

**Value-Based Multidisciplinary Optimization for
Commercial Aircraft Program Design**

by

Ryan E. Peoples

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Abstract

Traditional commercial aircraft design attempts to achieve improved performance and reduced operating costs by minimizing maximum takeoff weight, but this approach does not guarantee the financial viability of the program to the manufacturer. Improved design practices would take into account not only aircraft performance but also financial aspects of the design. The methodology suggested herein investigates multidisciplinary design optimization (MDO) involving performance and finance jointly in aircraft program design, as well as assessment of program business risk. A value-based MDO framework couples a performance model with an improved stochastic program valuation, accounting explicitly for both uncertain demand via market volatility and managerial flexibility by invoking Real Options theory. Stochastic program value is used as the new objective for the design optimization problem.

The methodology and framework developed are applied to a design example for the Blended-Wing-Body aircraft concept. Value-based optimization yields a design with a 2.3%-higher program value than that of the conventional minimum-weight solution. Comparing performance- and value-optimized designs, it is shown that the optimizer chooses to trade aerodynamic efficiency for reduced manufacturing costs. The effects of varying the aircraft range and speed on maximum-value solutions demonstrates that incorporating value into the design process permits more fully-informed program decisions that have optimal financial impact. Sensitivity analyses quantify the impact of technical and financial uncertainty on the stochastic value due to individual program parameters, and permit insight into the relative business risk associated with each for value-optimal designs. The results show that long-term cash flows should be emphasized over development costs. Traditional, deterministic net present value is shown to be inappropriate for use as a MDO objective function. Risk is not addressed adequately through the choice of discount rate, leading the objective to drive the optimization to make poor design tradeoffs and typically resulting in trends contrary to those of the improved stochastic valuation.

Value-based MDO represents a logical progression and necessary step in the continual evolution of the aircraft design process.

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Chapter 1

Introduction

1.1 Motivation and Context

The historical choice of minimizing gross take-off weight (GTOW) as the objective in aircraft design is intended to improve performance and subsequently lower operating costs, primarily through reduced fuel consumption. However, such an approach does not guarantee the profitability of a given aircraft design from the perspective of the airframe manufacturer. In an increasingly competitive market for commercial aircraft, manufacturers may wish to design for improved financial viability of an aircraft program in addition to technical merit before undertaking such a costly investment. The existing practice of designing aircraft from a technical perspective without simultaneously considering the impact on overall program value is suboptimal in a business sense.

Modeling the business case for a commercial aircraft program is undoubtedly challenging. Cost and revenue estimation is difficult, and the commercial airline and, by extension, aircraft industries are extremely susceptible to economic fluctuations. It is important, though, to bridge the gap between technical and financial analysis in design since business decisions so often drive the program. Recent industry events show this to be the case, as Boeing moved away from the Sonic Cruiser concept to the 7E7 based on the perceived value of speed versus efficiency, respectively, to the airline industry. Further, the 7E7 launch order consisted of a mix of two variants of the

aircraft: a high-capacity, shorter range version, and a long-range version. Although preferable to begin orders with a single design, Boeing was willing to accept orders for both to satisfy the airline customer — which placed a record-size initial order [26]. Given the emphasis on marketability and the end goal of profitability, how then to best design an aircraft program to meet business goals?

To assess the long-term financial viability of an aircraft program, a value-based design approach is recommended. Such an approach should still account for performance while also incorporating tools to estimate the profitability of the program. Financial models have been incorporated into multidisciplinary design optimization (MDO) of aircraft in the past by several researchers, to tie together value and performance. Mavris and co-workers have performed a considerable amount of work to incorporate business case aspects, including lifecycle cost analysis for aircraft design [25] and product development strategy for engine design [20]. Giesing and Wakayama considered direct operating cost as an objective function for commercial aircraft design and compared the resulting design to that obtained with a traditional performance-based optimization [13]. Other researchers have also looked to improve financial models in MDO. Messac and Chandra introduced cost estimating relationships as a design objective [27]. Value metrics, such as net present value (NPV), internal rate of return (IRR), and return on investment (ROI), were compared by Lee and Olds as objectives for the design of launch vehicles [16]. DeLaurentis and others also considered NPV to assess the value of personal air vehicles [10]. The problem has also been approached as a multi-objective optimization balancing cost and performance by Ross, Crossley, and Roth [31].

However, the costs and value metrics (NPV, ROI, and IRR) that have been investigated are based on a static valuation of the design, with expected costs and revenues assigned for the duration of the program lifecycle. These metrics do not attempt to capture explicitly technical or financial uncertainties that may arise, and, as such, do not properly account for the associated business risk of the program. Further, the related issue of flexibility — that is, the ability of the manufacturer to make decisions in response to unexpected or changing conditions — is not considered.

In the field of finance, considerable research has been performed to develop more sophisticated valuation techniques for corporate strategies and product development, in order to address the shortcomings of traditional valuation techniques. Substantial literature exists describing Real Options theory, which provides a way to quantify the value of a product or strategy in the presence of uncertainty [12, 15, 34]. Several applications of this theory to business strategy in the aerospace industry have been suggested. Clarke, Miller, and Protz proposed a methodology tying together Real Options and system dynamics to value air transportation infrastructure [7]. Weigel and Hastings considered the use of Real Options to manage the architecture for military satellite communications [36]. In addition, Airbus has adopted options theory for practical use in its marketing of aircraft [29]. These case studies do not specifically address the technical aspects of aircraft design, however.

Drawing on the improvement in valuation techniques, Markish and Willcox have developed a stochastic dynamic programming (DP) framework for decision making in the context of commercial aircraft program design [17, 19]. The framework links aircraft performance, cost, and revenue models to provide an optimal program strategy and a quantitative valuation in terms of expected NPV of an aircraft program in an uncertain market. Stochastic DP is a well-known optimization technique that has been used extensively in conjunction with Real Options theory, to provide decision aids in financial applications [4, 12].

Traditionally MDO has resulted in deterministic solutions for GTOW, value, or other objectives of interest. More recently, much effort has been devoted to probabilistic multidisciplinary approaches to address the issue of uncertainty, as well. A key focus of this work is the idea of design risk, and how technical or financial uncertainty will affect performance and value. Several research groups have proposed methods by which risk can be quantified for the technical and financial aspects of projects in the realm of aircraft design.

Mavris and colleagues have been active in this area, as well. Mavris and DeLaurentis examined design affordability, defined as a balance of technical performance, cost, and risk, given uncertainty [24]. They also worked with Bandte to develop a method

for probabilistic design to improve performance and program viability in terms of ROI [22], and well as cost per passenger-mile [23]. Mavris and Bandte again teamed up to suggest a probabilistic approach to maximize a parameter termed “probability of success” accounting for several financial aspects of an aircraft design [21]. In addition, Browning, Deyst, et al., looked at the ability to reduce risk throughout product development in order to increase value to the customer [6]. Deyst followed up on this work by optimizing product development to minimize risk, using an approach based on estimation theory [11]. These methodologies were applied to aircraft design examples to demonstrate how risk levels might be calculated. Finally, Bell and Pringle employed a sensitivity analysis approach to find the coupled impacts on performance and cost in fighter aircraft due to uncertainty in the technical design [3].

The progress discussed above can be broadly grouped into the areas of MDO including financial analysis, improved techniques for valuation, and quantifying risk or the impact of uncertainty. These interrelated subjects provide the basis for the research and case studies to follow.

1.2 Objectives and Approach

It has been shown by Markish that a stochastic valuation provides a more comprehensive method to assess commercial aircraft programs [19]. In that work, however, the valuation was applied *a posteriori* to aircraft designs resulting from a traditional performance-based optimization. This work, by contrast, seeks to achieve the following objectives:

1. Establishment of a new methodology using the stochastic valuation directly to make aircraft conceptual design decisions; and
2. Implementation of this methodology in an optimization framework combining technical design and value into a single problem.

The framework, in turn, can be used to quantify both the trades in design value and performance resulting from minimizing GTOW versus maximizing program value, as

well as the change in optimal program value due to the effects of uncertainty.

In the design framework, performance and financial models are coupled to generate a truly multidisciplinary design serving as the basis for the stochastic valuation. This valuation then serves as an objective function for the MDO problem formulation. A single program concept, incorporating technical design as well as financial parameters, can then be optimized in terms of specific performance or business goals, e.g., minimizing GTOW or maximizing program value. This value is defined strictly in terms of the profitability to the aircraft manufacturer.

The model is used to solve for financially optimal designs of a single aircraft concept with minimum range and passenger capacity specified. Case studies are presented for the Boeing Blended-Wing-Body (BWB) concept. The baseline configuration for this aircraft has been optimized for minimum GTOW, and features a capacity of 475 passengers and a design range of 7800 nmi.

Comparisons can be drawn between this baseline and the same aircraft concept optimized instead for maximum stochastic value to identify the potential tradespace between performance- and value-based optimization. The stage at which the value optimization is introduced in the design process (e.g., before preliminary configuration layout, after minimizing for GTOW, etc.) is then varied to determine how to most effectively account for the valuation in this new MDO approach. The results are also compared to the optimization outcome using traditional valuation techniques, as currently practiced, to establish the benefits of using the improved valuation methodology. In addition, examples are presented to quantify the effects of value-based optimization on improving design decisions.

Having established the role of the stochastic valuation in a coupled MDO approach, the remaining key focus is to address the issue of risk. As any commercial aircraft program is likely to encounter some form of uncertainty, the next logical step beyond the deterministic design solution is to answer “what if” questions that may arise given program uncertainty [33]. These uncertainties may be broadly divided into technical and financial categories. Technical uncertainties affect the ability of a design to meet its performance specifications, and might include exceeding or im-

proving upon a weight target, engines missing or bettering fuel consumption goals, and so on. Financial uncertainties directly relate to the value of an aircraft, whether in the form of decreased (increased) demand, higher (lower) manufacturing expenses, or other cost- or revenue- related factors.

How well, then, is the design suited withstand the effects of uncertainty and remain profitable? Taking a sensitivity analysis approach, several likely sources of uncertainty are applied at varying degrees to the optimum design. The resulting impact on the program value and sensitivity to further uncertainty help to answer the above question and effectively quantify the business risk of the program in light of these particular uncertainties.

1.3 Overview

The following layout serves to explain the models, calculations, and methodologies used to achieve the research objectives, before addressing the results that were obtained. Chapter 2 begins by discussing the traditional calculation of deterministic NPV and elaborates upon its limitations. The stochastic valuation technique is then explained in greater detail to show why the expected NPV it generates is the preferred metric.

This is followed by descriptions of the individual performance, cost, and revenue components of the simulation model in Chapter 3. These provide the inputs necessary for the valuation algorithm. Chapter 4 then illustrates how the models and value calculation are integrated into the overall optimization framework.

Results are presented in Chapter 5 for design of the BWB aircraft using this framework. Different design options resulting from different choices of objective function are analyzed. In particular, comparisons are made between performance-optimized and value-optimized designs, and stochastic and deterministic value objective functions. An example is presented to demonstrate how value-based MDO can be applied to the process of setting design requirements.

Chapter 6 features a discussion of the relationship between design uncertainty

and program risk, and how the financial impact of risk can be quantified. Sensitivity analyses to show the relationship between technical and financial uncertainties and the resultant program value are presented in Chapter 7.

A summary of the major findings is given, and conclusions about the usefulness of this new design methodology are drawn, in Chapter 8. Finally, recommendations for extensions to the work presented herein are made.

Chapter 2

Program Valuation

2.1 Introduction

In choosing to maximize program value as the design objective, the factors discussed previously — performance, cost, demand, and market uncertainty — can be considered by propagating their effects through to overall program costs and revenues. A properly chosen value calculation based on these cash flows can effectively summarize many important aspects of the program design in a single number. The resulting design optimization will then consider both performance and finance while maximizing the program profitability.

A number of metrics are available for assessing the value of the program, as mentioned in Chapter 1, such as NPV, IRR, or ROI. There are advantages and disadvantages to each, as well as particular investment scenarios for which some metrics are better suited than others. The relative arguments for and against several valuation techniques were discussed in detail by Markish, who showed that an improved stochastic form of the NPV calculation is the most appropriate choice for valuing an aircraft program [17].

This chapter will describe the calculation and shortcomings of traditional, deterministic NPV. That will be followed by an explanation of the improved stochastic method for calculating expected NPV ($E[\text{NPV}]$), which explicitly accounts for market uncertainty and decision-making flexibility throughout the aircraft program.

2.2 Deterministic Net Present Value

NPV is one of the most commonly-used metrics in engineering program valuation. It can account for the time value of money and provides a clear estimate of an investment's future value over a lengthy time horizon, which adds to its usefulness for valuing a commercial aircraft program.

NPV is computed by summing discounted future cash flows as follows [5].

$$NPV = \sum_{t=0}^N \frac{P_t}{(1 + r_d)^t} \quad (2.1)$$

In (2.1), t represents a future time period ranging from the current time ($t = 0$) to the final time period N , and P_t is the profit function consisting of the difference between the revenues and costs of the undertaking in a given time period t . The risk-adjusted discount rate, r_d , accounts for both the opportunity cost of capital and the perceived risk inherent in a venture. Typically assumed values of r_d for an aircraft program may range from 12% to 20% [9, 17]. In general, a positive NPV indicates a sound investment, while a negative NPV means that a program should not be pursued.

This approach is limited in some respects in its ability to provide a definitive valuation, however. NPV and other deterministic metrics are based on a static valuation of the design, since the expected cash flow must be assigned for each time period. The issue of flexibility — that is, the ability of the manufacturer to make decisions in response to changing conditions — is not considered. Further, uncertainty in future cash flows is handled only through choice of r_d . Finding or calculating a discount rate that includes the effects of risk is a difficult, and ultimately arbitrary, process. Using a high discount rate to reflect greater uncertainty does not properly account for risk, and often leads to a pessimistic valuation, since cash flows in later years will contribute a small amount to the sum in (2.1), as illustrated in Figure 2-1.

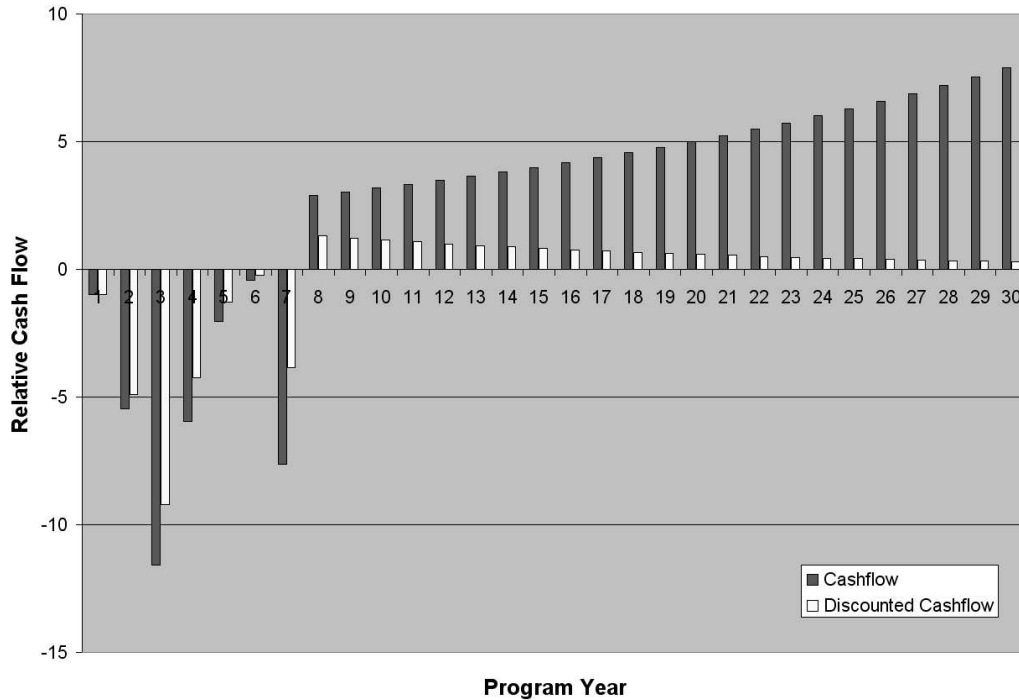


Figure 2-1: Comparison of discounted and undiscounted cash flows for baseline BWB design with $r_d = 12\%$, normalized by initial cash flow.

2.3 Stochastic Valuation Methodology

A stochastic valuation approach based on Real Options theory addresses several of the shortcomings of a deterministic NPV calculation. Rather than relying on a risk-adjusted discount rate, demand uncertainty is addressed explicitly via a stochastic model based on empirically-determined market volatility. To capture flexibility, the program is viewed as a series of investment decisions characterized by discrete program “modes,” including design, tooling, and manufacturing stages. This model is depicted in Figure 2-2. The manufacturer may choose to pause or cancel the program when in certain modes, investing no more money if future market conditions appear unfavorable, as determined by the demand model. A successful aircraft program will by necessity be a dynamic venture, so accounting for the ability to make decisions as the program progresses is essential to assessing its profitability.

The relevant parameters for the DP problem setup are summarized in Table 2.1.

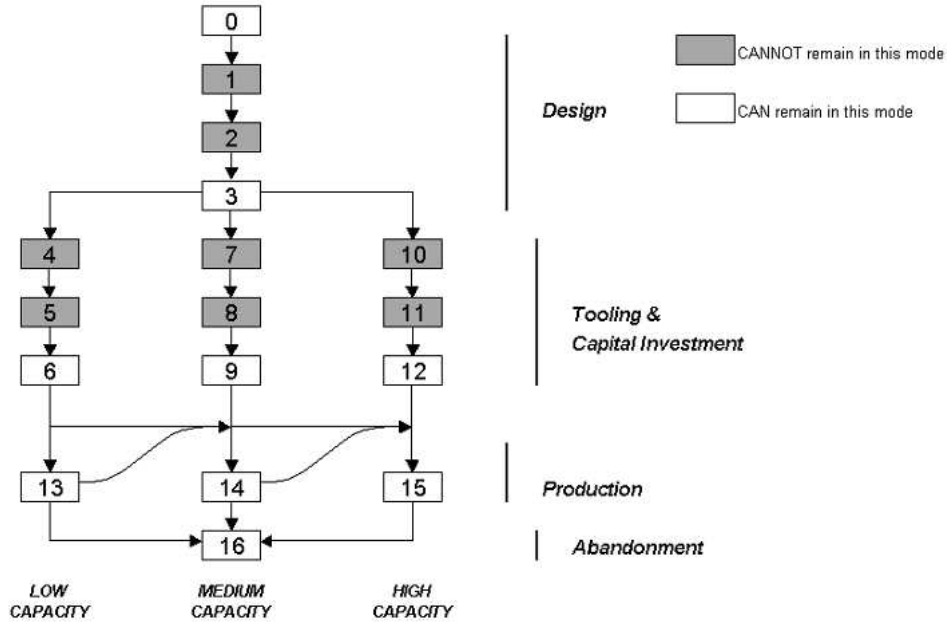


Figure 2-2: Block diagram of operating modes for commercial aircraft program (from [17]).

Expected NPV is calculated for this problem by solving Bellman's equation,

$$F_t(s_t) = \max_{u_t} \left\{ P_t(s_t, u_t) + \frac{1}{1 + r_f} E_t [F_{t+1}(s_{t+1})] \right\} \quad (2.2)$$

where $F_t(s_t)$ is the value (objective function) at time t and state vector s_t , P_t is the profit in time period t as a function of the state vector s_t and the control vector u_t , and r_f is the risk-free discount rate (accounting now only for the time-value of money and not for risk). E_t is the expectation operator, providing in this case the expected value of F at time $t + 1$, given the state s_t and control u_t at time t . For the aircraft program considered here, the state vector contains the current demand quantity and the current program mode, while the control vector contains the decision to be made, i.e., the program operating mode for the next period. The formulation of this stochastic valuation is described more fully in References [17] and [19].

Equation (2.2) can be solved using a DP algorithm that starts at the final time period, $t = N$, and works backwards to the current time, $t = 0$. Outputs of the valuation module are the program E[NPV], given by F_0 , and a set of program "decision

Table 2.1: Parameters for DP problem to calculate stochastic valuation.

DP Parameter	Symbol	Quantity
State	s_t	Demand Previous mode
Control	u_t	Current mode
Randomness	σ	Demand volatility
Dynamics	Change of demand state, mode	

rules.” These decision rules define the optimal control strategy u_t as a function of time, current market condition, and current operating mode. For example, if the program state is in the “wait” operating mode (i.e., design has not yet been started), the decision rules define, as a function of time, the minimum demand necessary to execute the decision to move into the design operating mode. In a given time period, if the demand does not reach this threshold level, the optimal strategy is to wait. Similar demand thresholds are defined for the decisions to move into tooling fabrication and aircraft production.

It is important to note that the *expected* NPV returned by the valuation module will never be less than zero, since zero E[NPV] can be obtained by choosing to always wait in the face of unfavorable design conditions. The DP solution will therefore not yield a strategy that, on average, produces a negative E[NPV].

2.4 Summary

Figure 2-3 summarizes the roughly analogous calculations for traditional NPV and stochastic E[NPV], while showing key differences between the two processes. The improved valuation technique permits the ability to capture program dynamics in assessing the financial viability of a project, providing a more appropriate measure of value than traditional metrics. The calculation of E[NPV] according to (2.2) requires estimates for the periodic cash flows in the profit function, P_t , and a model for the demand uncertainty. These inputs are provided by the financial models described in the next chapter, which are in turn based on the details of the aircraft design itself. By accounting for the effects of the technical design as well as market factors

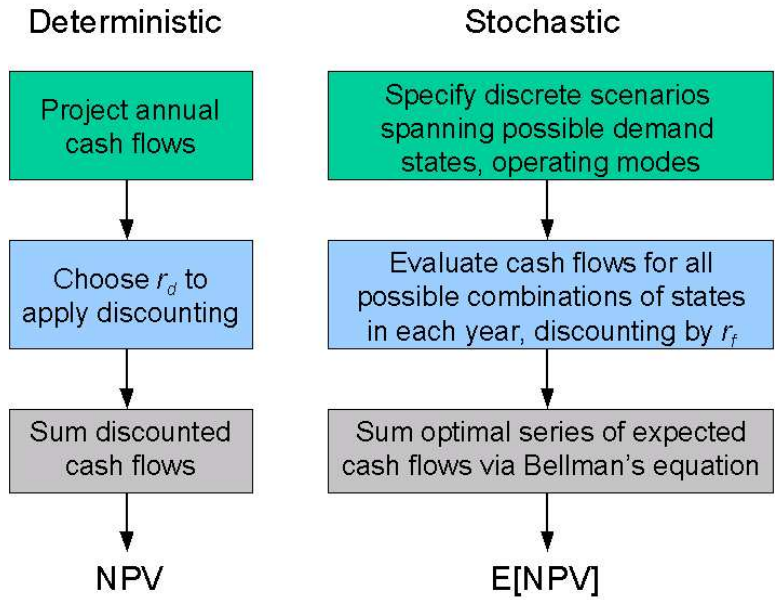


Figure 2-3: Overview of difference in parallel approaches to calculate deterministic NPV, stochastic $E[NPV]$.

in the financial assessment of the program, the valuation assigned by the approach suggested in this chapter is an excellent candidate for a new design objective in the MDO problem.

Chapter 3

Multidisciplinary Models

3.1 Introduction

The DP problem described in the previous chapter requires annual cost and revenue estimates for the aircraft program. These values are derived from models that take the aircraft design parameters as inputs. The simulation model first uses the design vector to generate size and performance estimates for an aircraft concept. Then, relevant design values are used by the financial modules to calculate cost, price, and baseline demand for the resulting aircraft program. These modules are described in further detail below, with results given for their application to the baseline BWB design. As described in Chapter 1, this is a 475-passenger aircraft with a design range of 7800 nmi, minimized for GTOW.

3.2 Performance Model

The existing WingMOD multidisciplinary performance and sizing model is used to calculate the sizing, weights, and flight characteristics of the aircraft concept. WingMOD incorporates a vortex lattice model for aerodynamic analysis and utilizes simple beam analysis for structural sizing in order to evaluate performance over 5 mission configurations and 26 flight conditions [35, 38].

The optimization problem using WingMOD is set up as a sequence of sub-opti-

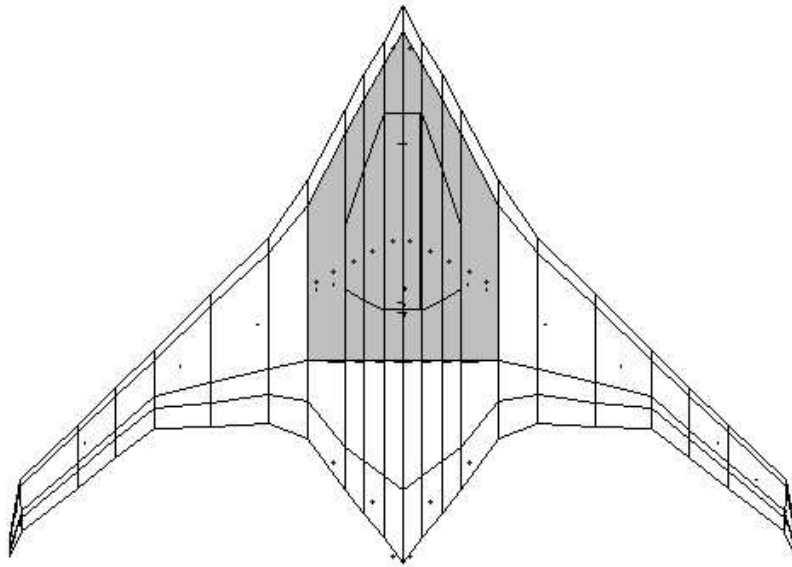


Figure 3-1: BWB planform view for baseline minimum GTOW design.

mizations, as will be described in Chapter 4. Due to the varying objective function, design vector, and constraints, a standard set of data describing the aircraft design is generated for each calculation. Inputs are provided by the data from a previous step, or initially, from the results of a previously optimized similar design. Key outputs include the wing geometry, lift and drag data, structural and operating weights, and stability characteristics of the aircraft. The resulting design can be visualized in planform view, as illustrated in Figure 3-1 for the baseline BWB.

3.3 Financial Model

The financial model (cost, revenue, and value modules) is based on empirical models developed by Markish [17, 18]. Cost, revenue, and demand trends were fit to historical aircraft data, and the resulting equations provide cost, price, and baseline demand estimates using the outputs of the performance model.

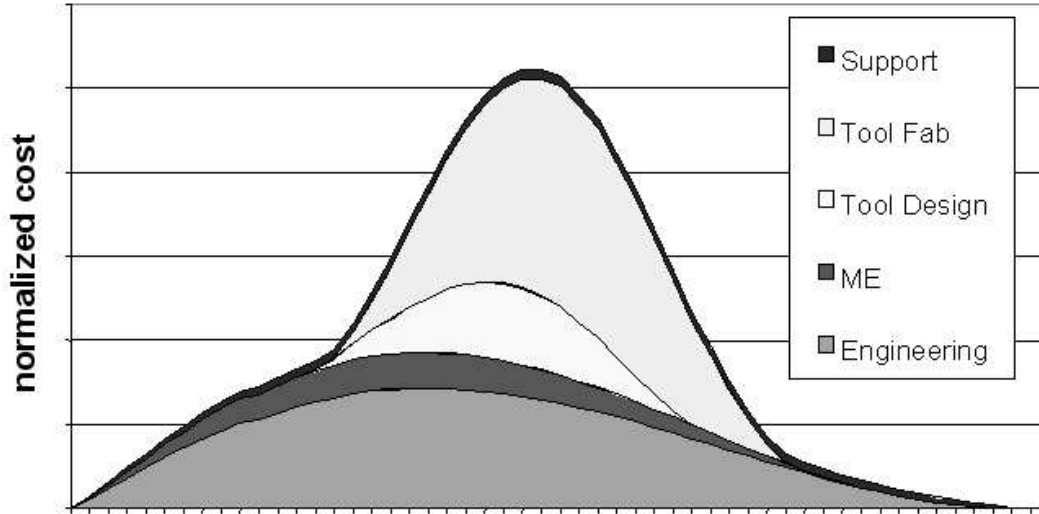


Figure 3-2: β -distribution approximating non-recurring program costs incurred over the development period (from [17]).

3.3.1 Cost

Costs are estimated from the weight breakdown of the aircraft generated from the sizing model. The overall weight is divided according to part categories (e.g., wing, fuselage, etc.), which are assigned costs per pound from empirical data based on both the part and process (e.g., labor, materials, etc.) type. The total costs are then calculated by multiplying each weight by its relevant costs per pound and summing over all parts and processes. Estimates are provided for both non-recurring (e.g., engineering, tooling, etc.) and recurring (e.g., manufacturing, quality assurance, etc.) costs.

Non-recurring costs for a typical aircraft program are modeled as being incurred over the development timeframe as an approximate β -distribution based on empirical data. This model is illustrated in Figure 3-2, showing the build-up of development costs by process type.

The application of this model to estimate non-recurring costs for the baseline minimum-GTOW BWB design is shown in Figure 3-3. The costs incurred, from the model, are superimposed on the historical development cost data, upon which the model was based, in Figure 3-2. This model takes time spent on development as

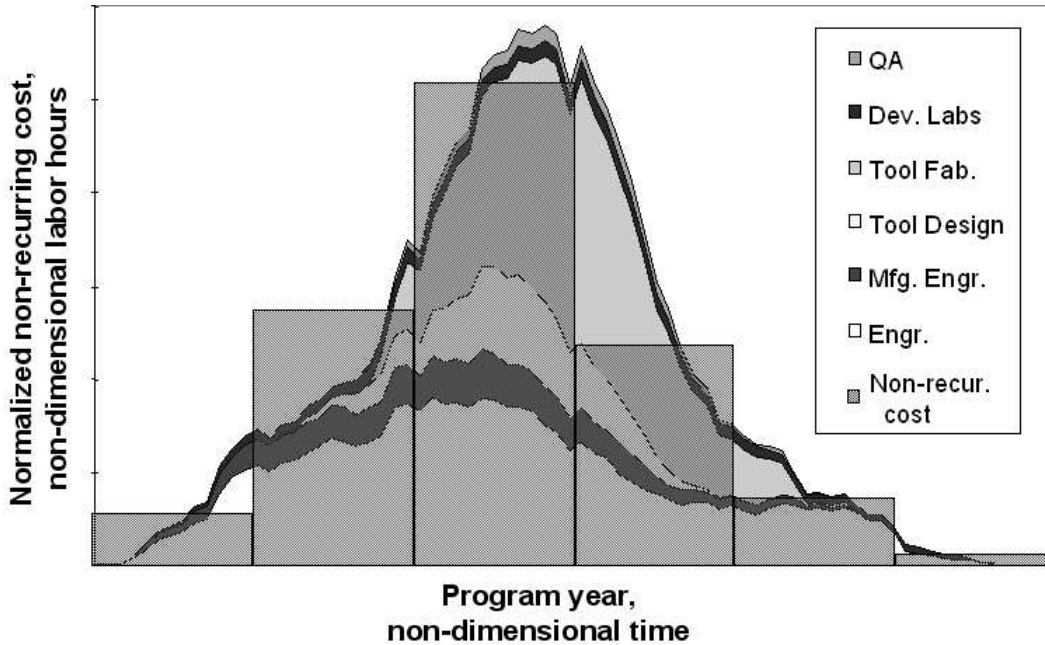


Figure 3-3: Distribution of estimated non-recurring program costs by program year for baseline BWB from development cost model, compared to labor data used in [17] to formulate the model in Fig. 3-2.

proportional to expenditures; while a reasonable assumption, the non-recurring costs are built up as a function of weight, strictly speaking. A six-year development period is assumed, with annual cost estimates provided by the model.

The actual breakdown of development costs for the baseline BWB is compared to such a breakdown for a typical, traditional tube-and-wing commercial airliner in Figure 3-4. This is presented as percentage of the total non-recurring cost by major empty weight component. Development costs for the fuselage are much greater for the BWB than typical designs due to the relatively much larger size of the BWB centerbody, considered “fuselage” weight in the cost model. The percentage of cost dedicated to the wing is subsequently lower, as well, as the centerbody is effectively a continuation of the wing for the BWB. The winglet cost is much lower than traditional empennage costs, again due to a much smaller size. Also related to the increased fuselage expense is the “payloads” cost for items installed in the cabin, which is much larger due to the increased centerbody cabin size and higher passenger capacity that are key features of the BWB design layout. In addition, there may be a different

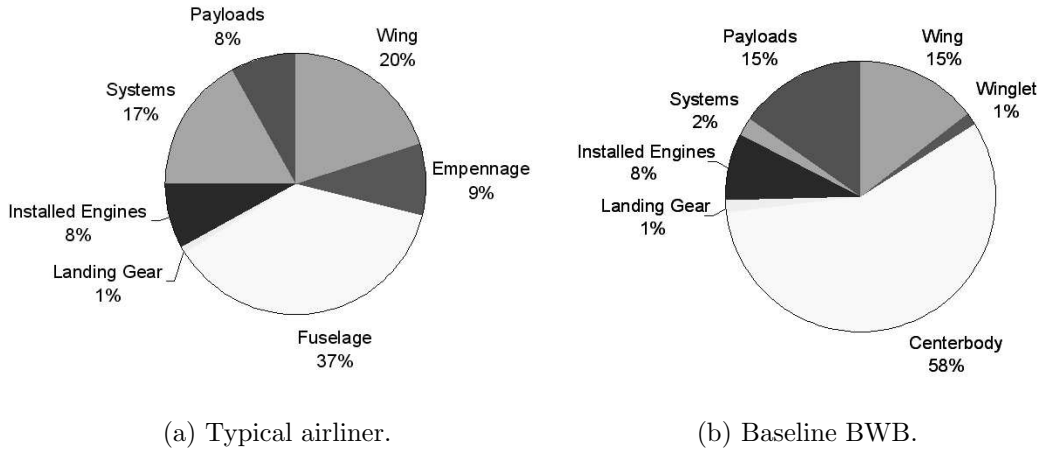


Figure 3-4: Comparison of non-recurring cost breakdown for 300-passenger traditional airline design from [17] and 475-passenger BWB, as percentage of total development cost.

accounting of payloads versus systems weights for the BWB since the systems cost is much lower. Engine and landing gear costs remain similar.

Recurring costs take into account a learning curve effect, such that the costs of manufacturing additional aircraft would be reduced over time. A theoretical first unit (TFU) cost for the first production aircraft is calculated through the process described above of multiplying cost/weight by component weights, further subdivided by process type. Additional unit costs are discounted according to the following learning curve equation to take into account improvements in the manufacturing process gained from experience.

$$Y_n = Y_0 n^{(\ln b / \ln 2)} \quad (3.1)$$

Y_0 represents the TFU cost, Y_n is the cost of unit n , and b is the learning curve factor or slope. For the processes modeled, the learning curve slopes are 85% for labor and 95% for all other categories [18]. The effects of these slopes on the cost of manufacturing subsequent units are illustrated in Figure 3-5.

As seen in Figure 3-5, the slopes of the learning curves are much less steep as the number of units produced increases. For the BWB example, the long-run marginal

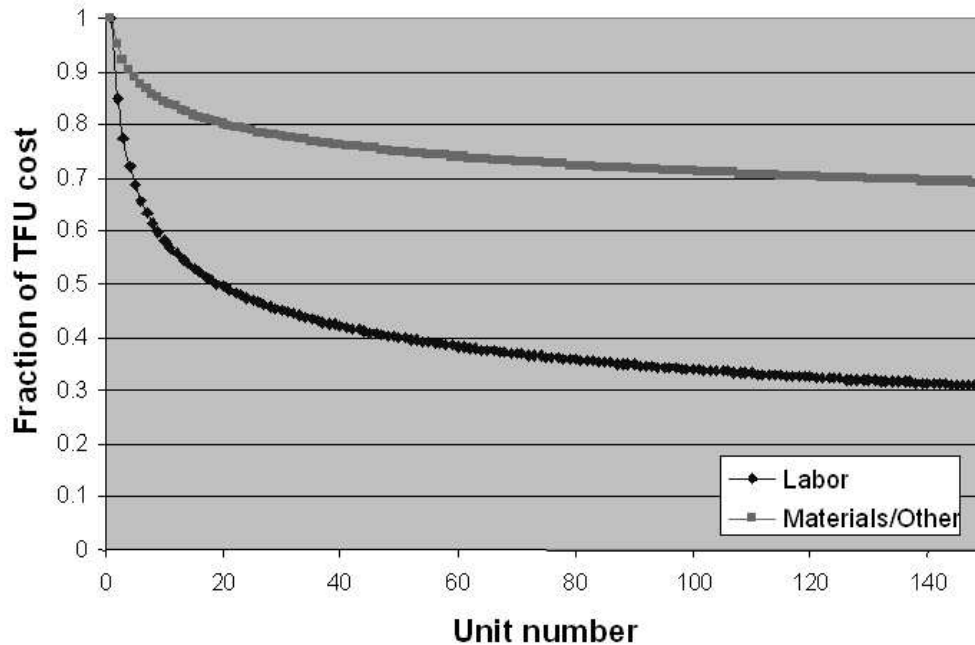


Figure 3-5: Learning curve effects for a commercial aircraft program on recurring costs by process type, according to (3.1).

cost (LRMC) is taken as the cost of the 100th unit — that is, the result of (3.1) for $n = 100$, multiplied by the TFU cost. All aircraft are assumed to have been manufactured at this cost, and the differences between the LRMC and actual costs of previously produced units are summed and applied as a one-time cost incurred at the start of production. This assumption is necessary for implementation of the DP algorithm, and also leads to a more conservative estimate of the program value, since a large negative cash flow earlier in the program will not be discounted as heavily as future profits.

Breakdowns of LRMC by component cost for a typical airliner and the baseline BWB are presented in Figure 3-6. As was the case with the non-recurring cost breakdown present in Figure 3-4, the fuselage accounts for a higher percentage of the BWB LRMC than might be expected, and the wing and winglet lower percentages, due to the fact that the centerbody serves as the fuselage while providing a substantial part of the wing area. The relative cost of installed systems is more in line with the expected percentage of total LRMC than it was in the case of development, while payloads

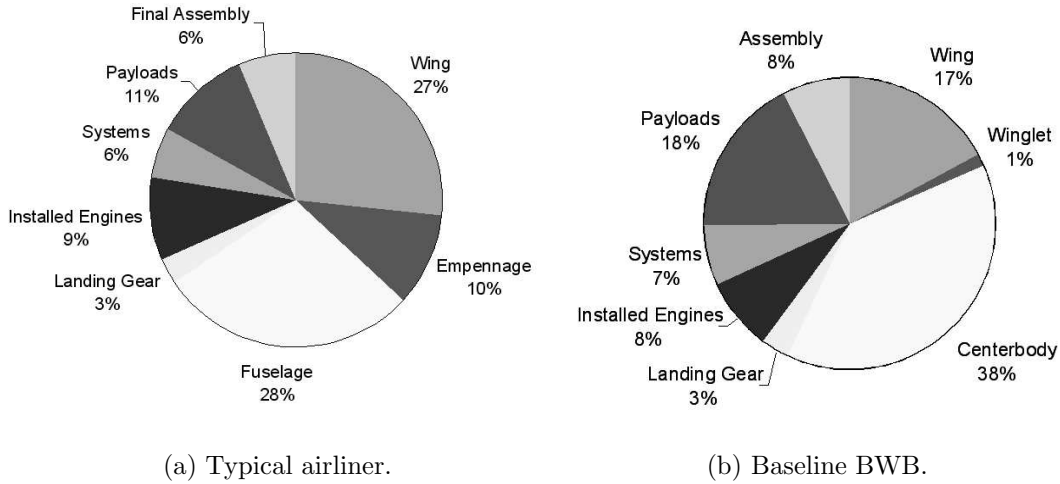


Figure 3-6: Comparison of LRMC breakdown for 300-passenger traditional airline design from [17] and 475-passenger BWB, as percentage of total LRMC.

cost has similarly increased compared to the rest of the design. Assembly, engines, and landing gear costs are close to the traditional component cost percentages.

3.3.2 Price

Price is calculated as a function of range, number of passengers, and an operating cost adjustment according to the following empirically-derived model.

$$Price = [k_1 \times (\frac{N_{seats}}{N_{seats_ref}})^\alpha + k_2 \times (\frac{Range}{Range_ref})] \times Price_ref - \Delta LC \quad (3.2)$$

Range and number of seats, N_{seats} , are normalized by reference values (N_{seats_ref} , $Range_ref$) so that the entire value can be scaled by a reference price, $Price_ref$. These reference parameters, as well as k_1 , k_2 , and α , were determined through regression analysis based on public domain aircraft sales data [1, 2]. The resulting values are summarized in Table 3.1. No correlation between price and demand is accounted for in (3.2); while such a relationship may exist, it was not apparent from the data underlying the revenue model [17].

The ΔLC parameter is a lifecycle cost adjustment based on fuel burn as a percentage of Cash Airplane-Related Operating Cost (CAROC). Its value accounts for

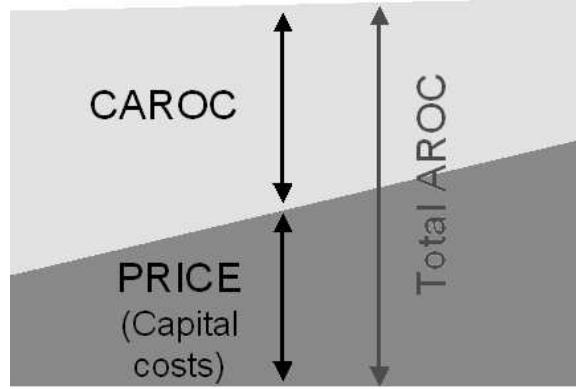


Figure 3-7: Relationship between capital costs and CAROC such that total ownership cost remains constant (from [37]).

differences in the efficiencies of competing aircraft designs, and reflects the idea that the more (less) efficient an airliner is to operate, the higher (lower) the price an airline is willing pay to own it. This concept is depicted in Figure 3-7, showing that the total airplane-related ownership cost (AROC) must remain nearly constant for varying ratios of capital costs and CAROC.

Table 3.1: Best-fit parameters for empirical price model in (3.2) from [19].

Parameter	Narrowbody	Widebody
k_1	0.735	0.508
k_2	0.427	0.697
α	1.910	2.760
N_{seats_ref}	419	
$Range_ref$	8810 nmi	
$Price_ref$	\$148.7 M	

The breakdown of total AROC for the baseline BWB example and a typical airliner are compared in Figure 3-8. The BWB features relatively low operating costs, which is beneficial in that the manufacturer can theoretically charge a higher price, as accounted for by the ΔLC term in (3.2). This is evidence of improved aerodynamic qualities, resulting in higher fuel efficiency, that are touted as a major benefit of the BWB design.

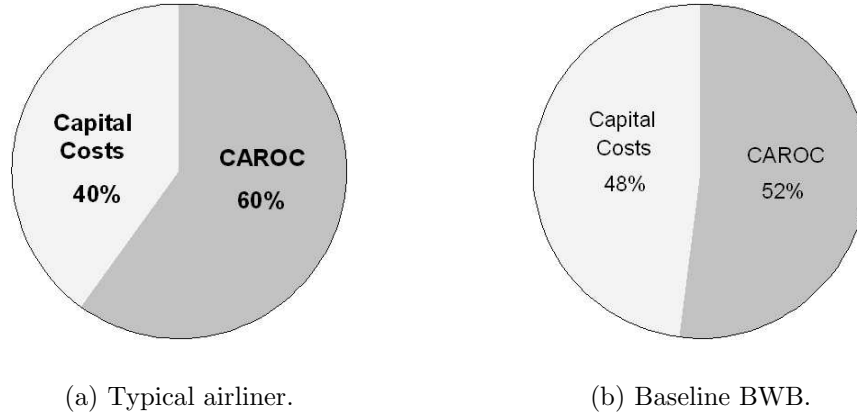


Figure 3-8: Comparison of AROC ratio of capital costs to CAROC for typical traditional airline design from [37] and BWB.

3.3.3 Stochastic Demand

In the demand model, the design is first classified in terms of its size (wide- or narrowbody, from a range threshold) and number of passengers. Each class corresponds to a demand “bucket” to determine a baseline quantity, assuming a 50% market share for either of the two major airframe manufacturers. Buckets are determined based on empirical demand data, as illustrated in Figure 3-9. Demand is then assumed to evolve stochastically from the baseline quantity.

Given this initial demand, a set of demand states is established using a geometric Brownian motion (GBM) model. This approach is commonly used in Real Options applications to model stochastically evolving processes. While the actual commercial aircraft market dynamics would not strictly follow GBM and other approaches, such as using a mean-reverting process, are possible, this model has been shown to provide a reasonable approximation for the demand behavior.

According to the GBM model, demand uncertainty is accounted for using a Weiner process with rate of return μ and volatility σ , as measured from empirical commercial aircraft data [17]. As such, for a given baseline demand x_0 , the demand in the next time period would be x_0u with probability p , or x_0d with probability $1 - p$ according

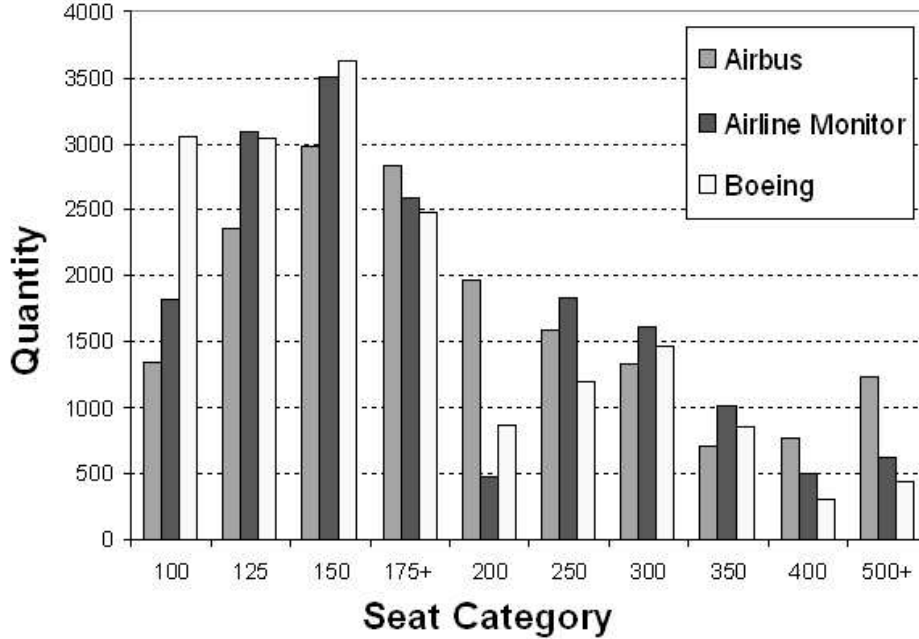


Figure 3-9: Demand data used to model baseline quantity demanded as a function of passenger class and airframe type (from [17]).

to the following equations [8, 14],

$$p = \frac{e^{\mu\Delta t} - d}{u - d} \quad (3.3)$$

$$u = e^{\sigma\sqrt{\Delta t}} \quad (3.4)$$

$$d = 1/u \quad (3.5)$$

where in this case $\mu = r_f$. A key advantage of capturing the market uncertainty explicitly is the ability to discount at a known risk-free rate in (3.3), and thus in (2.2) to calculate $E[\text{NPV}]$. Values for the parameters r_f and σ were determined from historical data [17] and are summarized in Table 3.2. The time step Δt was chosen to be one year.

Using this model, a binomial lattice of demand states is constructed, as illustrated in Figure 3-10, as well as a matrix of corresponding transition probabilities. These probabilities describe the likelihood of moving from a given initial demand state to a final demand state, according to the risk-neutral probabilities calculated using (3.3). The lattice of demand states and transition probability matrix are then used by the

Table 3.2: Parameters for stochastic demand model from [17].

Parameter	Narrowbody	Widebody
σ	42.7%	45.6%
Program length	30 years	
Δt	1 year	
r_f	5.5%	
Inflation	1.2%	

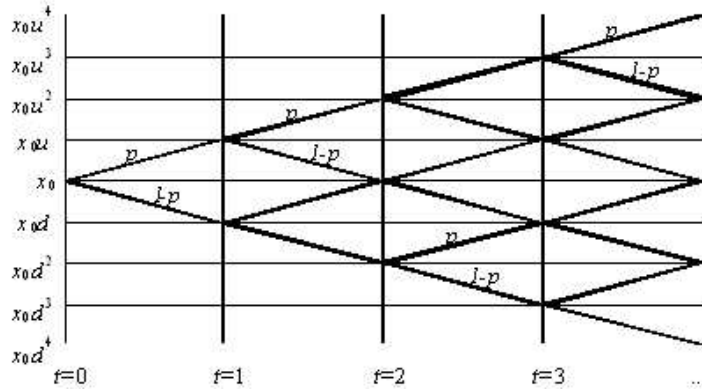


Figure 3-10: Binomial tree for estimating demand state as a function of program time (from [17]).

value module to calculate the optimal $E[\text{NPV}]$ in the DP algorithm.

3.4 Summary

This chapter has established the multidisciplinary tools necessary to evaluate an aircraft design's performance as well as its profitability. The financial models have been shown to provide reasonable cost and price estimates for baseline BWB example. Discrepancies between that design and traditional aircraft designs may be accounted for by the unique geometry, weight distribution, and performance of the BWB, stemming from its aerodynamically efficient design. These models are coupled with the valuation algorithm described in Chapter 2 to provide the basis for the overall value-based optimization framework.

Chapter 4

Value-Based Optimization

4.1 Introduction

A value-based optimization framework is created by linking the simulation model described in the previous chapter to the valuation algorithm described in Chapter 2. Including the financial models and value calculation in the optimization loop enables design based jointly on performance and financial parameters. Using the resulting setup for the Blended-Wing-Body problem, designs can be optimized for value or other performance or financial metrics.

The organization of the components into the overall framework is described below. The actual optimization of the BWB aircraft is solved sequentially, as a series of intermediate optimizations with varying objectives, as necessitated by the scope of the problem. To demonstrate the proposed methodology, the overall objective is the expected NPV of the program. However, since the value calculation is dependent on the performance model and the optimization sequence explicitly sets certain design requirements, it is important to note that the resulting design is optimized based on *both* performance and value.

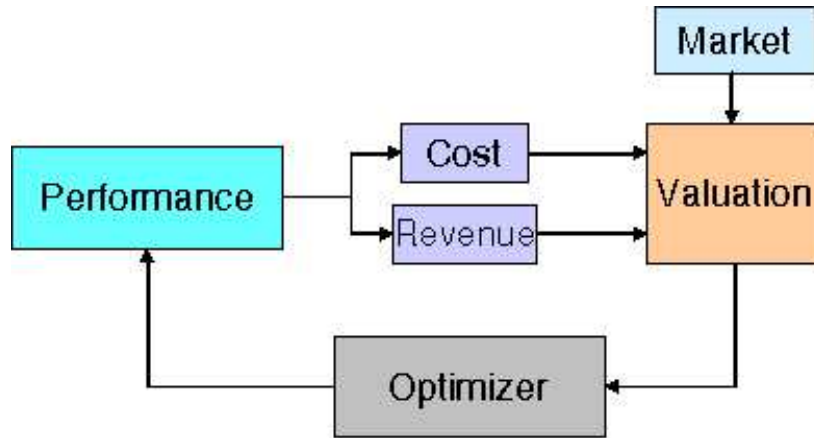


Figure 4-1: Block diagram depiction of value-based MDO framework.

4.2 MDO Framework

The multidisciplinary optimization framework provides the tool for applying the value-based design methodology. It couples the performance and financial models described in Chapter 3 and the stochastic valuation technique from Chapter 2 with an optimization algorithm. Figure 4-1 illustrates the process by which performance and financial factors are utilized jointly to ultimately optimize the design for maximum $E[\text{NPV}]$.

An initial design vector is provided to WingMOD to estimate aircraft sizing and performance characteristics. Its relevant outputs are then used by the cost and revenue models to approximate cost, price, and baseline demand figures for the design. These program parameters are the inputs to the valuation module, which uses the stochastic DP algorithm to determine a set of optimal design decisions and the objective function, $E[\text{NPV}]$, according to (2.2). Optimization is performed using a sequential quadratic programming (SQP) algorithm to maximize $E[\text{NPV}]$, via the sequence of steps detailed in the following section.

4.3 Optimization Problem Setup

Due to the extent of the BWB design problem, the overall optimization is performed sequentially as a number of intermediate steps as described in Wakayama [35]. It is necessary to break up the optimization in this fashion in order for the optimizer to converge on a solution that meets all design criteria.

Initially, this process consists of a series of performance-based optimizations. These steps progress the design to its overall solution in the following order (grouped into general categories entailing multiple steps): set the aircraft size and layout; set the performance, including range and speed; trim the aircraft and establish control limits; balance the aircraft while minimizing GTOW. The value-based design optimization adds an additional step: maximize $E[\text{NPV}]$.

Specifically, the sequence proceeds as listed in Table 4.1, although the best placement of the maximum- $E[\text{NPV}]$ step will be investigated. Each sub-optimization features its own objective, design vector with $O(100)$ variables, and $O(1000)$ constraints specific to the short-term goal.

Table 4.1: BWB optimization sequence from [35] with additional value-maximizing step.

Step #	Optimization Purpose	Objective
0	Upper deck geometry	minimize reference payload density
1	Lower deck geometry	minimize reference payload density
2	Weight & aerodynamics calibration for high speed conditions	maximize range
3	Trim low speed conditions	minimize GTOW
4	Establish stall speeds	minimize GTOW
5	Calibrate low speed control	maximize range
6	Establish control limits	maximize control limit breadth
7	Partially balance aircraft	minimize GTOW
8	Fully balance aircraft	minimize GTOW
9	Balance aircraft with planform optimization	minimize GTOW
10	Financial valuation	maximize $E[\text{NPV}]$

Each step of the sequence is formulated as a nonlinear optimization problem as follows.

$$\begin{aligned} \min \quad & F(x) \\ \text{s.t.} \quad & c_i(x) \geq 0, \quad i = 1, 2, 3, \dots, m \end{aligned} \tag{4.1}$$

The objective functions from Table 4.1 are substituted for $F(x)$, with x as the vector of n design variables, subject to m constraints, c_i . The SQP algorithm is then used to solve (4.1) for each intermediate problem, as described in [38].

Scaling of the problem objective and variables are critical to ensure convergence of the solution. This issue has been previously addressed for the original optimization sequence [38]. The additional step to maximize E[NPV] uses the same problem formulation as the existing step 9, with an updated objective function. Due to the overall complexity of the BWB problem, in terms of the dimensions of x and c_i , this decision was made to ensure that the problem remained well-scaled. The new E[NPV] objective was re-scaled, however, to improve the speed of convergence.

To reduce computational time, the financial model is evaluated only when maximizing E[NPV] in the optimization sequence. One may envision a direct link between the performance model and optimizer in the framework depicted in Figure 4-1 in order to bypass the cost, revenue, and value modules. This framework setup and sequential optimization allow flexibility in the design problem to investigate potentially more effective placement of value-based analysis in the overall design process. However, a single calculation of E[NPV] is performed at the end of each performance-based step of the sequence to understand the effect on program value throughout the design process as the aircraft converges to its final configuration.

Ultimately, the optimization for maximum E[NPV] consists of a combination of performance-only and value-based optimizations. Once again, this emphasizes the joint performance and financial nature of the proposed design methodology.

4.4 Summary

Design of an aircraft program combining both performance and financial analysis is accomplished through the optimization framework shown in Figure 4-1. The optimization is carried out as a sequential process, due to the scale of the problem, incorporating both traditional performance metrics and program value as objectives. This tool is used in the following chapters to quantify the effects of value-based MDO for the BWB problem.

Chapter 5

Value-Based MDO Design Example

5.1 Introduction

Results are presented for value-based optimization of a notional BWB program using the previously described design framework. The following results demonstrate first the most effective strategy for combining performance-based and value-based optimization sequences, and secondly the advantages of the stochastic valuation approach compared with a traditional deterministic approach. Analysis is also presented to show specifically how the different objective functions result in different designs. Finally, examples comparing $E[\text{NPV}]$ when the design specifications for range and cruise speed are varied illustrate how value-based optimization can be used to make more fully-informed decisions in the process of setting design requirements.

5.2 Performance vs. Financial Optimization

Comparison of performance-only and value-based optima demonstrates the advantages gained by including financial analysis in the MDO process. As discussed in previous chapters, the baseline design is a BWB concept with a range of 7800 nmi and passenger capacity of 475, optimized for minimum GTOW. Initial demand for this design is 13.5 aircraft per year. Other program parameters remain as defined in Table 3.2.

A series of runs with a single, varied step of the optimization sequence replaced by a value optimization provided insight into the best approach to maximize E[NPV]. The improvement in E[NPV] over the GTOW-optimal design was then increased by replacing multiple steps of the sequence with value optimizations. Analysis of the resulting designs shows how the new choice of objective changes the technical design to improve E[NPV].

5.2.1 Single-step E[NPV] Optimization

The first set of results shows the effect of introducing a value optimization at different points in the optimization sequence. Maximum E[NPV] was substituted as the design objective for just a single step in the sequence described in Table 4.1. This substitution was done for steps 2 through 10 in turn; steps 0 and 1 were not considered because the problem setup for those stages entailed only the geometry of the BWB cargo decks, and would not result in any changes to the value of the aircraft. This approach allowed assessment of the impact that E[NPV] had as an objective on changing the design to improve its value via the overall optimization. At the same time, the results provided insight into the optimization *process* for maximizing value — that is, for which steps in the sequence E[NPV] as the intermediate objective resulted in the greatest impact on the final value of the program.

Figure 5-1 presents the percentage change in the resultant E[NPV] and GTOW relative to the baseline solution for this series of design cases. Each case represents the outcome of a full optimization sequence from Table 4.1, with the single step listed having been replaced by an E[NPV]-maximizing step and all other steps retaining their objective function as given in Table 4.1. (In the case of step 10, an additional optimization was added.)

The best results are obtained by substituting maximum E[NPV] as the objective for minimum GTOW in step 9, or as an additional step 10, with an improvement of 0.91% over the baseline case in both problem setups. Introducing the value objective earlier in the sequence has a less beneficial effect, including decreases in the value of up to 3.2% (step 7). In all cases, the GTOW does not vary significantly from the

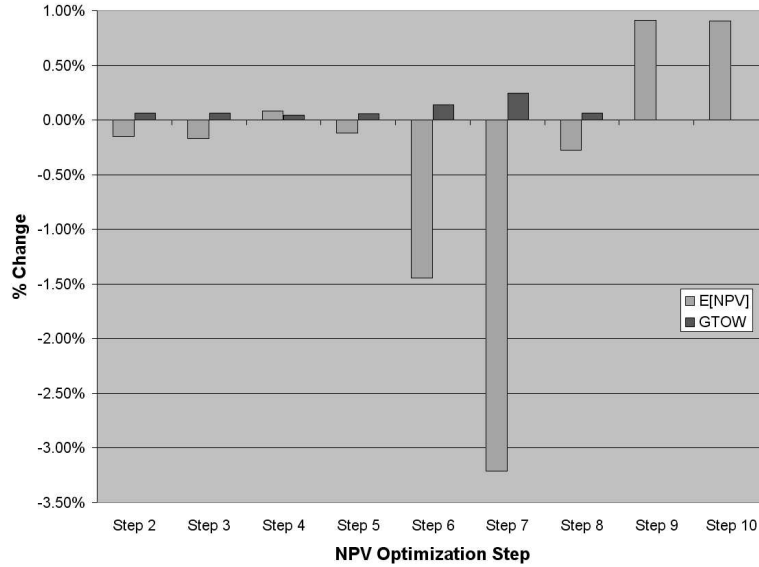


Figure 5-1: Percentage change in E[NPV] and GTOW for value-optimal designs relative to the baseline (min GTOW) design for the BWB. For each case, the step denoted was replaced with a max-E[NPV] optimization; all other steps remained as in Table 4.1.

baseline design, indicating little ability for the new objective to move the design to a different portion of the design space to improve the value.

In Figure 5-1, the effect of the new optimizations on E[NPV] was much larger in most cases than the changes in GTOW, particularly for the later steps. As the program value is more sensitive to seemingly small changes in the design than GTOW, the optimization can have a greater effect on E[NPV]. While a small change in GTOW represents only a minute portion of its large initial value, the profits used to calculate E[NPV] are small differences between large numbers; small changes in the price and cost translate to a much larger effect relative to the profit itself, accounting for the more significant effect compared to GTOW. As an example of the greater sensitivity of E[NPV], in step 9, the relative change in E[NPV] is approximately 1,860 times larger than the corresponding change in GTOW.

Figure 5-2 depicts the trend that evolved over the course of the baseline scenario for minimizing the GTOW. From Figure 5-2, E[NPV] remains virtually constant as key design requirements are satisfied in the early part of the sequence. Similarly, there is little ability at this point to influence the design via optimization to move

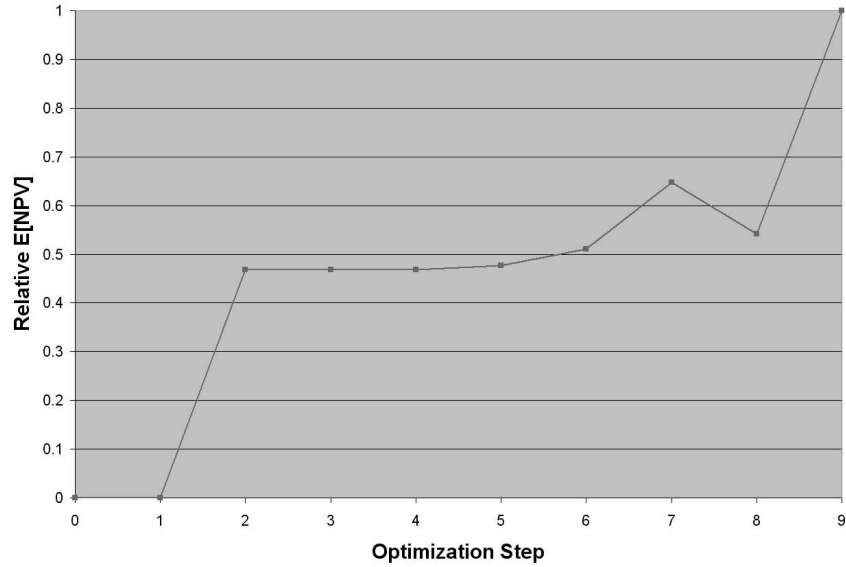


Figure 5-2: Intermediate $E[\text{NPV}]$ results over the course of the full baseline design optimization sequence, normalized by the final value of the baseline design.

to a different portion of the design space in order to increase $E[\text{NPV}]$. In the later stages, the optimization focuses on improving the design's performance and $E[\text{NPV}]$ consequently increases. The aircraft is fully balanced in step 6, and the optimizations to minimize GTOW begin with step 7. Here at step 7 is where the first significant increase in $E[\text{NPV}]$ is seen in Figure 5-2 since the earliest stages of the design process.

From Figure 5-1, however, it is clear that simply replacing step 7 with the maximum $E[\text{NPV}]$ objective does not return the value-optimal design. Interestingly, the optimization in which step 7 was replaced has the highest intermediate $E[\text{NPV}]$ at step 7, but the lowest final $E[\text{NPV}]$. This demonstrates that not only the choice of objective, but also the process by which the objectives are applied, are essential to the problem setup. As is illustrated in the following section, by both choosing the new $E[\text{NPV}]$ objective and applying it at multiple steps in the optimization sequence, further improvement was made in the overall program value.

5.2.2 Multiple-step E[NPV] Optimization

A second series of runs was carried out replacing the objective of multiple consecutive steps of the optimization sequence with E[NPV]. First, an optimization sequence was performed featuring E[NPV] as the objective for all steps, 2 through 9. This problem setup failed to converge on a profitable design, although the result was technically feasible. The resulting design was quite different from any of the above, however. The E[NPV]-maximized aircraft was 13% heavier than the baseline design, with a noticeably different layout. This suggests that the design settled at a different, but less favorable, local optimum in the design space.

Drawing from the results of the above experiments, the early stages of the design process (through step 6) retained performance-based objective functions, as in the baseline case. Multiple minimum GTOW optimizations were replaced with maximum E[NPV] optimizations late in the overall sequence. These results are summarized in Figure 5-3, in a fashion analogous to Figure 5-1. It can be seen that all three new cases represent an improvement. Replacing steps 7 through 9 with successive optimizations to maximize E[NPV] produces the best overall result. The value represents a 2.3% improvement over the baseline case, doubling the original improvement in Figure 5-1. The design resulting from this sequence will be referred to as “E[NPV]-optimal.”

These results offer insight into how value optimization should best be included in the early stages of the design process. Returning to Figure 5-2, introducing the E[NPV] optimization in the earlier steps, where the design is less defined, fails move the solution to a better part of the design space. Instead, replacing the final steps, in which a nearly complete design is refined to improve performance, offers the best chance at an improvement in the value of the program. For the BWB problem investigated, this meant leaving steps 0 through 6 with their original objectives, and replacing minimum GTOW with maximum E[NPV] as the objective function in steps 7 through 9.

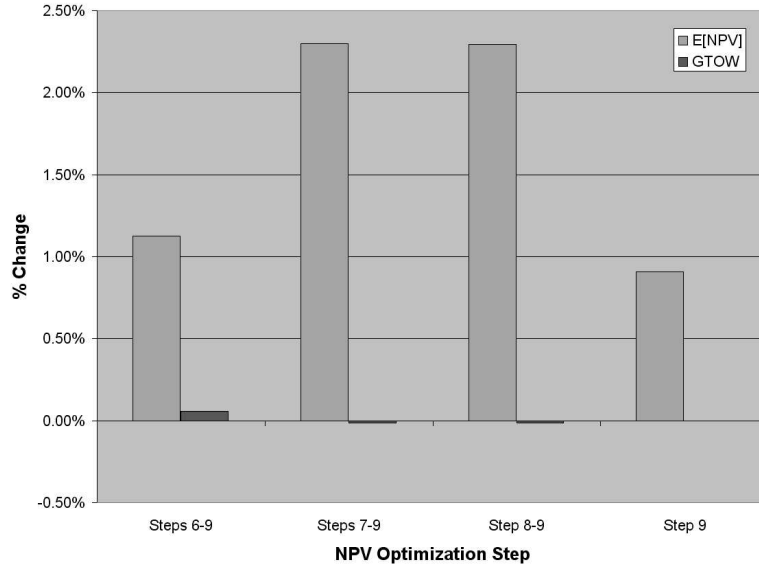


Figure 5-3: Percentage change in E[NPV] and GTOW for value-optimal designs relative to the baseline (min GTOW) design for the BWB. For each case, the multiple steps denoted were replaced with max-E[NPV] optimizations; all other steps remained as in Table 4.1.

5.2.3 Different Objective Functions, Different Designs

As emphasized by Sobieski [32], a different choice of objective function in a MDO formulation will result in a different design. While the E[NPV] optimum may appear outwardly very similar to the baseline performance optimum, several key changes are brought about by using the new objective. From Figure 5-3, it appears that a noticeable increase in E[NPV] can be gained for little change in the GTOW. Further, the GTOW is seen to actually decrease by a very small margin (0.01%), suggesting that the baseline design may not have been fully converged on a minimum-GTOW solution. Closer inspection of the E[NPV]-optimal design explains these findings and demonstrates that the design has actually moved to a nearby, but different, place in the design space.

Figure 5-4 compares the baseline and E[NPV]-optimal designs and Table 5.1 summarizes key differences between the two designs, relative to the baseline design. The differences in geometry and overall size between the two designs are not significant, again suggesting that the two solutions are in the same part of the design space. How-

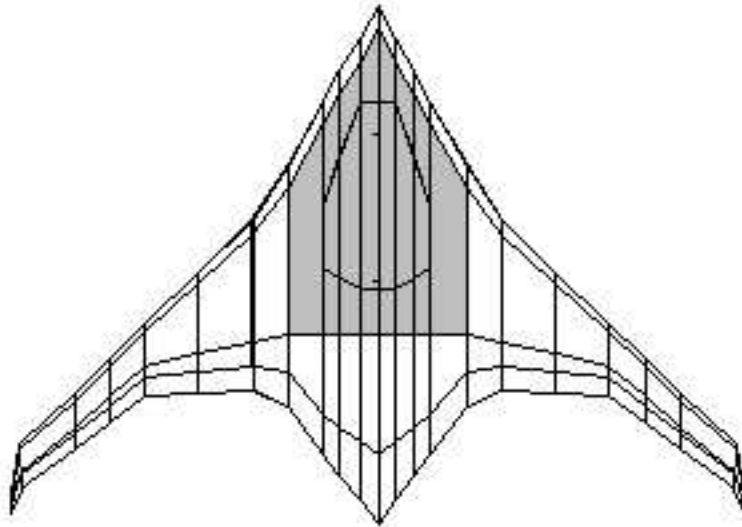
ever, a more detailed breakdown of the layout and weight shows that the E[NPV]-optimal design in Figure 5-4(b) trades aerodynamic performance and fuel efficiency, mainly as a result of reduced loading of the outer wing sections, for a lower operating empty weight (OEW), attributable largely to reduced structural weight. Consequently, the overall GTOW is lower and manufacturing costs are reduced.

Table 5.1: Percentage changes in E[NPV]-optimal design relative to baseline design.

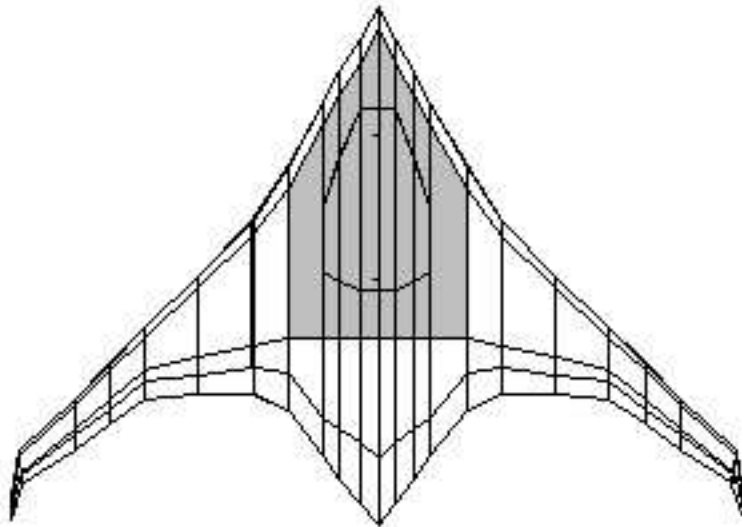
Parameter	% Change
GTOW	-0.01%
OEW	-0.45%
Structural Wt.	-1.1%
Fuel Wt.	+0.51%
Gross Area	+2.2%
Aspect Ratio	-2.2%
Leading Edge Sweep	-0.85%
Chord	
Root	+0.30%
Tip	-23%
Cruise L/D	-0.95%
Cruise C_L	+1.2%
E[NPV]	+2.3%
Unit Price	-0.14%
Unit Cost	-0.59%

As propagated through the financial models, this results in a lower price due to the lifecycle cost correction for increased fuel consumption in (3.2), but also lower cost, as the cost varies proportionally with weight — hence a greater expected value. Despite the appearance of little change in the GTOW, the ratio between structural and fuel weights shifts, ultimately decreasing the overall GTOW slightly and improving the expected program value. This captures the idea that changing the objective function will change the design, in this case since the sensitivity of E[NPV] is greater than that of the GTOW in this part of the design space.

A natural tradeoff between low weight and aerodynamic efficiency exists, but a long-term perspective of aircraft design shows that structure has often been subjugated to meet the requirements of aerodynamic performance [33]. Where improvements in materials and structural design actually benefitted aerodynamic design early



(a) Baseline design planform.



(b) Maximum-NPV design planform.

Figure 5-4: Comparison of design outcomes for baseline min-GTOW optimization and best-case max-E[NPV] optimization.

in the history of powered flight, later advances to make lightweight, optimal structures revived the idea that tradeoffs should be made between the two disciplines. Such were the roots of aeroelastic analysis, and joint structural-aerodynamic MDO to balance the conflicting design needs. In light of this progression, the addition of financial considerations to the design problem and the resulting effect on the question of trading aerodynamics for weight can be viewed as a new and necessary step towards truly optimized aircraft.

The $E[\text{NPV}]$ -optimal solution also demonstrates how the value-based approach can improve the value as intended, although perhaps not dramatically in the case of the BWB problem setup under consideration. In the early stages of the optimization, the design is poorly defined, and the results indicate that the optimizer has difficulty finding a solution to satisfy all design requirements while attempting to maximize $E[\text{NPV}]$. The sequences featuring $E[\text{NPV}]$ as the objective in steps 2 through 6 have more difficulty converging in the early design stages than the baseline case. Conversely, when the design is more fully developed in the latter stages, replacing the minimum GTOW objective with a maximum $E[\text{NPV}]$ objective has the desired effect but the problem has settled in the same general part of the design space as in the baseline case. In effect, the BWB problem as posed in WingMOD appears constrained such that, in order to find a technically feasible solution, it is difficult to improve significantly on the financial outlook of the program. In addition, the ability to improve program value is limited by the resolution of the cost models, which are based principally on component weights at a coarse scale.

The increase in program value of 2.3% is small; but, in an industry where profit margins are extremely tight, this difference could have a significant impact on the decision of whether to proceed with a program.

5.3 Stochastic $E[\text{NPV}]$ vs. Deterministic NPV

An important question to address is whether similar improvements in program value could be achieved by using a traditional deterministic value metric as the objective

function. The BWB value-based optimization was repeated using the deterministic NPV, defined in (2.1), as the objective function in steps 7 through 9. The demand is assumed to grow from the baseline demand level over the program span at an empirically-derived rate of 4.43% per year [17]. For the NPV metric, it is necessary to select a risk-adjusted discount rate. Two cases were considered: $r_d = 12\%$ and $r_d = 20\%$. A comparison between the resulting “NPV-optimal” designs and the E[NPV]-optimal design found previously (presented in Table 5.1) serves to illustrate that the stochastic calculation of E[NPV] according to (2.2) is a better optimization objective than the traditional deterministic value calculation, despite increased computational expense.

Two separate optimizations were run with deterministic NPV as the objective function: calculated in one case at $r_d = 12\%$, and $r_d = 20\%$ in the other. The resulting deterministic valuations were negative, indicating that for either discount rate the program would not be profitable. For more meaningful comparison, all three solutions were evaluated according to all three value metrics (i.e., NPV at $r_d = 12\%$ and 20% , and E[NPV] for each of the “ $r_d = 12\%$,” “ $r_d = 20\%$,” and E[NPV]-optimal solutions). This comparison is summarized in Table 5.2.

The comparison of these three designs shows two important problems with the deterministic value calculation. First, deterministic NPV is not an appropriate metric for assessing the profitability of an aircraft program, which has a long time span and a significant amount of uncertainty associated with market conditions. The NPV values corresponding to the designs in Table 5.2 are pessimistic — both because the value of flexibility is not considered, and also because use of a high discount rate to capture risk causes profits in later program years to carry very little weight. Moreover, the NPV result is highly dependent on the assumed value of r_d .

A second, separate issue is that deterministic NPV is not an appropriate metric to use as an objective function. Although the deterministic NPV estimates found above are poor representations of the program value, the computational cost of optimizing the design using NPV rather than E[NPV] is reduced by 90%. One could therefore conceive of using the efficient, deterministic calculation as an objective function in the

Table 5.2: Comparison of designs using E[NPV] vs. deterministic NPV as optimization objectives, expressed as percent increase or decrease relative to E[NPV]-optimal design.

Parameter	% Change	
	$r_d = 12\%$	$r_d = 20\%$
GTOW	+0.04%	+0.26%
OEW	-0.36%	-0.63
Structural Wt.	-0.85%	-1.5%
Fuel Wt.	+0.53%	+1.4%
Cruise L/D	-0.46%	-1.2%
Cruise C_L	-1.2%	-1.0%
NPV		
$r_d = 12\%$	+0.11%	-2.4%
$r_d = 20\%$	+0.52%	+0.62%
E[NPV]	-0.58%	-3.7%
Unit Price	-0.42%	-3.9%
Unit Cost	-0.46%	-0.78%
Computation time	-90%	

optimization process, and then to subsequently evaluate the resulting NPV-optimal designs using the more expensive stochastic method. However, the E[NPV] results in Table 5.2 clearly show that this is not a viable approach.

With the NPV objective calculated using $r_d = 12\%$, the expected value of the resulting design differs from the overall maximum E[NPV] by only 0.58% of the optimal value. At the higher discount rate of 20%, however, E[NPV] for the NPV-optimal design is significantly worse — in fact, the minimum GTOW objective used in the baseline case yields a more profitable design than the deterministic NPV objective. While the additional computational expense incurred in optimizing for E[NPV] represents only a small improvement over simply optimizing for NPV at a discount rate of 12% in this case, it becomes worthwhile at a rate of 20%. (The maximum timeframe for a single optimization sequence is on the order of one day.)

These differences are directly related to the choice of objective and its effect on the optimization progress. At both discount rates, the resulting designs gave up aerodynamic efficiency and lower fuel consumption to decrease structural weight. While the marginal unit cost for each of the resulting designs is lower than that of

the E[NPV]-optimal design, the prices are similarly lower due to the lifecycle cost adjustment in (3.2). This outcome is a side effect of the the cost model, specifically for non-recurring cost, which is based on the weight of the aircraft. At the higher discount rate (20%), the costs incurred earlier in the program have a greater effect on the overall value, since later profits have a negligible effect due to discounting. This phenomenon is illustrated in Figure 5-5, which shows the relative annual discounted cash flows for each NPV-optimal design. As a result, the optimization seeks to reduce the impact of development costs by reducing the structural weight. For a higher discount rate, this effect is magnified, resulting in an even worse design and a less favorable valuation. Using a risk-adjusted discount rate causes the optimization, and consequently the decision-maker, to focus too heavily on the near-term cash flows. In an aircraft program, large costs are necessarily incurred early in the lifecycle and revenues are not realized until later. Such overemphasis on the short term leads to poor decisions.

It is not surprising then that the E[NPV]-optimal solution performs worse than either maximum-NPV design, in terms of NPV, for three of the four comparisons in Table 5.2. Since the NPV-optimized solutions were both driven to lower-weight configurations to keep initial costs low, the (relatively) heavier E[NPV]-optimal design fares worse according to the NPV metric due to the effects of discounting on future profits. Again, the results from valuation using NPV are heavily dependent on the choice of discount rate, and in this case even give a misleading answer by indicating that the inferior NPV-optimal solutions may be more profitable than the E[NPV]-optimal design.

The significant disparity in designs resulting from the use of different values for r_d suggests that E[NPV] is the better choice of design objective given the inherent difficulty in choosing an appropriate discount rate. As opposed to adjusting r_d upward to account for risk, the stochastic valuation considers uncertainty explicitly. Using the DP algorithm also models the value of flexibility to respond in real-time to program events, thus avoiding unfavorable design changes due to the effects of over-compensating for discounting.

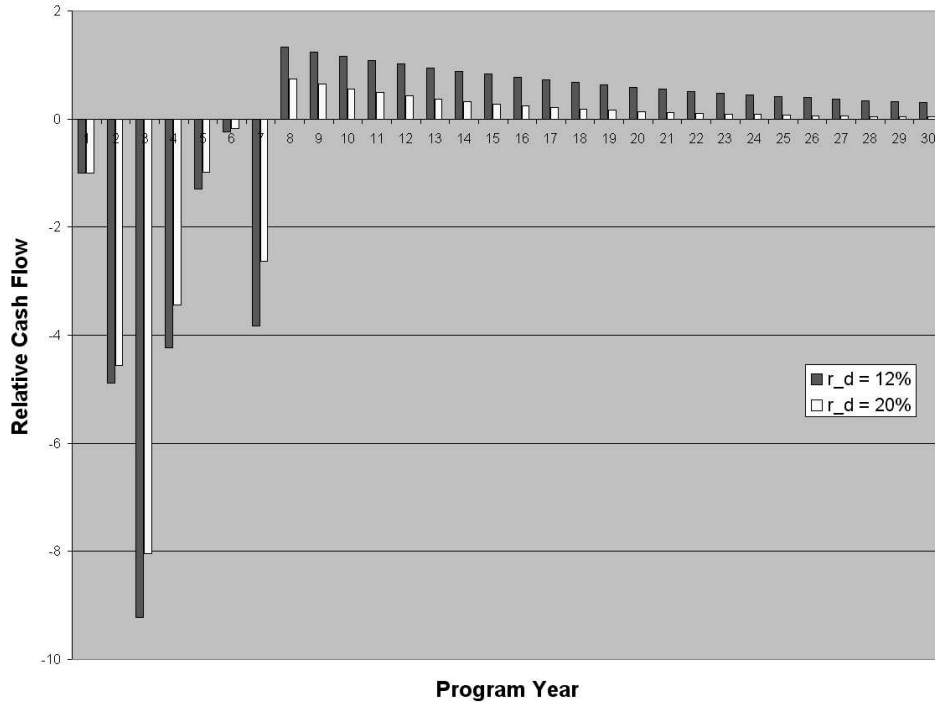


Figure 5-5: Series of cashflows for program designs optimized using deterministic NPV at discount rates of 12% and 20%.

5.4 Application of Value-Based MDO: Setting Design Requirements

An important potential use of this new value-based design methodology is to determine how to best set program requirements and performance specifications. By optimizing the design of commercial aircraft to maximize the expected value of a program, the impact of program decisions may also be better understood. These could include managerial decisions, such as how to best proceed with a program given particular market conditions, or technical decisions to set design performance requirements. Effects of said decisions can now be captured in terms of a specific dollar amount, and as outputs of the value-based MDO process, the resulting tradeoffs between designs will be financially optimal. Improved understanding of the financial implications of program decisions leads to better decisions being made. Examples are presented of the design tradeoffs inherent in setting the range and speed requirements for the BWB using the value-based approach.

5.4.1 Range vs. $E[\text{NPV}]$

This issue was examined in the context of the range requirement for the BWB, initially set at 7800 nmi. Adjusting the performance range may be a necessary step in the design or marketing processes. Such a case is exemplified by the 7E7 program, as mentioned in Chapter 1, where Boeing offered a modified shorter-range version along with the initially planned long-range design to meet the needs of the launch customer [26]. An aircraft with relatively long-range capability may be utilized most often on shorter-range routes by the airline customer, and its performance (namely in terms of fuel burn) will suffer from operating away from the design range. Just as the aerodynamic performance will vary with the range, so too will the financial characteristics of the design. In such a case, it is desirable to have an understanding of how setting the design requirement to best meet the customers' needs will additionally affect the profitability of the design. A traditional MDO approach would measure the change in terms of the impact on the minimum GTOW objective; the improved methodology is able to assess the impact on $E[\text{NPV}]$ directly.

The BWB concept was re-optimized for range settings varying from 5500 nmi to 9500 nmi. Resulting trends for the GTOW and $E[\text{NPV}]$ are presented in Figure 5-6. At most design points, the GTOW increases with increasing range as expected, due to the need for more fuel and corresponding structural growth. The $E[\text{NPV}]$ grows almost linearly between 6000 and 8500 nmi. For higher ranges, the slope begins to decrease. Finally, the trend reverses, and the 9500 nmi design is actually less profitable than the 9000 nmi design. This behavior is a function of the financial models, notably Equation (3.2) for price, which varies linearly with range. At a great enough range, however, the lifecycle cost adjustment for the necessary increase in fuel consumption outweighs the benefit of longer range. It was assumed for this analysis that the baseline demand remains constant. As per the financial models, baseline demand is a function of wide- or narrowbody classification and passenger capacity. In reality, range would certainly have some impact on the demand for an aircraft.

Comparison to designs optimized for performance over the same set of ranges, as

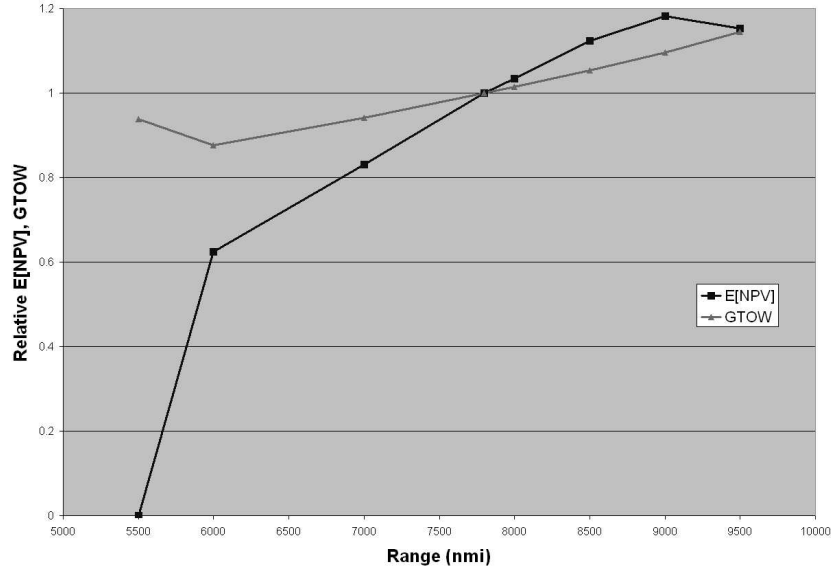


Figure 5-6: Comparison of trends for value-optimal E[NPV] and GTOW as a function of range, normalized by the E[NPV]-optimal design values.

seen in Figure 5-7, illustrates the benefits of using value as the design objective in addition to simply evaluating the design based on a combination of performance and financial analysis. At longer ranges, there is less disparity between performance- and financial-optimal designs, but at lower ranges the discrepancies become increasingly wider. Specifically, as shown in Table 5.1 and discussed previously, the E[NPV]-optimal (7800 nmi) design represents a 2.3% improvement in E[NPV] over the baseline; at the lower 6000-nmi range, the design optimized for value has an E[NPV] 19% greater than the corresponding performance-optimal design. In the case that a manufacturer wished to determine the value of a shorter-range, 6000-nmi variant in addition to the baseline 7800-nmi version, the traditional GTOW-minimum design would add far less value to the program than the E[NPV]-optimal 6000-nmi analogue. Program decisions based on performance-only optimization and analysis could be quite costly to the manufacturer in this case.

Key differences between the two 6000-nmi designs are summarized in Table 5.3, normalized as a percentage of the design optimized for GTOW. The much more impressive increase in value at a lower range is attributable to several factors. Overall GTOW, as well as structural and fuel weights, are lower on the aircraft optimized

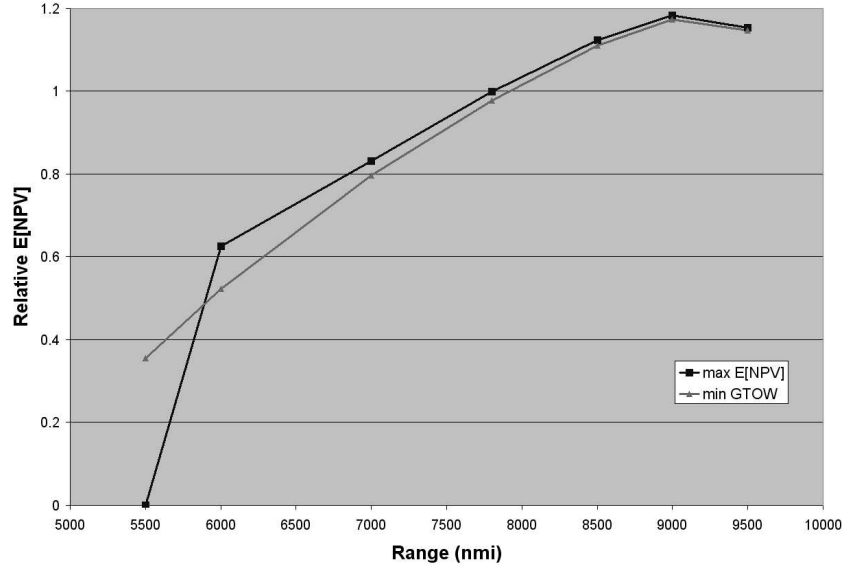


Figure 5-7: Comparison of $E[\text{NPV}]$ trends for performance- and value-based optimizations as a function of range, normalized by the $E[\text{NPV}]$ -optimal design value.

for $E[\text{NPV}]$. Partially this is due to numerical issues with the GTOW minimization, as opposed the physical representation of the design. Scaling problems prevented the solution from fully converging in twice as many iterations. In addition, the design maximized for value sought to decrease the structural weight to lower costs, as discussed for previous examples — but not at the expense of aerodynamic performance and fuel efficiency in this latest case. By attempting to maximize $E[\text{NPV}]$, the minimization of structural and fuel weights are effectively decoupled to simultaneously minimize cost and maximize price. In other words, by minimizing the structural weight instead of GTOW, the fuel weight and aerodynamic performance can remain essentially unchanged (as seen in Table 5.3). Fuel efficiency is improved nonetheless by the decrease in structural weight, resulting in an all-around improved design. Results are similar for the 7000-nmi design.

Figure 5-8 shows that over the sweep of ranges examined, the GTOW is nearly identical for the maximum- $E[\text{NPV}]$ and minimum-GTOW solutions at all but one range setting. This furthers the argument that the performance-optimal design does return the best GTOW, as expected, but not the best value, as hypothesized. By choosing maximum $E[\text{NPV}]$ as the optimization objective instead, a different break-

Table 5.3: Percentage changes in value-optimal 5500- and 6000-nmi design parameters relative to corresponding GTOW-optimal designs.

Parameter	5500 nmi % Change	6000 nmi % Change
GTOW	+9.7%	-0.75%
OEW	+13%	-0.50%
Structural Wt.	+20%	-1.2%
Fuel Wt.	+8.4%	-1.4%
Gross Area	+1.8%	-1.4%
Aspect Ratio	+1.2%	+9.5%
Leading Edge Sweep	+4.6%	+6.2%
Chord		
Root	-7.8%	-0.07%
Tip	+10%	-13%
Cruise L/D	+1.0%	+0.70%
Cruise C_L	+7.8%	+0.65%
E[NPV]	-100%	+19%
Unit Price	-9.8%	+1.5%
Unit Cost	+10%	-0.74%

down of the optimum GTOW is found that returns a higher program value. The fact that the overall GTOW is so similar in both cases is seemingly a byproduct of the many constraints on the design problem necessary to ensure a feasible design.

These results should be contrasted, however, with performance- and value-optimal designs having a range of 5500 nmi. Differences between these designs, relative to the minimum-GTOW case, are also summarized in Table 5.3. At this range, the design optimized for E[NPV] actually ends up having zero value, obviously far worse than the GTOW optimization. The design's structural weight increases markedly, while fuel efficiency is improved only slightly. As with the other comparisons at lower ranges, it appears that the new objective has moved the design solution to a different local optimum, although a significantly worse point in this case. In this case, though, the optimization is unable to move the design in a direction to improve the design to a profitable value. When E[NPV] is zero, depending on how the problem is conditioned, it may be extremely difficult for a gradient-based optimizer to move from the current point to one where the value is non-zero. If the sensitivities in all

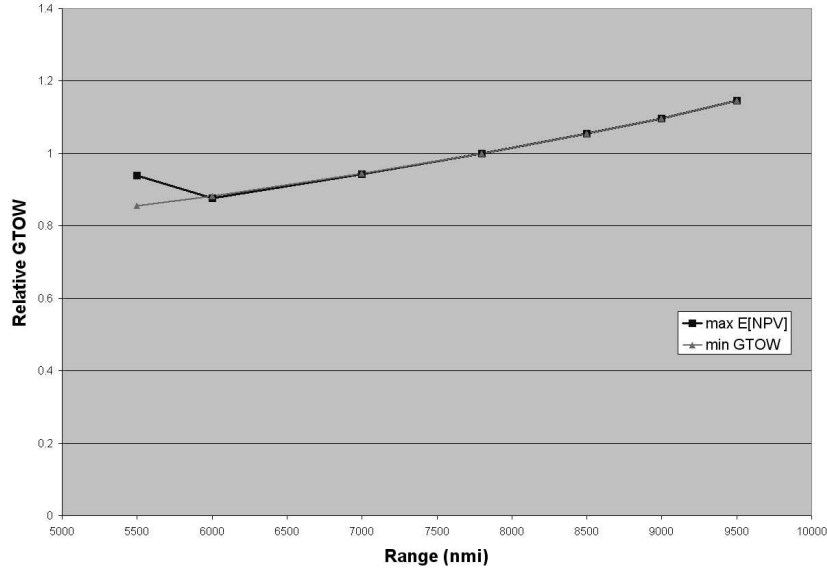


Figure 5-8: Comparison of GTOW trends for performance- and value-based optimizations as a function of range, normalized by the E[NPV]-optimal design value.

directions are zero at such a point, it will appear to the optimizer that no improvement in E[NPV] is possible. As such, starting with a profitable design may be necessary to use E[NPV] effectively as a design objective. This, again, is a numerical problem with the optimization since a lower-GTOW design with non-zero E[NPV] clearly exists, as seen in Figure 5-8 (also referring back to Figure 5-7).

An example of the practical application of these results could relate to a decision concerning whether to decrease the range of the BWB to potentially better satisfy customer demand. If this decision were made using the associated values for GTOW-optimal designs, they would show that the value drops significantly and the longer-range aircraft is highly preferable. By analyzing the trend for the value-optimal design, the lower-range design is found to represent less of a drop-off in value from the original, longer-range concept. Having this result would then allow the program managers to make a more fully-informed decision about the range. As mentioned, though, the demand model in the simulation does not distinguish between, say, 6000-nmi and 8000-nmi designs; more realistically, better demand estimates would be taken into account in the value calculation.

By using E[NPV] as the design objective, the tradeoffs between the changing range

and value are realized. A minimum GTOW objective would only demonstrate the increase in GTOW and other changes to the design performance that correspond to greater range. Subsequent value analysis of the strictly performance-based designs would not be guaranteed to find the optimal tradeoff in $E[\text{NPV}]$ for different ranges. Optimizing with maximum $E[\text{NPV}]$ as the objective instead allows both trends to be found simultaneously, and indicates how the program can best set the range requirement in terms of its effect on design performance and program value.

As seen above, the improvement in the expected program value outcome using the new objective demonstrates that $E[\text{NPV}]$ can be a better choice of objective than GTOW for lower design ranges for this specific design case. In general, however, it is indicative of the potential for the value-based MDO approach that has been established to more dramatically improve the value of designs than previously shown. For cases other than the baseline BWB design, the new objective is able to cause more marked changes in the design to improve the expected value of the program. This example makes clear the importance of evaluating an $E[\text{NPV}]$ -optimal solution rather than a design based on performance alone when making design decisions.

5.4.2 Speed vs. $E[\text{NPV}]$

An analogous study can be performed with respect to the cruise speed, to determine how to best set a cruise Mach number to maximize the value of the program. Again, the importance of such analysis is made clear by the 7E7 example, and the need to weigh the value of speed versus other performance concerns in choosing to develop the 7E7 rather than the Sonic Cruiser.

Figure 5-9 shows the resulting trend for a sweep of Mach settings from 0.8 to 0.9 for the conditions related to the cruise portion of the mission profile, as described in [35]. The baseline speed, 0.85 M, is very close to the actual best-case speed of 0.84 M, with only a 0.16% difference in $E[\text{NPV}]$. Optimizing the BWB design for both higher and lower cruise Mach settings is less beneficial. At the lower end of the speeds evaluated, setting the cruise requirement to 0.8 M results in an $E[\text{NPV}]$ 12% worse than the $E[\text{NPV}]$ -optimal solution. For higher speeds, the trend is even

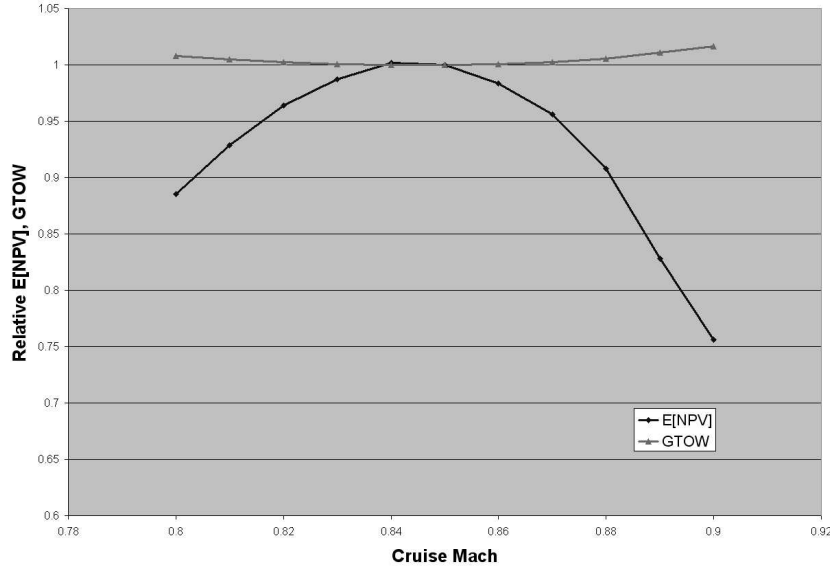


Figure 5-9: Comparison of trends for value-optimal E[NPV] and GTOW as a function of cruise Mach number, normalized by the E[NPV]-optimal design values.

more detrimental, with the 0.9 M design having a program value 24% worse than the optimum.

Within the assumptions of the models, which will be discussed shortly, higher-speed designs are less valuable than those at lower speeds, since the increase in slope is greater at the higher end of the Mach sweep considered. A comparison of the E[NPV]-optimal, Mach 0.8, and Mach 0.9 designs illustrates why this is the case, as summarized in Table 5.4 as percent differences relative to the previous E[NPV]-optimal (0.85 M) design. The slower design at 0.8 M has been optimized for a slight improvement in structural weight over the optimal design, with a lighter wing, and also features better aerodynamic qualities. The fuel weight, however, is much higher in spite of the improved aerodynamics, which also leads to increased GTOW.

This weight growth might be expected from looking at the Breguet range equation for the cruise flight segment [30],

$$R = \frac{V}{SFC} \frac{L}{D} \ln\left(\frac{W_i}{W_f}\right) \quad (5.1)$$

where R is the range, V is the cruise speed, SFC is the specific fuel consumption, $\frac{L}{D}$

Table 5.4: Percentage changes in value-optimal 0.8 M and 0.9 M design parameters relative to E[NPV]optimal design at 0.85 M.

Parameter	Mach 0.8 % Change	Mach 0.9 % Change
GTOW	+0.78%	+1.7%
OEW	-0.02%	+1.5%
Structural Wt.	-0.04%	+3.5%
Fuel Wt.	+2.0%	+2.3%
Gross Area	-0.42%	+3.2%
Aspect Ratio	-1.2%	+3.2%
Leading Edge Sweep	-4.3%	+8.0%
Chord		
Root	+0.22%	-0.60%
Tip	+4.6%	+33%
Cruise L/D	+3.0%	-6.8%
Cruise C_L	+14%	-12%
E[NPV]	-11%	-24%
Unit Price	-1.7%	-2.2%
Unit Cost	+0.00%	+2.1%

is the lift-to-drag ratio, and W_i and W_f are the initial and final weights, respectively, for the flight segment. The term $\frac{W_i}{W_f}$ then effectively represents the segment fuel fraction. The speed, V , is decreased from Mach 0.85 to 0.8 for a constant range. This effect is not fully compensated by the increase in $\frac{L}{D}$ given in Table 5.4, so the fuel fraction would necessarily increase (due to the longer flight time) for constant SFC. The decrease in price associated with increased fuel burn, despite an equivalent unit cost, accounts for the lower E[NPV] of the low-speed designs.

Conversely, the 0.9 M case features a much heavier wing and thus overall structure, coupled with less favorable aerodynamics, compounding its increase in fuel consumption. Both the price and cost suffer as a result, explaining the much greater drop off in E[NPV] at faster speeds compared to lower speeds.

It is important to note, however, that the model did not account for changes in SFC due to the varying design speeds. This would undoubtedly affect the trend in Figure 5-9, as the SFC would be lower at lower Mach settings, and higher in the opposite case. From (5.1), these effects would translate to lower GTOW around 0.8

M, and even higher GTOW around 0.9 M. Propagated through the financial models, it is reasonable to assume that the slope of the curve would then decrease at lower speeds and drop off even more steeply at higher speeds.

An additional limitation of this study is that the lifecycle cost adjustment, ΔLC , in (3.2) accounts for the operating cost effects of increased fuel consumption but not the utilization benefits of faster speeds. Shorter travel times resulting from higher cruise speeds would allow the airline operator to use the aircraft more often, the appeal of which could be accounted for by a price increase analogous to the fuel burn effect. It is unclear to what extent such an adjustment would offset the effects of varying the SFC, so the trends shown in Figure 5-9 could remain similar. Such an adjustment to account for utilization in the price would be a useful extension of the financial models.

Thus, as with the range study, $E[\text{NPV}]$ varies with speed due to the effects of the financial models in the calculation of the objective function. Again, this occurs despite the fact that the design is still constrained to a fairly constant layout, as seen by the very minor variation in GTOW with cruise Mach in Figure 5-9, except at much higher speeds.

Another recurring trend is that the designs optimized for maximum $E[\text{NPV}]$ are more profitable than performance-only designs for minimum GTOW across all speeds considered. This result is depicted in Figure 5-10. As shown previously, the $E[\text{NPV}]$ -optimal solution features an improvement of 2.3% over the minimum-GTOW solution. At lower speeds, the gap widens and $E[\text{NPV}]$ for the minimum-GTOW 0.8 M design is 12% worse than the corresponding maximum- $E[\text{NPV}]$ solution. For higher speeds, the disparity is smaller, with a 5.3% decrease in $E[\text{NPV}]$ from the 0.9 M value-optimal design to the performance-optimal equivalent. As was the case at shorter ranges in the previous section, the ability of the new objective to influence the design seems to be more important at lower speeds.

A breakdown of the performance-only and financial optima at 0.8 M illustrates why the difference in $E[\text{NPV}]$ is more noticeable. Table 5.5 shows only a relatively small decrease in structural weight in the value-optimal design; most of the difference

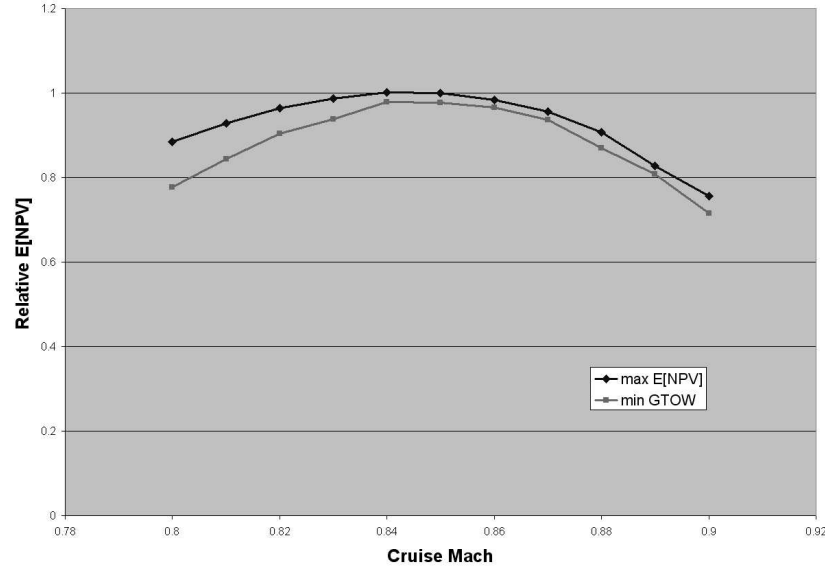


Figure 5-10: Comparison of E[NPV] trends for performance- and value-based optimizations as a function of cruise Mach number, normalized by the E[NPV]-optimal design value.

in E[NPV] is made up by the higher price of the maximum-E[NPV] solution due to improved fuel efficiency. This result is interesting in that the optimization drove the design to decrease the fuel consumption as opposed to decreasing the structural weight, as seen in previous comparisons between optimizations minimizing GTOW versus maximizing E[NPV].

On the other hand, the result is similar in that the new objective causes the optimizer to drive the design to a different part of the design space by redistributing the structural and fuel weight breakdown of the BWB in order to improve the program E[NPV]. Figures 5-9 and 5-11 also show that, as with the sweep of range settings, this is again accomplished despite only small variations in the overall GTOW due to the design constraints.

Figures 5-10 and 5-11 indicate that Mach 0.84 is the optimal cruise speed for using E[NPV] and GTOW as figures of merit to assess financial and performance viability, respectively (with the financial assessment taking performance into account, as well). Several other traditional metrics could be evaluated instead that relate the performance of the design to its marketability in order to estimate the optimum cruise

Table 5.5: Percentage changes in value-optimal 0.8 M design parameters relative to corresponding GTOW-optimal design.

Parameter	% Change
GTOW	-0.70%
OEW	-0.23%
Structural Wt.	-0.54%
Fuel Wt.	-1.4%
Gross Area	-2.1%
Aspect Ratio	-1.8%
Leading Edge Sweep	+7.2%
Chord	
Root	+0.47%
Tip	-34%
Cruise L/D	-0.97%
Cruise C_L	+1.4%
E[NPV]	+14%
Unit Price	+1.4%
Unit Cost	-0.46%

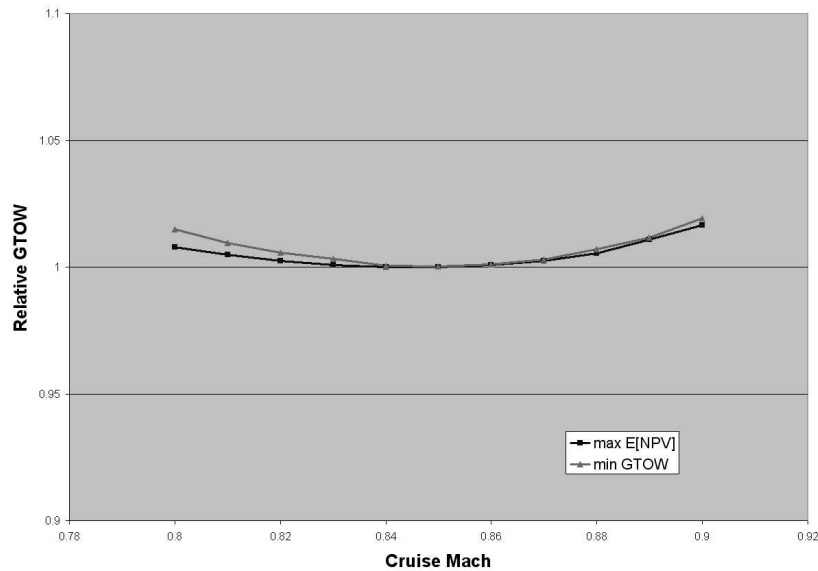


Figure 5-11: Comparison of GTOW trends for performance- and value-based optimizations as a function of cruise Mach number, normalized by the E[NPV]-optimal design value.

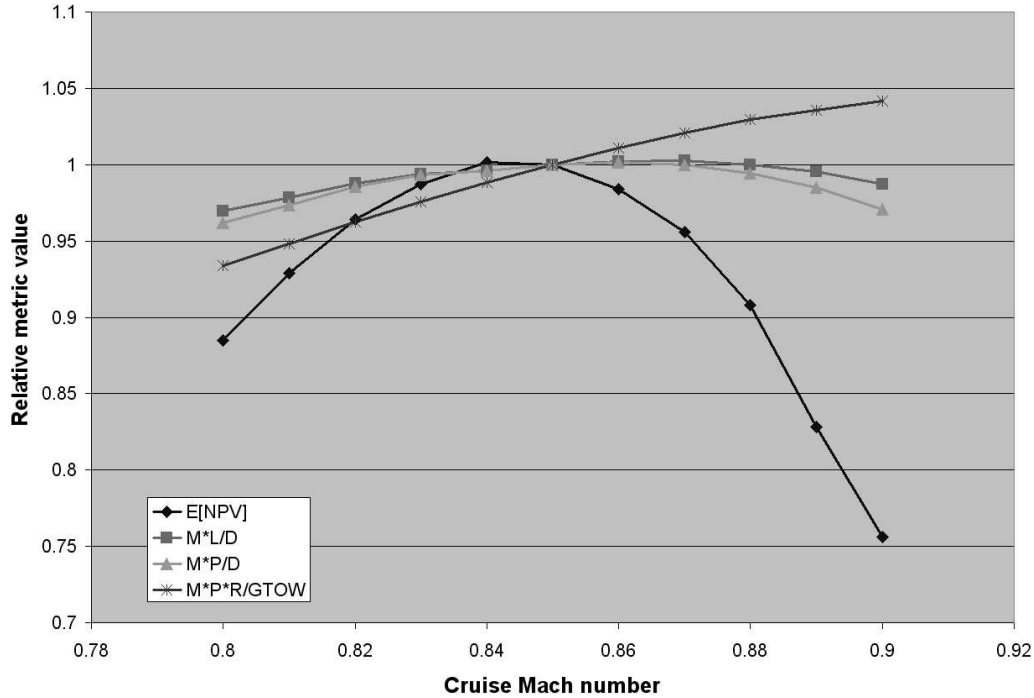


Figure 5-12: Trends for design performance and value metrics as a function of cruise Mach number, normalized by their respective baseline (0.85 M) values.

speed. Figure 5-12 presents the results for E[NPV] and three other such metrics for the range of Mach numbers considered previously, normalized by their value at the baseline cruise Mach (0.85). The additional figures of merit are as follows:

- $M \times \frac{L}{D}$ – Mach number multiplied by lift-to-drag ratio;
- $\frac{M \times P}{D}$ – Mach number multiplied by payload weight, divided by drag; and
- $\frac{M \times P \times R}{GTOW}$ – Mach number multiplied by payload and range, divided by GTOW.

The first metric is derived from (5.1) for constant SFC and weights, whereas the latter two focus on the traditional design merits of increased payload and range, traded against decreased GTOW. Emphasizing only speed and $\frac{L}{D}$, 0.87 Mach is the new optimum, reflecting better aerodynamic performance at a slightly higher cruise speed. Taking into account payload capacity instead of overall lift reduces that value slightly, to 0.86 M, recognizing that extra speed does not increase capacity as it does drag. Finally, introducing range and the traditional design metric, GTOW, in

addition to capacity shifts the trend dramatically, placing far more value on speed, with an optimum of Mach 0.9 or possibly higher if the trend were extrapolated. In this case, the value of added range is offset somewhat by an increase in GTOW to reflect added fuel consumption, allowing the metric to grow with higher Mach numbers for a fixed payload weight.

None of these design metrics explicitly estimate the profitability of a program, however, and $E[\text{NPV}]$ remains the most complete figure of merit for evaluating the contributions of the individual parameters featured above. This differences between metrics in Figure 5-12 may be evidence that the current financial models used to calculate $E[\text{NPV}]$, or one or more other metrics, do not account for all the necessary effects to determine the optimum cruise speed. Ideally, the models would be modified so that the valuation could encompass the impact on profitability of as many relevant design parameters as possible.

Despite potential limitations of the financial models in their ability to represent the value of cruise Mach, this case study further illustrates the usefulness of a coupled performance and financial approach to design. It provides a new framework for setting program requirements and, specifically, for understanding the impact of cruise speed on profitability. While there may seem to be value in increased speed, by knowing that a higher cruise speed would diminish the value of the program, designers could focus on a Mach setting in a more optimal range. In addition, using $E[\text{NPV}]$ as the objective would allow program decisions to be made with a more complete understanding of the tradeoffs in value when setting design requirements by providing a more realistic valuation than simply analyzing the NPV of a design previously optimized for minimum GTOW.

5.5 Summary

Optimization including financial analysis to maximize program value is shown to, in fact, improve upon the value of designs arrived at via performance-only optimization. The margin for improvement in the best-case scenario was 2.3% of the baseline design

$E[\text{NPV}]$, but additional examples have demonstrated the potential for even greater improvement. In addition, $E[\text{NPV}]$ has been shown to be more sensitive to design changes than the traditional GTOW design metric. By using MDO based upon value rather than performance alone, designs may be refined to enhance their value for solutions that gradient-based optimization of GTOW would not find. As a case in point, the $E[\text{NPV}]$ optimization managed to further reduce the GTOW beyond the baseline “minimum-GTOW” solution while simultaneously improving the value. By trading aerodynamic performance for reduced structural weight to increase profitability, the value-based approach to MDO can be seen as a continuation of the historic evolution of the aircraft design process.

Further, comparison of the results of value-based optimization using a traditional, deterministic NPV metric versus an improved stochastic $E[\text{NPV}]$ calculation underscore that a deterministic valuation provides a fatally flawed estimate of program value, and NPV is ill-suited as a design objective. These failings stem from the use of a risk-adjusted discount rate, which cannot reasonably be expected to fairly account for program risk or design uncertainty — leading in most cases to an undervalued program and bad decisions.

These findings emphasize the need for a new approach to design including financial analysis, using improved methods of valuation and optimization. Such an approach is demonstrated for the examples looking at how to best set specifications for range and cruise speed. By incorporating the $E[\text{NPV}]$ calculation as the design objective, the impact of design decisions on performance and value are understood simultaneously to provide the means for more profitable designs.

Chapter 6

Quantifying Risk

6.1 Introduction

In the MDO methodology and design examples illustrated in the preceding chapters, some design uncertainty was accounted for, specifically the demand volatility. In practice, many additional forms of uncertainty will arise including technical uncertainty related to the design performance, and other forms of financial or market uncertainty. It is desirable to understand the impact of such uncertainty, as well as the related risk faced by the program, by quantifying the effect on program value.

Starting with the previously optimized designs from Chapter 5, varying levels of uncertainty are applied to discover the impact on $E[\text{NPV}]$; results of this analysis are presented in Chapter 7. Techniques for uncertainty analysis to complete these assessments are discussed in this chapter, with a comparison of probabilistic simulation and sensitivity analyses. The trends resulting from the analysis are intended to give both a quantitative estimate of the actual effects of uncertainty on program values and relative levels of risk attributable to different design parameters, as well a qualitative indication of the robustness of the design to business risk.

6.2 Uncertainty and Risk

Any project as complex as an aircraft design is bound to face some degree of technical or financial uncertainty. Brealey and Myers [5] define uncertainty practically, as the idea “that more things can happen than will happen.” As applied to the design problem, it is the possibility of unexpected variability in program parameters, with the consequence that not all features of the design may turn out as modeled. A key issue then becomes how well the design is able to maintain its performance and profitability given changes in some aspects of the program. When uncertainties are realized, the expected program value will increase or decrease depending on the form and magnitude of the variability. Post-optimality analysis is required to quantify such changes in $E[\text{NPV}]$ for the previously described optimum BWB design.

A distinction must be made between risk and uncertainty, although the two concepts are related. Risk is the likelihood of an unexpected outcome due to uncertainty. Or, as Deyst [11] defines it, “risk in product development is defined as the probability that the product will not satisfy all of its requirements.” While risk usually has a negative connotation — i.e., the chance of a less favorable design or less profitable investment — it should be noted that more beneficial designs may also result from variability. By measuring the impact of uncertainty on $E[\text{NPV}]$, the “riskiness” of the program can be better understood, with a focus on *how* the value changes. The relative risks due to different forms of uncertainty will be investigated, then, to show which parameters have the greatest impact on $E[\text{NPV}]$. Unexpected changes in those parameters will then have been shown to pose the greatest risk to the program value.

An additional topic of interest is the robustness of the design value, or its ability to retain its intended $E[\text{NPV}]$ when uncertainties arise. The primary consideration with respect to this issue is to ensure that value robustness is not lost by maximizing $E[\text{NPV}]$, relative to a performance-optimal solution. By optimizing the program value, the design has been pushed to an extremum in the design space, so by definition, changes to program parameters will cause a decrease in $E[\text{NPV}]$, unless the design is re-optimized.

The studies undertaken in the following chapter do not involve probabilistic analysis and should not be confused with probabilistic design, such as design for reliability or robust design. In design for reliability, the solution is optimized such that a guaranteed level of performance is met based on probability distributions of uncertainties facing a project. Robust design instead seeks to minimize the variance in the objective given likely levels of uncertainty that a program might see.

However, the program valuation expressed by $E[\text{NPV}]$ is a probabilistic design metric. Some elements of probabilistic analysis, namely the demand volatility, have been incorporated into its calculation. Additionally, some level of robustness is inherent in the stochastic valuation and its optimization through the modeling of decision-making flexibility, which allows the program to retain value given demand variability. In terms of robust design, then, a limited ability to mitigate the effects of uncertainty is captured by optimizing $E[\text{NPV}]$, but the robustness with respect to design changes related to parameters besides demand is not explicitly considered.

For the purposes of risk analysis, though, $E[\text{NPV}]$ is maximized as seen in Chapter 5, and parameters of the resulting design are varied to quantify the level of change in value attributable to various forms of uncertainty. Modifying the suggested value-based MDO methodology for robust design to reduce the variability of $E[\text{NPV}]$ to a wide range of parameters, or additional probabilistic analysis to define the likelihood of various levels of decreasing value as well as the decrease itself, would represent useful extensions in the effort to better define and quantify risk.

In order to evaluate the impact of uncertainty on the optimal design, an analysis technique is required. Given levels of variability in program parameters must be translated into changes in $E[\text{NPV}]$ in order to assess risk.

6.3 Uncertainty Analysis

Several techniques for probabilistic analysis are available, most notably Monte Carlo simulation (MCS) and sensitivity analysis. While MCS would perhaps be able to more completely represent the effects of uncertainty on program value by generating

simulated distributions of $E[\text{NPV}]$, it is not appropriate to characterize the value with a probability distribution, as will be explained below. For this reason and a number of practical concerns, a sensitivity analysis approach has been devised to quantify the impact of uncertainty on $E[\text{NPV}]$ and thus gain insight into the business risk facing a program.

6.3.1 Monte Carlo Simulation

A commonly used probabilistic approach for assessing the effects of uncertainty is MCS. To apply MCS to valuation analysis, a distribution of values for one or more key program parameters must be specified first. Then, thousands of repeated runs of the valuation algorithm are conducted, sampling randomly from the specified input parameter distributions. These simulations result in distributions of the resultant program cash flows. From these cash flow distributions, two approaches to determining value can be taken.

The first would be to build a distribution of NPVs. It is tempting to calculate the value from the cash flows associated with each simulation run and generate such a distribution. However, using MCS to build probability distributions of deterministic NPV is not accepted in traditional financial analysis, as discussed in [5] and [34]. NPV is interpreted as the dollar value of a project in the current market; lacking a single number that best represents the actual value for a set level of uncertainty, distributions of NPV are not meaningful.

Other problems are presented by this approach, as well. In building a distribution of NPV, discounting should be done at the risk-free rate. The distribution itself is intended to account for the risk of the venture. Using a risk-adjusted discount rate to account for the opportunity cost would “double count” the inherent risk. Again, while such a more explicit presentation of risk may seem useful, the resulting distribution of NPV is not. In addition, the risk now modeled by probabilities does not account for the opportunity cost of the capital, and is sensitive to the project itself and not necessarily the market.

The same flaws would befall a similar approach to build distributions for $E[\text{NPV}]$.

Although the risk-free rate is already applied, discounting for market risk and opportunity cost are implicitly handled by using the demand volatility, returning to the issue of over-accounting for risk. An exact interpretation of varied $E[\text{NPV}]$ corresponding to set levels of technical or financial uncertainty would also remain unclear.

A second, recommended application of MCS to NPV analysis would be to generate a distribution of cash flows based on uncertainty in the technical or financial parameters of the program. Then an single *expected* NPV could be calculated from all possible cash flows to provide a more accurate or realistic valuation given uncertainty.

For the $E[\text{NPV}]$ metric used as the value-based MDO objective, the same process could be applied, but the nature of MCS may limit its usefulness for the intended analysis. Probabilistic simulation samples from the variability in many different parameters at once to capture their interactions and effects on the outcome. Further, the output of MCS is in the form of probability distributions as opposed to discrete system changes. This approach would not be able to quantify directly the impact on program value of variation from the optimal design in a single parameter.

Additional concerns about the applicability of MCS are specific to the problem at hand and more practically-based. One concern is that MCS involving the DP valuation algorithm would be too computationally intensive to generate a useful number of analyses. For the problem of aircraft design, it also may be difficult to specify or build probability distributions for technical parameters to be used as inputs in the MCS. Public-domain data on aircraft performance and details will contain little information pertaining to design uncertainty for the technical aspects of the design. Distributions can be estimated only by review of the internal history of similar aircraft programs, or by a “best-guess” approach based on the expert opinions of experienced designers. Financial uncertainty may be similarly difficult to characterize, given the relative scarcity of available data upon which empirical distributions can be modeled. The usefulness of the resulting trends in program value may be subject to some debate in either case.

For these reasons, the MCS approach was not pursued in the attempt to quantify risk due to design uncertainty. By instead turning to sensitivity analyses of the

optimum designs, the desired effects may still be achieved.

6.3.2 Sensitivity Analysis

Sensitivity analysis of the optimum design considers small, discrete changes in parameters one at a time to evaluate the effect on the objective. As opposed to building probability distributions to describe technical or financial uncertainty as in MCS, sensitivity analysis evaluates different scenarios to calculate the impact of discrete levels of uncertainty on $E[\text{NPV}]$. The sensitivities themselves are the derivatives of the objective function with respect to varying parameter settings. Sensitivity of the program value to a change in the uncertainty of a parameter can be equated to the business risk associated with that aspect of the design.

In order to calculate these sensitivities, a numerical approach to differentiation is required, since the objective function cannot be evaluated analytically. A finite differencing technique is used to estimate the derivative at varying levels of uncertainty. Given the optimum set of design parameters, x^* , and the corresponding $E[\text{NPV}]$ maximum, the value is recalculated by running the simulation model and valuation algorithm with a slight perturbation h in a single parameter. The difference between the optimum and perturbed values can be used to calculate the derivative, and the approach can be applied in general to any design described by a set of parameters x according to the equations below, from [28].

Based on the Taylor expansion of a function about a point x , for a forward expansion by a small amount h , the derivative can be approximated by forward differencing as follows.

$$f'(x) = \frac{f(x+h) - f(x)}{h} + o(h) \quad (6.1)$$

The function $f(x)$ is the objective function, $E[\text{NPV}]$, for application to sensitivity analysis of the valuation. Truncation error due to the omission of higher order terms is represented by the term $o(h)$.

Taking a backward expansion to $x-h$, as well, the derivative can be approximated

instead via central differencing to decrease the truncation error as follows.

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} + o(h^2) \quad (6.2)$$

Now the truncation error has been reduced since the magnitude of the $o(h^2)$ term will be less than that of the $o(h)$ term in (6.1), for small h . Since the derivative from the central difference is a closer approximation, then, the sensitivities of $E[\text{NPV}]$ to program uncertainty will be calculated using (6.2).

By using sensitivity analyses rather than MCS to assess the risk of a program, the intent is to identify key drivers of program value and quantify their discrete impact on $E[\text{NPV}]$. It is necessary to recognize the tradeoffs made in choosing one approach over the other, however. Sensitivity analysis also has shortcomings, as noted in [5] and as applicable to the aircraft valuation problem. It remains difficult to determine the range of uncertainties that should be analyzed — that is, how to find the likely best- and worst-case scenarios — or how to initially set the perturbation size h . Once again, reasonable bounds and changes must be set using an informed guess, but this may represent a substantially easier task than trying to characterize the possible uncertainty in a given parameter with a probability distribution for use in MCS.

Additionally, the parameters varied individually in sensitivity analysis may in fact be interrelated, which would be captured using MCS. This difficulty may be mitigated by trying to choose parameters encompassing distinct uncertainties, which is not always straightforward, as in the cases of non-recurring versus recurring cost variation discussed in the following chapter. A final benefit of using sensitivity analyses is that the computational time needed to evaluate the sensitivities is greatly reduced from that required for MCS.

6.4 Summary

An approach to the post-optimality analysis of the impact of uncertainty on $E[\text{NPV}]$ has been devised. Sensitivity analysis is performed instead of MCS, in light of the

relative merits and limitations of both methods, in an attempt to evaluate discrete effects on the valuation due to variability in individual program and design parameters. These analyses are carried out using the central differencing method for small perturbations about the optimal design solution and varying levels of further uncertainty.

The resulting sensitivities of $E[\text{NPV}]$ can then be used to show the relative risk faced by the design with respect to the program parameters that have been varied. In the following chapter, several sources of possible technical and financial uncertainty are discussed and example analyses are carried out as described above, in order to quantify the business risks for the BWB case study.

Chapter 7

Business Risk Examples

7.1 Introduction

The business risk of an aircraft program may be quantified by calculating the sensitivity of the design value to technical or financial uncertainty in a design or program parameter. By finding the magnitude of these sensitivities, a number is attached to risk, putting it directly in terms of profitability. In addition, the relative risks associated with different technical and financial aspects can be assessed by comparing the results of the analyses to determine the factors that drive the program value.

Sensitivity analyses have been performed using the BWB example resulting from the value-based MDO methodology developed in Chapter 4, as applied in Chapter 5. In each case, a single parameter of a previously optimized design is perturbed to find the change in $E[\text{NPV}]$, as described in the previous chapter. Both technical and financial uncertainties are examined, resulting in the characterization of the design sensitivities to the key financial aspects of the design: development and manufacturing costs, price, and demand.

Comparisons were made between the sensitivities of the $E[\text{NPV}]$ - and GTOW-optimal designs to investigate the advantages of the value-based MDO given program uncertainties, and specifically to determine if the value-optimal designs display a higher or lower degree of robustness. The robustness may be taken as the ability of the design to retain its value, relative to its baseline $E[\text{NPV}]$, given uncertainty.

Finally, the sensitivity of the NPV-optimal design, evaluated using the traditional deterministic metric at a discount rate of 12%, is contrasted with the results for the E[NPV]-optimal design.

7.2 Technical Uncertainty

A complicated and often cutting-edge venture such as a new aircraft program is subject to a high likelihood of technical uncertainty. This uncertainty could exist in many forms, many of which result in weight growth — hence the basis for the traditional design goal of minimum GTOW. The following analysis of technical uncertainty, then, will focus primarily on the possibility of exceeding the intended design weight. As the GTOW can be subdivided into two main weights subject to uncertainty, taking the design payload to be fixed for the BWB example, the cases of uncertainty in the OEW and fuel weights are considered separately.

When the aircraft GTOW is exceeded, the aircraft will not meet its range specification if payload capacity is maintained, from (5.1). However, the manufacturer still needs to meet performance guarantees to the customer. There are essentially three scenarios that may evolve as the program moves ahead with the design.

1. The aircraft is sold at the higher weight to be used at less than its maximum (intended) range, or with added fuel volume if possible to achieve its intended range. The aircraft may meet the operators' needs, but will be more expensive to operate. This scenario results in higher manufacturing costs or a lower price, or both.
2. The aircraft is redesigned or weight is eliminated in order to meet the original specifications, resulting in higher non-recurring development costs.
3. The aircraft is unable to meet its performance guarantees, either due to outside sources or failed redesign. Additional non-recurring costs may be incurred from attempts to fix the problem, and recurring costs will be higher despite a lower price due to missed performance goals.

For the purposes of the sensitivity analyses on OEW uncertainty presented here, it is assumed that the aircraft is successfully designed to meet its performance specifications (case #2). The subsequent effects on $E[\text{NPV}]$ are modeled as variations in non-recurring cost. To account for uncertainty in the fuel weight, engine SFC is varied explicitly, and case #1 above is applied. As a result, price uncertainty is effectively modeled as well. Some limitations of these assumptions are discussed below with the results of the sensitivity analyses.

7.2.1 Empty Weight

One possible result of technical uncertainty related to structure or installed systems in an aircraft program could be increased OEW, causing the aircraft to exceed its weight goals. In order to meet performance guarantees, it may be necessary to perform extra design work in the developmental stages of the program to reduce the excess weight. Such a scenario would result in an increase in program non-recurring costs. Thus weight uncertainty can be translated into a corresponding increase in non-recurring cost and ultimately a change in the program value.

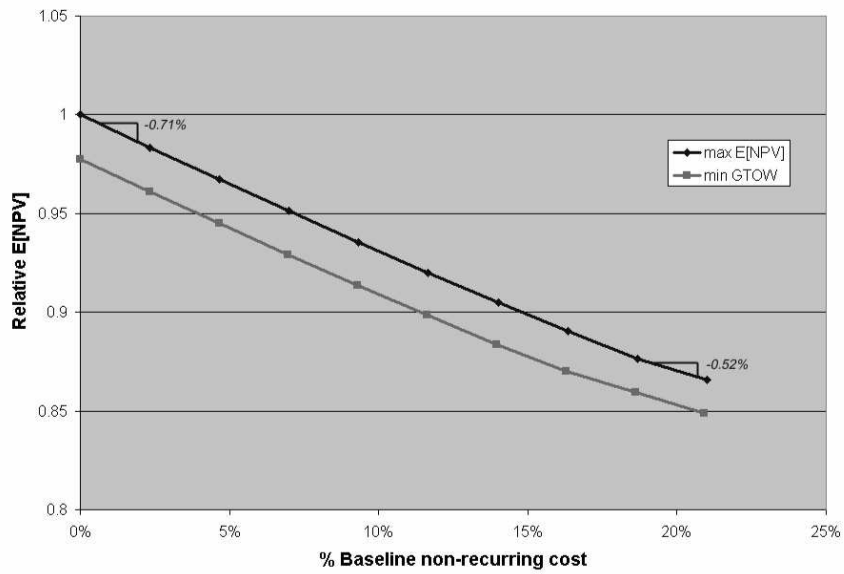
While it would be desirable, then, to find the sensitivity of $E[\text{NPV}]$ to weight directly, to be able to assign an accurate or meaningful dollar figure to the cost of engineering extra weight “off” of a design is not possible from available cost data. Instead, performing sensitivity analysis on $E[\text{NPV}]$ due to changes in non-recurring cost will provide insight on the same trends that would result from weight uncertainty. From the cost model, extra weight equates to extra cost, so non-recurring cost is a suitable surrogate for OEW in the sensitivity study. Increases in non-recurring cost up to approximately 20% of the baseline design (using a constant step size) were examined to find the related effect on $E[\text{NPV}]$; no decreases in development costs were considered, since a lower-than-expected OEW would not necessarily translate into cost savings. The change in non-recurring cost was added in the final time period of the development stages to represent re-engineering after a significant amount had already been invested in design and capital costs.

Figure 7-1(a) shows the results of this sensitivity analysis for maximum- $E[\text{NPV}]$

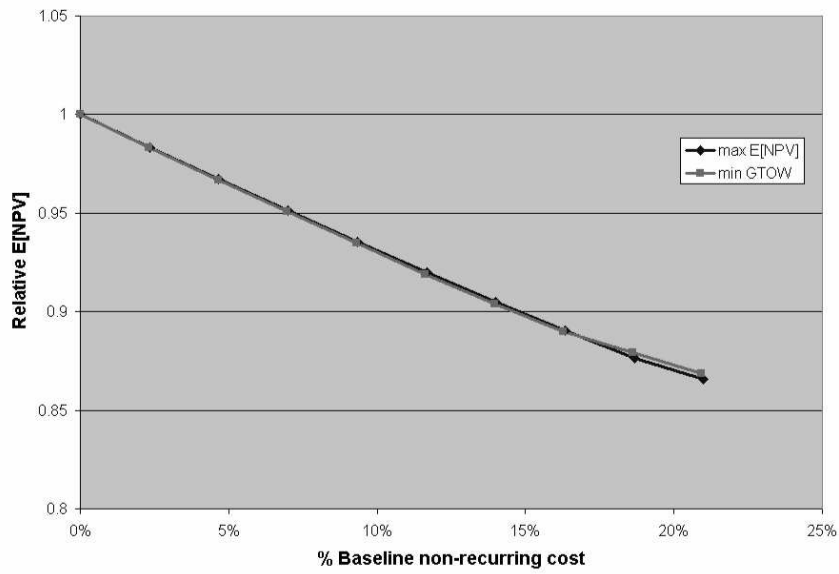
and minimum-GTOW designs, normalized by the baseline value optimum. Higher costs incurred result in lower program $E[NPV]$, and cost reductions increase value, which is unremarkable except that the sensitivity of $E[NPV]$ to non-recurring cost overruns is rather low. A 5% increase in development costs results in less than a 5% decrease in program value. Specifically, around the baseline design, the change in $E[NPV]$ is 0.71% of the baseline value for every percent change in non-recurring cost, as seen on the plot. In the case of larger development cost growth, the slope of the curve shifts, so that the sensitivity of $E[NPV]$ to non-recurring cost is 0.52% per 1% cost increase. As the design becomes more unfavorable, the Real Options approach dictates that proceeding with the program becomes less likely and its value decreases, but its expected value will never become negative.

The value-optimized design resulted in higher $E[NPV]$ for all changes in non-recurring cost than the performance-only design, as seen in Figure 7-1(a). Neither design appears clearly more or less susceptible than the other to changes in program value given uncertainty in the development cost. This trend is illustrated in Figure 7-1(b), showing the value for the maximum-value and minimum-GTOW designs as a function of non-recurring cost, normalized by the respective baseline value for each design. The value optimization objective is based directly, in part, on non-recurring cost, which helps explain why that design does not retain its value for even small changes in the non-recurring cost. The GTOW-optimal design objective is also linked to the non-recurring cost, via OEW, for similar results to the value-optimal solution. One difference is that the $E[NPV]$ -optimal solution is more heavily dependent on lower OEW to reduce costs, as seen in Chapter 5, as opposed to overall GTOW, which may account for slightly higher relative values of the performance-only design at higher levels of development cost uncertainty. In either case, optimizing to minimize the effects of design changes is necessary in addition to maximizing program value in order for the design to retain its optimal value given uncertainty.

Figure 7-2 compares the effects of varying non-recurring cost on $E[NPV]$ - and NPV-optimal designs, normalized by the baseline value of each. The maximum-NPV design is negative in all cases, providing a poor estimate of the program value. More



(a) Normalized by max-value E[NPV].



(b) Normalized by respective E[NPV].

Figure 7-1: Relative E[NPV] for max-value and min-GTOW designs vs. percent change in non-recurring cost.

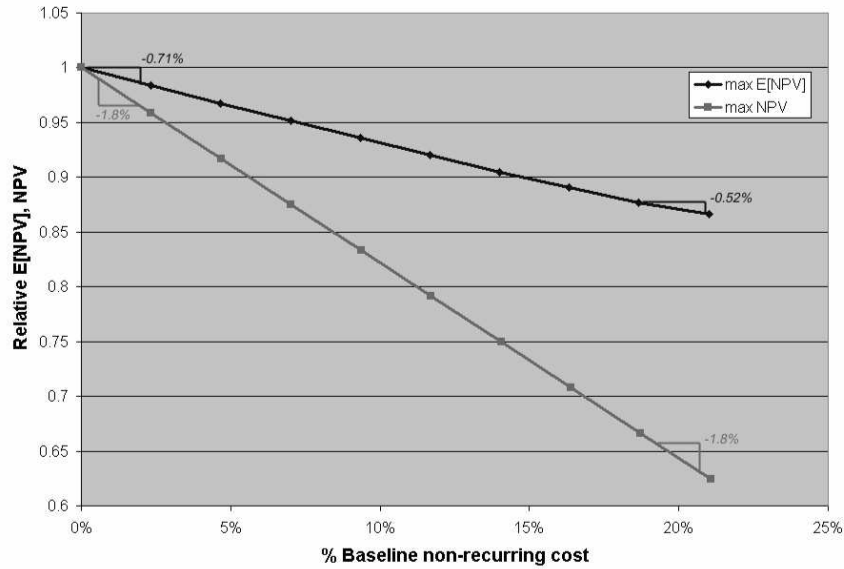


Figure 7-2: Relative E[NPV] and NPV (at $r_d = 12\%$) for max-E[NPV] and max-NPV designs, respectively, vs. percent change in non-recurring cost.

importantly, the sensitivity of NPV to changes in non-recurring cost is much greater than that of E[NPV] across the data points considered. For the baseline designs, NPV decreases by 1.8% of the initial value for a percent increase in development cost, versus only 0.71% for the E[NPV] solution. As the cost uncertainty grows, the gap in value grows as well. The NPV decreases linearly, with constant sensitivity of 1.8% NPV decrease per 1% cost increase, versus 0.52% for E[NPV]. Since the NPV calculation assumes a static set of program cash flows, it cannot account for program decisions to mitigate losses in profitability, as with E[NPV].

7.2.2 Fuel Efficiency

Another form of technical uncertainty could relate to changes in engine performance, such as fuel efficiency. If the engine manufacturer does not meet its SFC guarantees, the aircraft manufacturer may be forced to market an under-performing design. The situation would likely not be quite that simple in practice, as the powerplant supplier would almost certainly be contractually obliged to meet certain goals. Most modern aircraft also feature the choice of one of several types of engine options, based on indi-

vidual airlines' preferences. Different engine options may offer different performance levels, however, and unexpectedly poor fuel efficiency would no doubt negatively affect the aircraft program profitability. Conversely, if the engine exceeded its performance goals, the aircraft manufacturer could be justified in selling future units at a higher price.

In order to model such effects, sensitivity analysis was performed varying the engine SFC. The resulting changes in fuel consumption are reflected in the lifecycle cost adjustment in the price model. A range of SFC settings were examined between approximately -5% (improvement) and +10% (degradation) of the baseline SFC, in constant steps of 0.005 hr^{-1} . The effect of changing SFC is accounted for in Wing-MOD by holding the fuel weight constant and increasing or decreasing the effective range of the BWB as appropriate. This arrangement is similar to the first weight uncertainty case described at the beginning of this section; the effect of the uncertainty would be that the aircraft is unable to meet its goals but is still useful to airlines at a decreased range, albeit with an adjustment to the price.

Figure 7-3 illustrates the relationship between range and $E[\text{NPV}]$ for varying SFC, normalized by their respective baseline SFC values. From the Breguet range equation (5.1), for constant fuel weight and increasing SFC, range will decrease. The sensitivity of range to a 1% increase in SFC varies from a 1.1% decrease in the baseline range (7800 nmi) at the lowest SFC (-5%), to a 1% decrease at the baseline and a 0.83% decrease for the highest SFC considered (+10%). This trend also follows from (5.1), since range varies with the log of fuel weight. The sensitivity of $E[\text{NPV}]$ to changes in SFC is greater, as per (3.2), since the effects of varying range and lifecycle cost are compounded to drive the change in price. For a 5% improvement in the baseline SFC, a 1% increase results in an 11% decrease relative to the baseline $E[\text{NPV}]$; at the baseline this drops to a 10% decrease in $E[\text{NPV}]$ and continues to ease until a percent increase in SFC leads to a 5.6% decrease for the maximum case of a 10% degradation in fuel efficiency. The stochastic valuation is able to both capitalize on improved engine performance and better mitigate losses due to worsened fuel consumption by taking advantage of program flexibility.

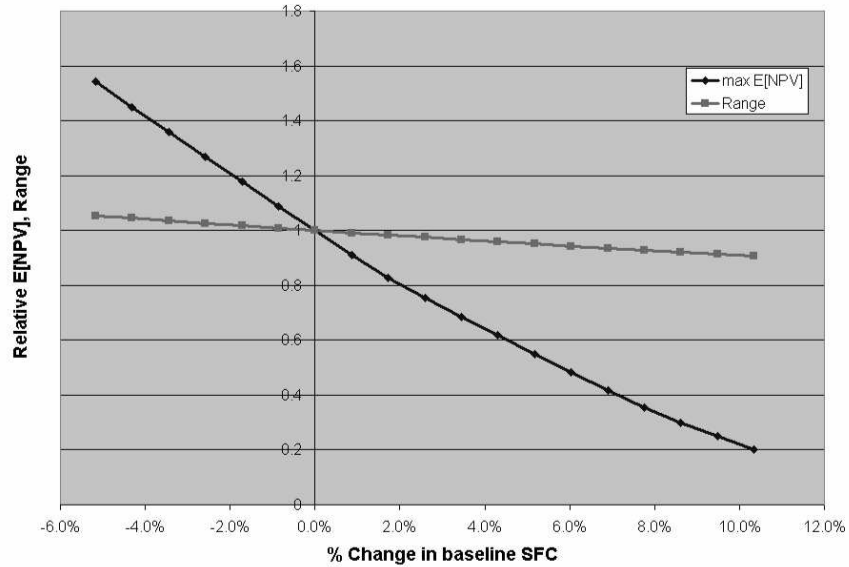
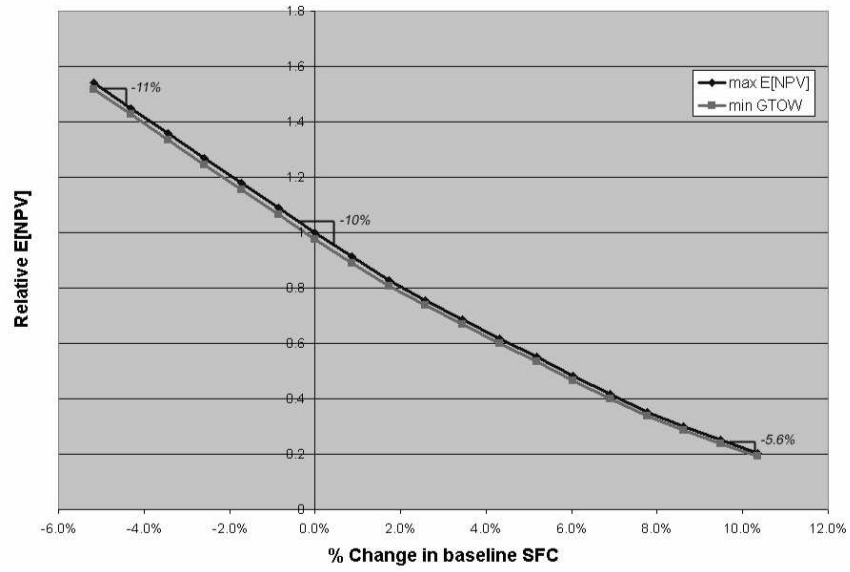


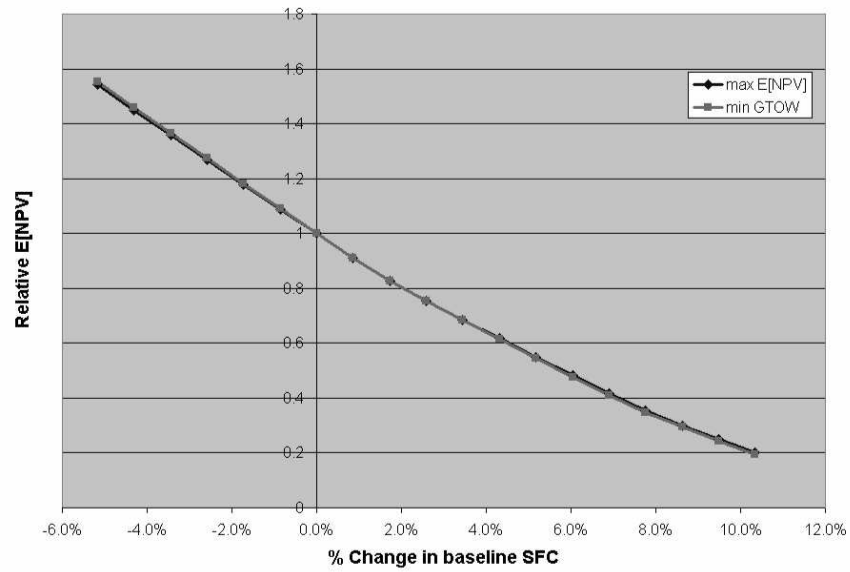
Figure 7-3: Relative E[NPV] and range for max-value design vs. percent change in SFC.

Compared to GTOW-optimal designs over the same range of SFC settings, the value of the E[NPV]-optimal design is higher for all cases, as seen in Figure 7-4(a) depicting the E[NPV] progression for each design versus SFC, normalized by the E[NPV]-optimal baseline value. The sensitivities of both designs to increases in SFC are quite severe, with 80% of the maximum-E[NPV] and 81% of the minimum-GTOW designs' values reduced for a 10% addition to the SFC. In addition, E[NPV] for each normalized by its respective baseline value (i.e., value- or performance-optimum) as a function of SFC is plotted in Figure 7-4(b). The GTOW-optimal design retains its initial value marginally better at lower SFC, and the opposite is true for higher SFC. However, both lose value rapidly for changing SFC, since both designs were optimized using objectives dependent implicitly on the fuel efficiency and fuel weight. Again, no pattern of improved robustness for either solution is obvious, so it is not justifiable to stipulate that either design is truly more robust than the other.

Finally, the sensitivity of the deterministic NPV solution to SFC is contrasted with that of the E[NPV] optimum in Figure 7-5, with both curves normalized by their baseline (no change in SFC) values. The deterministic NPV is negative for all SFC settings, providing a typically pessimistic estimate of program value. For improved



(a) Normalized by max-value $E[NPV]$.



(b) Normalized by respective $E[NPV]$.

Figure 7-4: Relative $E[NPV]$ for max-value and min-GTOW designs vs. percent change in SFC.

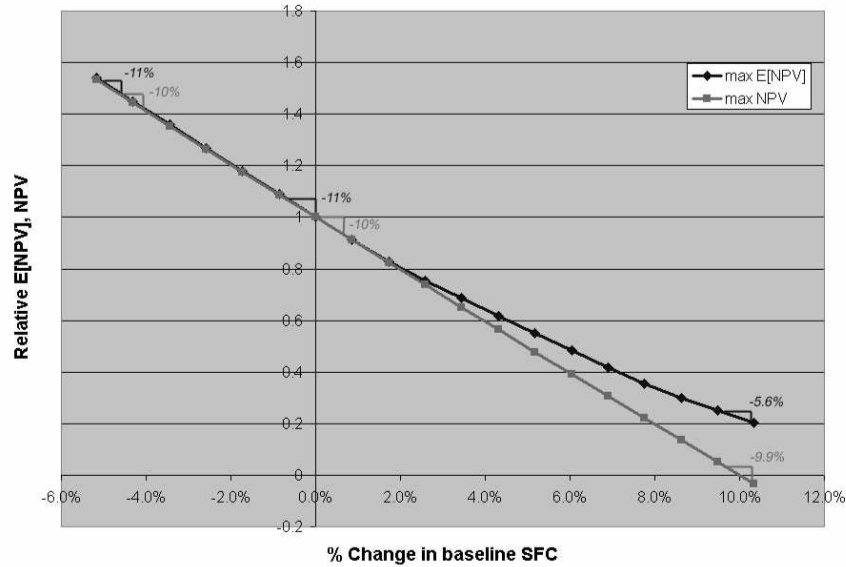


Figure 7-5: Relative E[NPV] and NPV (at $r_d = 12\%$) for max-E[NPV] and max-NPV designs, respectively, vs. percent change in SFC.

engine designs, the sensitivities are similar: an 11% decrease per 1% increase in SFC relative to the baseline E[NPV] versus a 10% drop per 1% increase in SFC for NPV. While the NPV is slightly better suited to maintain value given SFC degradation, by the same token it is unable to capitalize on SFC improvement as well as E[NPV]. The more important result is for the case of significant SFC increases, where the sensitivity of NPV to a 1% worsening of fuel consumption leads to a 9.9% drop in value, versus only a 5.6% decrease in E[NPV]. Given degraded engine performance, then, E[NPV] demonstrates an improved ability to mitigate the loss of profitability. Accounting for program flexibility allows the improved stochastic value to compensate for technical uncertainty with strategy, which the traditional, deterministic NPV cannot do.

7.3 Financial Uncertainty

In addition to the technical uncertainty inherent in an design program, the market for aircraft and general economic conditions can introduce separate financial uncertainties. These could relate to the non-recurring or recurring costs, price, or demand. While the above section addressed the impact of non-recurring cost and price uncer-

tainty caused by technical uncertainty, it is possible that the causes of changes in the financial aspects of an aircraft program can be due solely to external sources instead. Examples include the markets for materials or labor, or the current economic climate of the airline industry. The impacts of uncertainty *within* the stochastic demand model, pertaining to the volatility and initial quantity, as well as variable recurring costs on $E[\text{NPV}]$ are evaluated to quantify the risk associated with those aspects of a program.

7.3.1 Demand

The stochastic demand model attempts to account for demand uncertainty in terms of the volatility of the aircraft market. This volatility is based upon empirical data, however, and subject to uncertainty itself. Variance in the volatility — as well as the baseline or initial demand quantity — represent market risks that affect program value.

Demand Volatility

While the initial demand for an aircraft program may be viewed as predictable with a fair amount of reliability, it is much harder to forecast long-term demand patterns due to potentially varying economic conditions over a longer time horizon. A sensitivity analysis performed on the design by varying the demand volatility, σ , can help assess the level of risk faced due to shifting demand over the program lifetime as propagated through the stochastic demand model. The volatility was varied $\pm 15\%$ from its baseline value of 45.6%, which represents the average volatility for a widebody aircraft. Values for σ within a range of $\pm 10\%$ from the *aggregate* volatility for all widebody aircraft, or 19.6% as in [17], were also examined. The robustness of the $E[\text{NPV}]$ -optimal design versus that of the baseline GTOW-optimal design in the face of higher or lower demand variability was also evaluated. No comparison to the deterministic NPV solution was appropriate since the demand volatility is not accounted for by the static valuations using (2.1).

Table 7.1: Baseline parameters for convenience yield calculation in (7.1).

Parameter	Symbol	Baseline value
Risk-free rate	r_f	5.5%
Market risk premium	$(r_m - r_f)$	8.4%
Aircraft-market covariance	σ_{xm}	
Aggregate covariance	σ_{xm}^2	0.008
Aircraft volatility	σ	45.6%
Market volatility	σ_m	13.3%
Aircraft market growth rate	α	4.43%
Convenience yield	δ	2.19%

An adjustment in the demand model represented by (3.3) – (3.5) is necessary for this analysis, however, involving the rate of return μ . A parameter known as the convenience yield, δ , relates the shortfall between μ for freely traded commodities and the growth of the aircraft market, since aircraft are not freely traded commodities [15]. Since δ is based on the demand volatility for the aircraft market, σ , it needs to be varied as well to accurately calculate the sensitivities.

The actual value of μ in (3.3), then, is given by $(r_f - \delta)$, where the offset is found using the Capital Asset Pricing Model (CAPM) according to the following equation [17].

$$\delta = r_f + \frac{\sigma_{xm}}{\sigma_m}(r_m - r_f) - \alpha \quad (7.1)$$

As before, r_f is the risk-free rate of return; σ_{xm} is based on the covariance of aircraft market returns and market returns, σ_m represents variance of market returns, $(r_m - r_f)$ is the market risk premium, and α is the aircraft market growth rate. Specifically, the covariance term is based on the demand volatility, hence the need for this extra calculation. Values for these parameters, some of which remain as introduced previously, are summarized in Table 7.1. This method and CAPM are discussed in greater detail in [5] and [17].

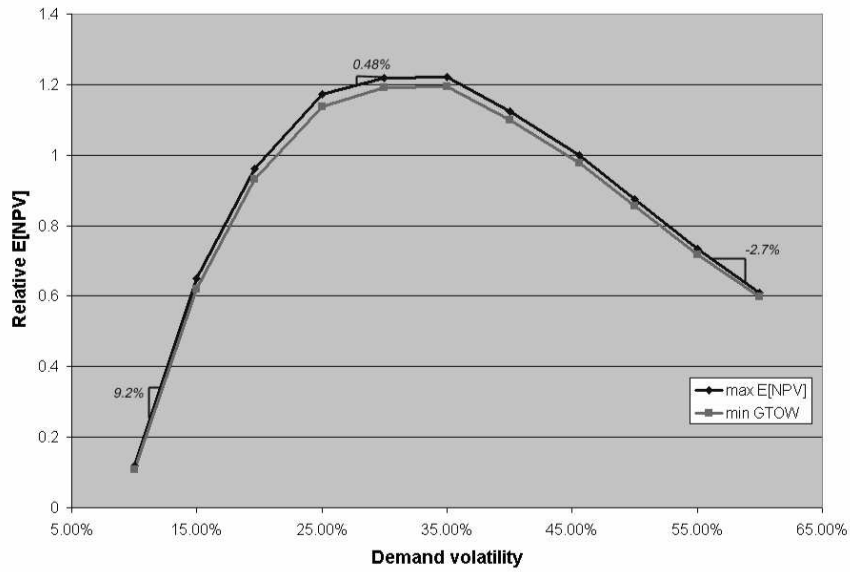
For each σ and its corresponding δ , E[NPV] results were found for both the maximum-E[NPV] and minimum-GTOW designs. Figure 7-6(a) compares the trends for the two designs at varying volatilities, with E[NPV] normalized by the optimum value at the baseline, $\sigma = 45.6\%$. In all cases, the E[NPV]-optimal solution shows

improved value over the performance-only solution. Due to its improved profitability, the maximum-value solution will provide value in both the case of fairly constant demand (low volatility) and at demand extremes in the case of higher volatility.

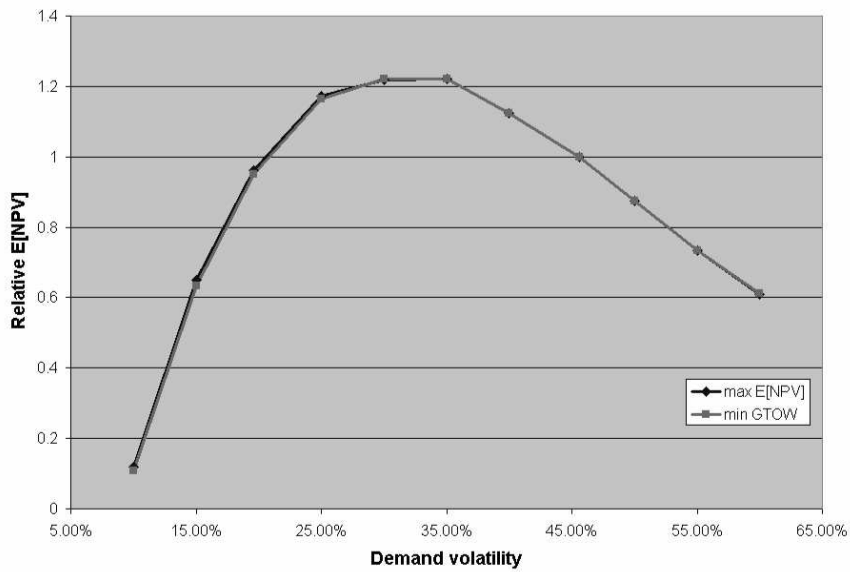
The relationship between $E[\text{NPV}]$ and demand volatility for both design solutions follows an expected pattern. At lower volatilities, near the aggregate widebody value, the overall program value decreases as the possibility for demand growth beyond the initial quantity is lessened. Conversely, at higher volatilities beyond the baseline average widebody value, $E[\text{NPV}]$ also decreases as the probability increases of low future demand quantities. Volatilities between the aggregate and average data points result in an even better valuation than the original maximum- $E[\text{NPV}]$ design, however, striking a balance between significant demand growth and the potential of markedly reduced demand. In a sense, these values for σ capture the idea of a “high-risk, high-reward” design where increased demand uncertainty is such that a confluence of beneficial events could result in a highly successful program, and the probability of a market decline is not high enough to drastically lower the expected value. It has been mentioned that no similar analysis can be performed for solutions optimized for deterministic NPV, due to the fact that increased volatility would simply be accounted for in (2.1) by increasing the discount rate. The resulting trend would be unable to capture any of the value of increased risk, as constantly decreasing NPV with increasing r_d would replace the curve seen in Figure 7-6.

Sensitivity analysis of the $E[\text{NPV}]$ -optimal results correlates the percentage increase or decrease in $E[\text{NPV}]$ due to a percentage point of volatility gained or lost. The most significant effects are seen at lower volatilities, where a 1% change as σ increases leads to a 9.2% increase in $E[\text{NPV}]$ relative to the baseline value. At the other extreme, continually increasing volatility past the baseline of 45.6% results in an approximately 2.8% decrease in program value. Sensitivities are at their lowest in the region around the peak estimates for $E[\text{NPV}]$, where a percent increase in σ from 30% causes less than a percent increase in program value, or 0.48%.

To evaluate the design robustness, comparison between the maximum-value and performance-only designs is shown in Figure 7-6(b), with each design normalized



(a) Normalized by max-value E[NPV].



(b) Normalized by respective E[NPV].

Figure 7-6: Relative E[NPV] for max-value and min-GTOW designs vs. demand volatility.

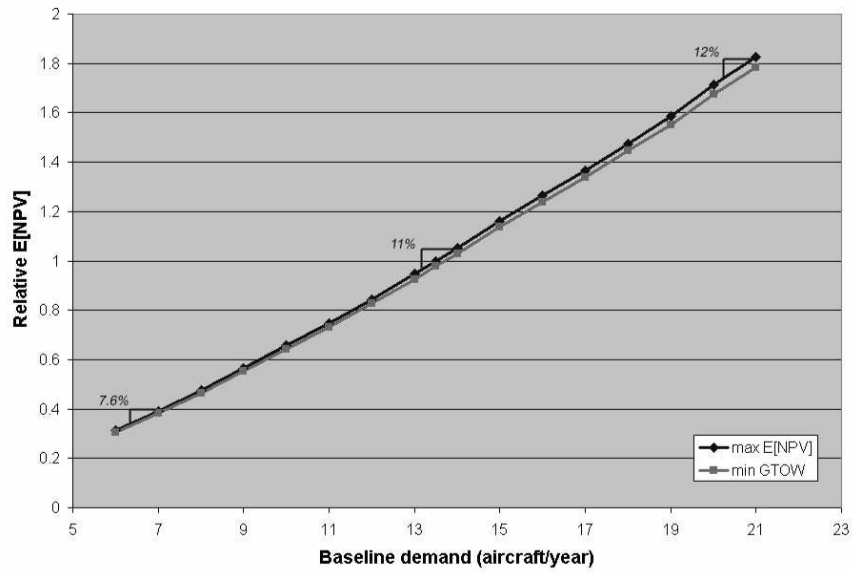
by its baseline $E[\text{NPV}]$ (at 45.6%). These results reveal that the $E[\text{NPV}]$ -optimal design retains its value better at lower volatilities, but that it is slightly more susceptible to losing profitability at higher volatilities than the GTOW-optimal design. The maximum- $E[\text{NPV}]$ design has been optimized based upon the baseline volatility, which is used to compute the objective function, whereas the GTOW minimum is not optimized using the volatility. Thus it is possible that the more profitable design could lose a higher percentage of its value at “off-design” points, suggesting a trade-off exists between the improved value of the $E[\text{NPV}]$ -optimal solution and retention of value for unpredictable demand volatility. It is unclear, however, that a definite pattern emerges as to whether either solution is more robust given higher demand variability. More importantly, this implies overall that design to increase value is not sufficient to guarantee maximum profitability, but that robust optimization is also necessary to minimize design variability in light of uncertainty.

Baseline Demand

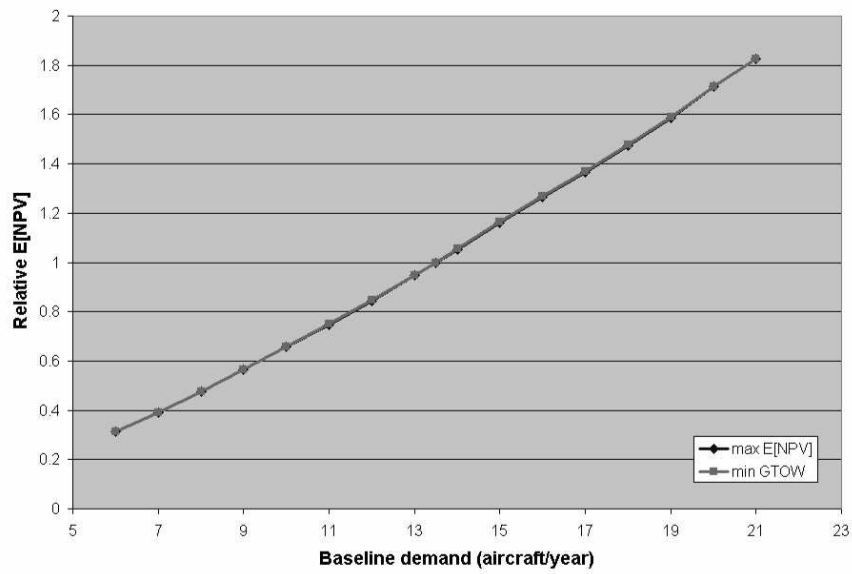
Related to potential uncertainty in the demand volatility is uncertainty in the initial annual market demand, which is also propagated through the demand model. The baseline demand quantity for a 475-passenger aircraft is 27 units per year, or 13.5 aircraft per manufacturer. A range of initial aircraft demanded varying from 12 to 42 units per year, or ± 15 aircraft, was examined to quantify the effect of shifting demand on $E[\text{NPV}]$ of the BWB design.

Figure 7-7(a) shows the $E[\text{NPV}]$ trend that evolves for a range of initial quantities demanded, with values normalized by the baseline $E[\text{NPV}]$ at 13.5 aircraft per year. The value-optimal solutions are higher at every level of demand, as would be expected since they represent the more profitable design. As the baseline demand increases, the disparity between maximum- $E[\text{NPV}]$ and minimum-GTOW values grows — again, since the effects of a higher profit margin for the value-optimal design are multiplied with increased demand.

The relationship between baseline demand quantity and $E[\text{NPV}]$ for the design, as seen in Figure 7-7(a) can be viewed in terms of business risk via sensitivity analysis.



(a) Normalized by max-value E[NPV].



(b) Normalized by respective E[NPV].

Figure 7-7: Relative E[NPV] for max-value and min-GTOW designs vs. baseline demand quantity.

An increase (decrease) in $E[\text{NPV}]$ of 7.6%, relative to the baseline value, for the corresponding addition (loss) of a unit demanded at the lower end of the quantity range, or 6 aircraft. At the other end of the spectrum, for 20 aircraft demanded annually, the change in value per aircraft is 12% of the baseline value. Closer to the baseline demand quantity of 13.5 aircraft per year, gaining or losing demand leads to a 11% increase or decrease, respectively, in $E[\text{NPV}]$.

Comparison of the designs optimized for value versus GTOW also allows assessment of the relative robustness of each solution. Figure 7-7(b) presents $E[\text{NPV}]$ for the two designs over the same range of initial demand quantities, normalized by the baseline $E[\text{NPV}]$ in each case (value- or performance-optimal). The results are nearly indistinguishable between designs, and no clear answer emerges for which design is more robust. At most data points, however, the minimum-GTOW design retains a slightly higher percentage of its baseline value. This further illustrates the idea that using $E[\text{NPV}]$ as the objective will improve the value of the specific design considered, at the expense of a greater reduction in value for minor program changes, due to the fact that the financial factors directly affect the optimization problem — not the case for the performance-based optimization. Once again the point is made that the maximization of $E[\text{NPV}]$ results in increased design value over the performance-optimum in all cases of baseline demand uncertainty, but a robust design approach coupled with value-based MDO could lessen the impact of the uncertainty on profitability.

Taking the same sensitivity analysis approach with a design evaluated using deterministic NPV further illustrates the problems with that metric. Figure 7-8 compares the trends in $E[\text{NPV}]$ and NPV resulting from varying the initial demand quantity, normalized by the baseline value according to each respective metric. In addition to the fact that NPV predicts that the design will be highly unprofitable, it is far more sensitive to changes in demand. At lower quantities for the baseline demand, around 6 aircraft per year, the sensitivity of NPV is 14% per aircraft relative to the baseline NPV at 13.5 aircraft per year, versus 7.6% for $E[\text{NPV}]$, as mentioned previously. For higher levels of demand, the change in NPV increases to 15% of the baseline value for each aircraft gained or lost in the initial demand, as compared to 11% for $E[\text{NPV}]$.

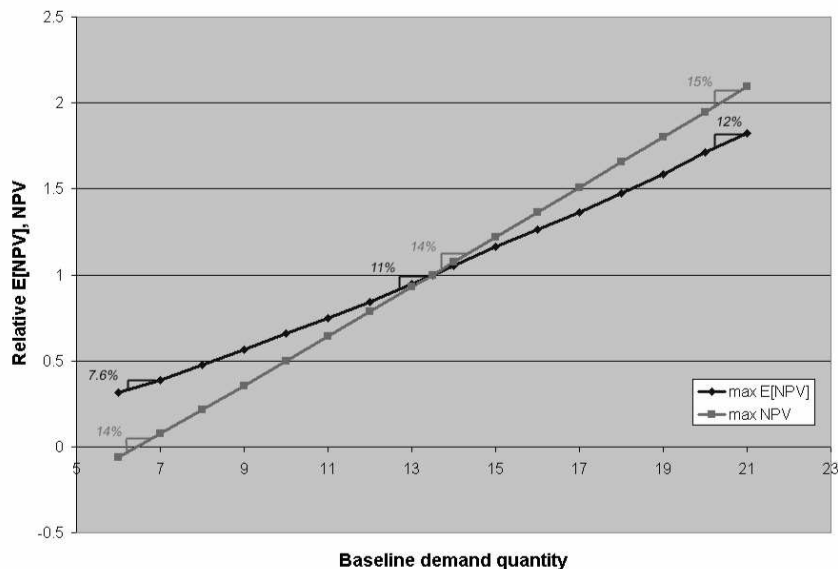


Figure 7-8: Relative E[NPV] and NPV (at $r_d = 12\%$) for max-E[NPV] and max-NPV designs, respectively, vs. baseline demand quantity.

These results show that, in the range examined, for higher-than-expected initial demand, the program will add value at a greater rate than would be estimated by E[NPV]. On the other hand, if initial demand predictions fall short, the program will shed value more quickly as well. It should also be noted that the slope of plot for E[NPV] is changing more quickly with demand than the slope for NPV, so that for lower levels of baseline demand the program retains more value, and at higher quantities the program will eventually converge to similar sensitivities. Given favorable enough demand conditions, the DP algorithm will make the decision to always move ahead with the project, generating a series of cash flows similar in trend (if not value, due to different discounting) to the deterministic case. For a more pessimistic valuation, at a discount rate of perhaps 20%, even greater sensitivity to the initial demand would predict more rapidly deteriorating profits if the initial demand decreased.

7.3.2 Recurring Costs

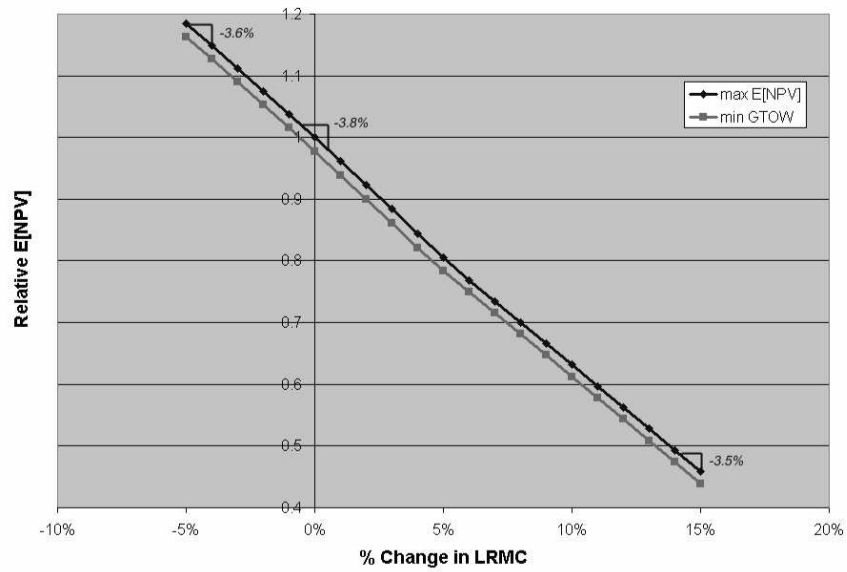
A final source of potential uncertainty that was investigated is variability in the long-run costs of aircraft production. These could be higher or lower material, labor,

or other costs. Sensitivity analysis of $E[\text{NPV}]$ given a change in the LRMC was performed by applying a multiplier to the baseline cost to model the effects of changes in one or more of the aforementioned cost categories. Values ranged from -5% to +15% of the baseline LRMC to examine the case of slight cost reductions and the more likely scenario of significant cost overruns.

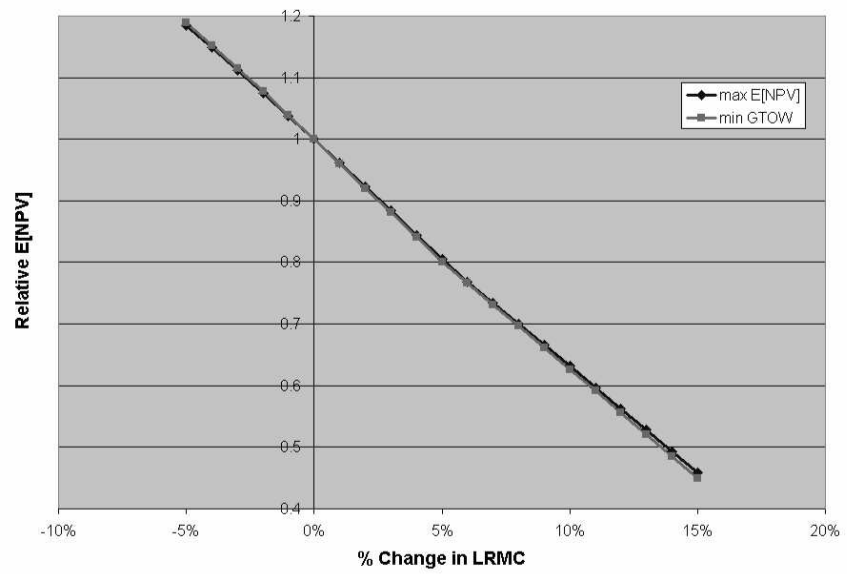
The resulting trends for manufacturing cost variability for the $E[\text{NPV}]$ - and GTOW-optimal designs are presented in Figure 7-9(a), normalized by the baseline (zero change in LRMC) maximum- $E[\text{NPV}]$ solution. An unexplained nonlinear effect in the valuation occurs in the trend relating the effect of varying LRMC on $E[\text{NPV}]$. As a result, the sensitivities are increasing, then rapidly decrease in the range of a 4% to 7% growth in LRMC, and then increase again at a much lower rate than initially. However, the overall trend for the sensitivity of $E[\text{NPV}]$ to changes in recurring cost is that it decreases with increasing LRMC. Reducing LRMC an additional 1% beyond a 5% decrease leads to a further increase in $E[\text{NPV}]$ of 3.6% of the baseline value. For the baseline design, a 1% change in LRMC now affects the value by 3.8%. Finally, a 1% increase in LRMC given a 15% increase further reduces $E[\text{NPV}]$ by an additional 3.5% of its initial value.

These sensitivities are much more significant than those relating the effect of non-recurring cost uncertainty to $E[\text{NPV}]$, indicating that eliminating design uncertainty earlier is more beneficial than producing a suboptimal design — despite the larger impact of incurring the cost of design changes earlier, due to heavier discounting of later cash flows. In addition, the net change in $E[\text{NPV}]$ sensitivity to LRMC variability is rather small, only 0.4% between the baseline and a 15% increase. As such, any increase in the long-term costs of the program has a much more detrimental effect than a corresponding increase (e.g., 15%) in development costs.

The $E[\text{NPV}]$ -optimal design is, as expected, more profitable than the GTOW-optimal solution at every level of uncertainty. Further, Figure 7-9(b), comparing the two trends instead normalized by the baseline value of each, shows that the value-optimal design is slightly more robust than the performance-only design given unfavorable LRMC uncertainty, in that it retains more of its initial value. This effect



(a) Normalized by max-value E[NPV].



(b) Normalized by respective E[NPV].

Figure 7-9: Relative E[NPV] for max-value and min-GTOW designs vs. percent change in LRMC.

is likely due to the fact that the optimization, as discussed in Chapter 5, specifically sought to reduce the manufacturing costs via lower OEW. As a result, the solution remains more valuable despite an increase in LRMC than the GTOW-minimal design. Conversely, as the price of the E[NPV] optimum is lower than that of the performance-based design, the latter gains profitability more quickly in the face of reduced costs.

While the design resulting from the optimization of E[NPV] retains more of its value given less favorable program conditions due to cost uncertainty than the performance-only optimum, it should still be noted that both designs lose approximately 20% of their value with only a 5% increase in LRMC. It is unclear, based on that finding, how much of an effect robust design could have on mitigating the loss in value due to uncertainty. There is a limited amount that even flexible or robust design can do to deal with the effects of uncertainty, emphasizing the point that it is important to retain a focus on reducing or eliminating potential sources of uncertainty where possible, in this case by managing program costs effectively.

A final comparison between the relationship of NPV to LRMC and the previously discussed trend for E[NPV] versus LRMC is presented in Figure 7-10, with each set of points normalized by its respective baseline value. Focusing on the changes in sensitivities, since the NPV results remain consistently negative, the deterministic value metric again depreciates significantly given less favorable design conditions. At the baseline LRMC, the sensitivity of NPV to a 1% increase in recurring cost leads to a 1.5% decrease in NPV; for E[NPV], the same increase results in a 3.8% decrease. While this may seem favorable, it is misleading. Due to the heavier discounting assumed by using the risk-adjusted discount rate, the loss of profitability in future cash flows is less noticeable in the NPV calculation. It is better to have an accurate assessment of value than a promising trend. In addition, NPV returns an unnecessarily pessimistic valuation given a reduction in LRMC. Overall, the trends for E[NPV] and NPV when faced with recurring cost uncertainty are inverted: the sensitivity of E[NPV] decreases with increasing LRMC, while the sensitivity of NPV increases. Looking at NPV versus cost, one would be led to incorrectly believe that managing costs downstream is less important than the E[NPV] trend indicates. A

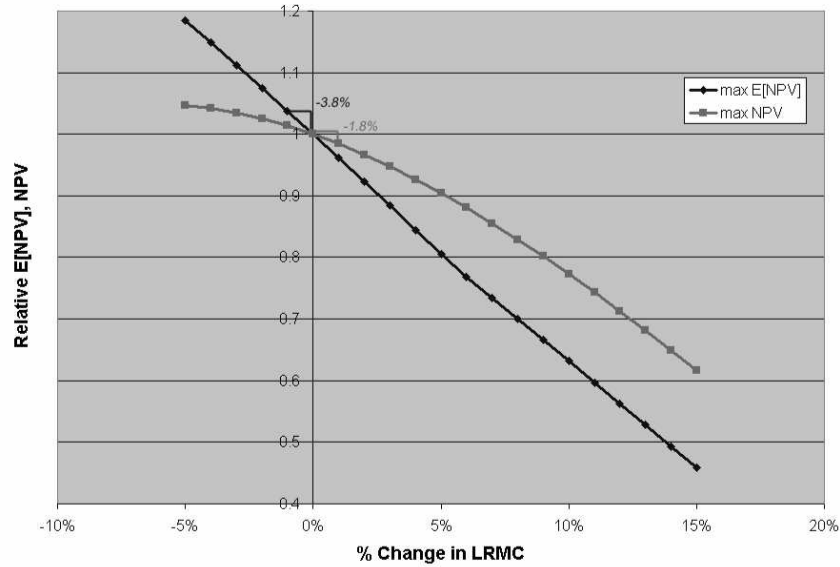


Figure 7-10: Relative E[NPV] and NPV (at $r_d = 12\%$) for max-E[NPV] and max-NPV designs, respectively, vs. percent change in LRMC.

15% growth in LRMC results in less than a 40% loss in NPV, compared to a more than 50% loss in the more realistic E[NPV] metric, due to the initially lower sensitivity of the deterministic value. Given variability in the long-term costs of a program, the value estimates provided by deterministic NPV provide little useful assessment of profitability.

7.4 Summary

Business risks attributable to technical and financial uncertainties have been assessed for a BWB example. Sensitivity analyses were performed on perturbed designs to quantify the impact on E[NPV] given a variation in a design or market parameter. The resulting change in value due to a change in the parameter can be used to describe the design risk with respect to that parameter.

Although both technical and financial uncertainties were considered, the overall effect of introducing variations in the actual design parameters was to simultaneously change a related financial parameter. Specifically, OEW growth was represented as a non-recurring cost increase, and higher fuel consumption translated into a price

decrease. By comparing the sensitivities of the value at the baseline (maximum- $E[\text{NPV}]$) design point, the relative importance of each financial quantity (and related design parameter) can be determined. Table 7.2 summarizes the sensitivity analyses, with the demand variability now normalized to show percentage change in $E[\text{NPV}]$ relative to a 1% change in the initial demand for comparison to the other parameters.

Table 7.2: Sensitivities of $E[\text{NPV}]$ -optimal design to uncertainties.

Parameter Varied	Related Parameter	% $E[\text{NPV}]$ Change <i>(per 1% parameter increase)</i>
Non-recurring cost	OEW	-0.71%
SFC	Price	-10%
Demand		
Volatility		-2.8%
Initial		+1.4%
Recurring cost (LRMC)		-3.8%

From Table 7.2, it is clear that the design is most sensitive to fuel efficiency, and by extension, price. The next largest effect on $E[\text{NPV}]$ is due to uncertainty in recurring costs, followed by the demand parameters. Changes to the long-term program cash flows, then, appear to be the leading source of business risk. It is also interesting that the sensitivity to the only technical parameter varied directly (i.e., SFC) is significantly higher than the sensitivities to the market parameters. Due to the small sample size of parameters examined, though, no strong conclusions can be drawn about the relative effects of technical versus financial uncertainty on program value.

The relatively low sensitivity of $E[\text{NPV}]$ to non-recurring cost compared to LRMC and price (indirectly) suggests that by correcting problems with the design in the development stage, more of the baseline value can be retained than would be the case for a design that does not meet its intended performance. In the latter case, program manufacturing costs could be higher and missed guarantees would require the aircraft to be sold at a lower price. While the idea that spending more money earlier to save money on a better design later appears to be the suggested strategy to mitigate business risk for the stochastic design example, it is worth noting that

a deterministic valuation would rule out such a strategy. As noted in Chapter 5, incurring large, up-front costs will instead drive a deterministic optimization to a less favorable solution, since later cash flows have less impact on the overall profitability due to heavy discounting.

In terms of probabilistic design, the significant change in $E[\text{NPV}]$ attributable to each of the parameters listed in Table 7.2 (with the arguable exception of non-recurring cost or OEW) and plots throughout this chapter indicate that the value-optimal design is no more or less robust than traditional performance-only designs. The value-based MDO methodology presented here provides a useful approach to characterize and improve the value of an aircraft design, but both the $E[\text{NPV}]$ - and GTOW-optimal designs are sensitive to uncertainty. It may be possible to design a program with $E[\text{NPV}]$ that is less sensitive (i.e., more robust) when faced with unexpected design changes, but a truly robust approach optimization would be necessary. Further, consideration would have to be given to potential tradeoffs in the magnitude of the value versus the amount of design robustness that might be gained.

Finally, the above sensitivity analyses have again demonstrated $E[\text{NPV}]$ to be an improved valuation metric over deterministic NPV. As NPV was evaluated at $r_d = 12\%$ for the cases presented, the results also represent the most favorable risk-adjusted discounting that is likely to be applied to an aircraft program. With generally higher sensitivities to more favorable program conditions, the stochastic valuation better represents the ability to take advantage of such conditions. Conversely, by accounting for program flexibility in the case of unfavorable uncertainty, the sensitivity of $E[\text{NPV}]$ to worsened design or market conditions is reduced, mitigating the impact on program value.

Chapter 8

Conclusions

A methodology has been described for including financial valuation in the design process for a commercial aircraft program. To implement this approach, a framework coupling performance and financial aircraft design optimization has been developed, combining a stochastic valuation technique to explicitly address market uncertainty with empirical cost and revenue models, and the existing WingMOD performance optimization setup. The methodology and tools developed help to bridge the gap between technical design and financial analysis, specifically by helping engineers and managers to better understand the financial implications of design decisions, including consideration of program risks.

Results of the case study performed using the BWB concept have shown that small improvements in the expected NPV of a program can be gained by incorporating valuation in design optimization. A 2.3% increase in $E[\text{NPV}]$ for the value-optimal design over the GTOW-optimal baseline is a modest gain, but nonetheless demonstrates the potential of value-based MDO. The best design strategy is to maximize the expected value at a later point in the design process, when the design is more fully developed and technical requirements have been satisfied.

In this study, the design was found to be tightly constrained, and the value-based results do not outwardly appear to be significantly different from those obtained using the traditional objective of minimized GTOW. Changes in the value-optimal design compared to the baseline minimum-GTOW configuration, however, do demonstrate

that changing the objective in the optimization results in a different design. As the sensitivity of $E[\text{NPV}]$ has been found to be higher than that of GTOW to small design changes, using program value as the MDO objective moves the solution to more profitable regions of the design space than the performance objective. In a larger sense, though, adding cost or value to the optimization problem simply represents a continuation of the historical process of balancing aerodynamic performance and structural weight in aircraft design.

As an example of the application of value-based MDO, its incorporation into the design process for setting range and speed requirements was considered. In the case of the design range, increases will eventually cause the program to become *less* profitable — an outcome that is not readily apparent from the results of traditional performance-only design. Using $E[\text{NPV}]$ as the criteria for choosing an optimal cruise speed shows that value will also suffer outside of the 0.84–0.85 M range, hence the value of extra speed is not nearly as great as sometimes perceived. In both cases, value-optimal solutions also represent higher- $E[\text{NPV}]$ designs than their performance-only counterparts. Taking a value-based approach to MDO allows more fully-informed program decisions regarding design specifications, in which the financial impact of design changes is understood and requirements may be set so that their effect on value is optimal. The relevance of such an approach is evident in the present-day market for commercial aircraft, in the case of Boeing’s shift in strategy between its Sonic Cruiser and 7E7 concepts.

Another important aspect of value-based aircraft design is the business risk associated with a program. By performing sensitivity analyses about the value-optimal design, the relative risks associated with uncertainty in both technical and financial parameters can be quantified. The sensitivities describe the impact of variability on $E[\text{NPV}]$ due to discrete changes in individual parameters. Although this overlooks potential coupling of the effects different parameters have, it provides a method of assessing which aspects of the program drive the value and, through comparison of sensitivities, which represent the greatest risk to profitability.

To demonstrate this approach to uncertainty analysis for the valuation, four

sources of likely uncertainty — two technical, two financial — were examined to quantify respective sensitivities of $E[\text{NPV}]$, and thus the business risk associated with each. In effect, the technical variability could be linked to financial parameters, resulting in a comparison of the effects of recurring and non-recurring costs, price, and demand (initial and its volatility) uncertainty on $E[\text{NPV}]$. The high sensitivities to recurring costs and price indicate that effects on the long-term profitability of the design pose the greatest risk to the BWB example. Market uncertainty is also a source of considerable risk; conversely, examination of a range of volatilities illustrates how the stochastic valuation is better able to account for demand uncertainty, by being able to take advantage of so-called high-risk, high-reward situations for moderate levels of volatility.

The observation that increases in recurring cost and decreasing price are more detrimental to program value than similar growth in development cost suggests that incurring costs early in a program to ensure a successful design represents a safer strategy than going to market with a design that has missed performance goals. Concerns that a value-optimal solution could suffer more from the effects of uncertainty, in terms of profitability, than a performance-only optimum were addressed; neither solution was found to be more or less robust.

Finally, throughout this work, examples have demonstrated deterministic NPV to be an unsuitable metric for estimating program value, as well the incorrect choice as an objective for value-based optimization. An inaccurate assessment of the value of a design is provided, and, more importantly, the optimizer is driven to undesirable places in the design space. The problems with deterministic valuation are centered on the arbitrary choice of a risk-adjusted discount rate, and through the use of r_d , the inability to account fairly for uncertainty and decision-making flexibility.

By attempting to adjust the discount rate upward to assess the effects of greater potential design variability, the deterministic valuation loses its ability to capture any beneficial effects of riskier situations, as the stochastic valuation has been shown to do. Further, when NPV is used as an objective, higher discounting drives the design to make poor trades to minimize the costs incurred early in the program. This

pattern of under-valuing future cash flows due to the effects of discounting is endemic to the deterministic valuation, even at a more generous r_d of 12%. Sensitivity analyses showed this to be the case, with the deterministic NPV continually de-emphasizing the importance of long-term profitability. These trends are directly contrary to those associated with the improved stochastic valuation.

Findings based on the suggested value-based design approach, as summarized above, represent the continuation of efforts to improve multidisciplinary design of aircraft, but several ends to further this work should be pursued. To move beyond many of the limitations described throughout, changes to the problem setup or optimization framework may be made by additional tailoring of the design constraints or variables. Improving the underlying simulation models could permit more significant changes to the profitability of designs optimized for value. In particular, higher-fidelity empirical financial models to better capture the effects of design changes on cost, price, and demand could allow the optimization to search a greater portion of the design space to improve upon the $E[\text{NPV}]$ -optimal solution. Similarly, a more sophisticated model for fuel consumption, affecting the lifecycle cost adjustment, could allow further freedom to more fully explore the design space. The utility of improving the fidelity of the performance model, usually a desirable goal, must be weighed against added computational expense. Additional improvements to the stochastic valuation itself could include a more thorough accounting for market competition, such as drawing on game theoretical concepts, or investigating the use of alternative models for stochastically evolving demand, such as a mean-reverting process.

A useful extension to this work, as discussed previously, would be to design towards the robustness of financially optimal designs to further uncertainty concerning the technical design or market factors. However, the effects a robust design approach may be limited; given the location of the value optimum in the design space, some decrease in $E[\text{NPV}]$ due to changing conditions is inevitable. As should be noted for all the optimization work presented here, an improved ability to account for the business aspects of an aircraft program in the design process is a worthwhile end, but managers and engineers should not lose sight of the fact that effective management

and design practices play a far more important role in program profitability.

As discussed in Chapter 5, the history of aircraft MDO originated in aero-structural optimization, and has proceeded to encompass many more important aspects of aircraft systems design. But Sobieski [33] notes, “there are still very few instances in which the aerospace vehicle systems are optimized for their total performance, including cost as one of the important metrics of such performance.” Introducing stochastic value to measure “cost” attempts to fill this niche and complement the similar work done by others to the same end, furthering the field of aircraft design.

Bibliography

- [1] *Aircraft Value News*, <http://www.aviationtoday.com/> .
- [2] *The Airline Monitor*, ESG Aviation Services, May 2001.
- [3] Bell, William A. and Pringle, Lon. “Aircraft performance assessment using sensitivity analysis for coupled systems.” Paper 96–4097, AIAA, 1996.
- [4] Bertsimas, Dimitris and Tsitsiklis, John N. *Introduction to Linear Optimization*. Athena Scientific, Belmont, MA, 1997.
- [5] Brealey, Richard A. and Myers, Stewart C. *Principles of Corporate Finance*. McGraw-Hill, Irwin, NY, 1996.
- [6] Browning, Tyson R. et al. “Adding value in product development by creating information and reducing risk.” *IEEE Transactions on Engineering Management*, 49(4):443–458, November 2002.
- [7] Clarke, John-Paul, Miller, Bruno, and Protz, Jonathan. “An Options-Based Analysis of the Large Aircraft Market.” Paper 2003–2795, AIAA, 2003.
- [8] Cox, John C., Ross, Stephen A., and Rubenstein, Mark. “Option Pricing: A Simplified Approach.” *Journal of Financial Economics*, 3(7):229–263, October 1979.
- [9] deNeufville, Richard. *Applied Systems Analysis*. McGraw-Hill, New York, NY, 1990.

- [10] DeLaurentis, Daniel et al. “System-of-Systems Modeling for Personal Air Vehicles.” Paper 2002–5620, AIAA, 2002.
- [11] Deyst, John J. “The Application of Estimation Theory to Managing Risk in Product Developments.” In *Proceedings of the 21st Digital Avionics Systems Conference*, volume 1, 2002.
- [12] Dixit, Avinash K. and Pindyck, Robert S. *Investment Under Uncertainty*. Princeton University Press, Princeton, NJ, 1994.
- [13] Giesing, Joseph P. and Wakayama, Sean. “A simple cost related objective function for MDO of transport aircraft.” Paper 97–0356, AIAA, 1997.
- [14] Hull, John C. *Options, Futures, and Derivatives*. Prentice-Hall, Upper Saddle River, NJ, 2000.
- [15] Kulatilaka, Nalin. “Valuing the Flexibility of Flexible Manufacturing Systems.” *IEEE Transactions on Engineering Management*, 35(4):250–257, November 1988.
- [16] Lee, Hosung and Olds, John R. “Integration of and Business Simulation into Conceptual Launch Vehicle Design.” Paper 97–3911, AIAA, 1997.
- [17] Markish, Jacob. *Valuation Techniques for Commercial Aircraft Program Design*. S. M. thesis, Massachusetts Institute of Technology, Cambridge, MA, 2002.
- [18] Markish, Jacob and Willcox, Karen. “Multidisciplinary Techniques for Commercial Aircraft System Design.” Paper 2002–5612, AIAA, 2002.
- [19] Markish, Jacob and Willcox, Karen. “Value-Based Multidisciplinary Techniques for Commercial Aircraft Design.” *AIAA Journal*, 41(10):2004–2012, October 2003.
- [20] Mavris, Dimitri and Birney, Mark. “Formulation of a Stochastic, Physics-Based Strategic Business Decision Making Environment.” Paper 2002–5850, AIAA, 2002.

- [21] Mavris, Dimitri N. and Bandte, Oliver. “Multiobjective Optimization Using a Joint Probabilistic Technique.” Paper 2000–4758, AIAA, 2000.
- [22] Mavris, Dimitri N., Bandte, Oliver, and DeLaurentis, Daniel A. “Determination of System Feasibility and Viability Employing a Joint Probabilistic Formulation.” Paper 99–0183, AIAA, 1999.
- [23] Mavris, Dimitri N., Bandte, Oliver, and DeLaurentis, Daniel A. “Robust Design Simulation: A Probabilistic Approach to Multidisciplinary Design.” *Journal of Aircraft*, 36(1):298–307, January–February 1999.
- [24] Mavris, Dimitri N. and DeLaurentis, Daniel A. “A Stochastic Design Approach for Aircraft Affordability.” In *Proceedings of the 21st Congress of the International Council on the Aeronautical Sciences (ICAS)*, September 1998.
- [25] Mavris, Dimitri N., Nottingham, Carrie R., and Bandte, Oliver. “The Impact of Supportability on the Economic Viability of a High Speed Civil Transport.” In *Proceedings of the 1st Joint International Conference of the International Society of Parametric Analysts and the Society of Cost Estimating and Analysis*, 1998.
- [26] Mecham, Michael. “A Big Start.” *Aviation Week and Space Technology*, 160(18): 26–28, May 3, 2004.
- [27] Messac, A. and Chandra, S. “Cost Optimization in Design Using Physical Programming.” In *Proceedings of the Third World Congress of Structural and Multidisciplinary Optimization*, 1999.
- [28] Papalambros, Panos Y. and Wilde, Douglass J. *Principles of Optimal Design*. Cambridge University Press, New York, NY, 2000.
- [29] Paul-Choudhury, Sumit. “Reaping Real Rewards.” *CFO Europe.com*, <http://www.cfoeurope.com/displaystory.cfm/1735903/1-print>, July 1999.
- [30] Raymer, Daniel P. *Aircraft Design: A Conceptual Approach*. American Institute of Aeronautics and Astronautics, Reston, VA, 1999.

- [31] Ross, Tamaira E., Crossley, William A., and Roth, Gregory L. “Multiobjective Optimization of a Commercial Transport Aircraft for Cost and Weight.” Paper 98–0911, AIAA, 1998.
- [32] Sobieski, Jaroslaw. *Optimal Design in Multidisciplinary Systems*. AIAA Professional Development Short Course, September, 2002.
- [33] Sobieszczanski-Sobieski, Jaroslaw and Haftka, Raphael T. “Multidisciplinary Aerospace Design Optimization: Survey of Recent Developments.” Paper 96–0711, AIAA, 1996.
- [34] Trigeorgis, Lenos. *Real Options: Managerial Flexibility and Strategy in Resource Allocation*. MIT Press, Cambridge, MA, 2000.
- [35] Wakayama, Sean R. “Blended-Wing-Body Optimization Problem Setup.” Paper 2000–4740, AIAA, 2000.
- [36] Weigel, Annalisa L. and Hastings, Daniel E. “Application of Real Options to Strategic Management of Military Satellite Communications.” Paper 2001–4572, AIAA, 2001.
- [37] Willcox, Karen and deWeck, Olivier. “Design for Value.” *Multidisciplinary Systems Design Optimization*, lecture given at MIT, May 2003.
- [38] Willcox, Karen and Wakayama, Sean. “Simultaneous Optimization of a Multiple-Aircraft Family.” *Journal of Aircraft*, 40(4):616–622, July–August 2003.