SYSTEM SYNTHESIS IN PRELIMINARY AIRCRAFT DESIGN USING STATISTICAL METHODS

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Abstract

This paper documents an approach to conceptual and early preliminary aircraft design in which system synthesis is achieved using statistical methods, specifically Design of Experiments (DOE) and Response Surface Methodology (RSM). These methods are employed in order to more efficiently search the design space for optimum configurations. In particular, a methodology incorporating three uses of these techniques is presented. First, response surface equations are formed which represent aerodynamic analyses, in the form of regression polynomials, which are more sophisticated than generally available in early design stages. Next, a regression equation for an Overall Evaluation Criterion is constructed for the purpose of constrained optimization at the system level. This optimization, though achieved in a innovative way, is still traditional in that it is a point design solution. The methodology put forward here remedies this by introducing uncertainty into the problem, resulting in solutions which are *probabilistic* in nature. DOE/RSM is used for the third time in this setting. The process is demonstrated through a detailed aero-propulsion optimization of a High Speed Civil Transport. Fundamental goals of the methodology, then, are to introduce higher fidelity disciplinary analyses to the conceptual aircraft synthesis and provide a roadmap for transitioning from point solutions to probabilistic designs (and eventually robust ones).

I. Introduction

Over the past few years, a significant amount of research has taken place on the topic of how to efficiently design complex aerospace systems, especially as historical databases (once the centerpiece of conceptual design) become increasingly obsolete. This obsolescence has resulted from departures from traditional products (configurations outside historical databases, changing missions and functionalities, etc.) *and* processes (manufacturing methods, information exchange, etc.). This connection of product and process characterizations form the heart of Integrated Product and Process Design (IPPD). To truly achieve the "Integrated" part of IPPD, numerous groups have been conducting research under the general term of Multidisciplinary Design Optimization (MDO). MDO has been defined as "A methodology for the design of complex engineering systems that are governed by mutually interacting physical phenomena and made up of distinct interacting subsystems".[1] One of the earliest and most well known approaches to executing MDO was through the Global Sensitivity Equations (GSE) approach, where "what if" questions are answered through so-called system sensitivity derivatives which relate a system response to changes in design variables, including the interactions of the disciplines involved. Examples are seen in References 2 and 3, though there are numerous others. Reference 4 provides an excellent survey of recent work and current tools being utilized by MDO researchers.

So a key to successful MDO is developing means to intelligently analyze these systems with mutually interacting phenomena. The strength of the GSE lies in the determination of interactions between disciplines in a structured and logical manner. These interactions, represented as sensitivities, can then be used as gradient information in a traditional optimization exercise. The GSE approach, though, provides only local gradient information and some of the derivatives may be difficult to calculate. Further, the point design paradigm is still employed. Thus, others, including the authors in Reference 5, have used the GSE approach in combination/coordination with other techniques and tools in an attempt to improve the process and give more insight to the designer. However, for conceptual level vehicle synthesis, with numerous interacting disciplines, many design variables (both continuous and discrete), and often times large deviations from the baseline, an effective and comprehensive methodology has not emerged.

This paper describes new developments which form the initial execution of an evolving IPPD approach, providing a potential solution to this methodology need. The approach puts vehicle synthesis in its proper role of the integrator of the mutually interacting disciplines. Traditional sizing and synthesis is generally performed with first order tools due to the impracticability of connecting complex codes together into an iterative sizing code. The use of statistical techniques in the proposed method allows for more flexibility in searching a design space by representing large amounts of knowledge (e.g. complex, expensive analysis codes or physical experiments) via response surface equations (RSEs). Caveats in the use of statistical approximations in the replacement of complex analysis include accuracy and scope issues. How well the fitted equations represent the given data will be important in determining the validity of the results. Also, the RSEs are valid only in the design space (multidimensional region bounded by the range extremes for each design variable considered) for which they were formed. These issues will be revisited throughout the remainder of this paper.

So then, the approach put forward here addresses a multidisciplinary problem (the synthesis of an aircraft) from an IPPD perspective, where the recomposition portion of synthesis is executed using Design of Experiments (DOE) and the above mentioned RSEs. These techniques allow for the introduction of more accurate contributing analysis into the synthesis and sizing process. RSEs have been used in the aerospace field over the past several years by several groups.[(6),(7),(8)] A key development presented here, however, is that a systematic plan for incorporating RSEs directly into a vehicle synthesis code as "model" equations has been developed. This process is demonstrated by modeling the mission aerodynamics (i.e. vehicle drag as a function of planform shape, overall geometry, and flight condition) via RSEs, incorporating these RSEs into a synthesis code, and then using this modified code to conduct a system level optimization. The key objective at the system level is *affordability*.

Finally, the last step of the approach involves the recognition that aircraft design is not truly deterministic in nature. Uncertainties, in a variety of forms, exist throughout the design sequence. Thus, a framework for creating probabilistic solutions is presented which transitions from the point design solution to one in the form of a distribution.

II. IPPD Approach to System Recomposition

IPPD specifically brings together design and manufacturing considerations. Designing aircraft in an IPPD (and Concurrent Engineering) framework could be viewed as designing with a focus on affordability, which implies an understanding of how the various discipline, mission, design, and economic variables affect the feasibility ("can it be built") and viability ("should it be built") of an aircraft. The Georgia Tech IPPD methodology can best be viewed as a recomposition process, employed once the various parts of the problem have been broken down and analyzed. In order to do this recomposition in an meaningful way, *Product* and *Process* design variables and constraints must be considered simultaneously. Product characteristics are those that pertain directly to the subject of product design, such as geometry, materials, propulsion systems, etc. Process characteristics, on the other hand, refer to those items related to how the product is designed, produced, and sustained over its lifetime. A rational approach to executing the integration process takes the form of a "Funnel", as illustrated in Figure 1.

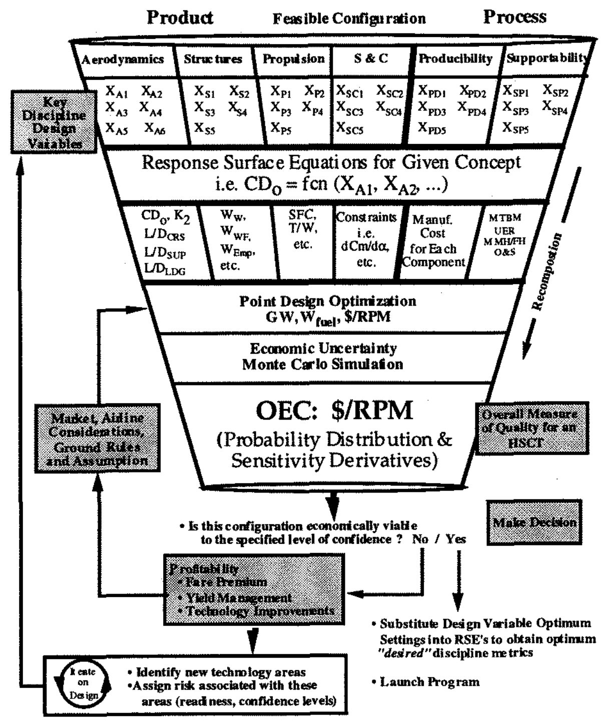

Figure 1: Systematic Recomposition-Implementing IPPD for Affordability

In essence, the Funnel represents a concurrent recomposition process in which all of the various disciplinary interactions, ideally, are accounted for during "synthesis", or recomposition. For this study, the aerodynamic and propulsion disciplines were examined in detail, and structures considerations being limited to component weight estimation based on historical data compiled in the sizing code FLOPS (FLight OPtimization System)[(9)]. The first level in the funnel represents fundamental design variables in each category. These are the parameters available to the engineer in formulating configurations. The importance of the next level, the introduction of RSM, lies in two facts. First, it allows the formation of response equations which can be used to replace complex simulation codes needed to arrive at a point design optimum. Second, as is illustrated at the bottom of the figure, once economically viable alternatives are synthesized, these RSEs can be used to obtain the *discipline metrics*, such as L/D or SFC, which correspond to the optimal configuration. After the equations are formed, this discipline level information is used to perform system synthesis (with appropriate constraints) through the use of a synthesis code. What is thus obtained are the various design variable settings which correspond to the point design optimum (i.e. one aircraft configuration) and a corresponding $/RPM value. The $/RPM (average required yield per Revenue Passenger Mile) is the selected Overall Evaluation Criterion (OEC) for commercial aircraft. This metric implicitly represents the ticket price, on a per mile basis, that an airline must charge in order to achieve a specified return on investment

(ROI) It also accounts for a required ROI for the manufacturer of the aircraft.

Unfortunately, this optimal OEC result can never be achieved *exactly* due to economic factors which the designer cannot control, such as market and airline considerations. These economic factors introduce *uncertainty* to the design process resulting in a *distribution* for \$/RPM. This distribution, or more precisely its characteristics (such as mean and variance for a normal distribution), is subsequently used to determine if economic viability has been achieved based on a the needs of the airline and manufacturer. If not, a design iteration (see Figure 1) is necessary.

The need for disciplinary approximations becomes evident in Figure 1, as the connection of complicated analysis tools (e.g. CFD for aerodynamics, FEM for structures, cycle analysis for propulsion, etc.) from each discipline would be impractical. Common design variables, if they exist, between areas can be represented as noise factors in the formation of particular RSEs. For example, the position of the engine nacelles, a decision generally made by the structures and propulsion and engineers, is kept as a variable in the aerodynamic model equation formation. A brief review of the fundamentals of DOE/RSM is presented next. More detailed information can be obtained from numerous references.[(10),(11),(12),(14)]

III. Design of Experiments and the Response Surface Method

Understanding the characteristics of the design space and behavior of the proposed designs as efficiently as possible is as important to the designer as finding the numerical optimum. This is particularly true for complex aerospace systems which require multidisciplinary analyses, a large investment of computing resources, and intelligent data management. As an alternative to standard parametric approaches to design space search and complex iterative optimization routines, the DOE/RSM application developed here appears to have several advantages. Before applying the methods, the following paragraphs outline the fundamentals of DOE/RSM.

The (RSM) comprises a group of statistical techniques for empirical model building and exploitation. By careful design and analysis of experiments, it seeks to relate a response, or output variable, to the levels of a number of predictors, or input variables. 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; thus, it should be possible to determine the best conditions (levels) of the factors to optimize a desired output[(11)]. Unfortunately, many times the relationship between response and predictors is either too complex to determine or unknown, and an empirical approach is necessary to determine the behavior. The strategy employed in such an approach is the basis of the RSM. In this paper, a second degree model of the selected responses in k-variables is assumed to exist. A notional example of a second order model is displayed in Figure 2 for two variables **x1** and **x2**.

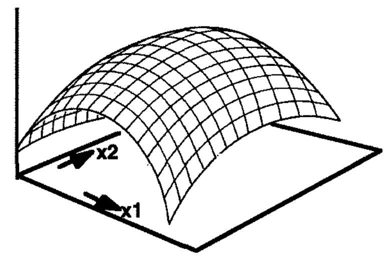

Figure 2: Second Order Response Surface Model

The second degree RSE takes the form of:

$$R = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j} \sum^{k} b_{ij} x_i x_j \quad (1)$$

where, b_i are regression coefficients for the first degree terms, b_{ii} are coefficients for the pure quadratic terms, b_{ij} are coefficients for the cross-product terms (second order interactions), and b_0 is the intercept term. To facilitate the discussion to follow, the components of equation (1) are further defined. The $\mathbf{x}_i$ terms are the "main effects", the $\mathbf{x}_i^2$ terms are the "quadratic effects", and the $\mathbf{x}_i\mathbf{x}_j$ are the "second-order interaction terms".

Since it is in a polynomial form (though other forms are possible, e.g. exponential or logarithmic, through a transformation of both the independent and dependent variables), the RSE can be used in lieu of more sophisticated, time consuming computations to predict and/or optimize the response R. If one is optimizing on R, the "optimal" settings for the design variables are identified (through any number of techniques) and a confirmation case is run using the actual simulation code to verify the results. Since the RSE is a regression curve, though, a set of experimental or computer simulated data must be available.

One organized way of obtaining these data is the aforementioned DOE, which is used to determine a table of input variables and combinations of their levels yielding a response value (but also encompasses other procedures, like Analysis of Variance). There are many types of DOEs. Table 1 displays a simple full factorial example for three variables (or factors) at two levels, a minimum and a maximum (sometimes also described as "-1" and "+1" points).

Table 1: Design of Experiment Example for a two-level, 2^3 Factorial Design[(11)]

	Factors			
Run	1	2	3	Response
1	-	-	-	y_1
2	+	-	-	y_2
3	-	+	-	y_3
4	+	+	-	y_4
5	-	-	+	y_5
6	+	-	+	y_6
7	-	+	+	y_7
8	+	+	+	y_8

The response can be any of a variety of metrics (such as thrust, drag, pitching moment, weight, etc.), while the design variables and their ranges define the design space.

For the approach in this paper, the factors become input variables to the analysis code, while the response is generally the desired output of the program.

The same full factorial DOE approach can be used for variables at three levels, requiring more runs but obtaining more information by going from a linear representation to a quadratic one. On the other hand, evaluation of all possible combinations of variables at two or three levels increases the number of cases that need to be tested exponentially, and thus quickly becomes impractical. In fact, testing 12 variables at three levels, their two extremes and a center point, would take a total of 531,441 cases for a 3^{12} factorial design.

Table 2 illustrates that one way of decreasing the number of experiments or simulation runs required is to reduce the number of variables. But as Table 2 also displays, a 3^7 full factorial design still requires an impractical 2,187 runs. Hence, fractional factorial and second order model designs (of which the Central Composite is an example) are proposed as a more plausible means to perform experiments. Table 2 provides three examples.

Table 2: Number of Cases for Different DOEs[11]

DOE	7 Variables	12 Variables	Equation
3-level, Full Factorial	2,187	531,441	3^n
Central Composite	143	4,121	2^n+2n+1
Box-Behnken	62	2,187	-
D-Optimal Design	36	91	(n+1)(n+2)/2

Fractional factorial DOEs use less information to come up with results similar to full factorial designs. This is accomplished by reducing the model to only account for parameters of interest. Therefore, fractional factorial designs neglect third or higher order interactions for an analysis (see RSE in Equation (1)), accounting only for main and quadratic effects and second order interactions.

Thus, a tradeoff exists in fractional factorial designs. The number of experiments or simulations (often referred to as "cases") grows as the increasing degree to which interaction and/or high order effects are desired to be estimated. Since generally only a fraction of the full factorial design number of cases can be run, high order effects and interactions are not estimable. They are said to be confounded, or indistinguishable, from each other in terms of their effect on the response. This aspect of fractional factorial designs is described by their *resolution*. Resolution III implies that main effects are entirely confounded with second order interactions. Thus, one must assume these interactions to be zero or negligible in order to estimate the main effects. Resolution IV indicates that all main effects are estimable, though second order interactions are confounded with other such interactions. Resolution V or greater means that both main effects and second order interactions are estimable (though for Resolution V designs, third order interactions would be confounded with second order effects, hence must be zero)[12]. The example presented in Section IV will employ a Resolution V design for the generation of RSEs.

Problems in aircraft design typically have many design variables, complicating sizing and optimization. As a general approach in DOE/RSM, a first DOE is performed in order to reduce the number of variables by identifying the significant contributors to the response. This exercise, termed a "screening test", uses a two level fractional DOE for testing a linear model, thus estimating the main effects of the design variables on the response. It allows for an investigation of a high number of variables in order to gain an initial understanding of the problem and the design space.

A visual way to see the results of this screening is through a Pareto Chart[13], displayed in Figure 3. It identifies the most significant contributors to the response based on the linear equation generated from the DOE data. Bars indicates which variables contribute how much while a line of cumulative contribution tracks the total response. By defining the percentage of contribution desired, the variables to be carried along to the RSE generation can be determined from the array of variables in the Pareto Chart.

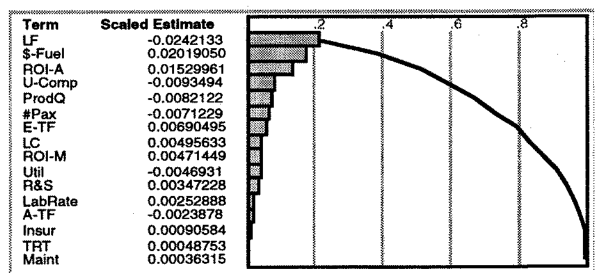

Figure 3: Sample Pareto Chart - Effect of Design Variables on the Response

After identifying the variables to be carried through to an RSE, a particular type of DOE must be selected. In this study, the Central Composite Design (CCD), an example of which is seen in Figure 4, was selected to form the RSEs. The particular CCD chosen is a five level composite design formed by combining a two level full or fractional factorial design with a set of axial or star and center points as described in References 10 and 14. It is an economical design in terms of the number of runs required, as Figure 4 illustrates by displaying a design for three variables as a cube with star and center points.

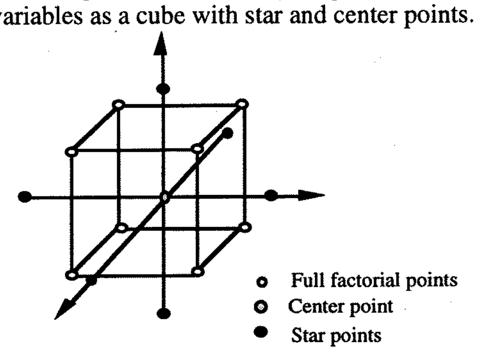

Figure 4: Central Composite Design Illustration for Three Variables

The distance between axial points describes the extent of the design space. The center provides multiple replicates, for estimating experimental error, which is assumed non-existent for simulation-based analysis. Hence, just one replicate is required for the center point.

Finally, with the Central Composite Design in hand, an RSE can be obtained by using Equation (1) as a model for regression on the generated data. Unlike for true experiments, a statistical environment without any error can be assumed, so that all deviations from the predicted values are true measures of a model fit. A lack of fit parameter for the model expresses how good the model represents the true response. A small lack of fit parameter usually indicates existing higher order interactions not accounted for in the model. Depending on the level of this lack of fit, a new design with a transformed model to account for these interactions should be used.

IV. Example: Aero-Propulsion Optimization for an HSCT

With the IPPD method and accompanying DOE/RSM tools described, the approach is now demonstrated via an example: synthesis and optimization of a High Speed Civil Transport. Choosing a wing planform shape for a supersonic transport is a task that to this day is still a long and tedious one. The need for efficient performance at both sub- and supersonic cruise conditions exhibit immediately the presence of conflicting design objectives. Studies by Boeing and Lockheed during the 1970's for the SuperSonic Transport (SST) program looked extensively at this issue[15],[16]. In brief, one resulting conclusion was that low aspect ratio, highly swept wings have low drag at supersonic speeds (since the cranked leading edge serves to provide subsonic type flow normal to the wing leading edge). Unfortunately, such planforms are poor in subsonic cruise. The variable sweep wing option had complications involving reduced fuel volume and weight and complexity penalties; thus this concept was never seriously considered. The so-called double delta emerged as a compromise. Here the outboard panel helps retain some subsonic performance while keeping acceptable supersonic cruise efficiency[15]. The study carried out presently employs a DOE technique which models and examines planforms ranging from the pure delta (arrow) to the double delta.

The trades involved in planform selection are complicated by other discipline considerations (e.g. propulsion) and the presence of design and performance constraints at the system level which are directly related to the wing. The limit on approach speed, for example, is mostly a function of wing loading. Fuel volume requirements impact the wing size and shape. Both of these issues become sizing criteria and both tend to increase the wing in size. Of course, increased wing area brings with it higher induced and skin friction drag. Terminal performance at takeoff and landing (especially field length limitations) also present a challenge. Increasing the low speed aerodynamic performance of the aircraft will reap benefits for noise control through reduced thrust and more modest climb rates. The HSCT will need its maximum C_L at takeoff, and the use of high lift devices will play a major role in making that maximum as high as possible. For this study, a configuration of flap settings was selected for the baseline aircraft based on the SST studies and the takeoff and landing polars were generated using the code AERO2S[19].

Problem Formulation

The problem consists of using the new techniques outlined in Sections II and III in synthesizing and eventually optimizing an HSCT type aircraft for a given mission. Improved aerodynamic procedures over what is currently available in the synthesis code FLOPS are incorporated via RSEs. Next, an RSE for the overall objective function ($/RPM) and several performance constraints are generated and a constrained, point design optimal solution (using aerodynamic and propulsion design variables) is found. Finally, steps necessary for introducing and accounting for economic uncertainty are described. The execution of this uncertainty exercise is described in Reference 8, also for an HSCT.

Forming RSEs for Mission Drag

The goal of introducing RSEs is to replace the existing drag calculation in the synthesis code FLOPS. As FLOPS is executing the input mission profile, it requires calls to an aerodynamics module for drag at that flight condition (M, h, C_L). Ordinarily FLOPS determines drag by one of three methods: internal calculations (based on the EDET aero prediction program[9]), externally generated drag table, externally generated polar equation. Considering the functional form of the drag polar equation:

$$C_D = C_{Do} + k_2 \cdot C_L^2 \qquad (2)$$

RSEs for $\mathbf{C_{Do}}$ and $\mathbf{k_2}$, are to be formed as a function of design variables and operational Mach number. Thus, the total drag for a given aircraft configuration will still be a function of Mach number and C_L as well as configuration design variables.

The first step in forming RSEs is to first conduct a screening test. Even with the computational advantages brought by DOE, an excessive number of design variables can make the RSE generation expensive/difficult (See Table 2). The design variables which are to make up the RSE model for vehicle drag must be the ones which have the most influence on the aerodynamic characteristics of the airplane. A screening test is designed to identify the subset of design variables which contribute most to a given response (i.e. the variables for which the response has the highest sensitivity). For all of the aerodynamic analyses performed in this study, public domain tools were used, including the Boeing Design and Analysis Program (BDAP)[17] for supersonic drag due to lift prediction and skin friction drag, WINGDES[18] for optimum camber and twist, AERO2S[19] for subsonic drag due to lift, and AWAVE[20] for fuselage area ruling.

To begin the screening process, a parametric wing planform definition scheme is selected which encompasses the variety of wing shapes considered for a supersonic transport, from a pure arrow wing to a kinked double delta. A summary of all the design variables selected can be found in Figure 5.

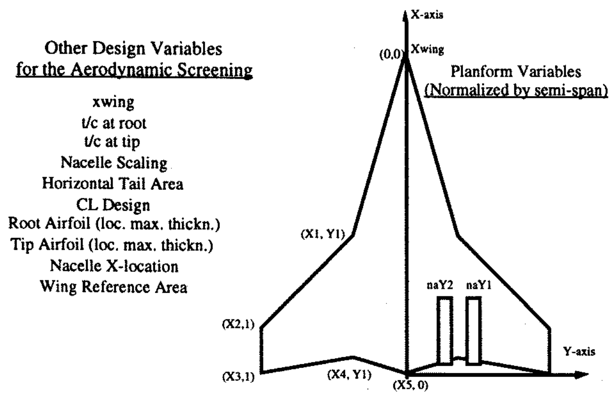

Figure 5: Aerodynamic Design Variable Selection

Choosing meaningful ranges for the design variables is critical. On the one hand, the ranges should be somewhat large to include the largest design space possible and increase the chances that the eventual optimal configuration is captured. On the other hand, the range must not be chosen so large as to reduce the prospects of a good regression fit of the RSE to the actual highly non-linear response. Additionally, there are physical restrictions which limit the range choices. For example, the wing at its aftmost location with longest root chord must not interfere with the horizontal tail. Table 3 shows a summary of all design variables with their chosen ranges. Recall that planform variables are normalized by span and their ranges are selected based on review of past and present concepts. Variable "xwing" is normalized by fuselage length. Note also that the screening test is a 2-level (or linear) test. Since we are not interested in forming an equation just yet, the linear sensitivities are expected to do just as well in determining which are the most important contributors. A sampling of some shapes investigated is shown in Figure 6.

Table 3: Ranges for Aerodynamic Design Variables

Variable	Symbol	Low Bound	Up. Bound
Kink, leading edge x-location	X1	1.54	1.69
Tip, leading edge x-location	X2	2.10	2.36
Tip, trailing edge x-location	X3	2.40	2.58
Kink, trailing edge x-location	X4	2.19	2.36
Kink, y-location	Y1	0.44	0.58
Root Chord	X5	2.19	2.50
Nacelle #1 y-location	nay1	0.25	0.35
Nacelle #2 y-location	nay2	0.45	0.55
Nacelle x-location	nax	10.30	16.50
Wing Area (sq. ft.)	S	8500	9500
Wing x-location	xwing	0.25	0.33
Root t/c	tci	2.70	3.30
Tip t/c	tco	2.30	2.80
Nacelle Scaling	nac	1.0	1.20
Area of Horizontal Tail (sq. ft.)	S-tail	400	750
C_L Design	Cl-desig.	0.08	0.12
Loc. of max thickness, Root	iaf	0.50	0.60

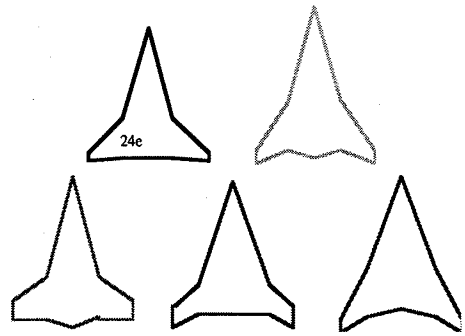

Figure 6: Variety of Planform Possibilities for HSCT Example

Two 2-level experiments are conducted, one each for the two selected responses ($\mathbf{C_{Do}}$, $\mathbf{k_2}$) and the results are visually inspected via the aforementioned Pareto Chart, an example of which appears in Figure 7 for the M=2.4 case as an example. As explained in Section III, the important information in the Pareto Chart is the relative importance of each term, as illustrated graphically by the cumulative bar chart. The scaled estimates listed in the figure are actual regression coefficients for the linear equation formed, though this equation is not used.

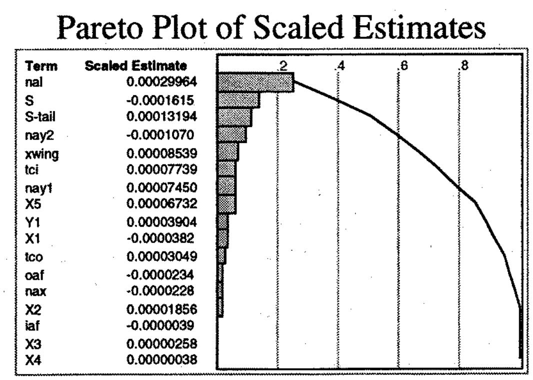

Figure 7: Screening of Aerodynamic Variables for C_{Do}, Mach 2.4

Table 4 shows some sample screening results for both sub- and supersonic screening. Often, screening tests confirm a designer's intuition as to which parameters are important. However, some important variables identified require further thought. For example, the area of the horizontal tail (S-tail) is important for the drag due to lift at supersonic speeds. In this case, it most probably is due to the comparatively large range chosen for this parameter, since tail area, intuitively, should not contribute greatly to drag due to lift. One might consider refining variable ranges in light of such conclusions. Other variables, however, clearly proved their importance. For example, the spanwise location of the kink (y1) was the most contributing parameter for lift induced drag in the subsonic flight regime. The outboard wing section with low sweep angle is the efficient source of lift in subsonic flight whereas in supersonic conditions it is more of a drag penalty. Once the screening results are collected, the RSE generation is performed with the identified most contributing parameters, leaving the others fixed at their nominal values.

Table 4: Results of Screening Tests: The Important Variables

Supersonic k_2	Subsonic k_2	Supersonic C_{Do}	Subsonic C_{Do}
S_{tail}	y_1	S_{tail}	nac
y_1	x_1	S	y_1
x_1	x_2	tci	x_1
x_3	x_5	x_5	x_4
x_5	x-wing	x-wing	x-wing
$C_{Ldesign}$	$C_{Ldesign}$	$C_{Ldesign}$	$C_{Ldesign}$
		nay_1	
		nay_2	
		nac	

With the number of variables now shrunk to a manageable level, a new DOE is set up to generate the data to be used in forming the actual response equations for C_{Do} and k_2. Since drag varies with Mach number which itself varies throughout the mission, it was decided that including Mach number as a variable in the RSE models for drag would add another nonlinearity to the already nonlinear model, thus complicating the fitting process. Therefore, RSEs for C_{Do} and k_2 are to be formed for a series of Mach numbers covering the expected operational speed range of the aircraft.

So then, following the procedure outlined in Section III, a 5-level Central Composite Design is constructed and the resulting series of simulation runs are executed using the aerodynamic analysis tools listed in Appendix A. The data generated is used to form the second-order polynomial RSEs for each of the two responses in the polar equation at each of the operational Mach numbers. A sample listing of the regression coefficients, or the "$b_{(*)}$", for one of the RSEs is shown in Figure 8 under the heading "Estimate".

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-5.878813	5.372921	-1.09	0.2891
x1	2.3984876	2.573549	0.93	0.3644
x3	2.3956492	2.503083	0.96	0.3519
y1	-0.674068	1.963603	-0.34	0.7356
x5	1.1983904	1.05529	1.14	0.2719
S-Tail	-0.000415	0.000745	-0.56	0.5846
CLDes	8.6087716	6.640273	1.30	0.2121
x1*x1	-0.933080	0.661597	-1.41	0.1765
x3*x1	0.4738990	0.484103	0.98	0.3413
x3*x3	-0.701553	0.459443	-1.53	0.1452
y1*x1	2.240618	0.622419	3.60	0.0022
y1*x3	-1.013835	0.518682	-1.95	0.0673
y1*y1	-1.678383	0.759487	-2.21	0.0411
x5*x1	-0.696132	0.281092	-2.48	0.0241
x5*x3	0.3819572	0.234244	1.63	0.1214
x5*y1	0.5088605	0.301170	1.69	0.1094
x5*x5	-0.257235	0.154901	-1.66	0.1151
S-Tail*x1	0.0003073	0.000249	1.23	0.2339
S-Tail*x3	0.0000541	0.000207	0.26	0.7975
S-Tail*y1	-0.000355	0.000267	-1.33	0.2008
S-Tail*x5	0.0000482	0.000120	0.40	0.6940
S-Tail*S-Tail	-1.814e-7	1.215e-7	-1.49	0.1538
CLDes*x1	-1.891504	2.178464	-0.87	0.3973
CLDes*x3	-1.331705	1.815387	-0.73	0.4732
CLDes*y1	1.7865949	2.334069	0.77	0.4545
CLDes*x5	-0.481944	1.054096	-0.46	0.6533
CLDes*S-Tail	0.0002250	0.000934	0.24	0.8124
CLDes*CLDes	-11.20019	9.303713	-1.20	0.2451

Figure 8: Response Surface Equation for k_2 at M=2.4

These are the actual coefficients which, along with the design variables, make up the RSE of the form of Equation (1). The "t-Ratio" and the "Prob>|t|" are statistical measures reporting the importance of each term to the regression equation.

There are several ways to validate the accuracy of the RSEs. The Whole Model Test in Figure 9 is a plot of the actual response values for $\mathbf{k}_2$ over the predicted values, based on the second order model for the RSE at M=2.4. The straight line indicates a perfect fit, i.e. all predicted values are equal to the actual for the same levels of input variables. As illustrated in Figure 9, the regression model predicts the values for $\mathbf{k}_2$ quite well, since all data points are rather close to the straight line. This model fit corresponds to an R-square value of 0.973728. The R-square value is the square of the correlation between the actual and predicted response. Thus, an R-square value of one means that all the errors are zero (i.e. a perfect fit)[11]. The dotted lines indicate the confidence interval for the model, showing a small range with no points falling outside of this range.

The quantification of statistical error is based on the assumption that the residuals will be normally distributed. The Residual Plot on the right side of Figure 9 is an important verification for the assumption of normality. The residuals are plotted against predicted values for $\mathbf{k}_2$, based on the assumed model. A "cloud" of data points, indicating no particular pattern, confirms the validity of the normality assumption for residuals.

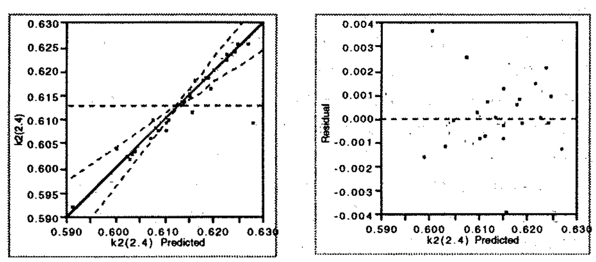

Figure 9: Whole Model Fit Test- A Validation

Once the series of RSEs representing parametric drag polars are obtained, the task is now to insert them into the synthesis code as the new "aerodynamics module".

Incorporating RSEs into Synthesis Code

FLOPS (FLight OPtimization System) is the code selected to perform the vehicle sizing portion of the design methodology shown in Figure 1. FLOPS, developed by NASA Langley Research Center, a multidisciplinary sizing tool used to assist in the conceptual and early preliminary design process[9]. FLOPS contains nine modules for aircraft synthesis: weights, aerodynamics, engine cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis, and program control. For a given initial gross weight estimate, FLOPS flies the input mission profile incrementally, comparing at the end the fuel expended versus the fuel available. This process is repeated (sizing iteration) until fuel balance is achieved. The code does have its own optimization routine, which allows for the variation of aerodynamic shaping variables such as taper, sweep, aspect ratio, and wing area. But for wing shapes such as those seen in Figure 6, variables like aspect ratio and sweep are not sufficient to uniquely define a cranked, variable sweep planform.

Key to correct sizing, then, is an accurate aerodynamic performance model. Unfortunately, for supersonic transport applications (with cranked wing planforms), FLOPS does not model the aerodynamic performance very well, generally because its routines were tailored to high aspect ratio, subsonic type planforms. This was an additional motivation (besides the general increase in aerodynamic analysis fidelity) for replacing the mission drag prediction with the RSEs. FLOPS does give the user the option to insert an externally derived series of polars. Of course, these polars apply only to a single configuration. To analyze a new configuration, a whole new set of polars would have to be generated and inserted manually via the input file, making any attempt of planform optimization difficult.

Alternatively, the use of RSM overcomes the limitations of using a single aerodynamic deck for each corresponding configuration. Further, the RSE drag models give the user the ability to optimize a configuration without regenerating aerodynamic decks (for each iteration). FLOPS was modified so that whenever a call was made to the aerodynamics module for drag, the appropriate RSEs ($\mathbf{C_{Do}}$ and $\mathbf{k_2}$) were evaluated for the current flight condition and design variable settings. In effect, the RSE has captured the essence of a complex external aerodynamic analysis and ported this capability to the synthesis level. This process is depicted in Figure 10.

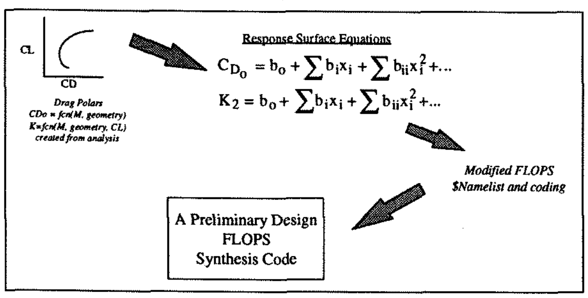

Figure 10: Incorporating Aerodynamic RSEs into FLOPS

Constrained AeroPropulsion Optimization

Revisiting Figure 1, it is seen that once RSEs for the discipline(s) are formed, the optimization process, given a mission definition, can proceed. So, attention turns toward the system level sizing and optimization problem involving both aerodynamic and propulsion considerations. Once again a DOE/RSM approach is employed, this time for the purpose of optimizing the system level objective, $/RPM, (as opposed to the modeling function represented by the aerodynamic RSEs) given 11 design variables. After determining variable ranges, a DOE for the generation of simulation results was selected. Since 11 variables, even in the DOE scheme, require many cases, the Central Composite Design (CCD) was selected to generate a minimum number of data points required to produce a quadratic estimation equation. Use of the fractional factorial CCD with eleven variables at 5 levels requires 151 simulation runs, if an additional center point is added and the cube design has Resolution V (see Section III).

FLOPS either attempts to complete the given mission with a specified engine or, if the user requests, sizes the engine (based on a given cycle) in order to complete the mission. The cycle itself is defined by certain key parameters: the Overall Pressure Ratio (OPR), the Fan Pressure ratio (FPR), the Turbine Inlet Temperature (TIT), and Bypass Pressure Ratio (BPR). The engine cycle analysis capability in FLOPS is sufficient for modeling a Mixed Flow TurboFan (such as the one proposed here in the HSCT example) and contains a fully operational ability to optimize an engine using the four selected cycle variables above. Thus, no RSEs for propulsion responses were required. Compressor and turbine component maps, which describe the component's off-design performance, are generated externally and provided to FLOPS at run time. Other data such as control laws, correct component map addresses, engine cycle constraints, and engine configuration are provided externally as well.

Next, the design variables for the optimization and their ranges are selected and shown in Table 5, based on experience gained during the aerodynamic RSE construction and previous supersonic transport studies. The ranges represent the outer points of the design space spanned by the star points of the CCD. Note that all variables included here are either aerodynamic or propulsion variables. Incorporation of RSEs into the simulation process which capture the effect of structures, manufacturing, and stability/control was not addressed here. It is, however, an interesting and important topic for future research, in order to fully complete the recomposition outlined in Figure 1. Also, for this study, parameters such as number of passengers (300) and design range (5000 nm) are fixed.

Table 5: Design Variables for the Aero-Propulsion Optimization

Aero / Prop. Variables	Lower Bound	Upper Bound
X1	1.54	1.62
X3	2.48	2.58
Y1	0.50	0.58
X5	2.19	2.35
S	8500 sq. ft	9500 sq. ft
xwing.	0.25	0.29
T/W	0.28	0.32
TIT	3000 °R	3250 °R
OPR	19	21
FPR	3.5	4.5
BPR	0.35	0.45

Figure 11 illustrates the sizing mission, a split subsonic-supersonic 5000nm profile consistent with the current requirement of subsonic flight over populated land. The stages of the mission are modeled in FLOPS, which then executes it, iterating on gross weight (by adding or subtracting fuel) until convergence.

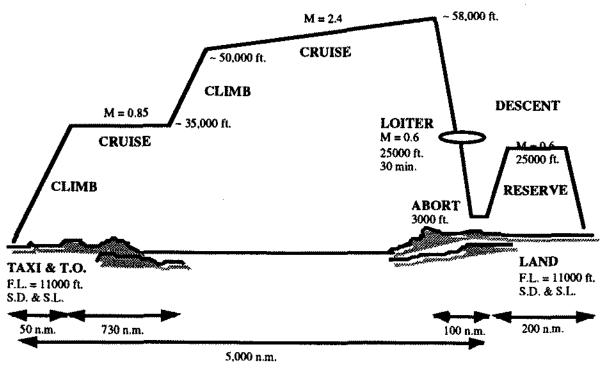

Figure 11: Typical HSCT Mission

Using the CCD for the variables and their ranges depicted in Table 5, the simulation runs are performed. A quadratic equation for \$/RPM is established using least square estimators for the parameters. The regression is performed using data from the DOE with 151 simulation runs for 11 variables (X1, X3, X5, Y1, xwing, BPR, FPR, OPR, TIT, T/W, S). These 151 cases represent 151 vehicle sizing problems in which the modified FLOPS code is used to size the vehicle and determine the response, \$/RPM, as well as performance constraints, for each run. This data is then used to form a RSE for \$/RPM *as well as* the constraints, including approach speed (Vapp), flyover noise in (FONoise), sideline noise (SLNoise), takeoff field length (TOFL), and landing field length (LFL). The noise measures are in units of Effective Perceived Noise Level (EPNL).

Figure 12 displays two statistics validating the \$/RPM RSE. The Summary of Fit lists several characterizations of the least square estimation. One is the RSquare (or RSquare Adjusted) value, indicating the quality of fit of the data points to the estimated line (See Section III).

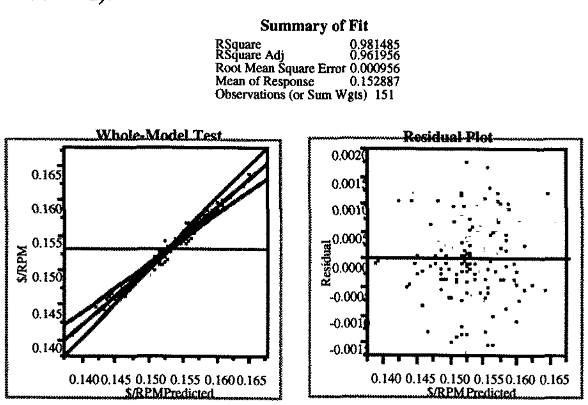

Figure 12: \$/RPM RSE Summary of Fit and Analysis Validation

As mentioned, a value of 1 denotes a perfect fit with all data points lying exactly on the regression line. The R-square of 0.981485 (0.961956) indicates a very good fit for the objective function \$/RPM. The Root Mean Square Error (RSME) is the standard deviation around the mean of the response, both listed in the Summary of Fit. The low RMSE value of 0.000956 for a mean of 0.152887, like the Rsquare value, attests to a very good fit of the regression line to the data points.

The Whole Model Test plots data of actual \$/RPM values against the values predicted with the equation. It displays a 95 % prediction interval, denoting that of all predicted outcomes, 95 % of the data points will fall between these two lines. As discussed for the aerodynamic RSE, the Residual Plot shows the residuals (difference of predicted and actual value) of the response against the predicted values. If this plot shows a pattern or a non-scattered behavior, the normality assumption can usually not be justified. For this analysis, the plot shows a distinct scatter, therefore validating the assumption of normality of the data.

Once validation is complete, the objective function can be optimized in consideration of the constraint equations. A flowchart of the entire approach is displayed in Figure 13.

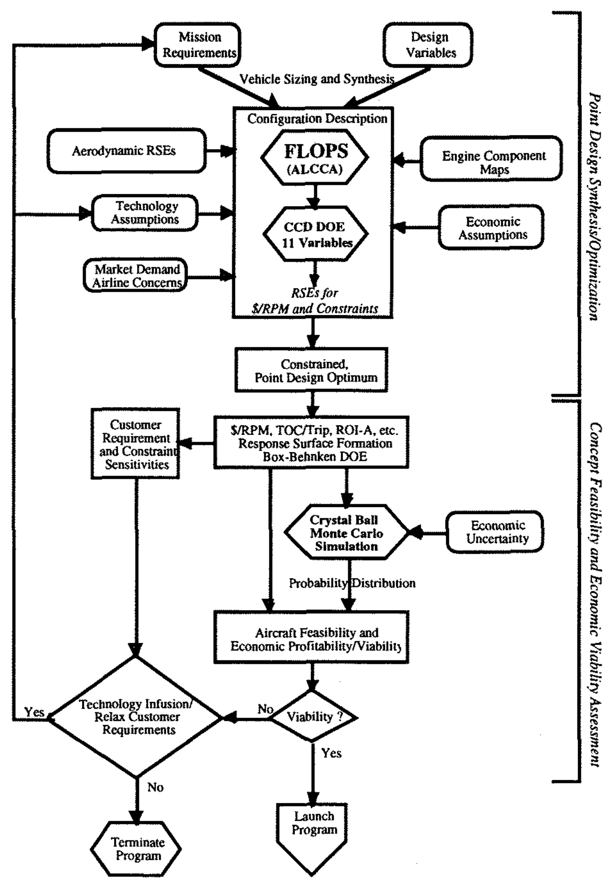

Figure 13: Summary of Approach HSCT Aero-Propulsion Optimization

From Figure 13, it is seen that the solution found is the constrained point optimal configuration for an HSCT within the design space specified by the ranges of the 11 variables. A confirmation test to validate results and obtain component weights is performed. These component weights, together with the mission parameters, describe the optimal configuration which is passed over to the Economic Viability Assessment, where economic uncertainty is introduced and the probability of meeting a target for the $/RPM is calculated.

The generation of both the aerodynamic RSEs as well as the just introduced overall objective RSE for $/RPM was accomplished via UNIX shell scripts, which managed the process of setting up input files, running the specified codes in remote shells, and parsing output files for the required response values. This process automation saved a considerable amount of time over a manual procedure of running hundreds of simulations from the command line.

Results

An important motivation for forming RSEs for the objective and constraints is presented in Figure 14. It displays the sensitivities, termed prediction profiles, of the objective function ($/RPM) and the constraints (GW, Vapp, TOFL, SLNoise, FONoise, and LFL) with respect to the design variables (X1, X3, X5, Y1, xwing, BPR, FPR, OPR, TIT, T/W, S). These sensitivities indicate the behavior of the response variables with respect to a change in the design variable settings. The statistical analysis tool used here (JMP[11]) translates a change in the settings with a real time update of the response values (made possible by the underlying simple polynomial equations), giving the designer a feel for the magnitude of the sensitivities. Recall that the perturbation of one design variable causes changes in the responses resulting from main effects, quadratic effects, and interactions.

A further capability is to select "desirabilities" for the objectives and constraints so as to perform an optimization. For example, the diagonal desirability shown for $/RPM indicates that its lowest possible value is the most desirable (i.e. minimize $/RPM). The constraints have their boundaries marked by a discontinuity. For example, all Vapp values above 154 knots have desirability of zero while all below 154 knots have desirability of one. One can adjust the design variables according to the desirabilities below them to quickly and interactively get near the optimum. For more rigorous optimization results, JMP can search the entire design space based on the RSEs and the given desirabilities to find the optimal settings. For the present case, the optimal settings are shown in Figure 14.

In terms of sensitivities, it can be seen that the effect of T/W on noise is highly significant, with the effect of root chord (x5) on $/RPM and the effect of wing area on approach speed being important to a lesser extent.

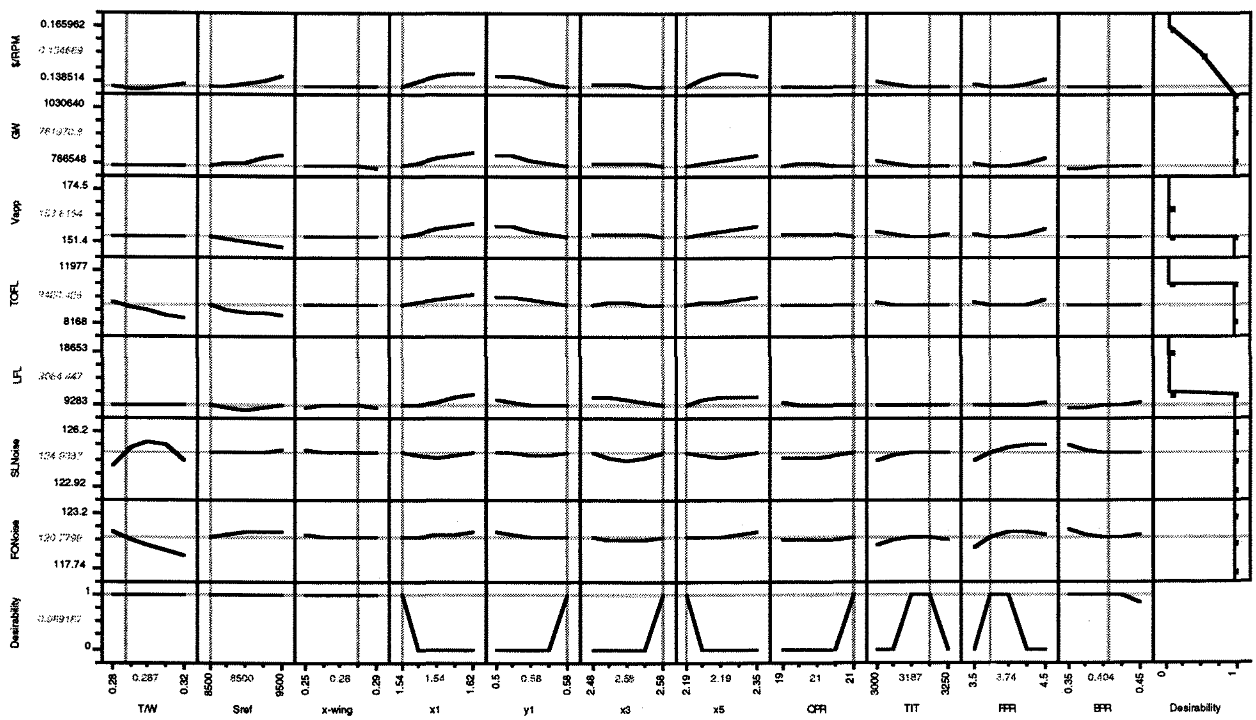

Figure 14: Prediction Profiles: Constrained Optimization and Sensitivities

The point design optimization results obtained for this example are summarized in Table 6 and Table 7. Table 6 contains the optimal setting of the design variables while Table 7 lists the minimal value for the objective function, $/RPM, and the values for the constraints generated by the RSEs as well as the results of a verification run of FLOPS. The right hand column displays the difference of these two values indicating a percentage error for the RSE-based approach. The errors are seen to be modest.

Table 6: Constrained Optimization for Minimum $/RPM

Design Variable	Optimized Value
X1	1.54
Y1	0.58
X3	2.58
X5	2.19
S	8500 (sq. ft.)
xwing	0.28
T/W	0.287
OPR	21.00
TIT	3187 °R
FPR	3.74
BPR	0.404

Table 7: Constrained Optimization Results and Accuracy Values

	RSE	FLOPS	% Error
$/RPM	0.1348	0.1360	-0.9 %
GW (lbs)	761,870	731,799	+3.9 %
Vapp (kts)	153.6	150.1	+2.3 %
TOFL (ft)	9420	9616	-2.0 %
LFL (ft)	9064	9053	+0.1 %
FONoise, EPNL	124.9	120.4	+3.6 %
SLNoise, EPNL	120.8	124.0	-2.6 %

Note that for this optimization, the maximum noise levels as specified by FAA FAR 36 were not activated since noise suppression techniques were not modeled in the synthesis code. Hence, the noise constraints are not met. The fact that the constraint RSE was formed, however, provides the capability to have a truly noise-constrained vehicle once suppression can be accurately modeled.

The optimum aerodynamic design variable settings from Table 6 yield a wing planform illustrated in Figure 15. The figure on the right displays the location of the variables and their nominal values. It can be seen from the overlay plot (left) that the baseline had a lager span but a smaller sweep in the outer part of the wing than the optimized planform. This may indicate that, for the given split mission percentage (~ 15% subsonic, 85% supersonic), the optimal planform prefers less outboard panel sweep. Note that the optimal planform had a root chord (variable X5) significantly smaller than the baseline. This concurs nicely with Figure 14, which shows that as x5 is reduced, $/RPM is reduced. In addition, with this set of optimized design variables, all component weights can be determined and passed through to an economic uncertainty assessment, where the transition from a point design to a probabilistic solution begins. Steps for the introduction of this uncertainty are outlined next, again with emphasis on an HSCT application.

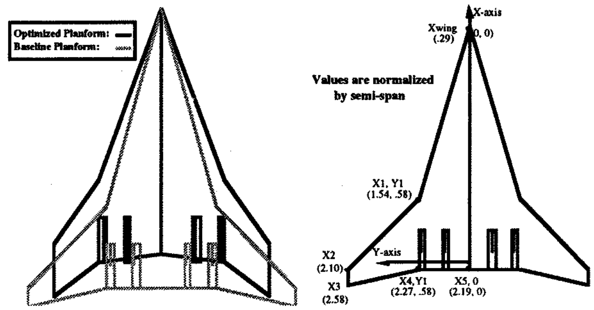

Figure 15: Optimal Design Planform Comparison

Steps for Economic Viability Assessment

The purpose here is to take the feasible, optimized vehicle and determine whether the concept is economically viable. The first realization which must be made is that deterministic approaches will not be appropriate, since economic considerations are dominated by "noise", or uncertainty, variables.

Returning to Figure 13, the emphasis now is on the bottom portion which depicts the procedure to address system variability due to economic uncertainty for a generalized HSCT configuration. The geometric, component weight, and mission information needed is provided by the point deign optimum configuration. As was the case for the point optimization, in order to determine the $/RPM value, a code accounting for manufacturing and airline business practices was utilized and linked to the actual synthesis code. The authors have found that ALCCA[21], the Aircraft Life Cycle Cost Analysis program, was the most suitable code to fulfill this purpose. Through the application of the DOE/RSM approach, an RSE representing the ($/RPM) as a function of the most significant economic variables is formed. These variables (such as load factor, cost of fuel, production quantity, engine technology factor, learning curve, return-on-investment, and aircraft utilization rate) are uncertain in that a designer cannot pre-specify (or control) their values. However, they affect *tremendously* the ultimate viability of the product[8]. These independent variables enter the problem by assigning probability distributions to them within certain ranges. An example of such a probability assignment is seen in Figure 16, with a normalized range depicted here for demonstration. The triangular distribution is just one of many available (normal, beta, etc.) to be used, depending on how much knowledge is available for that particular variable.

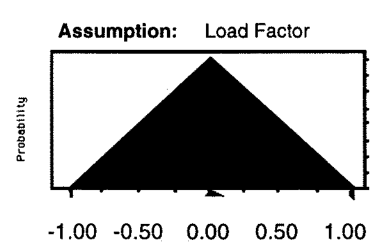

Figure 16: Triangular Distribution Representing Load Factor Uncertainty

Given the point design optimum aircraft and a set of economic variables with their corresponding distributions, a Monte Carlo Simulation is performed with the aid of a software package called Crystal Ball(22). Crystal Ball randomly generates numbers for the variables based on the defined probability distributions and computes a probability distribution for the response. Benefits of the RSE approach appear again, when one considers the number of runs required for a valid Monte Carlo Simulation (~10,000). Performing such a task with an actual program instead of a polynomial would be impractical at the very least. The product of the simulation is a probability distribution of $/RPM, a sample of which is shown in Figure 17.

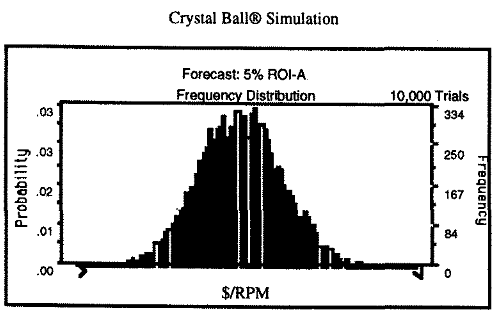

Figure 17: Economic Uncertainty (Frequency Distribution) for $/RPM

A distinction is now drawn between a *feasible* design and a *viable* one. Since the point design optimum satisfied all the performance constraints and was properly sized for the given mission, it is said to be feasible (i.e. it could be built). Thus, all outcomes in Figure 17 are feasible. However, the paradigm of design for affordability requires feasibility *and* economic viability. To investigate viability, the just obtained $/RPM distribution is compared against a desired target for both mean and variance. If the computed mean and variance do not compare favorably with desired targets (or management's requirements), areas of possible technology improvement (and their associated risk) must be identified to make the design both feasible and economically viable. This process is seen as the last decision box near the bottom of Figure 13 and is elaborated in Figure 18.

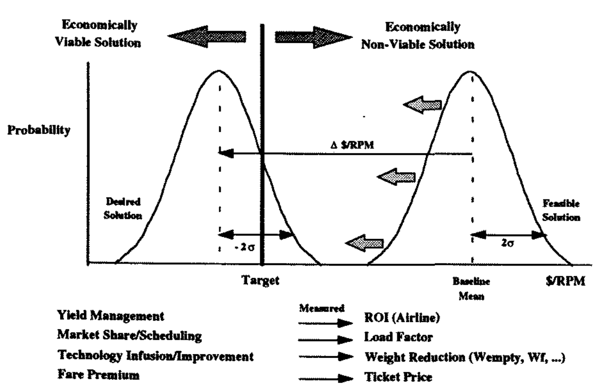

Figure 18: Feasibility vs. Viability: Shifting to Target

This figure stresses the difference between viability and feasibility and graphically illustrates how means for improvement would shift the distribution. As mentioned, this viability assessment is demonstrated in detail in Reference 8.

V. Conclusions

An improved design methodology has been developed and presented here which provides a means to bring sophisticated analyses to an MDO problem: aircraft synthesis and optimization. The implementation of the method is the first step towards a comprehensive IPPD approach to aerospace systems design being developed at ASDL.

A key objective in this work was the integration of aerodynamic and propulsion analyses into the sizing/optimization process and the investigation of their combined effects on the design of an HSCT. Under this task, the use of DOE/RSM was a central part of the solution approach. DOE/RSM was successfully used to generate Response Surface Equations (RSEs) representing vehicle drag as a function of geometry and flight condition parameters. These equations were subsequently validated and then integrated into the sizing program FLOPS, replacing prediction methods in the code. This transformation of the sizing code into a more powerful preliminary design tool enabled an innovative aerodynamic / propulsion integration to take place.

A five level, eleven (11) factor DOE was executed using this new tool to find the variable settings which minimized the objective function. Included in the 11 factors were critical aerodynamic, propulsion, and sizing design variables. The result of the experiment was a response equation for the average yield per Revenue Passenger Mile ($/RPM). This RSE was then used to obtain the optimal setting of the design variables which minimized the $/RPM in the presence of constraints such as takeoff and landing field length, noise, and approach speed. The resulting settings represent an "optimal point design" solution, as it represents a deterministic design where uncertainties such as economic variance or technology risk were not addressed. Finally, avenues for introducing and analyzing this economic uncertainty were presented.

The results presented here provide the impetus for further investigations. Specifically, the introduction of economic uncertainty (as performed in Reference 8) and the modeling of more complex tools (such as CFD for aerodynamics and FEM approaches for structures) via DOE/RSM merit extended research.

Acknowledgments

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