MULTIDISCIPLINARY TECHNIQUES FOR COMMERCIAL AIRCRAFT SYSTEM DESIGN

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ABSTRACT

This paper lays the groundwork for a design and analysis tool that applies multidisciplinary design optimization techniques to commercial aircraft development. While multidisciplinary analysis and optimization has seen extensive use for technical design problems in aerospace, there has been less emphasis on applying these techniques to larger scope system design. Specifically, the relationship of elements such as cost, revenue, and uncertainty to engineering is in large part unexplored. The models presented here may be used as the sub-components of a valuation tool to enable the design and optimization of an entire aircraft While they are not high fidelity, their program. purpose is to establish a useful foundation for further study and to gain insight into the interactions between technical and program design.

INTRODUCTION

Traditional methods for creating a commercial aircraft program typically consist of at least two distinct design efforts—the engineering development of the airframe itself, and the strategic development of the aircraft program. The latter addresses questions like which aircraft designs to invest in (product mix), how much production to plan for (sales volume), what prices and costs to expect (profitability), and how to plan for unforeseen market developments (flexibility).

In the past, the above two elements of program design—engineering development and strategic development—have often been executed entirely separately from each other. Engineering and finance are often handled by different groups and at different

times. By uncoupling engineering and finance, a firm runs the risk of overlooking important interactions between the two. A design system that performs engineering and financial analysis simultaneously may improve upon the efficiency and effectiveness of the traditional methods.

Numerous advances have been made in the application of multidisciplinary techniques to the engineering facet of aircraft development. The field of multidisciplinary design optimization (MDO) combines engineering disciplines, such as aerodynamics, structural dynamics and controls, to provide a design framework that "coherently exploits the synergism of mutually interacting phenomena"¹. MDO has been implemented across a wide range of applications for aircraft design ^{2,3}. However, there has been less exploration of the interactions between engineering design and financial design. These interactions may be specified as follows. The technical performance of an aircraft, which may be a combination of range, capacity, and operating cost, will affect the demand for the aircraft, and consequently the price and/or quantity of aircraft sold. The same elements of technical performance will also affect the cost of the aircraft-both manufacturing (recurring) and development (nonrecurring). Thus, cost and revenue-that is, finance-are linked by performance-that is, engineering.

The objective, then, is to couple engineering and financial design—or, phrased differently, product and program design—to extract maximum value from the commercial aircraft design process. This coupling will be effected by expanding an MDO framework to include financial considerations.

The next section summarizes the multidisciplinary approach taken to accomplish the above objective. An overview is given of three distinct analytical models used to solve the problem, as well as a scheme for linking them into one program value analysis tool. A more in-depth discussion of each of the models follows: performance, cost, and revenue estimation. Several ways of combining the three models to measure program value are then described, and two examples are given to demonstrate the linking process for analysis of a Blended-Wing-Body (BWB) family of

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aircraft⁴. Finally, results for the more substantive example are presented and discussed, and conclusions are drawn.

APPROACH

The multidisciplinary analysis is synthesized by creating several free-standing analytical models and linking them to compute a measure of program value. While this paper focuses on the models themselves, the linking process and the resulting valuation tool are described in more detail in Markish and Willcox⁵.

The analysis uses three analytical models, each of which can be considered a standalone tool, but can also be integrated with the others: a performance model, a cost model, and a revenue model. The performance model is a sizing and configuration tool, which closes the engineering design loop between technical parameters and performance metrics (range, capacity, fuel burn). The cost model generates estimates of manufacturing and development costs given the technical parameters specified in the performance model. The revenue model captures the behavior of the market for commercial aircraft, and characterizes the airline demand for the aircraft in question, given the performance model.

In order to link the above three models into an integrated multidisciplinary analysis tool, consideration must be given to the program structure—i.e., the decision structure affecting product mix, design and production plans, and pricing strategy. With this element in place, the stage is set for a quantitative valuation of the program. The ability to calculate program value based on technical and program-based elements of the system enables both technical and program-based trade studies to search for an optimal system design. This conceptual process is illustrated in Figure 1.

There are several possibilities for the actual implementation of the program valuation. The most straightforward is a Net Present Value (NPV) analysis, using an assumed discount rate and forecasted cash flows. There are also other alternatives, which may capture not only the time value of money but also more explicitly account for the effect of uncertainty and the effect of program flexibility—i.e., management's ability to make program decisions in real time as the market evolves. Two such alternatives are Monte Carlo simulation and dynamic programming.

The remainder of the paper presents and describes each of the models—performance, cost, and revenue. Subsequently, a simplified NPV-based technique is shown for linking the three models and performing a program valuation. The technique is illustrated with a brief example case study. A more complex technique, based on dynamic programming, is detailed in Markish and Willcox⁵.





PERFORMANCE ESTIMATOR

The performance estimator is based on the WingMOD aircraft design tool. WingMOD is an MDO code that optimizes aircraft wings and horizontal tails subject to a wide array of practical constraints^{6,7}. The BWB planform is modeled as a series of spanwise elements as shown in Figure 2. Optimization services for WingMOD are provided by the Genie framework⁸.

WingMOD uses intermediate fidelity analyses to quickly analyze an aircraft in over twenty design conditions that are needed to address issues from performance, aerodynamics, loads, weights, balance, stability and control. The low computational cost of the intermediate fidelity analyses allows the examination of all these issues in an optimization with over a hundred design variables while achieving reasonable computation time.

The basic WingMOD method models an aircraft wing and tail with a simple vortex-lattice code and monocoque beam analysis, coupled to give static aeroelastic loads. The model is trimmed at several flight conditions to obtain load and induced drag data. Profile and compressibility drag are evaluated at stations across the span of the wing with empirical relations using the lift coefficients obtained from the vortex lattice code. Structural weight is calculated from the maximum elastic loads encountered through a range of flight conditions, including maneuver, vertical gust, and lateral gust. The structure is sized based on bending strength and buckling stability considerations. Maximum lift is evaluated using a critical section method that declares the wing to be at its maximum useable lift when any section reaches its maximum lift coefficient, which is calculated from empirical data. Balance is evaluated by distributing weight over the planform as described in Wakayama⁹.



Figure 2: WingMOD BWB Model.

The WingMOD optimization framework takes a set of constraints representing mission requirements (range, payload capacity, cruise speed, approach speed, balance, etc.); and finds an optimal aerodynamic and structural configuration such that the resulting aircraft satisfies the constraints. Among the outputs of the optimization are weight characteristics, planform geometry, and fuel burn.

COST MODEL

The cost model has two components: manufacturing cost and development cost. The goal of the model is to determine the cost characteristics of an aircraft given its technical parameters. Importantly, these cost characteristics include the effect of commonality between several different airframes. In general, then, both the development cost and manufacturing cost of a new aircraft will depend upon (a) the aircraft's technical parameters and (b) the technical parameters of other aircraft types that have already been designed.

Both cost models are based upon the decomposition of the aircraft into a set of components. Existing cost models and statistical data are used for calibration, resulting in a baseline *cost per pound* for each aircraft component. This cost per pound is converted to a total cost through the technical parameters of the aircraft (i.e., component weight), and further modified based on other factors, such as other aircraft types already designed. Figure 3 shows the estimated weight fraction breakdown between components for a modern twoengine jet transport. The breakdown was constructed using weight data from Raymer¹⁰ and Roskam¹¹.



Figure 3: Estimated empty weight breakdown (two-engine transport)

The manufacturing cost model is described below, followed by the development cost model.

Manufacturing cost is the cash needed to build an aircraft. This number is built up as the sum of the component parts. Each component baseline cost per pound is split into three primary cost categories: labor, materials, and support. As recurring costs, each of these categories exhibits a learning curve effect, where the marginal cost decreases with the number of units built to date. However, the effect is generally seen as significant only for the labor category. The marginal cost of the Q^{th} unit is given by

$$MC = TFU \times Q^{\ln(s)/\ln(2)}$$
(1)

where MC is marginal (unit) cost; TFU is theoretical first unit cost; Q is quantity built to date; and s is the learning curve slope parameter. Thus, when the number of units built doubles, the marginal cost of producing one additional unit is s percent of its original value. Table 1 shows the value of the learning curve slope parameters used here.

Table 1. Learning curve slope assumptions

Labor	Materials	Support
85%	95%	95%

As additional aircraft are built, the number of new components used for the aircraft is accrued separately for each component, and learning curve effects are applied by component instead of by aircraft. Thus, if two aircraft types share some, but not all, components, having built a number of one type of aircraft will affect the recurring cost of some, but not all, of the components of the second type of aircraft. Development cost is the non-recurring effort required to bring the aircraft concept to production. It includes preliminary design, detail design, tooling, testing, and certification. Like the manufacturing cost model, the development cost model is built up by component, and by cost category within each component. The categories are engineering, manufacturing engineering, tooling, and support. For each (category, component) pair, a factor is specified by which the cost is reduced in that category if that component has already been designed for an older aircraft.

To model the time distribution of development costs, each non-recurring category is assigned a baseline duration and start time, with a cost profile over the duration defined by a beta curve,

$$c(t) = Kt^{\alpha - 1} (1 - t)^{\beta - 1}, \qquad (2)$$

where *c* is the cost; *t* is the normalized time; *K* is a scaling parameter; and α , β are curve shape parameters. The parameters *K*, α , and β were chosen to approximate a typical development effort¹². Figure 4 shows the model output of the overall baseline cost profile for all the non-recurring cost categories. Note that this illustration assumes there are no cost reductions due to commonality (previously designed components).



Figure 4: Baseline development cost profile

The cost per pound values for each component were calibrated by using the DAPCA IV model¹⁰ to estimate the total development cost for a Boeing 777-200, for which the operating empty weight (OEW) is known to be \sim 305,000 lb¹³. From the estimated weight breakdown shown in Figure 3 and an estimated fractional cost breakdown by component, baseline cost per pound values were calculated.

As any cost estimation expert will agree, calculating aircraft component cost as a linear function of its weight is a crude approximation at best. However, there are several reasons why this approach was chosen over a more rigorous one. First, it is worth pointing out that only so-called "baseline" values for component costs are calculated as a linear function of their weight. Actual cost values also take into account learning curve (for recurring costs) and commonality effects. Second, a higher-fidelity model, while conceivable, would be impractical for the purposes of this study. Specifically, a more accurate model would consider the geometric complexity of the components and the materials used, it would use nonlinear cost-estimating relationships (CERs), and, by necessity, it would split the aircraft into a much finer (more numerous) set of components. Because this study focuses on the conceptual design stage, many of these cost modeling techniques are very difficult to implement. The aircraft may not be well defined enough to break down into smaller components and classify all of them. Further, a bottoms-up partsbased cost buildup would be impractical for conducting trade studies because such a buildup is not readily automated.

REVENUE MODEL

Given an aircraft design, a production rate, and a time horizon, the revenue model must provide the following three outputs: potential revenue cashflow for the current time period, the expected value of future revenue cashflows, and a measure of the uncertainty of the future cashflows. Further, the model must demonstrate realistic sensitivities to changes in aircraft performance (e.g., reduction in fuel burn), changes in the aircraft target market (e.g. 100 v. 250 passengers), and changes in aircraft price charged (i.e., demand price elasticity).

To achieve the functionality described above, the model development is broken up into a static analysis and a dynamic analysis.

Static Demand Analysis

The static analysis estimates a baseline price and corresponding quantity demanded, along with a demand growth rate over the specified time horizon. The price estimator relies on a regression of known sale prices for existing aircraft on several parameters believed to represent the aircraft's value to airlines. The quantity estimator relies on a simple average of three separate 20-year aircraft sales forecasts released by Boeing¹⁴, Airbus¹⁵, and a third source—the Airline Monitor¹⁶. Estimated growth rate in demand is little more than an input, as forecasts of the distribution of 20-year aircraft sales over time are scarce, and thus very little hard data is available.

Price is modeled as a function of several variables representing an aircraft's value to its operator, an airline. Several sets of variables and several functional forms were tested by applying the price model to 23 existing aircraft: 11 narrowbodies and 12 widebodies. The outputs generated by the price model were compared to best estimates for the actual sale prices for each of the aircraft, compiled from two sources^{17,18}. For each functional form tested, the function parameters were adjusted to minimize the mean squared error of estimated price. The function sought is of the form

Price = f(Seats, Range, CAROC)(3)

where

Seats	=	Passenger capacity
Range	=	Design range
CAROC	=	Cash Airplane-Related
		Operating Costs
	=	Total Operating Costs
		less Ownership Costs

The resulting function and its variables are shown below. Note that speed (or Mach number) is not one of the variables. No significant statistical relationship between price and speed was found in the range of available data.

$$Price = \left[k_1 \left(\frac{\text{Seats}}{\text{Seats_ref}} \right)^{\alpha} + k_2 \left(\frac{\text{Range}}{\text{Range_ref}} \right) \right] Price_ref - \Delta(LC)$$
(4)

where

Seats, Range	=	Aircraft seat count and range (nm); input variables.
Seats_ref	=	Reference value used to normalize seat count.
Range_ref	=	Reference value used to normalize range.
Price_ref	=	Reference value used to normalize price.
k_1 , k_2 , α	=	Model parameters, selected to minimize mean squared error of estimated prices.
$\Delta(LC)$	=	Increment in lifecycle cost due to off-nominal CAROC.

The last term in the equation, increment in lifecycle cost, refers to the additional cost the operator incurs if the aircraft's CAROC is "off-nominal"—that is, greater than the industry average CAROC for an aircraft of its size. This term is a function of the difference between the aircraft's CAROC and the least squares estimate for the CAROC of an aircraft with the same capacity.

The prices generated by the above function are compared to the best estimates of the actual aircraft prices in Figure 5 and Figure 6.



Figure 5: Narrowbody price model results



Figure 6: Widebody price model results

While the aircraft seat count and range are provided by the outputs of the performance model, its CAROC must be estimated separately. For the example used in this paper, the assumption is made that fuel costs for a reference mission (3,000 nm) represent 20% of CAROC[‡]. Fuel burn is calculated using the Breguet range equation, and a fuel price of \$.65 per gallon.

Quantity data is based on three distinct forecasts of quantities of aircraft to be delivered from 2000 through $2019^{14,15,16}$.

Each forecast has a different set of aircraft categories which comprise the global airline fleet. All three forecasts were recast into a single, consistent set of aircraft categories based on aircraft class (narrowbody or widebody) and seat count. Forecasted deliveries are assumed equivalent with quantities demanded at current market prices. The results are shown in Figure 7.

Depending on seat category, there is considerable variance between the three forecasts. This reflects differences in the forecasters' assumptions, methodology, and to some extent, corporate strategy.

[‡] The figure of 20% is based on empirical data for several existing aircraft. See Markish¹⁹ for details.

Further, the high variance reflects the high degree of uncertainty regarding future revenue cashflows.



Figure 7: 20-year gross demand—forecasted deliveries through 2019

For a given aircraft design, the quantity model proceeds as follows:

- 1. Assign given aircraft to a seat category.
- 2. 20-year gross demand for that category = mean of three forecasts.
- 3. Assume a market share in that category.
- Quantity demanded = (market share)*(20-year gross demand)

If several designs are considered for production simultaneously, fractions of seat category demands are assigned to each design, such that total quantity demanded will not exceed the product of market share and 20-year gross demand.

Dynamic Demand Analysis

The dynamic analysis aims to quantify the stochastic behavior of the market for commercial aircraft. As detailed in Markish¹⁹, it is observed that quantities of aircraft purchased fluctuate significantly from year to year, and exhibit some cyclical properties. Thus, given a forecast for year 0, it is impossible to predict with certainty what the quantity of aircraft demanded will be in year 10. However, based on historical data, some representative characteristics were found to describe historical aircraft demand levels as geometric Brownian motions, not unlike stock prices. Therefore, as shown in Table 2, the dynamic analysis identifies an average annual growth rate and average annual volatility for typical demand evolution patterns for wide body aircraft.

Table 2. Dynamic demand analysis outputs

Average volatility, σ , per annum	45.57%
Average growth rate, α , per annum	4.43%

PROGRAM VALUE ANALYSIS

The most straightforward scheme for combining the above models into an analysis tool for the entire program is to perform a discounted cash flow calculation, assuming an accurate value is known for the cost of capital. This calculation is performed in a simple example below. A second example follows, which shows several results from a more complex scheme of linking the models and valuing the program. Specifically, the alternate valuation scheme addresses the effects of uncertainty and managerial decisionmaking throughout the duration of the program.

Example 1: Discounted Cash Flow

For the first example, a medium-gross weight aircraft is initiated at time 0, followed four years later by a larger aircraft. The aircraft are given values for CAROC, range, and capacity, as well as inputs specifying a production schedule once design is complete. These inputs are contrived only to demonstrate the basic functionality rather than to model an actual aircraft program. With an assumed discount rate of 15%, discounted cashflow values can be found for each time period of the program. The 20-year time horizon is broken up into months, and the program simulation is implemented in C, cycling over each period and calling each model as necessary. The output of a trial run is shown in **Figure 8**.



Figure 8: Cumulative discounted cashflow (2-aircraft example scenario).

Note that the cumulative discounted present value of the project does not become positive ("break even") until well into the project. The two "dips" in the curve are the non-recurring development efforts for each of the two aircraft, while the persistent upward trend is the profit from monthly sales, dictated by demand and by planned production capacity.

Example 2: Dynamic Programming

The second example uses the same set of models, presented above, as the first example, but employs a more sophisticated valuation scheme than NPV.

The valuation is based upon a dynamic programming algorithm that treats the aircraft project as an optimization problem with continuous decision-making by the aircraft manufacturer. The problem time horizon is split into periods, and demand for aircraft is treated as a semi-random process, starting from a deterministic initial value and evolving stochastically during every period. Depending on the level of aircraft demand in any given period at any given time, an optimal course of action is identified for the firm. For example, given that demand is low, it may not be optimal for the firm to develop a given aircraft. However, if demand is high, it may be optimal to commit to development. The threshold levels of demand that affect these optimal decisions are also, in general, functions of time-that is, a decision to develop an aircraft may depend on the number of periods left until the end of the time horizon. The end of the time horizon may be thought of as the point at which the product will be rendered obsolete, possibly by new technology or competition.

In brief, the dynamic programming algorithm is a more sophisticated valuation method than NPV, explicitly accounting for the uncertainty inherent in an aircraft program and the flexibility of managerial decision-making that can be used to cope with uncertainty. For a more detailed discussion of the dynamic programming algorithm, refer to Markish and Willcox⁵ and Markish¹⁹.

The inputs used in the example use three different aircraft designs, all based upon the BWB concept. Table 3 summarizes the key characteristics of the designs.[§] Three different airframes are possible: one large, 747-class vehicle (BWB-450), and two smaller, 250-passenger class designs. One of the smaller designs, the BWB-250C shares 39.7% of its parts, by weight, with the BWB-450. The other has no commonality with the BWB-450, being a point design, optimized without consideration for commonality. Note that the point design results in a lighter airframe, because the commonality constraint placed upon the BWB-250C results in a weight penalty. Specifically, the BWB-250C uses the same wing as the BWB-450 to save on development cost, but an individually optimized design for the BWB-250 would not need as much wing area.

Table 3. BWB example key characteristics

Design	BWB- 450	BWB- 250C	BWB- 250P
Seat count	475	272	272
Range (nm)	8550	8550	8550
GTOW (normalized)	1	0.756	0.624
commonality (by weight)	N/A	39.7%	0%

Using the dynamic programming method, the above three designs are evaluated in several different combinations to find program value. First, each of the designs is evaluated on an individual basis, as though it is the only design option available to the firm. Then, the BWB-450 and BWB-250C are evaluated simultaneously, to investigate any synergies that may exist as a result of commonality. In this case, both designs are available to the firm to develop and produce at its discretion. Finally, the BWB-450 and BWB-250P are also evaluated simultaneously. The key input parameters used for all test cases are listed in Table 4.

 Table 4. Key input parameters for all test cases

Number of periods	30
Timestep per period	1 year
Risk-free rate, $r_{\rm f}$	5.5%
Annual aircraft price inflation	1.2%
Annual aircraft demand volatility	19.6%

RESULTS AND DISCUSSION

The intermediate results of the test runs described above are summarized in Table 5. These represent the primary outputs of the models described in this paper: cost characteristics and demand characteristics (price and quantity) based upon a particular airframe and its performance. It can be seen that there is greater annual demand for the smaller-capacity wide bodies (BWB-250) than for the high-end BWB-450. Note that quantity demanded is modeled as independent of operating characteristics (i.e., performance)-rather, the quantity estimator considers only the size class of the aircraft. However, the price estimator distinguishes between all three vehicles. The baseline price is expectedly high for the BWB-450, as it is a much larger aircraft. However, while the two smaller aircraft have identical seat counts, the BWB-250P is significantly higher priced. This effect is due to its lighter weight, which results in significantly reduced fuel burn, and therefore a lower operating cost.

[§] The example designs are purely hypothetical and significantly simplified. They do not represent actual current Blended-Wing-Body configurations.

	Baseline quantity demanded	Long-run marginal cost	Baseline price
	(units/yr)	(\$M)	(\$M)
BWB-450	16.7	139.0	195.0
BWB-250C	27.6	93.8	116.1
BWB-250P	27.6	84.9	142.2

Table 5. Intermediate results for Example 2: demand characteristics.

Predictably, the long-run marginal cost (LRMC) scales with the vehicles' weight. LRMC is defined here as a limiting unit cost which the manufacturing process approaches as more and more units are produced. For this example, it is defined as the marginal cost of unit 100, produced without any commonality effects. Thus, because the point-designed BWB-250P is lighter than the derivative BWB-250C, its long-run cost of production is smaller. However, commonality should result in a reduced development cost and a reduced learning effort for the BWB-250C. That is, the marginal cost should reach LRMC faster.

Table 6 shows the final results of this example: the program values resulting from the several different combinations of designs evaluated.

Table 6. Final results for Example 2: program value (\$B)

(1)	BWB-450	5.95
(2)	BWB-250C	2.26
(3)	BWB-250P	14.62
	(1) + (2)	8.21
	BWB-450 & BWB-250C	8.95
	Commonality premium	9%

The first result to consider is the extremely high program value found for the BWB-250P. While it is probably too high to be realistic, it highlights the key design issues in this example: a considerable sacrifice was made in the 250-passenger class aircraft design to accommodate commonality. A modest increase in empty weight translated to a medium increase in takeoff weight, which translated to a significant difference in fuel burn and operating cost**, and an even greater difference in market price. The sensitivity of price to operating cost is difficult to observe in practice, and these results suggest that it is overestimated by this pricing model. However, regardless of the accuracy of the model, this snowballing phenomenon underscores the importance of considering the downstream effects of a design change on program value.

The other side of the coin is the value benefit gained by commonality: a savings in development and manufacturing costs. This is reflected in the existence of a commonality premium, albeit a modest one in this example. The value of the program with both designs (BWB-450 and BWB-250C) considered simultaneously is greater than the sum of the values of their individual programs. The program value of the BWB-450 and BWB-250P considered simultaneously is not shown, as it would be identical to the sum of their individual values, because there is no interaction between those two aircraft.**

Within the framework of flexibility and decisionmaking used by the dynamic programming algorithm, the choice to use commonality may be framed using real options. When the firm develops the BWB-450, it acquires an option to develop the BWB-250C for a reduced cost and at a time of its choosing. The penalty paid—i.e., the price of the option—is the present value of additional profits the firm would receive had it instead developed the BWB-250P as a point design to maximize its performance. From a program flexibility standpoint, the firm still has an option to develop a second aircraft even if there is no commonality-in such a case, the exercise price of the option is simply higher by the amount of cost savings from commonality.

The conclusion of this example, therefore, is not that commonality isn't justifiable. Rather, for commonality to be justifiable, the benefits must outweigh the costs. The benefits include the development and manufacturing cost savings gained if the derivative aircraft is in fact built. The costs include any additional design or manufacturing costs as a result of commonality, but most importantly, any resulting performance penalty on the aircraft. This performance penalty must be translated into an opportunity cost: the revenues foregone by *not* selling a higher-performance aircraft. The set of aircraft designs used in this example, with the baseline parameters specified, did not indicate a higher program value for commonality,

^{**} Refer to Markish¹⁹ for details on operating cost calculations.

^{††} It would be interesting to consider interactions in program value arising not from physical commonality but from market effects (e.g., complements or substitutes).

because the opportunity cost of lost revenues was very high^{‡‡}.

CONCLUSIONS

This paper presents a combination of three analytical models. Linked through one of several possible schemes, the models may be used to aid in the conceptual design effort of one or more commercial aircraft. Two of the method's distinguishing features are: (1) the combination of economic analysis with engineering analysis; and (2) explicit consideration of management's ability to make and defer decisions in "real time" in response to unfolding market conditions.

The dynamic programming algorithm used in this method is relatively fast: each test case took approximately ten minutes to solve, implemented in C on a Pentium III laptop.

Thus, this paper demonstrates the feasibility of an analytical tool that combines technical-level and program-level trade studies using the metric of value as the objective function. The tool allows for truly multidisciplinary analysis of the system being created, and forces designers to focus on the true objective function for the system: value to the company. If applied correctly, the method of system design to maximize program value will encapsulate multiple traditional objective functions—minimum gross weight, maximum performance, minimum cost, maximum revenue, etc.—but it will not place disproportionate weight on any one objective in particular. Rather, the maximum program value solution will optimize the entire system design.

For this work, the technical design was fixed (and was the output of a prior optimization that focused only on performance). In future work, the cost and revenue models presented here will be coupled with an optimizer that can make not only program-level decisions, but also technical design decisions. In this way, engineering design decisions will be effected using a true multidisciplinary system analysis.

REFERENCES

1 Zang, T. A., Green, L. L. "Multidisciplinary Design Optimization Techniques: Implications and Opportunities for Fluid Dynamics Research.." 30th AIAA Fluid Dynamics Conference. Norfolk, VA, AIAA Paper 99-3798, June 1999. 2. Anon., "Current state-of-the-art in multidisciplinary design optimization", AIAA MDO Technical Committee White Paper, 1991.

3 Kroo, I. "MDO Applications in Preliminary Design: Status and Directions," AIAA Paper 97-1408, 1997.

4 Liebeck, R. H., Page, M. A., Rawdon, B. K., "Blended-Wing-Body Subsonic Commercial Transport," AIAA paper 1998-0438, Jan. 1998.

5 Markish, J., Willcox, K. "A Value-Based Approach for Commercial Aircraft Conceptual Design." *ICAS* 2002 Congress, Toronto, Sep. 2002.

6 Wakayama, S., Kroo, I., "Subsonic Wing Planform Design Using Multidisciplinary Optimization." *Journal* of Aircraft, Vol. 32, No. 4, Jul.-Aug. 1995, pp.746-753.

7 Wakayama, S., *Lifting Surface Design Using Multidisciplinary Optimization*, Ph.D. Thesis, Stanford University, Dec. 1994.

8 Wakayama, S., Kroo, I., "The Challenge and Promise of Blended-Wing-Body Optimization," AIAA Paper 98-4736, Sep. 1998.

9 Wakayama, S., "Blended-Wing-Body Optimization Problem Setup." AIAA Paper 2000-4740, Sep 2000.

10 Raymer, Daniel P. *Aircraft Design: A Conceptual Approach*. Reston, VA: American Institute of Aeronautics and Astronautics, 1999.

11 Roskam, Jan. *Airplane Design. Part V: Component Weight Estimation*. Ottawa, KS: Roskam Aviation and Engineering Corporation, 1989.

12 Conversation with Dave Anderson, Director of Derivatives & Features, Boeing Commercial Aircraft, 3/5/01.

13 Jane's All the World's Aircraft. London : Sampson Low, Marston & Co., 2001.

14 Boeing Current Market Outlook, 2000. Appendix B, p. 42.

15 *Airbus Global Market Forecast*, 2000-2019. Appendix G, Detailed passenger fleet results, p. 74.

16 *The Airline Monitor*, ESG Aviation Services, July 2000. Projected Jet Airplane Deliveries—2000 to 2020, pp. 10-11.

17 *Aircraft Value News* Aviation Newsletter. http://www.aviationtoday.com/catalog.htm.

18 The Airline Monitor, ESG Aviation Services, May 2001.

19 Markish, J., "Valuation Techniques for Commercial Aircraft Program Design," S.M. Thesis, Massachusetts Institute of Technology, June 2002.

^{‡‡} Recall that the designs used for the example are not representative of actual Blended-Wing-Body configurations.