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Getting the Full Benefits of CFD in Conceptual Design

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Abstract

The applied aerodynamics community is struggling to develop a means of incorporating computational fluid dynamics (CFD) into the early stages of aircraft systems design, where it can have the greatest impact on vehicle design. This paper describes developments in computational design methodology arising from research into multidisciplinary design optimization (MDO) done recently by the authors that addresses this problem. The premise is that advanced CFD should be used to precompute a database of solutions which is then interpolated during the design process. Design of experiments theory is used to select the "conditions" or "design points" used to populate the database, and statistical methods are then used to develop a mathematical model of the CFD solutions which is used to "interpolate" the database. The specific models we use, called "response surface models" are quadratic least squares fits to functions of the CFD results. Populating the database is made possible through the use of coarse grained parallel computing. We demonstrate the method using a recent example from our MDO work.

Introduction

This paper is intended to alert members of the applied computational aerodynamics community to developments in computational design methodology arising from research into multidisciplinary design optimization (MDO) done recently by the authors. After attending the 15th Applied Aerodynamics Conference in 1997, it became clear that this work needed to be brought to the attention of aerodynamicists. Several sessions at that meeting touched on the problem of how to use the power of CFD in the early stages of design. Nixon[1] explicitly identified the need to use CFD to develop a database, which would then be interpolated during the design process. Thus it appears we need to describe the methods developed at Virginia Tech to incorporate CFD results in the early design phases.[2,3] As such, this paper uses results obtained in our MDO research, and could be viewed as a survey of work in one area, with illustrations of how to apply it to another.

Our MDO research has been addressing the issue of how to bring the benefits of high-fidelity, computationally-intense analysis and design to the very early stages of design.[4] The conceptual design stage is the point where the most freedom is available to change the design, thereby allowing CFD to make the largest impact. However, normally, advanced CFD tools aren't used until the start of preliminary design at the earliest. Many of the key early design configuration decisions such as wing aspect ratio, sweep, and thickness, which require explicit considerations from many disciplines, are made using simplified models of the various disciplines. Codes such as ACSYNT[5] and FLOPS[6] are examples of MDO methodology employing simplified models of the various disciplines.

After an introduction to the concepts, terminology, and issues of our approach we give a brief review of the aerodynamic design process and the use of CFD in design. We then discuss some relevant past work, and describe the process we've developed to incorporate CFD into the conceptual design process, and present an example from our MDO research.

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Concepts, Terminology and Issues

Obtaining the full benefits of CFD in the conceptual design process requires using some methodologies with which aerodynamicists are not generally familiar. We need to define our terminology. To carry out any systematic design the problem has to be defined in terms of a goal, which in optimization jargon is known as the *objective function*. The designer has to establish the parameters, called the *design variables*, that he can vary to alter the design. A specific set of design variable values defines a *design*. Any realistic design problem will also contain numerous *constraints*. For example, an aircraft must have a specified range requirement and the wing structure must not buckle under loading conditions. The objective function and constraints are functions of the design variables. For high dimensional design space many local extrema may exist. Ways to find a global minima are the subject of considerable current research. These ideas are from optimization theory, and a practical source of more details is available in the book by Vanderplaats.[7]

The region defined by the upper and lower values of the design variables is known as a *design space*. A collection of designs are selected in the design space to populate the database. The number of designs and theory for selecting corresponding design variable values use an approach known as *design of experiments* (DOE), see Montgomery.[8] The result found from analyzing a particular design is considered a *response* to that set of design variables. A set of responses found through analyzing many designs with varying values of their respective design variables forms a *response surface*. The response surface can be approximated by creating a function that relates the values of the design variables to the values of the responses, which may represent constraint or objective function values. These approximations are called *response surface models*, see Meyers and Montgomery. [9] The benefits of using response surface models are clear when one considers the vast number of design variable combinations (planform shapes, wing thicknesses, nacelle placements, *etc*.) that would be considered in early design. The cost of evaluating the response surface model is nearly negligible compared to the expense of a complete analysis. There is a significant computing requirement up front to perform the analyses necessary to create the response surface models, but these "one time" calculations are very amenable to parallel computing.

Several important issues are associated with the concepts described here. The first is the number of design variables and the fidelity of the analysis used to find the objective function and constraints. Statistical methods used here are simplest to apply to low dimensional design space. Textbook examples typically use two or three design variables. We have found in several problems that from 20 to 30 design variables are required to define the problem meaningfully. A 29 design variable problem that we have used in an HSCT design study used a quadratic model of a response surface which contained 465 terms, including all the cross terms. Accurate determination of the coefficients of each term required an even larger number of design evaluations (on the order of 2000). Thus creating a response surface in high dimensions requires large numbers of analyses and a method of reducing the computational cost is required, even with the utilization of parallel computing.

Another issue is the quality of the fit to the response surface obtained with the approximating function. Typically, the approximating function is a polynomial, and most response surfaces we've used are no higher than second order. The true response may not be quadratic, and care must be taken to ensure that the approximation to the response surface is adequate in the vicinity of the final results of an optimization.

In addition, visualizing the design space in more than three dimensions presents a problem. The problem becomes more difficult with higher dimension. Designers would like to be able to "see" the design space. Research is ongoing into this issue.

Aerodynamics at the conceptual design stage

At the conceptual design stage the aerodynamicist needs to be able to project the potential of a configuration very rapidly with very limited information. Perhaps the key requirements are a projection of the cruise drag, maximum lift at low speed, and a few key characteristics associated with handling qualities and flight safety. Maneuver characteristics may also be of interest. Moreover, although aerodynamic design is often done at a single point, *i.e*., a specified lift coefficient with consideration of specific off design conditions, such as buffet or low speed high-lift conditions, the designer actually needs a drag polar. The design lift coefficient can change with the design trades carried out early in the design process. The aerodynamic representation must characterize an optimum design, not an analysis of a non-optimum configuration. Traditionally, the aerodynamicist has done this using rapid methods that combine linear theory aerodynamics and past experience. Past experience includes results of previous studies and computer programs that reflect past experience in a computational form, *e.g*., Refs.10 and 11.

Conceptual design embodies two essential characteristics. First, there is no such thing as a purely aerodynamic design. The design process is inherently multidisciplinary. Detailed aerodynamic design takes place as a single discipline only after most key characteristics such as the wing planform and thickness, and the Mach number and lift coefficient are established. The standard multidisciplinary example in supersonic transport design is the conflict arising from the choice of wing thickness. Thicker wings are lighter structurally, yet have more wave drag. As we shall show below, the relative sensitivities of the structural and aerodynamic technologies are critical to making the correct choice. The fidelity of the analyses used in technology assessment is critical to the selection. Thus, aerodynamics is never alone in conceptual design.

The second characteristic is that no one ever does a design just once, especially in conceptual design. Numerous alternatives are evaluated. A single point design is only of interest relative to the effects of constraint changes, and a myriad of questions about the relative importance of various design variables. Typically the design is done with numerous parameters fixed, and the importance of the parameters will also be studied. Typical parameters might include aircraft range and/or payload, or assumptions about the amount of laminar flow on the airplane. Thus, although computational expense and design cycle time are critical, it is likely that cases will be run repeatedly. In the approach advocated in this paper we shift the computational expense from the optimization process, which will be done using algebraic approximations for the system, to a step carried out *before* the optimization where the system response is established. This provides a means of doing many optimizations.

A Navier-Stokes Nightmare

One can envision an attempt to couple a Navier-Stokes solver (actually RANS) directly into an optimization procedure. It is easy to imagine that over a hundred cases are run during each optimization (a *very* conservative estimate). Now, consider that the optimization is run repeatedly with different variations of the problem, as described above. In each case RANS solutions are computed which are within an epsilon of solutions already computed during previous runs. Surely there must be a saner way of doing the design!

CFD in Design

The problem of how to use the advances in CFD in conceptual design has been of interest for some years. Snyder discussed the problem in 1990.[12] More recently, Geising, *et al* addressed this issue[13] and it was the subject of the AIAA Wright Brothers Lecture by Paul Rubbert in 1994.[14] There have been several drawbacks to the use of CFD. Probably the most important is that the aerodynamicist in conceptual design needs to project the potential performance of the design after a complete detailed aerodynamic design has been done. A CFD analysis of a shape that has not been *designed* is of no particular value. Indeed, a detailed wing design may take months to perform. Historically, the conceptual design aerodynamicist *assumes* the performance level that can be achieved, *e.g.*, the percentage of full leading edge suction that can be achieved after the design process has been completed. For evolutionary development this is relatively easy. For radical departures from past designs this approach has more risk. The second problem is the cycle time for CFD solutions. Until very recently, it took too long to do analysis and design using CFD. Considerable effort is being made to reduce the cycle time, and progress is being made. However it may still be too long for most traditional conceptual design studies, which assume that several configurations can be evaluated daily.

Perhaps the best recent assessment of the use of CFD in design is contained in the papers by Jameson.[15,16] His work addresses the issue of preliminary and detailed design, but identifies the keys issues in using CFD in design in general. His recent experience came from his work on the detailed design of the MDXX project, which was canceled before his team's wing design was wind tunnel tested. He identified the serial nature of the computationally intensive activity as being a major problem.

Key early work

Since aerodynamicists have always used all of the available computing power to the fullest, the problem of integrating computationally intensive analysis methods into the design process is not new. Hints of the approach we advocate were first proposed many years ago. At the time they didn't get the recognition they deserved. The motivation then was the same as it is today, a search for methods to overcome the computational expense of high fidelity flowfield simulation.

In 1964 Powers[17] addressed the problem of using results from advanced methods in design using an approach similar to the one advocated here. He was interested in finding the minimum drag body of revolution with a hemispherical nose at Mach 7, including real gas effects. This required using both a real gas blunt body program and a real gas method of characteristics program. In the early '60s this was an extremely challenging computation. He approached it by finding the optimum values of shape change polynomials, where the effects of changes on drag were found by using the method of Latin Squares (one type of experimental design), which required analyzing nine different shapes. A least squares polynomial surface fit to the results from the nine computations was then used to find the coefficients of the shape change polynomials. He then found the minimum drag easily using the analytically defined response surface model. Thus the idea was to use solutions from high-fidelity computationally intensive analysis methods to develop inexpensive models for use in design optimization. Powers[18] continued to use this approach to solve a wide variety of problems in industry until his retirement a year or two ago.[*]

A similar approach was developed at Boeing in the early '70s and is best described in the paper by Healy, *et al*[19] regarding engine selection in aircraft design. Subsequently, the procedure was used by Jobe, *et al*[20] to investigate large airplane wing planform concepts. Three design variables were selected, aspect ratio, sweep and thickness. Then, a range of values for each design variable was selected. They picked four values for each of the three variables. The resulting 64 combinations of design variables, *i.e.*, the experimental design, then were reduced using the method of Latin Squares to 16 designs. The results from an analysis of the 16 different designs were then used to develop approximate functions for the objective function (TOGW) and constraints. The optimum values of the design variables were then found using the approximating functions. The full report shows that the approximating functions were quadratic polynomials.[21] This approach also was used by Jensen, *et al*[22] to study the effects of using different objective functions on the configuration of a military transport. No further results of studies using this methodology by Boeing have appeared in the literature.

Recent MDO Developments

Research in MDO has been very active in the last decade. Keys surveys are by Sobieski and Haftka[23] and Frank, *et al*.[24] The former survey reviews the types of MDO formulations that have been developed, and the latter reviews the ways to solve the optimization problem. A good overview is also contained in the paper by Kroo.[25]

At Virginia Tech, in the MAD Center, one of our projects has been HSCT design. We started by using a variable-complexity modeling (VCM) concept combing simple, typically algebraic, approximations with more detailed numerical methods. Typical aerodynamic analyses include wave drag and drag due to lift predictions. In the VCM approach we do most of the analyses using the simple models, which are then improved by adjusting them to agree with the detailed models occasionally. We use sequential approximate optimization methods that provide a natural means of updating the simple methods. The process is carried out using a sequence of optimization cycles, where the simple methods are compared with the higher fidelity methods at the beginning of each optimization cycle. We have used several techniques. We call the most basic approach *scaled approximation*. There, we find a constant scaling factor at the beginning of each cycle. Defining $f_d(\mathbf{x})$ to be the result from a detailed analysis, and $f_s(\mathbf{x})$ to be the result from a simple analysis, with $\mathbf{x}$ being the vector of design variables, the scaling factor σ is defined at the beginning of the cycle, $\mathbf{x}_o$, as

$$\sigma(\mathbf{x}_0) = \frac{f_d(\mathbf{x}_0)}{f_s(\mathbf{x}_0)},$$

and during an optimization cycle we approximate the analysis results as

$$f(\mathbf{x}) \approx \sigma(\mathbf{x}_0) f_s(\mathbf{x}),$$

and a new value of σ is found at every optimization cycle.

We were able to obtain results using this approach.[26] The most recent example is by MacMillin, *et al*.[27] However, there were several drawbacks with the variable complexity method as originally formulated. We had difficulty with the accuracy of the simple models. Sometimes they weren't general enough to predict the correct trends. Next, we found that almost all of the numerical calculations (both structures and aerodynamics) would produce slightly noisy results as the geometry changed (others have also discovered this problem[28]). This causes problems, especially for gradient-based optimizers. Convergence is poor and many local artificial extrema are selected by the optimizer. Finally, we found the problem of creating and maintaining the software associated with combining many disciplinary codes into a single program. This is a problem that has been encountered previously elsewhere.[29] It is impractical to consider directly incorporating the large CFD and finite element codes that would be included in the ultimate development of an MDO approach. The last two

[*] The first author was told about Powers' work in the mid '70s. Because the approach required the use of statistical methods, and Powers' references used agricultural examples, the first author failed to appreciate the potential of the approach, a significant error in judgment.

problems exist independently of the issue of computational cost.

Experience with our original approach made us reconsider our methodology. Two key changes emerged. First, we decided to represent the results of our analysis with response surface models described generally above. This led to the next major change. We no longer had to have high fidelity codes requiring considerable expertise to use embedded directly in our MDO code. This produced a computing architecture that has the potential to handle much more general optimization problems, where other disciplines can be included. The result is a process that is faster, eliminates artificial noise, and allows the software to be much simpler, being easier to maintain and modify. The detailed high-fidelity computationally intensive work can be much better coordinated, with disciplinary specialists working closely with the MDO designers, who specify the locations in design space where analyses are needed. Using the high fidelity results a response surface model is created. The optimizer then uses the *model* of the high fidelity results. We no longer need a monster code, and the process becomes manageable both computationally and organizationally.

This procedure has been demonstrated by Giunta, *et al*.,[3] using linear theory aerodynamics and by Knill *et al*.[30] using Euler models of the aerodynamics. We have also used this approach to model pitchup effects,[31] and include detailed finite element structural optimization results in place of the traditional wing weight equation methods.[32] At the same time that we started migrating to this approach, other MDO groups were reaching similar conclusions and have started using related techniques.[33,34,35]

The process outlined briefly above has omitted a key detail. There is still a major problem. The computational cost is still too high. To address this problem, we have had to introduce several additional considerations. The next section provides a more detailed discussion of the general approach we advocate, including our approach to managing the computational cost problem.

An Approach for Incorporating CFD in Conceptual Design

As discussed above, the large computational and calendar time expense associated with high-fidelity methods prohibits their serial use in an arena where there is a strong emphasis on reducing the design cycle time. Even heroic efforts, such as those cited by Jameson,[15] will not be sufficient. Here we describe the approach we are currently advocating. As we learn more our approach evolves. The exact details are necessarily problem dependent. However, the framework described here should form the basis for any attempt to use detailed CFD in the conceptual design process.

Step 1: First, the design geometry has to be represented parametrically by a set of design variables. We have found that perhaps twenty design variables can be used to define a wing planform and airfoil thicknesses. Adding design variables to allow for area ruling of the fuselage, sizing of the vertical and horizontal tails, and placement of engine nacelles, as well as mission variables led us to use 29 design variables in our HSCT work.[27] An upper and lower bound of each variable is selected, creating a design "box." If a projection of the performance(drag) is required, the camber will have to be designed. Essentially, the camber design will become a sub-problem, requiring a separate design problem be solved for many of the various designs requiring evaluation at the top level. This is essentially the problem addressed by Jameson.[15] For our work in supersonic flow we have made use of a modified linear theory code to obtain the camber shape and associated minimum drag for each design. We have addressed ways to handle this design problem previously.[36]

Step 2: Once the design variables are selected, a number of designs using various combinations of the design variables must be evaluated. The specific selection of these design variable combinations requires the use of design of experiments theory. Figure 1 presents a conceptual representation of a three variable problem with each design variable taking three different values. This type of a design is known as a *full-factorial design*. While this is an effective way to set up a database for a small number of design variables, the resulting number of cases that need to be completed to obtain results for our twenty nine design variable problem is too big to be considered (hundreds of millions). The drastic increase in the number of designs required to construct an adequate database as the number of design variables grows is known as the curse of dimensionality. A reduced number of cases must be evaluated. Various subsets of the full factorial experimental design; such as the central composite (Fig.2), small composite, and D-optimal experimental designs can be used to supply adequate information with a reduced number of required evaluations.[9] Figure 3 shows an actual result of generating different designs using design of experiments theory for an HSCT study. As many different designs should be generated as is practical for the computational resources available. Software is available for aerodynamicists to use that makes this task relatively straightforward. SAS is one source for the software.

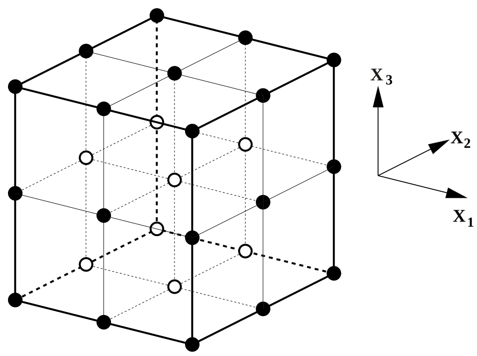

Figure 1. Example of a Full Factorial Design

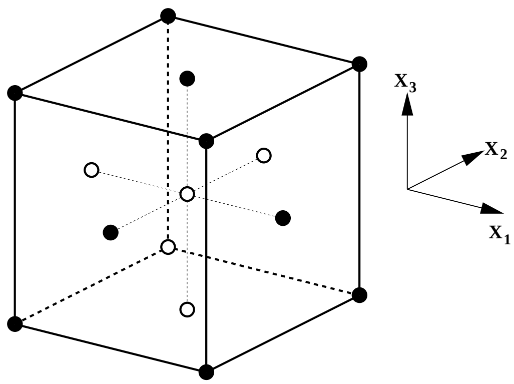

Figure 2. Example of a Central Composite Design

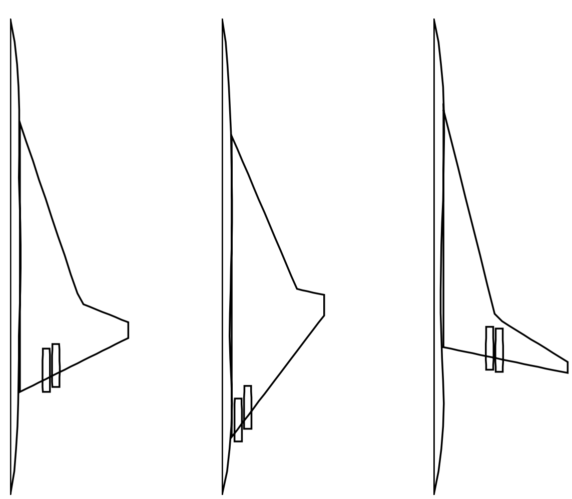

Figure 3. An Example of the range of planform shapes contained in the design space after applying the design of experiments ideas illustrated above.

Step 3: At this point the number of designs needs to be reduced. This is done in three stages. First we eliminate clearly ridiculous designs based on geometry (many combinations of design variables produce geometries that are clearly unreasonable). Then we use very approximate analyses of the constraints to reduce the design space still further, *e.g.*, if a design grossly violates the range constraint, we eliminate it. We call this the creation of a reasonable design space. Finally, based on the number of terms that will be required in the response surface model, we select a subset of the remaining points to analyze. Because we use a least squares fit to the surface, we need more points than we have coefficients. We have found that about 1.5 times the number of terms are required for a 5 design variable problem, progressing to about 3.5 times the number of terms for a 20 design variable problem. We use the D-optimal method to select these points. The D-optimal method works well with the irregular design space that results from the creation of the reasonable design space. D-optimal methods concentrate points on the outside edges of the design box.

Step 4: We are now ready to analyze the remaining designs using linear theory and Euler model aerodynamics to create response surface models. We need to define the precise form the response surface models will take. As noted above, the models are generally best limited to linear or quadratic functions, and some intelligence must be added to the process to formulate the response surface so that it is as close to a constant as possible. This is similar to the formulation of CFD problems so that behavior of dependent variables is well behaved. In predicting the drag, as noted above, we need to model the polar using response surfaces, not just the drag at a specific lift. We have found this to be a key consideration previously even in aerodynamics-only optimization.[36]

Here, we address the problem of defining drag polars, and make use of our knowledge of the problem from linear theory. Thus, rather than model the drag explicitly, we model the shape parameters of a drag polar. We can use either:

$$C_D = C_{D_0} + KC_L^2$$

or,

$$C_D = C_{D_m} + K(C_L - C_{L_m})^2$$

where we actually represent C_{D0} and K or C_{Dm}, K and C_{Lm} as functions of the design variables. To do this we must do either 2 or 3 analyses for each design. This is required to find the values of C_{D0} and K or C_{Dm}, K and C_{Lm} for each design. We then construct models of the variation of $C_{D0}(\mathbf{x})$ and $K(\mathbf{x})$ or $C_{Dm}(\mathbf{x})$, $K(\mathbf{x})$ and $C_{Lm}(\mathbf{x})$ with the design variables, $\mathbf{x}$.

We have obtained good results with either form. Figure 4 shows one example. Here we have the polar corresponding to a single design. The quadratic fit to the Euler solution is compared to the actual Euler results at a number of angles of attack and a linear theory analysis of the same configuration. Both the linear theory and quadratic fit to the Euler solutions compare well qualitatively to the Euler results. However, the Euler response surface is better than the linear theory, with the results being virtually indistinquisable from the actual Euler solutions near typical cruise lift conditions.

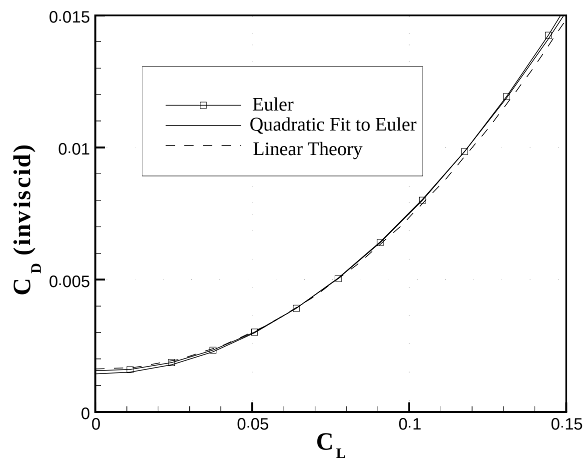

Figure 4. Example of a supersonic polar comparing Euler Analysis, a response surface model and linear trheory for an HSCT design.

Step 5: Evaluate the D-optimal designs selected in step 3 with a cheap method, typically linear theory. Then create a response surface model in the form selected in Step 4.

Step 6: Do a regression analysis of the response surface model obtained in Step 5. In addition to providing the basis for choosing the functional form of the drag polar, linear theory results also provide a means to reduce the number of Euler evaluations required to construct an accurate interpolation database. A relatively densely populated database of linear theory solutions can be created because the evaluations are so inexpensive. Using the linear theory database, statistical techniques are employed to determine the terms in the response surface models that have a significant effect on the aerodynamic quantity of interest. By eliminating these unnecessary terms from the CFD response surface models, the number of CFD evaluations required is drastically reduced. Figure 5 from Ref. 30 shows how many terms can be elliminated in our HSCT work. The regression analysis will identify which terms in the response surface model are important. As a sanity check, examine the results and verify that the statistical analysis is selecting terms that the aerodynamics would suggest are important. Our experience is that regression analysis works!

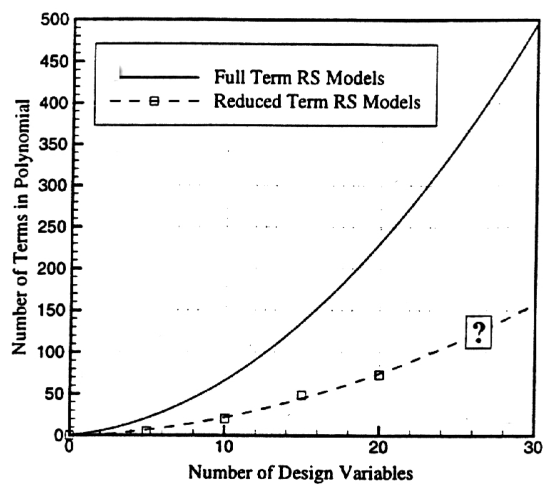

Figure 5. The number of terms required in the response surface model to obtain an accurate good drag predictions compared to the number of terms in the full polynomial (from Ref. 30).

Step 7: Assume that the important terms from Step 6 are also the important terms using the Euler analysis. This allows us to use a the reduced size model and thus requires many fewer Euler calculations than linear theory calculations. Use a subset of the D-optimal points used for the linear theory analyses. With parallel computing, it is possible to evaluate thousands of designs using an Euler analysis in a few days. At Virginia Tech, we use an Intel Paragon with over a hundred nodes, although we typically use only about sixty at a time. We use parallel computing in a very coarse, yet highly effective way. Because we need to evaluate numerous geometries using the same procedure, we can simply run many cases simultaneously. The critical contribution of the use of a parallel computer is to reduce the calendar time from weeks or months to a few days.

Step 8: Next, assess the accuracy of the Euler response surface model. This can be done by comparing the predictions of the response surface model with results of Euler calculation using D-optimal points not used to create the model.

Step 9: Once the response surface model is created and its accuracy assessed, a large range of conceptual design can be evaluated almost instantly (Figure 3 showed a typical range of planforms used to study potential HSCT configurations). Furthermore, for a particular design study, the resulting database can be used many times, with additional cases run to fill out a particular area as required.

Step 10: Finally, the result of the important optimization results need to be checked by making an Euler calculation for the design that was found by the optimizer.

Design Example

Figure 6, from Ref. 30, contains three plots showing a trade study for an HSCT configuration, comparing the results of linear theory and Euler aerodynamics for a change in the inboard leading edge sweep, holding the other design variables fixed. In this case, the wings are cambered using Carlson's attainable leading edge thrust methods[37] as implemented in the code WINGDES.[38] WINGDES provides a camber distribution which minimizes drag-due-to-lift and provides the maximum leading-edge suction parameter near the design lift coefficient. The various planforms are shown on the middle figure. As discussed above, the linear theory results are generally optimistic, and the fuel weight required to do the mission is higher using the Euler aerodynamics. Interestingly, the Euler results show that as the inboard sweep increases, resulting in a larger cranked tip, the fuel weight increases much faster than the results using linear theory. This occurs because the cruise drag penalty for the unswept tip is larger when using Euler analysis than when using linear theory.

The middle plot shows the variation in wing weight with inboard sweep. Here, because the configuration weight is higher for the Euler aerodynamics, the structural weight is higher. Note that there is very little variation with the sweep angle.

The bottom plot shows the combined results, which suggest that for an airplane with a given span the inboard sweep from Euler analysis should be lower than that from linear theory due to the penalty associated with the outboard section. For this class of configuration, the one degree of sweep at this large values leads to significantly different planforms. These studies are essentially trivial to carry out once the response surfaces are constructed, and allow the aerodynamicist to provide design insight into the configuration using the very best available analysis methods.

Figure 7 provides another example from our MDO work. In this case we compare the final results of a complete MDO optimization for a simplified five design variable case. Here the inboard planform sweep is found to be slightly less using Euler aerodynamics compared to linear theory, however, the primary finding focuses on the thickness. Because the linear theory drag results tend to be optimistic, the trade between structures and aerodynamics picks a thickness that is higher than that found using Euler analysis. Since the Euler predictions have a higher drag, the optimal design has a slightly thinner, and therefore heavier, wing. This example illustrates both the important coupling between disciplines and the importance of using high fidelity analysis.*

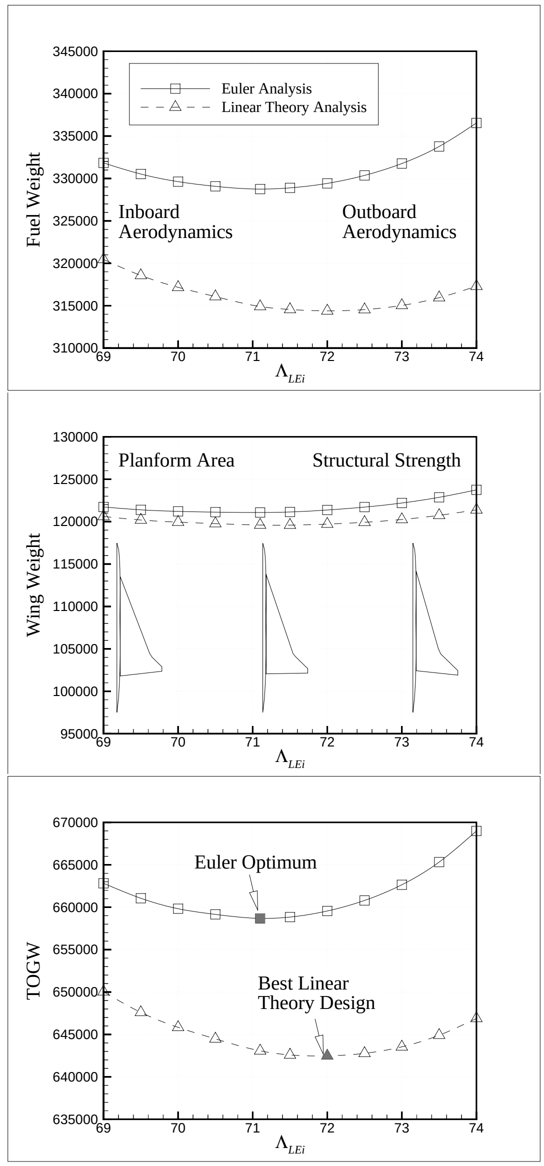

Figure 6. Parametric trade study of an HSCT using response surface models (Ref. 30).

* This result was exactly counter to the hopes of the first author, who has been an advocate of approximate methods in aerodynamics.

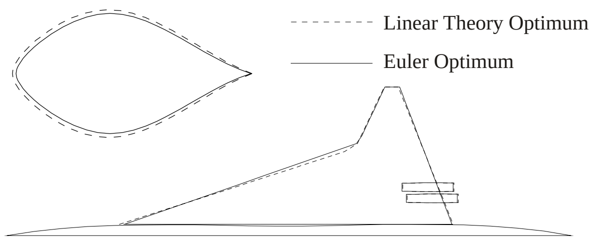

Figure 7. Comparison of MDO results using linear theory and Euler aerodynamics.

Conclusions

We have illustrated a rational method of using high-fidelity computationally-intense CFD methods very early in the design process, where the benefits of high-fidelity analysis and design can have the biggest impact in both vehicle performance and design cycle time. In effect, we develop a database of solutions and then interpolate the database. In higher dimensions (thus far as many as 29 design variables) the development of the database requires use of design of experiments theory and statistical methods. When coupled with a problem formulation that makes use of what we know based on linear theory, such as the form of the drag polar, good results can be obtained. We have shown that, around HSCT cruise conditions, it is virtually impossible to distinguish between the representation of the drag polar using our response surface model of the drag (computed using the Euler analysis) and the actual results from Euler solutions. In the same figure we showed that the response surface was better than using linear theory, where linear theory methods are usually employed in early design. While results from linear theory have inaccuracies, they do provide basic information as to which variables and combinations of variables play an important role in the prediction of aerodynamic quantities. This important information is used to significantly reduce the number of expensive CFD analyses needed to construct an accurate interpolation database. The example HSCT optimization presented, which was from an MDO problem that included the effects of wing structural weight, demonstrated that the minimum weight airplane found using the Euler results had a thinner wing than the results using linear theory to model the aerodynamics. Traditional design paradigms would likely make the change to a thinner wing difficult.

The method is even more effective because of the ease with which it can be incorporated into a parallel computing environment. Course grained parallel computing is relatively simple to implement and the computing resources required are beginning to be widely available.

We believe that aerodynamicists engaged in conceptual design should use the powerful methods described here. Further research into the issues associated with the creation of the database (point selection)and interpolation (response surface construction) is required. However, even at this stage of development our process has proven effective at including high-fidelity CFD solutions in the early stages of aircraft systems design.

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References

[1] Nixon, D., "Conceptual Design Method for Wings at Transonic Speeds," AIAA Paper 97-2241, June 1997.

[2] Giunta, A.A., Narducci, R., Burgee, S.L., Grossman, B., Haftka, R.T., Mason, W.H., and Watson, L.T., "Variable-Complexity Response Surface Aerodynamic Design of an HSCT Wing," AIAA Paper 95-1886, AIAA 13th Applied Aerodynamics Conference, San Diego, CA, June 21, 1995 , Pages 994-1002 of Proceedings.

[3] Giunta, A.A., Balabanov, V., Haim, D., Grossman, B., Mason, W.H., Watson, L.T., and Haftka, R.T., "Multidisciplinary Optimisation of a Supersonic Transport Using Design of Experiments Theory and Response Surface Modelling," *Aeronautical Journal*, Vol. 101, No. 1008, October 1997, pp. 347-356.

[4] Giunta, A.A., Golovidov, O., Knill, D.L., Grossman, B., Mason, W.H., Watson, L.T., and Haftka, R.T., "Multidisciplinary Design Optimization of Advanced Aircraft Configurations," *Fifteenth International Conference on Numerical Methods in Fluid Dynamics*, P. Kutler, J. Flores, J.-J. Chattot, Eds., in Lecture Notes in Physics, Vol. 490, Springer-Verlag, Berlin, 1997, pp. 14-34.

[5] Jayaram, S., Myklebust, A., and Gelhausen, P., "ACSYNT - A Standards-Based System for Parametric Computer Aided Conceptual Design of Aircraft," AIAA Paper 92-1268, 1992.

[6] McCullers, L. A., "Configuration Optimization Including Optimized Flight Profiles," in Proceedings of a Symposium on Recent Experiences in Multidis-

ciplinary Analysis and Optimization, pp. 395-412, April, 1984. J. Sobieski, compiler, NASA CP 2327.

[7] Vanderplaats, G.N., *Numerical Optimization Techniques for Engineering Design*, McGraw-Hill Book Co., New York, 1984.

[8] Montgomery, D. C., *Design and Analysis of Experiments*, New York, N. Y.: John Wiley & Sons, 1976.

[9] Myers, R.H., and Montgomery, D.C., *Response Surface Methodology: Process and Product Optimization Using Design Experiments*, John Wiley & Sons, New York, NY, 1995.

[10] Schemensky, R.T., “Development of an Empirically Based Computer Program to Predict the Aerodynamic Characteristics of Aircraft,” Air Force Flight Dynamics Laboratory AFFDL-TR-73-144, Nov. 1973.

[11] Feagin, R.C., and Morrison, W.D., Jr., “Delta Method, An Empirical Drag Buildup Technique”, NASA CR 151971, Dec. 1978.

[12] Snyder, J.R., “CFD Needs in Conceptual Design,” AIAA Paper 90-3209, Sept. 1990.

[13] Geising, J.P., Agrawal, S., and Bharadvaj, B.K., “The Role of Computational Fluid Dynamics in Multidisciplinary Design Optimization of Transport Aircraft,” *Proceedings of the Sixth International Symposium on Computational Fluid Dynamics, Technology, and Operations Congress*, Lake Tahoe, CA, September 4-7, 1995.

[14] Rubbert, P.E., “CFD and the Changing World of Airplane Design,” AIAA Wright Brothers Lecture, Anaheim, CA, Sept. 1994.

[15] Jameson, A., “Re-Engineering the Design Process through Computation,” AIAA Paper 97-0641, Jan. 1997.

[16] Jameson, A., “Essential Elements of Computational Algorithms for Aerodynamic Analysis and Design,” ICASE Report No. 97-68, Dec. 1997. (available online at http://www.icase.edu/)

[17] Powers, S. A., “Drag Minimization Using Exact Methods,” *AIAA Journal*, vol.2, pp. 941-943, May 1964.

[18] Powers, S.A., personal communication, June 1997.

[19] Healy, M.J., Kowalik, J.S., and Ramsay, J.W., “Airplane Engine Selection by Optimization on Surface Fit Approximations,” *Journal of Aircraft*, Vol. 12, No. 7, July 1975, pp. 593-599.

[20] Jobe, C.E., Kulfan, R.M., and Vachal, J.D., “Wing Planforms for Large Military Transports,” AIAA Paper 78-1470, 1978.

[21] Kulfan, R.M., and Vachal, J.D., “Wing Planform Geometry Effects on Large Subsonic Military Transport Airplanes,” U.S. Air Force Flight Dynamics Laboratory Report AFFDL-TR-78-16, Feb. 1978.

[22] Jensen, S.C., Rettie, I.H., and Barber, E.A., “The Role of Figures of Merit in Design Optimization and Technology Assessment,” *Journal of Aircraft*, Vol. 18, No. 2, Feb. 1981, pp. 76-81.

[23] Sobieszczanski-Sobieski, J., and Haftka, R.T., “Multidisciplinary Aerospace Design Optimization: Survey of Recent Developments,” *Structural Optimization*, 14(1), pp. 1-23, 1997

[24] Frank, P.D., Booker, A.J., Caudell, T.P., and Healy, M.J., “A Comparison of Optimization and Search methods for Multidisciplinary Design,” AIAA Paper 92-4827, Sept. 1992

[25] Kroo, K. “MDO for Large-Scale Design,” *Multidisciplinary Design Optimization State-of-the-Art*, Proceedings in Applied Mathematics 80, Eds.: N. Alexandrov and Y. Hussaini, SIAM, Philadelphia PA, 1997, pp. 22-44.

[26] M. Hutchison, E. Unger, W. Mason, B. Grossman and R. Haftka, “Variable-Complexity Aerodynamic Optimization of a High Speed Civil Transport Wing,” *Journal of Aircraft*, Vol. 31, No. 1, Jan-Feb. 1994, pp. 110-116.

[27] MacMillin, P. E., Golovidov, O. B., Mason, W. H., Grossman, B., and Haftka, R. T., “An MDO Investigation of the Impact of Practical Constraints on an HSCT Optimization,” AIAA Paper 97-0098, Jan. 1997.

[28] Geiselhart, K.A., “A Technique for Integrating Engine Cycle and Aircraft Configuration Optimization,” NASA CR 191602, Feb. 1994.

[29] Chalfan, K.M., “A Knowledge System that Integrates Hetrogenious Software for a Design Application,” *The AI Magazine*, Summer 1986.

[30] Knill, D.L., Giunta, A.A., Baker, C.A., Grossman, B., Mason, W.H., Haftka, R.T., and Watson, L.T., “Multidisciplinary HSCT Design using Response Surface Approximations of Supersonic Euler Aerodynamics”, AIAA Paper No. 98-0905, January 1996.

[31] Crisafulli, P., Kaufman, M., Giunta, A., Mason, W., Grossman, B., Watson, L., and Haftka, R., “Response Surface Approximations for Pitching Mo-

ment, Including Pitch-Up, in the MDO Design of an HSCT," AIAA Paper 96-4136, Proceedings of the 6th AIAA/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, pp. 1308-1322, Sept. 1996.

http://www.aoe.vt.edu/aoe/faculty/Mason_f/MRRpubs96.html.

[32] Balabanov, V., Kaufman, M., Knill, D. L., Haim, D., Golovidov, O., Giunta, A. A., Haftka, R. T., Grossman, B., Mason, W. H., and Watson, L. T., "Dependence of Optimal Structural Weight on Aerodynamic Shape for a High-Speed Civil Transport," AIAA Paper 96-4046-CP, Proceedings of the 6th AIAA/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Bellevue, WA, pp. 599-612, Sept. 1996.

[33] Tai, J. C., Mavris, D. N., and Schrage, D. P., "Application of a Response Surface Method to the Design of Tipjet Driven Stopped Rotor/Wing Concepts," AIAA 95-3965, Sept 1995. 1st AIAA Aircraft Engineering, Technology, and Operations Congress, Los Angeles, CA.

[34] Engelund, W. C., Stanley, D. O., Lepsch, R. A., and McMillian, M. M., "Aerodynamic Configuration Design Using Response Methodology Analysis," AIAA 93-3967, Aug 1993. AIAA Aircraft Design, Systems, and Operations Meeting, Monterey, CA.

[35] Sellar, R.S., Batill, S.M., and Renaud, J.E., "Response Surface Based, Concurrent Subspace Optimization for Multidisciplinary System Design," AIAA Paper 96-0714, Jan. 1996.

[36] Davis, W.H. Jr., Aidala, P.V., and Mason, W.H., "A Study to Develop Improved Methods for the Design of Transonic Fighter Wings by the Use of Numerical Optimization," NASA CR 3995, August 1986.

[37] Carlson, H., Mack, R., and Barger, R., "Estimation of Attainable Leading Edge Thrust for Wings at Subsonic and Supersonic Speeds," NASA TP-1500, 1979.

[38] Carlson, H.W., and Walkley, K.B., "Numerical Methods and a Computer Program for Subsonic and Supersonic Wings with Attainable Thrust Corrections," NASA CR 3808, 1984.