VARIABLE-COMPLEXITY RESPONSE SURFACE AERODYNAMIC DESIGN OF AN HSCT WING

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ABSTRACT

A design methodology which uses a variable-complexity modeling approach in conjunction with response surface approximation methods has successfully been developed. This technique is applied to an example problem of wing design for a High Speed Civil Transport (HSCT) aircraft involving a subset of four HSCT wing design variables. The wing design methodology is applied using a simple algebraic model for the wing weight. The applicability of the methodology for the multidisciplinary design of an HSCT is discussed.

1. INTRODUCTION

The use of multidisciplinary optimization techniques in aerospace vehicle design often is limited because of the significant computational expense incurred in the analysis of the vehicle and its many systems. In response to this difficulty, a variable-complexity modeling approach, involving the use of refined and computationally expensive models together with simple and computationally inexpensive models has been developed. This variable-complexity technique has been previously applied to the combined aerodynamic-structural optimization of subsonic transport aircraft wings[1] and the aerodynamic-structural optimization of the High Speed Civil Transport (HSCT)[2,3].

In related research conducted by members of the MAD Center at Virginia Tech, several improved HSCT designs have been obtained using these multidisciplinary design optimization tools. However, these efforts were hindered by convergence difficulties which were encountered in the aerodynamic-structural optimization of the HSCT[4]. The convergence problems were traced to numerical noise in the computation of aerodynamic drag components which inhibited the use of gradient based optimization techniques. To address this problem, a two variable example problem was investigated in which response surface models were used to produce smooth approximations for drag due to lift[4]. This example problem was used to determine the feasibility of using response surface methodology in conjunction with our existing multidisciplinary analysis tools. Such applications of response surface methods to vehicle design were proven successful by other investigators, c.f., References 5 and 6.

This study focuses on applying the response surface approximation methods to a new design problem involving four of the twenty-six design variables used in our previous HSCT design research[2,3]. Here, the four design variables define the HSCT wing. In this study we minimize the gross takeoff weight of the vehicle within the design space defined by the allowable variations in the four design variables. This wing design optimization takes place within the framework of our overall multidisciplinary design of the HSCT.

2. VARIABLE-COMPLEXITY MODELING

We have termed "variable-complexity modeling" the process by which simple, computationally inexpensive analysis techniques are used together with more detailed, expensive techniques in the design optimization process. Originally, this methodology was developed for gradient based optimization in which the overall

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design process was composed of a sequence of optimization cycles. With this method, the detailed analyses were employed at the beginning of each optimization cycle while the simple analyses, scaled to match the initial detailed results, were performed in subsequent calculations during each cycle[2,3]. A typical HSCT design optimization requires approximately twenty cycles until an optimal HSCT configuration is identified. The optimizer NEWSUMT-A[7], which employs an extended interior penalty function method, is used for this sequential approximate optimization process.

In this present work, this variable-complexity modeling approach is adapted for use with response surface approximation techniques. Here, the simple analysis methods are used to evaluate several thousand different HSCT configurations within a prescribed design space. By applying constraints to the design variables and to the objective function data, "nonsense" regions of the design space are excluded. The remaining design points form a ribbon like domain in which the optimal design is contained. From the several hundred points in the ribbon shaped design space, a small number of points, on the order of fifty to one hundred, are then selected for more detailed analyses. Using the results from these detailed analyses, response surface approximations can be created to model various factors which affect the HSCT design. For example, drag component data from the detailed analyses can be used to create a polynomial response surface model for the variation in drag on the ribbon shaped design space. In the final step of this process, the response surface models are implemented in the HSCT analysis software, and design optimization is carried out. This optimization uses constraints based on both the simple and detailed analyses, along with constraints which limit the design variables to values for which the response surface model is accurate. In addition, since the response surface models are based on the detailed analysis results alone, the sequential approximate optimization process is not needed here. Thus, only one NEWSUMT-A optimization cycle is needed to find the optimum design.

3. RESPONSE SURFACE METHODS

3.1 Polynomial Modeling

Response surface methodology (RSM) is a statistical technique in which smooth functions, typically polynomials, are used to model an objective function. For example, a quadratic response surface model has the form

$$y = c_o + \sum_i c_i x_i + \sum_{i(i<j)} \sum_j c_{ij} x_i x_j + \sum_i c_{ii} {x_i}^2 + \delta \quad (1)$$

where the x_i are the design variables, the c_i are the polynomial coefficients, y is the measured response, and δ is a random error term. In such a model the polynomial coefficients may be estimated using the method of least squares.

The construction of a response surface requires a minimum of n function evaluations where n is the number of coefficients in the polynomial. Results from Reference 4 confirmed that typically $1.5n$ function analyses were required to produce response surfaces which accurately approximated the global trends of the objective function data.

An example of the use of response surface modeling techniques is provided in Reference 4 where supersonic drag due to lift on an HSCT wing was calculated for various inboard leading-edge and inboard trailing-edge sweep angles (Fig. 1). Here, drag due to lift is calculated as

$$C_{Dlift} = \left(\frac{1}{C_{L\alpha}} - k_t \frac{C_T}{{C_L}^2}\right){C_L}^2 \quad (2)$$

where $C_{L\alpha}$ is the lift curve slope, $C_T/{C_L}^2$ is the leading-edge thrust term, and k_t is an attainable leading-edge thrust factor. The numerical noise in the drag due to lift evaluation may be attributed to numerical noise in the lift curve slope and leading-edge thrust terms. The methods of Carlson et al.[8,9,10] utilize a paneling scheme that is sensitive to planform changes. Thus, slight modifications to the leading and trailing-edge sweep angles, along with changes in the location where the Mach angle intersects the leading-edge, produce discontinuous variations in the predicted drag. Although the variations are small enough so that at all points the accuracy of the drag is acceptable, the oscillatory behavior creates difficulties for gradient based optimization techniques.

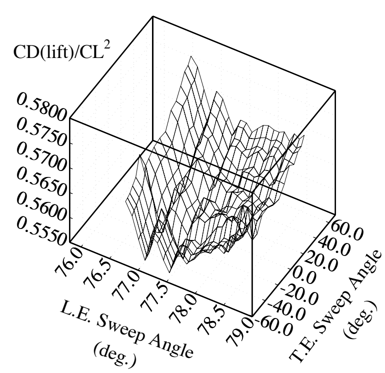

Figure 1. Noisy drag due to lift objective function data in the design space.

Figure 2 demonstrates the use of a quadratic polynomial response surface to approximate the noisy drag due to lift in Figure 1. The global minimum on the exact, noisy surface occurs for a leading-edge sweep angle of 77.6° and a trailing-edge sweep angle of −20.0°.

As shown in Figure 2, the quadratic response surface provides a reasonable estimation for the location of the global minimum.

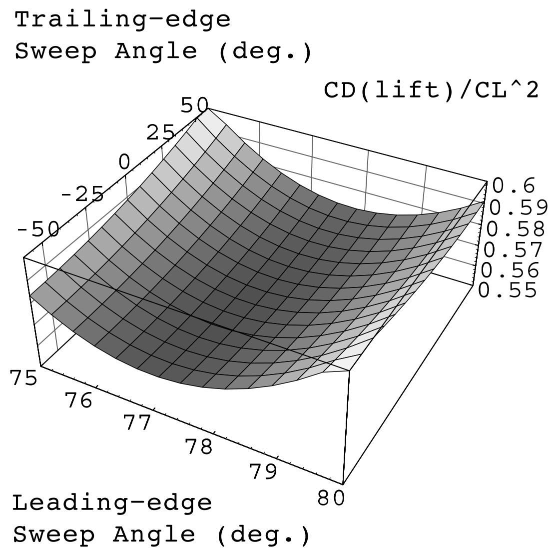

Figure 2. Quadratic polynomial response surface fit to the noisy drag due to lift data.

It is interesting to note that nonsmooth behavior of an objective function was encountered in a nozzle design problem[11] in which an Euler flow solver was employed. Problems associated with noisy or nonsmooth objective functions are not solely related to the use of panel methods.

3.2 D-optimal Point Selection

RSM typically employs a structured method such as central composite design (CCD) for selecting analysis points in the design space[12]. However, CCD is meant for use with regularly shaped design spaces and not the irregularly shaped design spaces, e.g., the ribbon shaped design region described above, that will arise in this design problem. Further, CCD is not a practical point selection method for design problems with a large number of variables. In a previous study[4], it was found that the *D*-optimal criterion[13] provided a rational means for choosing any number of points within an irregularly shaped design space.

The *D*-optimal criterion arises from the linear system $Y \approx \mathbf{X}c$, where Y is an m by 1 vector of objective function values, c is a k by 1 vector of coefficients to be estimated, and $\mathbf{X}$ is an m by k matrix of constants having rank k. The rows of the matrix $\mathbf{X}$ are the response surface basis functions evaluated at the design points. For this system, the least squares estimate of c is $\hat{c} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T Y$. The goal is to find the m points from a set of $l > m$ candidate points existing in the design space that will yield the best fidelity between the polynomial model and the actual objective function. The *D*-optimality criterion states that the m points to choose are those which maximize the determinant $|\mathbf{X}^T\mathbf{X}|$. Several relevant properties of this criterion are:

1. the set of points that maximizes $|\mathbf{X}^T\mathbf{X}|$ is also the set of points that minimizes the maximum variance of any predicted value of the objective function,
2. the set of points that maximizes $|\mathbf{X}^T\mathbf{X}|$ is also the set of points that minimizes the variance of the parameter estimates,
3. the design obtained is invariant to changes in scale.

Conceivably, one could consider each of the $\binom{l}{m} = l!/(m!(l-m)!)$ combinations of m points from the set of l candidate points, evaluate $|\mathbf{X}^T\mathbf{X}|$, and identify the set with the largest determinant. However, this is not a trivial task. For example, a small problem in two design variables may be to pick twenty-five points from 121 possible points (discretizing the design domain into ten sections in both directions leads to an 11×11 mesh). This leads to a total of $5.26\cdot 10^{25}$ possible combinations, one or more of which are *D*-optimal. For this reason, a genetic algorithm was developed to efficiently find a set of *D*-optimal points given a set of candidate points. In addition, the genetic algorithm allows *D*-optimal point selection for a design space of arbitrary shape.

3.3 Regression Analysis and ANOVA

When using RSM the designer often encounters what has been termed the "curse of dimensionality" in which the number of analysis points needed to construct a response surface model greatly increases as the number of design variables becomes large. Although this issue is not a problem in using RSM with a four design variable problem, it is sure to arise when RSM is applied to the full HSCT design problem, which we have modeled with twenty-six design variables. For this reason, it would be advantageous if less significant terms in the response surface model could be eliminated. As an example, a quadratic polynomial in p variables has $(p+1)(p+2)/2$ terms. A response surface in ten variables then would have sixty-six terms in the polynomial model and would require approximately one hundred analysis points to fit the model. However, if one third of the polynomial terms were insignificant, then the objective function could be represented with a forty-four term polynomial without a significant loss in accuracy. This reduced-term polynomial could then be constructed using approximately seventy analysis points. In multidisciplinary design optimization where each analysis may incur significant computational expense, the computational savings associated with the reduced-term polynomial may be substantial.

Fortunately, there are two statistical techniques, regression analysis and analysis of variance (ANOVA), which enable the less significant terms in the polynomial approximation to be identified. Regression analysis is the procedure by which the c_i coefficients for the response surface model are obtained and typically involves the method of least squares. ANOVA involves estimating the variance of the predicted polynomial coefficients and uses the variance-covariance matrix $(\mathbf{X}^T\mathbf{X})^{-1}$. The diagonal terms in this square matrix, ${\sigma_i}^2$, multiplied by $Var(\epsilon)$, the variance in the objective function values Y_i, are the variances of the respective coefficients, c_i, in the response surface polynomial model. The coefficient of variation, V, for each term in the polynomial is calculated as

$$V = \begin{cases} \frac{100|\sigma_i|\sqrt{Var(\epsilon)}}{c_i}, & c_i \neq 0, \\ 100, & c_i = 0, \end{cases} \qquad (3)$$

where the factor of 100 expresses the coefficient of variation as a percentage. The term $\sqrt{Var(\epsilon)}$ is usually estimated by the RMS error of the least squares approximation at the m data points. For the coefficient of variation calculations given below, we have assumed that $Var(\epsilon)$ is unity. Terms in the polynomial model having large coefficients of variation may be dropped from the polynomial without a significant loss in modeling accuracy.

4. HSCT DESIGN PROBLEM

We have previously considered an HSCT configuration which was parameterized using twenty-six design variables with the aircraft geometry specified by twenty-three variables and the idealized mission profile by the three remaining variables[3]. A typical optimization problem is to minimize the gross takeoff weight of an HSCT configuration with a range of 5500 nautical miles (n.mi.) and a cruise speed of Mach 2.4 while transporting 250 passengers. A total of sixty-one constraints, including both performance/aerodynamic and geometric constraints, have been employed to prevent the optimizer from creating physically impossible designs.

Our detailed aerodynamic analyses use the Harris program for the supersonic volumetric wave drag[14], a Carlson Mach-box type method for supersonic drag-due-to-lift[8−10], and a vortex-lattice program for landing performance. As part of our variable-complexity modeling approach we also employ simple aerodynamic analysis methods which are typically algebraic relations, and which require at least an order of magnitude less computational time than the associated detailed analysis methods. Details of each calculation are given in Reference 3. Compared to modern computational fluid dynamics tools, the detailed and simple analysis models used in this study are relatively inexpensive. However, the computational expense of using these methods quickly becomes substantial when they are employed in design optimization where the same calculation may be repeated thousands of times.

5. HSCT WING DESIGN PROBLEM

Difficulties were encountered previously[4] in design optimization of the HSCT due to the numerical noise in the calculation of drag due to lift and, to a lesser extent, supersonic volumetric wave drag. To counter this, we now are applying the variable-complexity response surface modeling strategy described above to gradient based optimization.

The baseline HSCT geometry used in this study is a modified version of an optimal HSCT configuration previously investigated by members of our research group at Virginia Tech[3]. However, in the time since this HSCT geometry was previously used, numerous modifications were made to our HSCT analysis software. Thus, this baseline HSCT no longer is an optimal configuration, but is still a "good" vehicle design by our analysis standards.

5.1 Wing Design Variables

In our work, the HSCT wing planform has been parameterized using eight design variables as shown in Figure 3. In addition, three variables describe the thickness-to-chord (t/c) ratios at the root chord, leading-edge break, and tip chord; one variable is used to specify leading-edge radius; and one variable defines the location of maximum t/c for all airfoil sections.

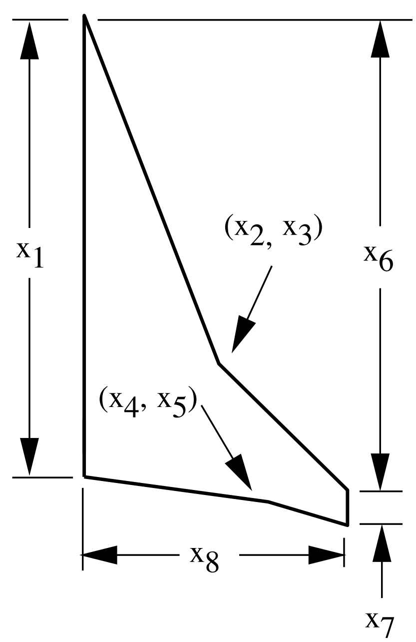

Figure 3. Planform variable definition for the HSCT wing.

To develop and test the variable-complexity response surface optimization strategy we decided to construct an example problem involving only a few variables. For this reason, a four variable wing design problem was chosen. Here, two of the original planform variables, root chord and tip chord, were selected along with two new design variables (Fig. 4). The first new design variable was the inboard leading-edge sweep angle which was calculated from the original planform variables x_2 and x_3. The second new variable is a constant scaling factor, ζ, by which the three t/c ratios from the HSCT baseline were modified. For example,

$$(t/c)_{root,new} = \zeta(t/c)_{root,baseline}, \quad (4)$$

$$(t/c)_{break,new} = \zeta(t/c)_{break,baseline}, \quad (5)$$

$$(t/c)_{tip,new} = \zeta(t/c)_{tip,baseline}, \quad (6)$$

for $0.8 \leq \zeta \leq 1.2$. Thus, this new variable, ζ, replaces the three t/c ratio design variables used in the original HSCT wing parameterization. In addition to the new variable definitions, planform variables x_5 and x_6 were eliminated so that the trailing edge of the wing was straight. Further, in this simplified model the span was held fixed.

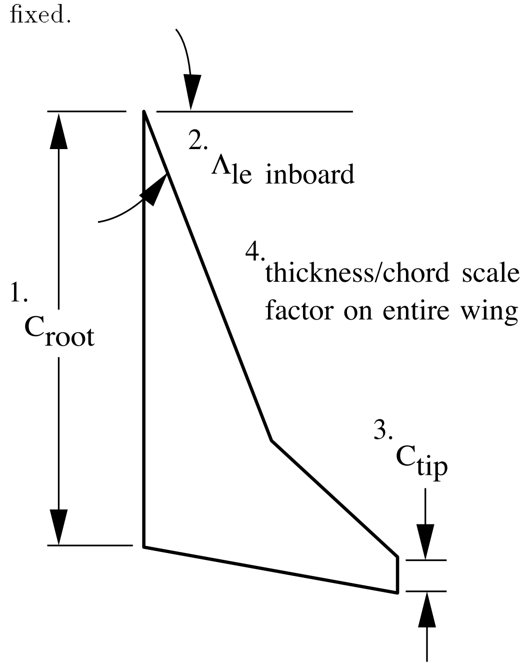

Figure 4. Wing design variable definition for the four variable problem.

Variations in the root chord have a significant effect on both the structural weight of the wing and on the volume available within the wing for fuel storage. These characteristics directly influence the gross weight of the HSCT. Perturbations in the leading-edge sweep and the t/c scaling factor primarily affect supersonic drag due to lift and the volumetric wave drag. Thus, the range and gross weight of the HSCT are affected through variations in the drag components.

The tip chord variable was selected specifically because it has only a minor impact on the weight and performance of the HSCT. For this reason, it was expected that the regression analysis and analysis of variance techniques would identify as negligible some of the response surface terms involving tip chord. This was confirmed by the analysis results and is discussed below. Note that although the tip chord is a relatively unimportant design variable for this example problem and the analysis methods used, the aerodynamics of the wing tip region can strongly influence the design of a particular aircraft. Therefore, the tip chord is not a design variable that can be ignored.

The design space for this four variable problem was determined by allowing the root chord and tip chord to vary ±20 percent from the values on the baseline HSCT. The t/c scaling factor also varied ±20 percent from a nominal value of unity. The leading-edge sweep was allowed to range only ±9 percent from its baseline value. Variations in the sweep angle outside of this range produced configurations which were not realistic.

5.2 Design Space Reduction

The first stage in the variable-complexity response surface modeling process was to evaluate numerous HSCT designs using simple algebraic analysis methods. This was performed by discretizing the design space using a $6 \times 6 \times 6 \times 6$ uniform coarse grid, i.e., each design variable had six discrete values. The 1296 (6^4) configurations defined by the combinations of the design variable values were then analyzed. At the center of the design space was the baseline HSCT configuration.

Using the constraint data obtained for each of the 1296 HSCT designs, obvious "nonsense" configurations were eliminated from consideration. Here, designs were excluded if any of the aerodynamic/performance constraints (e.g., landing angle-of-attack $\leq 12°$) were violated by more than twenty percent, and if any geometric constraints (e.g., minimum airfoil chord lengths $\geq$ 7 ft.) were violated by more than five percent. In addition, gross takeoff weight (GTOW) was allowed to vary within ±20 percent of the baseline GTOW of approximately 650,000 lbs. and range was required to be greater than 5000 n.mi. Both of these constraints were imposed to remove from consideration any unrealistic designs which had not been eliminated previously. After applying these constraints, only 157 acceptable HSCT designs remained out of the initial 1296 designs.

5.3 Regression Analysis and ANOVA

With the data from the 157 simple HSCT analyses a fifteen term polynomial response surface model was fit to the aircraft range data. Using the regression analysis and ANOVA methods described above, the coefficients of variation for the fifteen terms in the response surface model were calculated (Table 1). Here, the abbreviations ζ, c_r, c_t, and Λ_{LE} correspond to the t/c scaling factor ζ, root chord, tip chord, and leading-edge sweep angle, respectively. As shown, the higher order terms involving c_t have coefficients of variation greater than ten percent and can safely be dropped from the response surface model. Thus, the number of terms in the response surface model has been reduced to eleven and the modeling of the tip chord variable has been simplified from quadratic to linear.

Variable	Coefficient	Std. Dev.	V (%)
const.	0.058	0.197	3.416
ζ	-1.200	0.268	0.224
c_r	-0.555	0.206	0.372
c_t	-0.054	0.133	2.443
Λ_{LE}	0.755	0.261	0.346
ζc_r	-0.221	0.627	2.835
ζc_t	0.009	0.372	40.616
$\zeta \Lambda_{LE}$	0.170	0.848	4.990
$c_r c_t$	-0.025	0.290	11.621
$c_r \Lambda_{LE}$	0.058	0.572	9.907
$c_t \Lambda_{LE}$	-0.021	0.358	16.955
ζ^2	-0.095	0.623	6.588
${c_r}^2$	-0.147	0.352	2.399
${c_t}^2$	-0.006	0.234	42.143
${\Lambda_{LE}}^2$	-0.107	0.700	6.526

Table 1. Regression analysis and ANOVA data for the range response surface model.

Table 2 shows that the accuracy of the response surface fit is only slightly impaired after removing terms from the polynomial model for which the coefficient of variation is large. Here, the errors are calculated from the difference between the response surface prediction for the range and the actual value for the range at each of the 157 remaining HSCT design points.

Avg. Error	RMS Error	Max. Error
15 Term Polynomial		
0.034395	0.044025	0.126625
11 Term Polynomial		
0.035187	0.045363	0.113389

Table 2. Calculated errors for the fifteen and eleven term polynomial response surface models.

Since range is directly affected by numerical noise in the supersonic drag due to lift and volumetric wave drag calculations, a response surface model for range was used to determine the reduced-term polynomial model for the D-optimal point selection and for later use in modeling the drag components. An alternative approach, and one that will be considered in our future work, would have been to apply regression analysis and ANOVA separately to response surface models for each of the drag components.

5.4 Response Surface Models for Drag

From the remaining 157 HSCT designs, fifty were selected on the basis of the D-optimal criterion. The performance and constraint criteria for each of these were then evaluated using the detailed aerodynamic analysis models.

Using the same eleven term polynomial model found for range, new response surface models were constructed for the wave drag, the lift curve slope, and the leading-edge thrust term. These three response surface models were then used in the range calculation subroutine in place of the original noisy calculations of the drag components.

5.5 Optimization Techniques

As described above, the optimization for the variable complexity response surface approximation method uses constraints based on both the simple and detailed analysis models. For this example problem, this is accomplished by using two constraints on the calculated range.

The approximate constraint uses the original range calculation, i.e., range calculated from the simple analysis of drag components, which must be greater than 5000 n.mi. This is the same constraint used to remove unrealistic design points after the initial 1296 HSCT analyses.

The new range constraint employs the smooth response surface models for the three drag components. This constraint stipulates that the range must be greater than 5500 n.mi. The complication is that the range based on the response surface models is accurate only for certain regions of the design space defined by the allowable design variable values. One may picture the response surface models as being valid on a four-dimensional spheroid inscribed within a four-dimensional hypercube, where the vertices of the hypercube are defined by the allowable limits on the design variables. Without the approximate range constraint $\geq$ 5000 n.mi., the optimizer invariably moves to a vertex of the hypercube outside of the spheroid on which the response surface models are valid.

At first this seems counterproductive since two constraints are now used for range whereas only one sufficed before. However, this arrangement circumvents the problems created by numerical noise in the original range constraint evaluation. The use of both approximate and response surface based range constraints is successful because the simple, noisy range constraint is not active for much of the optimization. It serves only to keep the optimizer from moving to a region of the design space where the response surface model is inaccurate. In contrast, the response surface based smooth range constraint is nearly always active but it is not affected by numerical noise.

Due to improvements and corrections in various elements of our HSCT analysis software, the previously feasible baseline HSCT configuration, was found to slightly violate several constraints. In particular, these violated constraints pertained to takeoff and landing conditions regarding wing tip/runway scrape, engine/runway scrape, and landing angle-of-attack. Since span was not a design variable in this example problem, some of these constraints would have remained violated for all combinations of the four design variables. Therefore, to complete this investigation, the constraints in violation were removed, and the landing angle-of-attack constraint was relaxed from 12° to 13°. With the HSCT baseline configuration now providing a feasible starting point, optimization cases both with and without the response surface models for drag were conducted.

5.6 Optimization Results

With the range constraint based on the response surface models for volumetric wave drag and the two components of supersonic drag due to lift, the NEWSUMT-A optimizer was used to determine the optimal combination of wing design variables to yield minimum gross weight while satisfying all constraints. Since no sequential approximate strategy is needed for this optimization, the optimal design is found after one cycle.

The results of the optimization are shown in Table 3 in which the design variables and performance are compared for the initial and optimal HSCT configurations. Figure 5 shows the difference between the baseline HSCT planform from which the optimization was started and the optimal planform. The planform changes for the optimal wing design are most noticeable in the length of the root chord and in the leading-edge sweep angle. However, these differences are relatively modest.

	Initial Design	Optimal Design
root chord	174.0 ft.	168.1 ft.
tip chord	8.1 ft.	8.5 ft.
LE sweep	71.88°	72.45°
t/c scale	1.0	1.1
Exact Range	5577 n.mi.	5523 n.mi.
R.S. Range	5546 n.mi.	5556 n.mi.
Landing AOA	12.28°	12.58°
$C_{D wave}$	0.0017	0.0019
Total Drag	0.0053	0.0056
Wing Weight	107410 lbs.	99708 lbs.
Fuel Weight	328044 lbs.	328044 lbs.
Fuel/Gross	50.99 %	51.68 %
GTOW	640256 lbs.	634788 lbs.

Table 3. HSCT performance data for the initial and optimal HSCT designs.

The decrease in GTOW for the optimal HSCT design compared to the initial HSCT wing design arises primarily due to the ten percent increase in the wing t/c scale factor. Although the optimal wing is thicker than the initial wing, and incurs a drag increase, the loss in aerodynamic performance is offset by the structural weight savings that is realized with the thicker wing. Here, the optimal wing is approximately 7700 lbs. lighter than the initial wing.

For comparison, the optimization of the four variable design problem was repeated, but without using the response surface models for the drag components. In this case the sequential approximate optimization strategy was applied. The result of this optimization yielded a nearly identical optimal design as was obtained using the optimization with the response surface models. Differences in the optimal design variables and in the analysis results were negligible.

During each sequential approximate optimization cycle, a locally optimal design is found within the design space prescribed around an initial HSCT baseline design. This local region of design space is defined by the allowable move limits on the design variables. If all the constraints are not satisfied, the optimizer repeats the process using the previously found local optimum as the new baseline design.

In this case, the optimizer also found the minimum design after one sequential approximate optimization cycle. However, this was not unexpected since the baseline HSCT design was very close to an optimal design. In general, the optimal design will not be near the initial HSCT design and experience has shown that the sequential approximate optimization strategy will require approximately twenty global optimization cycles until convergence is reached.

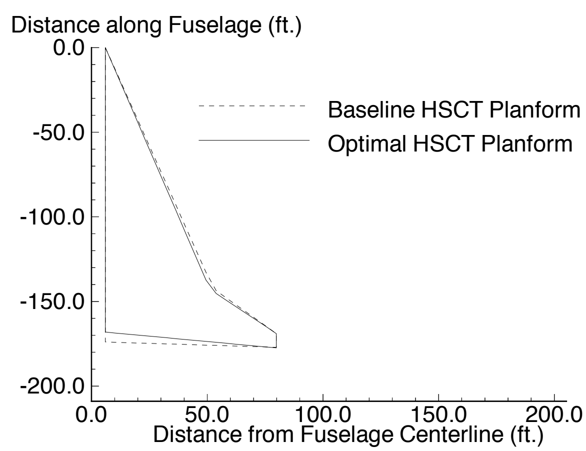

Figure 5. Baseline vs. optimal HSCT planforms.

6. PARALLEL COMPUTING

Our efforts at parallel computing involve a twenty-eight node Intel Paragon at Virginia Tech. The coarse grained parallelization of the aerodynamic analysis modules within the full HSCT analysis code makes use of a master-slave paradigm on the Paragon whereby one designated master node controls the data transfer and file input/output (I/O) of the remaining slave nodes. This coarse grained approach is used for the numerous independent analyses required for response surface construction.

To initiate the parallel multipoint analyses, a group of predetermined analysis points is input to the master node. The master node then computes the subset of the points which each slave node will analyze and sends that information to the appropriate slave. Both the master and slave nodes then analyze their respective subsets of the selected points and store the results in an array local to each node. When each slave has finished its portion of the analyses, it sends the array of analysis values to the master node for output.

To compare the computational savings for parallel versus serial execution of a code, the term *speedup* is defined as

$$\frac{T_s}{T_p}, \tag{4}$$

where T_s is the serial execution time and T_p is the parallel execution time using p processors. Figure 6 shows the speedup results for parallel execution of the HSCT analysis code compared to ideal, linear speedup. The actual results deviate from the ideal due to the file I/O demands of the analysis code which must be executed serially, and due to unavoidable communication overhead in the parallel code. Currently we are examining methods to reduce file I/O and improve the parallel execution of the HSCT analysis code. Our efforts to date are detailed in Reference 15.

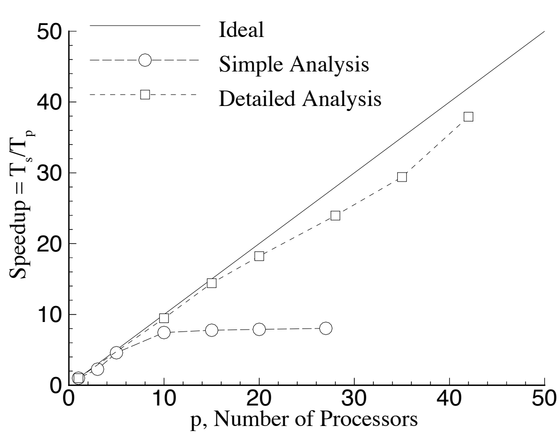

Figure 6. Ideal versus actual speedup for parallel execution of the HSCT analysis code.

7. CONCLUDING REMARKS

The use of response surface modeling for volumetric wave drag and for components of supersonic drag due due to lift has been shown to be an effective technique for alleviating the detrimental effects of numerical noise in design optimization. Further, the coupling of variable-complexity analysis methods with response surface modeling was demonstrated for an HSCT wing design optimization problem involving four design variables.

Future work with the variable-complexity response surface design optimization technique will focus on HSCT design problems involving ten or more variables to further validate this technique. Eventually this method will be applied to the HSCT wing-fuselage-nacelle design problem which will have twenty-six or more design variables. In addition to these developments, finite element structural analysis of the HSCT wing will be implemented in the design process. This will provide a more accurate calculation for the structural weight of the HSCT. Further, work will continue on the parallel implementation of the numerous HSCT analyses which are used in the variable-complexity response surface design optimization method.

ACKNOWLEDGMENTS

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