INVERSE OPTIMIZATION OF TRANSONIC WING SHAPE FOR MID-SIZE REGIONAL AIRCRAFT

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ABSTRACT

Multiobjective Genetic Algorithms (MOGAs) have been applied to design a transonic wing shape. First, the wing planform is optimized by solving a multidisciplinary optimization problem based on aerodynamic, structural and fuel storing objectives and constraints. Second, three-dimensional target pressure distribution is optimized for the aerodynamic inverse design with the previously designed planform. Minimization of the profile drag and the induced drag is performed under constraints on lift and other design principles. Corresponding wing surface geometry is obtained by Takanashi's inverse method. These two multiobjective optimization problems are solved by Pareto-based MOGAs coupled with appropriate CFD solvers. Applying these two wing design procedures, Pareto surfaces can be studied for trade-offs and a good compromised solution for the wing design can be obtained.

INTRODUCTION

In today's competitive environment of commercial aircraft industry, its success depends on the cost and timeliness of products as well as their quality. To reduce the development period and its cost, an automated design tool becomes very important. To construct the automated design tool, various numerical optimization methods have been investigated.

Real-world engineering problems, including an aircraft design problem, often require simultaneous optimization of multiple, competing objectives. Such problems are usually solved by combining the objectives into a single one using a certain utility function. However, this leaves the problem of finding a proper utility function. It is more natural to solve these multiobjective optimization problems (MOPs) without utility functions and to find a set of 'compromised' solutions known as Pareto solutions. Conventional optimization techniques have to seek such solutions one by one, by changing utility functions, and thus they are not efficient.

Genetic Algorithms (GAs) are known to be robust optimization algorithms, which are based on the mechanics of natural selection and natural genetics. GAs are different from the conventional algorithms since they use only objective function information, not derivatives or other auxiliary information of subproblems.[1] In addition, GAs search an optimum from a population of points in parallel, not a single point. These features are very attractive to solve MOPs, and GAs have been extended to MOPs as MOGA.[2]

In aircraft design procedure, the wing planform shape has to be determined at an early stage of aircraft design because the planform shape is closely related to aircraft sizing. In this stage, designers should account for tradeoff information between aerodynamic performance, structural strength and weight, fuel storage, and so on. Therefore, an automated design of the wing planform shape requires multidisciplinary design optimization (MDO) based on a system composed of aerodynamics, structural dynamics, etc.[3] To take advantage of cross-disciplinary tradeoffs, this MDO procedure should be solved with a multiobjective, system-level optimizer.

The next step of aircraft design is definition of wing surface geometry, namely airfoil sections, for the given wing planform. Aerodynamic design optimization methods of wing geometry are categorized into two classes: direct and inverse numerical optimization methods.[4] In the direct numerical optimization methods, aerodynamic objective functions are minimized (or maximized) by changing geometry directly. However, this approach requires numerous CFD evaluations through iterative optimization loops. Moreover, flow fields are often sensitive to the geometry, and thus those procedures do not seem practical even with the aid of the current supercomputers.

In contrast, the inverse optimization methods deal with pressure distribution rather than geometry. Since pressure is the primary force acting on aerodynamic objects, one can design desired aerodynamic characteristics by specifying pressure distribution. Once the target pressure distribution is

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optimized, a corresponding geometry can be determined by the inverse methods. The inverse approach is preferable for the construction of a design optimization tool requiring less computational costs and development periods.

In the inverse approach, design optimization has to be translated into target pressure optimization. A 'good' target pressure should yield elliptic loading, a straight isobar pattern and low profile drag. However, these design requirements conflict with each other in general. Thus, this optimization problem should be solved by the multiobjective optimizer as well as the MDO problem of wing planform design.

In this work, the three-dimensional wing design system has been constructed using MOGAs as optimizers. First, a wing planform shape is designed as the MDO system based on aerodynamic performance, structural strength and weight, fuel storage. Second, aerodynamic design of wing geometry is performed by the inverse optimization. The pressure distribution will be optimized to reduce the profile drag using the previous two-dimensional approach[5] as well as to minimize the induced drag. The straight isobar pattern will be enforced, too. Both design optimization problems are treated as multiobjective optimization problems, and thus MOGAs are employed as optimizers at both design stages. Finally, the design result is examined.

MULTIOBJECTIVE GENETIC ALGORITHM (MOGA)

Multiobjective optimization seeks to optimize the components of a vector-valued objective function. Unlike single objective optimization, the solution to this problem is not a single point, but a family of points known as the Pareto-optimal set. Each point in this set is optimal in the sense that no improvement can be achieved in one objective component that does not lead to degradation in at least one of the remaining components. GAs can search for many Pareto solutions in parallel by maintaining a population of solutions. Furthermore, a number of Pareto solutions create a locus in the design space where tradeoffs can be examined quantitatively.

To evolve Pareto solutions efficiently using GAs, the Fonseca-Fleming's Pareto ranking method[2] is used here. In this method, parent individual's fitness values are assigned according to not only the objective values but also the dominance property of population. The rank that determines the probability of selection is defined by one plus the number of individuals in the current population that dominate it. With this method, the individuals tend to seek the Pareto-optimal solution and to get the rank of 1 for mating.

In solving multiobjective optimization problems, it is required not only to obtain the Pareto-optimal solutions but also to sample solutions uniformly from the Pareto front. The Pareto ranking method mentioned above achieves the first requirement, not the second one. This is caused by the phenomenon known as the random genetic drift: the genetic diversity of the population is lost due to their stochastic selection process. In this work, the fitness sharing method is first adopted to avoid this genetic drift. In the fitness sharing method, the fitness value of each individual is reduced if there are other individuals in its neighborhood, and therefore an individual located in a more crowded area leaves less offsprings. But with this method, the Pareto surface is sometimes obtained sparsely because the determination of 'neighborhood' is difficult. To address this, a new fitness assignment method called the Coevolutionary Shared Niche scheme[6] is applied. This method is extended to multiobjective optimization problems in this study and the solutions are found to be distributed more uniformly over the Pareto-optimal surface.

In the present MOGA codes, other genetic operators are also arranged for the wing design problem. Although traditional GAs are characterized by the use of the binary coding for design variables, a real number coding is used for simplicity. Selection operator is defined by using the nonlinear function suggested in Ref. 7. Crossover and mutation operators are defined similar to those in Ref. 5. The elite strategy is also used to preserve the best individuals.

WING DESIGN SYSTEM

Multidisciplinary Planform Design

The present multiobjective optimization problem is described as follows: 1) minimize aerodynamic drag (mostly induced drag), 2) minimize wing weight, and 3) maximize fuel weight (tank volume) stored in wing; under these constraints: 1) lift is to be equal to given aircraft maximum takeoff weight and 2) structural strength is to be greater than aerodynamic loads.[8]

The model aircraft considered here is mid-size regional aircraft. Their sizes were assumed to have a wing area of 525 ft^2, a total maximum take-off weight of 45000 lb, at a cruise Mach number of 0.75 and Reynolds number based on the root chord of 1.5×10^7. The original wing was taken from an existing wing: its airfoil sections were supercritical, and its thickness and twist angle distributions were reduced toward the tip.

In this design stage, only two parameters are chosen as design variables: leading-edge sweep angle and taper ratio. A semi-span length is calculated from the taper ratio and the given wing area. The number of design variables used in this work was greatly reduced in order to check the performance of the present design system.

The objective functions and constraints are computed as follows. First, drag is evaluated, using a full potential flow solver called FLO27.[9] From the flowfield solution, lift and drag can be postprocessed. Because the flow is assumed inviscid, only a sum of induced and wave drag is obtained. Second, the wing weight is calculated, using an algebraic weight equation.[10] Third, the fuel weight is calculated directly from the tank volume given by the wing geometry. Finally, the structure is evaluated by using the model taken from Ref. 3. In this research, the wing box is modeled only for calculating skin thickness. Then the wing is treated as a thin-walled, single-cell monocoque beam to calculate stiffness. Flexibility of the wing is ignored.

The objective function values and constraint violations are now passed to the system-level optimizer, MOGA. When any constraint is violated, rank of the particular design is lowered by adding an integer according to the degree of violation.

Aerodynamic Design by Inverse Optimization

Pressure Distribution for Airfoil

The aerodynamic design of wing usually proceeds in two steps. First, the airfoil section at the midspan section is designed. This reduces the three-dimensional design problem into the two-dimensional one. In Ref. 5, a Genetic Algorithm (GA) has been applied to optimize target pressure distributions around airfoils for inverse design methods. An airfoil drag is minimized under constraints on lift, airfoil thickness and other design principles.

Chordwise pressure distributions are parameterized by B-spline polygons and split into two curves, corresponding to the upper and lower surfaces of an airfoil. As shown in Fig.1, seven points for lower surface and eight points for upper surface are used to define B-spline polygons, respectively.

The two-dimensional optimization problem is then defined as

Minimize:
Drag coefficient C_d
Subject to:
1. Lift coefficient C_l = specified
2. Airfoil thickness to chord t/c = specified
3. Additional constraints for chordwise pressure distribution

where C_d is evaluated by the Squire-Young relation, and C_l and t/c can be estimated from surface pressure integrations. The specification of airfoil thickness can be done approximately in two dimensions, but not in three dimensions. Thus, it was dropped in the following three-dimensional optimization. Additional constraints are required to guarantee the existence of a solution of the aerodynamic inverse problem. See Ref. 5 for details.

Pressure Distribution for Wing

The design principles for a three-dimensional wing are essentially twofold.[11] One is to preserve the two-dimensional performance as much as possible. This is easily achieved by the inverse method by specifying the same chordwise pressure distribution along the wing span. The resulting wing has the straight isobar pattern of pressure contours on the wing span.

The other is to minimize the induced drag, which is achieved by specifying a parabolic lift distribution in the spanwise direction when the structural constraint is imposed. The constraint in the total lift will specify a parabolic lift distribution uniquely. Thus, the objective function can be given by differences of the sectional lifts to the parabolic distribution at, for example, the seven spanwise sections.

The wing with the straight isobar pattern cannot have a parabolic lift distribution unless it has a parabolic planform. This means these two design objectives contradict each other in general. We overcome this problem by enforcing the isobar pattern only on the upper surface of the wing. The resulting straight isobar pattern of pressure on the upper surface of the wing is expected to produce the drag divergence at the same Mach number along the wing span and thus the resulting drag-divergence Mach number of the wing will be similar to that of the wing which has a fully straight isobar pattern.

The three-dimensional optimization problem is now defined as

Minimize:
1. Difference of the spanwise lift distribution to the parabolic distribution
2. Two-dimensional drag coefficient C_d at each spanwise section
3. Penalty function based on the additional constraints for chordwise pressure distribution

Subject to:
Straight isobar pattern of pressure contours on the upper surface of the wing

As mentioned in Ref. 5, random creation of initial population often produces infeasible solutions due to the severe constraints. To evolve a population of feasible solutions, the two-dimensional GA was first run by using only the constraints. Then, the resulting chordwise pressure distribution was distributed to seven spanwise sections from the 10.0% to the 93.0% spanwise sections so as to give the parabolic lift distribution approximately. The population of 200 individuals was used as the initial population for MOGA.

Inverse Design

Once the present MOGA finds an optimum target pressure distribution, corresponding wing geometry can be obtained by an inverse design method. This design loop is shown in Fig. 2. Here the inverse design code, WinDes,[12] is used. WinDes uses the following iterative procedure. Suppose the initial geometry and surface pressure distribution obtained from any CFD code are given. Then, pressure differences are calculated from the given initial and target pressure distributions. From these pressure differences, corresponding geometry corrections can be computed from the integral equations discretized at the panels on the wing planform. Improved geometry is then obtained from the initial geometry and the computed geometry corrections. Finally, the CFD code is used again to check how close the resulting pressure distribution is to the target distribution. If the differences are still large, the process will be iterated. In practice, 10 design cycles are sufficient to obtain the final geometry.

The inverse design code, Navier-Stokes code, and algebraic grid generator construct a nearly automated loop for the inverse design with reasonable computational requirements. These codes were implemented on a NEC SX-4 supercomputer at Department of Aeronautics and Space Engineering, Tohoku University. The inverse design for one cycle required about 45 min of single CPU time (most of the time is used for the Navier-Stokes computation).

RESULTS

First, multidisciplinary optimization of wing planform was performed with 100 individuals of population for MOGA. Upper and lower limits of the design variables were defined as 5 to 20 degrees for the sweep angle and 0.1 to 0.6 for the taper ratio. After 70 generations, almost all individuals were converged to the Pareto front. This corresponds to 8 hours of single CPU time of SX-4 computer.

Figure 3 shows the locus of the Pareto solutions in the objective function space. All three axes are arranged so that the left lower corner becomes the desired point. The Pareto front, namely the trade-off surface, is presented clearly. Figure 4 shows the extreme Pareto solutions. The minimum-drag wing has the smallest taper ratio among the feasible solutions, but slightly greater than the lower limit. This means that the lowest taper ratio (the largest aspect ratio) in the design space can achieve the lowest drag, but violates the structural constraint. The individual corresponding to the minimum wing weight and the maximum fuel weight has the same shape, because the wing area is fixed in this optimization. These shapes have the maximum taper ratio. The wing shape at the center of the Pareto surface has the most reasonable shape and can be considered as the best compromise between the multiple objectives here.

Next, the three-dimensional pressure distribution was optimized and then an inverse problem was solved for the best compromise planform obtained above. The parabolic lift distribution is monitored at seven locations from the 10.0% to the 93.0% span as indicated in Fig. 5. The inverse solver is used at the same spanwise locations for the geometry correction. For the Navier-Stokes analysis, the modification of wing geometry was linearly interpolated between those sections and twist angles of designed wing at those sections are smoothed for simplicity of manufacturing. In the tip and root region, the airfoil sections were extrapolated from the interior sections, while the wing twist was linearly extrapolated. At the root section the fuselage is ignored and the symmetry plane is assumed. It should be pointed out that the tip and root sections are usually designed by other means and thus they are not treated by the inverse method here.

The computational mesh for Navier-Stokes analysis has the C-O topology and contains 169×49×37 grid points in the chordwise, normal (to the surface) direction and spanwise directions, respectively.

Figure 5 shows the wing planform and the computed pressure contours on the upper surface of the wing designed by the inverse method based on the target pressure distribution optimized by MOGA. Flow condition was set to the freestream Mach number of 0.75, the Reynolds number based on the root chord of 1.5×10^7 and an angle of attack of 0 deg. The resulting straight isobar pattern satisfies the first design principle of the wing well and thus indicates good performance at higher Mach numbers.

Figure 6 shows the target chordwise pressures obtained from the present MOGA, the resulting airfoil shapes of the wing obtained from WINDES, and the corresponding pressures computed by the Navier-Stokes solver. It confirms that the inverse problem is solved satisfactorally.

Figure 7 shows the computed lift distribution of the designed wing in comparison to the parabolic distribution. The result is found to satisfy the second design principle of the wing except at the root region.

For a future work, the two design procedures constructed in this work may be iterated to improve the design accuracy. The inverse optimization code will be extended to include thickness constraint.

Capability of multipoint design should be investigated.

CONCLUSION

A design optimization system for transonic wings has been developed by using MOGAs based on the Pareto ranking method. First, planform shapes with minimum drag, minimum weight and maximum fuel weight under constraints of lift and structural strength were sought by using the multidisciplinary model that consisted of the potential flow, algebraic weight, and wing-box structure equations. A wide variety of Pareto solutions were obtained, including a good compromised solution.

Second, aerodynamic design by the inverse optimization was performed for the planform obtained. The optimization problem was formulated to minimize the induced drag as well as to minimize the profile drag. The present design procedure also enforced the straight isobar pattern on the upper surface of the wing at the same time.

These two design optimization procedures were successfully applied to the transonic wing design. The tradeoff information was given by the Pareto front and the best compromised wing was able to be designed. The present approach will provide a practical automated design tool for aircraft industry.

ACKNOWLEDGEMENT

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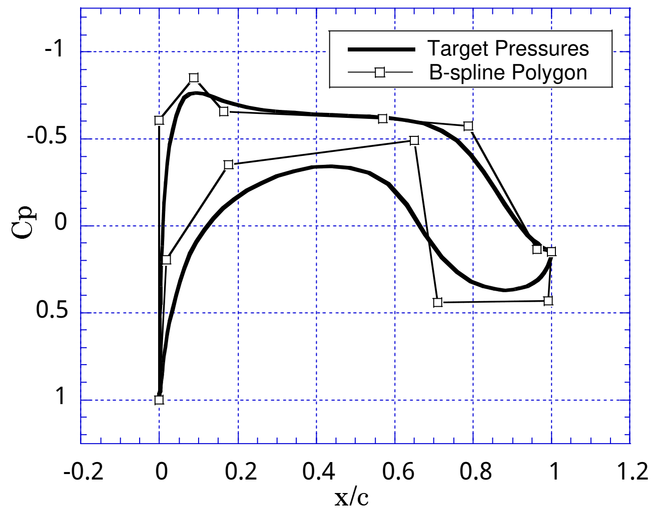

Fig. 1 B-spline polygon and corresponding pressure distribution.

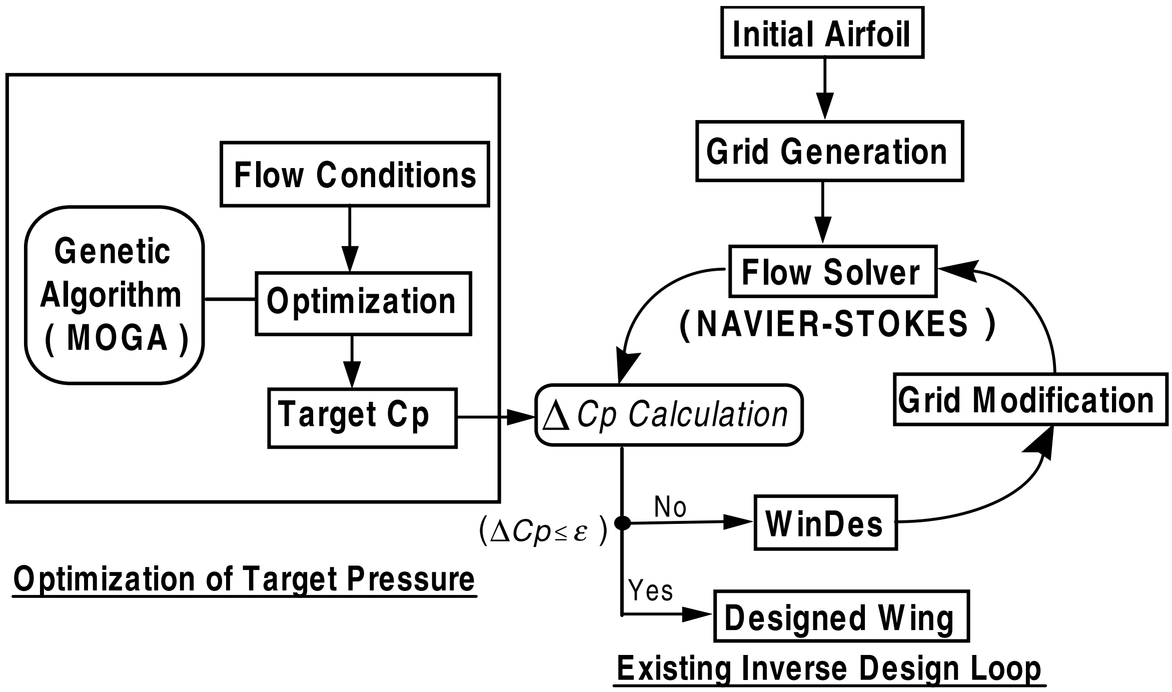

Fig. 2 Flowchart of the design procedure.

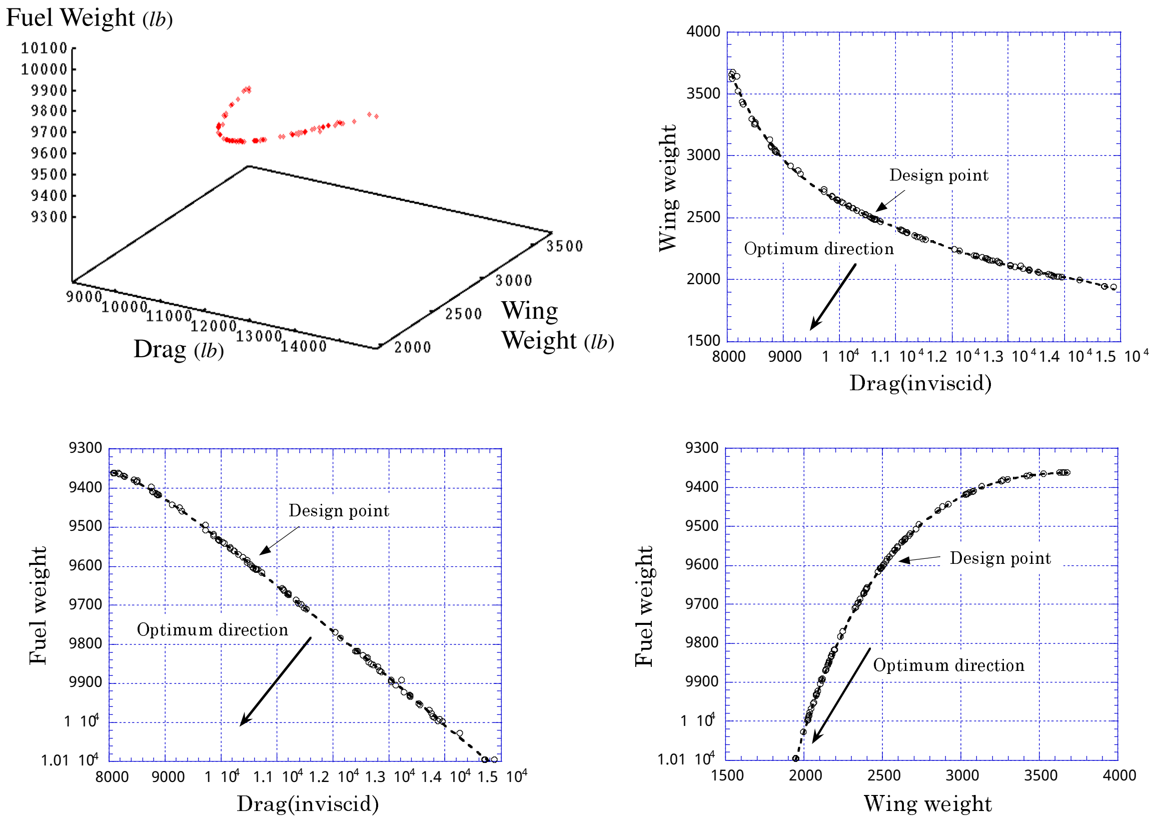

Fig. 3 Pareto solutions in the objective function domain.

Drag Minimum
Drag 8078
Wing Weight 3656
Fuel Weight 9361 (*lb*)

Center of Pareto Surface
Drag 9259
Wing Weight 2881
Fuel Weight 9449 (*lb*)

Wing Weight Minimum
Fuel Volume Maximum
Drag 14877
Wing Weight 1946
Fuel Weight 10095 (*lb*)

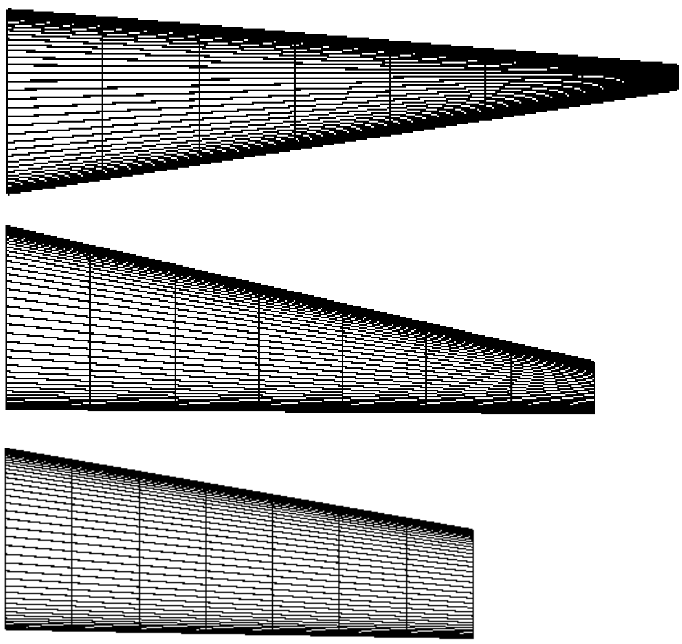

Fig. 4 Planform shapes of extreme Pareto solutions.

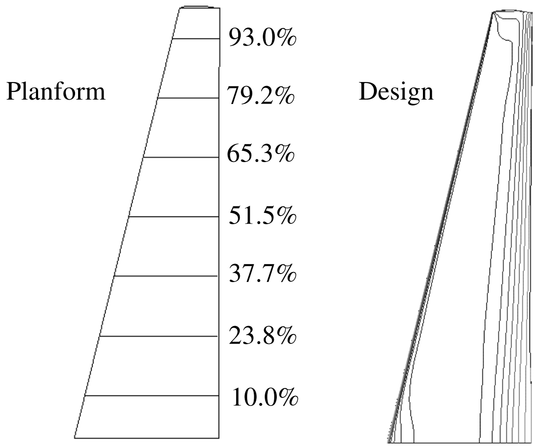

Fig. 5 Wing planform and computed pressure distribution on the designed wing.

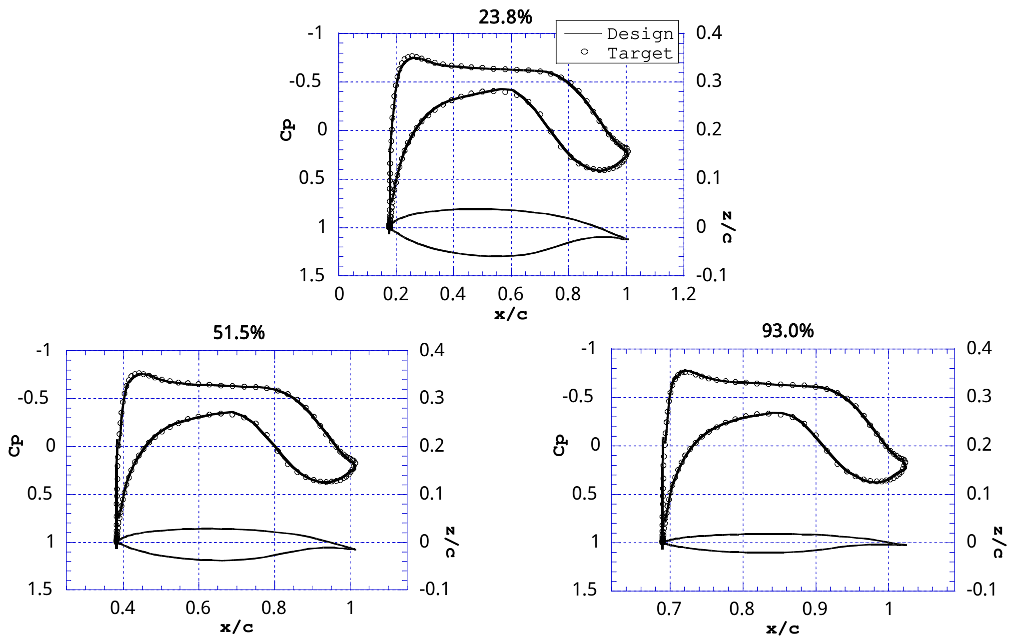

Fig. 6 Designed airfoil sections and corresponding chordwise pressure distributions.

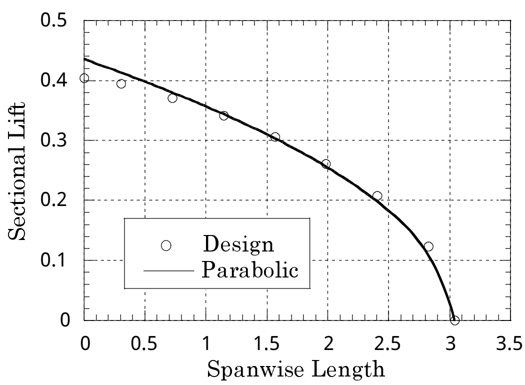

Fig. 7 Sectional lift distribution in the spanwise.