Multidisciplinary Optimization Strategies using Evolutionary Algorithms with Application to Aircraft Design

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1. Abstract

This paper describes the development of a framework for aircraft design employing the concepts of Multidisciplinary Optimization (MDO) and Evolutionary Algorithms. Aerodynamics, structural analysis and flight performance are the main disciplines considered for preliminary aircraft design. Aerodynamic analysis is performed using a 3D panel method with boundary layer correction and the structural analysis is performed using a finite element method, both by external software packages handled by the developed framework. A particle swarm optimizer was developed to handle the MDO problem with a large number of design variables, an Artificial Neural Network (ANN) was investigated to predict the Pareto Front (in a context of Multiobjective Optimization) and as an accelerator for the whole optimization process. The goal of developing an application that is fully independent from user input during the optimization process and is able to interact with external analysis tools was reached and several simple aircraft design optimization problems were solved, in order to demonstrate the advantages of the MDO concept and the developed optimization framework.

2. Keywords: Multidisciplinary Design Optimisation, Particle Swarm Optimisation, Artificial Neural Network, 3D Panel Method, Finite Element Method, Pareto Front.

3. Introduction

One of the biggest challenges that MDO tools have to overcome is flexibility to adapt to different engineering scenarios and are usually bound to solving a predetermined set of design variables. Furthermore, the analysis fidelity level is typically low, relying on methods that are often too much simplified to deliver the much needed accuracy.

The main objective of this work is therefore to create an MDO tool that moves towards higher fidelity tools, in the context of aircraft design and integrating the emerging concept of evolutionary algorithms. In order to fulfill this requirement, a suitable optimizer has to be chosen or developed. Analysis tools that meet the desired depth level must also be chosen taking in account the balance between accuracy and computational cost. This application must be developed to interact with the analysis tools considering them as independent blocks, functioning as external modules, so that more accurate tools can be easily used in the future, simply by swapping them. Finally, the computational cost of running an optimization problem should be reasonable.

The developed application should be validated by several optimization problems, both singlediscipline but, most importantly, multidisciplinary ones, particularly in the aircraft design field.

4. Approach to MDO

Traditionally, engineering design consists of a sequence of steps, beginning with a conceptual solution to a certain mission that is to be performed. This conceptual phase continues on to a preliminary stage until a configuration can be frozen. Only then are detailed analyses performed, corresponding to each discipline involved in the “product” to be developed.

However, this design methodology leads to a successive bottlenecking in design freedom as the analyses and design detail is increased (Fig. 1), a fact that has been formally demonstrated [1] and that may lead to a suboptimal design, furthermore emphasizing the advantages of an MDO approach.

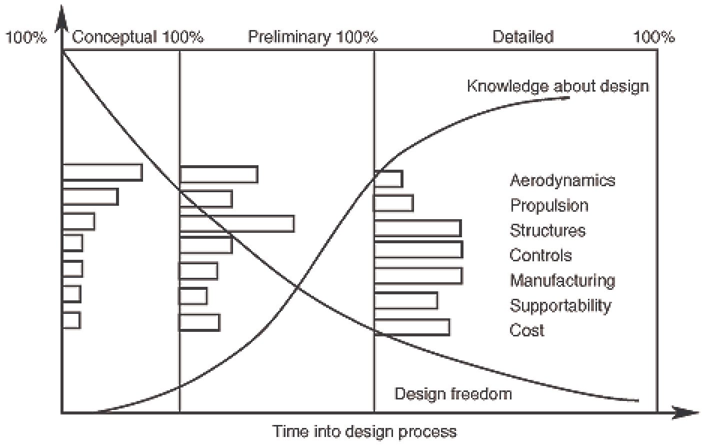

Figure 1. Traditional approach to product development.

For the purpose of this work, the following definition for MDO is considered: “A methodology for the design of complex engineering systems and subsystems that coherently exploits the synergism of mutually interacting phenomena” [1]. Multiple conflicting requirements have always had to be taken into account and, therefore, it can be considered that the multidisciplinary process has always been used. The key word in the definition, however, is methodology [2]. MDO provides a collection of tools and methods that permit the trade-off between different disciplines involved in the design process. “MDO is not design but enables it” [1].

Ideally, the MDO environment should be interactive and flexible enough to allow the problem definition, constraints to be applied and simulation depth to be fully specified by the design team, rather than the individual disciplines’ teams.

In order to facilitate information exchange between the various disciplines and respective teams (or for that matter, analysis tools), a single global parametric model of the whole system should be used, from which discipline specific models can be generated [3,4,5]. This consistency has been shown to offer advantages, both when it comes to communication between disciplines and eventual redefinition of the global parametric model [4,6,7].

This environment should be transparent, in the sense that it should allow the design team to monitor the evolution of variables, verifying whether these are dependent or independent with relation to the problem. This enforces the notion that the top design team should have full control of the process flow.

Taking in account that modern engineering systems are extremely complex, it is only natural to distribute the various disciplines over their respective groups, all interconnected by the MDO environment. Although process distribution may present some management challenges, it truly allows for the distribution to be a physical a resource distribution, more than just a process division. This enables groups to be able to be in different sites, often worldwide; it also enables the use of computational resources and data storage spread over a vast number of nodes [8].

In this work, an intermediate level of optimization is attempted, regarding the methods used for disciplinary analysis. The structure of the MDO process is described in Fig. 2:

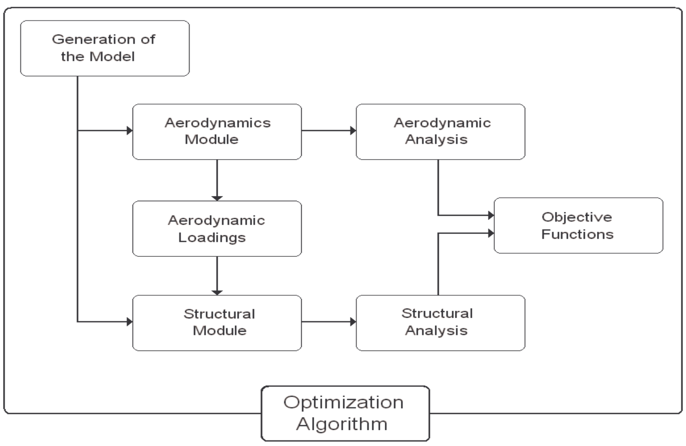

Figure 2. MDO process layout.

As seen from Fig. 2, suitable optimization algorithm and aerodynamic and structural analysis tools had to be chosen and eventually developed. Regarding the analysis tools, as a higher level of optimization was the goal and as computational resources allow, a 3D panel method with boundary layer correction was chosen for the aerodynamic analysis and finite element method for the structural analysis. The chosen optimization algorithm was the Particle Swarm, a population based algorithm, that research in the optimization field shows this method yields good results, when applied to engineering.

In the following sections of this paper, the optimization algorithm and the chosen analysis tools will be presented in further detail.

5. Particle Swarm Optimization

Being the topic of this work the development of an MDO application, a suitable optimizer needed to be chosen or developed. Using heuristic optimization methods was a decision made early on in this work, as only in the recent past have non gradient methods started to be explored.

Evolutionary algorithms are a set of a larger group of algorithms, so called metaheuristic methods. In these methods, the goal is to find the extremes (from this point on assumed to be the minima) of a certain objective function with the advantage that the exact state function needs not to be known, i.e., the evaluation module(s) of a possible solution can be looked at as a "black-box".

The Particle Swarm Optimization algorithm was chosen, as this is a reasonably recent method and research in the optimization field shows this method yields good results, when applied to engineering [10,11]. Particle Swarm Optimization is a population-based evolutionary algorithm based on the concept of social intelligence. In this algorithm, a group of initial individuals is randomly generated, containing information about their position and velocity within a subspace of the DV's. Each individual is then evaluated by an objective function that defines which individual holds the best position in relation to the problem at hand. On the next iteration, individuals are attracted to that point as well as to their respective best position ever, by changing their velocity. As the optimization process develops, the whole population further explores the subspace and will eventually converge to the optimum of the objective function in that subspace.

This method holds a number of advantages that makes it a suitable optimizer for the problem at hand: it has advantages over other EA's, regarding efficiency (lower number of iterations needed to attain an optimal solution) and flexibility (independence from the problem to solve) [10,11]; it is a robust minima finder (for both local and absolute minima), as noise insensitivity is well shown [12,13,14]; it has the ability of finding a minimum outside its initial bounds; there is independence between the dimension of the space in which the particles move and the number of particles in the swarm, regarding the algorithm's ability to find a minimum and it is an obvious choice for a distributed computation environment.

Although there are many available software packages with several variations on the basic PSO algorithm, a custom version was implemented for this work, as this approach leads to a better control and adaptability to the rest of the application.

According to the heuristics behind PSO, a certain particle is moving in a hyperspace of dimension N, with current position given by x_i and velocity by v_i. Dimension, N corresponds to the number of DV's in the optimization problem and each component of the vector x_i would be the corresponding DV's value. The distance d_i between any two points is simply calculated as the difference in position between them:

$$\begin{aligned} x_i^{t+1} &= x_i^t + v_i^t \Delta t \\ v_i^{t+1} &= \omega v_i^t + rC_G \frac{d_{i,Best\ individual}}{\Delta t} + rC_P \frac{d_{i,Best\ position\ of\ i\ ever}}{\Delta t} \end{aligned} \tag{1}$$

Parameters C_G and C_P correspond to group and particle confidence factors, respectively. The ratio between the two limits will determine the behavior of the swarm. If the ratio favors particle confidence, then it is most likely that an individual particle will move towards its own verified minimum, giving the algorithm good local minima search capability. On the other extreme, where higher group confidence is verified, all of the particles will tend to the global minimum, giving the algorithm a better global minimum search capability.

Parameter r is the craziness factor, a random number, giving the swarm random search capabilities.

Parameter ω is a value comparable to the particles' inertia. Again, choosing its value should be done taking in account what is the desired behavior of the swarm. A lower inertia particle will have a greater sensitivity to local and global minima, giving the swarm faster convergence behavior.

Typical values used throughout the work were $C_G = 2.5$, $C_P = 1.0$ and $\omega = 0.8$.

For this work, other features were added to the basic algorithm, in order to increase its stability and convergence behavior. Limiters were introduced, and greatly improved the algorithm's stability. This was done by limiting the maximum value for the particles' velocity at $v_{max} = 1.0$ for a time step of $\Delta t = 0.2$.

The developed algorithm was then tested against some typical benchmark functions[1], with different dimension and population size, and was found to be robust in finding local and global minima and therefore suitable to use as an optimizer for the MDO application.

As often the optimization problem is a multiobjective problem, the concept of Aggregate Objective Function is introduced. This concept allows turning a multiobjective problem into a single objective problem through the operator:

$$f_{AOF} = \sum_{n} a_n f_{n,singleobjective}, a_n > 0 \tag{2}$$

Prescribing the values a_n will result in the optimization process finding an optimal point. Naturally, a careful dimensional analysis should be performed *a priori* to find appropriate weights for the various singleobjective functions. This will ensure that the contribution of each singleobjective function is comparable and has relevance for finding a solution for the problem at hand.

6. Analysis Tools

6.1 3D Panel Method

As stated, a 3D panel method with boundary layer correction was chosen for the aerodynamics analyses.

Panel methods are techniques for solving potential flow. Therefore, their applicability would be reduced to incompressible flow and high Reynolds number and would fail to calculate the viscous component of the flow over the 3D body. However, after applying boundary layer corrections, calculated along streamlines of the potential flow and compressibility corrections, it is possible to achieve good accuracy outside its original bounds [15]. Computationally, its cost is much lower than that of a CFD approach (finite volume based methods), and the time per analysis allows this method to be used with the chosen optimization algorithm. Furthermore, it also allows an easy way to interact with an FEM application, as both meshes can have a common surface where aerodynamic pressure is applied to the FE model.

In order to use this method, an adequate panel discretization is needed for the surface of the aircraft, guaranteeing that the panels are quadrilateral, that adjacent panels share vertices and that the panels form a closed shape.

As for its implementation, the *CMARC* code was chosen, as it is already developed and validated, derived from Ames Research Center's *PMARC* code. *CMARC* conveniently creates an output file containing information on the geometry and aerodynamic coefficients at each panel, allowing for simple integration with the FE module.

6.2. Finite Element Method

As for the structural analysis tool, the use finite element method is widespread and allows the creation of models with as much fidelity level as wanted, from very simple models, that allow it to compete with other simplified methods (such as Equivalent Plate Theory) all the way up to high fidelity models with high geometric complexity. It also allows to directly applying the aerodynamic results (panel pressure and friction) to the shell elements on the FE model.

For this work, *Ansys®* was chosen, as it is a very complete package from mesh generation to element types available to a fast matrix solver. Furthermore, it can be fully controlled through the command line with the use of an input file declaring all actions to be taken. This is a key feature for both chosen tools, as the application described in this work is intended to be fully automatic and independent from external input.

7. Parametric Model

Typically, a geometry is first created and only then is the discretization done, defining global and local refinements in order to generate the panels and wake lines. A different approach was taken here, being a parameterization created for typical aircraft macro-components, such as the wings, stabilizers and fuselage. For a certain parameterization, i.e., a certain aircraft shape, all of the panels are then declared in a file format accepted by *CMARC*.

For wing-like elements, parameters span, chord, dihedral, incidence, sweep and thickness are DV's. Span is a one-dimensional DV, whereas all the other are given by a function:

$$DV_i = \sum_{k}^{p} a_k f_k(\bar{s}), \bar{s} = \frac{s}{Span} \tag{3}$$

[1] Extended Rosenbrock, Beale and Freudenstein & Roth functions.

where f_k are polynomial functions of degree k, with p as the maximum polynomial degree, and dependent on the nondimensionalized span, $\bar{s}$ (s is the local span value and *Span* is the full span that the element will have). The higher the degree p, the higher the variation the parametric model can suffer.

This approach can be extended to any other element of an aircraft, provided that a suitable parameter is chosen. This method also presents some advantages, as it makes possible for the DV's to assume different values in any point of the element using the same number of parameters a_k, regardless of the refinement of the discretization, i.e., number of panels, in the case of the aerodynamic solver.

All the parameters a_k for all the DV's will correspond to the values in the optimization vector x_i in Eq. (1).

For example, regarding the wing (and for that matter, any wing like element, such as stabilizers or winglets), the parameterization starts with span and the airfoil, which, in this work, is not a DV, but imposed *a priori* for each lifting surface, for simplicity. The airfoil is read from a file, being this a nondimensionalised airfoil, with unit chord. Then, the other DV's are calculated from Eq. (3), where f_k are:

$$\begin{aligned} f_1 &= \bar{s} \\ f_2 &= -4(\bar{s})^2 + 4(\bar{s}) \\ f_3 &= 16(\bar{s})^3 - 24(\bar{s})^2 + 8(\bar{s}) \\ &\vdots \end{aligned} \tag{4}$$

As can be seen from the above, f_k, for $k > 1$, are polynomials constructed in the interval [0,1], in such a way that for $\bar{s} = 0$, $\bar{s} = 1$, $f_k = 0$.

Naturally, bounds can and should be applied to any of the DV's, so that any physical imposed constraints are transported onto the aerodynamic model. Even if no physical constraints are to be added, it is a good practice to apply them, in order to avoid generating a model that would have severe geometric distortion to the point where numerical convergence issues of the solution could appear.

This parameterization philosophy can be extended to the structural elements. For beams, for example, a section geometry can be assumed (I-beam, T-beam, etc.) and parameterized to a single parameter. For shell thickness, this method was extended to a bidimensional parameterization to allow variations along any direction.

8. Results

In this multidisciplinary optimization problem, aerodynamics, structure and basic flight performance were analyzed. A simple scenario was created for a small surveillance UAV: a flying wing platform, with a central thicker "body", designed for long range, flying at an altitude of *5000* m and speed of *70* m/s. The geometry of this aircraft is presented in Fig. 3. In order to simplify the problem, the aircraft has a fixed span and sweep angle, $\Lambda = 27º$, and the central body has a fixed geometry. Airfoil was also constant throughout the span (except for thickness variations) and is a *Wortmann FX 69-H-098*. This airfoil was chosen for its low C_{m0} (zero lift pitching moment) as the aircraft is tailless. However, this is not a reflex airfoil and therefore is not a natural choice for this planform, regarding the aircraft's static stability. This choice was made on purpose to see the optimizer's capability to create a stable configuration even with this airfoil. Chosen geometry values are shown in table 1.

Table 1. Aircraft geometry dimensions.

	Chord (m)	Incidence (º)	Thickness	Distance from root (m)
Station *A*	1.80	4.0	20 %	0.00
Station *B*	0.80	3.0	10 %	0.60
Station *C*	*variable*	*variable*	10 %	2.50

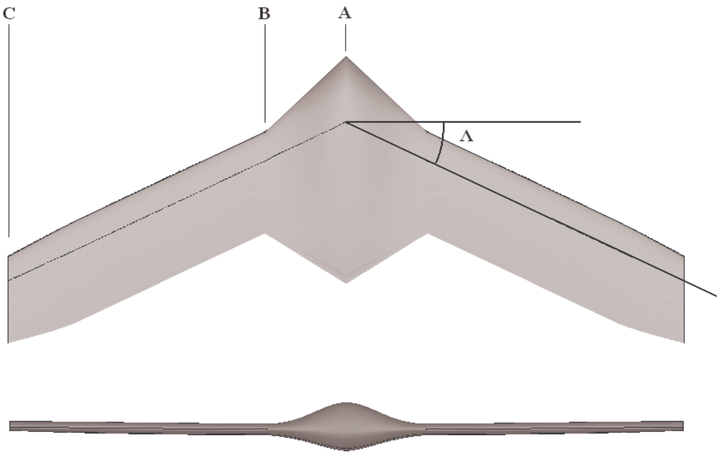

Figure 3. MDO problem: aircraft geometry.

Regarding the aerodynamics, chord and incidence in the "wing" (between stations *B* and *C*) were the DV's to be optimized. Dihedral and sweep were left out of this problem, as only a thorough flight stability analysis would be able to resolve these parameters. As for the structure, beams were simulated by adding their respective beam web at *25* % and *75* % of the airfoil, being that the wing skin serves as their caps, which approaches a box-wing like construction and aluminum was chosen for material. Skin thickness of the panels was the parameter to be optimized.

Table 2 summarizes the lower and upper bounds that were applied both to aerodynamic and structural DV's. Recalling Eq. 3, and taking in account that $p = 2$, this represents a total of 13 parameters a_k that were optimized. For this optimization run, a population with 10 individuals was used, with 40 iterations.

Table 2. Aircraft geometry dimensions.

Design Variable	Lower bound	Upper bound
Chord	0.10 m	0.80 m
Incidence	- 5.0 º	+ 5.0 º
Panel thickness	0.635 mm	20 mm

The main objective to be fulfilled by this aircraft is long range. This result was calculated by the Breguet range equation:

$$R = \frac{\eta}{SFC}\frac{L}{D}\ln\left(\frac{W_i}{W_f}\right), \tag{5}$$

where η is propulsive efficiency (a propeller propulsion was assumed, with $\eta = 0.8$), *SFC* is specific fuel consumption (here assumed to be 0.35 $kg \cdot kW^{-1} \cdot h^{-1}$), W_f and W_i are the weight of the aircraft at the final and initial points of its mission. W_i was calculated from the lift obtained by the aerodynamic solution and W_f was estimated by assuming a *20* % fuel fraction of the non-structural weight, derived from the structural solution:

$$W_i = \frac{L}{g}, \quad W_f = W_i - m_{fuel} = 0.8W_i + 0.2m_{structure} \tag{6}$$

The objective function was therefore constructed to evaluate each solution primarily for its range, but also included penalty functions to guarantee that wing tip displacement and rotation, maximum stress in the structure and pitching moment were within limits. A penalty is added to the objective function if wing tip rotation is not null, if wing tip deflection is greater than *5* % of semispan, if maximum stress is greater than *100* MPa and if pitching moment is not null (choosing that the center of gravity of the aircraft is at *60* % of root chord). Eq. 7 shows the weights given to each of these functions.

$$f_{Objective} = f_{Range} + f_{Wing\ Tip\ Rotation} + f_{Wing\ Tip\ Deflection} + f_{\sigma_{max}} + f_{C_M} \tag{7}$$

where (*Range* is in km, wing tip rotation in rad, deflection in m, stresses in MPa and pitching moment in Nm):

$$f_{Range} = -\frac{Range}{20},$$

$$f_{Wing\ Tip\ Rotation} = 100|Wing\ Tip\ Rotation|,$$

$$f_{Wing\ Tip\ Deflection} = \begin{cases} 0, \delta_{tip} \leq 0.125 \\ 400\left(\delta_{tip} - 0.125\right)^2, \delta_{tip} > 0.125 \end{cases}$$

$$f_{\sigma_{max}} = \begin{cases} 0, \sigma_{max} \leq \sigma_{adm} \\ 400\left[\dfrac{\sigma_{max} - \sigma_{adm}}{100}\right]^2, \sigma_{max} > \sigma_{adm} \end{cases}$$

$$f_{C_M} = \frac{M_y^{\ 2}}{1250}$$

The evolution of the objective function value is shown in Fig. 4. The optimization process evolved as expected, maximizing range (see Fig. 5) – the main contribution to the AOF – while maintaining the optimal solution within the applied constraints (these are not shown here as the limits are being respected and such graphs would add little to this discussion).

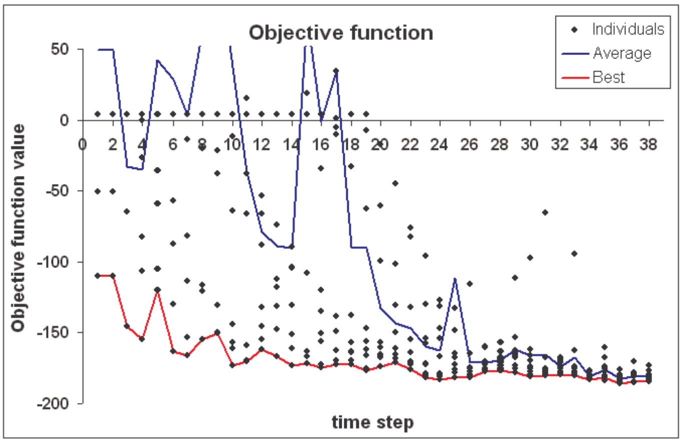

Figure 4. Objective function evolution.

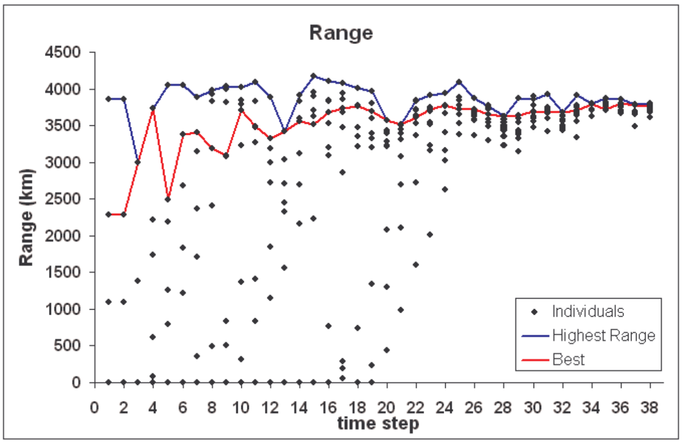

Figure 5. Range evolution.

Table 3 compares the best initial solution, i.e., the best random individual in the initial population and the final best solution in the population regarding Range, Lift, *L*/*D*, structural mass, maximum stress, payload (here defined as weight other than structural mass and fuel) and objective function.

Table 3. Table of Gains from the optimization process.

	Best Random Individual	Final Solution	Variation
Range (km)	2285	3772	+65 %
Lift (N)	2465	2267	-8.0 %
L/D	24.15	24.57	+1.7 %
$m_{structural}$ (kg)	117.5	38.1	-68 %
Payload (kg)	107.2	154.6	+44 %
σ_{max} (MPa)	25.5	97.7	+283 %
Objective Function	-110.1	-184.5	+68 %

From the analysis of these values, it is clear that there was optimization in both aerodynamic and structural fields but most importantly, optimization in a coupled environment. Analyzing only aerodynamic performance in lift shows an apparently weaker solution, but when data on structure is included and range is determined it becomes clear that the found solution is a better one. This is also verified when comparing other possible solutions found during the optimization process with the final solution.

The optimized solution shows a maximum stress value close to the allowed maximum, guaranteeing that the structure is capable of handling the aerodynamic loads, yet light enough to allow for a long range. The other important results of the optimized solution are a wing tip rotation of *0.08º*, low enough not to influence the aerodynamic solution (as no coupled aero-structural analysis is performed), a wing tip deflection of *34* mm and a pitch down moment of *100* Nm (for an aircraft of these dimensions and mass this is low, being easily compensated by control surfaces or slight shift of the center of gravity). The $C_{m,\alpha}$ is negative, therefore assuring static stability.

Fig. 6 shows the stress intensity on the optimized solution. As expected, the wing root and leading edge areas show higher stresses than the rest of the structure. Fig. 7 shows the thickness distribution from which the FEM solution is obtained.

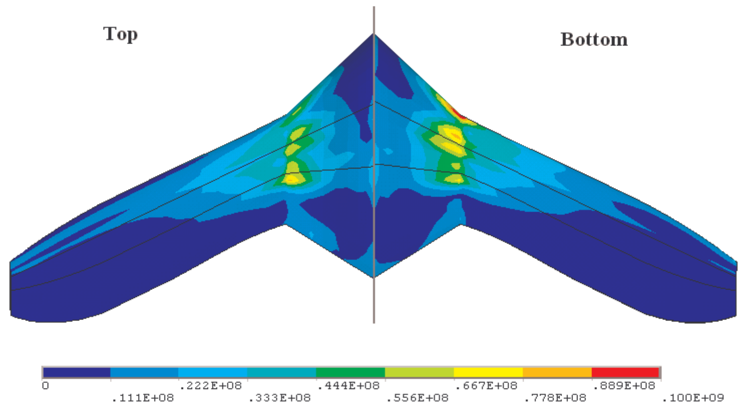

Figure 6. Stress intensity (top and bottom views, left and right, respectively; unit *Pa*).

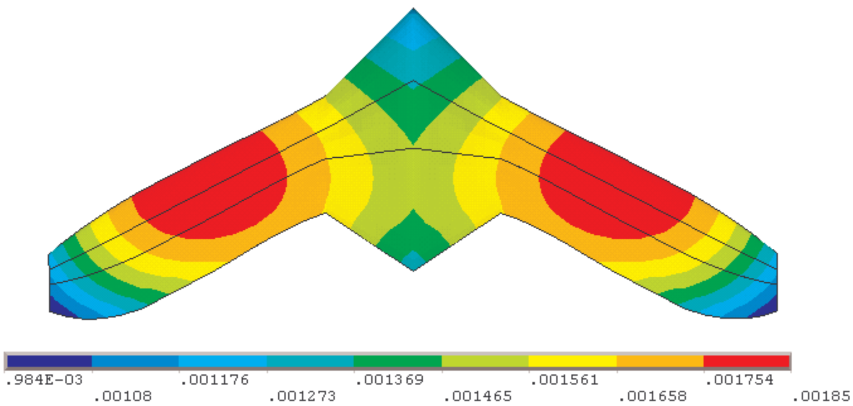

Figure 7. Shell thickness distribution (unit *m*).

Figures 8 and 9 show spanwise chord and incidence distribution. As can be seen in the chord distribution graph, chord is almost constant throughout the wing, with reduction at the wingtips. Even though this may not favor the best *L*/*D* ratio, it adds area to the wing, having a more significant effect on range (by means of a higher fuel mass) than another distribution. Regarding incidence, the graph shows it decreasing towards the wing tip in an almost linear fashion, favoring not only the *L*/*D* ratio (by means of a more favorable lift distribution) but also having significant effects stability wise, as noted before, due to the airfoil choice.

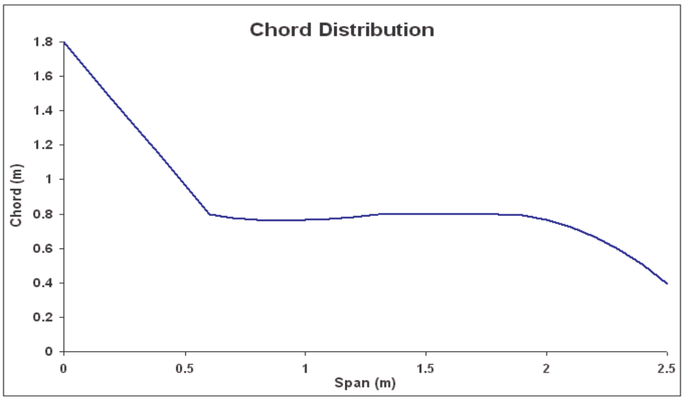

Figure 8. Spanwise chord distribution.

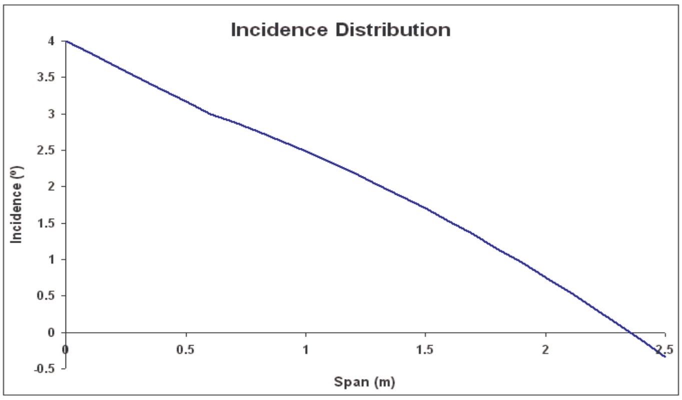

Figure 9. Spanwise incidence distribution.

9. Conclusion

Aircraft design is an area where MDO can offer clear advantages, by exploring the interactions between all involved disciplines and taking those into account from the very beginning of the whole design process.

In this work, a number of issues were addressed in order to develop an independent MDO application. A suitable optimization tool was investigated and developed, being the Particle Swarm Optimization algorithm the chosen one. This proved to be a suitable method, particularly for its robustness and noise insensitivity. Furthermore, any optimization algorithm that is population based is particularly suited to parallel computation, which is becoming a common reality.

Analyzing the obtained results, one can conclude that the optimizer tool is able to do what it is expected to: find the minima of the prescribed objective functions and therefore reach an optimal solution for the problems at hand. The developed application proved to be flexible, in the sense that it is not limited only to aircraft design, but, with the adequate models and analysis tools, can be applied to any multidisciplinary problem in the engineering field.

As for future developments, possibly one of the most interesting concepts that can be applied to this type of applications is distributed computation. The use of evolutionary algorithms is particularly suited to this strategy that can be implemented on any network of computational resources.

As for using the Artificial Neural Network as a universal approximator, it is not yet fully integrated in the developed framework. Using real analysis to train the ANN should provide some advantages. Determining the Pareto Front is one, truly enabling the application to be a Multiobjective Multidisciplinary tool and giving designers the ability to understand the possible trade-offs that can be done along this surface. Doing this with an ANN allows approximating this surface in a very short time, if compared to obtaining the exact Pareto Front. Integrating the ANN into these applications should also allow a reduction in the computational cost of the solution, as solutions far from optimality would not be fully analyzed, only approximated in a first instance.

In order to use applications like the one developed in a real life situation, ideally, aerodynamic analyses should be performed by generating a solid model of the solution and, using CFD methods, evaluate the solution in a number of situations large enough to cover the whole flight envelope. Along with the aerodynamic solution, a highly detailed structural model should be generated, based on the typical aircraft structural elements, and the coupled aero-structural analysis performed. To be able to do this detailed analysis a preliminary solution should be determined and that is where this work aims to be.

Other disciplines should also be included, outside of the domain of more traditional structures, aerodynamics and flight performance analysis that are done in the preliminary stage of aircraft design. Propulsion, aeroelasticity, active control of surfaces, environmental performance (fuel consumption and noise, increasingly important aspects) and operational cost, just to name a few disciplines that matter in the life cycle analysis of an aircraft, should be modeled and included in the MDO process.

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11. References

[1] AIAA Technical Committee on MDO, White Paper on Current State of the Art, http://endo.sandia.gov/AIAA_MDOTC/sponsored/aiaa_paper.html , January 1991.

[2] Joseph P. Giesing and Jean-François M. Barthelemy, A Summary of Industry MDO Applications and Needs. At request of the AIAA Technical Committee on MDO, 1998.

[3] S. Wakayama and I. Kroo, The Challenge and Promise of Blended-Wing-Body Optimization, 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysisand Optimization, September 1998.

[4] H. Hoenlinger, J. Krammer, and M. Stettner, MDO Technology Needs in Aeroservoelastic Structural Design, 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 1998.

[5] M. H. Love, Multidisciplinary Design Practices from the F-16 Agile Falcon, 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 1998.

[6] J. Bennett, P. Fenyes, W. Haering, and M. Neal, Issues in Industrial Multidisciplinary Optimization, 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 1998.

[7] N. Radovcich and D. Layton, The F-22 Structural Aeroelastic Design Process with MDO Examples, 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 1998.

[8] N. M. Alexandrov and R. M. Lewis, Analytical and Computational Properties of Distributed Approaches to MDO, 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, September 2000.

[9] Ricardo M. Paiva, Development of a Modular MDO Framework for Preliminary Wing Design (MSc. Thesis). IST, Lisboa, 2007.

[10] J. Kennedy and R. Eberhart, Particle Swarm Optimization, IEEE International Conference on Neural Networks, Vol. IV, pp. 1942-1948, 1995.

[11] Ruben E. Perez and Peter W. Jansen, Aero-Structural Optimization of Non-Planar Lifting Surface Configurations, 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, September 2008.

[12] Y. Deremaux, N. Pietremont, J. Négrier, E. Herbin, and M. Ravachol, Environmental MDO and Uncertainty Hybrid Approach Applied to a Supersonic Business Jet. 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, September 2008.

[13] D. Lim, Y.-S. Ong, Y. Jin, B. Sendhoff, and B. S. Lee, Inverse multi-objective robust evolutionary design, Springer Science & Business Media, September 2006.

[14] Y. Jin and J. Branke, Evolutionary Optimization in Uncertain Environments – A Survey, IEEE Transactions on Evolutionary Computation, Vol. 9, No. 3, June.

[15] Dale L. Ashby, Michael Dudley, and Steven K. Iguchi, Development and Validation of an Advanced Low-Order Panel Method, NASA Technical Memorandum 101024, 1988.