Design of transonic Airfoil using Multiobjective Genetic Algorithms

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ABSTRACT

In this work a transonic wing design problem is faced by means of a Multiobjective genetic algorithm, and using a 2D Euler flow model. The application here presented regards to the airfoil shape optimization. The introduction of basic concepts of multi-objective optimization is followed by the description of a multiple objective genetic algorithm used for optimizing the shape of the Korn airfoil for (inviscid) drag minimization for a particular Mach Number and lift, and with constrained pitching moment. It is shown how both geometric and aerodynamic constraints can be taken into account, and how the Multiobjective approach to optimization can be an effective way to handle conflicting design criteria for complex aerodynamic designs.

1. Introduction

The aerodynamic design problem can be defined as the determination of the shape of bodies that satisfy design goals and constraints that can be either of aerodynamic or geometrical and structural nature. Transonic wing design is a very complex task, even if considered from a purely aerodynamic point of view. In fact, several criteria must be met in the design of any efficient transport wing, including good drag characteristics, buffet boundary high enough to permit cruising at design lift coefficients, no pitch-up tendencies near stall, no unsatisfactory off-design performances etc.

Recent advances in computational techniques have made it possible to effectively address much more complex design problems than was previously possible, and concurrently reduce the design cycle flow time. The rapid improvements in the speed of computers have then originated a growing development of numerical optimization techniques for applications to aerodynamic design. Several techniques are today available, from mature gradient based methods to more recent approaches like automatic differentiation, control theory based methods and genetic algorithms (GAs). It is not possible, generally speaking, to state the overall superiority of one method over the others; in fact, there are several characteristics that must be considered, and that may assume different importance depending on the specific problem at hand. Among these characteristics we may mention:

1) the generality of the formulation, i.e. the possibility to rapidly set up different optimization problems, including also the use of different analysis tools;
2) robustness, intended as the capability to find global optima and reduce the need of human interaction and expertise;
3) the possibility to deal with multiple design objectives and constraints;
4) computational efficiency, for a practical use of the design approach.

On the other hand, because aerodynamic shape design represents only a part of the overall design of a flying vehicle, and because the need for an effective multidisciplinary approach to the design task is rising, it is important to identify the difficulties which are typical of multidisciplinary environments. Among these we may mention the necessity to operate at system level, and consequently managing and interrelating design objectives of different nature. Moreover, the dimensionality of the design space may increase to a point where traditional mathematical programming methods are likely to find severe difficulties. The design problem may be characterized by a mix of continuous, discrete and integer design variables, and the resulting design space can be non convex or even disjointed. For all these reasons, optimization methods which do not rely on the computation of gradients, in particular evolutionary programming and genetic algorithms, are receiving a considerable growth of interest; in fact, these strategies are less susceptible to pitfalls of convergence to local optima, and generally offer a more robust approach to complex design problems. Indeed, the major weakness of such methods lies in their poor computational efficiency, which still prevents their practical use when the evaluation of the cost function is expensive, as happens with three dimensional aerodynamic problems and complex flow models.

2. Background

Now, when conflicting requirements have to be satisfied at the same time, the usual approach is to reduce the multiobjective problem into a classical single objective one. Here, instead, will be described a different technique based on direct solution of the multiobjective problem. The ideal solution of such a problem is a point where each objective function assumes its best possible value. This ideal solution in most cases does not exist due to the conflicting nature of the objectives. Hence, solutions to these problems have to be a compromise between the various requirements. An usual approach to find a compromise solution is the reduction of the multiobjective problem into a classical single objective one through a weighted combination of the objective functions. The drawback of this technique is that the solution obtained depends on the arbitrary choice of the relative weights assigned to the objectives. It would be interesting, instead, to find all the best compromise solutions available, and choose `a posteriori' the solution best fitted to the problem.

The objective function passed to the operator is obtained as a weighted linear combination of the problem objectives, i.e. as $obj = \alpha obj1 + (1-\alpha)obj2$, where $\alpha \varepsilon [0, 1]$, in the case of $n = 2$. It fixes the parameters of so that only one solution is found rather than a non-dominated set. This however is not a limit, because the gradient based operator acts like a local improvement operator. Therefore the weight can be chosen at random or assigned explicitly to give greater importance to one of the objectives.

As already stated, a peculiar feature offered by GAs is their capability to face multiobjective optimization. When several design goals need to be achieved in an optimization problem, these are usually combined together so that a single scalar objective function is obtained. In this way, the problem becomes amenable to all classical optimization algorithms. The drawback of this approach is that the solution of the problem is strongly dependent on the (arbitrary) choice of the relative weights assigned to the objectives; moreover, if the objectives to be minimized are of different nature, as happens for example when multidisciplinary optimization problems are faced, it is difficult to understand how to interrelate them properly.

Among all optimization techniques, Genetic Algorithm (GA) is attractive for aerodynamic design as it is capable of finding a global optimum compared to a gradient-based technique. It is a search algorithm based on the principles of the natural selection and genetics. It utilizes three operators: reproduction, crossover and mutation. The basis of Genetic Algorithms can be found in reference.

In traditional GA, the binary representation of the design variables discretizes the real design space. Although such GA has successfully been applied to a wide range of optimization problems, it suffers from some disadvantages when applying it to a real problem involving a large number of design variables. One of them is a huge string length. For example, a problem with 100 variables with a precision of six digits results in string length of about 2000. GA would perform poorly for such design problems. Another drawback comes from the discrepancy between the binary space representation and the actual problem space. Even two optimization points close to each other in the actual space are far from each other in the representation space.

A simple solution to these problems is the use of floating point representation of the design variables where an individual is characterized by a vector of real numbers. This representation is accurate and efficient because it is conceptually closer to the real design space. Moreover, the string length is reduced to the number of design variables. Implemented in the previous work [1], this representation was still used in the present study.

The aerodynamic shape optimization consists in determining the values of the design variables, which usually represent the geometry of the aerodynamic components, such that the objective function is minimized subject to the satisfaction of the aerodynamic constraints. This means that the flowfield variables must satisfy the governing flowfield equations. Nowadays, the computational fluid dynamics (CFD) has matured to deal accurately and efficiently with a wide range of flow problems such as subsonic, transonic and supersonic, potential, Euler and Navier-Stokes flows. It can be widely used as a key tool for aerodynamic design. It should be mentioned that GA is independent of the CFD solver used. This means that GA can be applied to any kind of aerodynamic optimization problems as long as an appropriate CFD solver is used.

To obtain a realistic shape, the design variables, which represent the geometry, must also satisfy the geometry constraints. For example, in the aerodynamic wing shape optimization, the geometry parameters such as wing span, sweep, taper and twist, chord, thickness, leading edge radius and trailing edge angle on the wing sections, must be limited to reasonable values.

3. Problem Statement

The design problem here presented consists in the minimization of (inviscid) drag for the Korn Airfoil wing, at the design point Mach Number (M) = 0.75, Lift Coefficient (cL) = 0.3 and with a constrained pitching moment for the airfoil. The pitching moment coefficient of the Korn Airfoil at the design point is Pitching moment coefficient (cM) = -0.124 (evaluated using the 2D potential flow model); thus, the considered constraint cM = -0.124 corresponds to a maximum allowable decrease of about 2.5%.

The wing planform shape and the maximum thickness of the wing sections are assumed to be constant in the optimization process. Two geometrical constraint are introduced as penalty functions and act as a filter, by assigning a very high value to the objective function of those geometries which violate them, and skipping the aerodynamic analysis.

4. Method

The flow chart for the method adopted for performing the optimization process is as shown in Figure 1.

Two geometrical constraint are introduced as penalty functions and act as a filter, by assigning a very high value to the objective function of those geometries which violate them, and skipping the aerodynamic analysis.

The first geometrical constraint on the minimum allowable trailing edge angle (TE) is used to avoid unfeasible geometries. The second one controls the leading edge radius to avoid undesirable off-design performances. The pitching moment coefficient is controlled introducing an additional objective function.

4.1 Individual and Population

GA works on a coding of the design variables subject to certain performance constraints. A 6^{th} order B-spline curve is used to represent each section of the wing. The actual values of the (x, y) coordinates of the control nodes for the B-spline curves are designated as the design variables (Figure 2). There are 8 control points for each of the lower and upper sides of the section profile. The wing planform shape and the maximum thickness of the wing sections are assumed to be constant in the optimization process. Generally, the work starts from a given initial shape of the airfoil section, which is precisely defined by the coordinates of a large set of coordinate points. The first step is therefore to find the control points based on the initial shape coordinates by using the least square function method.

(x1 y1), (x2 y2), (x3, y3)… => (100101…)

shape co-ordinates *chromosome*

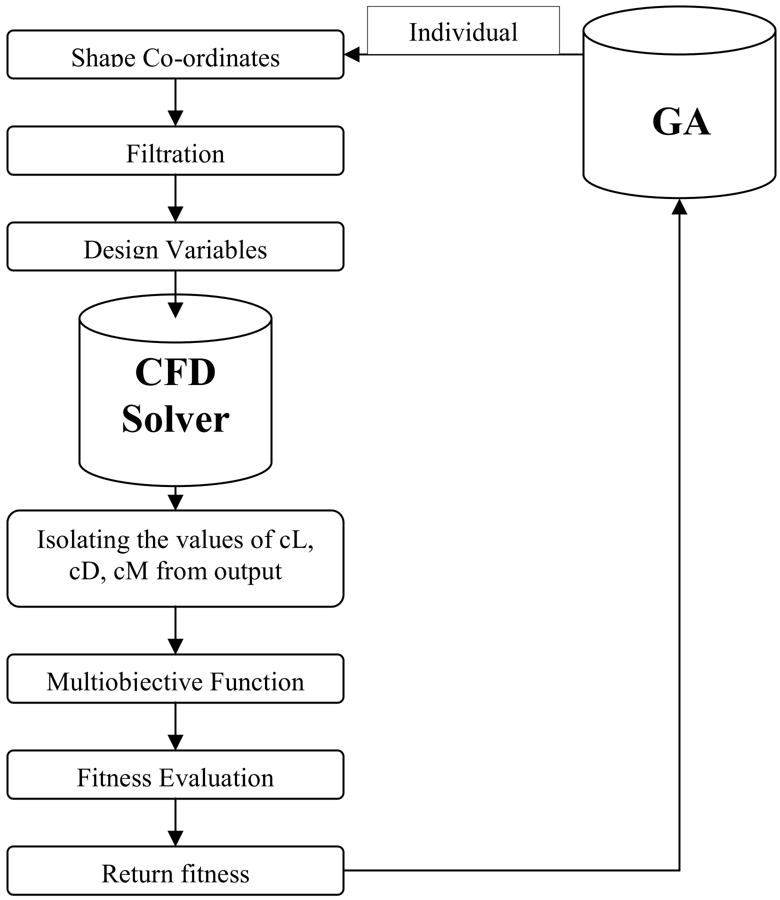

Figure 1. Flow Chart for the Multiobjective GA process

In this analysis, a given population represents a number of airfoil configurations, whereby each configuration itself is regarded as a single chromosome. Usually, the initial population should be created randomly in order to guarantee that the global optimal can be found. But this is a pitfall that one encounters in case of optimization of aerodynamic shapes, as the evaluation of these absolutely randomly generated population causes waste of a lot of evaluation time and is not the best way to go proceed with. In this study, the initial population is generated by mutation with randomly selecting the mutation point from the original airfoil which is to be optimized.

As suggested in reference, the use of Micro-Genetic Algorithm (μGA) can facilitate fitness convergence and enhance the algorithm's capability to void local optima. The implication behind μGA is that with a small population size, the sub-optimal solution can be rapidly achieved in a cycle of GA operation. Then a new cycle of GA operation starts with the new population members generated from the sub-optimal member in the previous cycle of GA operation. In this study, this technique was also used. The population size is set to 10. There are 10 generations in a cycle of GA operation.

4.2 Filtration

Two geometrical constraint are introduced as penalty functions and act as a filter, by assigning a very high value to the objective function of those geometries which violate them, and skipping the aerodynamic analysis as this might result in crashing the flow solver being used.

The first geometrical constraint on the minimum allowable trailing edge angle (TE) is used to avoid unfeasible geometries. The second one controls the leading edge radius to avoid undesirable off-design performances.

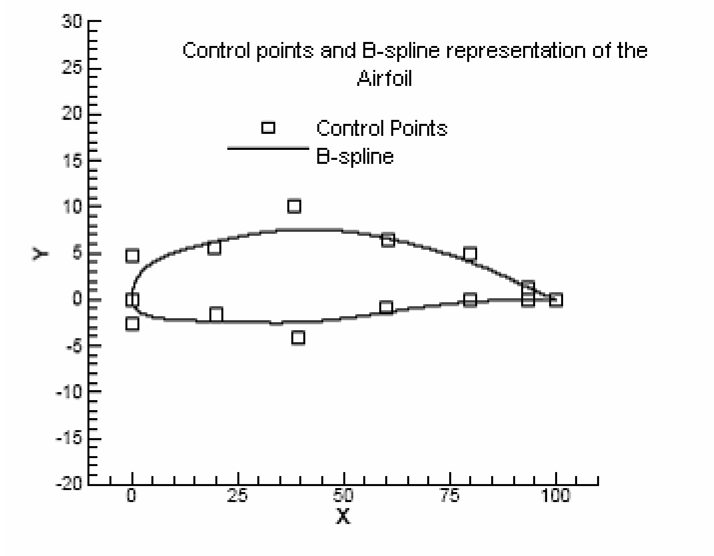

Figure 2. Control points and B-spline representation of Airfoil

4.3 CFD Solver

For CFD based performance assessment, the Flo82 solver developed by Jameson was used, which is a 2D flow solver for inviscid flow for transonic airfoils. The overall crude grid spans the entire computational domain. The fine grids are imbedded in the global crude grid to model the aircraft components such as wing and fuselage. The purpose of the fine grids is to provide detailed computation in regions where the flow field gradients are large and other flow details are of importance for numerical resolution. They improve the resolution of shock waves and the calculation of forces and moments, while the global crude grid provides a link between the fine grid solutions and the crude grid solutions. The solver usually takes about five to six seconds for a run, but it was modified by reducing the number of grids and also the mesh, so that the calculation time was reduced to about one second or less.

Once the design variables are ready by the GA, the solver which was written in FORTRAN has to be called and the design variables are fed in it. It now calculates the values for lift cL, cD and cM. These values are then stored in the file by the modified Flo82. These values can now be used by the GA for calculation of its objective and hence the fitness function.

For a member in a population, at least one CFD call is needed. Therefore, an enormous number of CFD calls are needed for the entire optimization. Numerical experiments showed that the CPU time spent for the GA operations is negligible when compared to the CPU time of flow solution.

4.4 Multiobjective Fitness Function

Fitness evaluation is the basis for GA search and selection procedures. GA aims to reward individuals (chromosomes) with high fitness values and to select them as parents to reproduce offsprings. The purpose of optimization in this study is two fold, viz. minimization of (inviscid) drag for the Korn Airfoil wing, at the design point M = 0.75, cL = 0.3 and drag minimization with a constrained pitching moment for the airfoil at cM = -0.124.

In the first case the objective function to minimize was cD/cL^2 to account for small variations of the lift coefficient around the design value. The constraint on the maximum thickness of the wing sections, so as to maintain it at the same value of the original geometry, is imposed by scaling the sections to the desired thickness after each geometry modification.

In the second case, the considered constraint cM > -0.124 corresponds to a maximum allowable decrease of about 2.5%. The objective function to minimize was $(cM - cMT)^2$. The value of cMT = -0.120 has been used.

Hence as dicussed earlier the multiobjective approach adopted in this case would be with obj1 = cD/cL^2 and obj2 = $(cM - cMT)^2$. Thus, we have the Multiobjective fitness function as:

$$F = \alpha\,(obj1) + (1-\alpha)\,obj2$$

$$\text{Therefore, } F = \alpha\,(cD/cL^2) + (1-\alpha)\,(cM - cMT)^2$$

Here the value of α was taken as 0.5, which was chosen keeping in mind that both the fitness cases are of same importance.

4.5 Genetic Operators

4.5.1. Selection and Reproduction

Parents are chosen based on the Roulette wheel method where the probability of a parent of being chosen is proportional to its fitness value. Each pair of parents produces one offspring (chromosome) by crossover. Then, mutation is applied to the offspring. After a new population is produced, the fitness of each member is compared to that of the parent generation and the best and the second best members in the generation are assigned to the new generation without crossover or mutation. Using this technique guarantees that the best member in all the populations will not be filtered out by using the GA operators during the optimization procedures.

4.5.2. Crossover

A simple one-point crossover scheme is applied. The crossover point is selected randomly. Figure 3 shows a kid wing section, demonstrating how the crossover operates on a wing section. Some design variables (control nodes) on the kid wing section are from the dad wing section (squares) and some from the mom wing section (crosses). The probability of the crossover is set at 80%, as the use of smaller values was observed to deteriorate the GA performance.

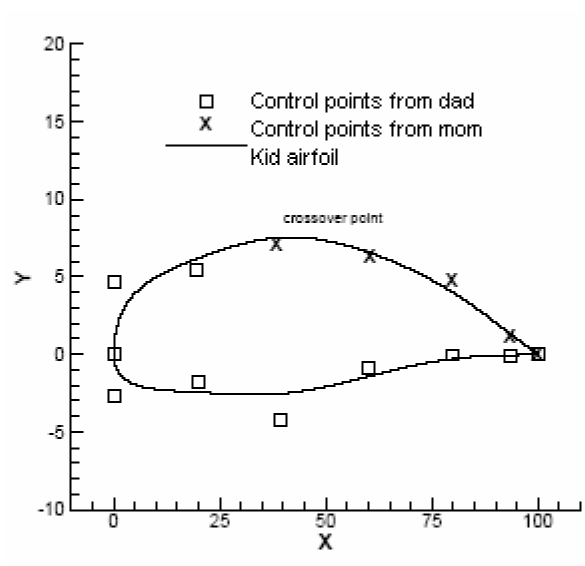

Figure 3. Control points for Crossover

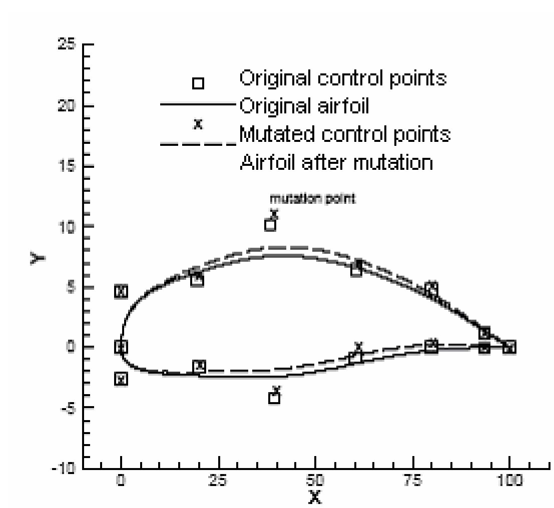

Figure 4. Control points for Mutation

4.5.3. Mutation

Mutation is carried out by randomly selecting a gene (control node) and changing its value by an arbitrary amount within a prescribed range (1% chord), as illustrated in Figure 4. As this change is applied to the selected node, its neighboring nodes are also adjusted so that the change in slope and curvature of the section profile will not be too abrupt. As discussed by Mantel et al. [11], a high mutation rate of 80% is chosen for better GA performance with real number coding.

The tableau below shows the various parameters and data that has been used in the method:

Objective	To optimize the shape of the Korn Airfoil for minimization of drag
Representation Scheme	• Structure: Fixed length array of homogeneous structures • Array length: L = 16. This is the co-ordinates of the control points of the airfoil • Alphabet size: K = 8
Fitness Cases	There is one fitness case but involves two objective functions $F = \alpha\,(obj1) + (1-\alpha)\,obj2$ So, $F = \alpha\,(cD/cL^2) + (1-\alpha)\,(cM - cMT)^2$ Where $\alpha = 0.5$
Raw Fitness	Difference in the values of cM and cL from the target values set.
Parameters	• Population size: $M = 50$ • Maximum number of generations $G = 25$. • Pc = 1.0, Pm = 0.05 and 0.8 for initial population generation
Termination Criteria	The GA has to run till it converges to a minimum value of drag coefficient
Result Designation	The best so far individual

Table 1: Tableau for the Genetic Algorithm

5. Results and Discussion

The convergence history of the computation is shown in Figure 5. It was noted that after about a 1000 CFD calls, the fitness value reached its converged value. It should be mentioned that the maximum fitness corresponds to the best member in each generation and the averaged fitness to the entire members in the generation. The trend of the fitness in this figure strongly shows that the optimum was approaching from one generation to another, demonstrating the reliability of the Genetic Algorithm.

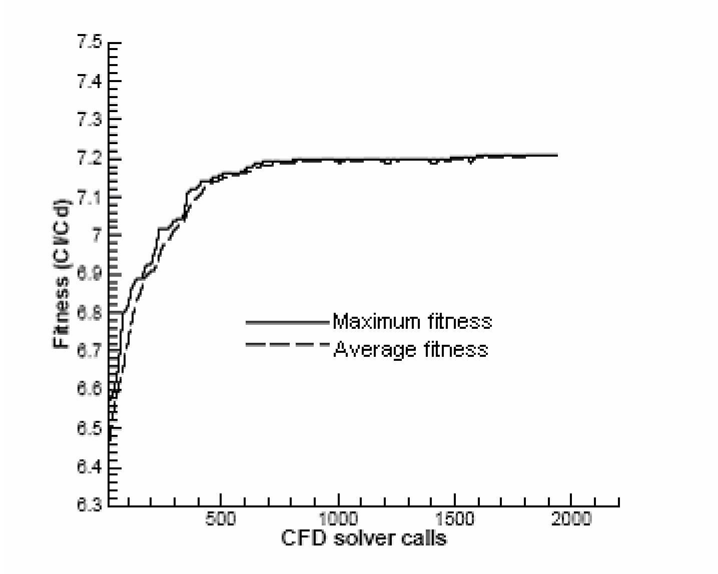

Figure 5: Convergence history

The figure 6 shows the modified airfoil and the pressure distribution of the airfoil and it can be seen that the modification of the airfoil has taken place towards the tail end, which has resulted in reduction of suction peaks at the leading edge and there is a considerable reduction of shock intensity as seen.

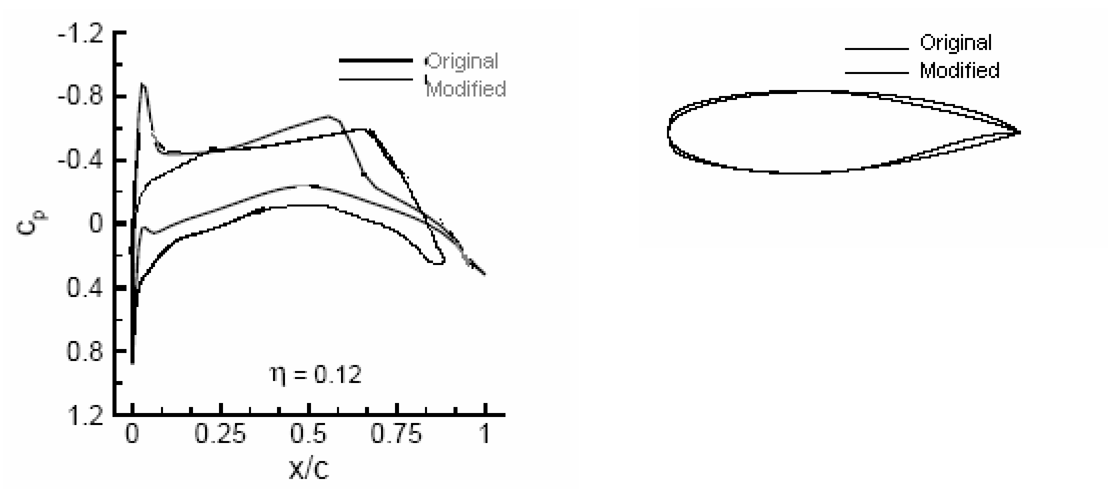

Figure 6: Modified shape of airfoil and pressure distribution curve for both original and modified airfoil

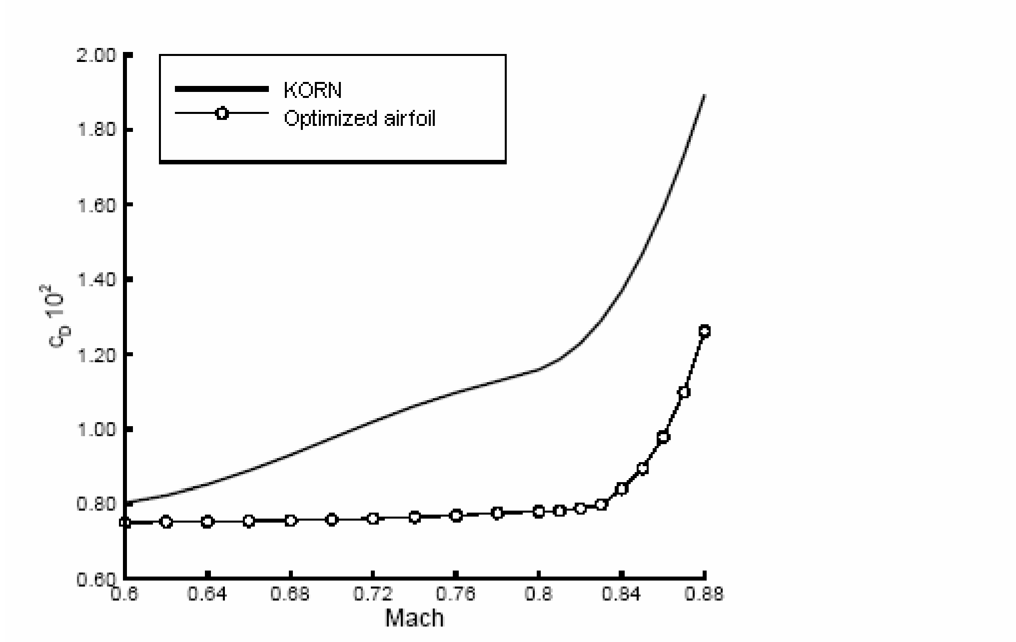

Figure 7: Modified values of drag coefficient for the original and optimized airfoil

The drag drop has taken place over the design point that was decided and it is observed to be around 30 drag counts. This is a considerable amount of drag drop keeping in mind that the solver that was used was modified for a courser grid and that the solutions that were being obtained were fairly approximate. The drag coefficient thus decreased by almost 7%, for the optimized airfoil. Thus there is a drag reduction that has been obtained having both the constraints – on the lift as well as the pitching moment and an optimal airfoil has been generated.

These results were not obvious in the initial runs during the projects, as the value of the population taken initially was too large, due to which there was a difficulty in converging. And then further ahead the time taken by the Flo82 solver was too large, and hence that had to be modified so that the computational time cold be reduced considerably. This resulted in some approximations in the calculations though, but still after the final runs, there was a relative improvement observed in the shape and the drag coefficient of the airfoil.

7. Conclusions

A multiobjective genetic algorithm has been used successfully for the optimization of an airfoil in transonic flow. In the design problems that have been described both geometrical and aerodynamic constraints have been taken into consideration, and it has been shown in particular how Multiobjective optimization can be an effective approach when conflicting design criteria must be met. In the application described this approach has been used to devise an optimum airfoil shape taking into account both aerodynamic drag and to control the value of the pitching moment while minimizing aerodynamic drag. Genetic Algorithms offer unparalleled flexibility in the implementation of Multiobjective optimization procedures.

Though genetic algorithms are effective and robust design tools, well suited for multidisciplinary environments, the critical issue still lies in the computational effort they require. This makes their application unpractical when the fitness evaluation becomes computationally expensive.

8. Future Work

Solving of the aerodynamic problems may be tried using parallel GA operation, which handles many different populations simultaneously. This may become necessary when the optimization would be applied to the entire wing instead of the section.

Also, it may be of good interest to develop and use appropriate hybrid optimization techniques of both GA and the gradient solvers so that it can help in quick convergence of the design problem involving many different design variables and complex geometries that would be required for industrial applications.

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