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Multidisciplinary Design Optimisation of Unmanned Aerial Systems (UAS) using Meta model Assisted Evolutionary Algorithms

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Abstract

Unmanned Aerial Systems (UAS) is recognised to be the next revolution in aviation as information technology matures in the aerospace sector. UAS systems are multidiscipline systems as they integrate several disciplines, e.g. avionics, flight control, aerodynamics, structures. The design and optimisation of these vehicles can be multi-modal, non-convex or discontinuous, with multiple local minima and with noise. Traditional gradient based optimisation method might fail to find true optimal solutions or Pareto Fronts. This paper explores the design and coupling of Meta-model Assisted (MMA) with Multi-Objective Evolutionary Algorithms (MOEA) for Unmanned Aerial Systems (UAS) design. Results indicate an improvement on optimisation performance and both practicality and robustness of the method in finding optimal solutions and Pareto trade-offs between the disciplines.

Introduction

Conceptual and detailed multidisciplinary optimisation seems to be one of the challenges for industry and academia [6]. Now the computation of real life flows such as that about a complete aircraft which was until the end of the 60' out of reach due to the limited performance and memory of computers has now become a common task. On a different scale, researchers and engineers are now considering multi disciplinary challenges such as the strongly coupled aero-structural analysis. A logical extension to this progress is undoubtedly optimisation. Design and optimisation itself has emerged as a new discipline and most of the aerodynamic and structural optimisation efforts focus on the use of gradient based techniques. One drawback of these methods is that they are most suitable when there is only one objective (in a single discipline) to be met with or when the objectives are differentiable. At the same time a real design of any aerodynamic shape or for that matter of any entity will have usually more than one objective such as minimising drag at two different values of lift. New robust techniques are required, one of such techniques, even though computationally more intensive than gradient based methods are Evolutionary Algorithms (EAs). These algorithms are based on Darwinian evolution; whereby populations of individuals, which represent the design variables, evolve over a search space and generate offspring by the use of different mechanisms such as mutation, crossover and selection. An attractive feature of EAs is that they evaluate multiple populations of points and are capable of finding a number of solutions in a Pareto front. EAs have been successfully applied to different aircraft, wing, aerofoil and rotor blade design and optimisation problems [1,2,6,10]. One major drawback of EAs [9] is that they are slow in converging, as they require a large number of function evaluations to find optimal solutions and have poor performance with increasing number of variables. Hence the continuing effort has been on developing robust but faster numerical techniques to overcome these challenges and facilitate the complex task of design and optimisation in aeronautics. In this work we describe the coupling of Design of Experiments (DOE), metamodel and MOEA for the design and optimisation of UAV systems.

Meta-models/Design of Computers Experiments (DACE) Assisted Evolutionary Algorithms

Introduction

EAs suffer from slow convergence; by providing a DOE/metamodel capability into the framework we wish to hybridize the desirable characteristics of EAs and surrogate models such as Response Surface Methods (RSM) to obtain an efficient optimisation system [1]. Within this context, the DOE samples a number of design candidates run by the analysis code (CFD), the surrogate model is then constructed for the computationally expensive problem. Different sampling and DOE strategies can be used; Latin hypercube, RSM or DACE/Kriging. There is plentiful literature and software developed specifically for DOE, after a careful selection of software packages it was decided to implement the approach described in Reference 5 in combination with DACE [8] which is robust and allows different options for sampling strategies and DOE.

Different approximation and meta-model approaches in combination with EAs are studied in this research. Figure 1 shows an EA assisted by *off-line* meta-models. In this case a global meta-model/DACE is constructed before the EA starts. This meta-model is used by the EA optimiser to evaluate candidate solutions and the 'optimal' (in the sense of evaluated with an approximation) solutions are re-evaluated with the exact high fidelity model to update the meta-model. The iteration loop continues until there is no discrepancy between the exact optimal solution and the 'optimal' one found using the meta-model.

Implementing Kriging/Metamodel Assisted HAPMOEA

A Meta-model Assisted (MMA) coupled with Hierarchical Asynchronous Parallel Multi-objective Evolutionary Algorithms (HAPMOEA) was devised and tested. The concept is illustrated in figure 1. It combines a meta-model which can be DACE/Kriging or any other meta-model and the HAPMOEA technique.

The HAPMOEA is based on Evolution Strategies and incorporates with the concepts of Covariance Matrix Adaptation (CMA) [3], a hierarchical topology [11], parallel evolutionary algorithms [2,12], asynchronous evaluation [2,13] and a Pareto tournament selection. The optimiser is applicable to single or multi-objective problems. The hierarchical topology offers different mathematical modellings of the environment including precise, intermediate and approximate models. In the different layers of the topology each node can be handled by a different EAs code and or meta-model.

When assisted by meta-model, the computational approach takes the following form: First the population is initialised and two or three models are defined, precise, intermediate and coarse. Then an initial design of experiments and local databases for the intermediate and coarse models are created. The top level is evaluated with the exact / high fidelity analysis; the lower levels are evaluated using the meta-models. Then while a stoping condition has not been satisfied, the algorithm evolves the population at each level, at each level the algorithms do the processes of recombination, mutation, evaluation and selection. The algorithm checks if the migration criteria has been satisfied (this can be equal to a fix number of evaluations or a number of population size function evaluations). If a migration criterion has been satisfied, the algorithm sorts the populations; at the top level the population is sorted based on the fitness functions, while at the bottom level the populations are sorted based on the expected improvement. During migration the evaluated solutions from the top level are feed to update the meta-model. Following the original HAPMOEA, the algorithm migrates the third best of the population from the lower levels to the top levels and a random third of the population to the lower levels. In this process promising solutions from the lower levels are re-evaluated with the exact model and the meta-model is updated. The optimisation continues on the top level using high fidelity analysis and on the lower levels using and improved meta-model, if the stopping criteria (max number of function evaluations – computational resources expired) has been reached the algorithm stops, compute statistics and produces outputs of the computed Pareto fronts and progress evaluations.

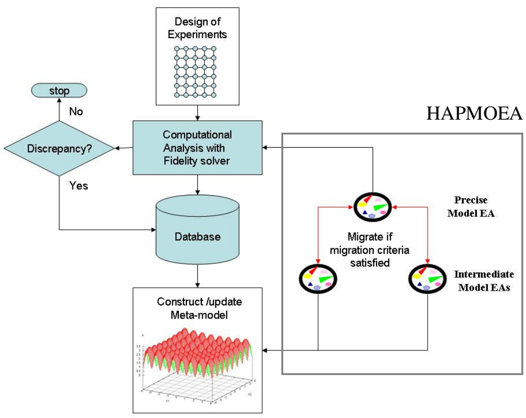

Figure 1. HAPMOEAs assisted by on-line Meta-models 3. Kriging/Metamodel Assisted HAPMOEA Test Cases

The concepts indicated in the previous section are best illustrated with an example in the following section.

Multi-objective and Multidisciplinary Wing Design

The use and development of Unmanned Aerial Vehicles for military and civilian applications are rapidly increasing but there are difficulties in the design of these vehicles because of the varied and non-intuitive nature of new configurations and missions that can be performed. Similarly based to their manned counterparts, the challenge is to develop trade-off studies of optimal configurations to produce a high performance aircraft that satisfies mission requirements. It is always desirable to use a FEA for structural analysis or a Navier-Stokes solver for aerodynamics but sometimes this is prohibitive due to the computational expense involved. In this research a compromise - an analytical expression that describes the structural model and a potential flow solver - is used to demonstrate the workings of the methodology.

Problem Definition

The test case considers a multi-objective optimisation of an Unmanned Aerial Vehicle (UAV) wing similar to the Sperwer SAGEM UAV [5]. There are three objectives; maximisation of lift-to-drag ratio, (L/D*)*, minimisation of pitching moment coefficient C_M and minimisation wing weight *(*W_{sc}*)*. The cruise Mach number is 0.69, the cruise altitude is 10000 *ft*. and the wing area is set to 2.94 m^2.

First, for the candidate solution –wing shape - the pressure distribution over the wing are computed using the potential flow solver in order to obtain the wing aerodynamics characteristics that include the span-wise pressure distribution, CL and, pitching moment CM and total drag coefficient (CD). Then, the lift distribution is replaced by concentrated loads and the spar cap area is calculated to resist the bending moment. The weight is then approximated as the sum of the span-wise cap weight. The local stress has to be less than the ultimate tensile stress in this case for Carbon Fibre $\leq \sigma_{ult}$. The interaction between the aerodynamic pressure distribution and the structural deflections is ignored (loosely coupled multi-physics).

The complexity, non-linearity and multi-objective characteristics of this problem make it suitable to be solved by an EA optimiser. The computational cost is an important consideration, open wide upper and lower bounds in the search space and depends of the computing facilities used, in particular in industrial design environments. Therefore it is also desirable to use both parallel computations and a multi-fidelity approach.

The wing geometry can be represented with up to 57 design variables with three aerofoil sections and nine variables for the wing plan form. Figure 2 llustrates the design variables that can be considered for the optimisation. In this case the same aerofoil along the span the RAE2822 and only six design variables are used for the wing plan form.

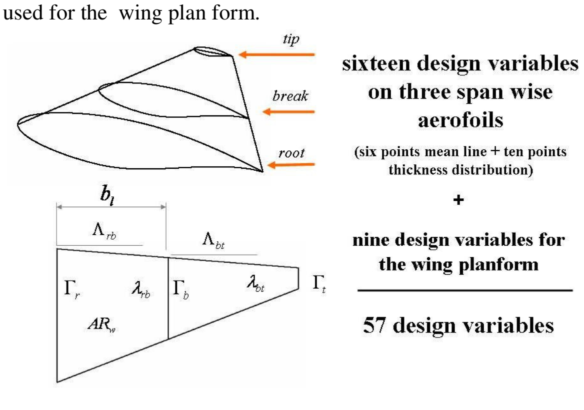

Figure. 2 Design variables for multidisciplinary wing design.

Analysis Tools

The aerodynamic characteristics of the wing configurations are evaluated using the FLO22 software. *FLO22* is a 3-D full potential analysis software developed by A. Jameson and D. Caughey for analysing inviscid, isentropic, transonic shocked flow past 3-D swept wing configurations [4]. The algorithm is based on free stream Mach numbers limited by the isentropic assumption and weak shock waves are automatically captured wherever they occur in the flow. Also the finite difference form of the full equation for the velocity potential is solved by a relaxation method, after the flow exterior to the aerofoil is

mapped to the upper half plane. The mapping procedure allows exact satisfaction of the boundary conditions and use of local field supersonic velocities. Details on the formulation and implementation can be found in Reference [4].
For the structural analysis the lift distribution is summed into concentrated loads. The wing weight is estimated from the wing spar cap area designed to resist the bending moment.

Three approaches are compared:

1) Single Population

- No meta- models are used.
- EA with CMA/Pareto tournament selection, Asynchronous Evaluation.
- Population size of 30, intermediate recombination used between two parents.
- All individuals are evaluated using a potential flow solver with a mesh size of 96 *x* 12 *x* 16. (Note: a study was undertaken to determine mesh resolution requirements, a 96 *x* 12 *x* 16 was accurate for this problem)

2) Meta-model *-static-* assisted HAPMOEA (MMA-*static* HAPMOEA)

- Meta-model is constructed before optimisation starts.
- Meta-model is not updated.
- EA with CMA/Pareto tournament selection, Asynchronous Evaluation.
- Hierarchical Topology with two levels.
  Top Layer: A population size of 30, intermediate recombination used between two parents. The exact – potential flow solver with a mesh size of 96 *x* 12 *x* 16.
  Middle Layer: A population size of 30, discrete recombination used between two parents, and use of the meta-model for the evaluation of each candidate wing.

3) Meta-model -*dynamic*- assisted HAPMOEA (MMA-*dynamic*-HAPMOEA)

- Meta-model is constructed before optimisation starts.
- The algorithm described in figure 1 is used in this case.
- Meta-model is updated at each migration step.
- EA with CMA/Pareto tournament selection, Asynchronous Evaluation.
- Hierarchical Topology with two levels.
  Top Layer: A population size of 30, intermediate recombination used between two parents. The exact – potential flow solver with a mesh size of 96 *x* 12 *x* 16.
  Middle Layer: A population size of 30, discrete recombination used between two parents, and use the meta-model for the evaluation of each candidate wing.

Optimisation Results and Post-processing of Optimal Solutions

Figure 3 shows a comparison of the exact evaluated points (red – circles- with the highest fidelity solver) and the results of the predictor (crosses-light green). As expected, the value of the prediction for a sample point matches the exact evaluation.

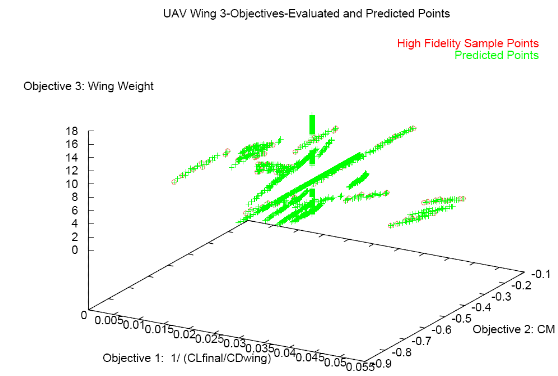

Figure 3.UAV Wing –Sample points evaluated with high fidelity solver (red –circle) and Predicted values (light green -crosses).

The optimisation was run for 500 function evaluations. Figure 4 and 5 shows the Pareto fronts obtained by using the three approaches, figure 4 shows a 3D representation, and figure 5 shows the projection for objective 1 and 2. By comparison we can see that the use of a multi-fidelity meta-model *dynamic* assisted EA approach provides a lower Pareto front as compared to a single model and the meta-model –*static*- assisted HAPMOEA approach. In addition *dynamic* assisted took 0.43 to reach the same front as the single population approach while the –*static*- assisted HAPMOEA took in average 0.55 to obtain the same Pareto Front as the single population approach. For illustration purposes a compromise design, Pareto member ten (PM10), taken from the middle of the Pareto set is taken for evaluation. Figure 6 shows the Cp distribution at 10, 20, 40, 60, 70, 80, 90% of the wingspan. Table 2 indicates the design variables and objective function values for this member of the Pareto front.

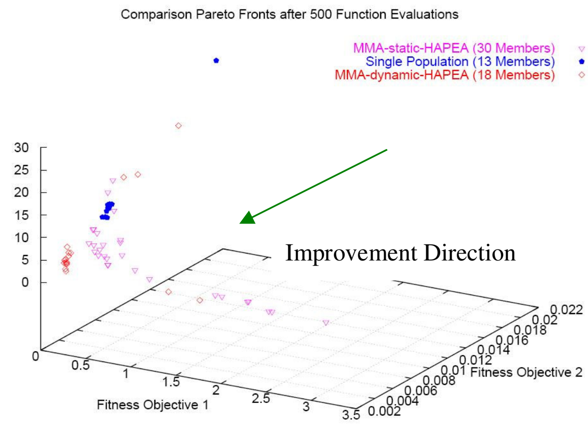

Figure 4. Comparison of Pareto fronts after 500 function evaluations (Single Population- blue dots, meta-model-static- assisted HAPMOEA – pink triangles, meta-model-dynamic- assisted HAPMOEA – red diamonds).

4. Conclusions

The use of Metamodel Assisted HAPMOEAs was explored. Results indicate a computational gain on using the meta-model assisted hierarchical topology as compared to a single model during the optimisation.

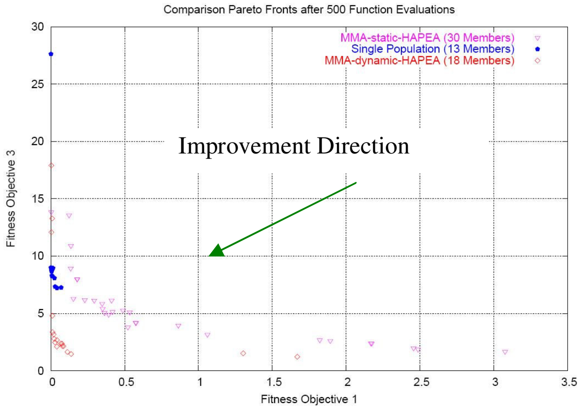

Figure 5. Comparison of Pareto fronts projection: Fitness objective 1 (maximisation lift-to drag) and fitness objective 3 (minimisation of weight) after 500 function evaluations (Single Population- blue dots, meta-model-static- assisted HAPMOEA – pink triangles, meta-model-dynamic- assisted HAPMOEA – red diamonds).

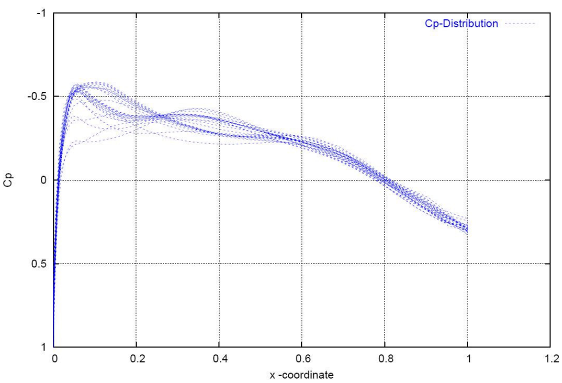

Figure 6. Cp distribution for Pareto Member 10.

Description	Value
Wing Aspect Ratio [AR]	2.38403
Break to root Taper [λ_{br}]	0.923232
Break to tip Taper [λ_{bt}]	0.43364
Wing 1/4 Chord inboard Sweep, deg [Λ_i]	17.8782
Wing 1/4 Chord outboard Sweep, deg [Λ_o]	27.521
Angle of Attack	0.0680236
Break Location, [b_l]	0.210697
Lift to Drag Ratio [L/D]	12
Moment Coefficient, CM	0.0040063
Weight	2.14688

Table 2: Optimum design variables for UAV wing Pareto Member 10.

The algorithm was capable of identifying the trade-off between the multi-physics involved and provides aerodynamic shapes as well as alternative configurations from which the designer can choose and proceed into more detailed phases of the design process. Further work on refining the model and comparing it to other meta-model approaches is underway.

Acknowledgements

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