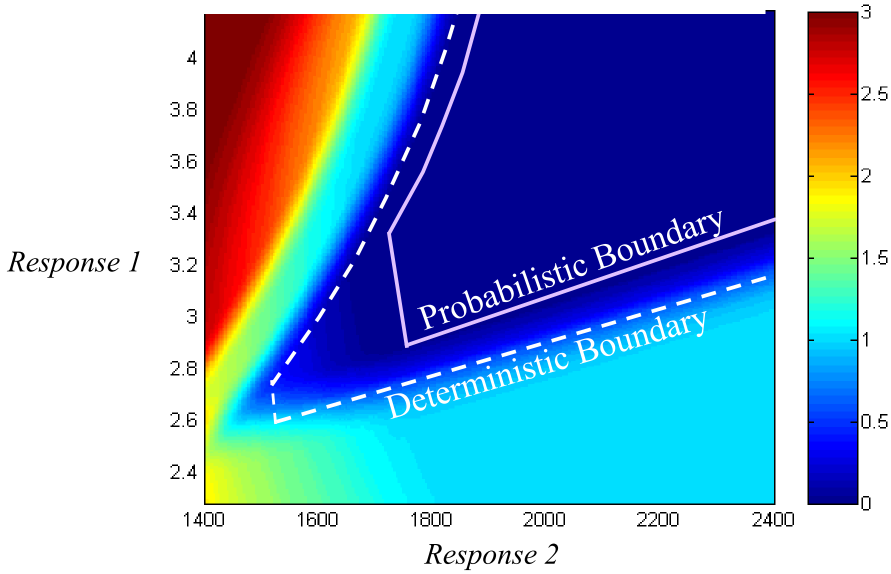


Figure 51: Reduction of the actual design space due to uncertainty [25].

separate models: cost, revenue and performance [79]. The result was a quantification of value to make program level trades.

4.5 Technology and Manufacturing Risk

As previously described, the total program risk is sensitive to the uncertainty around the development and success of technologies that are critical to the overall program. The example described in the motivation was the advanced materials technology associated with the fastening of the upper wing joint to the airframe. The upper wing joint issue–if found earlier–would have allowed time for re-design to correct the problem before certification testing. The original joint passed sub-component testing. Had the issue been identified during an earlier phase of development, the impact to the risk frontier would have been much smaller.

As manufacturers have become increasingly aware of the relationship between technology maturation and program schedule, quantification approaches to the risk have been introduced. Metrics such as technology readiness level (TRL), manufacturing readiness level (MRL), and systems readiness level (SRL) have entered the development paradigm.

These readiness levels help gauge the progress and integration of program aspects. New technologies programs are often measured by their *TRL Level*. In 1995, NASA released their widely accepted definitions for Technology Readiness Levels, a measure by which to gauge the development of new technologies [77]. The definitions are given in Figure 52.

New technologies are developed and integrated in a *just-in-time* basis with new aircraft design. This is done to maintain competitive advantage because technology factors are often the deciding factor for customer procurement. Therefore, the technology, and its integration are typically managed simultaneously. This simultaneous integration means that if certain elements are behind schedule or development then it increases the schedule risk and therefore overall program risk. An example of this relationship is given in Figure 53. In this figure, the technology maturity (described by TRL) is plotted clearly against program phase, showing the gradual increasing risk as supporting technologies fail to reach maturity milestones.

Much research has been done to succinctly define and correlate the TRL and MRL levels to program phases. The relationship between the two is also a source for risk entry. Figure 54 relates technology readiness levels, manufacturing readiness levels, and the defense acquisition lifecycle framework. While the defense acquisition framework is somewhat comparable to the program phases of commercial development, the key relationship shown here is there exists risk entry opportunity based on the timing of the program milestones and the technology transfer into manufacturing and product application.

Definition Of Technology Readiness Levels

TRL 1 Basic principles observed and reported: Transition from scientific research to applied research. Essential characteristics and behaviors of systems and architectures. Descriptive tools are mathematical formulations or algorithms.

TRL 2 Technology concept and/or application formulated: Applied research. Theory and scientific principles are focused on specific application area to define the concept. Characteristics of the application are described. Analytical tools are developed for simulation or analysis of the application.

TRL 3 Analytical and experimental critical function and/or characteristic proof-of-concept: Proof of concept validation. Active Research and Development (R&D) is initiated with analytical and laboratory studies. Demonstration of technical feasibility using breadboard or brassboard implementations that are exercised with representative data.

TRL 4 Component/subsystem validation in laboratory environment: Standalone prototyping implementation and test. Integration of technology elements. Experiments with full-scale problems or data sets.

TRL 5 System/subsystem/component validation in relevant environment: Thorough testing of prototyping in representative environment. Basic technology elements integrated with reasonably realistic supporting elements. Prototyping implementations conform to target environment and interfaces.

TRL 6 System/subsystem model or prototyping demonstration in a relevant end-to-end environment (ground or space): Prototyping implementations on full-scale realistic problems. Partially integrated with existing systems. Limited documentation available. Engineering feasibility fully demonstrated in actual system application.

TRL 7 System prototyping demonstration in an operational environment (ground or space): System prototyping demonstration in operational environment. System is at or near scale of the operational system, with most functions available for demonstration and test. Well integrated with collateral and ancillary systems. Limited documentation available.

TRL 8 Actual system completed and "mission qualified" through test and demonstration in an operational environment (ground or space): End of system development. Fully integrated with operational hardware and software systems. Most user documentation, training documentation, and maintenance documentation completed. All functionality tested in simulated and operational scenarios. Verification and Validation (V&V) completed.

TRL 9 Actual system "mission proven" through successful mission operations (ground or space): Fully integrated with operational hardware/software systems. Actual system has been thoroughly demonstrated and tested in its operational environment. All documentation completed. Successful operational experience. Sustaining engineering support in place.

Figure 52: Definitions of NASA's Technology Readiness Levels [77].

			Product Development Phases			
Technology Readiness Level	Readiness Level Definition	Concept Exploration & Definition	Demonstration/ Validation	Engineering / Manufacturing Development	Production/ Deployment	Operations/ Support
9	Production Flight Proven					
8	Flight Test Qualified	No Risk				
7	Full Scale Ground Test					
6	Component Level Ground Test		Low Risk	Medium Risk	High Risk	
5	Subcomponent Ground Test					
4	Panel Level Testing					
3	Proof of Concept Testing				Unacceptable Risk	
2	Concept/Application Identified					
1	Basic Principles Reported					

Figure 53: Technology maturity risk matrix overlaid on the product development phase timeline [110].

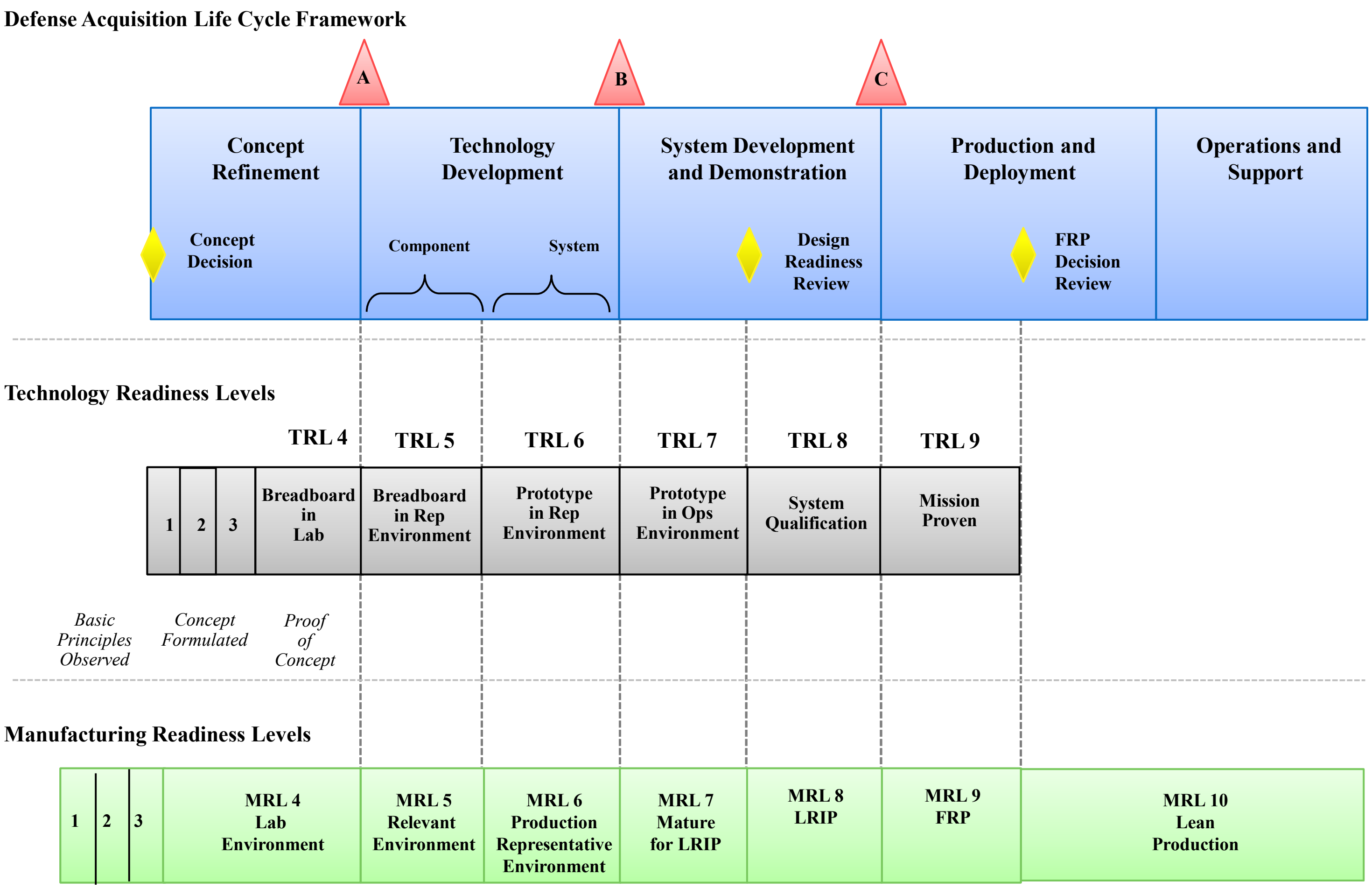


Figure 54: Technology and manufacturing readiness maturity in relation to a product development phase timeline (in this case, the DoD Acquisition Framework [96].

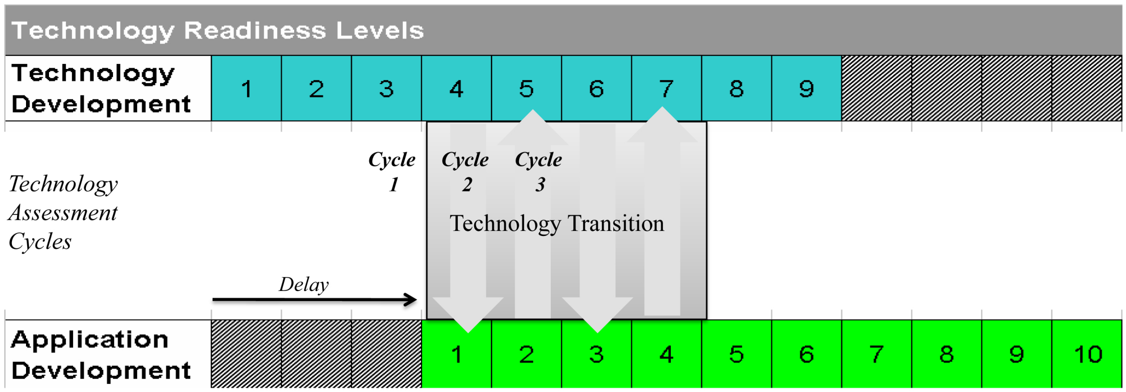


Figure 55: Risk entry due to the differing view of technology readiness with system (application) readiness levels [110].

The uncertainties associated with technology development and integration are often estimated using modeling and simulation. These models help organize and schedule as well as estimate the impact of technology integration.

However, models introduce additional errors to the ones already existing due to lack of knowledge, inability to represent physics with mathematical expressions, incomplete information, numerical arithmetic errors, uncertainty, and its propagation, as illustrated in the Equation 14: [69]

$$R = f(x) + e_{Physics} + e_{Model} + e_{Metamodel} + e_{Data} + e_{Numerics} + e_{Uncert.} + e_{Uncert.Prop}. \quad (14)$$

4.5.1 Modeling Technology Schedule and Cost

Technology costs and duration have been notoriously difficult to estimate accurately, due to the largely aleatory nature of the steps involved. They may not reach desired readiness levels on time and on budget due to physical, technological, human or management causes. There are empirical models which can be used to estimate deterministically. An example breakdown of the technology development and personnel costs per TRL step is given in Figure 56. Note the peak in cost and personnel during TRL Phase 5, precisely when integration between the technology development team and the manufacturing and application of the technologies are typically applied.

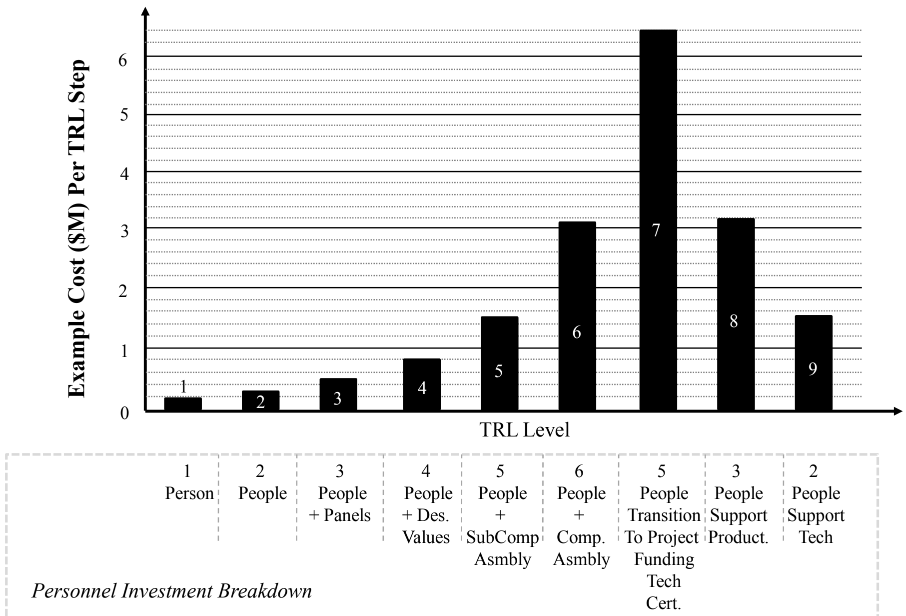


Figure 56: Chart showing the approximate cost per step of TRL as well as the breakdown in personnel for each phase of the technology maturation [110].

In addition to the cost and schedule uncertainty, the performance impact is also uncertain during the technology development phases. To model this approach, Kirby gives a probabilistic depiction of TRL versus desired capability in Figure 57, showing the transformation of uncertainty throughout the development process.

As identified in the previous sections, the interaction between the technology development process and its application causes uncertainty in cost and schedule for the technology development processes. This uncertainty causes schedule and cost slippage when individual elements do not meet their estimated schedule. Some of the development aspects cannot be done concurrently, causing later steps (or development goals) to be pushed further back in time.

To address the serial development aspect of technology and manufacturing (or alternatively application) readiness, the interaction between technology readiness and manufacturing readiness, was modeled using a networked approach for the implementation and total RDT&E cost and duration scheduling. This led to the conceptual exploration of what was

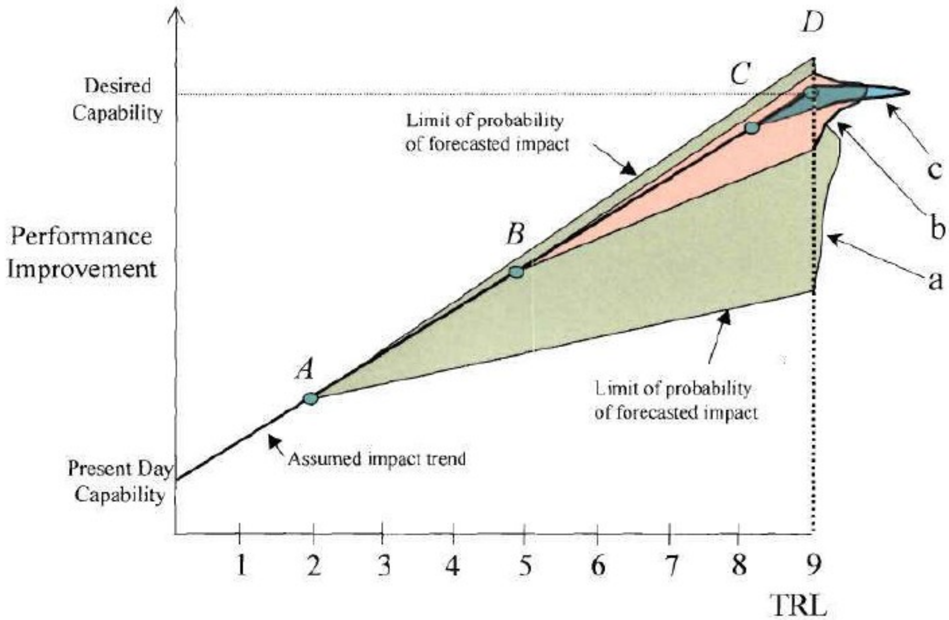


Figure 57: Probabilistic illustration of Technology Readiness Levels [67].

called a Technology Network Model (TNM).

Figure 58 shows the flow of uncertainty elements into the technology network matrix model. Here the cost and time elements are combined together, producing a single distribution for the total development cost and time for the technologies in consideration. These distributions then serve to map to input variables in the experimentation framework.

Looking inside the model, the core functionality of the TNM is to enable stop-gap requirements for the readiness levels of technologies and their manufacturing readiness. These stops trigger delays and increments in cost when the condition is not met. It then functions similar to a FIFO queuing model with multiple servers and a processing condition imposed.

To illustrate this effect with the technology and manufacturing example, consider the composites technology Stitched Resin Film Infusion (S/RFI, detailed in the next section): the TNM could specify what TRL level this technology must reach (for example, TRL 7) before the applications development team may reach MRL readiness level (MRL 5).

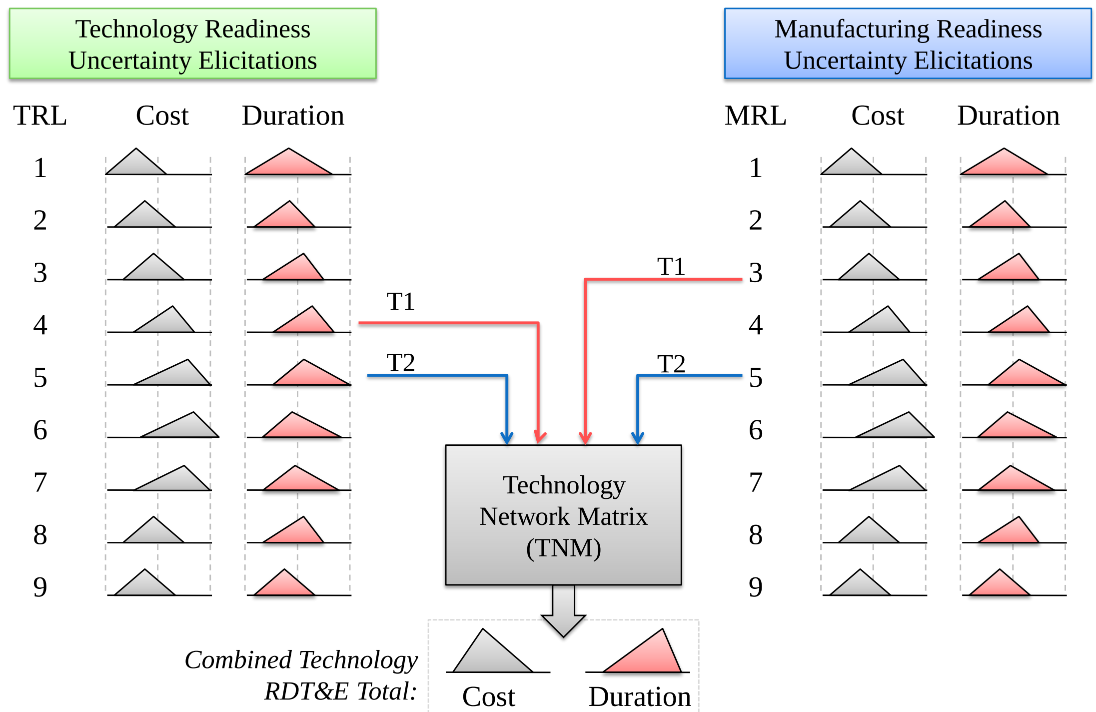


Figure 58: Illustration of the uncertainty flow into the Technology Network Matrix (TNM).

Deterministically, this constraint may not cause any issue as the MRL and TRL of the S/RFI have already been scheduled; but, due to the probabilistic nature of the duration and costs of those steps, it is possible for the technology to be delayed in reaching TRL 7, thus forcing the development of the application to idle at MRL 4 until TRL 7 is reached. This is illustrated in Figure 59.

This was demonstrated and was explored in a MATLAB code called TekNET. This code takes a set of Technologies, their mean development times per TRL, and symmetric triangular uncertainty and produces a time-based portfolio growth model. The code is then expanded to handle enabling technologies (by TRL) that often exist within the technology network. Each of the lines in Figure 60 is a different technology as it progresses through the development stages. At launch, the technologies are at different stages; but, the sequenced requirement of manufacturing readiness levels means that once the requirement is imposed, the MRL development must idle until the required TRL of the technology is reached.

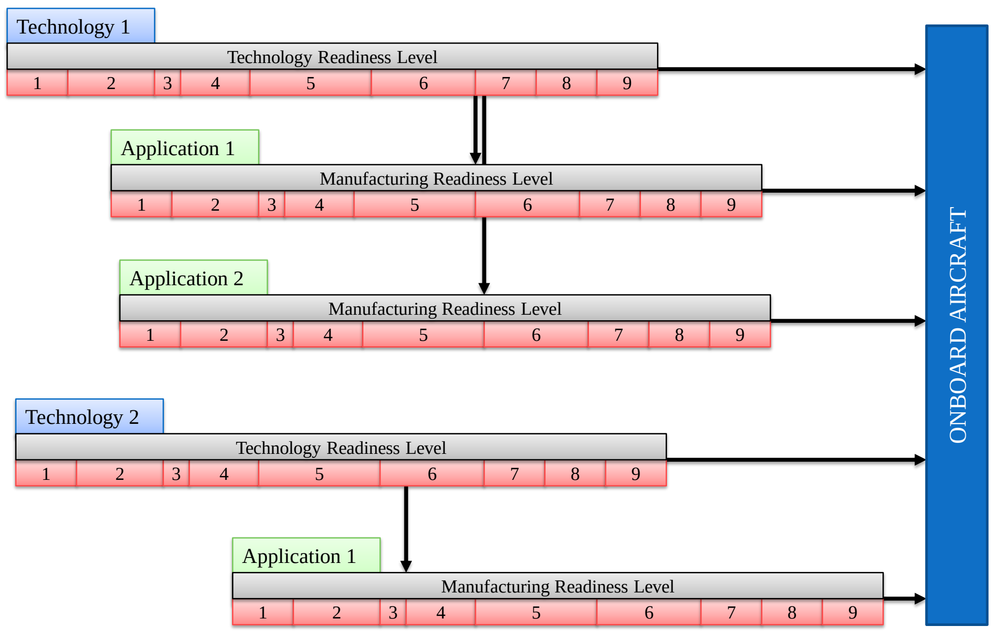


Figure 59: Illustration of the Technology Network Matrix (TNM) which requires pre-set technology readiness levels to be reach goals before manufacturing levels may be reached.

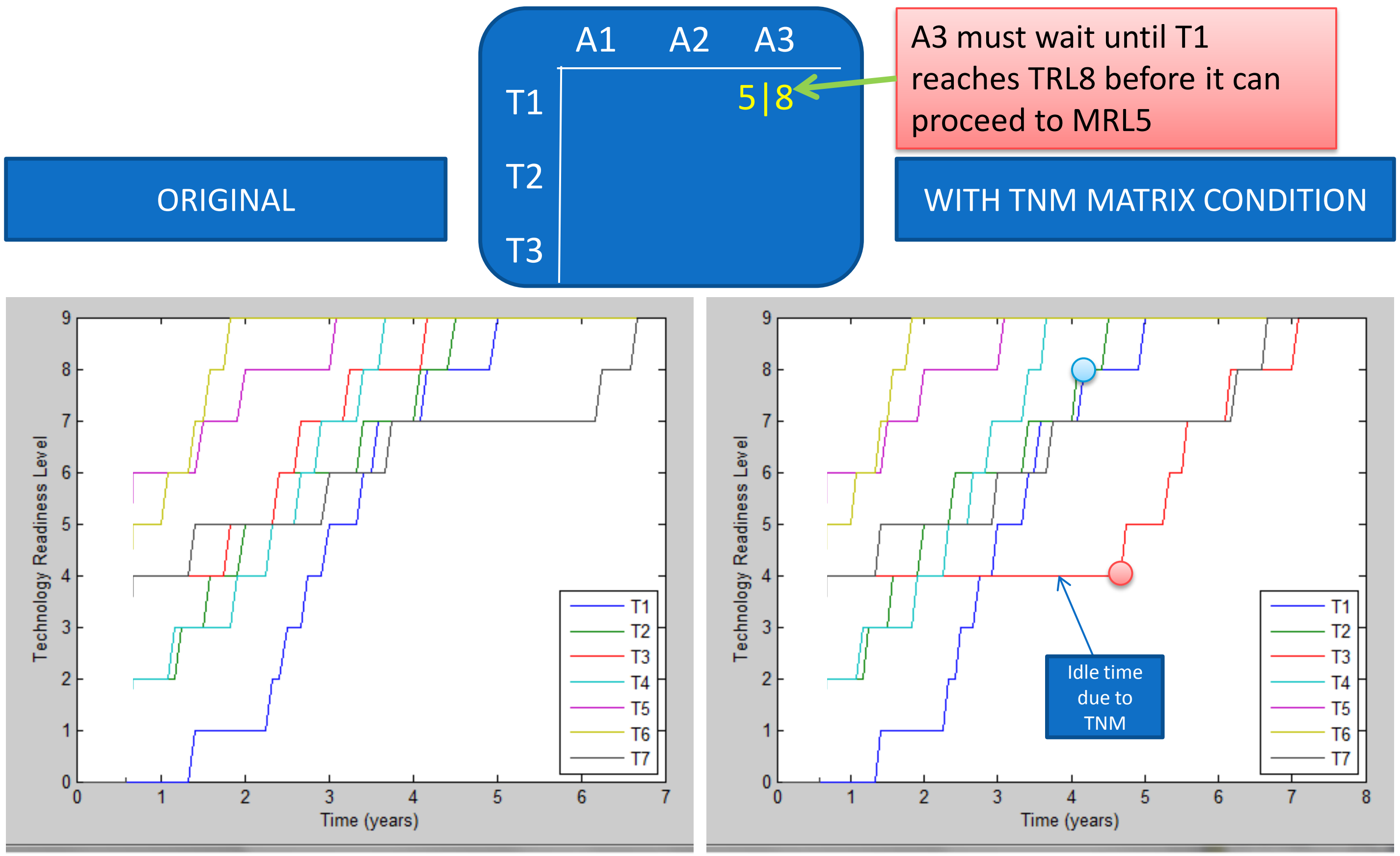


Figure 60: Demonstration of the Technology Network Matrix (TNM) which requires pre-set technology readiness levels to reach goals before manufacturing levels may be reached.

4.5.2 Demonstration Technology and Calibration

NASA released an AST report in 2001 [65] that verified the manufacturing and implementation of a new low-cost composite technology in primary wing structures of civil transport aircraft while maintaining a strength-to-weight performance advantage over aluminum. The technology, called stitched resin film infusion or S/RFI, enables cost savings by assembling the dry composite preforms with a computer-controlled stitching machine, then infusing the epoxy resin and curing the assembly as a whole. This approach has several procedural advantages in the manufacturing of complex parts and assemblies, as mechanical fasteners are replaced. The report focused around a composite redesign of the aging McDonnell Douglas MD-80 (also a single aisle transport with approximately 150 passenger capacity and 2000+ nautical mile range), and included several new manufacturing technologies and detailed cost estimations. This report provided a detailed reference for technological and fiscal cost methodology calibration. The unique availability of this report, and the detail provided in the cost estimation and manufacturing technology proof-of-concept were therefore ideal for use as a baseline to evaluate the methodology.

Figure 61 gives a detailed overview of the trade study between aluminum wing weight and the S/RFI technology. It shows the weight savings over the aluminum structures broken down by the wing components. The baseline trade study shows approximately 30 percent improvement in part weight at both room temperature and with environmental effects taken into account. Only a single component, the rib and spar shear clip, actually increased in weight with S/RFI technology. The NASA AST report verifies the economics associated with this new technology by actually building a full-scale wing box. Figure 62 shows the full-scale wing box design with the stitched cover panel design.

Figure 63 shows a close-up photograph of the computer-controlled stitching machine assembling the drive preforms of a rib clip to the skin. This technology made it "possible to incorporate various elements of the wing box into interval structure that eliminates the requirement for thousands of mechanical fasteners" [65]. The challenge with this technology which introduced risk and uncertainty into both the economics and performance, was whether or not the resin could be reliably infused into the drive preform assembly. Failure

		Trade Study (Baseline) Stitched/RFI Composite Wing					
	Aluminum Wing	(at Room Temperature/Dry)			(w/ Environmental Effects)		
Components	Weight (lb.)	Weight (lb.)	Comp/AL Wt. Ratio	Part Wt. Saving (%)	Weight (lb.)	Comp/AL Wt. Ratio	Part Wt. Saving (%)
Upper Skin	1212	895	0.74		974	0.80	
Upper Stringer	664	542	0.82		552	0.83	
Upper Spar Cap	407	152	0.37		155	0.38	
Upper Intercostal (or Shear Clip)	30	70	2.36	28%	70	2.36	24%
Lower Skin	1588	761	0.48		803	0.51	
Lower Stringer	536	413	0.77		425	0.79	
Lower Spar Cap	210	131	0.62		136	0.65	
Lower Intercostal (or Shear Clip)	17	80	4.72	41%	80	4.72	39%
Front Spar Web	235	183	0.78		188	0.80	
Rear Spar Web	232	167	0.72	25%	169	0.73	24%
Ribs (excluding MLG Bulkhead)	422	303	0.72		303	0.72	
MLG Bulkhead	89	75	0.84	26%	75	0.84	26%
Rib/Spar Shear Clip & Attach. Bracket	53	67	1.26	-26%	67	1.26	-26%
Bolts & Nuts	90	80	0.89	11%	80	0.89	11%
Pad-up (at SOB)	5	25	4.91		26	5.27	
Pad-up (at MLG)	4	31	7.63		33	8.18	
Pad-up (at Access Holes on Lower Cover)	149	45	0.30	37%	47	0.32	32%
Total (lbs. or Saving):	**5942**	**4019**		**32.4%**	**4184**		**29.6%**
Weight Saving (%)		32.4%			29.6%		

Figure 61: Weight comparison for aluminum and Stitched/Resin film infusion (S/RFI) composite wing structures [65].

to penetrate the entire drive preform structure could introduce mechanical weaknesses and therefore safety concerns at this was for use in primary aircraft structure. The final part of the AST report verifies the structural integrity by measuring ultimate load of the proof of concept part. It was shown that the assembly failed within acceptable limits.

The economic results of the technology demonstration are given in Figure 64. The cost data are given for the cumulative average of 300 aircraft, and show an average of 20 percent cost improvement over the baseline aluminum structure for the wing box, the wing cover, and wing assembly. The wing substructure achieved its goal of approximately 7 percent. These results provide valuable calibration key points to testing the CASSANDRA methodology, as detailed cost and weight information of composite structures relative to equivalent aluminum structures provide.

4.6 Summary

This chapter reviewed the technology and development factors that drive cost and uncertainty during the RDTE phase of the design process. Recalling the figure illustrating the

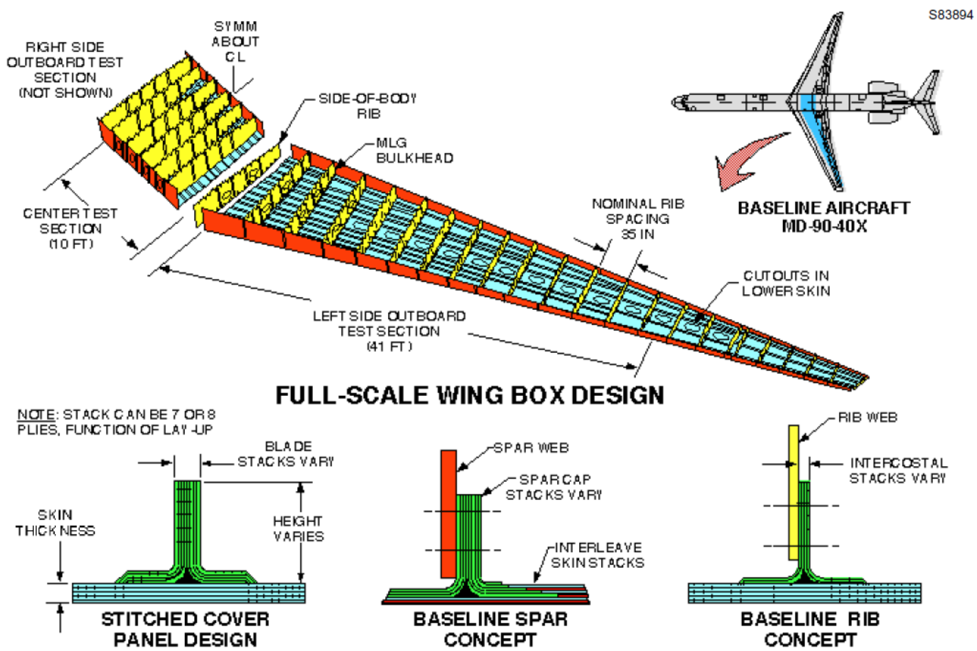


Figure 62: Detail view of the MD-90 wingbox and sections of the S/RFI joining processes [65].

Technical Uncertainty on the cumulative cash flow space and its relationship to the *Market Uncertainty*, this chapter addressed the factors driving the manifestation of cost and schedule. The human resources, materials, technology development, manufacturing setup, testing, and certification processes all contribute during this phase. The core management problem of addressing how and where uncertainty could be allocated in this phase was addressed through the use of risk management processes and modeling and simulation. Several analysis techniques were identified, specifically Monte Carlos simulation and the associated sampling techniques (fast probability integration, response surface modeling, etc). The entry points of uncertainty during these phases were discussed, and the consequence of that uncertainty were mapped to several risk measurement methods. First, the use of risk matrices was reviewed, especially in relationship to the technology modeling approaches with readiness levels. The author also addressed how the readiness of a technology and manufacturing were interrelated, and could be probabilistically modeled using the Technology Network Model, giving the total networked cost and schedule density distributions as a

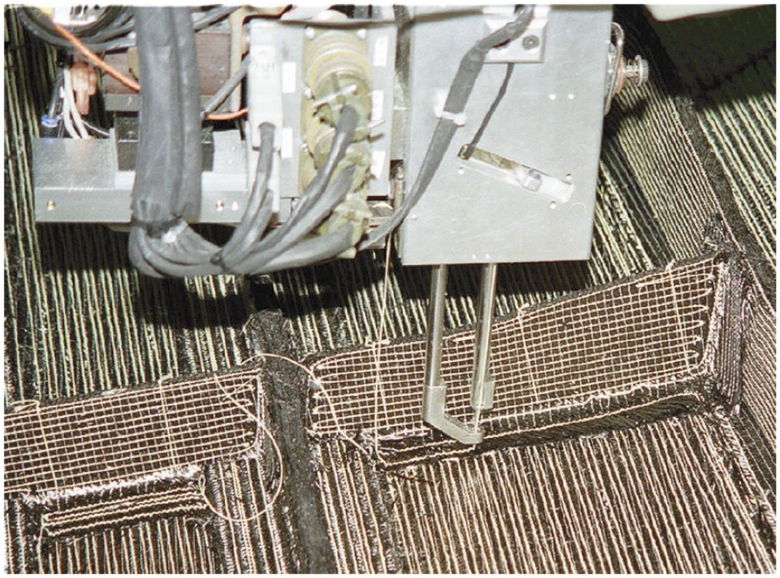


Figure 63: Photograph of the stitching of a rib clip the skin prior to resin infusion [65].

function of the elicited inputs for each technology level.

Finally, a technology called Stitched Resin Film Infusion for improving the weight and cost of the primary structure was detailed following a NASA report. The cost models and schedule models used in this dissertation were able to be iteratively calibrated thanks to the detailed report of the technology demonstrator.

This modeling and simulation framework sets up the CASSANDRA methodology to evaluate how the uncertainty in technology affects not only the cost and schedule impacts of the development, but then prepares the estimation for the market and production effects. In this way, the payback and profitability of the technology infused aircraft can be addressed.

MDXX Cost Parameters (CY96 M$)	Aluminum Wing Box Cost	S/RFI Wing Box Goal Cost	S/RFI Cost	Program Performance Goal vs. Actual	Program Performance Actual
Structural Wing Box (Cum. Avg., 300 Ships)	$3.181	$2.544	$2.557	-20.0%	-19.6%
Structural Wing Cover (Cum. Avg., 300 Ships)	$1.516	$1.147	$1.160	-24.3%	-23.5%
Wing Substructure (Cum. Avg., 300 Ships)	$0.461	$0.429	$0.429	-6.9%	-6.9%
Wing Assembly (Cum. Avg., 300 Ships)	$1.204	$0.968	$0.968	-19.6%	-19.6%

Figure 64: Aggregated cost comparison of the aluminum wing to the S/RFI wing, over 300 sets of wing boxes [65].

CHAPTER V

MANUFACTURING RISK AND MARKET ESTIMATION

5.1 Introductory Remarks

Recalling the Figure 65, the program uncertainty arose from two fundamentally different sources that were illustrated on the cumulative cashflow diagram. The technical uncertainty was covered in the previous chapter, focusing heavily on the costs and time to develop and integrate new technology. The result was a modeling approach that identified the uncertainty between development costs and program sunk cost, as well as the development time and the production launch year. These characterize the Technical uncertainty described by Figure 65, shown here again for convenience.

This chapter addresses instead the drivers for the second element shown on this figure: the Market uncertainty. Identification of design risk and technology implementation risk is one thing, propagating their impacts to the revenue, production costs, and program profitability are another.

This chapter reviews the manufacturing cost drivers and revenue capability. The learning effect and discount factor theory is reviewed and demonstrated through modeling and simulation on the baseline problem.

The cost structure of the new aircraft development and operation lifecycle is shown in Figure 66. This diagram gives an overview of the cost structure experienced during the lifecycle, organized by acquisition and sustaining costs.

5.2 Aircraft Program Economics

As with almost any new product development, there is an initial investment required to explore the feasibility and viability of the product. The cost can be generalized by the point of maximum sunk cost (sometimes referred to as acquisition cost) which usually occurs at the point of delivery of the first example of the new product. The schedule can be considered as the mean time expected to reach first delivery (or as time to break even, but

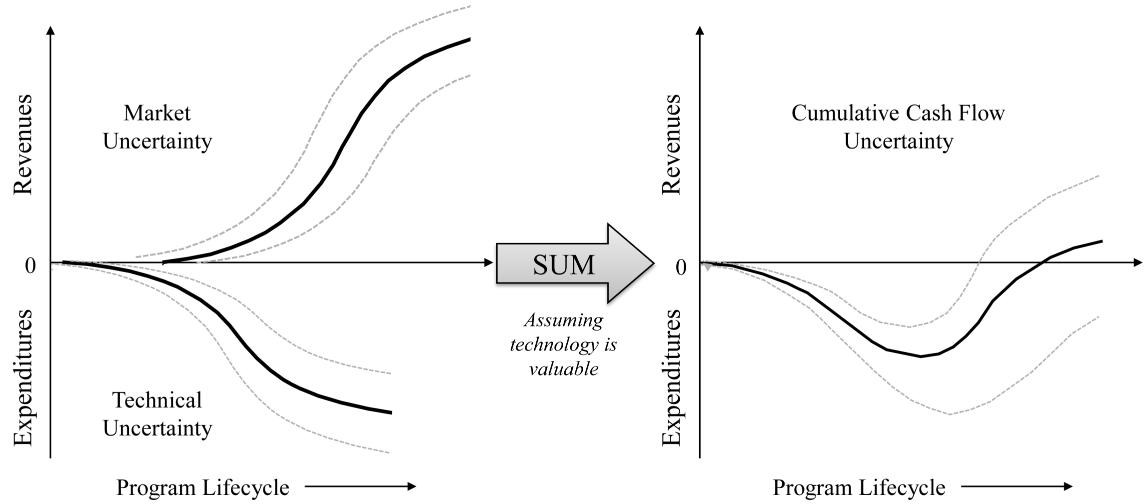


Figure 65: Life cycle cost tree hierarchy for both acquisition and sustaining costs, broken down by branch [110].

that assumes more information related to performance). The performance, or desirability of the product by the market, is related to the slope at which products are generating revenue from sales. Products with poor relative performance (or high variable manufacturing costs) tend to have shallow payback slopes and may never reach break even. There are many other convoluted factors at play during this period, such as in the sales or production rate, and unit sale price (which tends to vary based on order size, partnership agreements, and program maturity level).

Recall in Chapter 1, where it was stated that products with a positive expected return on investment (or positive Net Present Value) are green-lighted, but the assumptions substantiating the product performance, cost, market availability and future presence of competition are subject to sizable uncertainty. This uncertainty ultimately can be translated to a possible shift in the expected cash flow chart, shown with the lines above and below the mean expected return in Figure 65. Note that the uncertainty around the expected line increases with time, following general assumptions of stochastic diffusion processes.

Figure 68 shows the estimated annual cash flows for a modern commercial transport

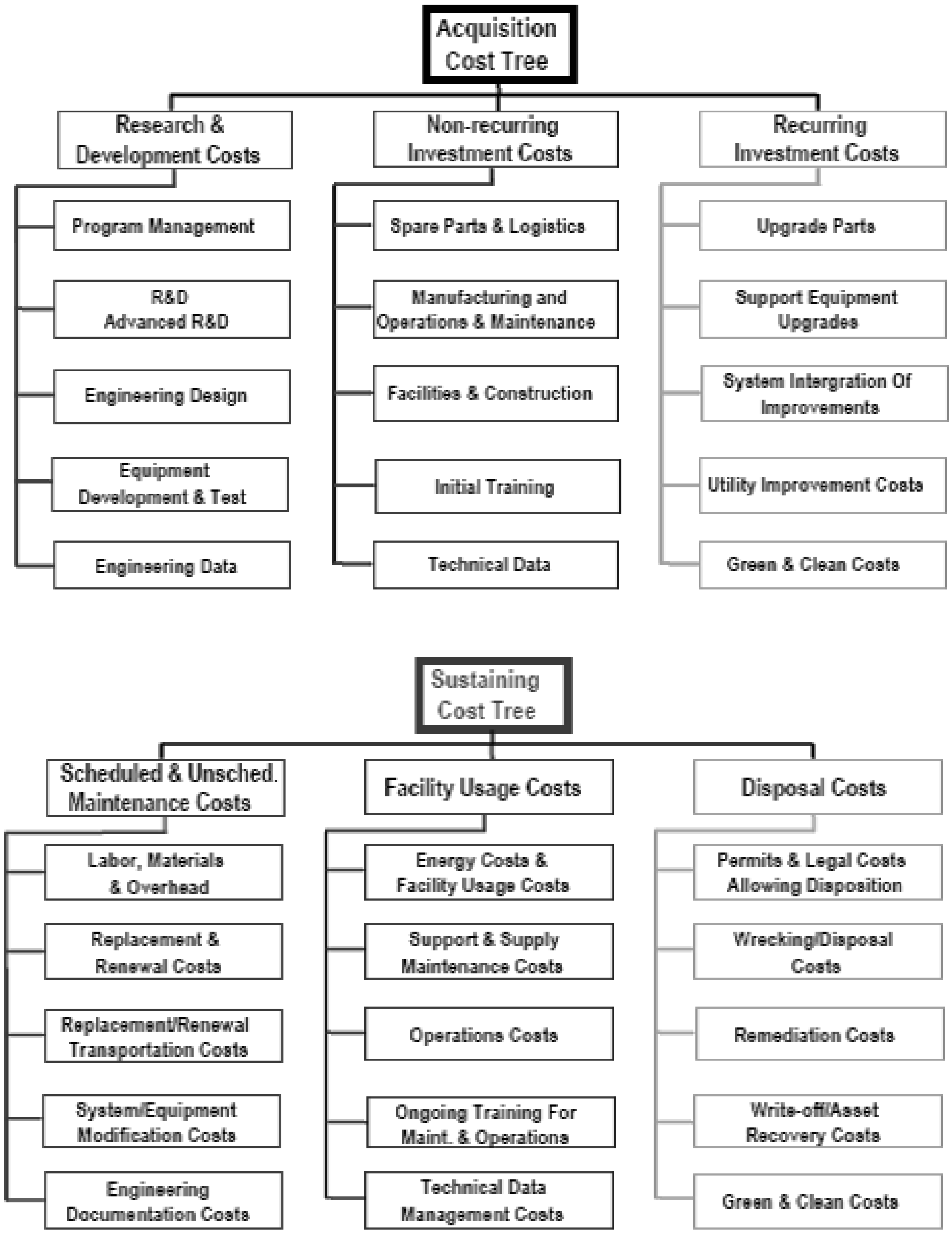


Figure 66: Total uncertainty in cumulative cash flow for complex engineered systems broken down by technical and market uncertainty [110].

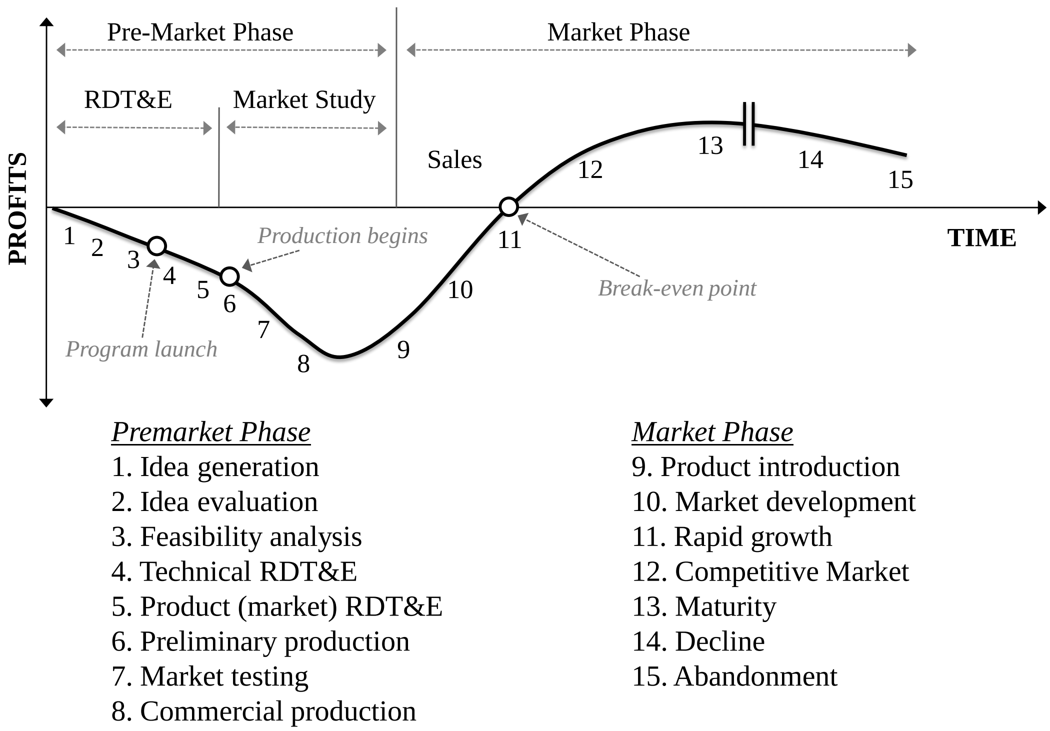


Figure 67: New product development profits and their key product life cycle milestones [110]. .

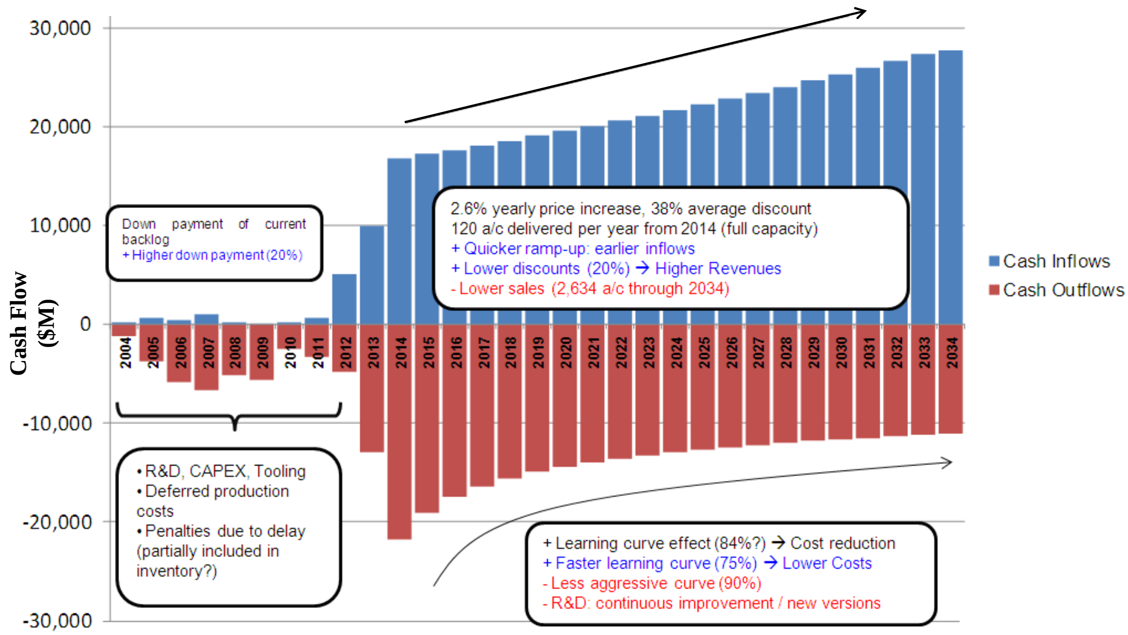


Figure 68: Cumulative cash flow for a typical commercial transport aircraft, without correction for discount factor [91]. .

aircraft program. Note the sharp ramp up in magnitude of both costs and revenues as production begins, as well as the exponential decrease in production costs over time. Also note that there are typically some payments early in the development phase. These inflows are typically a result of purchase agreements with customers, as many sales incorporate a down-payment of approximately 10-50 percent of the aircraft. This down-payment varies between customers as a function of the other purchase agreement details.

Figure 69 shows annual cash flows similarly, but this time with the discount factor demonstrated. In this example a discount rate (similar to inflation rate adjustment) of 10 percent was used. The effect of this is that as the value of money now is greater than money in the future, the large capital returns in the future may not balance with large expenditures in early phases of the program [91].

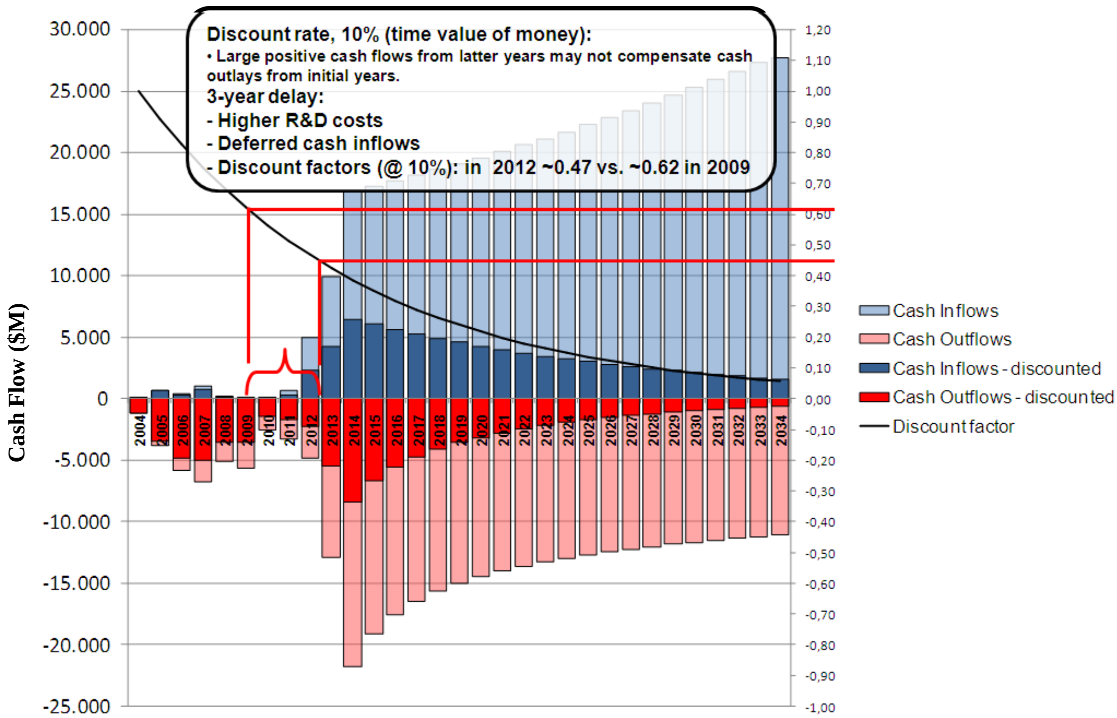


Figure 69: Cash flow diagram, showing the annual and cumulative cash flows for a typical commercial transport aircraft. Also note the discount factor and its effect on the present value of future payments (in the darker shading) [91]. .

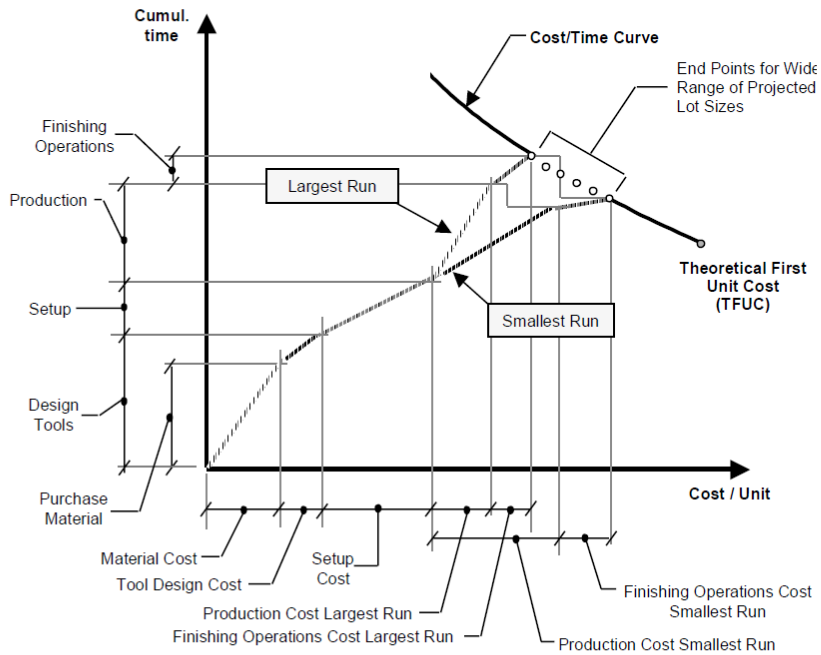


Figure 70: Program costs by category and time spent on a unit basis, reaching the cost-time frontier [110].

5.2.1 Development of Unit Cost Versus Time

Another approach of visualizing the constituent parts of the cash flow data is to look at the cost-time frontier, as shown in Figure 70. This view of the development and setup costs illustrates essentially the same information as the cashflow diagram: both time and cost dimensions are decoupled. However, in this representation the cost is normalized by *unit*. This representation is useful for estimating the relationship between desired production rate and unit production cost attribution. The key points of this graph are the point at which the first aircraft can be produced and the placement of the theoretical first unit cost curve. The production run then drives the cost per unit up or down along the curve as a function of the run quantity.

As more new technology is introduced, the location of the first unit key point tends to become higher and to the right, reflecting schedule slippage and cost overrun. The programmatic value of this effect can be restored *either* by increasing the production quantity (and thus lowering the unit cost) or by increasing the product price.

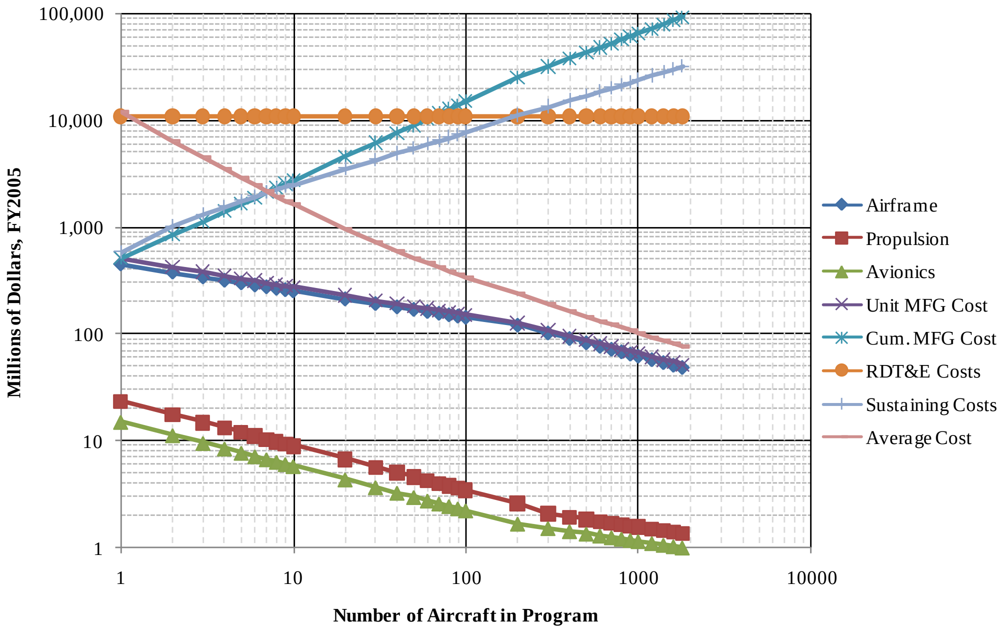


Figure 71: Program costs by category versus number of aircraft planned in amortization schedule.

5.2.2 Production Quantity and Program Cost Amortization

On the customer or airline operator side, Figure 75 gives a visual description of the operating cost metrics relationships between the direct operating costs (DOC), indirect operating cost (IOC) and total operating costs(TAROC). In FLOPS and ALCCA, these are given by flight hour, by flight (over two different trip lengths) and by year. These metrics heavily influence the airliner acquisition decision making [135].

5.2.3 Inflation Rate Effect

Inflation is a fundamental concept of economics that describes how the value of money changes over time in conjunction with two things: 1) the available supply of money and 2) the generation of valuable goods and services. The principle measure of inflation is the *inflation rate*, typically as a percentage per year, which is based off a price index such as the Consumer Price Index. Changes in the inflation rate have a direct effect on the viability and general attitude toward investment [78]. As future uncertainty in the inflation rate

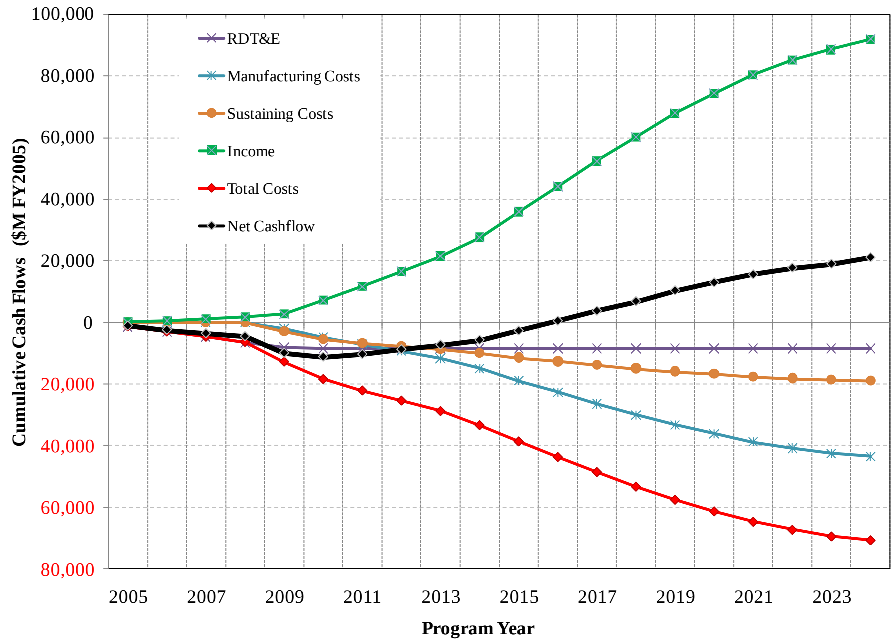


Figure 72: Cumulative cash flow diagram for baseline aircraft, showing both the cumulative costs and incomes for the aircraft price of 104 Million.

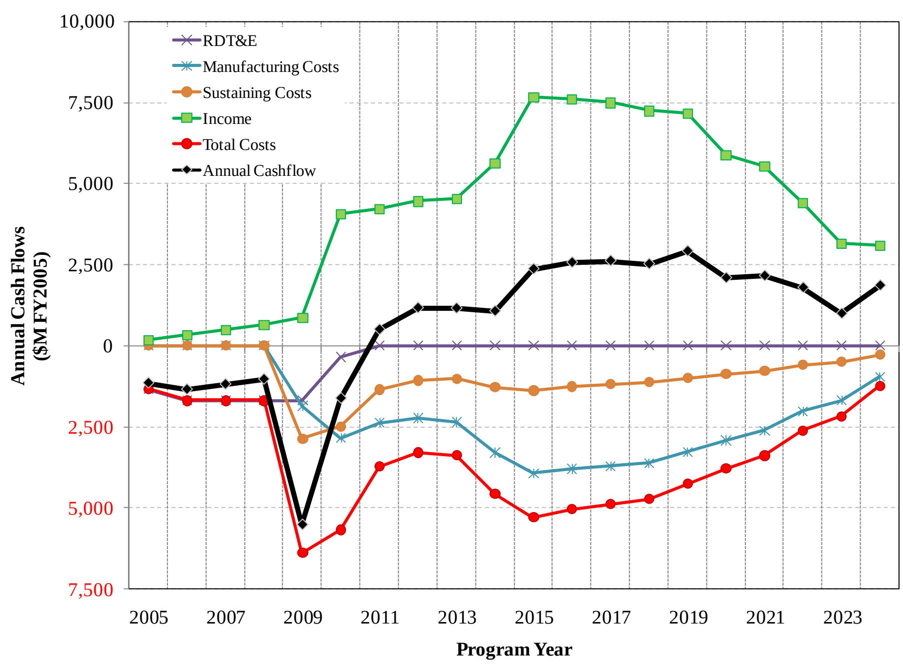


Figure 73: Annual cash flow diagram for baseline aircraft, showing both the cumulative costs and income for the aircraft price of 104 Million.

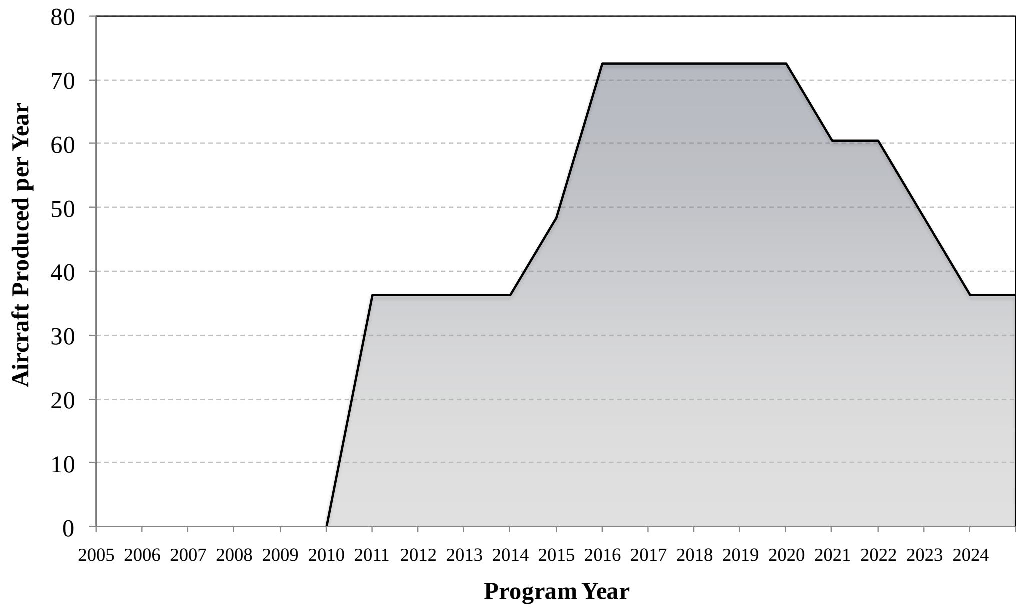


Figure 74: Annual aircraft production schedule over the life of the program. Note the 5 year development and manufacturing delay, and the second hike in production rate during Block 2 of the manufacturing schedule.

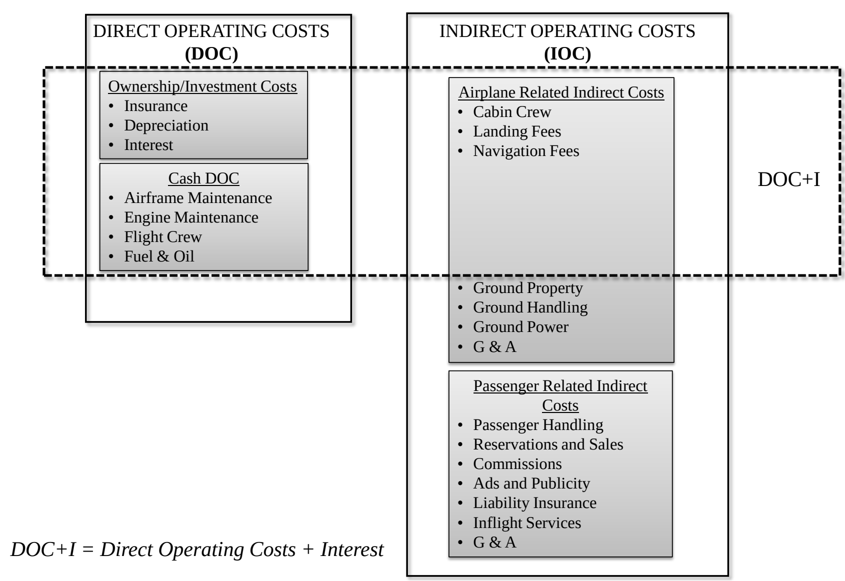


Figure 75: Visual descriptions of the relationship between Direct Operating Costs (DOC), Indirect Operating Costs (IOC) and DOC+I [62].

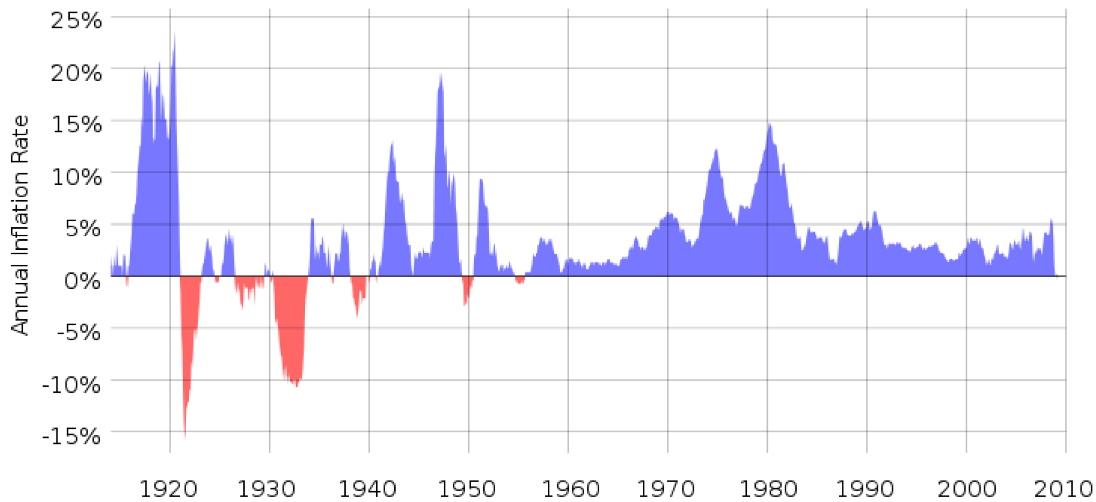


Figure 76: Historical percent inflation rate (API) in the United States through 2009 [45].

increases, it has an adverse effect on likelihood for a person or enterprise to undertake a risky prospect. This effect is found to exist in the uncertain cumulative cashflow profiles as well. Figure 76 shows the historical inflation rate for the US dollar over the last century.

5.2.4 Learning Effects on Manufacturing Cost

As mass production of aircraft (and vehicles in general) was continuously improved, a cost-savings effect was discovered. It was found that as the number of produced vehicles increased, the costs of each subsequent vehicle tended to drop. This was called the learning curve effect, and it has historically played a strong role in the overall lifecycle cost of the program. A feature of the learning curve effect is that it diminishes as the most efficient tasks for each of the elements of the work breakdown structure are discovered.

The learning curve exhibits an exponential decay in cost as a function of vehicles produced. Figure 77 shows the learning curve effect on production cost as the quantity of vehicles produced is increased. Note the two differing learning curves: one with $LC = 0.8$ and the other with $LC = 0.7$, and note how their magnitude affects the long-term unit production cost, and the location of the first unit cost point.

The general approach is to calculate the first unit cost (FUC), then amortize that costs

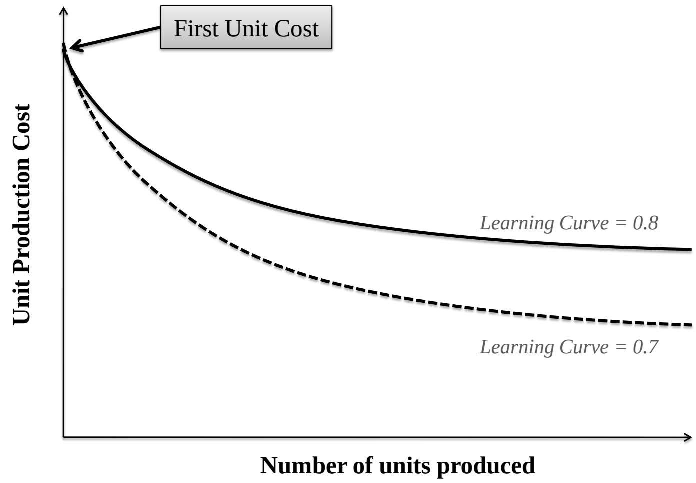


Figure 77: Effect of the *learning curve* on long term production costs per vehicle produced.

over the entire estimated production run. The production effort P (expressed as either cost per unit or labor hours per unit) is given as:

$$P_{unit} = P_0 * x^{LC_{rate}} \tag{15}$$

where x is the number of units since the first unit and P_0 is the first unit production effort. The LC_{rate} is given as:

$$LC_{rate} = \frac{\log(PercentLearning)}{log(2)} \tag{16}$$

An alternative view of the risks associated with the *amount* of technology infusion is given in Figure 78. In this graphic, the *net*, aggregate measure of system risk is given as a function of the amount of technologies applied to the product. With little to no additional technologies, the main driver of product risk arises from the Performance Risk as requirements and the voice of the customer continually demand better performance. The lack of new technology to meet those demands thus creates a substantial probability of failure.

However, when many or all available technologies are assigned to the future product, the integration complexity and development effort required drives the cost and schedule risk, as

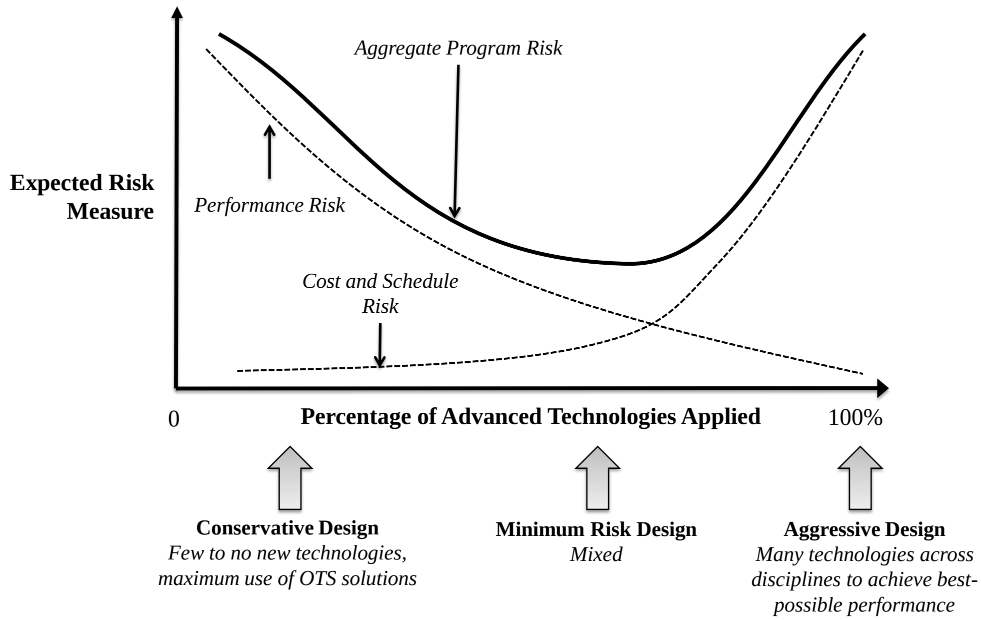


Figure 78: Notional aggregate risk versus the amount of technologies applied to an aircraft design, with the risk driver types illustrated below the aggregate line.

limited resources reduce the probability of successfully incorporating the maximum set of technologies. The minimum aggregate risk design lies somewhere in the middle, considering the costs and schedule risks associated with integration difficulty and the ability to meet customer requirements.

Traditionally, this minimum risk point could be collapsed to a single variable: aircraft weight. Before the rise in advanced materials, weight has been empirically shown to be well correlated with performance and cost. Advanced materials technologies have broken this heuristic, as the costs and development time associated with composite materials does not follow the same trend.

Research Observation V

There exists a trade- off in systemic risk between aircraft design parameters, scenario variables, and technologies.

The subsequent *Research Question*:

Research Question V
How should risks associated with portfolios of advanced technologies be optimized for a given aircraft design and scenario description? How does this change as a function of the system-level objectives? Which is preferred: a normative approach (*what risks must be assumed to reach target*) or an explorative approach (*What is achievable within the tolerable level of risk?*)?

The performance, cost and schedule risks can be interpreted from this probabilistic representation of the cash flow chart. If the expected return is held as the target objective (keeping with the established definition of risk), then the variance around the expected line *is the risk*. In the schedule dimension the horizontal uncertainty in time, before and after the first delivery (sunk cost) point is the schedule risk. The variance in cost (vertical dimension) around that same point is a description of the cost risk by the same token. The performance risk, however, can be simplistically illustrated by the longevity of aircraft production and sales, under the rationale that better performing aircraft deliver customer value longer into the future. Put a different way, a higher performance aircraft buys the manufacturer a longer period of time to maintain a competitive edge, thus staving off the threat of substitute products and competitive rivalry for a greater time period.

The risks in performance, cost and schedule are given notionally by the shift in these lines shown in Figure 79.

The result is a region of uncertainty around the resultant positive net cash flow region (known as *in the money* by financial traders). Unfortunately, history has several examples of real aircraft programs that never reached this region; a noteworthy example is the Lockheed L-1011 Tri-Star, which produced roughly half the aircraft needed to break even, ultimately losing approximately one billion dollars [51].

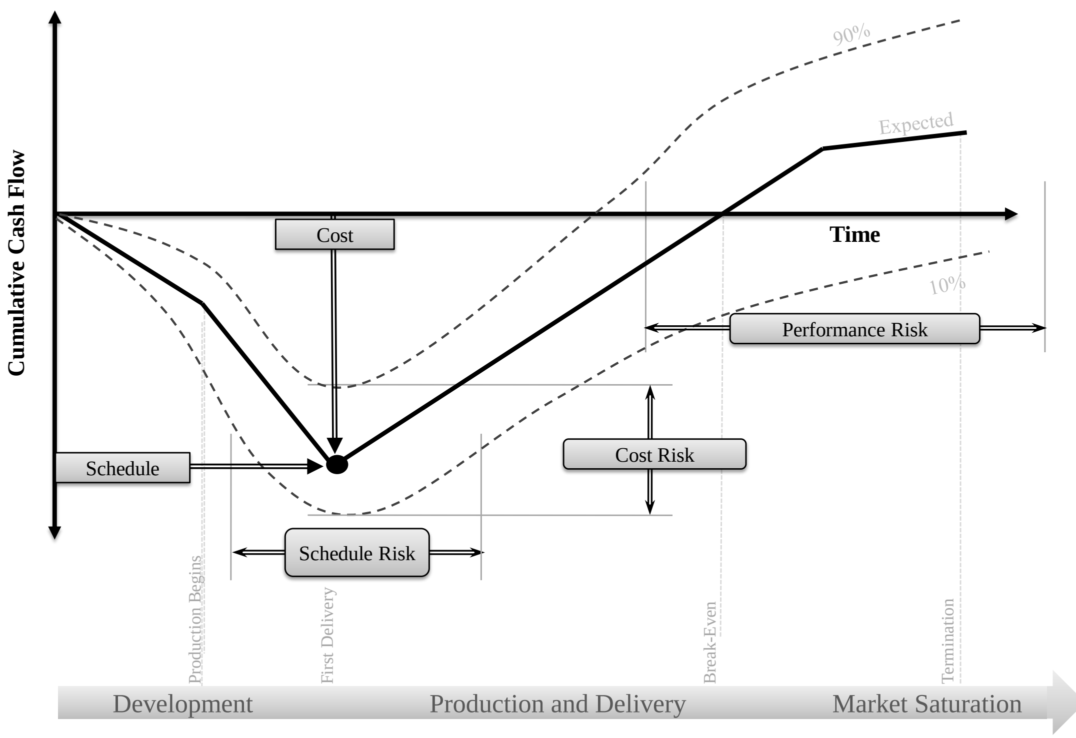


Figure 79: Notional cumulative cash flow chart illustrating the performance, cost and schedule risk in each dimension for a typical product development program.

From this depiction of the cash flow and related risks, one can see that there are several possible paths to end up with positive net cash flow. If the acquisition costs are reduced, the required time to break-even is shortened, or the required sales rate (performance) is relaxed. Therefore, it follows that a key concept is that they must all be managed simultaneously and that there exists a trade-frontier between risk types. Making these trades, or exchanges between types of risk exposure, is a central task of the risk mitigation and strategic alignment of the program.

In the previous phase, price and volume trends were observed to have large impact on the cash flow response. This result was not unexpected, however, it became obvious that there existed a need for connecting the value of the aircraft product to the number of aircraft produced. This phase addresses the need for a model to connect those two metrics in a traceable manner. It begins with a review of the observations from the software economics discovered in the results from the previous phase. Next, a set of alternative routes is identified and an approach is selected, then developed to meet the market and manufacturing requirement. Finally, the section ends with a demonstration of the model, an expert-based calibration process, and the filtration process of results.

5.3 Market Share Modeling

Following the Observations in previous sections, the preliminary results from the FLOPS/ALCCA exploration indicated that the parameter *Number of Vehicles (NV)* greatly affected the resulting cash flow trajectory due to its connection to aircraft price and the amortization of the development costs. It was particularly important with regard to the likelihood of profitability by the end of the program duration. This result is expected, as with most manufacturing problems, the break-even (and consequently profit) is a function of costs per unit, revenue per unit, and volume. The volume of goods sold scales the revenue linearly. Flops and ALCCA treat the number of vehicles and the production rate as inputs, and therefore treat the market capacity independently from the value (or saleability) of the aircraft design itself.

A brief review of Porter's famous publication in the Harvard Business review about the *Five Forces* of business [103] is perhaps useful in preparing the experimentation and development of the Market model for this phase. Porter argues that there are the *Five Forces* at the core of successful business practices. They are given here with commentary about their relationship to the commercial transport market:

1. *Bargaining power of suppliers* - commercial transport integration is extremely sensitive to the supply chain. A typical commercial airliner contain hundreds of thousands of parts sourced outside the airframe manufacturer/integrator. The risks associated with the fragility and schedule of these supply networks were covered briefly in Chapter 1.

2. *Bargaining power of customers* - The trade space between volume and sales price generally changes during the life of the aircraft program as the manufacturer recovers more and more of their investment in the program [59] [39]. The list price typically increases 3-5% annually to account for inflation and the reduction in program risk by the manufacturer [9].

3. *Threat of new entrants* - The development and growth of alternatives have recently occurred that threaten the stability of the recent duopoly between Airbus and Boeing, particularly from Asian and South American manufacturers [117] [19].

4. *Threat of substitute products* - Substitutes for air travel, such as high-speed train systems and high-efficiency automobiles have increased in the last 20 years, slowly threatening the commercial air transport market [59].

5. *Competitive rivalry within an industry* - The 150 passenger commercial transport aircraft is captured principally by Airbus and Boeing, but other alternatives exist such as Bombardier and Comac [98] [61]. Appendix F gives a selection of figures showing the struggle between the two manufacturers over the last twenty years.

The interaction of the Five Forces is given in Figure 80, showing the four satellite forces feeding into the competitive rivalry at the business challenge core.

Reviewing this literature, it became apparent to the author that each of the Five Force areas represent possible risk entry points. Recall Figure 19 showing the interrelationship

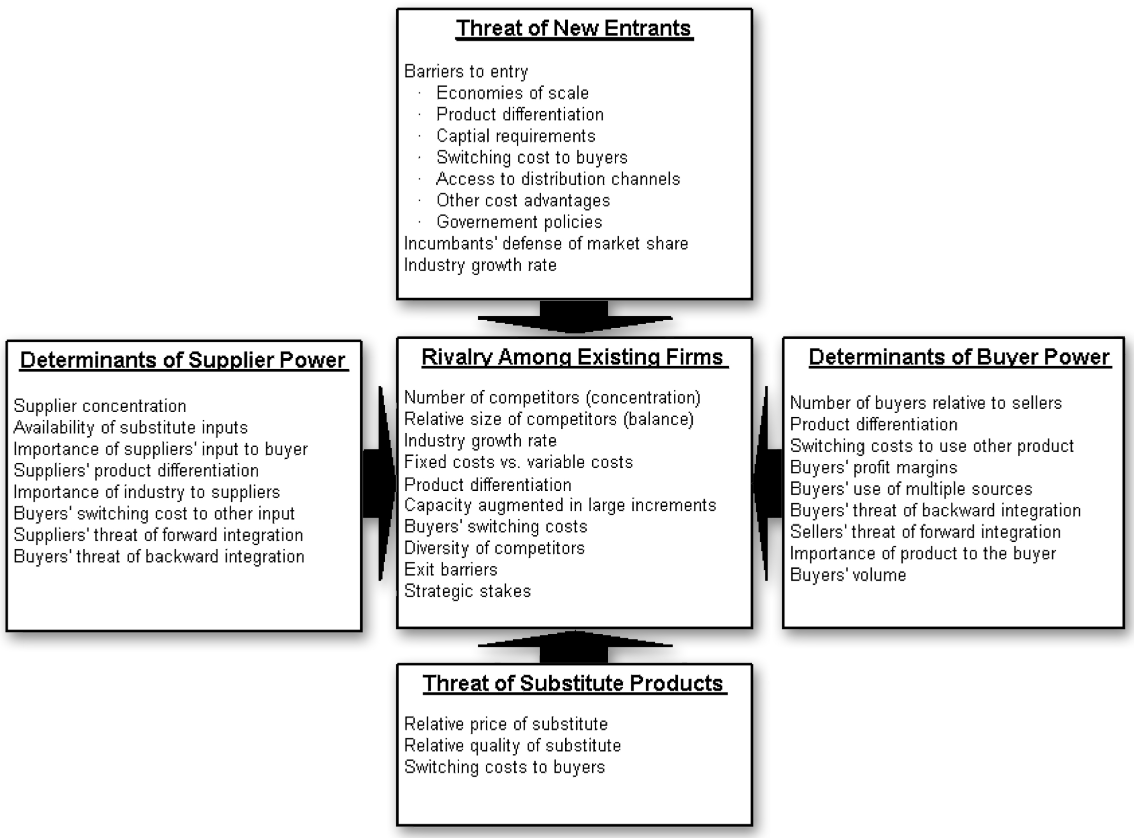


Figure 80: Porter's Five Forces illustrates a complete dissection of business challenges to economic success [103] [120].

between the risk dimensions typically discussed in business practices. In Chapter 1, a short discussion was introduced about the rivalry between Boeing and Airbus, as well as the impact of the sensitivity to the supply chain and risk-sharing approach and subsequent schedule risks realized during the Boeing 787. For the focus of this phase of experimentation, it was determined that the core of the Five Forces, the Competitive Rivalry, was the area most capable of delivering the relationship between product value to the customer and the market capacity assumable as a function of aircraft specifications. It should be noted though that each of these areas is fertile for risk investigation and could provide a rewarding depth of research. Olson [99], Romli [106], and Thomas [126] have addressed some of these areas in similar contexts.

Moving forward then with the issue of competition, several approaches were considered in how to develop a relationship between the market capacity achievable and the performance and value to the customer:

1. **An empirical regression model** - Based on previous aircraft sales and their relative performance. This approach requires an in-depth exploration, a large historical dataset, and thorough decomposition of the competitive alternatives and scenario variables.

2. **Real Options and Game Theoretics model** - This approach is excellent for quantitative analysis of competitive and decision alternatives as a program or project moves forward in time, addressing the value of decisions and the lead time a competitor might face. Several researchers have conducted Real Options approaches to design and situational selection [16] [15] [102]; however, it is not as effective in addressing the *customer* value of the product based on product metrics, nor how to aggregate those metrics based on customer preferences. Rather, Real Options measures the value of the availability of the decision itself.

3. **Overall Evaluation Criterion** - This approach is relatively simple compared to the other alternatives, and is excellent at quantitatively capturing the (sometimes qualitative) preferences of the customer. The drawbacks are reliance on a subject

matter expert to deliver weightings and the lack of a direct competitive function in the model. However, this formulation could be modified to include competitive effects directly and the subject matter expert opinion input kept to a minimum.

The historical approach was attractive due to its simplicity and basis on real-world purchasing decisions, however those decisions may have been confounded with other situational and internal factors that are not easily resolved or included *a posteri*. In addition, the availability of the data may have proven to be challenging and of varying fidelity. For this reason, Approach 1 was eliminated.

The problem of aggregation of metrics was previously discussed, which was solved by including cumulative cash flows as an approach for capturing total program risk. While a Game Theoretics and Real Options approach could be adapted to capture the value of the option to the customer as a function of the aircraft value, it was likely a poor fit for solving the market capacity and a costly approach to develop the model. It was preferred to implement an approach which will aggregate the customer value easily and in an traceable manner. For this reason, Approach 2 was eliminated.

Consequently, it was therefore determined that using a modified Overall Evaluation Criterion to include competitive effects directly was the most promising.

Hypothesis

A modified OEC can relate the aggregate measure of design value to consumption quantity amidst competition.

5.3.1 Overall Evaluation Criterion

In 1995, Mavris and Delaurentis [88] published a formulation for scoring alternatives based on a non-dimensionalized metrics of interest and so-called *importance coefficients*. The method arose from a need to measure weapon system effectiveness, an objective that comprised many diverse disciplines, namely affordability, survivability, readiness, capability and safety. These disciplines were reduced to quantifiable attributes of the design and grouped into life-cycle cost (LCC), mission capability index (MCI), engine related attrition (ERI), survivability and availability. Because the score comprised multiple disciplines, it was called the Overall Evaluation Criterion (OEC). The original formulation is given in Equation 17. BL represents the baseline value in each dimension. Also note the reversal of the numerator and denominator when the metric is *smaller-the-better*.

$$OEC = \alpha(\frac{LCC_{BL}}{LCC}) + \beta(\frac{MCI}{MCI_{BL}}) + \gamma(\frac{EAI}{EAI_{BL}}) + \delta(\frac{P_{surv}}{P_{surv_{BL}}}) + \epsilon(\frac{A_i}{A_{i_{BL}}}) \tag{17}$$

The vector of importance coefficients scaling each individual effectiveness metric is determined by subject matter expert opinion (SME) or customer voice. To position the resulting OEC magnitude in relation to the baseline, the sum of the importance coefficients is scaled to 1.

$$\alpha + \beta + \gamma + \delta + \epsilon = 1 \tag{18}$$

The overall evaluation score of competing designs can thus be compared *apples to apples* in relation to the design effectiveness of the baseline (whose score is 1). The comparative assessment is comprehensive, definable and traceable [88].

Equation 19 gives the generalized form of the OEC definition, with the taxonomy of disciplines relaxed and a variable introduced to handle the switching between larger-the-better and smaller-the-better.

$$OEC = \sum_{i=1}^{n} \alpha_i (\frac{F_i}{F_{baseline_i}})^{j_i} \quad (19)$$

and

$$\sum_{i=1}^{n} \alpha_i = 1 \quad (20)$$

where:

- F is the individual metric
- n is the number of metrics
- j is -1 for metrics that are *smaller-the-better* and 1 otherwise

5.3.2 Connecting Aircraft Value to Sales/Production Quantity

It was determined that there was a strong need to connect the number of vehicles produced (or sold) to a quantifiable value assessment of the individual aircraft design. This was discovered when conducting the original analysis with BASUCA: outlier designs in the cumulative cash flow, upon close inspection, were found to have attributes that were not congruent with the feed-forward variable setting of NV (number of vehicles). These outliers effectively distort or dilute the design space with nonsensical results (a basic example being an aircraft design whose performance is measurably worse than existing alternatives and yet still captures a large percentage of the available market). This is a result of the permission of NV input to vary in the screening test phase of the methodology.

As this parameter is strongly coupled with the terminal cumulative cash flow (or manufacturer ROI), the decision was made to increase the fidelity of the model to accommodate this effect and reduce the potential of these nonsensical points to affect the design space.

Table 12: Aircraft Criteria for Customer Buying Practices.

Customer Criteria	Units
Delivery Date	Years from now
Aircraft Purchase Price	Millions of Dollars
Base Passenger Configuration	Number (1-class)
Dollars per RPM	Dollars
Range	Nautical miles
Specific Fuel Consumption	Dimensionless
Gross Takeoff Weight	Pounds
Direct Operating Cost	Dollars per flight
Indirect Operating Cost	Dollars per flight
Takeoff Field Length	Feet
Landing Field Length	Feet

5.3.2.1 Incorporating value-driven estimation into market filtration schema

In order to develop a model for estimating the number of aircraft saleable by a commercial transport manufacturer, customer buying practices were evaluated. This subject was addressed in detail by references [101] [79] [18].

This resulted in the creation of an adapted OEC-based formulation for estimating the aircraft sales volume as a function of aircraft design responses.

$$OEC = \sum_{i=1}^{n} \alpha_i \left(\frac{F_i}{F_{baseline_i}}\right)^{j_i} * (1+\beta)^{\frac{j_i(F_i - F_{competitor})}{F_{baseline_i}}} \tag{21}$$

and

$$\sum_{i=1}^{n} \alpha_i = 1 \tag{22}$$

where:

- F is the individual criterion with subscripts for *Baseline*, *Design (i)*, and *Competitor*
- n is the number of metrics
- j is -1 for metrics that are *smaller-the-better* and 1 otherwise
- β is the scale factor for competitive effect

5.3.2.2 Assumptions for the OEC+ competitive valuation

The following assumptions must be declared about the competitive-enabled OEC+ model for determining market share:

- The customer is rational.
- Old customers are just as hard to keep as new customers are to get. If something performs better or costs less, the customer always favors those attributes. Put another way, the customer is not brand-loyal.
- All of the planes are produced and delivered on time. *Note that this enables study of how production slippage could affect the incoming order rate.*
- An identical aircraft in terms of the metrics will capture exactly 50 percent of the market segment.
- A categorically **better** product will capture 100 percent of the market segment.

- A categorically **worse** product will capture 0 percent of the market segment.

- There is only one competitor (as in the duopoly between Airbus and Boeing). This assumption could be argued as invalid because at the time of this dissertation there exists several other manufacturers in the 150-passenger aircraft market. However, expansion of the OEC+ model to include non-duopolies is left for discussion in a later section.

With these assumptions identified, it is now possible to establish the three calibration points needed to bound the OEC+ competitive market model. In practice, the boundary constraints were found to be too idealistic, so a slight change was made to the center and upper boundary points. In reality, a pure duopoly does not exist, so a correction factor $\Delta M_{share} = 10\%$ was introduced to shift the center point (equivalent product to the competitor. This factor shifts the center calibration point down from 50% to 40%, and the upper boundary (Categorically better) down by $2 \times \Delta M_{share} = 20\%$ to 80%. Thus the three calibration bounding points become:

1. **Lower Bound** - This results from Assumptions 1 and 6: a categorically worse product captures zero percent of the available market.

2. **Upper Bound** - This results from Assumptions 1 and 5: a categorically better product captures 80 percent of the available market. This bound might be a little aggressive as in practice even the best possible product does not always reach this goal for reasons external to the ability of the OEC+ to capture. For this calibration though, this bound still suffices.

3. **Even Market** - In considering the commercial aircraft market as a duopoly, we can assume that an equally valuable product achieves 50% minus $\Delta M_{share} = 40\%$ of the available market. Therefore, a competitive OEC+ score of 1 (equally *valuable*) should yield exactly 40 percent of the market.

There now remains only 3 sets of inputs for a subject matter expert (SME) to populate. They are

1. The α_i Weightings for each of the metrics-of-interest.

2. The β weighting for the level of competitive intensity.

3. The shape factors for the market penetration rate versus the OEC+ score.

5.3.3 OEC+ market modeling environment

Experimental Apparatus

A dashboard in EXCEL was developed to elicit customer value functions as well as competitive offering, enabling the quantification of market penetration estimates.

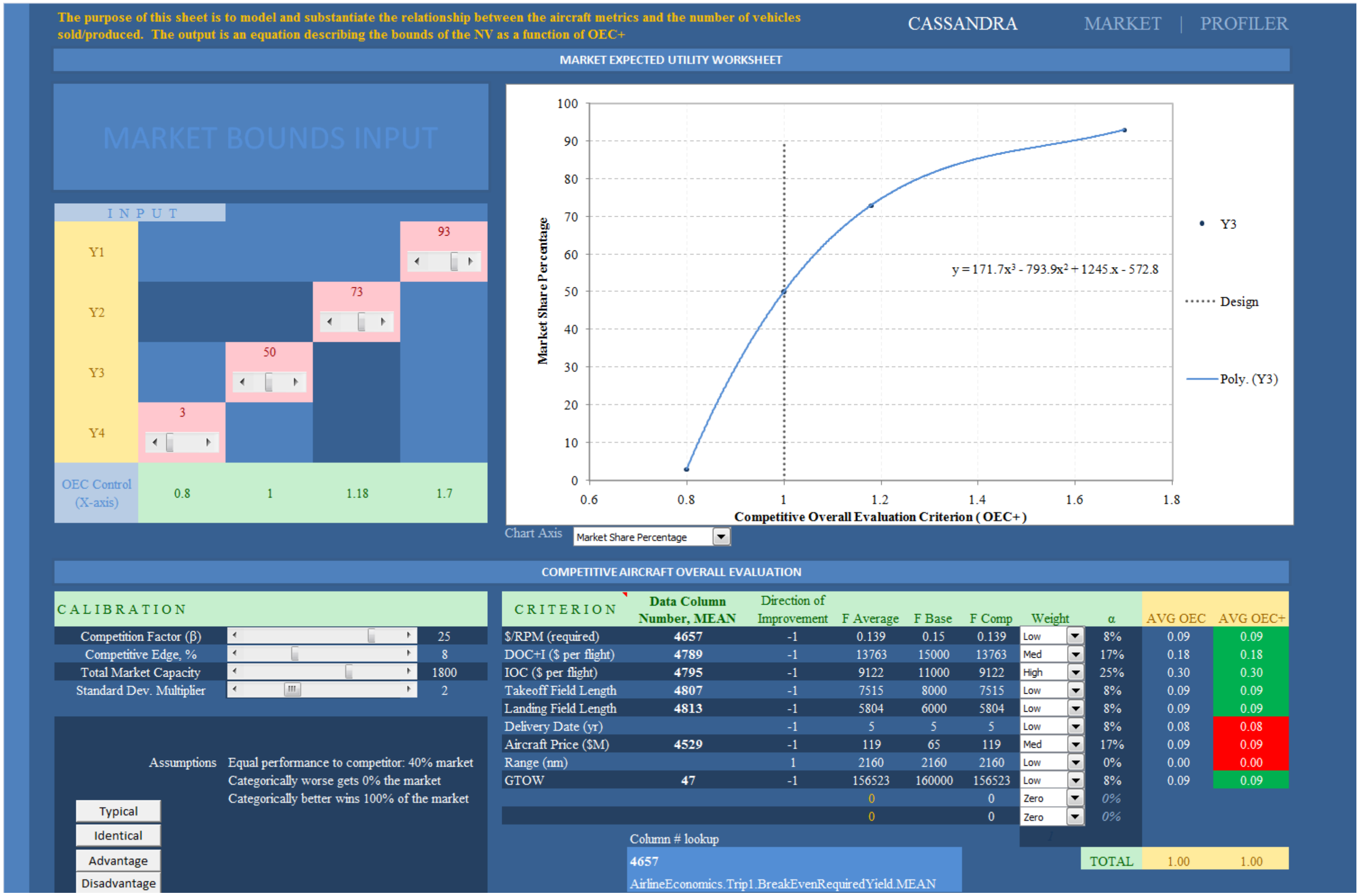
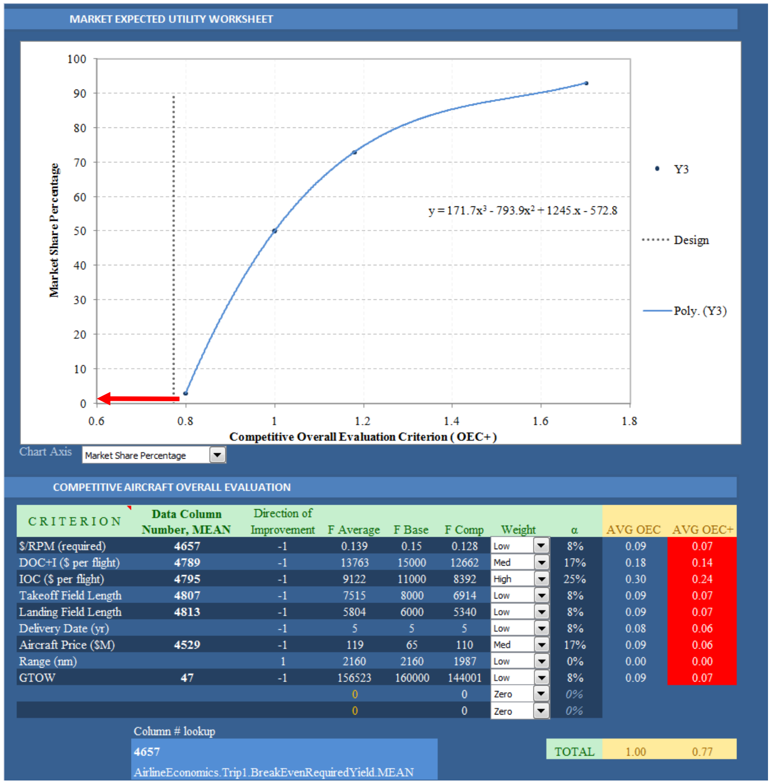


Figure 81: The dashboard in Excel used to elicit the Subject Matter Expert opinion and calculate the competition-enabled OEC+ scoring.



CRITERION	Data Column Number, MEAN	Direction of Improvement	F Average	F Base	F Comp	Weight	α	AVG OEC	AVG OEC+
$/RPM (required)	4657	-1	0.139	0.15	0.128	Low	8%	0.09	0.07
DOC+I ($ per flight)	4789	-1	13763	15000	12662	Med	17%	0.18	0.14
IOC ($ per flight)	4795	-1	9122	11000	8392	High	25%	0.30	0.24
Takeoff Field Length	4807	-1	7515	8000	6914	Low	8%	0.09	0.07
Landing Field Length	4813	-1	5804	6000	5340	Low	8%	0.09	0.07
Delivery Date (yr)		-1	5	5	5	Low	8%	0.08	0.06
Aircraft Price ($M)	4529	-1	119	65	110	Med	17%	0.09	0.06
Range (nm)		1	2160	2160	1987	Low	0%	0.00	0.00
GTOW	47	-1	156523	160000	144001	Low	8%	0.09	0.07
			0		0	Zero	0%		
			0		0	Zero	0%		
							TOTAL	1.00	0.77

1. Lower bound calibration point

CRITERION	Data Column Number, MEAN	Direction of Improvement	F Average	F Base	F Comp	Weight	α	AVG OEC	AVG OEC+
$/RPM (required)	4657	-1	0.139	0.15	0.151	Low	8%	0.09	0.11
DOC+I ($ per flight)	4789	-1	13763	15000	14865	Med	17%	0.18	0.23
IOC ($ per flight)	4795	-1	9122	11000	9852	High	25%	0.30	0.37
Takeoff Field Length	4807	-1	7515	8000	8116	Low	8%	0.09	0.11
Landing Field Length	4813	-1	5804	6000	6268	Low	8%	0.09	0.11
Delivery Date (yr)		-1	5	5	6	Low	8%	0.08	0.10
Aircraft Price ($M)	4529	-1	119	65	129	Med	17%	0.09	0.15
Range (nm)		1	2160	2160	2333	Low	0%	0.00	0.00
GTOW	47	-1	156523	160000	169045	Low	8%	0.09	0.11
			0		0	Zero	0%		
			0		0	Zero	0%		
							TOTAL	1.00	1.30

2. Upper bound calibration point

Figure 82: The OEC+ dashboard during two states of the calibration process. On the left the lower bound of the market capacity model is set as *categorically* worse than the competitive offering, and vice versa for the right figure.

5.3.3.1 Results from the market modeling

The market model proved to be a success. It identified the range of production quantities as a function of the performance and value to the end customer, allowing filtration of nonsensical design points. The filtration step is shown in Figure 83 in the form of a scatterplot matrix relating the overall evaluation criterion to the number of vehicles produced.

Beginning with the upper left box, the data points reveal a uniform distribution over both the OEC and the number of vehicles. This reiterates the feed-forward dilemma of production quantity, as they are independent of customer value, represented by OEC. The areas shaded in red which represent the candidate aircraft designs predicted to sell in large quantities, yet having insufficient overall design value. This set of points is the most important to filter because they potentially mislead the Program Manager using the methodology to design points of unrealistic economic success.

The areas shaded in blue suffer reverse problem (although less potentially damaging): designs which score well in customer value yet are predicted to sell poorly.

Using the market model and the OEC+ approach, the design space is reduced to the arc shown in the lower two plots. Here, a relationship between the customer value and the production run quantity is correlated.

Experimental Result
The OEC+ score was used to calibrate design performance in relation to customer value functions and competitive offering. This enabled filtration of nonsensical results from BASUCA.

New Research Observation VIa

A posteri filtration using the OEC+ technique reduces the design space significantly, there may be improvement in efficiency by generating the designs *a priori* using response surface equations.

New Research Observation VIb

The apparatus is now ready to explore and test strategic risk mitigation techniques.

Also note the difference between the OEC and OEC+ versions when plotted against the same data. OEC+ value metric shows a narrower variance versus the number of vehicles than the OEC. This is likely due to the low impact of competitive differentiation for the example problem. In the penultimate chapter, a case study is reviewed in detail further exploring this effect.

5.3.4 Expansion of the Market Model to Non-Duopoly Markets

An additional concern is the evaluation of the OEC+ formulation when the duopoly assumption no longer holds. In practice, duopoly markets tend to be more present in larger passenger-count where the aircraft programs are more capitally and technologically intensive. As the passenger capacity and capital requirement shrink, the number of manufacturers competing increases. This is especially evident in the regional transport category market, where there are over a dozen manufacturers offering competent aircraft.

Therefore, the OEC plus formulation needs to be modified slightly to accommodate non-duopoly markets. This is done by adjusting calibration bounds of the OEC+ setup. Here Assumption 3 must be modified, such that the manufacturer captures an equal share to all of the other competitors, instead of an achieving 50% of the total market. If there are n competitors, which all have equally valuable and performing products, then the market share percentage would instead be $1/n$. This formulation is essentially the same as in the

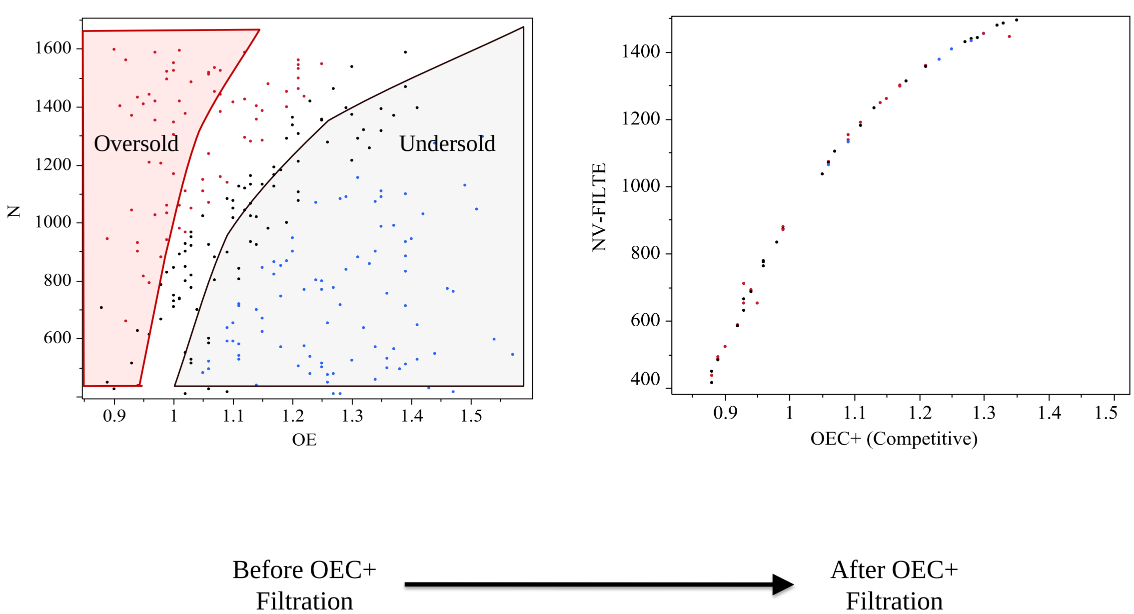


Figure 83: Scatterplot matrix of the Monte-Carlo aircraft design set, before and after filtration using the Value and Market model.

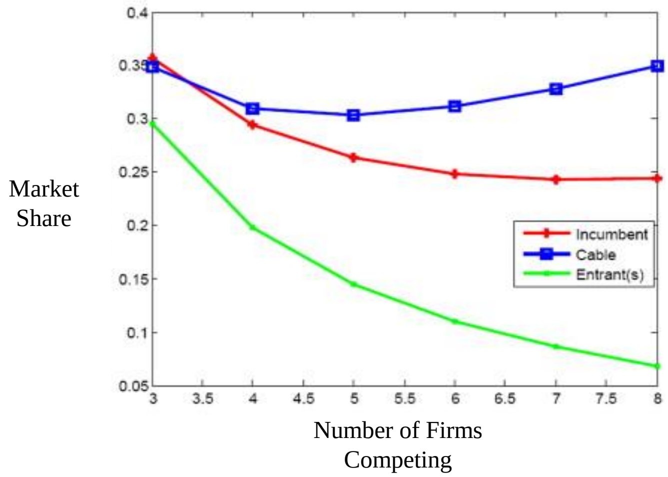


Figure 84: The trend of the telecommunications market share versus the number of competitors in a market, shown for new entrants and incumbents [56].

duopolies, only that the total number of competitors is two and thus captured 1/2 or 50% of the total market.

This proportional effect of the number of competitors and average market share has been examined by researchers. Hoernig [56] conducted a study on telecommunications and cable providers, and found the similar $1/n$ relationship shown in Figure 84.

The bounds for categorically worse, and categorically better, theoretically remain the same; however, the curve calibration between mounting points will be much sharper. This is due to the overall effect that as the number of competitors increase in the market, it takes a substantially better product to achieve disproportionate percentage of the market share. The cell phone market is an example of this. There are a large number of cell phone manufacturers, however a product such as the Apple iPhone enjoys a large market share due to its high performance appeal.

5.4 Risk Measurement of Uncertain Cumulative Cashflows

In this phase of the CASSANDRA methodology development, an approach was developed to aggregate the uncertainty of cash flows into a sparse set of metrics that capture the value of those cash flows to a program manager. The need for these metrics arose from

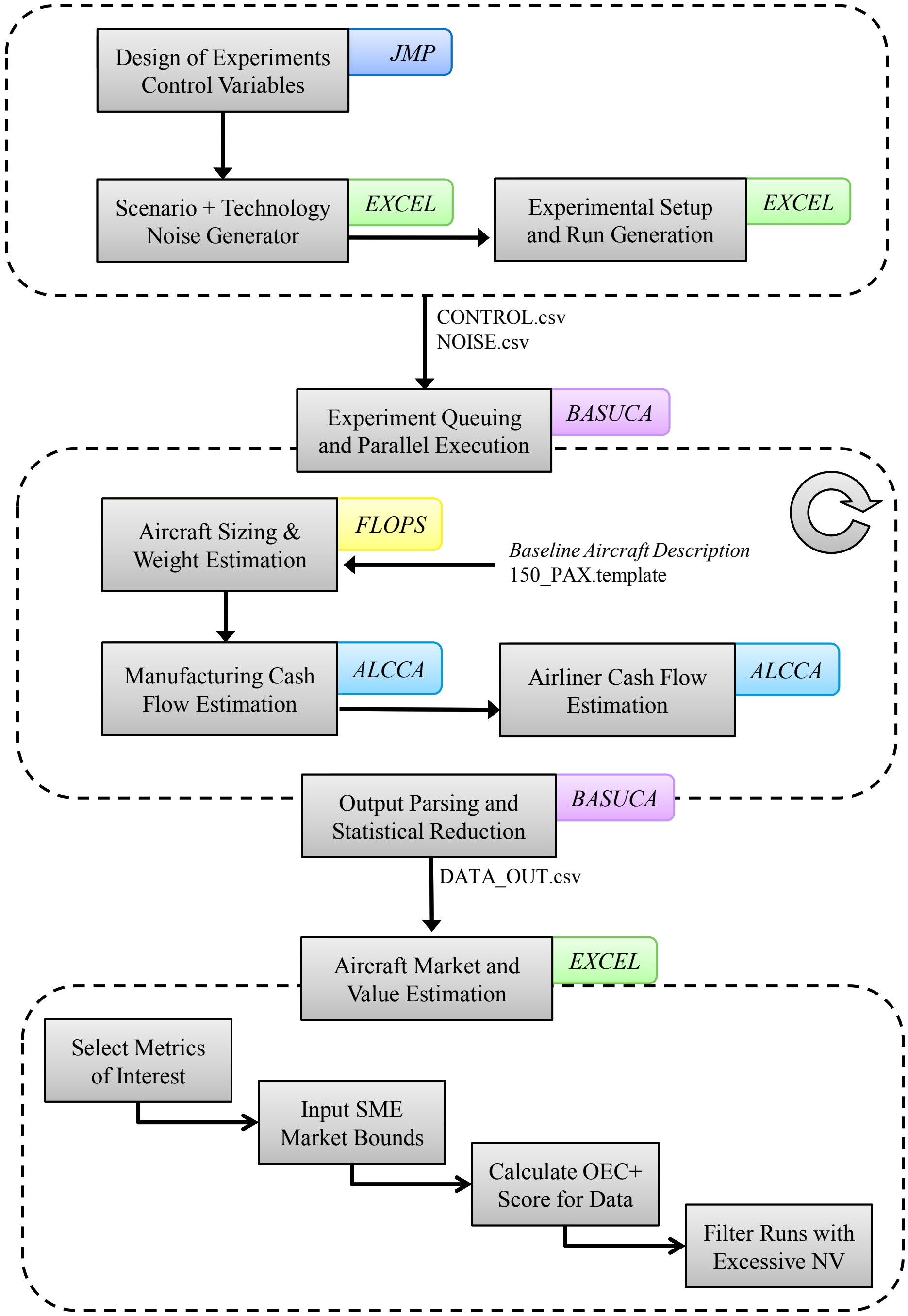


Figure 85: Overview of the information and data flow of the experimental apparatus used to capture the market and number of vehicles sold.

difficulty in capturing the economic value of the program by singular metrics taken from the uncertain cumulative cash flow charts. It was found that when considering these metrics alone it became difficult to fit models and predict program value. Additionally, it was found that the reduced set of metrics proved to be useful in filtration of candidate designs.

Several approaches were investigated, and are enumerated below:

1. **Algebraic Distance to Ideal** - This approach requires the program manager to elicit an ideal uncertain cashflow, and then calculates a distance based on the similarity between the candidate cashflow and the ideal. Several methods are possible for the distance estimation, most notably being the Hausdorf Distance. The shorter the distance, the more similar the cashflow regimes are.

2. **Least Squares Distance to ideal** - Similar to the Algebraic Distance to ideal in that it requires an ideal uncertain cashflow input, this approach calculates the cumulative square error between the candidate cashflow and the ideal. Also similar to the distance approach, the lower the summed squares of the error, the better the cashflow regime.

3. **Geometric relationships** - More abstract than the other approaches, this approach looks at the fields in the uncertain cumulative cashflow space and develops parameters describing the placement of the cashflows relative to the profit and loss zones.

At the onset of the CASSANDRA methodology development, a similarity approach using an ideal elicitation Program Manager was explored. This approach required the expert opinion to be polled and inserted into a worksheet. That data would then be compared to the expressed uncertainty in the candidate aircraft design. Figure 86 shows the input worksheet originally considered, showing the elicitation of the expected (mean) and the upper and lower bounds.

The approach defines two metrics in particular: a risk-benefit ratio and a risk aversion angle. These metrics are based off of a geometric analysis of the uncertain cumulative cash flow. The theoretical approach is given in the next section.

Upon reviewing the uncertain cumulative cashflows from both effects screening and the composites materials study, it was observed that the spread of uncertainty was expressed

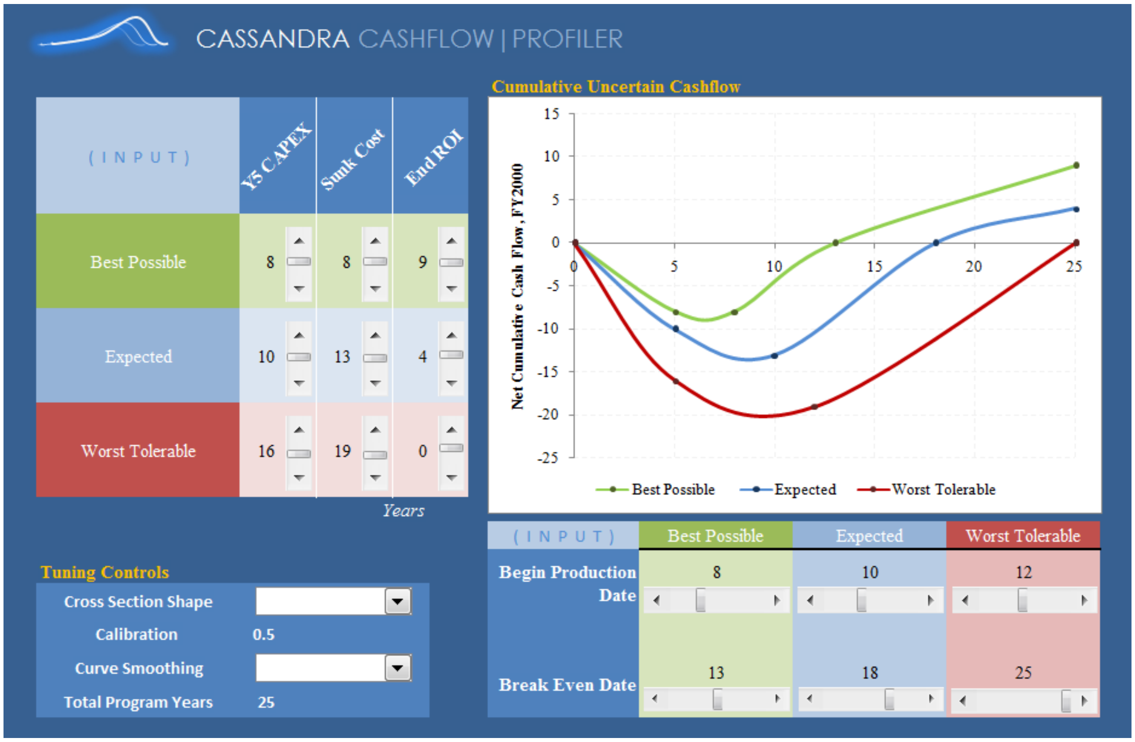


Figure 86: Executive input worksheet for eliciting ideal uncertain cumulative cashflow.

in both of the time and cash domains, and the value of those cashflows to the program manager could not be explicitly defined by one or two dimensions alone. The positive return on investment and its uncertainty were coupled with the maximum sunk cost and the break-even dates and their uncertainties. If each of these three basic metrics are considered important to the program manager (the end net cash flow, the break-even date, and the maximum sunk cost), and they are measured by mean, variance, upper and lower bounds (or 100^{th} and 0^{th} quantiles), then there are 12 simultaneous dimensions to consider. However, it was found that an experienced eye could just *look* at the uncertain cashflow and gather a judgment of the associated program quality. This led to the hypothesis that there exists a geometric, spatial or visual quality metric to the cashflow quality. This hypothesis led to the original development of a geometric approach that could connect these 12 uncertain cashflow dimensions into a small set of comprehensible metrics. Formally declared:

Hypothesis

Uncertain cumulative cashflows can be aggregated into two core metrics: the *Risk aversion angle* and the *Risk benefit ratio*, which provide better measures of project risk than cost or schedule risk alone.

5.4.1 Geometric aggregation theory development

The theory given here is the original development of two uncertain cumulative cashflow metrics, known here forth as the *risk benefit ratio* and the *risk aversion angle*. They are defined as:

- **Risk Benefit Ratio,** Γ_{RB} - This metric describes the ratio of the cashflow region that sits in the profit region of the cumulative cashflow chart, and therefore a measure of the likelihood (not scale) of the resulting cashflow to end up in the profitability region. It is called the risk benefit ratio as it is similar in mathematical form to a cost benefit ratio. A large risk benefit ratio does not guarantee that the ending cashflow expectation will be large, rather that it be positive.

- **Risk Aversion Angle,** θ_{RA} - This metric describes how narrow the cone of uncertainty is over the manufacturing phase of the cumulative cashflow diagram. Risk aversion typically describes an individual's preference for taking risks (see Chapter 2). The risk aversion angle describes a risk-averse cashflow space when narrow, and a risk-seeking cashflow when the angle is large. The risk aversion angle tends to scale both upside and downside losses in the same way that a financial derivative is *leveraged* in both potential returns and cost.

A graphical representation of the two metrics is given in Figures 88 to 89.

The risk-benefit ratio can be simplified to just the fundamental triangular area, as shown in Figure 88. This simplification allows the calculation of the denominator area (A_{COST}) to

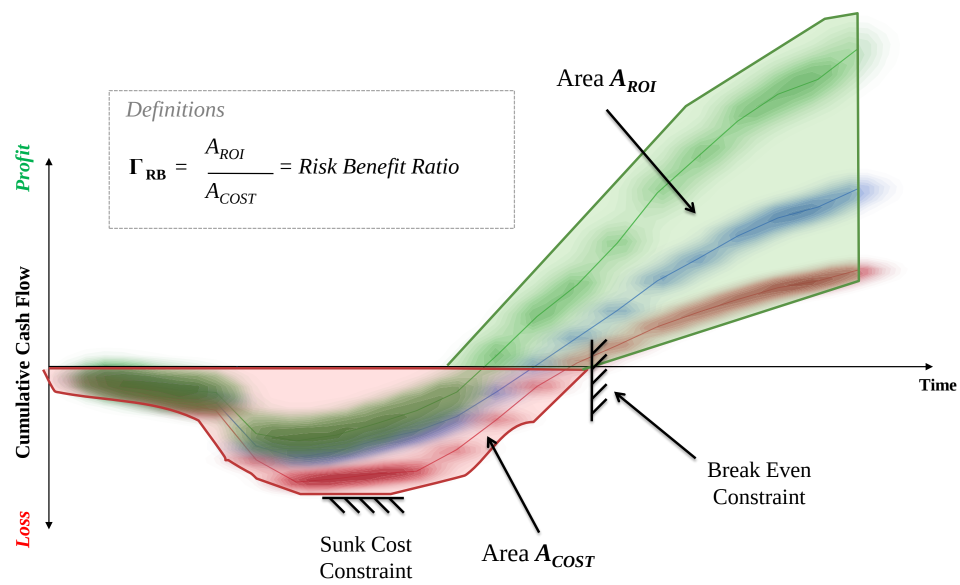


Figure 87: High-fidelity definition of the hypothesized uncertain cumulative cashflow metric (the Risk benefit ratio Γ_{risk}) which uses a geometric ratio measurement assess to uncertain program value.

be calculated using the same triangles as the risk aversion angle. It was found in separate tests that the ratio increased substantially with the simplification, yet the sorted *ordering* of designs did not change. The simplification therefore gives a more optimistic nominal value, yet provides the same value to the designer using the metric for selection and risk evaluation.

The theoretical derivation of the two metrics begins by evaluating the metrics available that capture the cashflow space. A table of the cashflow metrics available and required by the geometric approach to calculate the risk benefit ratio and risk aversion angles are given in Table 13.

The required key points are then positioned as shown in Figure 90 to form an extended triangle over the production phase of the uncertain cumulative cashflow. The triangle is then bisected across the x-axis to from a right triangle in the upper profitability section, then a quadrilateral in the loss region. The beginning production date is typically year 5 of the program as in the baseline aircraft design).

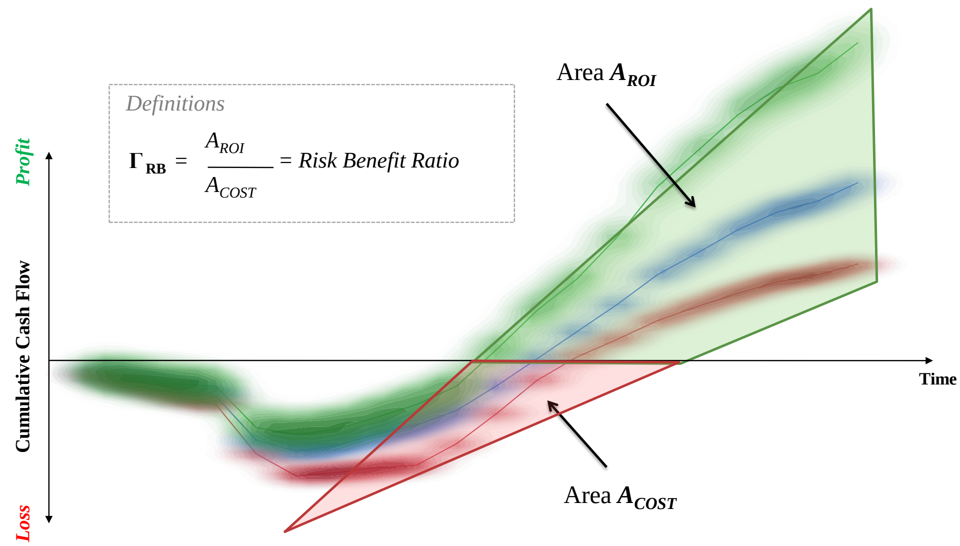


Figure 88: Simplified definition of the hypothesized uncertain cumulative cashflow metric (the Risk benefit ratio Γ_{risk}) which uses a geometric ratio measurement assess to uncertain program value

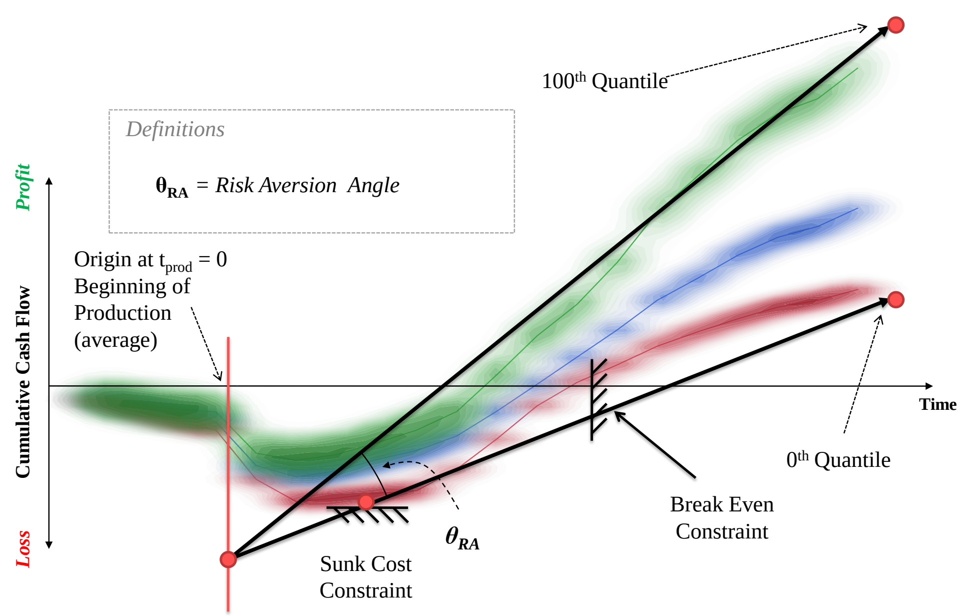


Figure 89: Graphical definitions of the second uncertain cumulative cashflow metric (Risk aversion angle θ_i) using a geometric approach to program value aggregation.

Table 13: The uncertain cashflow metrics available and required by the geometric approach to calculate the risk benefit ratio and risk aversion angle.

Variable	Available Statistics	Method Requirement	Handle
Maximum Negative Cost	Mean μ		
	Variance σ		
	0^{th} Quantile	*Required*	E
	100^{th} Quantile		
Break Even Date	Mean μ		
	Variance σ		
	0^{th} Quantile	*Optional*	F
	100^{th} Quantile		
Final Net Cash Flow	Mean μ		
	Variance σ		
	0^{th} Quantile	*Required*	B
	100^{th} Quantile	*Required*	D
Production Date	Mean μ	Required	A
	Variance σ		
	0^{th} Quantile		
	100^{th} Quantile		

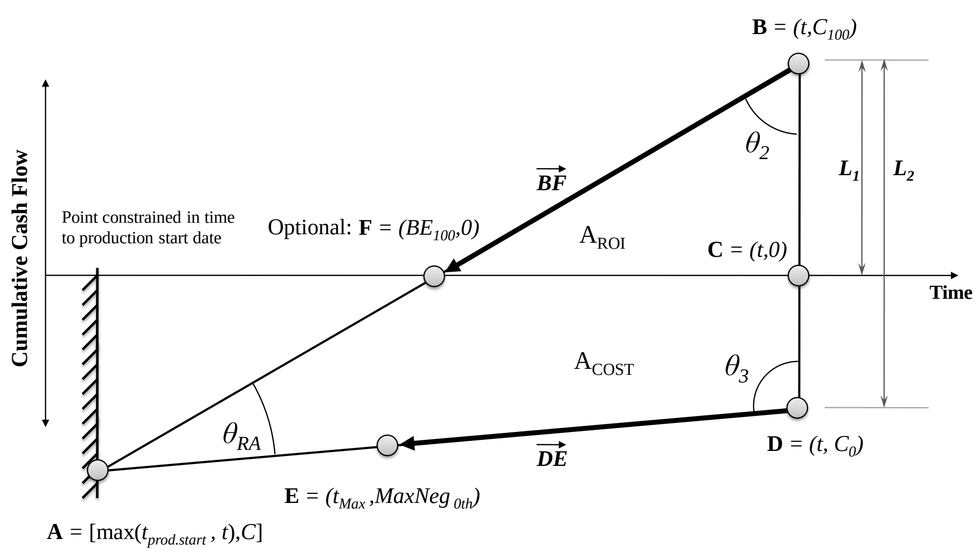


Figure 90: Graphical definitions of the components required to model the risk benefit ratio and the risk aversion angle.

Beginning with the *risk aversion angle* derivation, the first step is to calculate the interior angles of the triangle. This is done by calculating the vectors $\vec{BF}$ and $\vec{DE}$. From these vectors the angles θ_2 and θ_3 can be calculated respectively using the line from $\overline{BD}$ as the basis.

With these angles known, the risk aversion angle θ_{RA} can be calculated from the triangle identity regarding interior angle sums, given in Equation 23:

$$\theta_{RA} = \theta_1 = \pi - \theta_2 - \theta_3 \tag{23}$$

Note that the origin of the triangle vertex to the lower left is constrained by the beginning production date and later. This eliminates the possibility that the vectors $\vec{BF}$ and $\vec{DE}$ are parallel or divergent, leading to an invalid angle calculation. In this case, the break-even date (Point F) no longer is necessary for the calculation, as it would over-constrain the drawing of the triangle.

The next step is to calculate the total area of the triangle. This is most direct using the identity:

$$Area = \frac{b^2}{2(\cot\theta + \cot\phi)} \tag{24}$$

Where b is the length of the side between θ and ϕ. Using the length of the side L_2 from Figure 90, this gives the total area A_{Total}

$$A_{Total} = \frac{L_2^2}{2(\cot\theta_2 + \cot\theta_3)} \tag{25}$$

And subsequently the area of the upper triangle by the same theorem (although it could be calculated other ways as it is a right triangle):

$$A_{ROI} = \frac{L_1^2}{2\cot\theta_2} \tag{26}$$

The final area can be calculated by remainder from the total area A_{Total}:

$$A_{COST} = A_{Total} - A_{ROI} \tag{27}$$

The risk benefit ratio can then be defined as:

$$\Gamma_{RB} = \frac{A_{ROI}}{A_{COST}} \tag{28}$$

Combining terms

5.4.2 Exploring the metrics and their implications on different uncertain cash-flows

In this section, the risk-benefit ratio and risk aversion angles is evaluated for their relative representation of the uncertain cumulative cashflow. Three scenarios are presented here, with a further comment on the risk efficiency and how it relates to the two metrics.

Experimental Apparatus
The geometric measurements for uncertain cumulative cashflow were calculated in a MATLAB environment from results from the BASUCA apparatus.

Figure 92 gives three scenarios taken from notional uncertain cashflow data. In the first Example A, $\Gamma_{RB} = 0.4$ and $\theta_{RA} = 40$. In this case, the proportion of positive return on investment to negative cumulative investment is roughly balanced and is notionally representative of a new aircraft development. Looking next at example B, the effect of reducing the risk aversion angle at constant risk-benefit ratio is shown. Here, the program experiences much smaller variance in the cashflows during production phases (given by the low risk aversion angle), yet has the same proportion of A_{ROI} to A_{COST}. The peak positive and negative net cash flows are both lower, meaning that the opportunity for large returns as well as the opportunity for extreme failure are both lower. This uncertainty cumulative cashflow diagram may represent something similar to a derivative aircraft or military aircraft program.

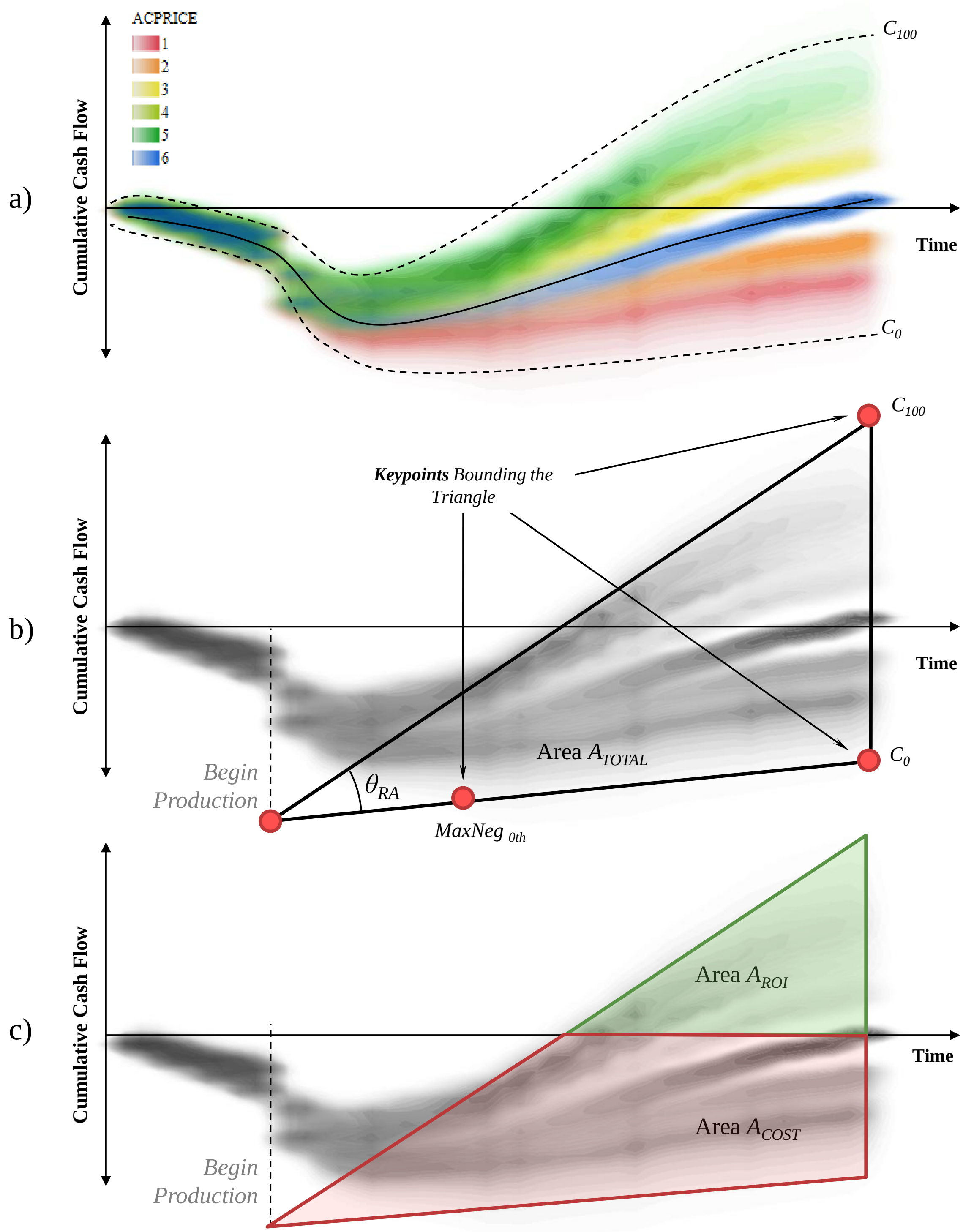


Figure 91: Development of the two uncertain cumulative cashflow metrics (Risk aversion angle θ_{RA} and the Risk benefit ratio Γ_{RB}) using a geometric approach to program value aggregation.

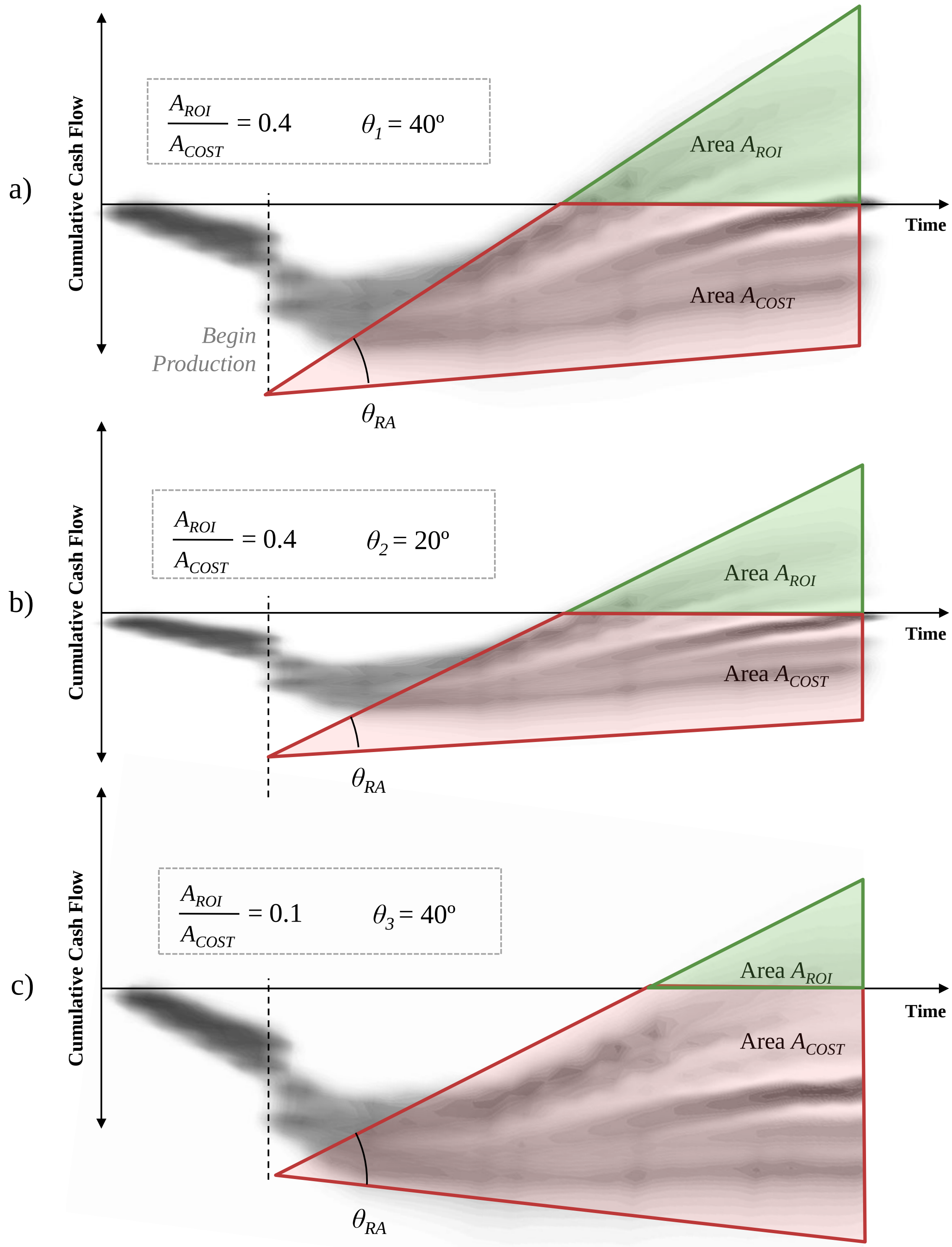


Figure 92: The risk aversion angle and the Risk benefit ratios given for three different cashflows. Note the *risk aversion angle* θ_{RA} is held constant at 40deg in Parts A and C, and the *risk benefit ratio* Γ_{RB} is held constant at 0.4 in Parts A and B.

5.4.3 Limits of the Risk Aversion Angle and Risk Benefit Ratio

It is perhaps worthwhile to offer the limitations or numerical constraints of the risk aversion angle and risk benefit ratio. There are two types of limitations on these metrics: the geometric and the representative. The geometric limitations result from the mathematical definition of the metrics, and the representative limitations result from the definition of the metrics on the uncertain cumulative cashflow chart. They are given here:

$$0 \leq \theta_{RA} > \pi \tag{29}$$

$$0 \leq \Gamma_{RB} > \infty \tag{30}$$

$$A_{COST} > 0 \tag{31}$$

The first constraint results from the definition of a triangle, and is that the risk aversion angle must be greater than or equal to zero and less than π. The second constraint is on the risk benefit ratio, and results from the cashflow representation and calculation of area. Here the numerator A_{ROI} may be zero (no positive return) but less than infinity, which relates to the third constraint: that A_{COST} must be greater than zero for the risk-benefit ratio to exist as it is the denominator of the ratio.

In practice, the mathematical approaches have resulted in numbers less than zero for both risk aversion angle and risk-benefit ratio, but these were indicative of failed cases in the analysis.

5.4.4 Suggested Relationship to Efficiency of Risk Allocation

In Part C of Figure 92, the risk aversion angle is held the same as in Part A, but the risk-benefit ratio is now $\Gamma_{RB} = 0.1$. This illustrates the need for the combination of both metrics to grasp the cumulative cashflow uncertainty. In this case, the low risk-benefit ratio, when combined with a higher risk aversion angle, leads to an unfavorable and uncertain

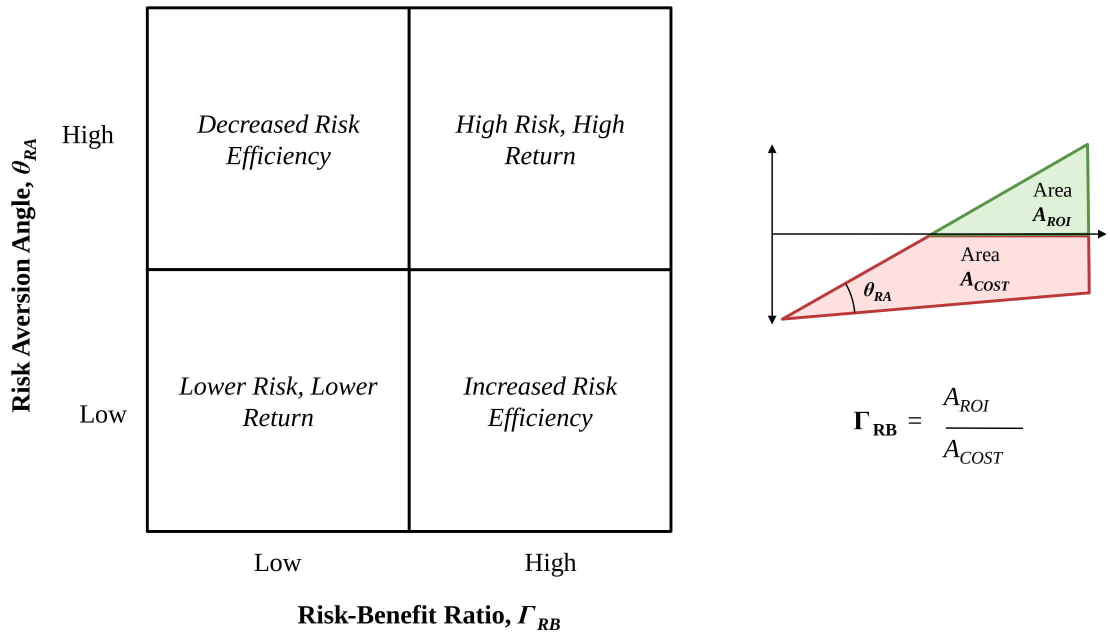


Figure 93: Comparison of the risk aversion angle θ_{RA} versus the risk-benefit ratio Γ_{RB} in relation to a conjecture about risk efficiency.

.

cumulative cashflow response. Here, the opportunity for positive return on investment is relatively low, and comes at great expense in likelihood for extreme failure.

Next, a further observation is made about the efficiency of the uncertain cumulative cashflow metrics: the combination is important to risk efficiency. When programs experience higher Risk-benefit Ratios, and low Risk Aversion angles, they experience a higher risk efficiency, and the inverse is true: a program with low risk-benefit ratio and high risk aversion angles is inefficient (and potentially disastrous). This relationship is given in Figure 93.

5.4.5 Risk Aversion Angle and the Width of Uncertainty Analyses

The risk aversion angle describes the conical spread in cumulative cashflow results concluding from a risk analysis. It should be noted that its nominal score is proportional to the *completeness* of both the ranges of uncertain noise variables and the *exhaustiveness* of the noise variable set. A reduction in either the ranges or the noise variable set will generally result in a smaller risk aversion angle. Another element of consideration in this research was the combination of two partial and mutually exclusive risk analyses. In this case, the risk aversion angle resulting from one uncertainty analysis (studying effects of inflation rate *alone* for example) may be combined under certain conditions with another uncertainty analysis (uncertainty in the labor rate *alone*, for example), provided there is some a priori knowledge of the interaction between the two. Following the summation of variance from two correlated variables:

$$Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y) \tag{32}$$

Using the same formulation, it is hypothesized that the summation of two risk aversion angles from two separate yet correlated analyses is

$$Total[\theta_{RA}] = \theta_{RA,1} + \theta_{RA,2} + 2Cov(\theta_{RA,1}, \theta_{RA,2}) \tag{33}$$

Capturing the covariance term $2Cov(\theta_{RA,1}, \theta_{RA,2})$ may prove difficult in practice, yet if the term can be identified in a separate study, the summation of risk angles may prove to follow the hypothesis given in Equation 33. Testing of this hypothesis is left for future research.

5.4.5.1 Risk Aversion angle and Risk Benefit Ratio results

The Risk metrics defined in this dissertation were evaluated over a representative set of control and noise variables of the baseline aircraft. The control and noise variables and their ranges are those used as shown in Table 6.

The first review of the results evaluated the correlation between the risk-impact ratio and the risk aversion angle. These parameters are mildly coupled through the geometry of their definitions, yet it was unexpected to see the correlation shown in Figure 94.

In this scatterplot comparison, the correlation from the results is shown. The author identifies two boundaries, the upper and lower boundary. As these are shown for candidate designs, these two bounds form a frontier. On the upper frontier, this represents the edge

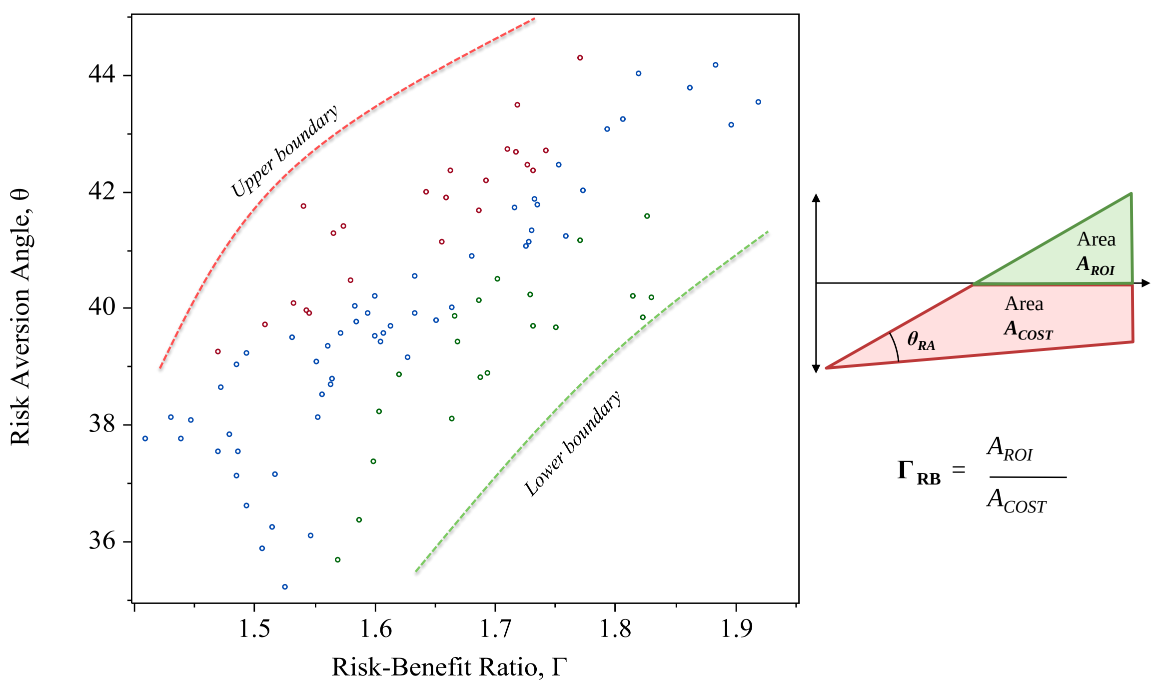


Figure 94: Comparison of the risk aversion angle θ_{RA} versus the risk-benefit ratio Γ_{RB}. Note the general correlation between the two, and the associated upper and lower boundaries. The lower boundary identifies designs that exhibit better efficiency in becoming cashflow positive by the end of the program.

.

of designs whose risk-benefit ratio was low yet the risk aversion angle was high. This represents cases where the efficiency of the risk exposure is lower overall: more variance in the results by year is taken on in exchange for a lower ratio of risk benefit. Similarly, the lower boundary in green identifies the frontier of more risk-efficient designs. Here, the cumulative cashflows experienced a higher return on their risk exposure as the risk angle was lower yet the benefit stemming from that risk was higher. These designs are presumed to be more favorable to the program manager.

Next, the metrics were evaluated against the degree of composites introduced into the aircraft program. This is represented by as a single parameter, given as the average of the percentage of composite structures in the aircraft program. The data is given in Figure 95, and shows an unexpected result: as the risk-benefit ratio increases, the mass-weighted risk aversion angle effect decreases with average composites. This indicates that as more and more composite structures are introduced, the efficiency of the risk increases. This does not necessarily mean that the overall risk does not increase, but instead that the return on the risk you are assuming increases.

Experimental Result

The *Risk aversion angle* and *Risk benefit ratio* provided better uncertain cumulative cashflow metrics than breakeven date, maximum negative cashflow, and total cashflow metrics alone.

5.4.6 Criticisms and areas of future development

The risk aversion angle and the risk-benefit ratio are metrics that describe the overall risk perspective of uncertain cashflows. However, in retrospect, it may prove beneficial to use the areas defined for the risk-benefit ratios as *zones*, and accumulate the uncertain cashflows within those zones. This alternative approach eliminates the possibility that the Black Swan result could heavily affect the area scores. By mass-weighting or expected utility weighting

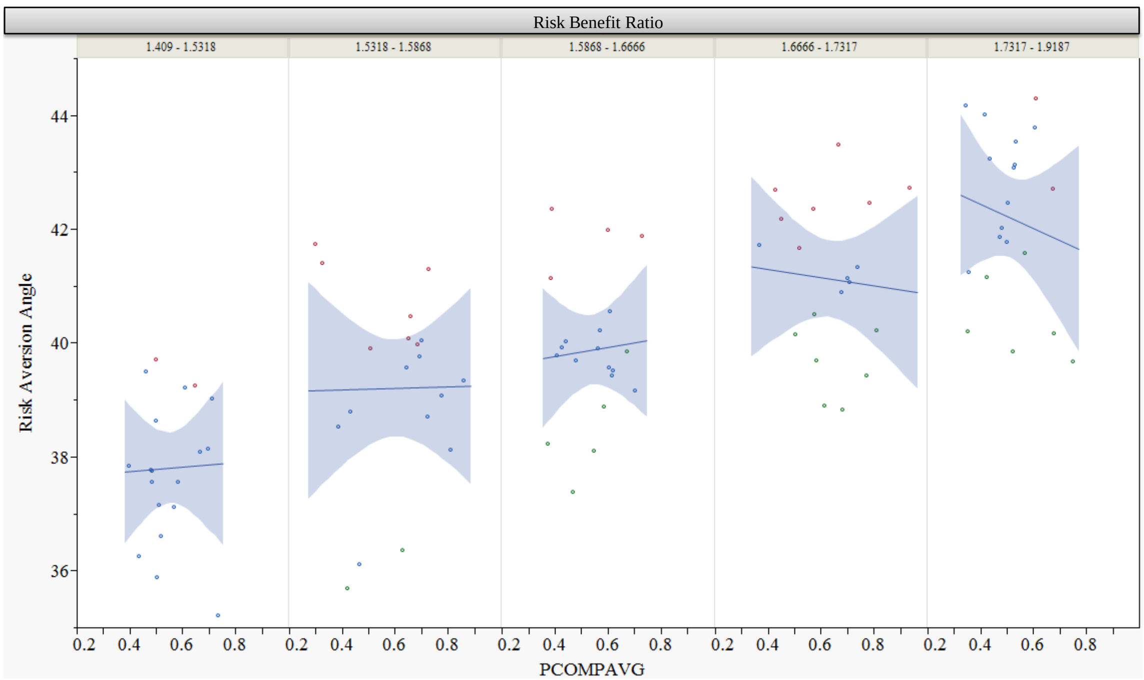


Figure 95: Review of the effect of average percentage of composite technologies to the relationship between risk aversion angle θ_{RA} versus the risk-benefit ratio Γ_{RB}. It is shown that as the risk-benefit ratio increases, the risk aversion angle decreases as more composites are introduced. This indicates an increase in risk efficiency as more of the aircraft is made of composite structures.

.

the histograms of candidate cashflows within the A_{ROI} and A_{COST} regions, Black Swan (of either success or failure) could be accounted for appropriately.

The second criticism is that the risk aversion angle and risk-benefit ratio captures effects primarily in the production phase, not in the research, development and production set-up phases. Therefore, factors such as the First Unit costs are directly rather than indirectly addressed. In the present approach, the First Unit Cost (or alternatively the Maximum Sunk Cost) are accounted for in the risk-benefit ratios as the ratio is defined by the overlap across the break-even line.

5.5 Summary

This phase of the Methodology development generated a scoring approach for uncertain cumulative cashflows, by generating two new metrics: risk-benefit factor and risk aversion angle that are geometrically defined on the cashflow space.

New Research Observation VIIa

The combination of risk aversion angle and the risk benefit ratio are needed to describe how efficiently the risk and cost has been allocated in the program.

New Research Observation VIIb

Designs with lower risk aversion angle and higher risk-benefit ratio are more risk efficient and form a Pareto risk frontier.

CHAPTER VI

GENERATION OF RISK MITIGATION STRATEGIES

Recalling the objective of this dissertation, the strategic challenge addresses the core deliverable of the methodology: an exploration of possible *what-if* scenarios and an approach for how those scenarios might be mitigated. This last step aimed to bring substantial value to the program manager, as clarification of the difficulty and cost of the candidate mitigation alternatives gives further insight into the value and robustness associated with the current design.

6.1 Overview of the Strategic Mitigation Challenge

In approaching the strategy development problem, two distinct methods are considered. Recall the identification of two design paradigms: normative and explorative, as described in Figure 97. Recapitulating, the explorative approach looks outward using available controls to see what states are possible, and the normative looks from the perspective of the target state and identifies what is required to reach it.

Similarly, the risk mitigation strategy development method follows the same schema with two approaches: one from the perspective of the target state looking backward, and the second from the perspective of current state. Instead of considering the mitigation strategy as a design change, it is considered a *program* change in state.

It was not clear at the onset of the strategic mitigation development whether the normative or explorative approaches were preferable. Therefore, the author explored both approaches and the results are given in detail.

6.1.0.1 Strategic Mitigation by Exploration

The first approach that was reviewed is to evaluate the explorative paradigm. In this approach, the methodology begins with a program state that is initially considered acceptable to the program manager. The driving experimental question becomes *What range of states* *are possible while remaining within the current locus of control?* Of all of the possible ways to answer this question, the most direct way was to evaluate the program space by Monte Carlo simulation over the set of input variables. Other approaches include a structured Design of Experiments (DOE) over the input space. Typically a fractional factorial design, a central composite design, or a Latin Hypercube design are applied to similar design methodologies [10] [14] [107] [99] [67]. However this presents two problems: a balanced and orthogonal design itself may be difficult to construct for the large number of input variables, and secondly the number of runs may be too few or two many for the desired experimental evaluation time. Monte Carlo simulation is advantageous in these regards, because each sequential run generates a random variable for each input from an elicited distribution (thus averaging out in the whole to be semi-orthogonal and semi-balanced), and the user may execute as many simulations as desired. The DOE however benefits from efficiency on an information extracted about the design space on a per-run basis. However, the earlier phases of the CASSANDRA methodology development have treated the execution time per experiment, and the experimental cost of Monte Carlo simulation is already generally acceptable.

The setup of the Monte Carlo simulation is comprised of three separate steps:

1. Identify candidate input variables.
2. Set ranges on those variables that are *acceptable*.
3. Elicit the distributions and their shape controls around those variables.

The first element was to identify which inputs were candidates for exploration. This step is initially troubling, as there are quite a large number of possible or available inputs. FLOPS / ALCCA alone offer 200-300 inputs to the user, and in real programs the available inputs or controls to a program manager may be innumerable. In addition, it was not known what specific combinations of inputs may generate high-risk results. Therefore, a sensitivity analysis was performed to capture the variables that were likely to have the most impact. The experimental apparati in Chapter 3 were used to execute the sensitivity analysis and pare down the list from 73 variables to 15-20.

6.1.1 Strategic Mitigation Analogy of CASSANDRA

Consider the analogy of the pilot of an airplane which is in level cruise. The pilot's objective is to maintain the aircraft in level flight. The pilot has several controls available at his disposition: the up/down and side/side of the flight yoke, the throttle, the trim tabs, the spoilers and rudder pedals. In cruise, level flight is maintained with relative ease to the pilot.

Now imagine that an external perturbation is introduced which forces the pilot to react in order to maintain the objective of level flight: the landing gear accidentally is lowered, and is mechanically unable to be brought back up. The drag from the landing gear causes the nose of the aircraft to pitch downwards, and thus lower the altitude. The pilot must mitigate this perturbation using the controls available. There are several possible combinations of the controls which could return the aircraft to level flight, however, to the well-trained pilot some are more efficient than others.

One alternative might be to pull back on the flight yoke to counteract the pitch-down moment and return the aircraft to level flight. She may also use trim tabs, or throttle up the under-hung engines. Each of these accomplish the objective independently and are independently selectable, however there is a preferred method or (path of least resistance). If the pitch down moment is small enough, the trim tabs may likely be the preferred approach as they do not require a constant manual input from the pilot. If the moment is large, the trim tabs alone may not be sufficient; the flight yoke or engine throttle setting, or both, are required to meet the objective. Additionally, if the nose down moment is extremely large, then it is possible that no combinations of control inputs meet the pilot's objective. Lastly, the absolute altitude of the airplane may be different in the new equilibrium, but the objective of level flight is met.

Now we relate this example to the focus problem of the thesis: the pilot in this case is the program manager, whose task is to maintain the program at a constant profit and risk level. The pilot's situation where steady, level flight is returned once the state is perturbed– *yet at a different altitude*– is analogous to the program manager who returns the program to an *equivalent but not identical* risk exposure and profit expectation state. The principle objective of the CASSANDRA methodology is the automation and discovery of these equivalent state alternatives to the program manager. However, some of the strategic mitigation vectors may be impossible, unreasonable or are subject to uneven difficulty levels of implementation. Therefore, the CASSANDRA methodology aims to also take these considerations into account. This approach follows the normative design problem of *What is required to get where I want?* and then evaluate how reasonable those requirements are.

This example highlights four aspects of the scenario mitigation problem faced by a program manager of a new aircraft development program:

1. There may be multiple, or no combinations of the control inputs to meet the objective.
2. Control inputs are likely to have ranges of effectiveness limiting their use.
3. Among many successful combinations of control settings, there is a ranking or preference to the controller.
4. The objective may be met, but other state variables may change as a new equilibrium is achieved.

This closely resembles the general properties of a linear system of equations, whereby a linear system may function in three ways:

1. The system has an infinite number of solutions. This usually occurs when there are fewer equations than unknowns (known as under-determined).
2. The system has a single solution, known as a unique solution. This usually occurs when there are exactly as many equations as unknowns.
3. The system has no solution. This usually exists when the system has more equations than unknowns (Known as overdetermined).

The above general behavior of linear systems of equations is also given in Figure 96.

Note that this is the general behavior for linear systems of equations. If the systems are not linearly independent, then it is possible for the equations to have no intersection

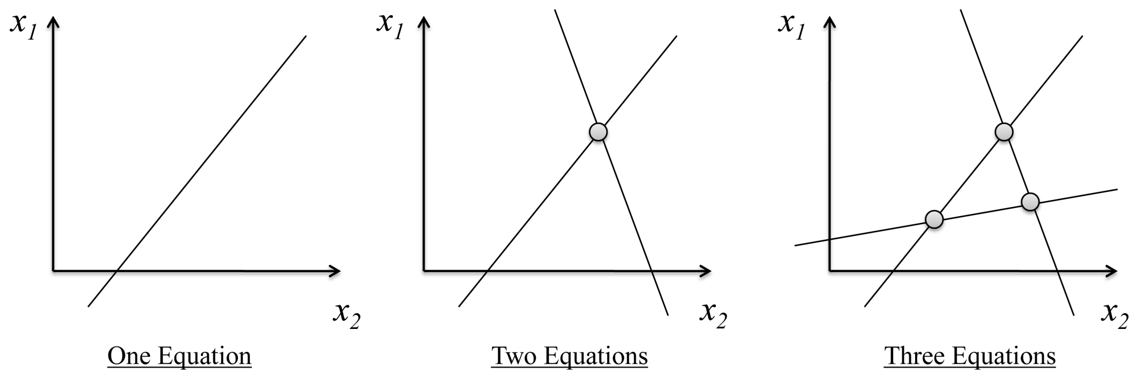


Figure 96: Diagram illustrating the relationship between number of solutions (intersections) and number of equations (lines) for general linear system of equation behavior [44].

(visualize parallel lines in the above diagram). This holds true regardless of the number of equations given as they could theoretically all be parallel.

6.1.1.1 Normative versus Explorative Design Approaches

There are two fundamental development approaches to design involving technology and scenario considerations. The explorative approach looks forward to evaluate what might be possible to achieve given two things: 1) a clearly described baseline, and 2) a set of sufficiently known perturbations to that baseline. These perturbations can be a set of mature technologies that are already available, such as a newly developed engine design [67]; or known future conditions such as implementation of a new concurrent design practice. This is a combinatorial problem, where many possible states looking forward are explored by different combinations of the available controls. Exhaustive analysis of the combinatorial problem will locate the possible reach of the baseline outward toward many states, but those states may not be unique.

The normative approach instead evaluates the set of changes required to reach a desired level. Here, the end state is known, but the changes required to reach that state are possibly non-existent, non-unique, impossible or unreasonable. This instead becomes a minimization problem, where the designer may look among the possible set of paths or

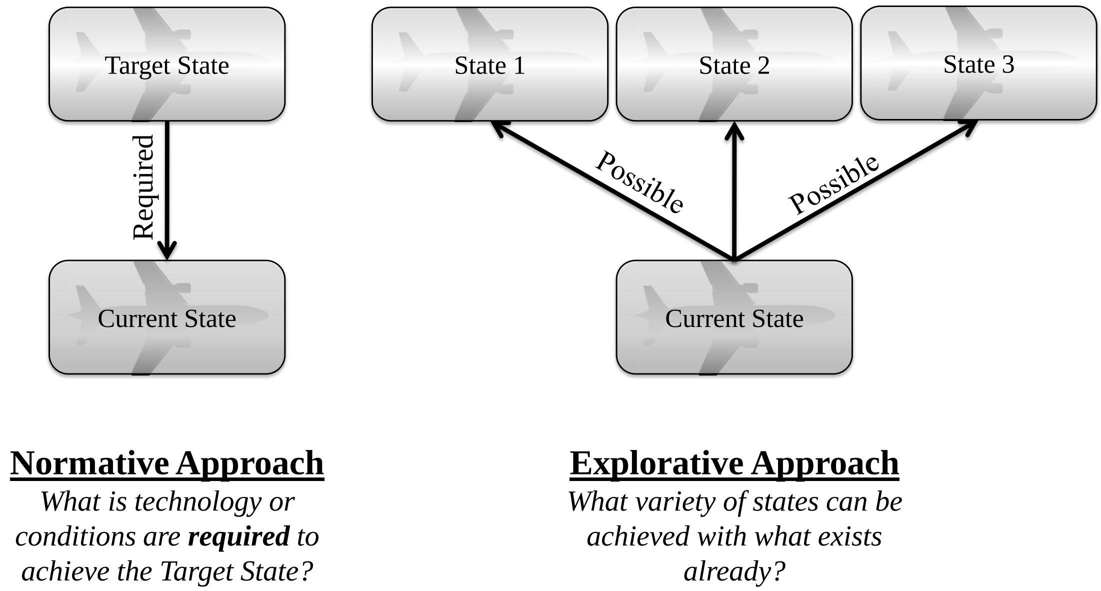


Figure 97: The two fundamental differences in design approaches involving technology and scenario considerations [132] [85].

changes and attempt to minimize cost, time, risk, or some combination of those and other factors to identify a minimum or *best* approach.

6.1.2 Development of the Program Value Model

It was hypothesized and demonstrated that the cashflow presented additional dimensions of utility to describing the business case of the aircraft program. Those dimensions were represented in a curve that is augmented by an uncertainty zone with regard to the future expectation of the cumulative cashflow. It is at this point that the development of the methodology faced two alternatives: 1) develop an approach for evaluating the utility of this uncertain cashflow using qualitative metrics, or 2) develop an approach for the program utility using quantitative metrics. As it was assumed that the strategy development would result from a quantitative approach to mitigating program risk, it follows that a quantitative approach towards capturing the program utility be employed.

There are several candidate approaches to interpreting value from a two-dimensional

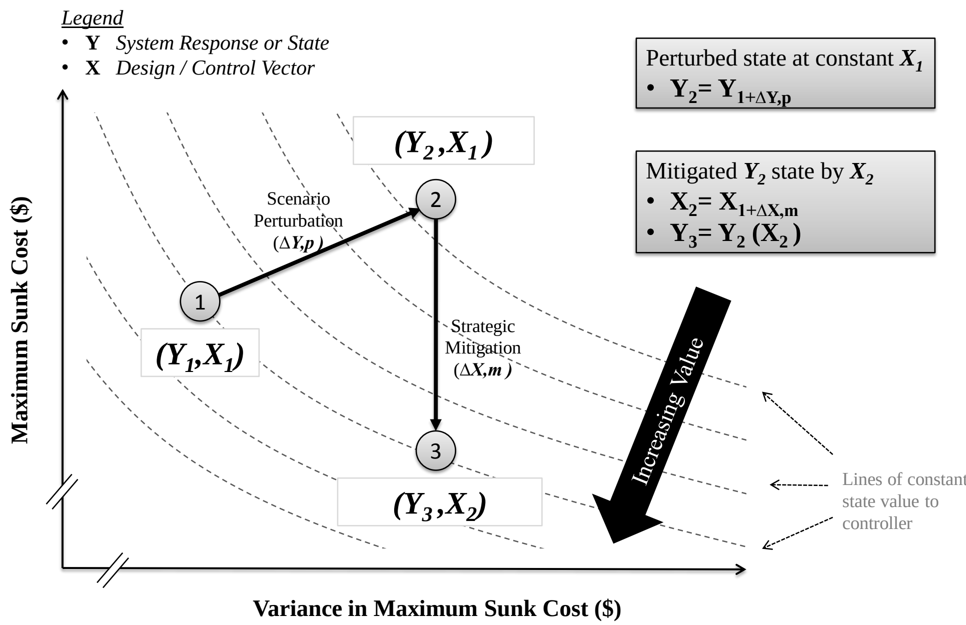


Figure 98: Pictorial describing the strategic mitigation of a design whose scenario expectation is perturbed. Note the strategically mitigated state (*Point 3*) is not necessarily identical to the original state, but a state of equivalent value.

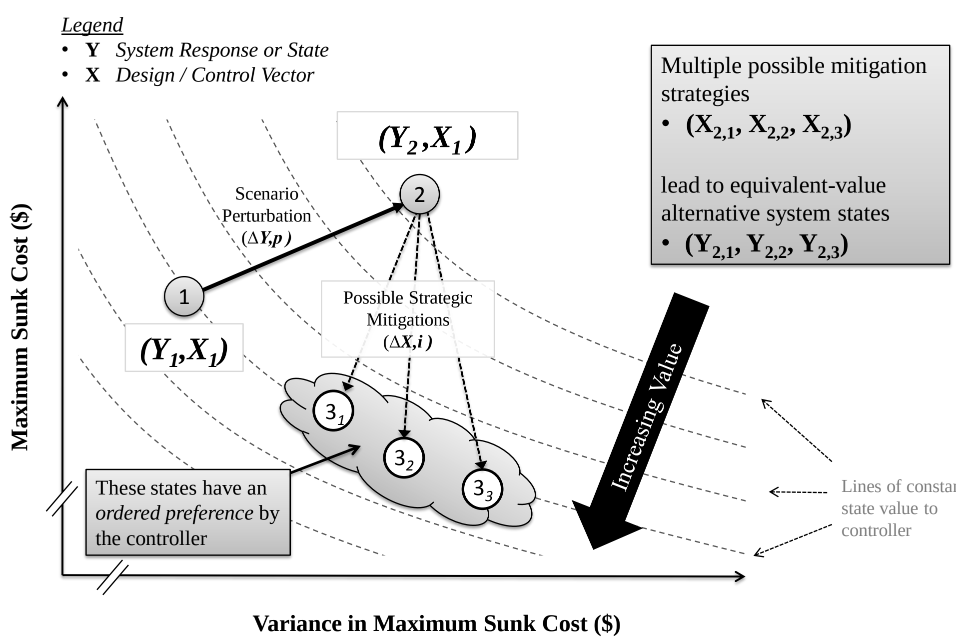


Figure 99: Pictorial describing the strategic mitigation of a design whose scenario expectation is perturbed, this time with multiple candidate mitigation strategies of equivalent overall value.

curve, with the additional dimension of uncertainty. This effectively creates a three-dimensional *surface* from which the program manager interprets value. Several approaches were considered and are compared in this section and given below.

1. *Weighted Sum* - Similar to the Overall Evaluation Criterion (OEC), this approach aggregates various measures from the BASUCA outputs, or from the 3D surface itself. This bears the advantages of reducing the dimensionality of the problem and directly incorporating a program manager's preference or weighting to the outputs.

2. *Boundary Analysis* - This approach makes strong assumptions about the program manager's preference to the moments of the uncertain distribution of cumulative cash-flow data: essentially that the decision tipping point lies in the bounds of the space, and that the information once inside is essentially ignored. This approach is useful for disaster and catastrophic risk analysis, but may not be the desired approach for an explorative risk and strategy mitigation study. It does however lend itself well to constraint-based valuation.

3. *Bottom Line* - This approach looks only at the distribution of the cumulative cashflow at the perceived end of the program (20 year outlook). While this benefits from simplicity and a reduced set of variables to analyze, it ignores the cost and temporal aspect of the program economics.

4. *Risk-versus-Reward* - This approach uses a method similar to the cost-benefit-analysis approach, whereby the positive economic characteristics of the program are normalized by the cost and uncertainty simultaneously.

5. *Least Squares from Ideal* - This approach takes an executive input of the desired cash-flow, at every point in the program, and performs a least-squares regression between the desired and actual cashflows. This has the benefit of capturing all of the cost and time aspects; however, it requires foresight from the executive to be able to correctly input a realistic cashflow, and to identify the distribution shapes at each point in

the program. This level of information may be difficult to extract from the executive, and it may setup a Pareto frontier in the results space that is actually spurious. This occurs when points that have low value to the executive (such as early on) weigh equally to points later in the program (which may have more value). The least squares algorithm, unmodified, treats these points identically.

6. *Aggregated score* - This approach uses an Overall Evaluation Criterion (OEC) method of combining individual responses into a weighted sum of the constituent metrics of interest. Using an OEC method, the responses can be grouped to generate scores for different value categories, such as performance, schedule, cost risk and cost.

Hypothesis

Inversion of the linearized Jacobian around a target uncertain design allows the generation of independent strategic mitigation alternatives that are robust to perturbation of the expected scenario.

6.2 Strategy Generation in Large Data Sets

This section covers the analysis situation where data and simulation capacity to generate new data is readily available. The situation applies when modeling and simulation codes are inexpensive to execute or when large databases exist with applicable empirical data with which to draw conclusions.

When simulation capacity or existing data are readily available, the core analyst challenge becomes selection and identification of the particular strategic mitigation that will bring about the desired programmatic risk effect. This section focuses on a particular approach for the selection process that is expanded to include not only the mean statistic of the output responses, but those describing the propagation of uncertainty and its characteristics. It is known as Filtered Monte Carlo when simulation capacity is abundant.

6.2.1 Filtered Monte Carlo approach to risk mitigation

Filtration of response metrics from Monte Carlo simulation provides an approximated inversion of the modeling framework directly. In this approach, the response metrics are filtered simultaneously across all of the simulations. This reduces the design space substantially to a set of designs which represent the population meeting the constraints. Ideally, in looking at the input variables, a trend or correlation can be identified, this gives the user insight into the variables and their associated ranges which *tend* to produce the responses meeting the filtration.

Figure 100 shows the results from the apparatus before and after filtration. In this filtration step, the maximum sunk cost was limited by year to the values shown in the data filter. It is clear that the space has been reduced substantially, and the main drivers for meeting this constraint became identified: annual inflation rate (API) and aircraft price.

6.2.2 Results from Previous Research

This research leverages an existing state of the art design trade method called Manufacturing-Influenced Design methodology (MInD) that captures manufacturing influences on conceptual and preliminary design and applies the proposed risk-influenced design approach. This approach was opportune because the trade study produced an extensible set of models in the form of Response Surface Equations (RSEs) that were built from multiple high-fidelity codes at the manufacturing level.

6.2.3 MInD Analysis Overview

The goal of the MInD was to bring key manufacturing-level aspects into conceptual and preliminary design before the majority of product cost is committed. It defines system level parameters and tool sets that permit conceptual and preliminary design trades that include manufacturing information. The methodology was a preliminary design level decision trade to compare manual versus automated manufacturing processes on an F-86F Sabre fighter-interceptor wing. To accomplish this, it approximated industry-supported high fidelity

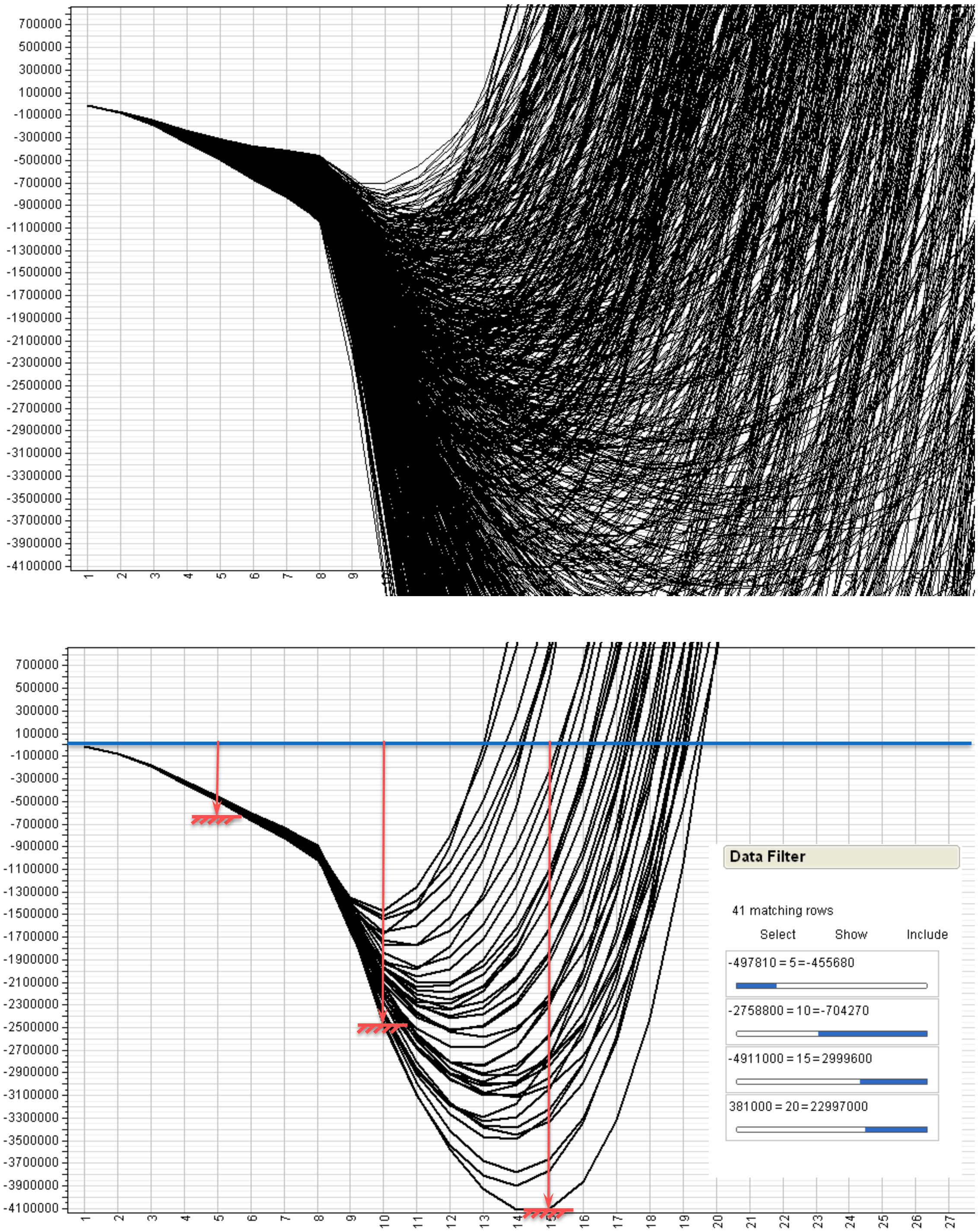


Figure 100: Before and after Monte Carlo filtration of designs in the cumulative cashflow space from the Model Center apparatus used in the methodology development.

codes (SEER-MFG, FLOPS and MALCCA) with the speed and space-complete, range-specific attributes of response surface methodology.

Hypothesis
Mean and Variance are simultaneously valuable to the design environment, and to ignore the variance around a design metric leaves the opportunity for high-risk, low-reward alternatives to go unnoticed.

6.2.4 MInD Baseline Aircraft and Target Specification

The MInD study used the baseline aircraft to explore how manufacturing details affect conceptual design level concerns. The wing was selected as the primary design element and was decomposed into 6 primary components: Spars, Spar Assemblies, Ribs, Rib Assemblies, Stringers and Skin. The manufacturing setup, fabrication and assembly processes were modeled in SEER.

6.2.4.1 Response Surface Methodology

The MInD study assembled several detailed codes to capture the desired system behavior of the F-86F design problem. In particular, SEER-MFG was used for estimating costs and labor associated manufacturing parts for the primary wing structure. The combine modeling network took several minutes to complete one design, so the behavior in the ranges of interest were captured and converted into a reduced polynomial form without substantial statistical loss of accuracy. The Response Surface Methodology (RSM) is the multi-variate reduced-form used in this study. The acceleration enabled Monte Carlo simulations with high run count, and thus thorough explorations of the uncertain permutations. The formulation of response surface methodology is given below in Equation 34.

$$R = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \epsilon \tag{34}$$

The b coefficients result from linear regression of the empirical outputs (R) with respect to the inputs (x_i and x_j). The response surface equation is suitable for smooth outputs with few non-linearities within the range of interest. It was found that the majority of the responses in the MInD could be modeled with response surfaces with an acceptable R^2 fit.

Experimental Apparatus
Response surface equations derived from the Excel-based MiND study for the F-86F aluminum wing re-design. Based in MATLAB alone.

The uncertainty in the outputs was calculated from Monte-Carlo simulation on the inputs by generating random variables from a previously elicited distribution. This caused the propagated uncertainty in the response metrics to scale smoothly with the local slopes of the response surfaces. This is a heavy assumption made by the MInD study, as uncertainty and particular *risk* are not physically bound to smoothness constraints.

The following Risk taxonomy was used in the presentation of the MInD Risk analysis project, and serves as an example mapping of aircraft level metrics to cost, performance, and schedule risks.

The Table 15 illustrates the high-level performance and economic aircraft metrics for the baseline F-86F Sabre and the associated targets for the new aircraft wing design. The risk-influenced design methodology only evaluates aircraft designs that meet or exceed the target specifications. The process used to evaluate the manufacturing influenced risk is given in Figure 101.

Experimental Result
Confirmation of improvement of design robustness by simultaneous filtered Monte Carlo of both mean and variance of design metrics.

Table 14: Risk Taxonomy developed for F-86F study.

Category	Engineering Response Metric	Single Risk Descriptor
Performance	Operating Empty Weight (OEW, lbs)	Std. Dev. OEW
Performance	Maximum Climb Rate (CR, m/s)	Std. Dev. CR
Performance	Minimum Turn Radius (TR, m)	Std. Dev. TR
Performance	Wing Loading (WS, lb/ft2)	Std. Dev. WS
Performance	Thrust Loading (TW lbForce/lb)	Std. Dev. TW
Cost	Net Present Value (NPV, $FY2010)	Est. Std. Dev. NPV
Cost	RDT&E Cost (RDTEC, $FY2010)	Est. Std. Dev. RDTEC
Cost	Average Cost per Unit (CPU, $FY2010)	Est. Std. Dev. CPU
Cost	Revenue (RV, $ FY2010)	Est. Std. Dev. Revenue
Schedule	Total Man-hours (Ltime, hours)	Est. Std. Dev. Ltime
Schedule	Break Even Year (BEY, rel. to 2010)	Est. Std. Dev. BEY

Table 15: Baseline and Target Specification for the F-86F Sabre Wing Design

Metric	F-86F (Baseline)	Goal	Target Value	Units
Variable Cost	191.89	-5.00%	182	$K per Wing
Tooling Investment	112.00	-5.00%	106	$M
Net Present Value	289.37	5.00%	275	$M
Acquisition Price	538.60	-5.00%	510	$K
Operating Cost	5.20	Minimize	—	$M/year
Thrust/Weight	0.42	3.00%	0.4326	—
Wing Loading	47.9	-3.00%	46.5	lbf./ft.$\hat{2}$
Climb Rate	42.4	5.00%	49.8	m/s
Minimum Turn Radius	475	-5.00%	452	m
Approach Velocity	74.3	Minimize	—	m/s

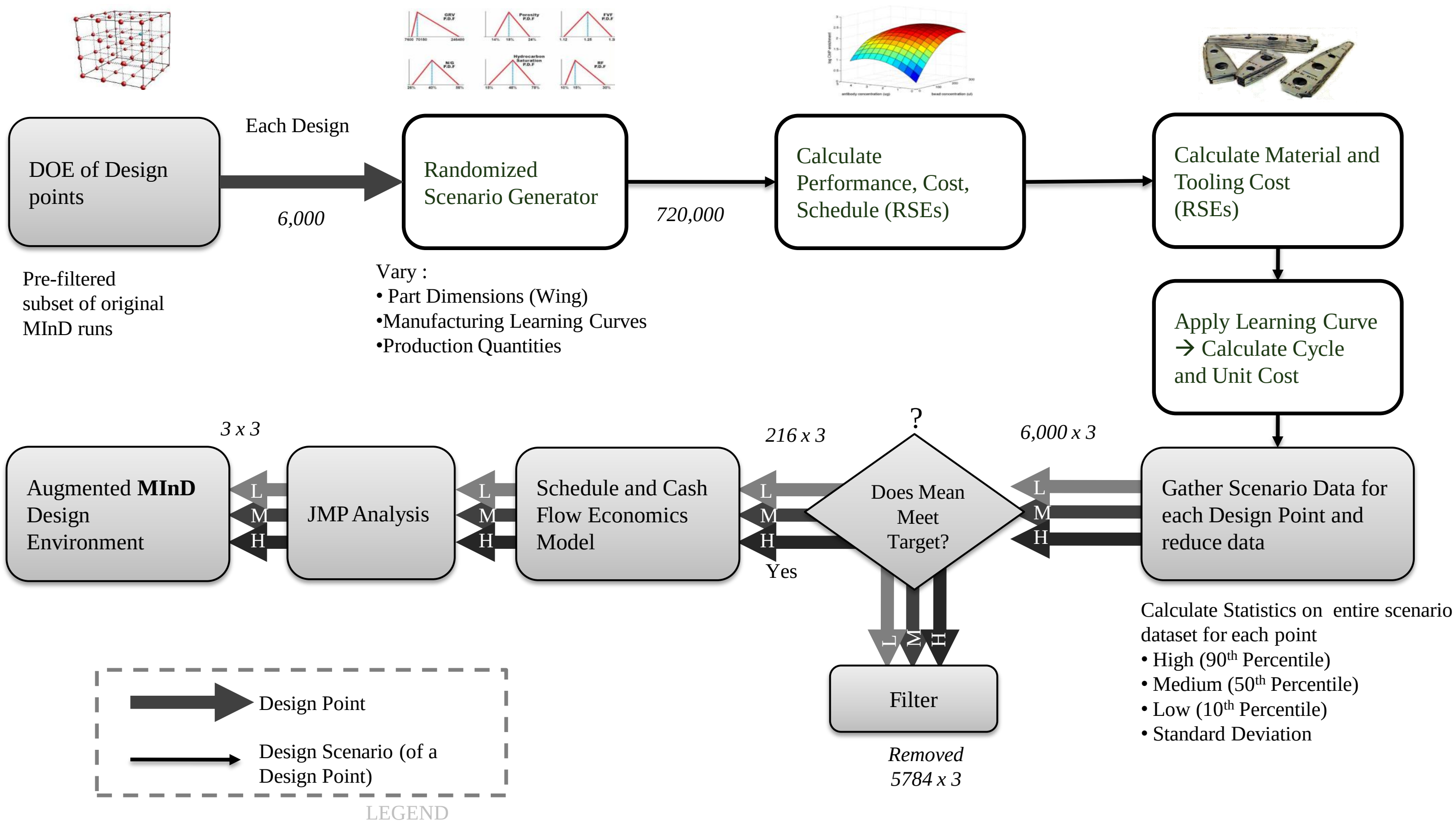


Figure 101: The process used to evaluate the manufacturing influenced design risk in the F-86F study [23].

Figure 102 gives an illustration of the strategies characterized by slight displacement from the Pareto frontier to dominated points where risk in other dimensions is mitigated. Considering Part A: in the risk-influenced design environment, risk dimensions are viewed simultaneously with traditional design responses (notionally Performance and Cost in this case). The current design point is Pareto-optimal in the performance and cost domains, but when viewed in the Risk space, it is dominated by other, lower risk alternatives [23].

Due to this effect, there may exist design points that are acceptably sub-optimal but offer gains in certainty and insensitivity to adverse states, as shown in Part B of Figure 102. These alternatives may offer greater value to the decision-maker and the risk-influenced methodology is designed to facilitate these trades [23].

In this environment, risk dimensions are viewed simultaneously with traditional design responses (notionally Performance and Cost in this case). At the top of Figure 102 shows the current design point is Pareto-optimal in the performance and cost domains, but when viewed in the Risk space, it is dominated by other, lower risk alternatives.

However, there may exist design points that are within the frontier (Pareto-dominated) but offer acceptable gains in certainty and insensitivity to adverse states (reduced risk), as shown in the bottom of Figure 102. These alternatives may offer greater value to the decision-maker and the risk-informed methodology is designed to facilitate these trades.

This final step of CASSANDRA is the knowledge extraction phase of the process, where key strategic information can be explored. Uncertain cash flows are evaluated and compared, and interactive filtration of design, scenario, and technology can take place. Here, trade studies and what-if analyses can be explored: *What is the sensitivity of Technology K2 to the Scenario Assumption L4? Are there design settings that minimize this sensitivity if desired?*

6.2.5 Concluding Observations

It was found that in the absence of information regarding uncertainty and associated sensitivity to inherent process variance, an executive decision maker *may settle on a design carrying disproportionate risk* relative to the expected improvement offered.

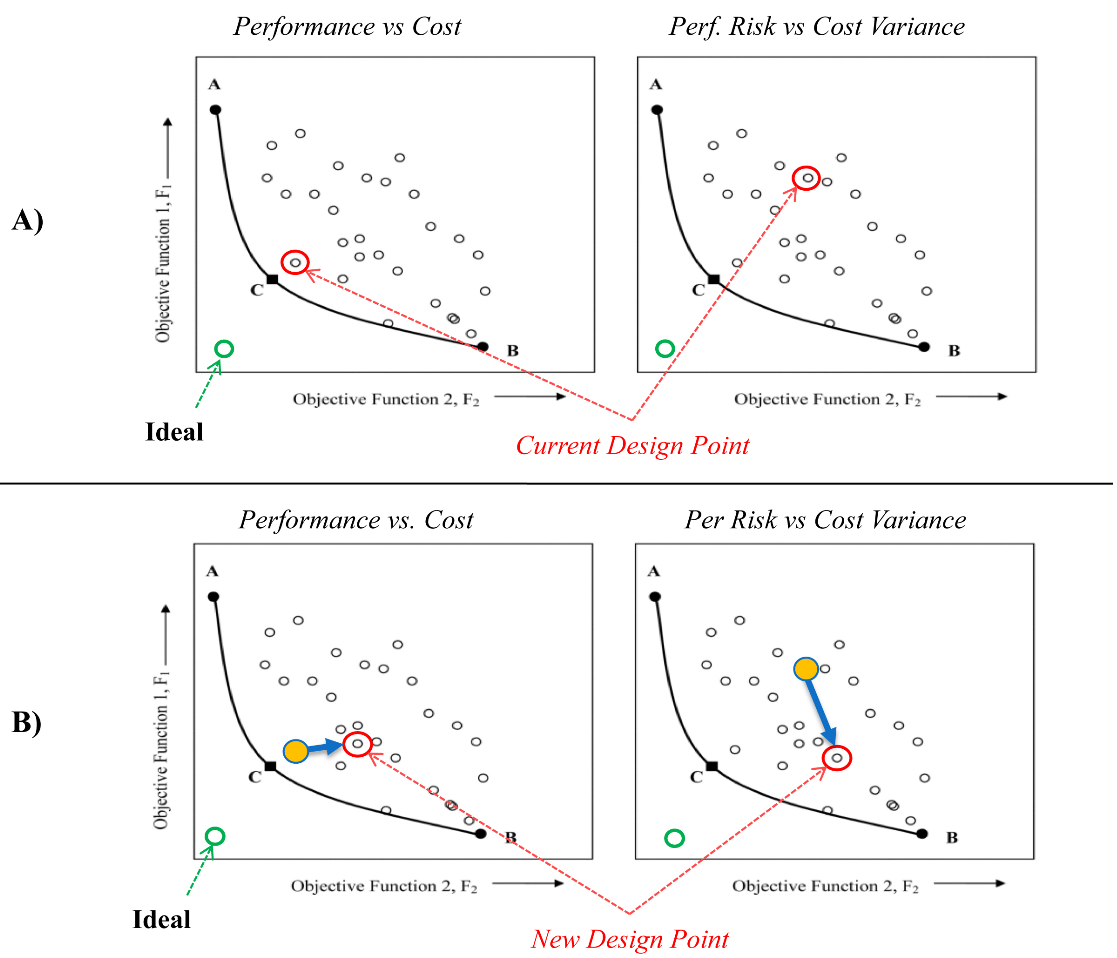


Figure 102: Illustration of design risk mitigation by displacement from the Pareto frontier [23].

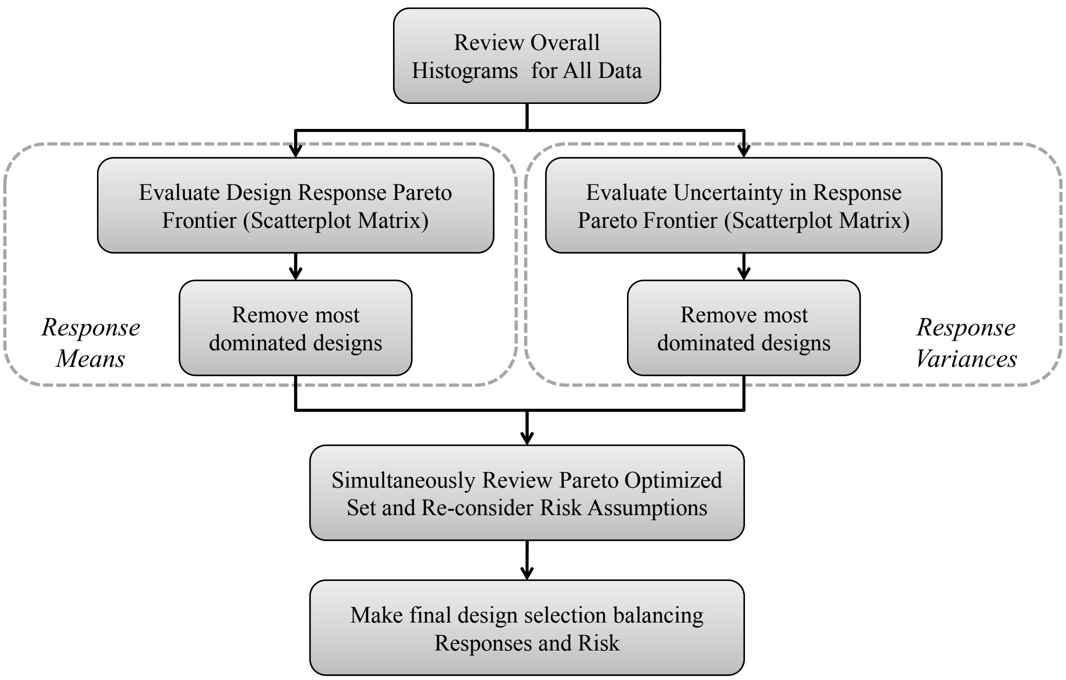


Figure 103: Method for design selection under uncertainty by simultaneous filtration of Pareto-dominated designs by response means and response variances [23].

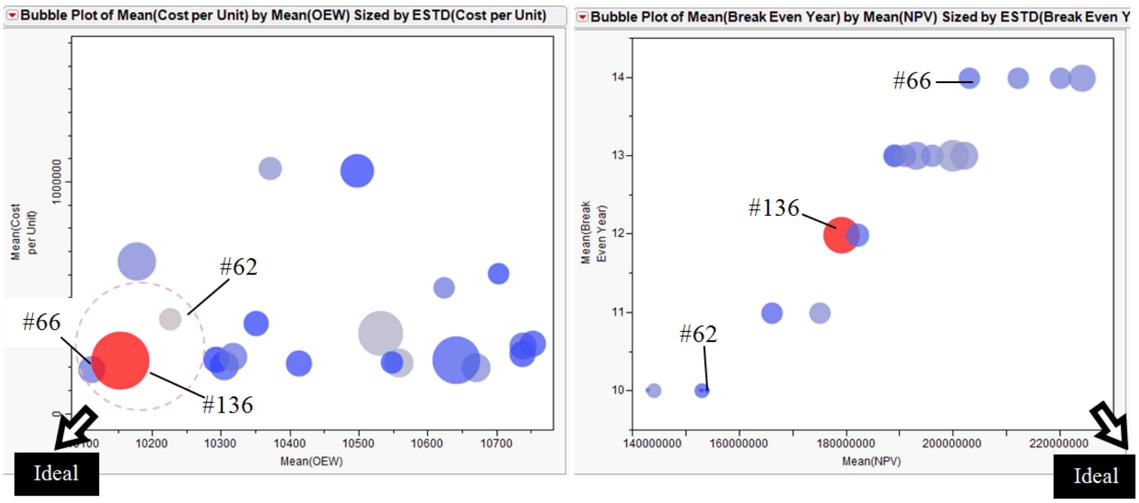


Figure 104: Bubble plots illustrating three design alternatives. When viewed absent of information about variance, a potentially high-risk design point may be selected. In the left plot, the variance in cost is given by bubble size, and the variance in operating weight is given by the bubble color (red being high variance). In the right plot, variance in the break-even year is given by color and the variance in the net present value is given by bubble diameter [23].

As large system designs increase in complexity and cycle time, careful attention must be paid toward the balance of risk and reward. The method presented in this study is an example of how risk analyses may be executed and incorporated into conceptual design trades spaces in order to improve decision quality. A complex, manufacturing-influenced aircraft wing design method was used as an example and modified to incorporate risk views using both Response Surface Equations and Monte Carlo simulation. The resulting data were reduced to a Pareto-optimal subset where trade studies that balance risk in performance, cost and schedule could be closely evaluated.

6.2.5.1 Criticisms to the MInD study and moving forward

Response surface equations were able to model the continuous, smooth output spaces with low fit and representation error and were generally suitable for example aircraft wing design problem. It was assumed that the associated risk and risk states exhibit the same spatial smoothness, which may not always be true in real-life environments.

The second criticism of the MInD study is that the results are not risk by a formal definition given in Chapter 2. Instead, they are actually propagated uncertainty, and that uncertainty is represented singularly by variance. Converting them to *risk* proper requires mapping the uncertainty to a utility curve (or cost measure). This approach works well where the utility function is target-oriented, but the majority of the metrics of interest are actually smaller-the-better. This means that the variance measure is incomplete: the deviation could possibly be advantageous or detrimental. On cost metrics (or profit metrics), the utility space is indeed directional, causing the variance measure to be insufficient in distinguishing *which side* of the mean the variance tends to lie.

The third criticism is that the metrics of interest were difficult to aggregate. In the study, all of the metrics were considered equally and simultaneously. In reality, a program manager has very clear preferences toward which metrics matter. This approach suffers from the dilution effect, where important metrics of interest are considered equally (and therefore averaged in the program managers' view) with several potentially non-important metrics. The other problem with this is that not all of the metrics were completely independent, and aggregating them into a focused decision space becomes difficult. An example here is the relationship between weight and cost. The cost models were built with weight-based cost estimating relationship (CERs), so aggregating cost and weight equally has the effect of scaling weight at a greater rate than cost alone.

Moving forward into the next phase, the experimental apparatus was changed to better enable the aggregation of the metrics of interest into a more holistic approach using the cumulative cashflow diagram.

New Research Observation VIIIa

No aggregated measure for design selection that sufficiently captured the economic viability and business case of alternative designs.

New Research Observation VIIIb

Variance is non-directional, where there exists in reality a utility space or preference for lower/higher/target values.

From these observations the following hypothesis can be stated:

Hypothesis VIa

The uncertain cumulative cashflow diagram is a candidate measure for holistic business case evaluation and risk mitigation.

6.3 Strategy Generation in Small Data Sets

Chapter 2 touched briefly on the subject of making prediction and ultimately decisions in the presence of sparse or missing data. The following section gives a method for addressing the development of risk mitigation strategies where data is missing, sparse, or expensive. This approach uses the normative paradigm, where a target is identified a priori and then sought out by the control system. The approach given here leverages linear algebra and first-order approximations of the objective space.

6.3.1 Development of the Jacobian matrix

The CASSANDRA methodology uses vector calculus to identify and discriminate between the possible strategic mitigation alternatives. It employs heavy use of the *Jacobian* matrices and associated vector sets. The notion of this linear algebra approach came from discussion with fellow researchers, who considered a similar approach to stabilizing flame combustion in a supersonic ramjet motor [105], and the exergy allocation of thermal systems in a more-electric aircraft [82]. The Jacobian, named after the German mathematician Carl Gustav Jacobi (1804-1851), plays an important role in higher dimensional mathematics [71] [119]. As the dimensions and risk mitigation strategies span across many dimensions simultaneously, it was found to be a useful approach in identifying the mitigation strategies.

In this thesis, the Jacobian will refer to the partial derivatives of the response or state (dependent) vectors, with respect to the control or independent vectors. As a reminder, the state vectors describe the state of the program economic expectation of a new aircraft development program. This programmatic economic expectation is expressed as the uncertain expectation of the cumulative cashflow profiles associated with the implementation of an aircraft design.

6.3.1.1 Definition of the Jacobian Matrix

The Jacobian matrix J, or commonly known as just the Jacobian [116], is the matrix of all of the first order partial derivatives of a vector with respect to another vector. It is used to obtain the state values of the system in the vicinity of the current state. If functions can be written using n endogenous variables, and m outputs:

$$\begin{aligned} q_1 &= f_1(x_1, \ldots, x_n) \\ q_2 &= f_2(x_1, \ldots, x_n) \\ &\vdots \\ q_m &= f_m(x_1, \ldots, x_n) \end{aligned} \tag{35}$$

Let $F(x)$ be a vector valued function $F: R^m \rightarrow R^n$ which is at least once differentiable: These can be re-written to be a single function that maps spaces $R^m \rightarrow R^n$ as $\mathbf{F(x)}$:

$$\begin{gathered} \mathbf{F} = [f_1(x_1, \ldots, x_n), f_2(x_2, \ldots, x_n), \ldots, f_m(x_1, \ldots, x_n)] \\ \mathbf{x} \in R^m \end{gathered} \tag{36}$$

The general partial derivative can thus be represented in matrix form as

$$J = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \tag{37}$$

This matrix is known as the *Jacobian* or *Jacobian Derivative.*

6.3.1.2 Numerical Approximation

Finding the Jacobian at point x^* allows F to be approximated in the neighborhood of x^*. It also reveals the sensitivities to F with respect to all of the inputs. If this point is taken to be $x^* = (x_1^*, \ldots, x_n^*)$, then the approximation around this point by $\Delta x = (\Delta x_1, \ldots, \Delta x_n)$. Using first order Taylor expansion of each term in f_i, the functions comprising F become:

$$\begin{aligned} f_1(x^* + \Delta x) - f_1(x^*) &\approx \frac{\partial f_1}{\partial x_1}(x^*)\Delta x_1 + \ldots + \frac{\partial f_1}{\partial x_n}(x^*)\Delta x_n \\ f_2(x^* + \Delta x) - f_2(x^*) &\approx \frac{\partial f_2}{\partial x_1}(x^*)\Delta x_1 + \ldots + \frac{\partial f_2}{\partial x_n}(x^*)\Delta x_n \\ \vdots \qquad &\vdots \qquad\qquad \vdots \\ f_m(x^* + \Delta x) - f_m(x^*) &\approx \frac{\partial f_m}{\partial x_1}(x^*)\Delta x_1 + \ldots + \frac{\partial f_m}{\partial x_n}(x^*)\Delta x_n \end{aligned} \tag{38}$$

Using matrix notation to combine the vectors into a matrix form to describe the linear approximation at x^*:

$$F(x^* + \Delta x) - F(x^*) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(x^*) & \cdots & \frac{\partial f_1}{\partial x_n}(x^*) \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(x^*) & \cdots & \frac{\partial f_m}{\partial x_n}(x^*) \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \vdots \\ \Delta x_n \end{bmatrix} \tag{39}$$

The Jacobian derivative of F at x^* can then be written completely as

$$DF(x^*) = DF_{x^*} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \frac{\partial f_m}{\partial x_2} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \tag{40}$$

The CASSANDRA methodology uses this numerical approximation of the linearized space of the impact of the control variables (design, technology and scenario) to state variables describing the value of the uncertain and at-risk cumulative cashflow metrics.

6.3.1.3 Nullspace vector set of a matrix

The Jacobian matrix describes the approximated n-dimension tangent plane to the point it is calculated around, (x^*). The goal of calculating this matrix is to use the information it provides to linearly extrapolate effect of changing the input and facilitate the identification of control strategies (identified as unit vectors) along which produce the most (or in some cases no) change. This is useful in two ways:

1. Identification of the set of directions which produces the most change - which is useful for mitigating adverse strategies in the normative design mode (see Figure 97.)

2. Identification of the set of directions which produce no change - useful for exploring the set of scenario or design/technology changes which have no impact on the resulting state space value. Exhaustive analysis of this space gives insight to the robustness of the particular design point in consideration (see Figure 105.)

Consider the matrix A, which is an m by n matrix, and the homogeneous system below:

$$Ax = 0 \tag{41}$$

The set of vectors x which satisfy this system form a non-empty subspace of R^n called the *nullspace* and are denoted by *N(A)* .

Once the Jacobian matrix is determined, the null space associated with the matrix may be calculated. The nullspace is an independent set of vectors in the input (x) dimension that produce no change on the output. The nullspace of A must satisfy both addition and scalar multiplication:

$$\begin{gathered} Ax_1 + Ax_2 = 0 \Rightarrow A(x_1 + x_2) \Rightarrow x_1 + x_2 \in N(A) \\ and \\ k(Ax) = 0 \Rightarrow A(kx) = 0 \Rightarrow kx \in N(A) \end{gathered} \tag{42}$$

if $k \in \mathbf{R}$.

Table 16: Variation in the filtration level of linearized Jacobian matrix of the CASSANDRA methodology.

Threshold (ϵ)	Percentage of Jacobian removed
10	99
1	95
0.1	80
$1x10^-2$	75
$1x10^-3$	60
$1x10^-4$	40
$1x10^-5$	10

6.3.2 Nullspace of the Jacobian

In practice, the CASSANDRA methodology relaxes the constraint slightly to identify subspaces of R^n which are approximately nullspaces, or

$$\begin{gathered} Ax \approx 0 \\ or \\ |A_{i,j}| \leq \epsilon \end{gathered} \tag{43}$$

Where i and j are the individual elements of A, and ϵ is a small positive prescribed threshold. This is done to filter and reduce large nullspaces to manageable and impactful workspaces following the Pareto 80/20 rule. The numerical nature of the linear approximation to the Jacobian give the opportunity for spurious micro perturbations, so ϵ is selected at a level commensurate for isolating only the most relevant dimensions of the input spaces.

6.3.2.1 Uniqueness and the constraint on the number of input and output variables

As the Jacobian approximation method solves a linear system of equations, there exist bounds on the number of linearly independent inputs and outputs to the Jacobian linearized system around x^*. The linear system requires that the number of unknowns–or in this case the m inputs or dimensions of $x-$ be equal to or greater than the number of output dimensions (n). If the input dimensions are given as the control variables in the CASSANDRA methodology, then they comprise the m core design variables, technology

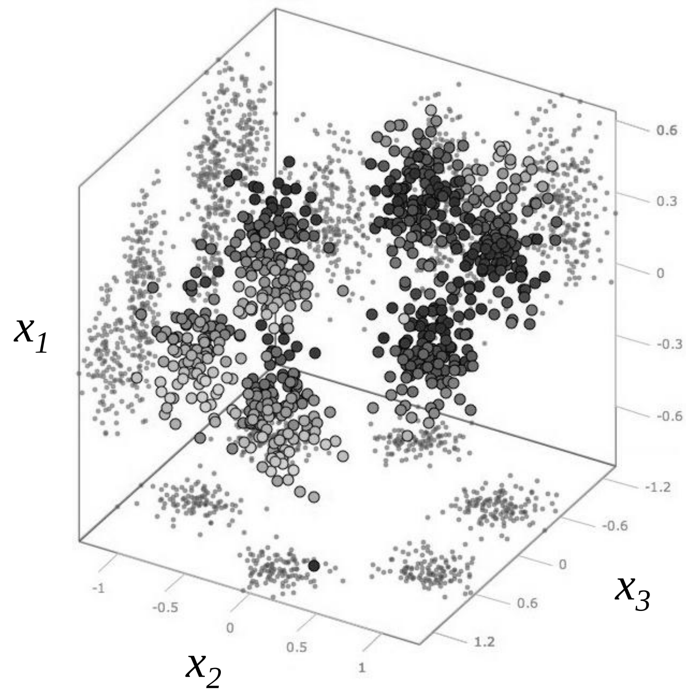


Figure 105: Locus of independent points describing the nullspace of the Jacobian matrix of a notional design problem. Each of these points in the input space produce no change in the output space [30].

variables, and certain scenario variables. Refer to Table 7 for a complete taxonomy of the variable types, examples, usage and their justification in the methodology.

Therefore, following the linearization system of equations principle, the following observation is made regarding the dimensionality of the inputs and outputs to the methodology:

Research Observation IX

If there are m independent inputs, and n dependent output of the model which describe the product value, and the set Z of vectors describing program-level strategic mitigation alternatives, then if:

$$m \leq n \tag{44}$$

then the set of vectors Z is non-empty.

6.3.2.2 Nullspace of the Jacobian matrix as a strategic development tool

Recalling the objectives of the program manager, one of the tasks of strategy development is to identify the directions of managerial action which produce little or no change to the program value expectation. The sensitivity of the current program state value to the variables within and outside of control is of value to this goal. To this end, the Jacobian offers valuable information. The trace of the Jacobian offers the direction of the greatest change (or gradient), and the nullspace of the Jacobian offers a set of input directions producing no change. Changing nomenclature slightly from the previous definitions of the Jacobian and nullspace, let the state space Y be given as

$$y = F(x) \tag{45}$$

The strategic mitigation approach compresses the state space into a representation of state value. Let *Value space* be given then as:

$$G(F(x)) = G(y) \tag{46}$$

If the current program state value is $G(Y(x))$ at the point X, and the Jacobian at that point is $J(G(y))$, and the s, i script refers to s strategies defined in i inputs, then:

$$Null(J(G(y)) = \hat{X}_{\Delta x,s,i} \tag{47}$$

where $X_{\Delta x,s,i}$ is the set of differential vectors, usually called the *vector basis* of $Null(A)$ such that any linear combination of strategies in X:

$$Y(X + X_{\Delta x,s,i}) \approx G(Y(X)) \tag{48}$$

which yields the same value function $G(Y)$. When the nullspace is calculated on the Jacobian matrix, it identifies the principle, linearly independent directions in which the input vector X may change and cause no change in the output vector Y (similar to walking along a line on a topographical map, the altitude is held constant).

The unique value in this approach is that it produces a *set* of directions (versus an approach which identifies a single direction) causing no change in state value. If this set is large, and the magnitudes of the change are in directions previously interpreted as sensitive, then the set itself becomes a measure of robustness. That is, the program state value is insensitive to change (see the section on *Robustness* in Chapter 3 for more information).

This approach is by its definition explorative: the nullspace of the Jacobian evaluates change outwardly. The nullspace of the Jacobian is but one set of program information that can be captured from this linearized approach. In the next section, an approach for normative of strategy mitigation development is identified using similar toolsets from algebra.

6.3.2.3 Normative approach to strategy development using the Jacobian

In this section, an approach is developed for the generation of strategic mitigation plans to return a perturbed state to a state of equivalent value. As described in the analogy of the pilot maintaining level flight, the theory given here estimates the direction and magnitude needed to reach that equivalent state. The resulting plan is a mitigation vector in X that is given in the variables within control.

Several things are required in this normative approach. Recall that if there are n dimensions describing the output states, then this approach requires

1. The original or desired state, given by its value as $G(Y_{1,n})$ for independent input vector X_1.

2. The current or perturbed state, given by its value $G(Y_{2,n})$ for independent input vector after out-of-control perturbation $X_2 = X_{1+\Delta X_{p,noise}}$.

3. The Jacobian at the perturbed state, $J(G(Y_{2,n}))$.

4. The ability to invert the Jacobian.

The first three requirements have been addressed in earlier sections, but the inverse of the Jacobian matrix has not been discussed. In practice, the CASSANDRA methodology rarely operates in cases where $m = n$, or the number of control variables is equal to the number of dependent response variables (or state variables). Calculating the inverse of non-square matrices is possible by approximation and use of the Moore-Penrose method [8] [54]. This *pseudoinverse* method computes solutions by minimizing the least squared error of a system of linear equations. Though this approach is computationally costly when compared to the inversion of a square invertible matrix, MATLAB was able to calculate the psuedo-inverse matrices of the Jacobian with relatively zero delay.

Beginning with the two state vectors, $Y_{1,n}$ and $Y_{2,n}$

$$\Delta G_{p,n} = G(Y_{2,n}) - G(Y_{1,n}) \tag{49}$$

Where $\Delta G_{p,n}$ describes the change in the j between the original and perturbed states. Letting Z be the Jacobian at $Y_{2,n}$, or

$$Z = J[G(Y_{2,n})] \tag{50}$$

Taking the inverse of Z the multiply it by ΔY_p, it achieves

$$Z^{-1} * \Delta G_{p,n} = B\Delta \hat{X}_{m,control} \tag{51}$$

where B is the scaled vector norm and $\Delta \hat{X}_{m,control}$ is the unit mitigation vector required to return the state to one of equivalent value. This vector is in differential form, so to arrive at the total input vector the program manager should give

$$X_{2,m} = X_{1,m} + B\Delta \hat{X}_{m,control} \tag{52}$$

Combining terms yields

$$[J[G(Y_{2,n})]]^{-1} * [G(Y_{2,n}) - G(Y_{1,n})] = B\Delta \hat{X}_{m,control} \tag{53}$$

This equation yields the formulation for finding the linearized solution to the perturbed state problem. The mitigation vector $B * \Delta X_{m,control}$ is of unit length and is scaled by B and is forthwith referred to as the ***principle strategic mitigation vector***. As in other gradient-based methods for numerical optimization, this approach yields a single strategic vector. This leads to the following observations:

1. The mitigation vector may contain elements which are beyond the physical capability or range of the controls. An example of this from the previous analogy is the mitigation input for trim tabs, which has a control range of $+/-$ 5deg. The linearized range may indicate that the controller (or program manager) set the trim tabs to $+10$ deg, in which case this is not possible.

2. The method produces a single vector (denoted here as the principle strategic vector), but that vector may be projected onto vectors from within the nullspace at Y_2 to create independent strategic alternatives that surround the principle strategic vector to create a *strategic vector set.*

6.3.2.4 Expansion of the principle strategic mitigation vector into a vector set

As mentioned in the last section, this method produces single *principle* strategic mitigation vector. The CASSANDRA methodology aims to deliver many strategic alternatives to the program manager, so it is therefore of interest to explore expanding the specter into a vector set. Several approaches were considered, some borrowing from multidimensional optimization techniques, including probabilistic techniques for evaluating adjacent strategic mitigation factors. For the sake of simplicity methodology delivers an approach that does not require extensive programming nor identification of all of the covariance terms needed in a probabilistic approach. Instead, this approach makes use of the nullspace available at both the original and the perturbed program states.

As the principle strategic vector and the nullspace of the Jacobian are orthogonal in all dimensions, it is possible to create a set linearly independent vectors that are a weighted projection of the principle vector to each of the vectors in the nullspace.

Recalling Equation 47 of the nullspace at X_1, we define similarly the nullspace at the perturbed state at X_p

$$Null(J(G(Y_p) = \hat{X}_{p,i} \tag{54}$$

where $\hat{X_{p,i}}$ is the set of i vectors describing the nullspace of the Jacobian. Each vector is also of unit length, and may be projected onto the principle strategic mitigation vector $\Delta\hat{X}_{m,control}$. Let θ_i is the angle between $\Delta\hat{X}_{m,control}$ and each vector within $\hat{X_{p,i}}$, then the interior hypercone angle $\Delta\theta_i$ creates the set of vector projections, given as:

$$X_{m,hypercone,i} = Bsin(\Delta\theta_i)\hat{X}_{p,i} \tag{55}$$

$X_{m,hypercone,i}$ is the set of i surrounding strategic mitigation vectors, each containing m elements in the control dimensions.

The principle strategic mitigation vector and the nullspace-projected hypercone are shown for two dimensions in Figure 106.

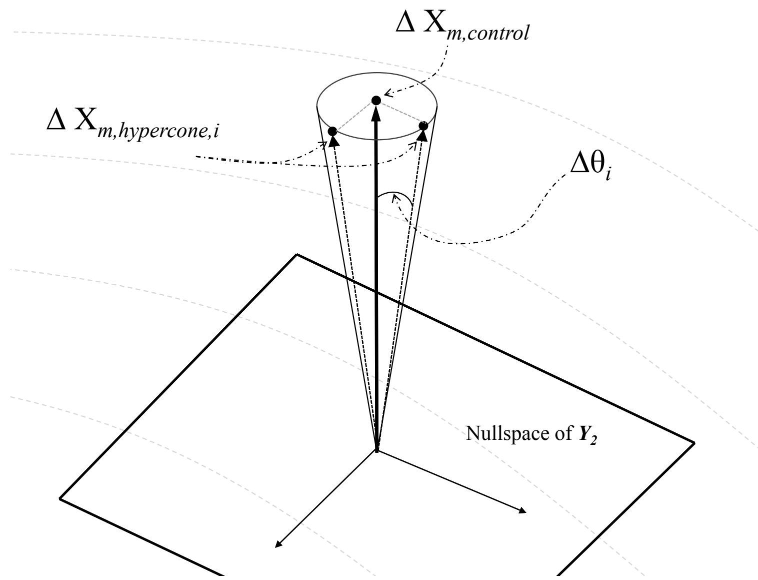


Figure 106: Hypercone in 2 dimensions created by projection of the principle strategic mitigation vector onto the nullspace vector set. This approach generates surrounding mitigation vectors from the nullspace at the perturbed program state.

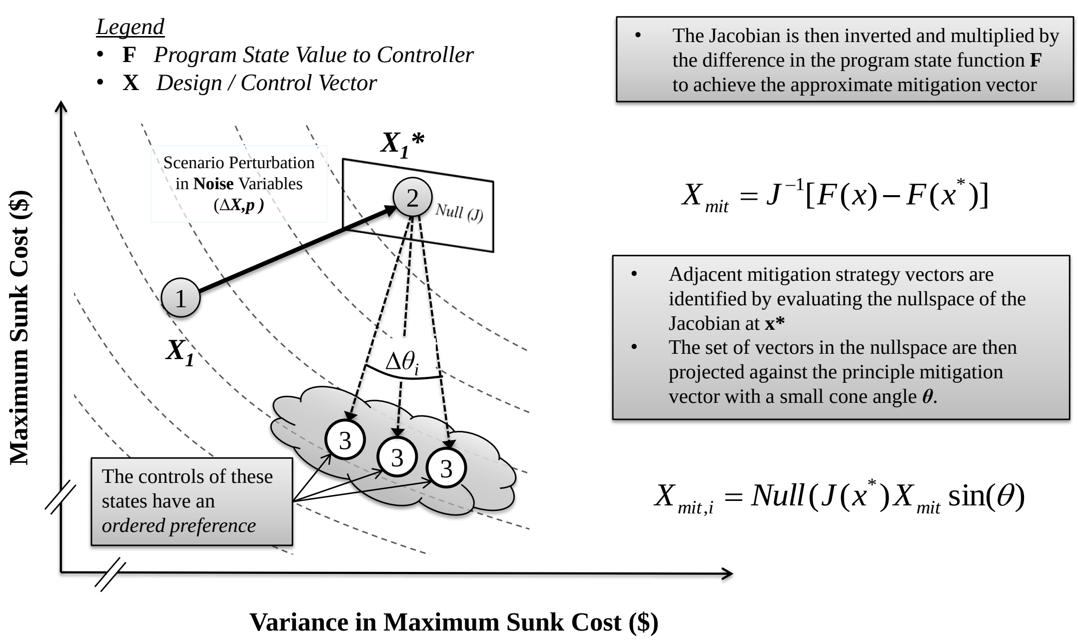


Figure 107: Pictorial describing the strategic mitigation of a design using the nullspace and a hypercone angle θ of the jacobian to identify candidate risk mitigation strategies.

.

Table 17: Control variables and their limits in the example strategic mitigation approach.

Control Variable	Value	Lower Bound	Upper Bound	Control Range
AR	9	6	13	7
SW	1250	500	2000	1500
DESRNG	2000	1000	3500	2500
SHT	400	100	600	500
ARHT	6	1	12	11
SVT	270	100	600	500
ARVT	1.1	0.3	2	1.70
SWEEP	22	0	45	45
PWINGTI	0	0	1	1.00
PWINGCO	0.13	0	1	1.00
PWEMPTI	0.6	0	1	1.00
PWEMPCO	0.13	0	1	1.00
PWBODYTI	1	0	1	1.00
PWBODYCO	0	0	1	1.00
PWNACTI	0	0	1	1.00
PWNACCO	0	0	1	1.00

6.3.2.5 Example results from the strategic mitigation approach

Experimental Apparatus

Codes were written in MATLAB that approximate the inverted Jacobian matrix for nullspace and gradient space identification.

Experimental Result

The nullspace and gradient spaces give information about the direction an impact of linearly independent mitigation strategies.

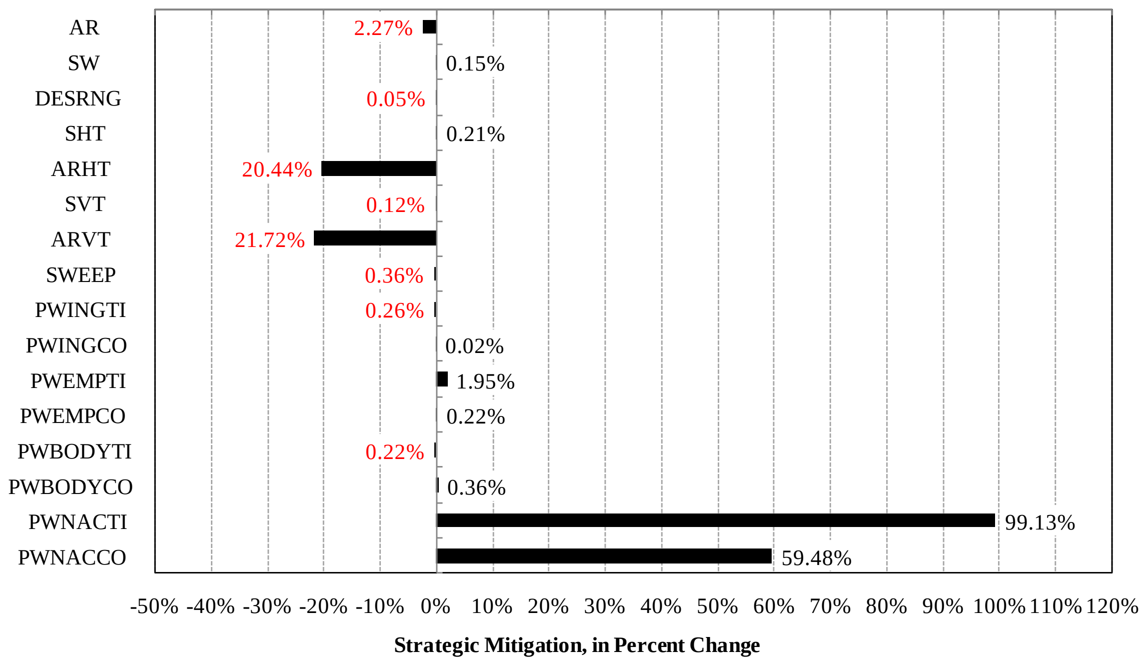


Figure 108: Percent change in the allowable control space that tries to achieve the normative strategic mitigation target.

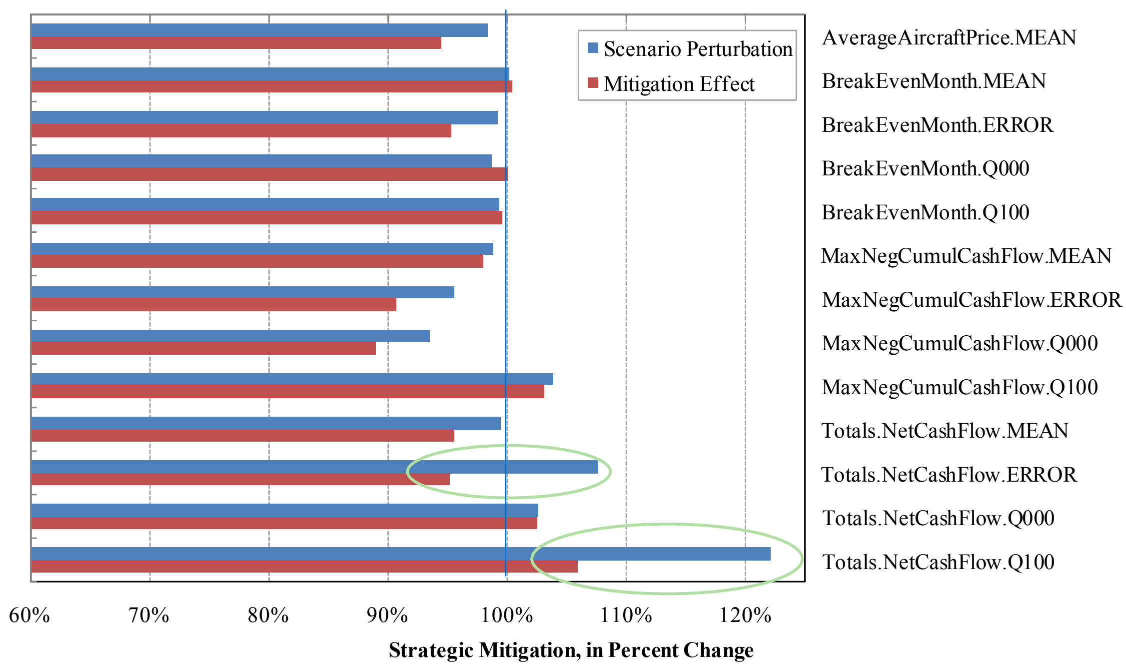


Figure 109: Percent change in the results space that tries to achieve normative strategic mitigation target.

New Research Observation Xa

There exists a mitigation preference to the controller among the input dimensions as well as physical limitations.

New Research Observation Xb

Some mitigation strategies are effective, some are not effective. The non-effective strategies give value to the program manager as *a priori* insight to dangerous states.

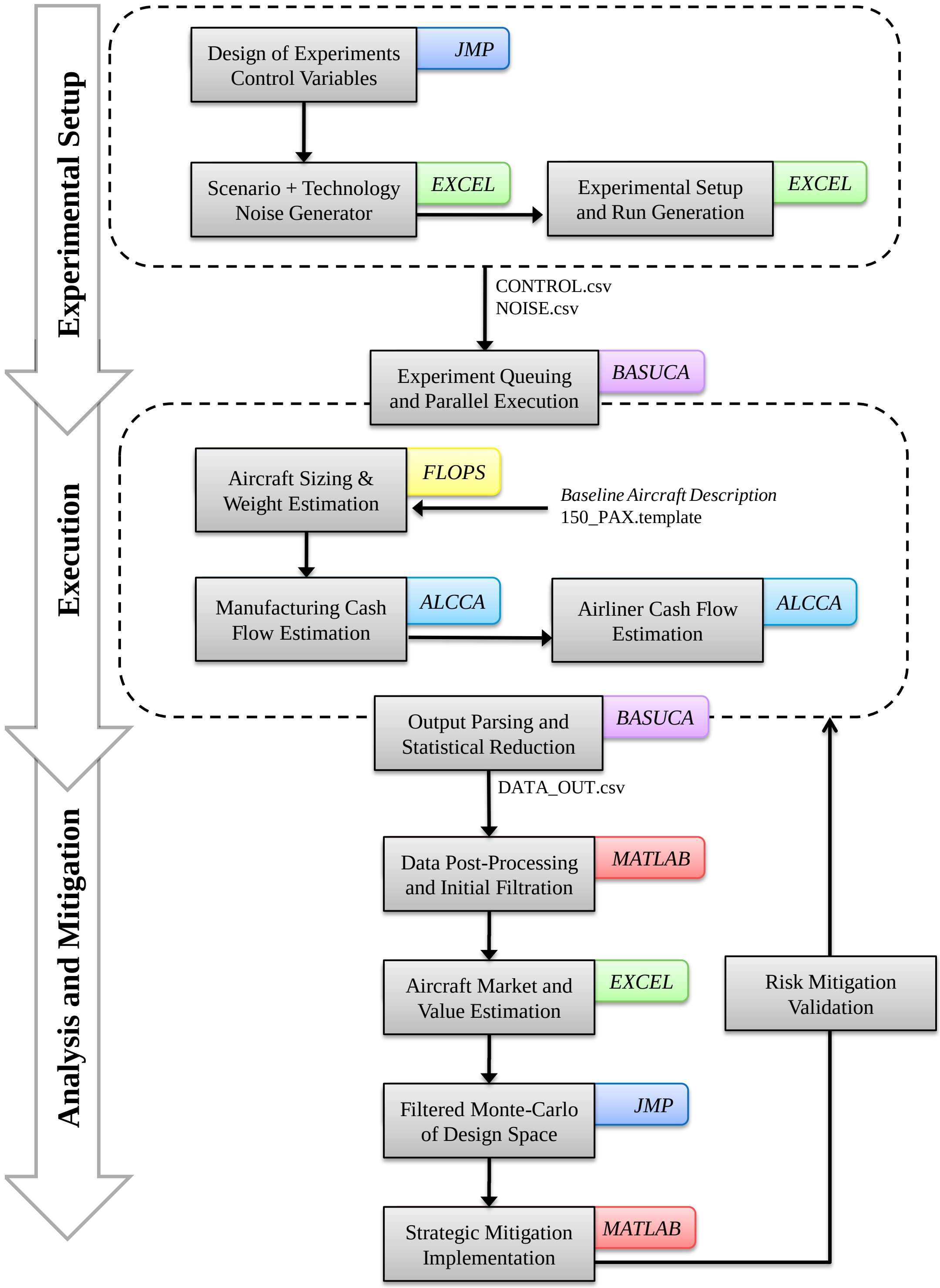


Figure 110: Overview of the information and data flow of the experimental apparatus used to test the *CASSANDRA* methodology.

CHAPTER VII

PROBLEM FORMULATION AND METHODOLOGY

7.1 Introduction

The goal of this chapter is to identify and structure the dissertation contribution, design problem, and to formalize the measures of success. The previous chapters focused on the motivation, literature review of the current paradigms of risk analyses and their applications in aircraft design processes. The aircraft design exercise has the following key attributes: a highly multi-dimensional problem with non-linear interactions, mixing varying types and fidelity of data, not all of which is quantitative nor certain.

This chapter presents the following key aspects of the dissertation and methodology:

1. Identification of the design problem.

2. Declaration of the decision perspective and methodology user.

3. Technologies available and their impact.

4. User preference towards risk, the analysis outputs, and strategy channels.

5. The baseline aircraft design problem.

6. The three case study scenarios.

The systems engineering and aircraft design fields present a stunning variety of problems bearing risk and risk alternatives. Several candidate design problems were considered; it is generally believed that the approach, if successful, is adaptable to a large majority of these problems. The particular selection of the design problem for this thesis is therefore based on access to public data and high fidelity codes. The Aerospace Systems Design Laboratory offers a variety of tool sets for research. The most relevant tool sets for broad economic evaluation of aircraft designs that integrate manufacturing (and thus a variety of interesting trade study opportunities) are FLOPS, ALCCA and SEER. These are codes that have been developed over decades and incorporate a wide variety of empirical cost data from many sectors of the aerospace industry. The author has experience in risk analyses using these tool sets (see Appendix C for a description of the Manufacturing-INfluenced Design study), therefore they were preferred to ground-up cost codes for this dissertation. This study was carried out for a F-86F Sabre fighter jet. While this aircraft study is both fruitful and readily accessible, the business management perspective of cash flow analysis and risk aversion is more applicable to a commercial aircraft problem as the profit and loss attitudes towards risk are magnified for these problems.

7.2 Identification of the Design Problem and Baseline identification

The CASSANDRA methodology is demonstrated on the executive-level decision-making problem of a large-scale commercial transport aircraft manufacturer.

7.3 Identification of the CASSANDRA Methodology user

The executive level manager is in charge of a product development program, and is responsible for the market estimation, design, and manufacture of an all-new technologically-infused aircraft. Her core objectives are the following:

- Produce *maximum* profit
- Assume *minimum* risk
- Achieve *minimum* break-even time
- *Compete* favorably with a single competitor by delivering value to the customer

Her problem is therefore multi-objective as the time, profit and risk are assumed to be independent dimensions. This thesis will refer to this person and her responsibilities as the *Designer*, or *Program Manager* interchangeably. The range of variables in her control include design variables, technology inclusion/exclusion variables, and some limited control of manufacturing. Outside of her control are external (market) variables, aleatory noise variables, complexity factors and certain labor and materials costs. A complete breakdown of the control locus is given in the methodology and experimental platform sections of this dissertation.

7.3.1 Beginning with the end in mind

The core deliverable, as outlined in the *Thesis Objective*, is the generation of a **strategic risk mitigation plan**. Put formally, this is an **identification of an adjustment in the program strategy to insulate the business case from external perturbation or influence (or scenario)**. It is appropriate at this time to re-iterate and focus definitions for the terms in the Thesis Objective.

- **Identification**: Declaration, discovery generation or calculation and of a strategy.
- **Strategy**: A vector of settings (or changes to) of the variables within control that constitute a plan to achieve the specific goal.
- **Business Case**: The risk-reward or economic viability and understanding of the associated financial (not safety) risks of a business decision.
- **External**: Forces or influences that originate outside of the control of the Program Manager.
- **Scenario Perturbation or Influence**: Deviation from the planned development, manufacturing, or market expectations.

7.3.2 Definition and Etymology of Scenario

As the term scenario appears in the title of this dissertation, it is perhaps appropriate to formally declare its meaning and its implication to the design problem presented to the program manager. A scenario is an account or synopsis of a possible course of action or events [133]. This dissertation focuses on the scenario as descriptors or more formally, as the set of state variables that describe a possible course of events. Those events are given as the internal and external state variables. Internal state scenario variables include the role as an aircraft manufacturer or airframe integrator, the core technologies or intellectual property owned, or the availability and quality of the human resources. External state

Table 18: Incomplete taxonomy of candidate input variables to the BASUCA.

Description	Variable Handle	Design Type	Taxonomy Category
Aspect Ratio (Wing)	AR	Control	Design
Area (Wing)	SW	Control	Design
Design Range	DESRNG	Control	Design
Area (Horizontal Tail)	SHT	Control	Design
Aspect Ratio (Horizontal Tail)	ARHT	Control	Design
Area (Vertical Tail)	SVT	Control	Design
Aspect Ratio (Horizontal Tail)	ARVT	Control	Design
Weight (Engine)	WENG	Control	Design
Sweep (Wing)	SWEEP	Control	Design
Percentage of Titanium (Wing)	PWINGTI	Control	Technology
Percentage of Composites (Wing)	PWINGCO	Control	Technology
Percentage of Titanium (Empennage)	PWEMPTI	Control	Technology
Percentage of Composites (Empennage)	PWEMPCO	Control	Technology
Percentage of Titanium (Body)	PWBODYTI	Control	Technology
Percentage of Composites (Body)	PWBODYCO	Control	Technology
Percentage of Titanium (Nacelle)	PWNACTI	Control	Technology
Percentage of Composites (Nacelle)	PWNACCO	Control	Technology
Number of Vehicles Produced or Sold	NV	Control and Noise[1]	Scenario
Annual Percentage Inflation	API	Noise	Scenario
Complexity Factor (Engine)	CFENG	Noise	Scenario
Learning Curve (Block 1)	LEARN1	Noise	Scenario
Learning Curve (Block 2)	LEARN2	Noise	Scenario
Learning Curve, Assembly (Block 1)	LEARNAS1	Noise	Scenario
Learning Curve, Assembly (Block 2)	LEARNAS2	Noise	Scenario
Learning Curve, Avionics (Block 1)	LEARNA1	Noise	Scenario
Learning Curve, Avionics (Block 2)	LEARNA2	Noise	Scenario
Learning Curve, Engine (Block 1)	LEARNP1	Noise	Scenario
Learning Curve, Engine (Block 2)	LEANRP2	Noise	Scenario
Learning Curve, Fixed-Equipment (Block 1)	LEARNFE1	Noise	Scenario
Learning Curve, Fixed-Equipment (Block 2)	LEARNFE2	Noise	Scenario
Manufacturer's Rate of Return	RTRTN	Noise	Scenario
Engineering Labor Rate	RE	Noise	Scenario
Tooling Labor Rate	RT	Noise	Scenario

variables may include things like the inflation rate, competitive factors and availability and position in the market. Both of these types of factors influence the economic viability of the airplane program, however they may impact its economics in different ways. There is a hierarchy to the scenario state variables worth mentioning. Various researchers, engineers and managers may refer to scenario variables while describing the same thing or within the same hierarchy, so for clarity, a sample hierarchy of the scenario state variables is given in Table 18. In this table, the taxonomy of variables allows the user to understand exactly to which point of the hierarchy they may be referring.

A complete description of the scenario space is challenging to develop due to the sheer dimensionality; however, identifying various bounds or nodes makes describing the space more accessible. The methodology identifies several key scenarios and their associated state variables, and a space can be developed around those scenarios using those as nodes. The states themselves may be discretely described (where elements of the scenario are binary), but they can be mapped to continuous spaces through combinations. Any linear combination of the scenario variables, provided they are not mutually exclusive, can form a new candidate scenario. Monte Carlo simulations can be executed for the combination of states in between the key scenarios which build a progressively more filled spatial representation and ultimately lead to greater understanding [126] [34].

7.3.3 Definition of Strategy and Implications on the Design Problem

The term strategy is derived from the Greek word *stratgos*, and was first used in its current form in writing in 1810. Merriam Webster defines strategy as *an adaptation or complex of adaptations (as of behavior, metabolism, or structure) that serves or appears to serve an important function in achieving evolutionary success* [134]. With respect to the CASSANDRA methodology, a strategy is a plan of programmatic adjustment to controls to mitigate an unforeseen degradation (or perturbation) of the programmatic value by external (and generally uncontrollable) forces. In this regard the strategy, or *strategic mitigation*, is described mathematically as a vector in X that accomplishes one of two goals:

1. **Perturbation mitigation** - Returns the programmatic state to a state of value

equivalent to the original and desired, or

2. **Conditional state value optimization** - Maximizes the state value given a perturbation.

The first strategic mitigation approach is similar to a control problem where an output is fed back to a controller who adjusts the input as a function of the feedback and seeks to maintain the current value. This strategic mitigation approach tends to favor stability. This approach has the advantage of knowledge at the current state, and therefore a direct awareness of the change from the original to the perturbed state. This enables the normative approach to be employed in discovery of mitigation strategies. However, this imposes more on the program manager (or controller), in that the original state be one of already acceptable value. In an explorative design paradigm, this may be more challenging.

The second strategic mitigation approach makes no assumption about the value of the original state. It focuses instead on how the new (perturbed) state may seek a maximized programmatic value. This approach lends itself better toward the explorative design paradigm yet suffers the difficulties of optimization. These difficulties include the potential for settling on local instead of global minima, expensive function call requirements, and continuous and discrete factor influences.

7.3.4 Dissertation Limitations on Risk and Modeling Fidelity

In order to scope the work of this work, several assumptions were made on the type, nature, and magnitude of the environments and the risks modeled therein.

1. *Uncertainty Elicitations are valid and complete* - The selection of distributions on the scenario variables, technology costs, technology cycle times, technology impact factors, and design space exploration are given to be accurate and sufficiently broad. This single assumption limits the realistic application of the results presented in the notional problem, however with access to internal data a program manager could potentially apply the method to improve decision making.

2. *Modeling and Simulation sufficiently capture the potential risk* - The physics and process based simulations are of acceptable validity to measure risk. Secondly, the high speed surrogate models fit the range sampled with an acceptable degree of precision. Response surface equations are generally able to model continuous, smooth spaces with low fit and representation error, and are generally suitable for modern aircraft design problems. It was assumed that the associated risk and risk states exhibit the same spatial smoothness, which may not always be true in real-life environments.

7.4 Baseline Aircraft Selection

The generation of technology was selected to be of the early 1990's, when large-scale use of composite materials for primary structure became prevalent [11] [51] [75] [80]. The baseline aircraft class was selected to be a single aisle, tube-and-wing aircraft carrying approximately 150 passengers and a range of approximately 2500-3000 nautical miles. This was selected as both major commercial vehicle manufacturers (Boeing BCA and EADS Airbus) investigated replacing their existing products in that time frame. This design problem has been called the *Next Generation Narrow Body* and is of current interest to both Airbus and Boeing, which may aim to replace their aging A320 and 737 aircraft. Table 19 gives a short overview of the basic specification of the 150-passenger, single aisle Next-Generation narrow body aircraft.

Several studies, including the Next-Generation single aisle effort, have shown that an approximated 15-20% reduction in Direct Operating Cost may be possible for this class of aircraft. This is by incorporating new lighter-weight (and thus fuel-saving) technologies, specifically in the replacement of aluminum primary structure with carbon-epoxy structures described in Chapter 1. The reduction in direct operating costs come in part from lighter weight structures, however the total cost of ownership may be affected by the increase in acquisition cost. Therefore, there exists a trade between the variable cost savings of the lighter weight structure to the end user, and the program costs by the manufacturer or airframe integrator.

[1] In billions of USD, corrected to Fiscal Year 2010. Amounts are approximates, as development aid and subsidies shroud actual development cost.

Table 19: Baseline geometric, performance and economic aircraft specification for the CASSANDRA methodology demonstration. Resembles the Next-Generation Narrow Body aircraft that major manufacturers explored in the early 21st century.

Description	Handle	Value	Unit
Passenger (2-class)	PAX	150	-
Maximum Range	RANGE	2040	Nautical Miles
Gross Takeoff Weight	GW	150000	lbs
Fuel weight	FUEL	34000	lbs
Aspect Ratio	AR	9.4	-
Wing Area	SW	1360	$feet^2$
Wing Taper Ratio	TR	0.201	-
Wing Sweep angle	SWEEP	25	deg
Wing Thickness-to-Chord	TCA	0.133	-
Wing Loading	W/S	114	lbs/ft^2
Horizontal Aspect Ratio	ARHT	5.6	-
Horizontal Tail Area	SWHT	360	$feet^2$
Horizontal Tail Taper Ratio	TRHT	0.28	-
Horizontal Tail Sweep angle	SWPHT	33	deg
Vertical Aspect Ratio	ARVT	1.2	-
Vertical Tail Area	SWVT	290	$feet^2$
Vertical Tail Taper Ratio	TRVT	0.28	-
Vertical Tail Sweep angle	SWPVT	39	deg
Thrust-to-Weight	T/W	0.265	-
Approach Speed	VAPP	125.3	knots
Takeoff Field Length	FAROFF	7515	feet
Landing Field Length	FARLDG	5800	feet
Total Thrust	THRUST	20700	lbs
Cruise Speed	VCMN	0.787	Mach
Cruise Altitude	CH	41000	feet
Acquisition Price	ACPRICE	100	Million Dollars
Revenue Passenger-Mile	$/RPM	0.14	Dollars
Direct $/Flight Hour	$/FH-DOC	4600	Dollars
Indirect $/Flight Hour	$/FH-IOC	3400	Dollars

One of the key literature review sources was a report by NASA and Boeing for the Advanced Subsonic Technology (AST) program, which was dedicated to exploring the viability of more affordable composite structures technologies. The report authors verified an economically viable, full-scale technology application on an all composite wing box for an MD-90 passenger aircraft. The MD-90 is similar in size and in role to the Next-Generation single aisle commercial transport, making the AST report particularly well-suited as a way to calibrate and develop the CASSANDRA methodology.

For these reasons, the 150-passenger aircraft infused with new composite wing technology is appropriate a baseline aircraft for this dissertation research.

7.5 Methodology Overview

This chapter covers the proposed approach to achieving a process with which to address the Research Questions. This new method, called *CASSANDRA*, is named after the mythological Trojan woman of such incredible beauty that an enamored Apollo gave her the power of prophecy and the ability to see the future, shown in Figure 111. However, when his love was not reciprocated, he cursed her so that no one would believe her prophecies. It is hoped that the method is successful in measuring risks, while avoiding the latter curse of disbelief.

CASSANDRA stands for **C**omputational **A**ircraft **S**ub-**S**ystem **AN**alysis of **D**esign **R**isk **A**lternatives.

The goal of CASSANDRA is to quantitatively measure the risk of uncertain aircraft systems and generate sets of risk mitigation strategies. The approach leverages elements of the existing state of the art of probabilistic design methodology with a geometric scoring of uncertain cumulative cashflows.

The CASSANDRA method is given in four separate sections: A) Problem Formulation, B) Realization, C) Analysis, and D) Strategic Risk Mitigation. The constituent steps for each section are listed below, and are also arranged graphically in Figure 112.

(A) **Problem Formulation**

(1) *Define the Problem and Executive Voice*

(2) *Elicit Executive Cash Flow Utility Profile*

http://waltermooresays.blogspot.com http://www.maicar.com/GML/Cassandra.html Ajax and Cassandra by Solomon J. Solomon. Ballarat Fine Art Gallery in Victoria, Australia

Figure 111: Artists' renditions of the mythological beauty Cassandra, who was gifted with prophecy but cursed with everyone's disbelief.

   (3) *Establish OEC weightings*

   (4) *Identify the Expected and At-Risk Scenarios*

(B) **Realization**

   (1) *Define the Concept Space*

   (2) *Identify the Control and Noise Variables*

   (3) *Setup Fast multi-disciplinary System Model*

   (4) *Execute Design of Experiments and Monte Carlo Simulations*

   (5) *Filter factor effects by Analysis of Variance*

(C) **Analysis**

   (1) *Calculate Market Capacity Based on Product Value*

   (2) *Filter Candidate Designs*

   (3) *Calculate Uncertain Cumulative Cashflow Metrics: Risk Aversion Angle and Risk Benefit Ratio*

(4) *Analyze the Uncertain Cumulative Cashflow Distributions*

(5) *Calculate Program State Value*

(D) Strategic Risk Mitigation

(1) *Identify and Compare Perturbed Program State Value*

(2) *Identify Principle Risk Mitigation Strategy Vector*

(3) *Identify Alternative Risk Mitigation Strategies*

(4) *Implement Mitigation Strategy and Verify*

The overall approach to CASSANDRA is indeed a blend of many existing methods. There is fundamental resemblance to the risk management methods covered in Chapter 4, where context is given, risks are identified and analyzed, and proactive decisions are made to address the risks. The process is adapted to probabilistic aircraft design processes where the emphasis on technology infusion is given [87, 67]. Indeed, CASSANDRA leverages these proven approaches with a new, additional layer of complexity: the Prospect Theory approach to risk interpretation measurement made possible through the use of Target Cascading the objectives and targets to the sub-system level.

An overview of CASSANDRA illustrating the process and the areas of thesis contribution is given in Figure 112.

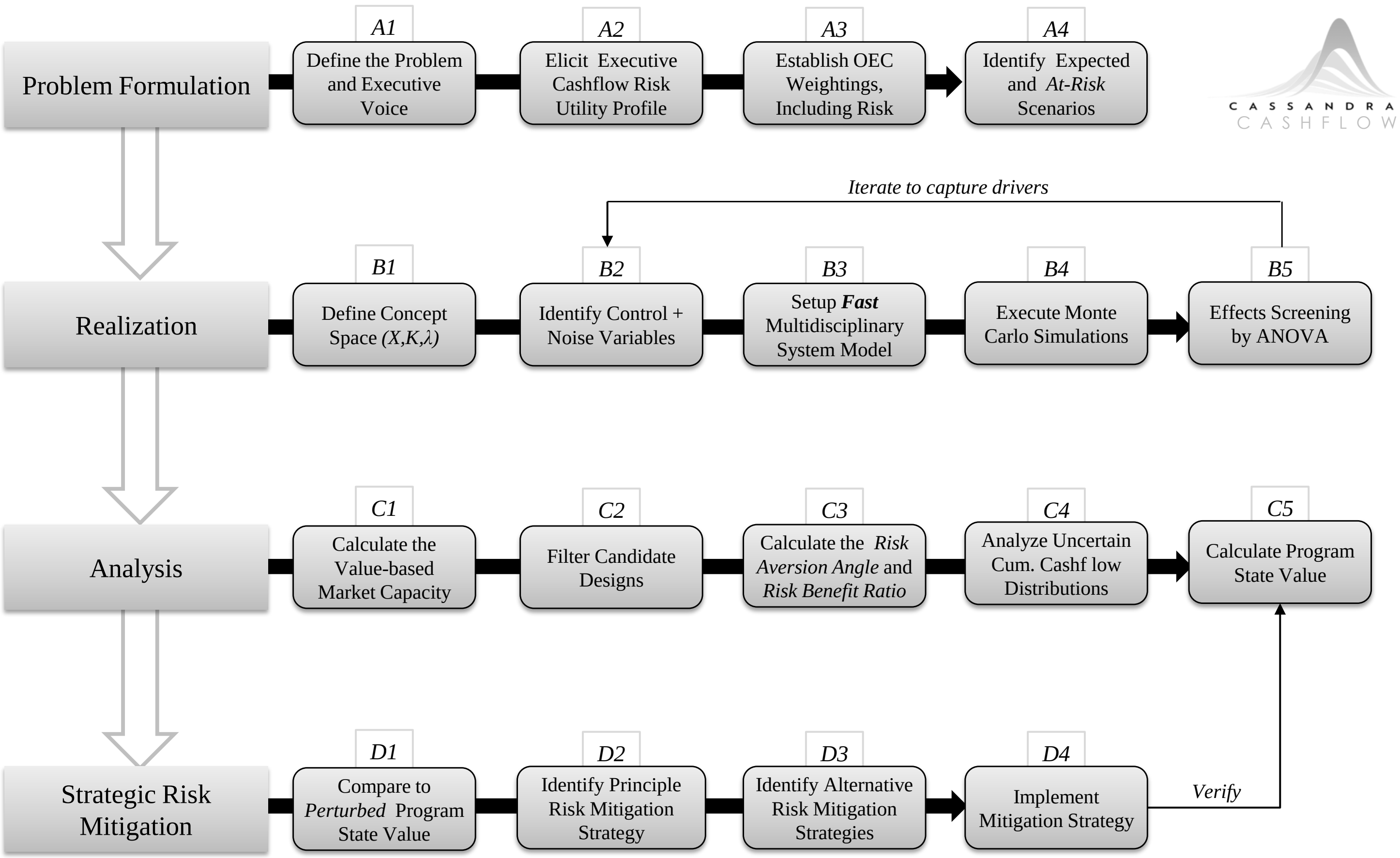


Figure 112: Overall CASSANDRA methodology for treatment of aircraft program risk.

7.5.1 Problem Formulation

7.5.2 Defining the Program Metrics and Executive Voice

As with many processes addressing risk assessment and aircraft technology evaluation, the first step of CASSANDRA is to formally describe the problem, scope, perception of value, and the system objectives. In this step, the context of the system and fundamental risk areas of interest are established. The goal of this step is to develop target system objectives and a tractable relationship between the product voice of the customer and aircraft manufacturer elicitation of the value function. There are many methods for mapping the voice of the customer to explicit system objectives (for example, an 8% reduction in the $/Revenue-Passenger-Mile), notably a Qualitative Functional Deployment (QFD). Aircraft marketing research helps establish the voice of the customer who establishes the design objectives. In addition, the system-level value functions are established by parameter-izing the cash flow curves and mapping them directly to a utility curve. This process involves mapping objectives to the cash flow parameters, for example break-even year (as an objective) is mapped to the intersection of the cashflow line with zero net cash flow. An example of the risk mapping to system objectives is given in Appendix C.

7.5.3 Realization

This set of steps in the methodology assembles and organizes the input variables, the economic cashflow responses, and builds the simulation framework. A diagram illustrating this arrangement is given in Figure 113.

In these steps, the various spaces are identified and bounded for the CASSANDRA methodology. There are three distinct spaces considered: the design space (x *space*), the scenario space (or λ *space*) and the technology space (or k *space*. The definition of the baseline vehicle and the ranges associated with each of the spaces is defined.

The Scenario and Technology spaces require an understanding of the risk intended to be evaluated. This step involves high level assessment of the exchanges of risk to be made. Therefore, the elicitation of the Scenario and Technology spaces should come after an evaluation of the technologies and scenarios pertinent to the baseline problem. Technologies here refers to materials, processes, or measurable improvements to the baseline design. The scenario and scenario assumptions are all the descriptions of the system and environmental state that are typically defaulted or assumed in a deterministic or non-risk probabilistic analysis.

7.5.3.1 Separation between Control and Noise Variables

Figure 113 illustrates a combined view of design inputs, scenario assumptions, technology forecasting, and results analysis. The design inputs are treated as separate candidate designs, and conducting a design of experiments (DOE) on likely ranges is considered a design space exploration process. This portion is deterministic.

The scenario assumptions, illustrated at the top of the diagram, are the representation of the variance in underlying (non-design variable) assumptions that could occur in future states. The vector describing the shifting assumption in this space is called the λ space. Possible examples of λ space assumptions could be the price of oil, machining labor rates, manufacturer learning curves, production rates, etc. The technology forecasting section (illustrated on the bottom) represents the new probabilistic effects on design responses, stemming from the addition of new technologies. Their space is known as the k space [87]. An example of this organization of the variables is given in Table 20.

7.5.3.2 Conduct Uncertainty Elicitation and Propagation

This step carries out the uncertainty analysis through the multi-disciplinary system: the scenario assumptions (manufacturing labor tate, production quantity, etc) and technology forecasts (materials specification type, manufacturing process, Young's Modulus, etc) are executed probabilistically *for each design*, similar to a nested Monte Carlo approach. This allows the complete system model interaction between design variables, scenario assumptions, and technology forecasts to populate the candidate design response space. For each of the preliminary designs, candidate "future risky scenarios" or "instances" are generated to represent the potential drift from natural processes of the design specification. These instances were generated by creating local distributions centered on each sub-system level parameter in the DOE. This is done for each design point instead of on the whole so that the conditional robustness of each design point can be evaluated in post-processing. This conditional probability calculation arrangement is what separates the *risk* assessment process from a conventional *sensitivity analysis*: the deviations experienced by each design point are based around the values defining the design itself, and not on the whole design population. The values describing relative distributions applied to each design are selected to represent discrete, likely scenarios defined by subject-matter-experts (SME) during the risk declaration and distribution elicitation workshop. The result of the workshop will be, in addition to the set of requisite Monte Carlo distributions, a formal description of the assumptions and likely states substantiating the uncertainty range of the subsystem level. This step is a key element of the risk analysis as it brings to light the discrete sources of uncertainty.

Domain	Type	Example	Symbol
Design Variables	Geometry	*Aspect Ratio*	X_G
Design Variables	Configuration	*Number of Engines*	X_C
Design Variables	Architecture	*Fly by Wire*	X_A
Scenario Assumptions	Economic	*Price of Oil*	λ_ϵ
Scenario Assumptions	Labor	*Assembly Labor Rate/hour*	λ_γ
Scenario Assumptions	Manufacturing	*Learning Curve*	λ_ρ
Scenario Assumptions	Materials	*Aluminum-Lithium Cost/lb*	λ_m
Scenario Assumptions	Market	*Orders Received*	λ_μ
Technology Factors	Materials	*Carbon-Epoxy Composite*	k_m
Technology Factors	Manufacturing Process	*Automated Tape Layup*	k_ρ
Technology Factors	Aerodynamic	*Circulation Control*	k_α

Table 20: Taxonomy of uncertainty quantification in design inputs, scenario assumptions and technologies.

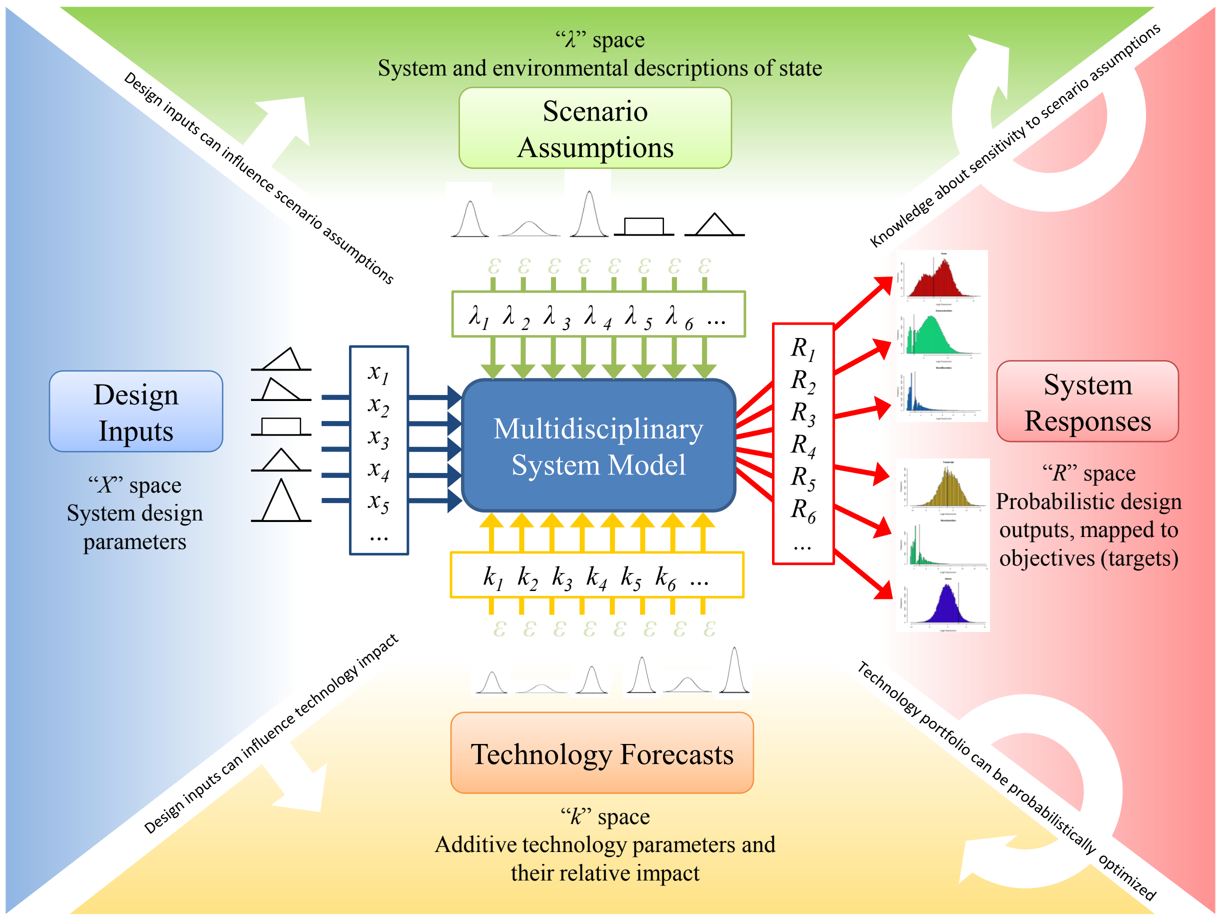


Figure 113: The overall *CASSANDRA* method illustrates an approach to balancing at-risk technology alternatives.

7.5.3.3 Build the Fast Multi-disciplinary System Model

In this step, the assembly of the codes describing the multi-disciplinary system is done in the same fashion as existing probabilistic design processes. Modeling and simulation of large system design problems have expanded to incorporate investigations in the propagation of uncertainty at the system level. As overall complexity rises, the simulations must increase in fidelity to maintain accuracy. Monte Carlo technique requires thousands upon thousands of samples to resolve the probability and variance information needed, posing serious constraints on using the high fidelity truth codes. Fortunately, methodological developments in system-wide design have enabled high-fidelity codes to be captured and converted into a reduced-form surrogates that can be accelerated without substantial statistical loss of accuracy. The use of high-speed surrogate models (developed specifically over the range of interest) are a common solution for achieving the probability density function resolution needed for resolving uncertainty and risk.

7.5.3.4 System Model Fidelity

For CASSANDRA, the model of the system used is required to be of *sufficient* fidelity. A natural question a user might ask is: *What is the level of sufficiency (fidelity) needed*? The system model itself is considered an input to the CASSANDRA process; no model fit error or model representation error is assumed at this time. Stults provides a separate method used for propagating and developing required fidelity for uncertainty propagation of complex systems [121]. Response surface equations are generally able to model continuous, smooth spaces with low fit and representation error [87] and are generally suitable for modern aircraft wing design problems. It was assumed that the associated risk and risk states exhibit the same spatial smoothness, which may not always be true in real-life environments.

7.5.3.5 Effects Screening by Analysis of Variance

A two-level Design of Experiments (DOE) is used to develop a wide, space-spanning list of candidate design factors. The purpose of this step is to reduce this number of factors to a smaller set that is more active for the design problem and scenario set of interest.

By statistical analysis of Variance (ANOVA), factors may be separated by their Contrast, t-Statistic and p-value. Each design contains a vector of design parameters X space (Wing Span, Aspect Ratio, Sweep, Airfoil, Rib spacing, etc) as well as k and λ vectors of their respective settings (defaulted at this stage). Each design will then produce an associated vector or responses, denoted as R.

7.5.4 Analysis

This portion of the methodology contains the bulk of the thesis contributions prior to the development of risk mitigation strategies. Here the CASSANDRA methodology focuses on the analysis of the output from Part B. In these steps the output data is transformed, filtered and measured by the proposed metrics, ultimately reaching a valuation of the programmatic state to the executive or program manager. It comprises five steps (C1-C5), given here in summary:

1. *Calculate Market Capacity Based on Product Value* - Addresses the feed-forward variable of market capacity and production quantity found in FLOPS by defining a window of likely sales volume as a function of the product specifications, the existing customer's baseline, and the level of performance offered by a competitor. This capability is measured by an enhancement of the Overall Evaluation Criterion formulation, called OEC+.

2. *Filter Candidate Designs* - Results from Monte-Carlo simulation are filtered *a posteri* by the number of vehicles sold using the prediction window given by the OEC+ formulation.

3. *Calculate Uncertain Cumulative Cashflow Metrics: Risk Aversion Angle and Risk Benefit Ratio* - Here additional metrics are offered which capture the driving factors of program value and risk on the uncertain cumulative cashflow space. These metrics and their development were covered in Chapter 5, and give insight into the balance of risk and reward to the program manager.

4. *Analyze the Uncertain Cumulative Cashflow Distributions* - In this step, the CASSANDRA methodology user reviews the results from the results processing steps and draws initial design and technology conclusions based on the distribution and frontiers of the uncertain cumulative cashflow metrics. An example conclusion would be *Design Range drives the risk aversion angle larger and the risk-benefit ratio remains unchanged.*

5. *Calculate Program State Value* - The responses within the uncertain cumulative cashflow space and their metrics are fused with the executive voice and weightings from Phase A of the methodology to compile the results into a state value. This value function will be held as the baseline or target in the risk mitigation steps from within Phase D.

7.5.5 Strategic Risk Mitigation

In this section of the methodology, the user identifies an Expected program state. This state is held as the reference, or baseline, and is selected such that it be considered to be the target or program risk neutral state. This state is based on a single setting of the control variables (both design and technology as well as the defaulted scenario variables within control), and an *expected elicitation* of the distributions of the noise variables that are out of user control.

The CASSANDRA methodology is comparative and gives a normative approach to strategic mitigation. Therefore, when analyzing the risks to the assumption set in the noise variables, the scenario is perturbed. This perturbation occurs in the *a priori* elicitation of the noise variable. Put another way, the perturbation is defined by a shift in the expected distribution of the noise variables. Recall the example in the Development chapter where the pilot is tasked with maintaining level fight. The pilot is then faced with a change in the variables outside his control: the landing gear will not retract, causing a shift in the expectation of the noise variables, and he must work within the control space to maintain the objective. In practice these elicitation are in assumptions about material costs, market forces such as competitive entry or customer requirement shift, availability of capital, etc.

Mapping the scenario description and associated elicitation of uncertainty has been addressed by many researchers studying scenario-based risk assessment, specifically Millet [94] who used an Analytical Hierarchical Process approach, Savci who used a knowledge-base [109], and Holbrook [57].

The process for mapping the scenario description and *associated perturbation* to the control and noise variables is given below:

1. Identify baseline control variable set and ranges.

2. Identify the baseline noise variables.

3. Elicit the baseline noise variable distributions settings.

4. Elicit any change in control variables or their ranges due to the scenario perturbation.

5. Elicit the change in baseline noise variables distribution settings.

6. Append any additional noise variables, and their ranges not previously captured in the noise variable set description.

Using the known difference between the Expected and the Perturbed states in the uncertain cumulative cashflow space, the CASSANDRA method then leverages the linearized approach for solving for the Jacobian at the perturbed state location. This then generates the partial derivative sensitivities of each of the controls to the state value metrics. From this, the principle Risk Mitigation strategy vector can be identified, which points the user in the direction and magnitude of the control space mitigation strategy. This is a linearized approach and prone to error yet, so alternative strategies are also identified using the Nullspace of the Jacobian and a hyper-cone angle around the principle mitigation vector. Finally, each of these strategies is tested under the perturbed noise variable elicitation and the mitigation selection is made.

7.6 *Demonstration and Results of the Methodology*

This chapter applies the CASSANDRA methodology to a case study, demonstrating the ability of the methodology to create risk measurement for the aircraft programs and develop strategic risk mitigation strategies. These strategies aim to minimize or remove the effect of a perturbation in noise variables by offering a set of changes within the control space. The resulting impact of the perturbation and subsequent risk mitigation strategy is demonstrated and compared to an alternative approach.

7.7 *Case study: A Shift in Manufacturing Cost Estimation*

In this case an event has forced the program manager to react to a sudden lack of advanced material resources abroad and move engineering and tooling processes to the United States. This causes a reduction in efficiency and an increase in the manufacturing labor and tooling costs. The case study begins with a current aircraft design and program state that is near launch ready. The economic risks have already been identified. The associated value of that program state is given by the value state vector *G(y)* in Table 21. The case studies will review the effectiveness of the strategy generation by using the independent sets of metrics: statistics from the uncertain cumulative cashflows and the set of geometric parameters (risk aversion angle and risk-benefit ratio).

7.7.1 Setup

Table 22 give the mapping of the scenario to the noise variables. This mapping shows the original state assumption as well as the perturbation change caused by the external shift in forces. The disaster is modeled by causing a shift in the distributions of two types of variables in the noise space: the efficiency factors and the manufacturing labor rates. The efficiency factors of the composite technology variables were permuted by 9% due to the supply chain effects, and the labor and tooling costs were increased by 4% due to a shift in some of the manufacturing to the United States.

Table 21: Metrics in the program manager's value function. This function translates the program state variables from the uncertain cumulative cashflow chart into a weighted consideration to the program manager.

Term	Statistic	Aircraft Price No.	Weighting
Maximum Sunk Cost	Mean, μ	3	Medium
	Variance, σ	3	Low
	100^{th} Quantile	1	Low
	0^{th} Quantile	5	High
Break-even Month	Mean, μ	3	0
	100^{th} Quantile	5	High
	0^{th} Quantile	1	High
Total Net Cash Flow	Mean, μ	3	Medium
	Variance, σ	3	Low
	100^{th} Quantile	1	Low
	0^{th} Quantile	5	High
Risk Aversion Angle	θ_{RA}	-	High
Risk -Benefit Ratio	Γ_{RB}	-	High

Table 22: Mapping of scenario variables to the noise space, and the relative change caused by the external perturbation described in the Case Study.

		Perturbed			Original	
Factor	Distribution	Mean (UB)	Var (LB)	Change	Mean (UB)	Var (LB)
CFWINGCO	Normal	0.47	0.10	-	0.47	0.10
CFEMPCO	Normal	0.47	0.10	-	0.47	0.10
CFBODYCO	Normal	0.35	0.05	-	0.35	0.05
CFLGCO	Normal	1.00	0.10	-	1.00	0.10
EFWINGCO	Normal	1.35	0.10	9%	1.23	0.10
EFEMPCO	Normal	1.35	0.10	9%	1.23	0.10
EFBODYCO	Normal	1.44	0.10	9%	1.31	0.10
EFLGCO	Normal	1.10	0.10	9%	1.00	0.10
EFNACCO	Normal	1.10	0.10	9%	1.00	0.10
API	Normal	0.07	0.02	-	0.07	0.02
LEARN1	*Uniform*	90	70	-	90	70
LEARN2	*Uniform*	90	70	-	90	70
RGA	*Uniform*	1.45	0.82	-	1.45	0.82
RMANSUP	*Uniform*	76	41	4%	73	41
RQA	*Uniform*	80	43	4%	77	43
RTENGMHR	*Uniform*	120	65	4%	115	65
RDEVPMHR	*Uniform*	71	38	4%	68	38
HIMAT	Normal	1.00	0.08	-	1.00	0.08

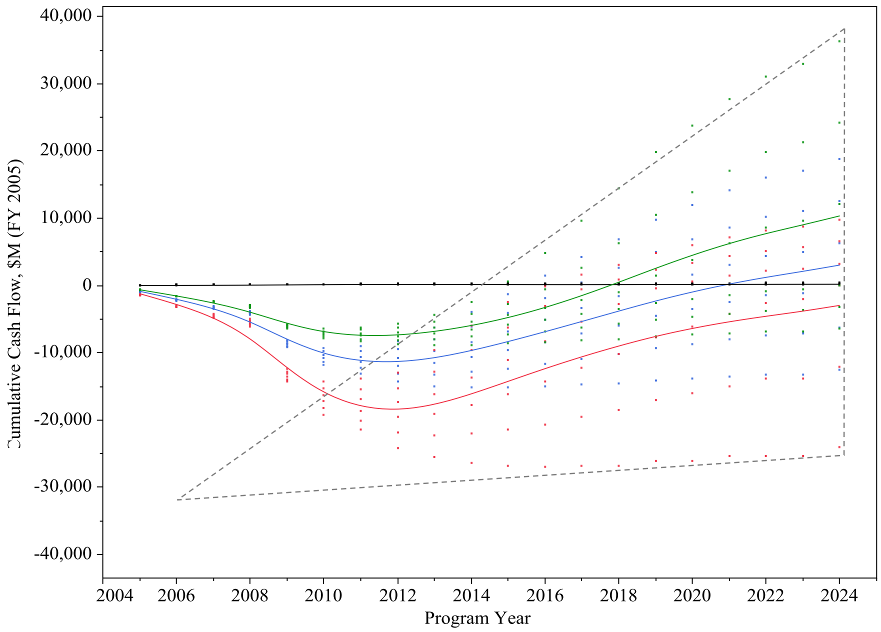


Figure 114: Original uncertain cumulative cashflow from Case study, showing the uncertainty space and the triangle used for generating the risk aversion angle and risk-benefit ratio.

7.7.2 Analysis

The baseline cumulative cashflow was executed under the original set of noise variable distributions. The resulting cashflow was then calculated using the BASUCA apparatus, and the risk aversion angle and risk-benefit ratios were calculated following the CASSANDRA method. The initial uncertain cashflow and risk triangle is shown in Figure 114. The risk aversion angle was 37.2 degrees and the risk benefit ratio was 0.47.

The noise variables were then perturbed per the mapping of the external scenario shift (keeping the design and technology variables constant), and the resulting effect on the uncertain cumulative cashflow diagram is given on Figure 115. Here, the main change was a reduction in the risk-benefit ratio, as the portion of area in the positive return on investment region of the chart is reduced and the break-even date is extended. This caused a negligible change in the risk aversion angle as the maximum negative sunk cost and the ending 0^{th} quantile net cash flow reduced by approximately the same amount.

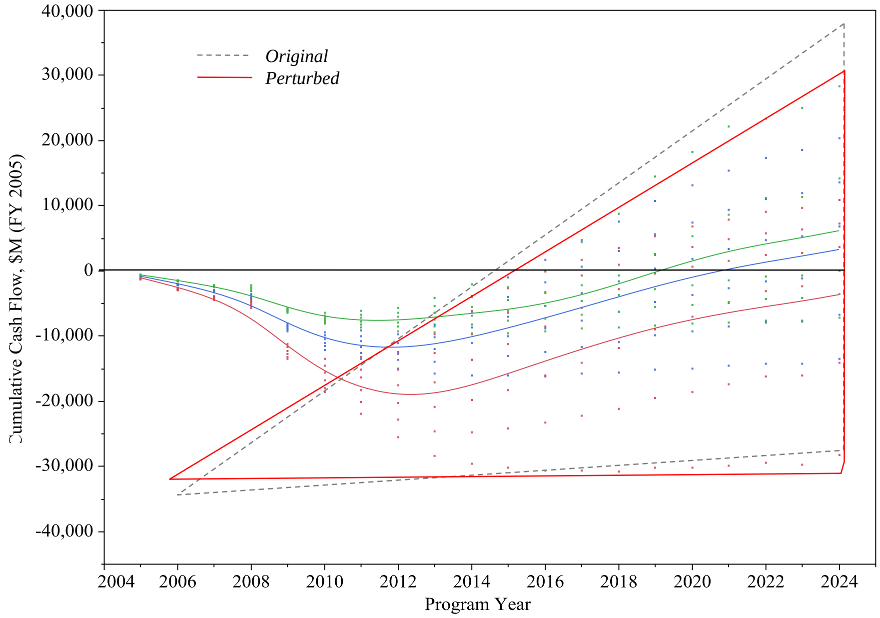


Figure 115: Perturbed uncertain cumulative cashflow from Case study, showing the uncertainty space and the triangle used for generating the risk aversion angle and risk-benefit ratio.

Following the guidelines given in Chapter 5 regarding the efficiency of risk, the perturbed state experienced a reduction in risk efficiency (by an overall increase in risk at constant risk aversion angle). This is due to the increased cost structures introduced by the scenario perturbation: efficiency factors for the technology costs and increased labor and tooling costs.

The Jacobian was estimated and inverted per the CASSANDRA process, producing the cell plot in Figure 117. Here the linearized sensitivities of the inputs to the outputs is easily visualized.

The principle strategic mitigation vector was calculated by the approximated inverted Jacobian approach shown given in the CASSANDRA methodology. The result was a mitigation vector and an associated mitigation vector set calculated from the vicinity of the perturbation state. The vector is given in Figure 118 as a relative change from the original design and technology variables. The results are normalized by the range of control power

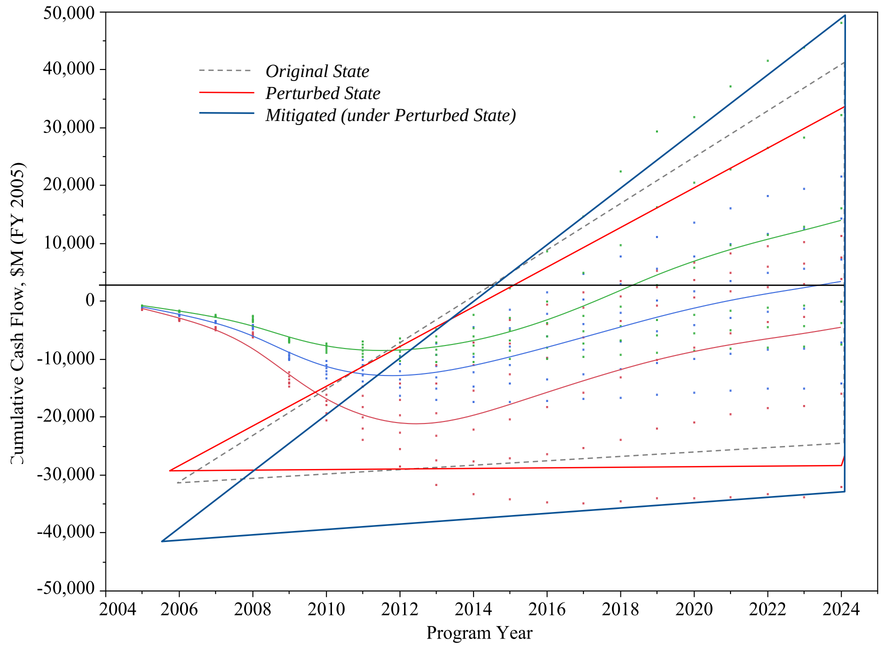


Figure 116: Mitigated uncertain cumulative cashflow from Case study, showing the original state, the perturbed state (due to the scenario mapping to the noise variables) and the mitigation (under the perturbed state.)

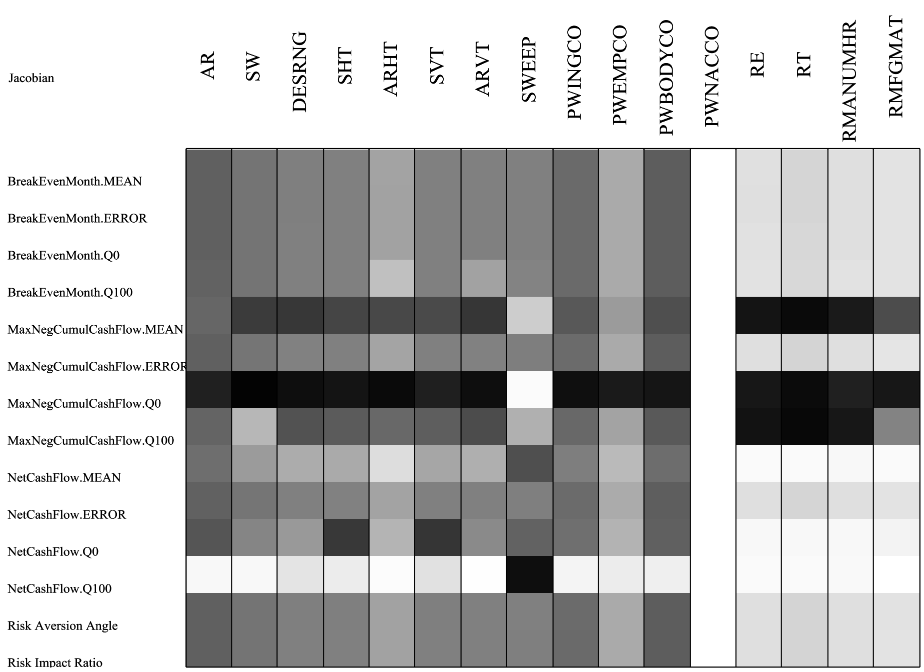


Figure 117: Jacobian matrix for generating mitigation strategies, shown for Case Study 2.

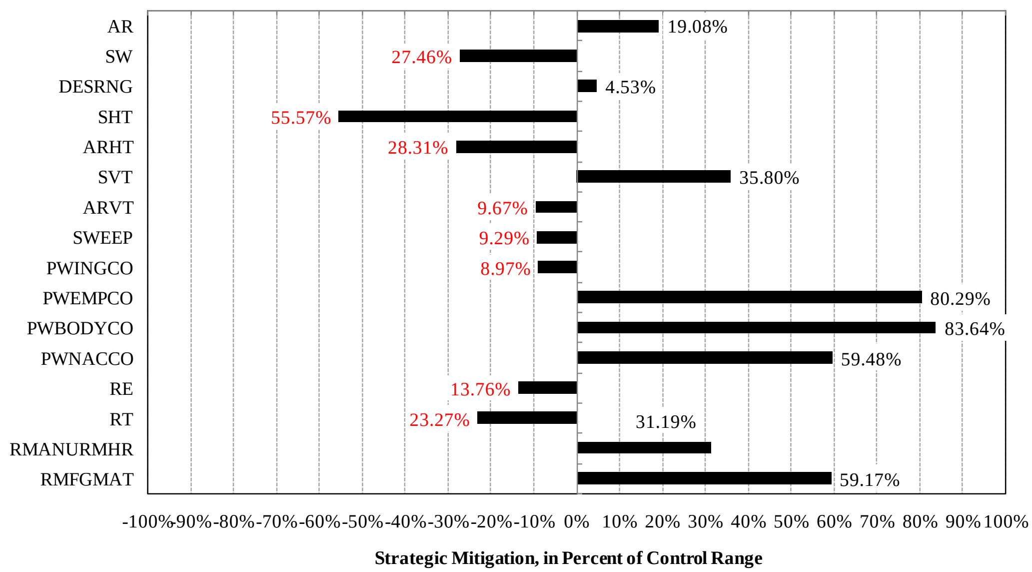


Figure 118: Principle strategic mitigation vector (shown as a percent change of control variable range) that tries to return the program to equivalent program state value in the Case Study.

given in Table 17 so they may be plotted on the same scale. Here, it is shown that the mitigation required change in the design and technology variables. Among the design variables, the strongest change was in the reduction of horizontal tail area.

7.8 Methodology Summary

There are many possible approaches to risk mitigation of complex systems. Chapter 4 reviewed some of the issues regarding the ambiguous nature of their effectiveness yet prevalence in past and present managerial parlance. The CASSANDRA methodology is but one, but its focus is on the *measurable and actionable* implementation of a risk measurement and mitigation method. From these measurable strategy implementations, further insight about the economics and the technological, design, and scenario sensitivities to risk become clear.

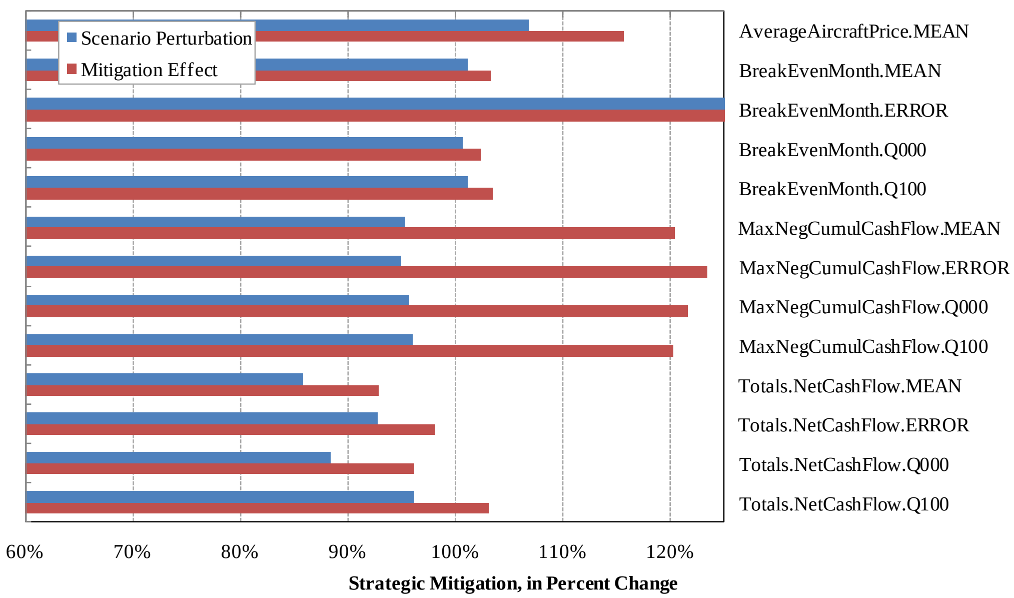


Figure 119: Percent change in the allowable control space that tries to achieve the normative strategic mitigation target for Case Study 2.

CHAPTER VIII

CONCLUSIONS

Risk management is a challenging, probabilistic task that deals with multiple sources of uncertainty that in turn affect many areas and disciplines simultaneously. The task of guiding a successful new aircraft design is not immune to these risks, as real-world managers on these projects must balance infusing unproven technologies and manufacturing processes with programmatic constraints on cost, schedule, and performance risks.

Dealing with the risks requires a combination of judgmental and technical analyses, involving many disciplines and perspectives towards risk. This thesis adopted the definition of risk as a manifestation of uncertainty on program objectives and their consequences, and went a step further to specifically express those manifestations onto the cumulative cashflow space using modeling and simulation.

Modeling and simulation have become the standard practice for addressing these issues: detailed simulations and explorations of candidate future states of these systems help reduce a complex design problem into a intuitive, manageable form where decision factors are prioritized. There have been several important advancements in system design methods that have leveraged modeling and simulation to carry out structured analyses. Yet, the field is still growing quickly, especially in domain of probabilistic methods that treat uncertainty quantification and mitigation. These analyses attempt to reduce overall uncertainty in cost, performance and schedule by delivering holistic analyses with the ability to examine the key engineering and programmatic trades: *Should I risk making the product in-house or outsource the manufacturing? What is the best technology portfolio and how do I optimize and adapt it to my risk tolerance constraints?* While there are still fundamental criticisms about using modeling and simulation approaches (pertaining to fidelity, model form, applicability of assumptions and scalability, etc), the emerging challenge becomes *How do you best configure uncertainty analyses and the information they produce to address real world* *problems?*.

These high level questions motivated the dissertation research, and its objective is recalled below:

> *Research Objective*
>
> In order to contribute to the present techniques for integrating risk management practices into the design process, the objective of this research is to deliver three things:
>
> 1. A methodology that a program manager can use to measure and allocate the risk arising from technology and manufacturing uncertainty onto the business case of a new aircraft development project.
> 2. Development of metrics in the uncertain cumulative cashflow space which better express the extent and usefulness of the risk being assumed.
> 3. A process for identifying robust risk mitigation strategies in the presence of either large or small available data sets.

The CASSANDRA methodology structured several modeling and analysis techniques into one functional process for the exploration and management of technology and manufacturing risk in aircraft design. It sought to answer the question *What are the financial and schedule implications on the business case about including uncertain technology onto a concept aircraft, and what can be done about it?* To answer these questions, this investigation combined Monte-Carlo simulation, expert-based elicitation and a structure of models to generate probabilistic results in the value space and a strategic mitigation approach for the methodology user. This user is ideally a program manager (or executive) of a manufacturer/integrator working on a concept future aircraft. In this role, it was assumed that the program manager has the ability to control design elements as well as the new technology distribution on that aircraft. She is also responsible for the elicitation of the uncertainty in those dimensions within control as well as the external scenarios (that are out of program control).

Unlike other methods treating uncertainty within the aircraft design process, this method placed emphasis on the uncertainty in the cumulative cashflow space as the integrator of economic viability. From this perspective, it then focused on exploration of the design and technology space to tailor the *business case* and its associated risk in the cash flow dimension.

The methodology was applied on a future single-aisle 150-passenger aircraft design, and evaluated the cost and schedule implications of a composite materials technology called Stitched Resin Film Infusion. As such, the problem was scoped away from searching for highly improbable or unforeseeable failure modes (such as Black Swans and safety considerations) and focused on a programmatic impact of design, technology and scenario uncertainty.

8.1 Review of Research Questions, and Hypotheses

The research contributions resulting from the development methodology are at two levels. The first level addresses the overarching hypothesis about the CASSANDRA method itself:

Methodology Hypothesis

The CASSANDRA methodology improved design awareness by forecasting the cost and time risks caused by uncertainty in the technology and manufacturing decisions during the conceptual design phase.

The overall methodology was compared to existing approaches and was shown to identify more economically robust design decisions under a set of at-risk program scenarios. Using the methodology, the fiscal robustness of candidate designs could be identified and projected onto the uncertain cumulative cashflow space, causing the frontier of *best* designs to shift relative to the existing approaches.

Research Question

The CASSANDRA methodology improved design awareness by forecasting the cost and time risks caused by uncertainty in the technology and manufacturing decisions during the conceptual design phase.

The methodology hypothesis led to the creation of the BASUCA apparatus. This apparatus allowed experiments with control and noise arrays to be executed rapidly over a modeling framework for design sizing, synthesis, and cost estimation. The stitching of these codes allowed the exploration of not only driving factors for the risk in the design responses (captured by extensive screening tests), but the execution requirement for *sufficiently* assessing risk-burdened technology. Recall the research structure:

Research Question I

How many executions of the noise array are enough to propagate the uncertainty to the cumulative cashflow space and draw the same design selection?

Hypothesis I

Approximately 1000 simulation runs in the noise array for each control run to is sufficient to propagate the uncertainty and deliver an actionable estimate of the cumulative cashflow risk.

Result

It was found that between 50-125 simulation runs in the noise array for each control sufficiently propagated the uncertainty and enabled the Jacobian approach to risk mitigation.

Additionally, a set of metrics in the uncertain cumulative cashflow space were developed to assist the methodology user in the identification, evaluation, and selection of design and technology. These metrics are compared to alternate approaches and are shown to better identify risk efficient design and technology selections. At the modeling level, an approach is given to estimate the production quantity based on an enhanced Overall Evaluation Criterion method that captures the competitive advantage of the aircraft design. This model was needed as the assumption of production quantity is highly influential to the business case risk.

Research Question II

How should total program risk impact of technology and manufacturing uncertainties be measured so as to make cost and schedule allocations?

Hypothesis II

The probabilistic use of the uncertain cumulative cash flow space enables the aggregation of many business case metrics, and allows for a small set of geometric risk measures that prioritize design alternatives based on program risk attitude.

Result

It was found that the risk aversion angle θ_{RA} and the risk-benefit ratio Γ_{RB} capture decoupled dimensions of the program risk perspective and allow for efficient selection and allocation of at-risk design alternatives.

Finally, the research explored the capacity to generate risk mitigation strategies in to two analysis configurations: when available data and simulation capacity is abundant, and when they are sparse or incomplete. The first configuration leverages structured filtration of Monte Carlo simulation results. The allocation of design and technology risk is then identified on the Pareto Frontier. The second configuration identifies the direction of robust risk mitigation based on the available data and limited simulation ability. It leverages a linearized approximation of the cashflow metrics and identifies the direction of allocation using the Jacobian matrix and its inversion.

Research Question III

How should risk mitigation strategies be generated and assessed to best allocate design and technology risk within program and business profitability constraints?

Hypothesis IIIa

Assuming availability of data and simulation capability, the design and technology control variables should be selected by evaluating the Pareto frontier of the uncertain cumulative cashflow program metrics.

Hypothesis IIIb

If data or simulation capability is sparse or unavailable, design and technology control variables should be selected by identifying a target uncertain cumulative cashflow state and generating the normative risk mitigation strategy by inversion of the Jacobian matrix approximation.

Result

It was found that under both assumptions of data simulation capacity, the CASSANDRA methodology user was able to identify more economically risk-robust design and technology strategies than existing methods that do not leverage uncertain cumulative cashflow information.

8.2 Final Remarks

This research grew out of the observation that risks entered the design space via many avenues concurrently. The investigation of their integrated mitigation during the design process is necessary for the program manager to improve her chances of program success in an uncertain world. The present research demonstrated the benefit of integrated modeling and simulation and new metrics for the valuation and exploration of the business case.

The major focus of this research was on the implications of those risks onto the cumulative cashflow realm. It was argued that this is an appropriate holistic measure of the business case dynamics, and that it was able to capture the risk implications better than discounted cashflow or net-present value techniques.

While the aircraft design challenge and example problem provided the specific problem dimensions leading to the development of the methodology, there are other similar systems-of-systems on which CASSANDRA could reasonably be applied. One application of particular interest is in the infrastructure for telecommunications and data centers. This system exhibits large scale investment projects with lengthy cycle and payback periods, and are also burdened with the perpetual obligation to adopting new technology.

8.2.1 Assumptions and Future Work

There were several major assumptions underlying the research and methods which should also be explored in future work. Firstly, the uncertainty elicitations are valid and complete. The selection of distributions on the scenario variables, technology costs, technology cycle times, technology impact factors, and design space exploration are given to be accurate and sufficiently broad. This single assumption limits the realistic application of the results presented in the notional problem, however with access to internal data a program manager could potentially apply the method to improve decision making.

Secondly, modeling and simulation sufficiently captures the potential risk. The physics and process based simulations are of acceptable validity to measure risk. Secondly, the high speed surrogate models fit the range sampled with an acceptable degree of precision. Response surface equations are generally able to model continuous, smooth spaces with low fit and representation error and are generally suitable for modern aircraft design problems. It was assumed that the associated risk and risk states exhibit the same spatial smoothness which may not always be true in real-life environments.

Other areas for future work include:

1. Development of the risk aversion angle for multiple correlated studies. This topic was covered in Chapter 7 and involves investigating the independence of both width of the noise ranges and the noise variable breadth with the risk aversion angle. Identifying how the resulting risk aversion angle may be combined would provide a valuable contribution as studies from separate researchers may be integrated to better improve the combined risk aversion angle measurement.

2. Correction for the risk-benefit ratio denominator. The denominator A_{COST} extends leftward towards the risk aversion angle vertex, and thus increases the area of the cashflow space without representation of this space by actual cashflows. This results in sightly lower overall risk-benefit ratios. An envisioned improvement would be to correct this effect by trimming the lower left triangle of this area to the lowest cumulative cashflow line (Q_{0th} for $ACPrice_1$.)

3. Exploring the OEC+ further for the case of non-duopoly competitive markets. This assumption of a duopoly becomes more invalid as new manufacturers enter the competitive space. Game theory may also be applied to positive effect in this area. The regional transport vehicle (RPV) category is a particularly diverse market where the OEC+ formulation would need to be adjusted substantially.

4. Unit Cost-Time curve. Instead of the cumulative cashflow space, the author believes that this plot (shown in Figure 70) may also be fruitful for risk and uncertainty propagation analyses of the business case.

APPENDIX A

GAUSSIAN BOUNDARY ANALYSIS

There exists a group of studies dedicated to resolving risk and uncertainty by analysis of the boundaries of a system. Major research contributions to boundary-based risk analysis methods are covered in detail by Morgan [95] and Fishburn [38]. In some of these studies, the risk dimensions are assumed to be monotonic and the analytical range is solved deterministically, offering rapid assessment of the propagation of uncertainty and a *feel* of system limits. This applies well for systems exhibiting low internal coupling and linear behavior [95], but in larger and more complex systems the linearity assumption weakens and the Central Limit theorem drives Gaussian-like behavior, particularly in the extrema in which the tails extend to infinity.

The bounds of the cumulative cashflow problem are indeed of value to the executive, but Gaussian process will demonstrate a widening of bounds as a function of Monte Carlo simulations. Effect is studied in great detail, particularly in 6-Sigma approaches, which specifically define the number of failures per million. It is then worthwhile to examine this effect, and answer the following Research Question:

Research Question VI
How many simulations need to be executed, and how does that affect the bounds of a Gaussian system?

$$R_{required} = X_{designs} * K_{portfolios} * \lambda_{scenarios} \tag{56}$$

The effect of number of samples on the the extreme bounds of a discrete sample set is illustrated in Figure 120. In this demonstration, the number of standard normal random variables in the sample set was steadily increased from 1 to 100,000 iterations. The normal distribution is unbounded in both directions, but the rate at which the extrema tend toward infinity is of interest in understanding the number of runs needed to resolve the bounds of the aircraft design problem.

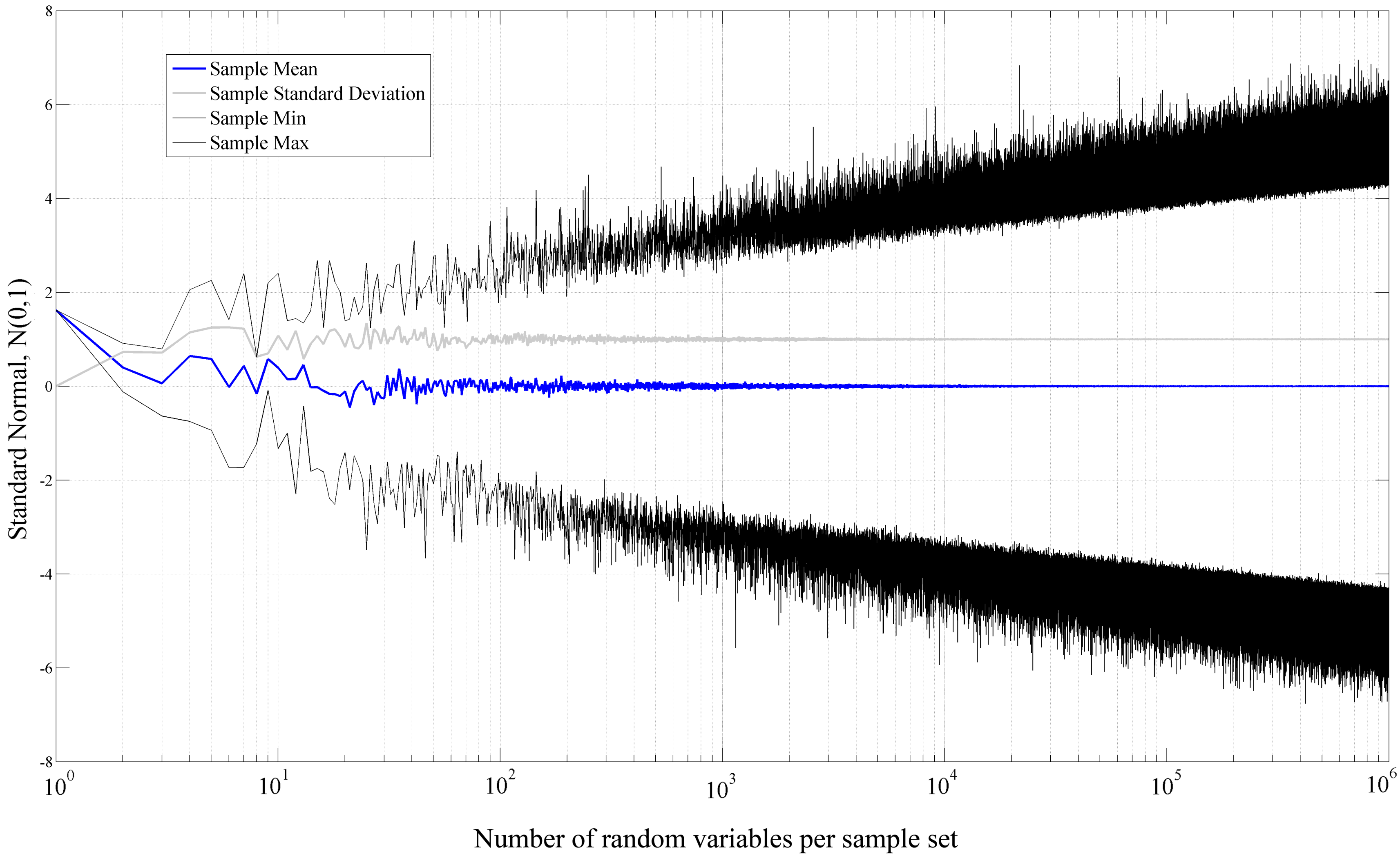


Figure 120: Demonstration of the effect of number of samples versus the mean, standard deviation, and bounds for a pseudo-random standard normal variable $N(0,1)$.

From this small experiment, one can easily see that for every order of magnitude increase in the number of samples, the bounds of the normal distribution expand an additional 1-σ. The implications of this in the exploration of a design space at risk are significant: increasing the order of magnitude of the number of samples takes you an approximate 1-1σ further outward in the risk space. This of course assumes a perfect Gaussian distributed risk space which will be evaluated in detail in later sections. It is of interest at this time to examine how the number of samples in the set relates to the number of factors able to be resolved. For a *full factorial* experiment, the minimum number of cases required to completely resolve is given by Equation 57.

$$R_{Required} = 2^n \tag{57}$$

where n is the number of two-level factors. Transforming the x-axis of Figure 120 by Equation 57 gives the relationship between the number of fully resolvable factors in an experiment and the growth of the extremas, shown in Figure 121. Here it shows that 1 million samples approaches 20 fully resolvable 2-level factors, with an associated aggregate extrema at approximately 6 σ from the mean.

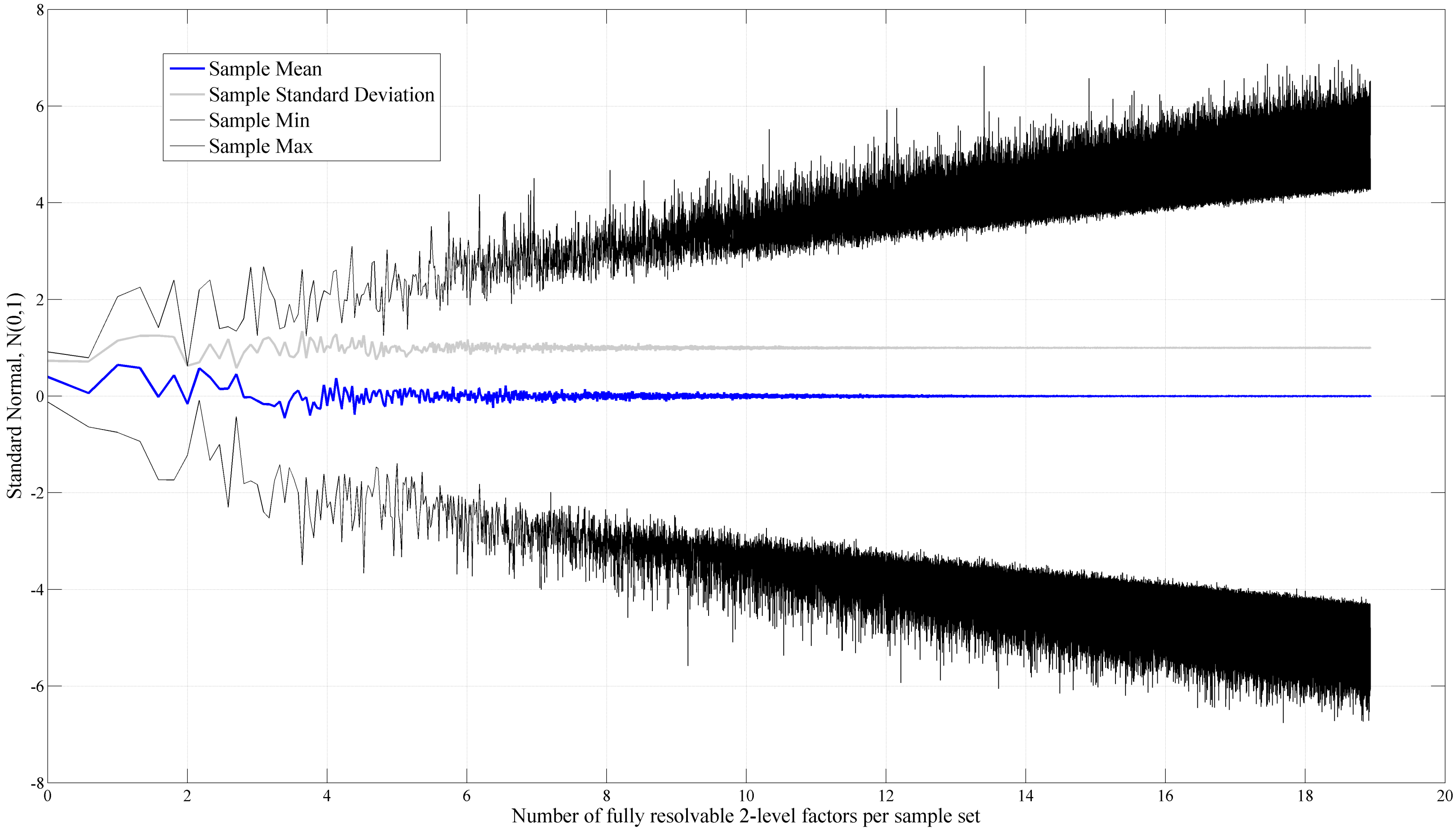


Figure 121: Demonstration of the effect of fully resolvable factors versus the growth and stability of the mean, standard deviation, and bounds for a pseudo-random standard normal variable $N(0,1)$.

APPENDIX B

FUTURE AND PRESENT VALUE

As the inflation rate assumption affects the future value of money, it is worth deriving how sets of future payments and expenses can be corrected to a present equivalent value (and vice versa). The following equation calculates a present equivalent amount with annual percentage inflation rate i and number of years n:

$$PE(i) = F_0(^{P/F,i,0}) + F_1(^{P/F,i,1}) + F_2(^{P/F,i,2} + \ldots + F_n(^{P/F,i,n}) \tag{58}$$

$$PE(i) = \sum_{r=0}^{n} F_r(^{P/F,i,n})^{-t} \tag{59}$$

But as:

$$(^{P/F,i,0}) = (1+i)^{-t} \tag{60}$$

Then substituting yields

$$PE(i) = \sum_{r=0}^{n} F_r(1+i)^{-t} \tag{61}$$

The Future Equivalent (FE) value can be calculated similarly using the same approach:

$$FE(i) = F_0(^{F/P,i,n}) + F_1(^{F/P,i,n-1}) + \ldots + F_2(^{F/P,i,1}) + F_n(^{F/P,i,0}) \tag{62}$$

$$FE(i) = \sum_{r=0}^{n} F_r(^{F/P,i,n-t})^{n-t} \tag{63}$$

But as:

$$(^{F/P,i,n-t})) = (1+i)^{n-t} \tag{64}$$

Then substituting yields

$$FE(i) = \sum_{r=0}^{n} F_r(1+i)^{n-t} \tag{65}$$

The last approach commonly used to correct future and annual cashflows is the Annual Equivalent (AE) amount. The AE at a given interest rate is:

$$AE(i) = PE(i)(^{A/P,i,n}) \tag{66}$$

Substituting Equation 61 yields

$$(^{A/P,i,n}) = \left[\frac{i(1+i)^n}{(1+i)^n{=}+}\right] \tag{67}$$

$$AE(i) = \left[\sum_{r=0}^{n} F_r(1+i)^{-t}\right]\left[\frac{i(1+i)^n}{(1+i)^n+1}\right] \tag{68}$$

APPENDIX C

SUPPLEMENTARY AIRCRAFT DESIGN AND UNCERTAINTY ASSESSMENT PROCESSES

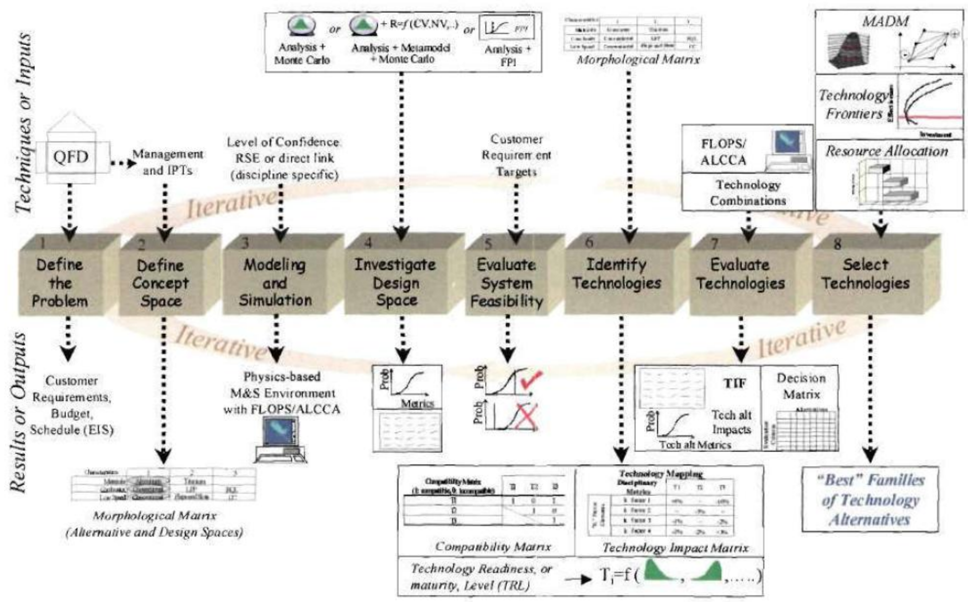


Figure 122: Method flowchart for the TIES process (Technology Identification, Evaluation and Selection) [67].

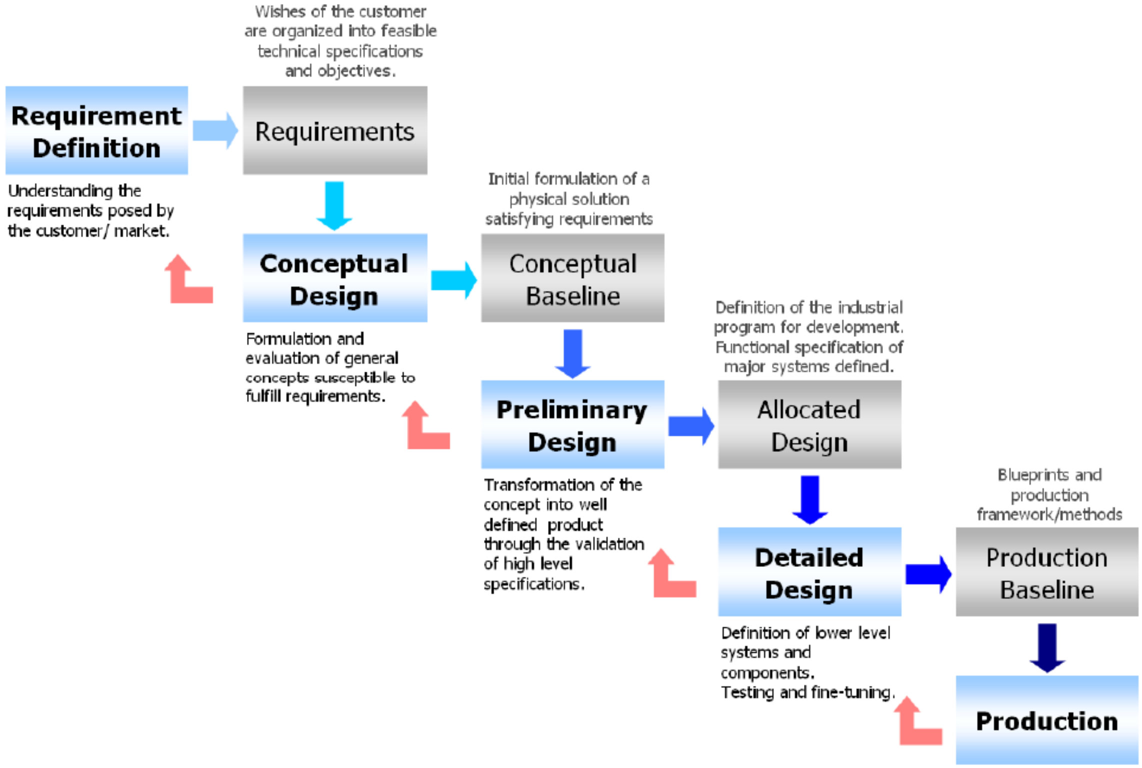


Figure 123: Overview of key design processes for new aircraft development [84].

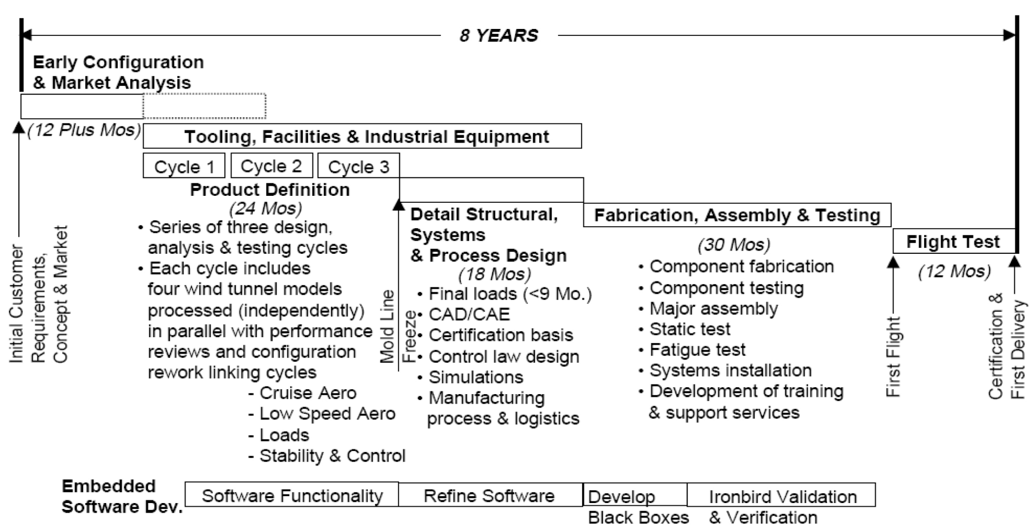


Figure 124: State of the art airframe development cycle duration, circa 1990 [118].

APPENDIX D

FLOPS AND ALCCA OVERVIEW

D.1 FLOPS

The Flight Optimization System (FLOPS) is a multidisciplinary system of computer programs for conceptual and preliminary design and evaluation of advanced aircraft concepts. It consists of nine primary modules: 1) weights, 2) aerodynamics, 3) engine cycle analysis, 4) propulsion data scaling and interpolation, 5) mission performance, 6) takeoff and landing, 7) noise footprint, 8) cost analysis, and 9) program control [89].

FLOPS was originally written by Linwood Arnie McCullers at NASA. Version 8.11 is used for the research in this dissertation.

D.2 ALCCA

The stand-alone version of ALCCA was written and modified by Dimitri Mavris and Thomas Galloway. It is the prediction of:

- AircraftManufacturingCosts(NASACR-152278)
- ProductionandRDT and ECosts
- ProductionCostvs.QuantityComparisons
- ManufacturerCumulativeandAnnualCashflow
- ManufacturerReturnonInvestment
- ManufacturerCostAnalysis(NASACR-152278)
- AirlineDirectOperatingCosts
- MaintenenceCostsandLaborCosts(NASACR-145190)
- AirlineIndirectOperatingCosts

- AirlineReturnonInvestment
- AirlineReturnonInvestment-Operations

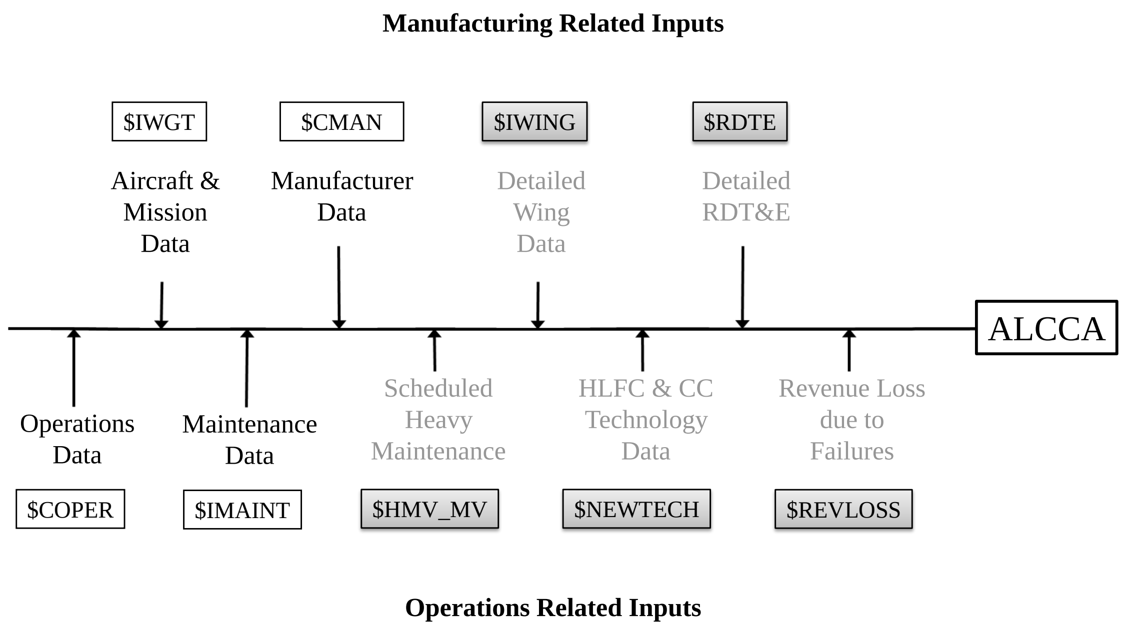


Figure 125: The manufacturing and airline namelists and analysis chain of ALCCA.

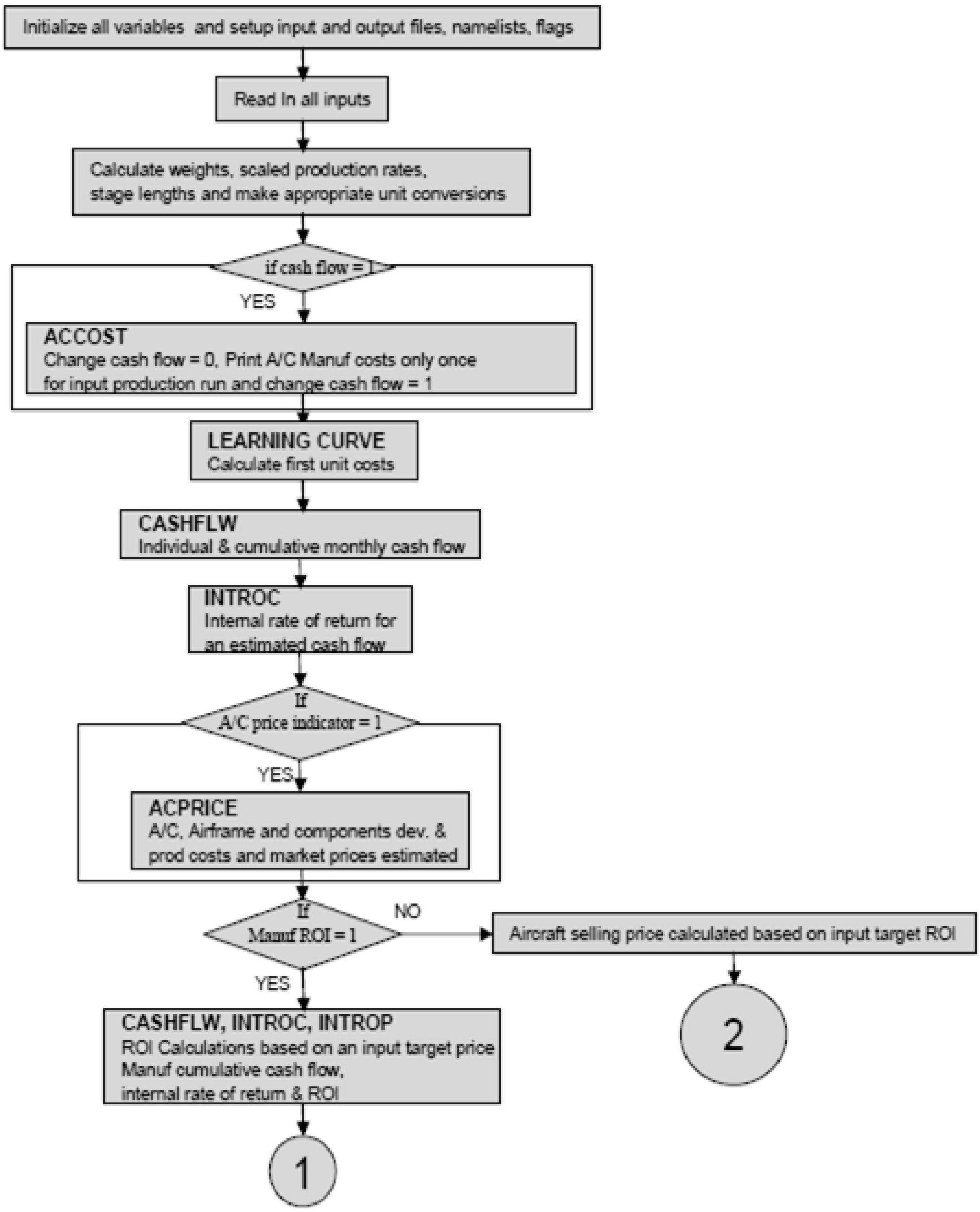


Figure 126: Cashflow calculations process of ALCCA [42].

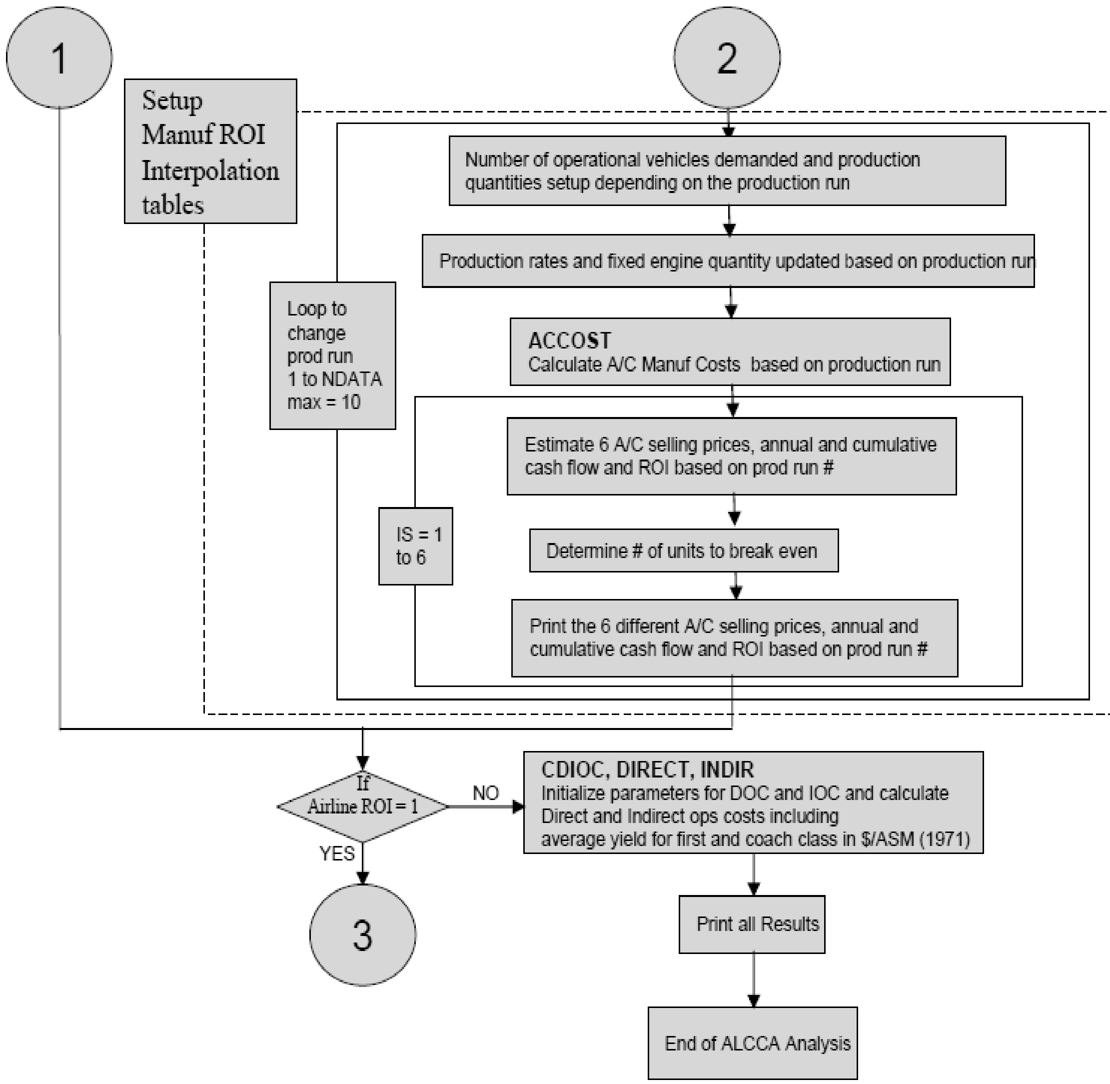


Figure 127: Manufacturer's ROI calculations process of ALCCA [42].

APPENDIX E

AIRBUS AND BOEING COMPETITION

E.1 Duopoly dynamics of large commercial transport aircraft manufacturers

Figure 128 illustrates the steady battle between Boeing and Airbus, showing both total orders by year and total deliveries by year [12]. Airbus has grown steadily over the period from 1989 to 2011 to capture roughly 50 percent of the new aircraft market.

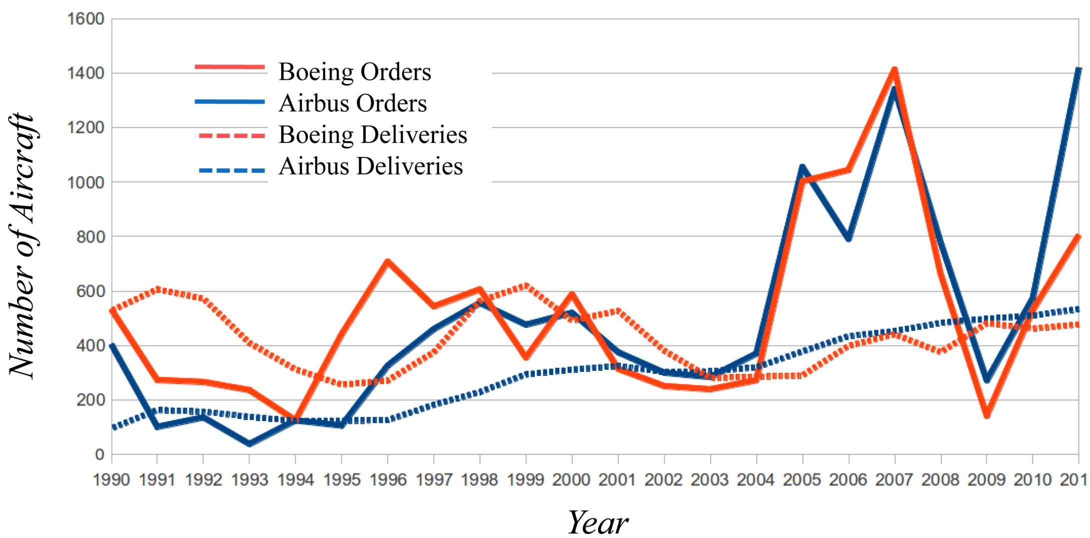


Figure 128: Total orders and total deliveries for Boeing and Airbus over the period 1989-2011 [12] [1].

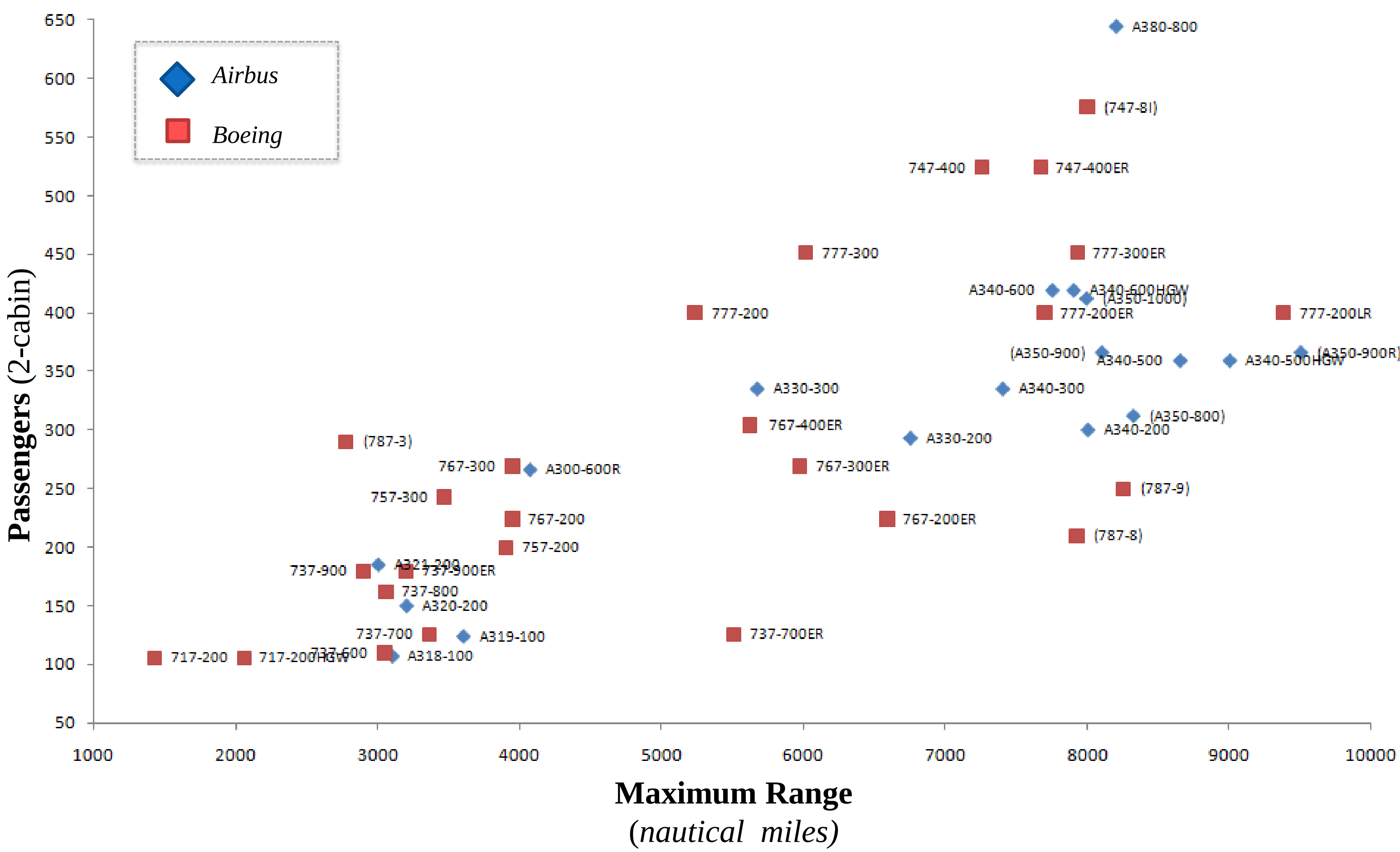


Figure 129: Chart of Airbus and Boeing commercial transport aircraft, organized by passenger count and maximum range

REFERENCES

[1] Airbus, "Orders & deliveries: The month in review: January 2013." Web, January 2013. http://www.airbus.com/company/market/orders-deliveries/.

[2] Anscombe, F. J., "Graphs in statistical analysis," *The American Statistician*, vol. 27, no. 1, pp. 17–21, 1973.

[3] Aumann, R. J., "The st. petersburg paradox: A discussion of some recent comments," *Journal of Economic Theory*, vol. 14, no. 2, pp. 443–445, 1977.

[4] Baroum, S. M. and Patterson, J. H., "The development of cash flow weight procedures for maximizing the net present value of a project," *Journal of Operations Management*, vol. 14, no. 3, pp. 209–227, 1996.

[5] Batson, R. and Love, R. M., "Risk analysis approach to transport aircraft technology assessment," *Journal of Aircraft*, vol. 25, pp. 99–106, 1988.

[6] Beck, J. L., Chan, E., Irfanoglu, A., and Papadimitriou, C., "Multi-criteria optimal structural design under uncertainty," *Earthquake Engineering And Structural Dynamics*, vol. 28, pp. 741–761, 1999.

[7] Belsky, G. and Gilovich, T., *Why Smart People Make Big Money MistakesAnd How To Correct Them: Lessons From The New Science Of Behavioral Economics*. Simon & Schuster, 1999.

[8] Ben-Israel, A. and Charnes, A., "Contributions to the theory of generalized inverses," *Journal of the Society for Industrial & Applied Mathematics*, vol. 11, no. 3, pp. 667–699, 1963.

[9] Besanko, D., Dranove, D., Shanley, M., and Schaefer, S., *Economics of strategy*. Wiley, 2009.

[10] Biltgen, P., *A Methodology for Capability-Based Technology Evaluation for Systems-of-Systems*. PhD thesis, Georgia Institute of Technology, 2007.

[11] Boeing, "Boeing revises 787 first flight and delivery plans; adds schedule margin to reduce risk of further delays," 2008.

[12] Boeing, "Total orders and Total Deliveries of Boeing vs Airbus, a combined comparison between 1989-2011." Website, February 2012. http://active.boeing.com/commercial/orders/index.cfm.

[13] Boeing, "Long-term market outlook 2012-2031." Web, January 2013 2013. Boeing Commercial Aircraft.

[14] Briceno, S., *A Game-Based Decision Support Methodology for Competitive Systems Design*. PhD thesis, School of Aerospace Engineering, 2008.

[15] Briceno, S. and Mavris, D., "Applications of game theory in a systems design approach to strategic engine selection," in *AIAA*, 2006.

[16] Brickley, J., Smith, C., and Zimmerman, J., "An introduction to game theory and business strategy," *Journal of Applied Corporate Finance*, vol. 13, no. 2, pp. 84–98, 2000.

[17] Browning, T., "Sources of schedule risk in complex system development," tech. rep., Lockheed Martin, 1999.

[18] Browning, T., Deyst, J., Eppinger, S., and Whitney, D., "Adding value in product development by creating information and reducing risk," *IEEETransactions On Engineering Management*, vol. 49, pp. 443–459, 2002.

[19] Carbaugh, R. J. and Olienyk, J., "Boeing-airbus subsidy dispute: A sequel," *Global Economy Journal*, vol. 4, no. 2, 2005.

[20] Chen, T., "An integrated real options evaluating model for information technology projects under multiple risks," *International Journal of Project Management*, vol. 27, pp. 776–786, 2009.

[21] Chen, W., Allen, J. K., leung Tsui, K., and Mistree, F., "Integration of response surface method with the compromise DSP in developing a general robust design procedure," *Advances in Design Automation*, vol. 82, pp. 485–492, 1995.

[22] College, D. A. U. D. S. M., "Risk management guide for DoD acquisition," tech. rep., United States Department Of Defense, 2006.

[23] Combier, R., "A probabilistic risk-based methodology for manufacturing-influenced aircraft design," in *SAMPE Long Beach 2011 Conference*, 2011.

[24] Cox, L. A., "What's wrong with risk matrices?," *Risk Analysis*, vol. 28, 2008.

[25] Crespo, L., Giesy, D., and Kenny, S., "Robustness analysis and robust design of uncertain systems," *AIAA Journal*, vol. 48, No. 2, pp. 388–396, 2008.

[26] Curran, R., "Uncertainty and sensitivity analysis in aircraft operating costs in structural design optimization," *Journal of Aircraft*, vol. 46, 2009.

[27] DeLaurentis, D. A. and Mavris, D., "Uncertainty modeling and management in multidisciplinary analysis and synthesis," in *AIAA*, 2000.

[28] Dezfuli, H., "Risk-informed decision making handbook," tech. rep., NASA, 2010.

[29] Dodson, M., "Robust aerodynamic design optimization using polynomial chaos," *Journal Of Aircraft*, vol. 46, 2009.

[30] Doka, G., "Life Cycle Analysis: 3D Scatterplots for MS EXCEL." Webspace, 2013. http://www.doka.ch/Excel3Dscatterplot.htm.

[31] Dostal, C., *Engineered Materials Handbook - Composites*. CRC Press, 1988.

[32] Driouchi, T. and Bennett, D., "Real options in multinational decision-making: Managerial awareness and risk implications," *Journal of World Business*, 2010.

[33] Du, X. and Chen, W., "Efficient uncertainty analysis methods for multidisciplinary robust design," *AIAA*, 2002.

[34] Engler, W. O., Biltgen, P. T., and Mavris., D. N., "Concept selection using an interactive reconfigurable matrix of alternatives IRMA," in *45th AIAA Aerospace Sciences Meeting and Exhibit*, AIAA, 2007.

[35] Etsy, B., "Airbus A3XX:Developing the World's Largest Commercial Jet," *Harvard*, vol. 201, 2004.

[36] FAA, "Aerospace forecast fiscal years 2011 2031," tech. rep., Federal Aviation Administration, 2011.

[37] Figueiredo, P., Silveira, G., and Sbragia, R., "Risk sharing partnerships with suppliers: The case of embraer," *Journal of Technology Management and Innovation*, vol. 3, pp. 27–38, 2008.

[38] Fishburn, P. C., "Mean-risk analysis with risk associated with below-target returns," *The American Economic Review*, pp. 116–126, 1977.

[39] Fisher, D. I., "Super jumbo problem: Boeing, Airbus, and the Battle for the Geopolitical Future," *Vand. J. Transnat'l L.*, vol. 35, p. 865, 2002.

[40] Galway, L., "Quantitative risk analysis for project management," tech. rep., RAND Corporation, 2004.

[41] Garcia, E., *Development or a framework ror the assessment of capacity and throughput technologies within the national airspace system.* PhD thesis, Georgia Institute of Technology, 2002.

[42] Garcia, E. and Subramanian, J., "Aircraft life cycle cost analysis (ALCCA) for a commercial aircraft: an insight."

[43] Garcia, E. and Subramanian, J., "Aircraft life cycle cost analysis (ALCCA) for a commercial aircraft: an insight." Electronic, 2003.

[44] Garcia, S. R. and Shoemaker, A. L., "On the matrix equation," *Linear Algebra and its Applications*, vol. 438, no. 6, pp. 2740 – 2746, 2013.

[45] Garrett, J., "Historical inflation rate." Web, 2009. http://www.comparativepoliticseconomics.com/historicalinflationrate.html.

[46] Gates, D., "Boeing 787 wing flaw extends inside plane." Web, July 2009. http://seattletimes.nwsource.com/html/boeingaerospace/2009565319boeing30.html.

[47] Gidel, T., "Decision-making framework methodology: an original approach to project risk management in new product design," *Journal of Engineering Design*, vol. 16, p. 24, 2006.

[48] Goodman, L. A., "On the exact variance of products," *Journal of the American Statistical Association*, vol. 55, no. 292, pp. 708–713, 1960.

[49] Grebici, K., Wynn, D. C., and Clarkson, P. J., "Modelling the relationship between uncertainty levels in design descriptions and design process duration," in *IDMME - Virtual Concept 2008*, 2008.

[50] Green, L. L. and Lin, H.-Z., "Probabilistic methods for uncertainty propagation applied to aircraft design," *AIAA*, 2002.

[51] Haffner, S., *Cost Modeling and Design for Manufacturing Guidelines for Advanced Composite Fabrication.* PhD thesis, Massachusets Institute of Technology, 2002.

[52] Hastie, R. and Dawes, R. M., *Rational Choice in an Uncertain World: The Psychology of Judgment and Decision Making.* Thousand Oaks: Sage Publications, 2001.

[53] Heltona, J. C., Johnsonb, J. D., Oberkampf, W. L., and Sallaberry, C. J., "Representation of analysis results involving aleatory and epistemic uncertainty," *International Journal of General Systems*, vol. 39, pp. 605–646, 2010.

[54] Hernández, A., Lattanzi, M., and Thome, N., "On a partial order defined by the weighted Moore–Penrose inverse," *Applied Mathematics and Computation*, 2013.

[55] Hillson, D., "The risk definition debate: Iso31000." Website, 2009. http://www.executivebrief.com/blogs/risk-definition-debate-iso31000/.

[56] Hoernig, S., Jay, S., Neumann, K.-H., Peitz, M., Plckebaum, T., and Vogelsang, I., "The impact of different fibre access network technologies on cost, competition and welfare," *Telecommunications Policy*, vol. 36, no. 2, pp. 96 – 112, 2012.

[57] Holbrook III, H., "A scenario-based methodology for conducting requirements elicitation," *ACM SIGSOFT Software Engineering Notes*, vol. 15, no. 1, pp. 95–104, 1990.

[58] Hubbard, D. and Evans, D., "Problems with scoring methods and ordinal scales in risk assessment," *IBM Journal Of Research And Development*, vol. 54, no. 3, pp. 1–2, 2010.

[59] Irwin, D. A. and Pavcnik, N., "Airbus versus Boeing revisited: International competition in the aircraft market," *Journal of International Economics*, vol. 64, no. 2, pp. 223–245, 2004.

[60] ISO2009, "Risk management principles and guidelines." Web PDF, 2009. International Organization for Standardization (ISO).

[61] JIN, F.-j. and WANG, C.-j., "Hub-and-spoke system and china aviation network organization," *Geographical Research*, vol. 5, p. 015, 2005.

[62] Jones, S., "Affordability goal assessment." Peer Review, NASA Langley, 2000. NASA: Systems Analysis Branch.

[63] Kahneman, D. and Tversky, A., "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, pp. 263–293, 1979.

[64] Kamrani, A. and Azimi, M., *Systems Engineering Tools and Methods.* Engineering and management innovations series, Taylor & Francis, 2010.

[65] Karal, M., "AST composite wing program executive summary," tech. rep., The Boeing Company and NASA, 2001.

[66] King, J., "The Airbus 380 and Boeing 787: A role in the recovery of the airline transport market," *Journal of Air Transport Management*, vol. 13, pp. 16–22, 2002.

[67] Kirby, M., *A Methodology For Technology Identification, Evaluation, And Selection In Conceptual And Preliminary Aircraft Design.* PhD thesis, Georgia Institute of Technology, 2001.

[68] Knight, F. H., "Cost of production and price over long and short periods," *The Journal of Political Economy*, vol. 29, no. 4, pp. 304–335, 1921.

[69] Kokkolaras, M., Mourelatos, Z. P., and Papalambros, P. Y., "Design optimization of hierarchically decomposed multilevel systems under uncertainty," in *Proceedings DETC'04*, vol. 128, Issue 2, pp. 1–13, 2004.

[70] Kothiyal, A., Spinu, V., and Wakker, P., "Prospect theory for continuous distributions: A preference foundation," *Journal of Risk and Uncertainty*, vol. 42, pp. 195–2010, 2001.

[71] Laval, P., "Multiple integrals: Change of variables in the Jacobian." Course Notes, Math 2203, 2003. http://science.kennesaw.edu/ plaval/math2203/jacobian.pdf.

[72] Lee, B. D., *An Investigation Of Prescribed Risk Management Practices In Engineering Design.* PhD thesis, Georgia Institute of Technology, 2010.

[73] Lessard, D. and Miller, R., "Understanding and managing risks in large engineering projects," *International Journal of Project Management*, vol. 19, Issue 8, pp. 437–443, 2001.

[74] Little, R. J., "A test of missing completely at random for multivariate data with missing values," *Journal of the American Statistical Association*, vol. 83, no. 404, pp. 1198–1202, 1988.

[75] Long, M. W. and Narciso, J. D., "Probabilistic design methodology for composite structures," tech. rep., Federal Aviation Administration, 1999.

[76] Madachy, R. J., *A Software Project Dynamics Model For Process Cost, Schedule And Risk Assessment.* PhD thesis, University Of Southern California, 1994.

[77] Mankins, "Definition of technology readiness levels," tech. rep., NASA, 1995.

[78] Mankiw, N. G., *Macroeconomics.* Worth Publishing, 6th ed., 2012.

[79] Markish, J., "Value-based multidisciplinary techniques for commercial aircraft system design," *AIAA*, vol. 41, 2003.

[80] Marsh, G., "Airbus takes on Boeing withi Reinforced plastic A350 XWB," *REINFORCED plastics*, vol. 34, pp. 26–19, 2007.

[81] Marx, W., *Integrating Design And Manufacturing For The High Speed Civil Transport.* PhD thesis, Georgia Institute of Technology, b, 1996.

[82] Maserr, A., *Optimal allocation of thermodynamic irreversibility for the integrated design of propulsion and thermal management systems.* PhD thesis, Georgia Institute of Technology, 2012.

[83] Masten, S., "The organization of production: Evidence from the aerospace industry," *Journal of Law and Economics*, vol. 27, no. 2, pp. 403–417, 1984.

[84] Mavris, D., "Advanced Design Methods - Course Notes II." Class material, 2006. Georgia Tech - Course Notes ADM-6374.

[85] Mavris, D., "Advanced Design Methods - Course Notes I." Class material, September 2007. Georgia Tech - Course Notes ADM-6374.

[86] Mavris, D. and Bandte, O., "Comparison of two probabilistic techniques for the assessment of economic uncertainty," in *19th annual conference of the International Society of Parametric Analysts in New Orleans*, 1997.

[87] Mavris, D., Bandte, O., and DeLaurentis, D. A., "Robust design simulation: A probabilistic approach to multidisciplinary design," *Journal of Aircraft*, vol. 36, pp. 298–307, 1999.

[88] Mavris, D. and DeLaurentis, D., "An integrated approach to military aircraft selection and concept evaluation," in *1st AIAA Aircraft Engineering, Technology, and Operations Congress*, September 1995. AIAA-95-3921.

[89] McCullers, A., "Flight optimization system release 8.11 user's guide." Electronic, 2009.

[90] Mclellan, J. M., "The really big risk for composite airplanes." Web, February 2011. http://macsblog.com/2011/02/the-really-big-risk-for-composite-airplanes/.

[91] Mediavilla, J. I., "787 break-even for dummies." web, November 2011. http://theblogbyjavier.com/2011/11/03/787-break-even-for-dummies/.

[92] Messica, A., "Valuation of high-risk high-technology ventures," in *Working Paper Series*, 2006.

[93] Miller, C., "Cartoons illustrating the different design discplines."

[94] Millet, I. and Wedley, W. C., "Modelling risk and uncertainty with the analytic hierarchy process," *Journal of Multi-Criteria Decision Analysis*, vol. 11, no. 2, pp. 97–107, 2003.

[95] Morgan, M. G. and Henrion, M., *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis.* Cambridge University Press, 1992.

[96] Navy, "MRL Assist Charts - Documentation from the MRL Assis Tool." Web, 2013. Department of the Navy, https://www.mrlassist.bmpcoe.org.

[97] OConnor, B., "Agency risk management procedural requirements," tech. rep., National Air and Space Agency NASA, 2008.

[98] Olienyk, J. and Carbaugh, R. J., "Boeing and Airbus: Duopoly in Jeopardy?," *Global Economy Journal*, vol. 11, no. 1, 2011.

[99] OLSON, E., *Conceptual Design and Technical Risk Analysis of Quiet Commercial Aircraft Using Physics-Based Noise Analysis Method*. PhD thesis, Georgia Institute of Technology, 2006.

[100] PARK, H. K., HAN, S. H., and RUSSELL, J. S., "Cash flow forecasting model for general contractors using moving weights of cost categories," *Journal of management in engineering*, vol. 21, no. 4, pp. 164–172, 2005.

[101] PEOPLES, R., "Value-based multidisciplinary optimization for commercial aircraft design and business risk assessment," *Journal of Aircraft*, vol. 43, No. 4, pp. 913–922, 2006.

[102] PINON, O., *A methodology for the valuation and selection of adaptable technology portfolios and its application to small and medium airports*. PhD thesis, Georgia Institute of Technology, 2012.

[103] PORTER, M. E., "The five competitive forces that shape strategy.," *Harvard Business Review*, vol. 86, pp. 78–93, 2008.

[104] PRITCHARD, D. and MACPHERSON, A., "Boeings Diffusion of Commercial Aircraft Design and Manufacturing Technology to Japan: Surrendering the US Aircraft Industry for Foreign Financial Support," *Canada United States Trade Center Occasional Paper*, 2005.

[105] RETAUREAU, G., *On Recessed Cavity Flame-holders In Supersonic Cross-flows*. PhD thesis, Georgia Institute of Technology, 2012.

[106] ROMLI, F., *A Strategic Planning Methodology For Aircraft Design*. PhD thesis, Georgia Institute of Technology, 2009.

[107] ROTH, B., *A Theoretical Treatment of Technical Risk in Modern Propulsion System Design*. PhD thesis, Georgia Institute of Technology, 2000s.

[108] SAS, "The Taguchi Design Approach." JMP Help documentation, 2012.

[109] SAVCI, S. and KAYIS, B., "Knowledge elicitation for risk mapping in concurrent engineering projects," *International journal of production research*, vol. 44, no. 09, pp. 1739–1755, 2006.

[110] SCHRAGE, D. and SAFF, C., "AE4803 life cycle cost analysis course notes." Georgia Institute of Technology, May 2009.

[111] SEWELL, M., "Decision making under risk: A prescriptive approach," in *Behavioral Finance & Economics Research Symposium*, 2009.

[112] SEWELL, M., "Prospect theory." Website, April 2011. http://prospect-theory.behaviouralfinance.net/.

[113] SHAVELL, S., "Risk sharing and incentives in the pricncipal and agent relationship," *The Bell Journal of Economics*, pp. 55–74, 1979.

[114] SHIMOYAMA, K., OYAMA, A., and FUJII, K., "Development of multi-objective six-sigma approach for robust design optimization," *Journal Of Aerospace Computing, Information, And Communication*, vol. 5, pp. 215–234, 2008.

[115] Shleifer, A., *Inefficient Markets: A Introduction to Behavioral Finance.* Oxford University Press, 2000.

[116] Simon, C. P. and Blume, L., *Mathematics for Economics.* W. W. Norton and Co., LTD, 1994.

[117] Sismanidou Amadeus, A., Palacios Fernández, M., and Tafur Segura, J. J., "Progress in airline distribution systems: The threat of new entrants to incumbent players," *Journal of industrial engineering and management*, vol. 2, no. 1, pp. 251–272, 2009.

[118] Spitz, W., Golaszewski, R., and Berardino, F., "Development cycle time simulation for civil aircraft," tech. rep., NASA, 2001.

[119] Stewart, J., *Multivariable Calculus: Concepts and Contexts.* Bob Pirtle, Thomson Brooks/Cole, third ed., 2005.

[120] StrategicAdvantage, I., "Porter's five forces." Web, 2005. http://www.strategy4u.com.

[121] Stults, I., *A multi-fidelity analysis selection method using a constrained discrete optimization formulation.* PhD thesis, Georgia Institute of Technology, 2009.

[122] Taguchi, G., Elsayed, E., and Hsiang, T., *Quality Engineering in Productions Systems.* McGraw-Hill, 1989.

[123] Taleb, N. N., *The Black Swan.* Random House, 2007.

[124] Taylor, W., "Methods and tools for process validation." web, 2012. http://www.variation.com/techlib/val-1.html.

[125] Thaler, R., "Toward a positive theory of consumer choice," *Journal of Economic Behavior & Organization*, vol. 1, pp. 39–60, 1980.

[126] Thomas, V., *A Method for Scenario-based Risk Assessment for Robust Aerospace Systems.* PhD thesis, Georgia Institute of Technology, 2007.

[127] Thornton, A. C., "Variation risk management using modeling and simulation," *Journal of Mechanical Design*, vol. 121, no. 2, pp. 297–304, 1999.

[128] Tombak, M. M., "Strategic asymmetry," *Journal of Economic Behavior & Organization*, vol. 61, pp. 339–350, 2006.

[129] Tong, Y. C., "Literature review of aircraft structural risk analysis and reliability analysis," tech. rep., Airframes and Engines Division Aeronautical and Maritime Research Laboratory Australian Department of Defense, 2001.

[130] Tumer, I. Y., Barrientos, F. A., and Mehr, A. F., "Towards risk based design (RBD) of space exploration missions: Aa review of RBD practice and research trends at NASA," in *ASME International Design Engineering Technical Conferences*, 2005.

[131] Tversky, A. and Kahneman, D., "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, vol. 5, pp. 297–323, 1992.

[132] Twiss, B. C., *Forecasting for Technologists and Engineers*, vol. 9 of *IEE Management of Technology Series 15*. Peter Peregrinus, London, April 1993.

[133] Webster and Merriam, "Definition of "scenario"." Web, 2013. http://www.merriam-webster.com/dictionary/scenario.

[134] Webster and Merriam, "Definition of strategy." Web, 2013. http://www.merriam-webster.com/dictionary/strategy.

[135] Wei, W. and Hansen, M., "Cost economics of aircraft size," *Journal of transport Economics and Policy*, pp. 279–296, 2003.

[136] Wheeler, D. J., "Detecting a shift in process average: tables of the power function for X charts," *Journal of Quality Technology*, vol. 15, no. 4, 1983.

[137] Wheeler, D. J., *Understanding industrial experimentation.* SPC Press, 1988.

[138] Wu, Y.-T., *Efficient Methods for Mechanical and Structural Reliability Analysis and Design.* PhD thesis, University of Arizona,, 1984.

[139] Younghans, J. and et al, R. D., "Preliminary design of low cost propulsion systems using next generation cost modeling techniques," *Journal of Engineering for Gas Turbines & Power*, vol. 121, No.1, 1999.

VITA

Robert Combier was born in Mexico City, Mexico in 1982 to a French father and American mother. He resided in South Carolina, Georgia, Quebec and France before beginning his academic career at Georgia Tech in 2001. He received his Bachelor's diploma in Aerospace Engineering in 2006 with high honors and led his senior design team to win the annual Fixed-wing Design competition. After joining the Aerospace Systems Design Laboratory a Georgia Tech, he earned his Masters diploma in 2008. Robert enjoys photography and filmmaking and is a member of the Georgia Tech Waterski team.