ECONOMIC UNCERTAINTY ASSESSMENT USING A COMBINED DESIGN OF EXPERIMENTS/MONTE CARLO SIMULATION APPROACH WITH APPLICATION TO AN HSCT[†]

Dimitri N. Mavris[*]
and
Oliver Bandte[⁑]

School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0150

Recently, the aerospace industry has felt the impact of the combined effect of increasing aircraft systems costs and budget restrictions and is reacting through a series of initiatives to help minimize their overall Life Cycle Costs. These growing concerns have prompted the appearance of various risk assessment and reduction techniques. These techniques have been incorporated into a Robust Aircraft Design Simulation methodology which is based on an Integrated Product and Process Development (IPPD) approach. This IPPD environment accounts for the effects of each discipline (i.e. aerodynamics, structures, propulsion, producibility, supportability, etc.) and their corresponding technological advances on the overall system evaluation criterion, the average yield per revenue passenger mile. This paper reviews this IPPD methodology by describing the techniques on which it is based, such as the Design of Experiments, Response Surface Methods, and Monte Carlo Simulation, and illustrates the steps taken for its implementation for the economic uncertainty assessment of a High Speed Civil Transport vehicle.

Introduction

As affordability and the cost of performance become a major focus for aerospace systems, it is becoming evident that the design methodology utilized in future systems must reflect this new focus. A suitable method is based on an Integrated Product and Process Development (IPPD) approach where trade-offs are allowed early in the design phases to leverage the design and cost freedoms available[1]. It also allows for an adequate assessment of risk and uncertainty with regards to performance, cost, or schedule, which are always high in the early phases of a new aerospace systems program.

Recognizing the design philosophy changes taking place in the aerospace industry, the authors have taken steps to introduce a systematic approach to design. This program has not only begun to address the interdisciplinary interaction of the traditional aerospace engineering disciplines with design, but is also addressing the integration of design and manufacturing to support the IPPD environment being created in industry. This is achieved using a Robust Design Simulation (RDS)[1] approach.

Although the RDS method encompasses such disciplines as aerodynamics, structures, propulsion, producibility, and supportability, this paper describes only the affordability aspects of the newly developed IPPD methodology and the way in which it is implemented. A proof of concept implementation is applied to the High Speed Civil Transport (HSCT), but this methodology can be utilized to assist in developing, quantifying, and evaluating metrics for any type of aerospace vehicle in general.

Robust Design Simulation (RDS)

The premise behind robust design is that the best way to achieve customer satisfaction is to deliver a product that performs well not only in the environment for which it was designed, but in all environments. This is accomplished in RDS by incorporating all elements essential to the success of the design into an IPPD framework with the overall goal of making the design insensitive to changes in external noise factors that are beyond the designer's control.

For example, the economic viability of a fuel-hungry aircraft such as the HSCT is highly sensitive to the cost of fuel. It may be that the aircraft will be profitable to operate today, but unprofitable if the cost of fuel rises tomorrow. From the designer's viewpoint, the cost of fuel is a noise factor because it is beyond control. However, the designer can take steps to influence the sensitivity to fuel cost by reducing the fuel consumption of the aircraft. In many cases, this might be accomplished through the introduction of new technology which will in turn introduce added risk to the design.

The essential elements and goals of RDS are illustrated in Figure 1. Traditionally, design is

[†] Presented as Paper at the 17th Annual Conference of the International Society of Parametric Analysts, May 1995, San Diego, CA.

[*] Associate Director and Manager, Aerospace Systems Design Laboratory (ASDL).

[⁑] Graduate Research Assistant, ASDL.

comprised of a simulation code (sizing/synthesis or economic analysis) and an optimization routine which varies the design or economic parameters (i.e. aspect ratio, wing loading, return on investment, etc.) to yield an "optimum" solution subject to all imposed environmental and design constraints.

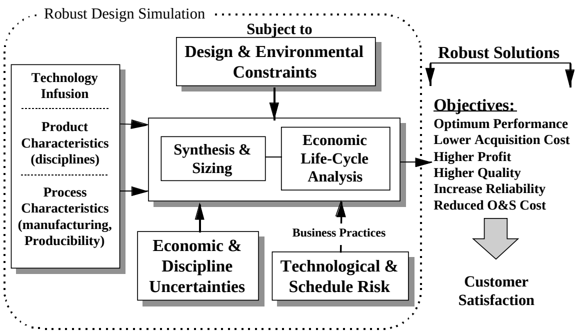

Figure 1: IPPD through Robust Design Simulation

RDS differs from traditional design techniques in that it identifies key product and process characteristics, as well as their relative contributions to the chosen evaluation criterion in the presence of risk and uncertainty, as depicted in Figure 1. Robust Design accounts for manufacturing issues (i.e. process characteristics) and risks associated with new technologies. These can be measured in terms of confidence and readiness levels (i.e., concept feasibility, producibility, and potential of fielding according to the program schedule). In addition, Robust Design allows for variability due to uncontrollable factors (economic uncertainty, noise factors, etc.). In this way, a product is designed and optimized concurrently, yielding a probability distribution for the evaluation criterion, rather than a single point design solution as is the case with traditional methods.

Uncertainty in Design

The presence of uncertainty in the operational environment of an aircraft results in an inability to predict the exact response of the system. By definition, noise is an inherently random phenomenon. As a result, a system subject to noise can never be expressed in terms of a single solution, but must instead be expressed in terms of a probability distribution[2].

For example, if one were to assume a fixed cost of fuel for an economic analysis, it would be possible to explicitly calculate the DOC for that aircraft using established economic analysis methods. However, the cost of fuel is not known *a priori* and the best that one can hope to do is define a range and probability distribution for fuel cost based on historical data. One could then randomly pick a value for fuel cost based on the probability distribution and calculate the DOC for the aircraft.

If this procedure is repeated many times with the result from each trial being sorted into a bin to form a histogram, the result is a distribution for DOC. This method is known as Monte Carlo simulation[3] and the result is a probability distribution similar to the one shown in Figure 2.

Design Viability and Feasibility

It is important to note the difference between concept viability and feasibility. In this paper, feasibility is associated with the technological capability of producing an aircraft, while viability is associated with the economic performance of the aircraft.

Figure 2 illustrates this and shows how a feasible solution is not necessarily an economically viable one. In this figure, the economic target is set to be the average yield per revenue passenger seat mile ($/RPM) for a current long range wide body transport aircraft similar in size to the Boeing 777, MD-11, and A-340.

The probability distribution on the right corresponds to an HSCT concept using existing materials, processes, and proven concepts. This solution is technologically feasible, but not economically viable and a mechanism for shifting it towards the target needs to be identified.

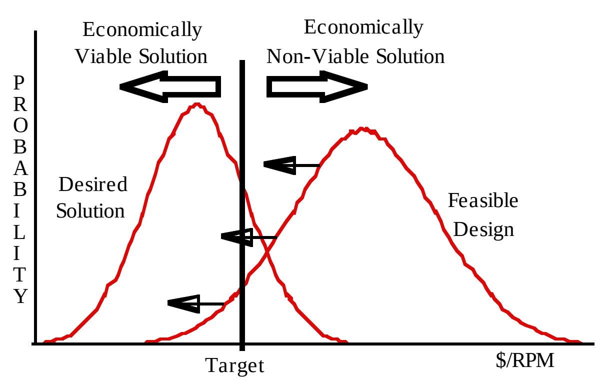

Figure 2: Need to Shift Design from Feasible to the Aspiration Space

One way of shifting the probability distribution is through the introduction of new technologies. As the program becomes better defined and means of reducing cost by employing new technologies are identified, the response mean will be shifted closer toward the target. The probability distribution now accounts for both risk of unproven technology and economic uncertainty. This is the premise of the robust design simulation: identify all critical design variables and technologies, show their effect on the economics of the vehicle, and offer suggestions for how this concept can become economically viable.

DoE and Response Surface Methodology

The Response Surface Methodology (RSM) can be used as one of the elements comprising the Robust Design Simulation method. It is based on a statistical approach to building and rapidly assessing empirical models[4,5]. By careful design and analysis of experiments or simulations, the methodology seeks to relate and identify the relative contributions of the various input variables to the system response.

In most cases, the behavior of a measured or computed response is governed by certain laws which can be approximated by a deterministic relationship between the response and a set of design variables. Usually the exact relationship between this response and the design variables is either too complex or unknown, and an empirical approach is necessary to determine it. The strategy employed in such an approach is the basis of the RSM.

In order to reduce the number of variables before constructing a Response Surface Equation (RSE), a screening test is needed to identify the contribution of each variable to the response of the system. The screening test is a two level fractional factorial DoE that accounts only for main effects of variables (i.e. no interactions)[4]. It allows the rapid investigation of many variables (in this case 16) to gain a first understanding of the problem. This analysis yields a Pareto plot[12] such as that shown in Figure 3 which enables the identification of the most significant contributors[7].

The solid line in Figure 3 indicates the cumulative contribution to the overall response while the individual contribution from each variable is indicated by the horizontal bar. It is obvious from Figure 3 that the first 7 variables contribute 80% of the overall response. Thus, one could use these 7 as the variables in the RSE while fixing the remainder at some "most likely" value and still be assured of getting a reasonable data fit.

After identifying the variables which will form the RSE, a design has to be selected from the list of potential candidate methods. For the purposes of this study, the Box-Behnken Design was used to develop an RSE. The Box-Behnken Design is a three level composite design formed by combining a two-level factorial with an incomplete block design[4].

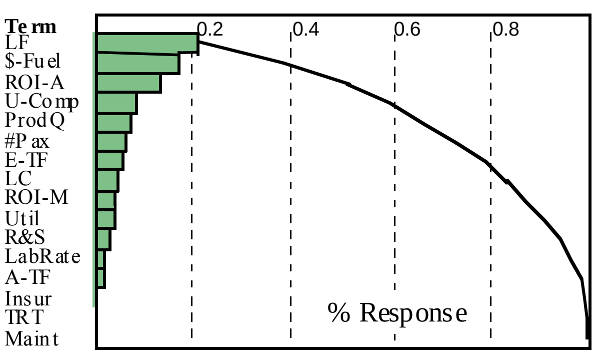

Figure 3: Sample Pareto Plot - Effect of Design Variables on the Response

For this study, a second degree model in k-variables is assumed to exist. This second order polynomial for a response, R, can be written as:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum \sum_{i<j}^{k} b_{ij} x_i x_j$$

where: b_i are regression coefficients for linear terms
b_{ii} are coefficients for pure quadratic terms
b_{ij} are coefficients for cross-product terms (second order interactions)
x_i, x_j are the design variables and $x_i x_j$ denotes interactions between two design variables

Once this equation is constructed, it can be used in lieu of more sophisticated codes to predict the response of a sub-system or the entire system. The "optimal" settings for the design variables are identified by finding the maximum or minimum of this equation. Since the RSE is in essence a regression curve, a series of experimental or computer simulation runs need to be performed to obtain a set of data for varying inputs.

The combination of cases that need to be tested can be found in various textbooks or, as in this paper, through the use of a statistical computer analysis program called JMP[6]. JMP not only builds the tables, but also carries out all necessary analysis once the responses are provided from the simulation runs. The same DoE approach can be used for variables at three levels, requiring more runs to obtain the same information.

Monte Carlo Simulation

After the RSE is developed, the effect of noise factors can be incorporated into the model through the use of Monte-Carlo simulation[3]. A Monte Carlo Simulation is effectively a random number generator that creates values for each uncontrollable variable. Values are chosen within specified ranges for each variable and with a frequency proportional to the shape of the probability distribution associated with each variable. Usually 1,000 to 10,000 cases are needed for a good representation of the probability distribution of the response for engineering analysis at this fidelity level. Without the aid of the RSE approach, this task would be computationally demanding and in many cases impractical when one considers that this Monte Carlo Simulation would have to be wrapped around an actual simulation program.

Economic Uncertainty Assessment Methodology

The IPPD methodology used herein is based on the premise that the core competency of prime aerospace companies is large scale systems integration. Parallel product and process design trades at the system, major component, and part level through system decomposition and recomposition activities are required in such a framework[1]. Therefore, simulation analysis is the key linkage for continuously evaluating whether evolving robust designs satisfy the goals that will ultimately result in customer satisfaction.

Figure 4 depicts the implementation of this procedure for a generalized HSCT configuration. For the vehicle sizing and synthesis, the FLight OPtimization System (FLOPS)[7] is used to translate mission requirements, design variables, and constraints at a given technology level into an aircraft configuration. The geometric, weight, and propulsion characteristics of this vehicle are then passed on to the Aircraft Life Cycle Cost Analysis (ALCCA)[8] module to perform an economic assessment.

Through the application of a Design of Experiments (DoE) approach, a regression analysis is used to determine an equation giving the response as a function of the most significant economic variables based on calculations performed by ALCCA. In the case of commercial transport aircraft, the most suitable response was found to be the average yield per Revenue Passenger Mile ($/RPM), a metric that implicitly captures the interests and concerns of all parties involved[9]. This encompasses airline and manufacturer profitability measured in terms of their corresponding Return on Investment and passenger acceptance captured by an affordable ticket price.

Next, economic uncertainty is introduced into the model, and a Monte Carlo Simulation is performed with the aid of a software package called Crystal Ball[3]. Crystal Ball randomly generates numbers for these variables based on user-defined probability distributions and computes a probability distribution for the response as shown in Figure 2. This distribution of $/RPM is based on a feasible design. However, the design must be economically viable as well as feasible, and if a Monte Carlo simulation indicates an economically non-viable solution, areas of possible technology improvement have to be identified to make the design both feasible and economically viable. If no improvement is possible the program can be terminated early in its evaluation process without cost intensive test programs and market studies. In the case of identifiable technology improvement, the entire procedure can be repeated until an economically viable solution is obtained.

A Case Study: The High Speed Civil Transport

An economic uncertainty assessment exercise based on the next generation High Speed Civil Transport (HSCT) was analyzed as an illustration of this technique. This combined RSM/Monte Carlo Analysis was applied to an existing HSCT configuration and the effect of economic uncertainty associated with it was quantified.

The HSCT is envisioned to be an aircraft capable of flying supersonically (~Mach 2.4) and carrying 300 passengers to destinations in excess of 5,000 nautical miles[10]. Furthermore, stringent requirements are being placed on this aircraft to make it economically viable, as well as environmentally friendly. Because this vehicle is being forced to abide by all appropriate FAA and EPA regulations, this initiative can only succeed through the introduction of new technologies, risk management, and yield management.

Designing such an aircraft from an affordability point of view implies that one understands how the various design, discipline, and economic variables affect the Overall Evaluation Criterion (OEC), namely the average yield per Revenue Passenger Mile. The objective is to achieve a robust design that meets the target value set for the criterion function, as illustrated in Figure 2. A feasible design, based on today's technology, can be converted to an economically viable one based on new technology development and maturation. As shown in the figure, the desired $/RPM probability distribution must be shifted to the left of the target (roughly $0.13 based on an approximate 30% fare surcharge above the ticket price of a comparably sized subsonic aircraft) with fairly high confidence (>50%) and reduced variability. This evaluation can be realized in the form of an IPPD robust design simulation, and is illustrated in Figure 1.

In order for a concept such as the proposed HSCT to be produced, it must abide by stringent FAR Stage III or IV noise regulations[11], be comparable in safety and comfort to the current long range subsonic fleet, and provide economic benefits to all interested parties (manufacturer, operator, passenger). Therefore, it is essential to maintain an affordable ticket fare for the passenger, while retaining a reasonable Return on Investment for both the airline and the airframe/engine manufacturers. In order to satisfy all of these conflicting requirements, a method must be developed to increase the aircraft productivity and reduce its production, operation and support costs. The study of this complex multi-disciplinary problem can be greatly facilitated by taking advantage of advancements made over the past few years in the area of Robust Design.

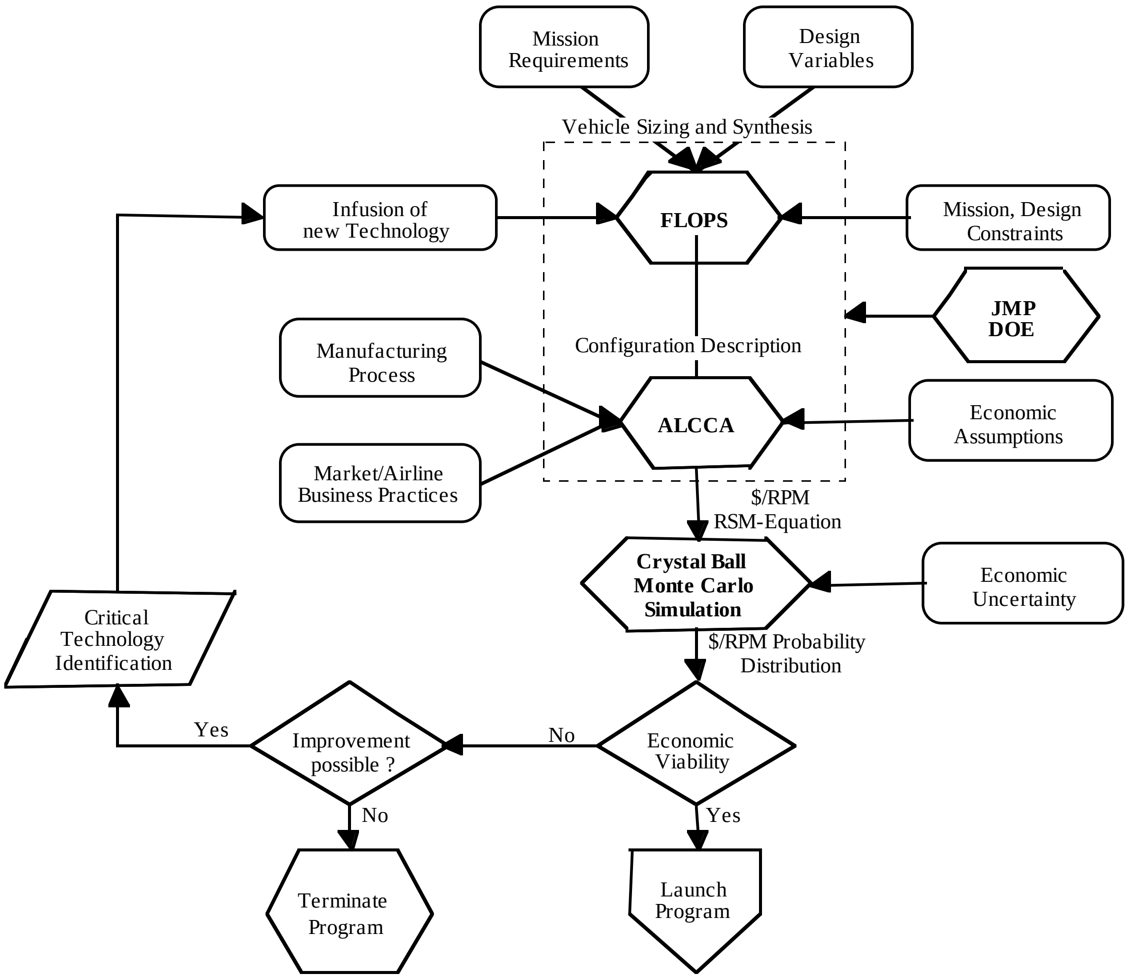

Figure 4: Economic Uncertainty Assessment Execution

Baseline configurations of an HSCT (an arrow-wing, and a double-delta wing concept) have been generated based on a series of specified requirements and constraints. The configuration was sized by FLOPS for the split subsonic/ supersonic mission, depicted in Figure 5. This configuration provided all data necessary to perform the economic analysis.

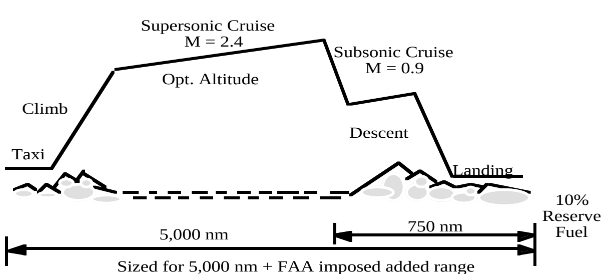

Figure 5: Baseline Mission Profile

Economic Uncertainty Assessment of an HSCT

Identification of Critical Design Variables

The first step in an economic uncertainty assessment is the identification of all pertinent cost parameters. Figure 6 depicts the considerations addressed by ALCCA for an economic study. The Ishikawa or "fishbone" diagram[12] displayed in this figure presents the various design and cost variables which affect the chosen OEC, $/RPM.

This diagram shows an airline's point of view; all of the economic variables above the horizontal vector leading to $/RPM refer to airline revenue, while all entries below that vector correspond to expenditures.

From this breakdown, the 16 variables shown in Table I were identified as the most pertinent and ranges for each were selected. The remaining

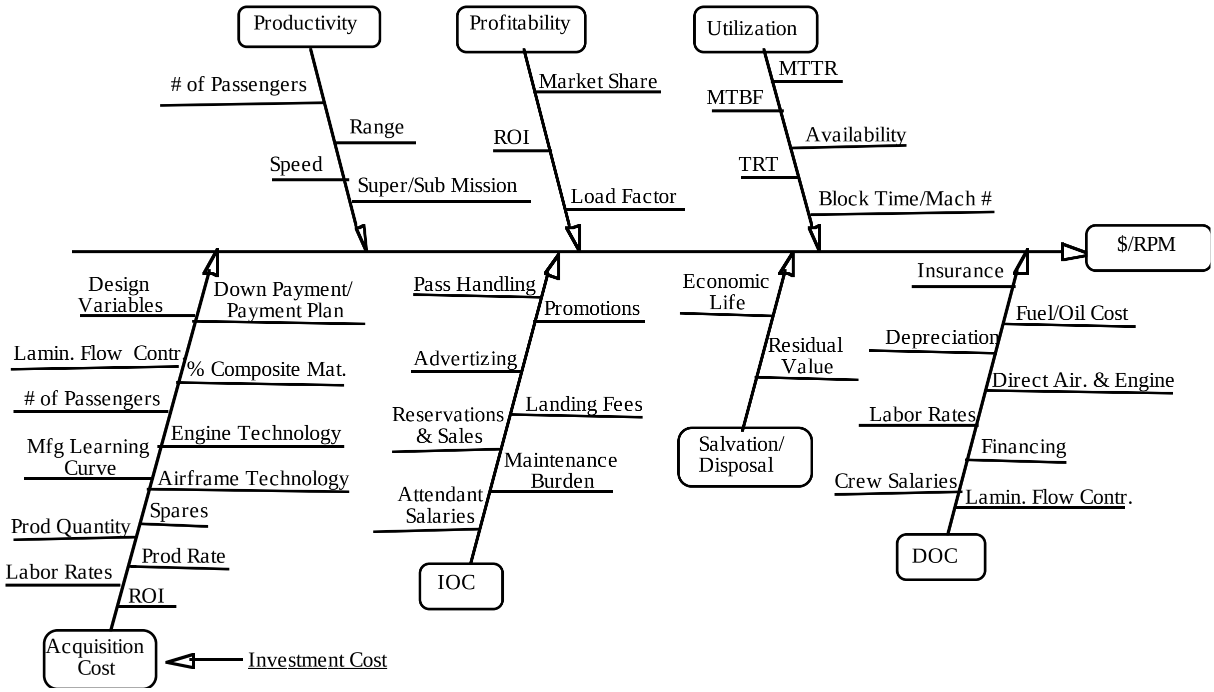

Figure 6 : Ishikawa Diagram for Cost Parameter Organization of $/RPM

variables were set to their default values in ALCCA or they were based on results from recent market studies. In general, since the range, the Mach number at optimum altitude, and the number of engines were fixed for the configuration studied, the number of passengers and use of composites were the only remaining sizing or synthesis variables allowed to vary in FLOPS.

The definition of some of the variables in Table I is not intuitively obvious and needs further explanation. The uncertainty associated with engine acquisition cost, for example, is accounted for by the engine technology factor. The engine technology factor is an adjustment factor affecting engine cost, which accounts for the unpredictability of engine development cost. It has been the author's experience that the engine purchase cost of a supersonic engine is about two to four times more than that predicted by the CER in ALCCA. Therefore, the maximum and minimum levels were set according to the values obtained from an economic uncertainty assessment.

Similarly, the Airframe Technology Factor captures the variability of the cost to manufacture airframe components made of composite materials. The lower level of this factor corresponds to present levels of manufacturing cost for composites, while the higher level refers to the optimistic expectation of reducing the production cost to that of aluminum. Obviously, this factor will only apply if composites are actually used on the aircraft.

The use of composite materials itself is treated only at two levels: either no use at all or use of composites to the maximum extent possible for the wing, fuselage, and empennage structure. The Labor Rates, Reservation & Sales (accounting for all premiums paid to travel agents, etc.), and Maintenance expenses were varied by 10% in either direction from their default or most likely values. The insurance rate was also varied to account for the risk associated with the use of new technologies and engines, which will increase the value of the aircraft in comparison to proven, existing wide-body transports.

Screening and Response Surface Equation Evaluation

The second step of the economic risk study is the development of an equation for the metric response in terms of economic variables using RSM. As previously shown, a 3-level DoE for 16 variables requires too many runs to obtain an equation in a reasonable amount of time. Therefore, a screening test was conducted using a 2-level DoE linear model in order to identify which seven of the sixteen variables make the greatest contribution to the response After obtaining the $/RPM and the acquisition cost for all level combinations displayed in the DoE table, an ANOVA[13] (Analysis of Variance) for the main model effects is performed to obtain each contribution. The Pareto plots shown in Figure 7 display these contributions.

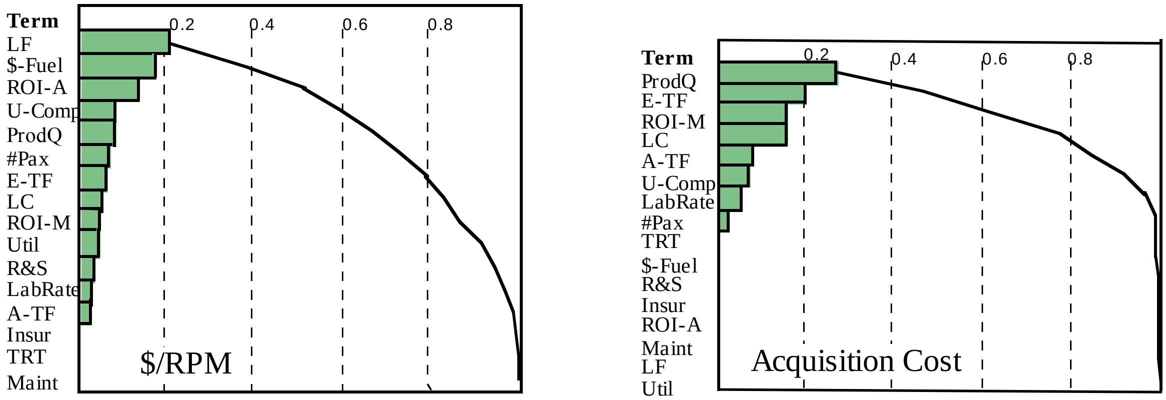

Figure 7: Pareto Plots from Screening of Main Effects for $/RPM and Acquisition Cost

Using the Pareto chart in Figure 7, the seven highest contributing variables to the response $/RPM are identified as: the load factor, cost of fuel, production quantity, engine technology factor, learning curve, ROI-manufacturer, and utilization. These independent variables were next used to form the RSE for the $/RPM. As Figure 7 indicates, these variables constitute 90 to 95 % of the response. The remainder of the variables are insignificant to the response and are set at a fixed value. The configuration used for the RSE also assumed a high level of composites while the number of passengers was fixed at 300. No synthesis or sizing was needed for this particular set of variables. Hence, FLOPS was not part of the RSM, while ALCCA simply used the fixed configuration depicted above. All other variables not addressed in the RSE were set to their default or most likely values.

Table I summarizes the independent RSE variables and their values. It also lists the remaining variables that were fixed during the RSE development. Furthermore, separate RSEs at two discrete levels were developed for ROI_A of 5% and 10% so that the general trend of $/RPM with respect to ROI_A could be observed.

The prediction profiles[5,6] in Figure 8 illustrate the key variables on the interval from -1 to 1. These numbers are just the indicators for the levels at which the variables are examined. In fact, all simulation runs were performed using the actual values for each input variable.

Figure 8 displays the RSM outcome for Airline-ROI of 5 and 10 %, based on an ANOVA for parameters of a quadratic model with second order interactions. This figure illustrates the relationship of each variable and the response. The Cost of Fuel, for example, has approximately a linear influence, as indicated by the equivalent plot in Figure 8. On the other hand, the Load factor, Production Quantity, and the Learning Curve show a weak quadratic response, which is reflected in Figure 8 as curvature. The lin-

Table I : Independent RSE and Fixed RSM Variables

Independent Variables	minimum	most likely	maximum
Load Factor (LF)	55 %	65 %	75 %
Fuel Cost ($-Fuel)	0.09 $/lb	0.13 $/lb	0.17 $/lb
Production Quantity (Prod Q)	300	548	798
Engine Technology Factor (E-TF)	2	3	4
Learning Curves (LC)	75 %	80 %	85 %
ROI - Manufacturer (ROI-M)	10 %	15 %	20 %
Utilization (Util)	4,500 hr/yr	5,000 hr/yr	5,500 hr/yr

Fixed Variables	Value
ROI - Airline (ROI-A)	5% and 10%
Number of Passengers (#Pax)	300
Use of Composites (U-Comp)	Yes
Ground Time (TRT)	1.0 hr
Labor Rate (Lab Rate)	19.50 $/hr
Reservation & Sales (R&S)	1 $/pax
Maintenance (Maint)	19.50 $/hr
Insurance (Insur)	0.75 % of acq. cost
Airframe Technology Factor (A-TF)	Cost Today

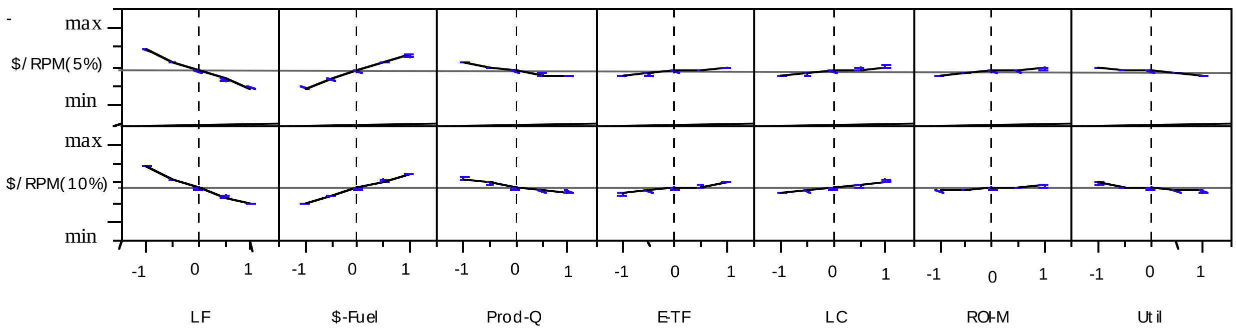

Figure 8: Prediction Profiles of the RSE for 5% and 10% ROI for the Airline

earity in the response is due to the small investigation intervals of the variables, hardly indicating a practical significance for the quadratic slope.

Variability Assessment

An uncertainty assessment was performed based on the equation determined above. Since the Monte Carlo Simulation is basically a random number generator, ranges for the variables used in the response surface equation had to be identified. Each of these variables was assigned a probability distribution over the range addressed for the RSM. In principle, these distributions could be normal, beta, or triangular. For this study all variables except for the Engine Technology Factor were assigned a triangular distribution with the mean at the most likely point as shown in Table 5. The triangular distribution was chosen because little knowledge was available about the probability of achieving certain values. Therefore the triangular distribution was treated as a kind of first approximation, knowing that the interval midpoint is the most likely and the range endpoints are very unlikely to be achieved. For the Engine Technology Factor, no real most likely point could be identified. Hence, a uniform distribution was assumed over the entire range.

After assigning these probability functions to the economic variables, Crystal Ball generated values for the independent variables according to the probability functions. Those values were then used to compute the $/RPM value through the response surface equation. This procedure was repeated 10,000 times to obtain the probability distribution sown in Figure 9. For proprietary reasons, the values on the horizontal axis were eliminated in Figures 8-10.

The decision supportability aspects of this methodology are illustrated by the cumulative plot[3,14] shown in Figure 10. The cumulative probability distribution visually displays the probability of achieving a certain value of $/RPM. Alternatively, this figure can be used by decision makers as a means of assessing the economic viability of a feasible aircraft design. This can be achieved by determining the $/RPM which corresponds to the confidence target set by management. Thus, if the probability distribution of $/RPM relative to the target is as shown in Figure 16 with an 85% probability of success, the program can be launched. If, on the other hand, the probability distribution is as shown in Figure 2, i.e.- to the right of the target, a means of shifting the distribution towards the viable region must be found. This can be accomplished through the infusion of new technology, increasing the ticket fare premium, and/or lowering the acceptable airline return on investment. This is visually illustrated in Figure 11.

The summation of the three portions of this pie chart are equivalent to the actions necessary to move the $/RPM into the viable region. Although the figure shows an equi-proportional distribution of viability modifiers, this will not be the case in general. In fact, one can determine the relative proportions of each of the three factors that is required to force the distribution into the viable region by conducting sensitivity studies.

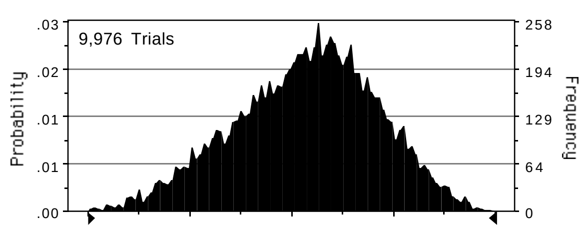

Figure 9: Economic Uncertainty (Frequency Distribution) for Average Yield / RPM

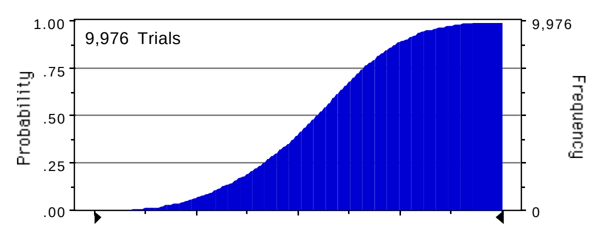

Figure 10 : Cumulative Function of Risk Assessment for Average Yield per RPM

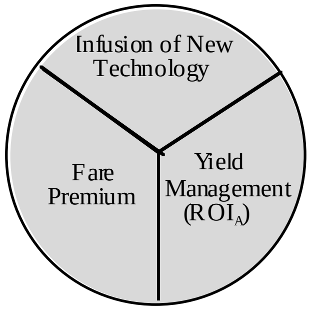

Figure 11: Methods of Increasing the Economic Viability of an HSCT

Conclusions

This paper explained a new IPPD methodology and provided a case study example. The results of this execution were verified even though the actual numbers could not be published for proprietary reasons. Since this paper was only concerned with variability due to economic uncertainty, it did not examine in depth the effects that the various discipline design variables will have on the overall design. The methodology execution using these disciplinary design parameters will be the subject of future research.

In summary, this paper addressed the following objectives:

- An insight was provided into what Robust Design Simulation is and what benefits can be achieved through its use.
- The methodology behind this RDS was described along with its association to an overall integrated product and process approach to design.
- The newly developed ASDL RDS approach was implemented for the economic uncertainty assessment of an HSCT configuration.
- The economic viability of such an aircraft was examined and a probability distribution for the overall evaluation criterion, the average yield per revenue passenger mile, was calculated.

Acknowledgments

The work presented in this paper was supported by NASA Ames Research Center Systems Analysis Office. Hence, the authors would like to thank the technical monitor for this contract, Mr. Tom Galloway, Acting Chief of Systems Analysis Branch, NASA Ames Research Center, for his support, guidance, and encouragement he has provided throughout this investigation. In addition, the contributions made by Mr. Jason Brewer and Mr. Bryce Roth throughout the course of this study are greatly appreciated.

References

1) Mavris, D.N., Brewer, J.T., Bandte, O., "A Method for the Identification and Assessment of Critical Technologies Needed for an Economically Viable HSCT," AIAA-95-3887, Proceedings of the 1st AIAA Engineering, Technology, and Operations Congress, Los Angeles, CA, September, 1995.

2) Taguchi, G., *Introduction to Quality Engineering*, Unipub, New York, 1986.

3) Decisioneering, Inc., *Crystal Ball, Computer Program and Users Guide*, Denver, CO, 1993.

4) Box, G.E.P., Draper, N.R., *Empirical Model-Building and Response Surfaces*, John Wiley & Sons, Inc., New York, NY, 1987.

5) Montgomery, D.C., *Design and Analysis of Experiments, 3rd Edition*, John Wiley & Sons, Inc., New York, NY, 1976.

6) SAS Institute Inc., *JMP, Computer Program and Users Manual*, Cary, NC, 1994.

7) McCullers, L.A., *Flight Optimization System, Computer Program and Users Guide*, Version 5.7, NASA Langley Research Center, Hampton, VA, December 1994.

8) Galloway, T.L. and Mavris, D.N., *Aircraft Life Cycle Cost Analysis (ALCCA) Program*, NASA Ames RC, Moffett Field, CA, September 1993.

9) Mavris, D.N., Bandte, O., Schrage, D.P., "Economic Uncertianty Assessment of an HSCT Using a Combined Design of Experiments/Monte Carlo Simulation Approach," Proceedings of the 17th Annual Conference of the International Society of Parametric Analysts, San Diego, CA, May, 1995.

10) Mavris, D.N., Schrage, D.P., Rohl, P.J., Lee, J.M., "A Nacelle-Wing Integration Design Methodology for the High Speed Civil Transport," Proceedings of the 7th European Aerospace Conference, Toulouse, France, 1994.

11)Olson, E.D., "Advanced Takeoff Procedures for High-Speed Civil Transport Community Noise Reduction," AIAA-921939.

12) Haaland, P.D., *Experimental Design in Biotechnology*, Marcel Dekker, Inc., New York, NY, 1989.

13) Dieter, G.E., *Engineering Design, A Materials and Processing Approach, 2nd Edition*, McGraw-Hill, Inc., New York, NY, 1991.

14) Box, G.E.P., Hunter, W.G., Hunter, J.S., *Statistics for Experimenters*, John Wiley & Sons, Inc., New York, NY, 1978.