Advanced Aircraft Wing Optimization.

—A.J. Keane*

* School of Engineering Sciences, University of Southampton, U.K.

Abstract.

In this paper an empirical drag prediction model plus design of experiment, response surface and data-fusion methods are brought together with CFD to provide a wing optimisation system. This system allows high quality designs to be found using a full three-dimensional CFD code without the expense of direct searches.

Keywords: design, optimisation, aerodynamics, CFD, DoE, Krig

Introduction

In this paper we make use of the Southampton multi-level wing design environment[1] to study the merits of data fusion when applied to three-dimensional CFD solves over a transonic wing system. Here the aim is to build a multi-fidelity Response Surface Model (RSM) [2] using both empirical [3] and CFD data to model variations in drag at fixed lift as gross changes are made to the overall wing parameters. All the results reported here have been produced using the OPTIONS design exploration system [4].

The work reported here fuses together data coming from empirical and CFD based drag routines using Design of Experiment (DoE) techniques[5, 6] and Kriging[7] to build RSM's[8]. Variants on these methods have been used in aerospace design for some time. However, so far they have mostly been used to accelerate direct optimisation approaches using expensive codes[9]. It is only relatively recently that it has been proposed that they might be helpful in multi-level analysis (sometimes termed multi-fidelity or zoom analysis)[10-14]. The main aim in multi-level analysis is to use the DoE and Krig to produce a RSM that models *corrections* to the low cost, empirical analysis so that the correction model, together with the drag model of the original concept tool may be used in lieu of the full CFD code. This provides results that are both well calibrated and capable of being used outside of the scope of the original concept tool in a seamless fashion.

An example and some basic searches

Before commencing a discussion of multi-level approaches it is useful to first briefly illustrate the use of the wing design environment for direct searches, using either the empirical or CFD solvers. Here the response being studied is the drag of a transonic civil transport wing. A simple test problem has been constructed with the aim of optimising the wing for operation at Mach 0. 785 and a Reynolds number of 7.3 million. The objective is minimization of wing *D/q* as calculated by the CFD solver with target lift, wing weight, volume, pitch-up margin and root triangle layout chosen to be representative of a 220 seat wide body airliner. Limits are placed on the design variables that are typical of work in this area.

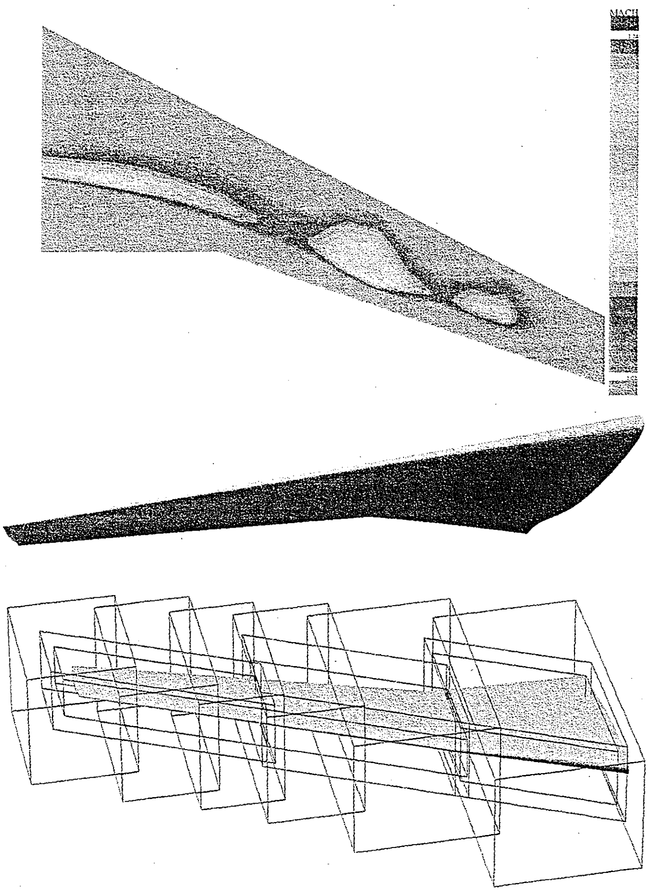

Figure 90-1. initial wing geometry and overall CFD meshing (plan view shows upper surface supersonic Mach contours).

The drag is computed either using the Tadpole concept design tool developed by the former Airbus division of BAE SYSTEMS[3] or by using the commercial MGAERO CFD code which is a viscous coupled Euler solver[15]. The input geometries to the CFD solver are created using a set of orthogonal functions derived from NACA transonic foils [16,17]. Typically the Tadpole analysis takes a few seconds while the Euler analysis may require up to two hours on a 1GHz Pentium III processor. Results from these two systems are detailed in Table 1 while Figure 1 illustrates the equivalent geometry. Notice that in this case the wing is defined by 11 parameters and also that constraints are placed on the wing volume, under-carriage bay length, pitch-up margin and weight. At all times the angle of attack is set to generate the required lift and the wing weight changes in a realistic fashion as its dimensions alter. Here, the two methods yield drag estimates that differ by some 8% despite the careful validation of the Tadpole code and considerable effort in attempting to get the drag recovery from the Euler code to work in a directly compatible fashion[18, 19, 20]. This is partially due to the public domain wing airfoil sections used to generate the CFD geometry, which differ from the commercial sections for which Tadpole is calibrated

Lower limit	Value	Upper limit	Quantity (units)
100	168	250	Wing area (m^2)
6	9.07	12	Aspect ratio
0.2	0.313	0.45	Kink position
25	27.1	45	Sweep angle (degrees)
0.4	0.598	0.7	Inboard taper ratio
0.2	0.506	0.6	Outboard taper ratio
0.1	0.150	0.18	Root t/c
0.06	0.122	0.14	Kink t/c
0.06	0.122	0.14	Tip t/c
4.0	4.5	5.0	Tip washout (degrees)
0.65	0.75	0.84	Kink washout fraction
	127984	135000	Wing weight (N)
40.0	41.73		Wing volume (m^3)
	4.179	5.4	Pitch up margin
2.5	2.693		Undercarriage bay length (m)
	3.145		D/q (m^2) — from Tadpole
	2.922		D/q (m^2) — from MGAERO

Table 90-1. initial design parameters, constraint values and objective function values.

Having set up this simplified design problem it may then be very rapidly optimised if the empirical code is used to estimate the drag. Here a 25 generation Genetic Algorithm (GA) search with a population size of 200 members has been used[21] followed by a gradient descent search to fine-tune the final optimum[22, 23], see Table 2. Notice that the optimisation has driven the wing volume constraint down to its limit and also that the sweep angle has been increased considerably, although the total wing area is little changed. The drag has been reduced by over 9%

(as predicted by the Tadpole code). Such a search process represents the current everyday activity of a concept design team. Having carried out this study the Southampton system then allows the drag to be checked by invoking the CFD solver — this result is also recorded in the table and it is seen that again the predictions still differ, now by 12%. The CFD predicted drag has, however, been decreased by nearly 13%.

Lower limit	Value	Upper limit	Quantity (units)
100	168.5	250	Wing area (m^2)
6	9.32	12	Aspect ratio
0.2	0.244	0.45	Kink position
25	31.8	45	Sweep angle (degrees)
0.4	0.516	0.7	Inboard taper ratio
0.2	0.227	0.6	Outboard taper ratio
0.1	0.104	0.18	Root t/c
0.06	0.115	0.14	Kink t/c
0.06	0.063	0.14	Tip t/c
4.0	4.7	5.0	Tip washout (degrees)
0.65	0.68	0.84	Kink washout fraction
	133895	135000	Wing weight (N)
40.0	40.0		Wing volume (m^3)
	5.04	5.4	Pitch up margin
2.5	3.51		Undercarriage bay length (m)
	2.853		D/q (m^2) — from Tadpole
	2.555		D/q (m^2) — from MGAERO

Table 90-2. final design parameters, constraint values and objective function values for the best design produced by the direct Tadpole search.

Given the difference in drag between the two predictions it is interesting to check whether a direct search applied to the CFD code would have produced a similar design geometry. Table 3 gives the results of such a study, although now the GA optimisation has been reduced to 15 generations and a population size of only 100 and the final hill-climbing search has been omitted, all to save time. Even so this search represents some 150 *days* of computing effort, here carried out on a cluster of PC's running in parallel over two weeks (the Tadpole search took ten minutes!). The extreme cost of such searches makes them infeasible for everyday use — but they do provide benchmarks against which to compare other results. Notice that in this case the drag is reduced by some 14% (as predicted by the Euler CFD code) and that the two codes still do not agree on the resulting drag, now differing by 19%. Comparing Tables 2 and 3 it is apparent that the two methods converge to somewhat different optima for this design study — the Tadpole predicted drag in Table 3 being nearly 5% higher than that in Table 2 while at the same time the CFD predicted drag is slightly more than 1% lower. Moreover, the CFD based wing has a significantly larger area.

Response Surface Modelling

The two searches described in the previous section simply involved applying optimisation methods directly to the analysis codes, in this case using Genetic Algorithms for wide ranging searches and then gradient descent methods for local improvement (if they can be afforded — recall that gradient descent methods cannot normally make use of parallel computing environments). Even with parallel computing, searches on the full Euler code are still very expensive to carry out. Consequently, many workers in this field advocate the use of Response Surface Models (RSM's) where surrogate meta-models are produced by curve fitting techniques to samples of the expensive data[7, 8].

Lower limit	Value	Upper limit	Quantity (units)
100	177.5	250	Wing area (m^2)
6	9.30	12	Aspect ratio
0.2	0.406	0.45	Kink position
25	25.2	45	Sweep angle (degrees)
0.4	0.683	0.7	Inboard taper ratio
0.2	0.259	0.6	Outboard taper ratio
0.1	0.143	0.18	Root t/c
0.06	0.096	0.14	Kink t/c
0.06	0.069	0.14	Tip t/c
4.0	4.5	5.0	Tip washout (degrees)
0.65	0.67	0.84	Kink washout fraction
	130166	135000	Wing weight (N)
40.0	41.6		Wing volume (m^3)
	3.67	5.4	Pitch up margin
2.5	2.56		Undercarriage bay length (m)
	2.998		D/q (m^2) — from Tadpole
	2.524		D/q (m^2) — from MGAERO

Table 90-3. final design parameters, constraint values and objective function values for the best design produced by the direct MGAERO search.

The basic RSM process involves selecting a limited number of points at which the expensive code will be run, normally using formal Design of Experiment (DoE) methods[5, 6]. Then, when these designs have been analysed, usually in parallel, a response surface (curve fit) is constructed through or near the data. Design optimisation is then carried out on this surface to locate new and interesting combinations of the design variables, which may then, in turn, be fed back into the full code. This data can then be used to update the model and the whole process repeated until the user either runs out of effort, some form of convergence is achieved or sufficiently improved designs are reached. This process is illustrated in Figure 2. It is no surprise that there are a number of variations and refinements that may be applied to the basic RSM approach — the literature offers many possible alternatives. Here, by way of example, a LPτ DoE sequence [24] is used to generate the initial set of points and a Kriging model applied to build the RSM [7].

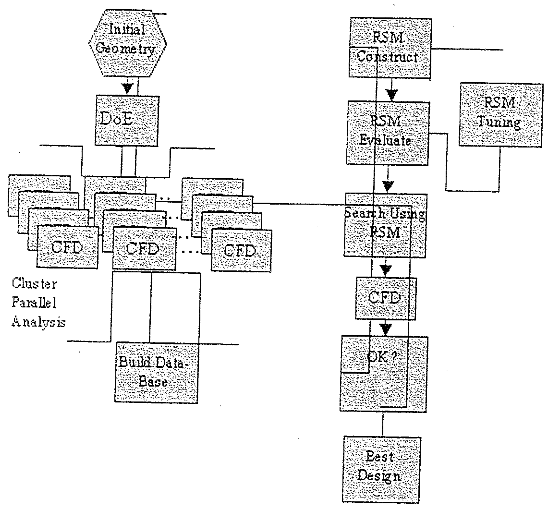

Figure 90-2. RSM based optimisation strategy

Application of Doe and Kriging

To demonstrate basic RSM production, 250 points of an LPτ array have been applied to the example problem of Table 1, which has 11 variables, using the inexpensive Tadpole code and a Krig built [7] using a Genetic Algorithm and gradient descent two-stage search of the concentrated likelihood function to tune the hyper-parameters. To demonstrate the accuracy of this model 390 further random design points were also computed with Tadpole and then the results at these further points were predicted using the Krig. Figure 3 shows the correlation plot for this test data and it may be seen that while some differences occur, the overall correlation coefficient is 0.991. This good predictive capability is also indicated by a standardised cross-validated (SCV) residual test on the original data, where the mean SCV residual turns out to be 0.541 with just two of the 390 residuals being greater than three (values of less than one represent a good model, while those over three indicate poor correlations, i.e., outliers). Moreover, negligible regularization (regression) is needed to model the data.

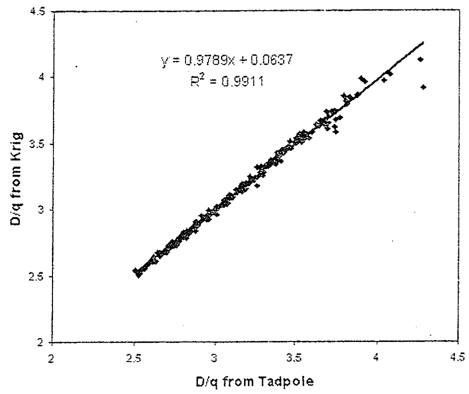

Figure 90-3. correlation between 390 random Tadpole D/q calculations and those predicted by the Krig trained on a separate set of 250 LPτ calculations.

These results show that it is possible to build Krigs successfully with this many dimensions using 250 data-points. This is hardly necessary for Tadpole given its run-time, however, which is barely more than that for using the Krig itself. The real use of the approach arises when attempting to model expensive data coming from the CFD code itself. This process is not so successful since the CFD data is intrinsically much less smooth and contains significant noise. Figure 4 show an equivalent set of results for a Krig built on CFD data, which yields a correlation coefficient of only 0.4903 — it is clear from the figure that there is much more scatter in these results, fortunately, mostly for the higher drag data. With this model the mean SCV is 0.929 and now 10 residuals are greater than three, again indicating that this data is harder to model with many more outliers. Significant regularization is also required.

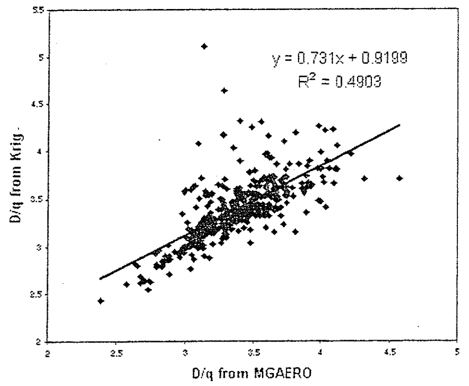

Figure 90-4. correlation between 390 random MGAERO D/q calculations and those predicted by the Krig trained on a separate set of 250 LPτ calculations.

Of course, the real test for the Krig of the MGAERO data is whether or not it can be successfully used to optimise the wing design as predicted by the CFD code. So next a two stage GA and gradient descent search has been carried out on the Krig RSM and the resulting design evaluated with the CFD code Then following the update strategy of figure 2, this design point is added to the set used to produce the Krig, and the hyper-parameters re-tuned before it is again used to try and find an improved design. This process can be repeated as many times as the designer wants or until some form of convergence is achieved. Here 10 such iterations are carried out to yield the result of Table 4. This final design, although better than the initial design before updates, fails to give *D/q* values as good as those achieved either by the direct search on the empirical Tadpole code or on the Euler based MGAERO CFD code. Its performance is 0.7% worse than the best design achieved by Tadpole optimisation (and using Tadpole predictions for comparison) and 0.6% worse than that from the direct CFD optimisation. This result indicates that although the RSM approach commonly yields improved results, these may well not be as good as direct searches on the underlying codes. This can occur even when suitable steps are taken to update the surface as part of the process and represents a fundamental limitation of meta-modelling. The approach is, however, much faster than the direct CFD search since it requires nearly six times fewer CFD evaluations.

Lower limit	Value	Upper limit	Quantity (units)
100	158.7	250	Wing area (m^2)
6	9.781	12	Aspect ratio
0.2	0.367	0.45	Kink position
25	30.18	45	Sweep angle (degrees)
0.4	0.467	0.7	Inboard taper ratio
0.2	0.300	0.6	Outboard taper ratio
0.1	0.133	0.18	Root t/c
0.06	0.106	0.14	Kink t/c
0.06	0.0627	0.14	Tip t/c
4.0	4.838	5.0	Tip washout (degrees)
0.65	0.679	0.84	Kink washout fraction
	134982	135000	Wing weight (N)
40.0	40.0		Wing volume (m^3)
	4.99	5.4	Pitch up margin
2.5	3.05		Undercarriage bay length (m)
	2.316		D/q (m^2) — from Krig
	2.879		D/q (m^2) — from Tadpole
	2.543		D/q (m^2) — from MGAERO

Table 90-4. final design parameters, constraint values and objective function values for the best design produced by the search on the refined MGAERO Krig produced with 10 updates.

Multi-level Analysis

Multi-level (multi-fidelity or zoom) analysis assumes that the designer has at least two different ways of computing results of interest for the design under consideration. The most obvious way o use such codes is to search large areas of the design space with the cheap code, followed by a local search using the expensive code in the areas showing most promise. However, despite the improvement this can give over a direct search there remain two fundamental problems with this approach: i) unless the methods agree very well, there is a danger that the results coming from one may mislead the other — such differences are apparent in all the results given here, and ii) the final direct search of the CFD code is still too computationally expensive for routine use. Clearly what would be preferable is a more sophisticated approach to integrating these sources of design information, i.e., some kind of data fusion system.

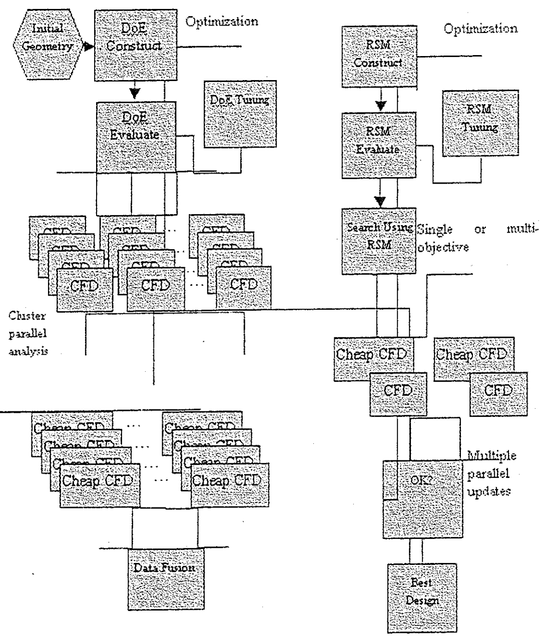

Figure 90-5. fusion based modeling strategy.

This may be achieved if instead of using the RSM to model the expensive CFD code directly, it is used to capture the differences between this and the cheaper empirical alternative. The RSM then serves as an online correction service to the empirical code so that when designs are studied where it is less accurate, the corrections derived from full three-dimensional CFD are automatically included. To begin this process we first take the data coming from the DoE run on MGAERO and compute an equivalent set of drag results for each point, using Tadpole. The differences between the two are then used to form the Krig. Then, when searches are carried out and new predictions are needed, these are calculated by calling *both* Tadpole and the Krig and summing their contributions, see figure 5.

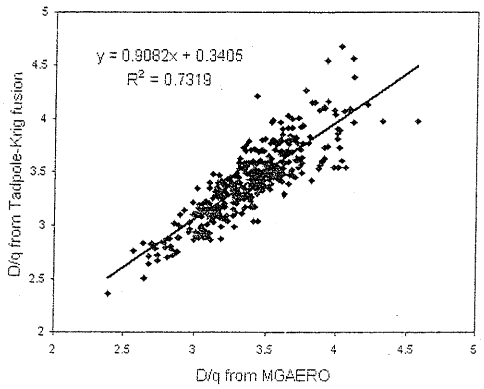

Figure 90-6. correlation between 390 random MGAERO D/q calculations and those predicted by the Tadpole - Krig fusion trained on a separate set of 250 LPτ calculations.

This fusion model may also be tested by its ability to predict unseen data. Figure 6 shows such a plot where the same 390 results used earlier are compared with the drag values coming from direct calls to MGAERO and it may be seen that while significant differences do still occur, the overall correlation coefficient is now 0.7319 as compared to 0.4903 for the Krig based solely on the MGAERO data. This improved predictive capability arises despite the mean SCV residual of the Krig being 1.224 with 22 of the 390 residuals being greater than three. This is because the Krig is now not used alone, but as a corrector to an already well set up empirical method, i.e., a *combination* of black-box and physics based estimators is being used and so deficiencies in the Krig are compensated for by Tadpole and vice versa. The correlation coefficient measures the effectiveness of this combined process. Having produced this fusion model it can then be used to try and optimise the design being studied. Table 5 shows the results if 10 updates are added following the strategy already outlined.

With this approach the improvement in MGAERO drag *before* updates is almost as good as that from the direct search on the code while after updates it is 0.3% better. Moreover, after the updates the Tadpole drag is over 1% better than for the direct search on the Tadpole code *at the same time*. The final design is illustrated in Figure 7. This optimisation process again uses around one sixth of the computing effort of the direct search on the CFD code.

Lower limit	Value	Upper limit	Quantity (units)	Initial Value from Table 1
100	156.6	250	Wing area (m^2)	168
6	10.25	12	Aspect ratio	9.07
0.2	0.436	0.45	Kink position	0.313
25	31.2	45	Sweep angle (degrees)	27.1
0.4	0.438	0.7	Inboard taper ratio	0.598

Lower limit	Value	Upper limit	Quantity (units)	Initial Value from Table 1
0.2	0.200	0.6	Outboard taper ratio	0.506
0.1	0.118	0.18	Root t/c	0.150
0.06	0.124	0.14	Kink t/c	0.122
0.06	0.0667	0.14	Tip t/c	0.122
4.0	4.601	5.0	Tip washout (degrees)	4.5
0.65	0.717	0.84	Kink washout fraction	0.75
	128888	135000	Wing weight (N)	127984
40.0	40.1		Wing volume (m^3)	41.73
	5.4	5.4	Pitch up margin	4.179
2.5	2.96		Undercarriage bay length (m)	2.693
	2.012		D/q (m^2) — from Krig	
	2.817		D/q (m^2) — from Tadpole	3.145
	2.515		D/q (m^2) — from MGAERO	2.922

Table 90-5. final design parameters, constraint values and objective function values for the best design produced by the search on the refined MGAERO / Tadpole difference Krig produced with 10 updates (together with those for the initial design).

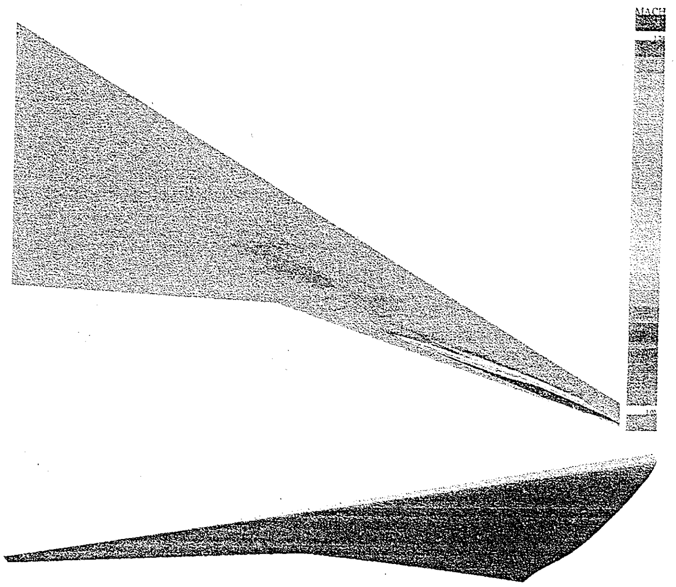

Figure 90-7. geometry of final design produced by the search on the refined MGAERO / Tadpole difference Krig with 10 updates (plan view shows upper surface supersonic Mach contours).

Conclusions

In this paper three distinct methods for carrying out aerodynamic design optimisation are described: direct optimisation of the user's analysis codes, search of a response surface derived from the user's codes and search of a response surface derived from two related but different fidelity user codes. The latter multi-level or _fusion based" approach seeks to combine the speed of fast empirical codes with the precision of full three-dimensional CFD solvers. In the study reported here the fusion based approach is shown to outperform direct search of the CFD code at considerably reduced cost while also being more accurate than a simple response surface method using only data from the CFD code.

Acknowledgements

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