Designing high-lift airfoils using genetic algorithms

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Abstract

A multi-component airfoil design procedure is presented. It is based on a multi-objective genetic optimizer coupled with a boundary layer flow field solver capable of working in high-lift conditions. Examples of unconstrained and constrained lift coefficient maximization are reported.

1 Introduction

In this work an approach to the design of multi-component airfoils for high lift applications, based on a multi-objective genetic algorithm, is described.

The design of high-lift systems presents two main types of problems when faced using a numerical approach. The first one is the definition itself of the design objectives, that can range from lift maximization, possibly with constraints on drag, pitching moment and on the high-lift device structure, to drag reduction for an assigned lift and using, possibly, different types of high lift devices. The second problem, and maybe the most critical, concerns the limits of the current numerical CFD technology. High-lift flows are characterized by many complex features, such as multiple laminar to turbulent transition regions, confluences of wakes into boundary layers, regions of separated flows etc.; for this reason, their prediction through numerical simulation is still a very challenging task.

In the approach that is here presented a simple interactive integral boundary layer model coupled to a potential solver that computes the external flow has been used. The obtained results should therefore be considered from a qualitative point of view, as a basis for a further refinement step to be performed using either a more accurate flow field model or wind tunnel tests.

2 Algorithm description

The optimization procedure is based on a Pareto multi-objective genetic algorithm with hybrid capabilities [1, 2], coupled with an interactive boundary layer flow solver.

Classical one-point crossover and bit mutation operators have been used, together with two different types of random walk selection schemes.

The first one is the “simple random walk” described in [3] while the second one is performed in two phases, as described below, and will be named “enhanced random walk”.

The population is distributed over a toroidal landscape as in the case of the simple random walk (see figure 1).

In the first phase, a starting point in the landscape is chosen at random, and the locally non dominated individuals met in a random walk of assigned number of steps from that starting point are marked as possible candidates to be the first parent; the second parent candidates are selected in the same way in a successive random walk starting from the same starting point.

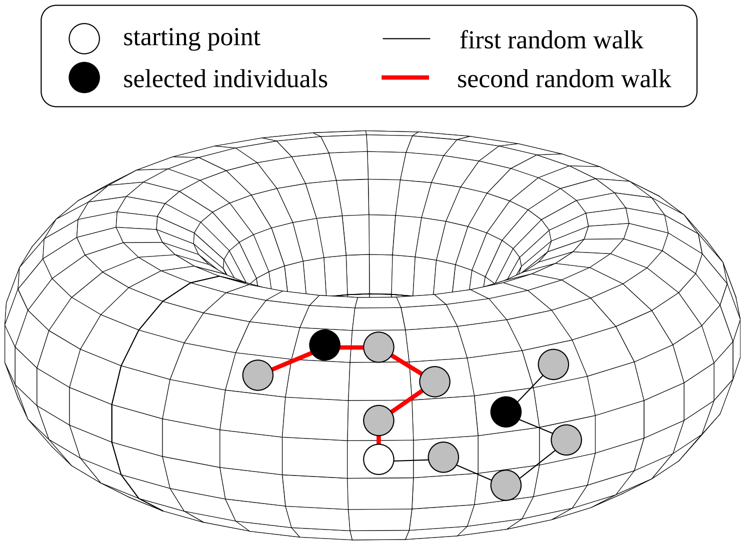

Figure 1: Random walk selection scheme

In the second phase the parents are chosen from the two sets of possible candidates following a ranking criterion. Two different ranking criteria have been introduced to that purpose:

1. minimum euclidean distance of the candidate from the current Pareto front;
2. minimum value of a given objective between the solutions belonging to the candidate set.

In the case here presented both criteria have been used in the same run; the ranking criterion to be used in a particular random walk is randomly selected, and the activation probability is 30% for the first criterion and 50% for the second one. In the remaining cases the parents are randomly chosen among those belonging to the two candidate sets.

The flow model used here for the airfoil design in high lift conditions is an integral compressible boundary layer coupled to a potential external solver through the interaction velocity

$$v_i = \frac{d}{dx}(U_e \delta^*)$$

where U_e is the external flow velocity, and δ^* is the displacement thickness. The laminar-turbulent transition can be either imposed or computed using the Granville correlation. The flow field solver has been developed by CIRA and is called MAVIAN (Multi-element Airfoil Viscous-inviscid Interactive ANalysis). An analysis and validation of the high lift capabilities of the MAVIAN code can be found in [4].

Figure 2 shows the interface modules that couple the optimization library with the flow field solver that evaluates the objective functions.

2.1 Unconstrained c_l maximization

An application of the optimization procedure to a lift force maximization problem is reported in this section. The pitching moment is unconstrained and the flow is characterized by $M = 0.15$ and $Re = 9000000$.

The design variables are:

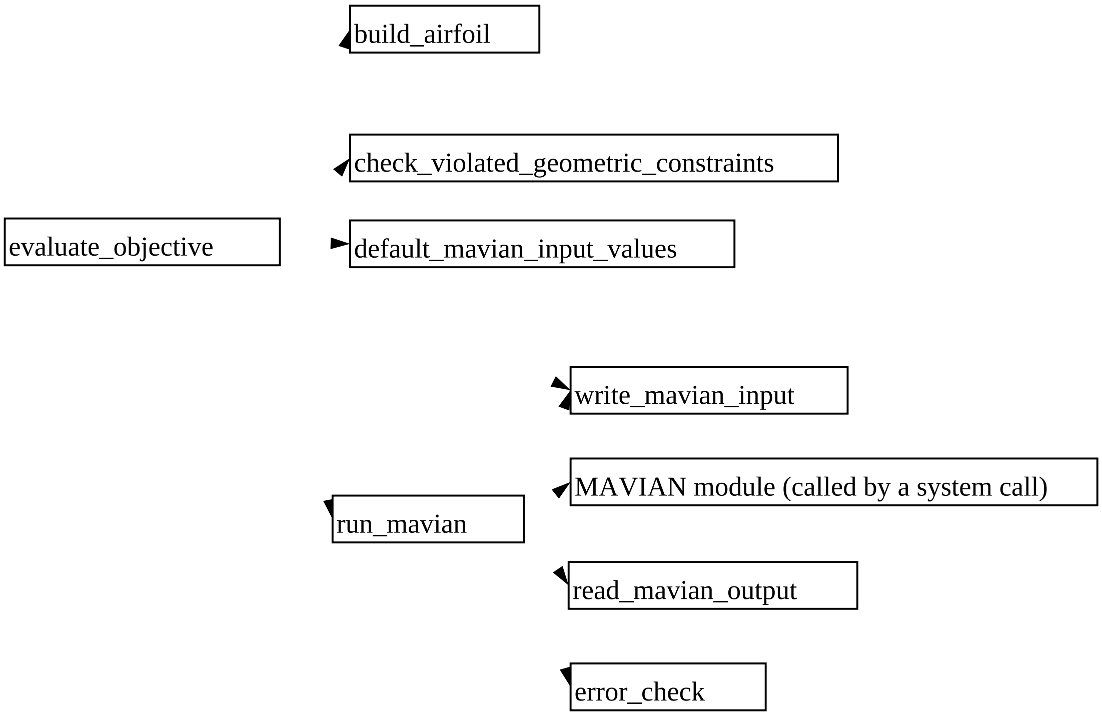

Figure 2: Sub-tree of the optimization procedure related to the objectives evaluation

- the angle of attack α;
- the flap deflection angle δ_f;
- the flap leading edge position (x, y).

The main parameters of the genetic algorithm have been set as follows:

- maximum number of generations: 10;
- population size: 10;
- mutation probability: 1%;
- crossover probability: 80%.

A geometric constraint controls that the main body of the profile and the flap are not overlapped.

Figure 3 reports the base and the final configurations obtained after 100 objective function evaluations.

Figure 4 reports the allowed variation range for the flap leading edge position, and the leading edge positions tried by the genetic algorithm in a single run.

Finally, fig. 5 reports the c_p distribution of the base and final configurations with details in the flap cove zone.

The c_l computed by the solver for the base configuration is 3.85, and for the final one is 4.63. The number of coupling iteration performed by the solver is 10.

Since it has not been fixed any constraint on the value of the pitching moment coefficient c_m, its value changes from -0,711 for the base configuration to -0,960 for the final one.

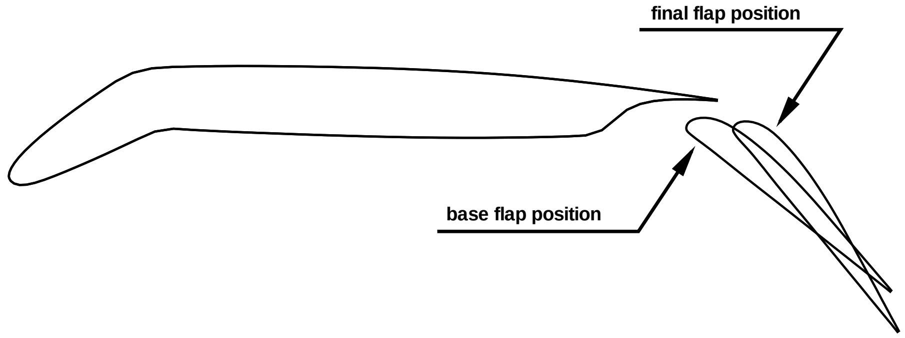

Figure 3: Comparison between base and final configurations.

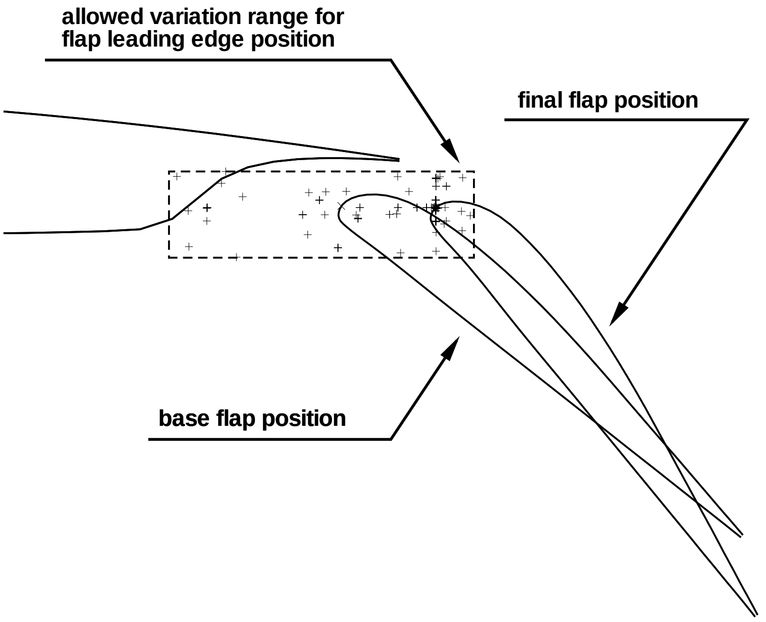

Figure 4: Flap leading edge positions tested, and allowed variation range.

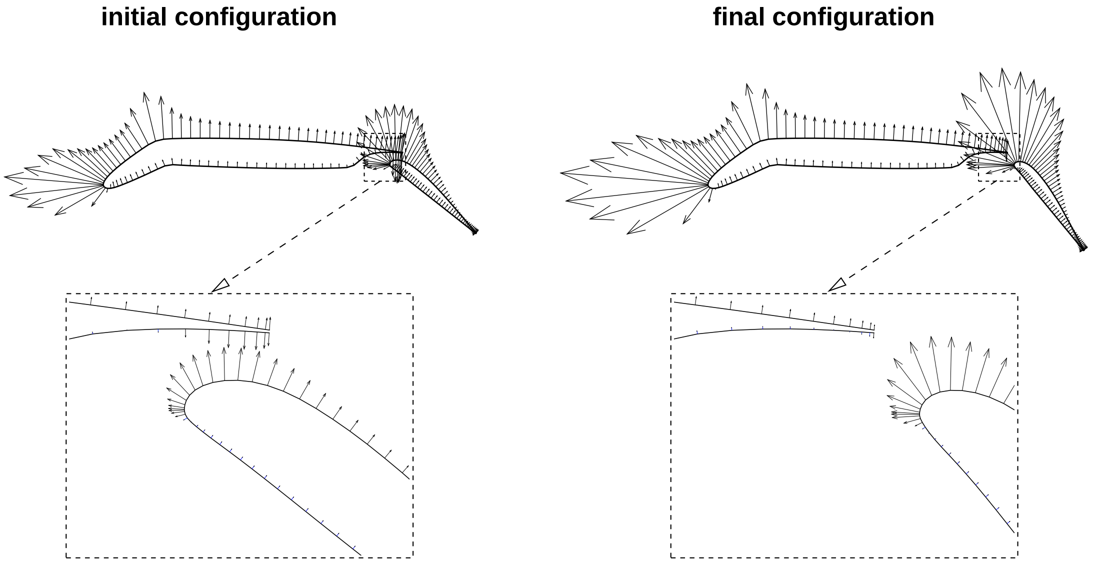

Figure 5: Base and final cp distributions.

2.2 c_l maximization with c_m constrained

A multi-objective approach has been used to carry out the same optimization problem with the added requirement of controlling the values assumed by the pitching moment coefficient. A new objective has been added to this purpose:

$$o_2 = (c_m + 0.6)^2 \tag{1}$$

Figure 6 shows the results of two different optimization runs with a population of 30 elements that evolved for 30 generations. The dashed line shows the Pareto front obtained with the "simple random walk" selection scheme, while the continuous line is related to the run that adopted the "enhanced random walk" selection.

In fig. 7, instead, the same fronts are reported in the $c_l - c_m$ plane. In this plane the optimization results can be better compared to the initial configuration. However it must be observed that in this plane the two curves are no more Pareto fronts.

3 Conclusions

One of the most critical points in the construction of a design procedure for high-lift devices is the choice of the fluid dynamic model for the estimation of the fitness. In fact, while a full potential flow solver is often sufficient for the evaluation of the cruise characteristics of a single-component airfoil, the accurate estimation of the aerodynamic characteristics of a multi-component airfoil in high-lift conditions requires the use of sophisticated and expensive computational models. Furthermore, in some cases, like for airfoils close to stall conditions, even the best computational fluid dynamics technology can have problems to give adequately accurate forecasts.

The procedure here presented uses, on the converse, a very simplified flow field model, and one could wonder if such a simplification does not lead to misleading results. The answer is twofold. From a pre-design point of view, it is often more important to compare the relative performance of two different configurations rather than to know exactly their behavior, and the adopted model is capable of giving this kind of information when the flow conditions are not too critical. On the other hand, the use of complex flow field models will require considerable computational effort even in the next future. Therefore is probable that the next generation of evolutionary optimizers for high-lift problems will introduce a hierarchical approach for the fitness evaluation. Following this idea, several levels of precision will be introduced in the evaluation of the fitness, so that the the more computationally expensive models can be used only when this is really necessary.

References

[1] D. Quagliarella, and A. Vicini, "Coupling Genetic Algorithms and Gradient Based Optimization Techniques", in Quagliarella D. et al., editors, *Genetic Algorithms and Evolution Strategies in Engineering and Computer Science*, John Wiley & Sons Ltd., England, Nov. 1997, pp. 289–309.

[2] A. Vicini, and D. Quagliarella, "Airfoil and Wing Design Through Hybrid Optimization Strategies", *AIAA Journal*, Vol. 37, No. 5, May 1999, pp. 634–641.

[3] A. Vicini, and D. Quagliarella, "Inverse and Direct Airfoil Design Using a Multiobjective Genetic Algorithm", *AIAA Journal*, Vol. 35, No. 9, Sep. 1997, pp. 1499–1505.

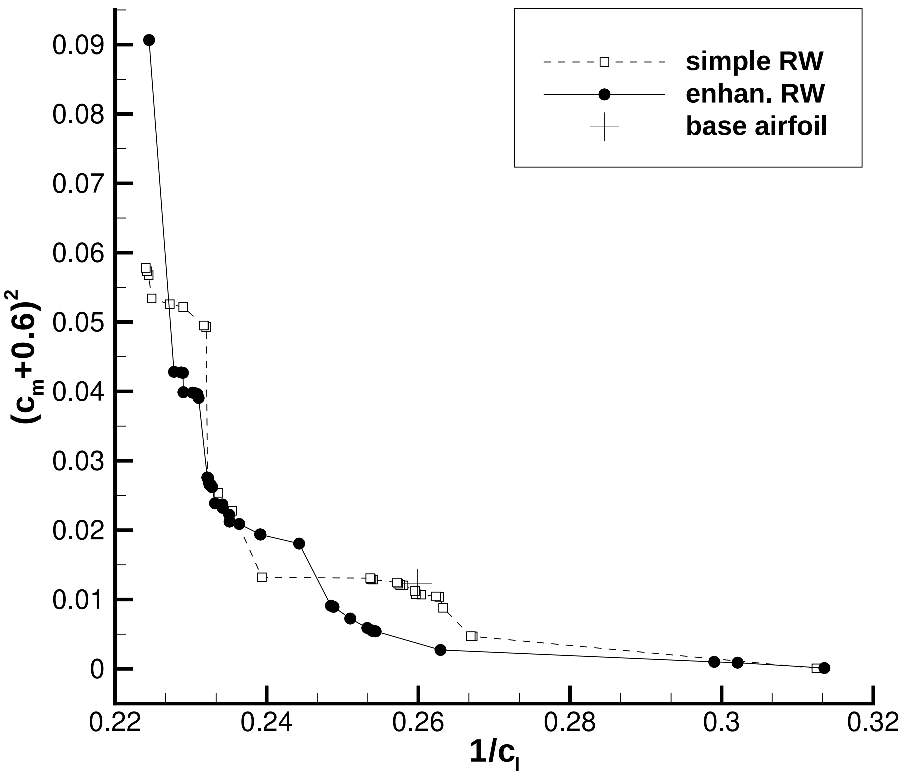

Figure 6: Pareto fronts resulting from the multi-objective optimization of the flapped airfoil.

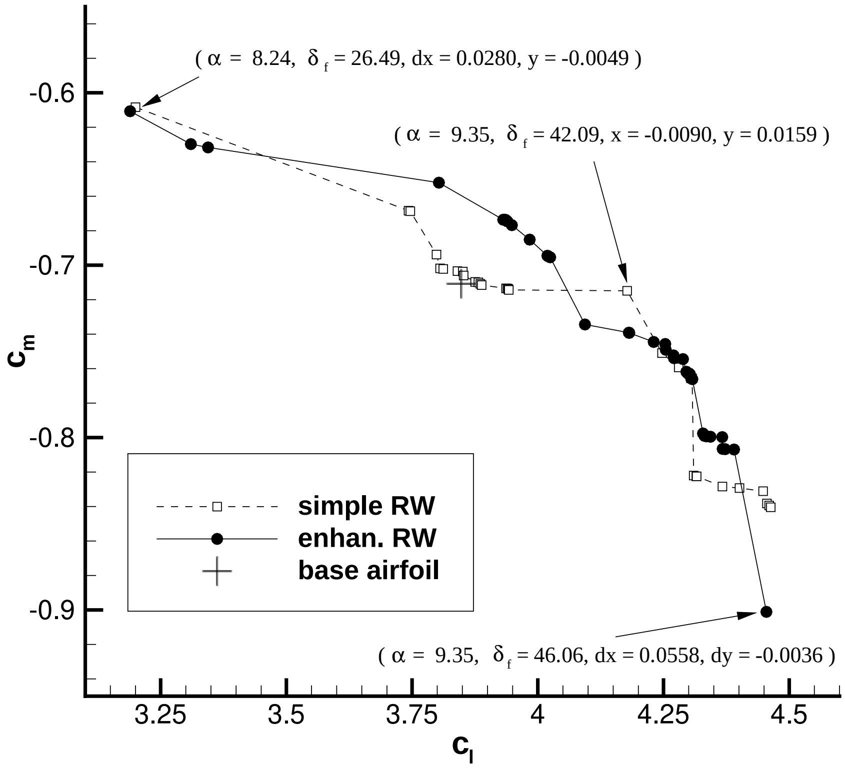

Figure 7: Pareto fronts reported in the c_l-c_m plane.

[4] D. Quagliarella, “Airfoil Calculations in High-Lift Conditions Using the MAVIAN Program”, Technical Note CIRA-TN-98-124, CIRA — Centro Italiano Ricerche Aerospaziali, Via maiorise, 81043, Capua, Italy, Dec. 1998.