Design Optimization of Supersonic Wings Using Evolutionary Algorithms

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Abstract. Feasibility of evolutionary computations for supersonic wing design optimization was demonstrated by the single-objective aerodynamic optimization and multiobjective, multidisciplinary optimization. The aerodynamic optimization problem seeks an optimal supersonic wing shape using the Euler equations. The multidisciplinary optimization problem seeks an optimal supersonic wing planform shape using linearized aerodynamics and wing weight algebraic estimation.

1 INTRODUCTION

Evolutionary algorithms, Genetic Algorithms (GAs) for example, are known to be robust [1] and have been enjoying increasing popularity in the field of numerical optimization in recent years. GAs are search algorithms based on the mechanics of natural selection and natural genetics. One of the key features of GAs is that they search from a population of points and not from a single point. In addition, they use objective function information (fitness value) instead of derivatives or other auxiliary knowledge. These features make GAs robust and thus attractive to practical engineering applications. GAs have been applied to aerodynamic optimization using Computational Fluid Dynamics (CFD) [2-5].

Another advantage of GAs is their suitability to parallel processing. Since the majority of computational time will be consumed by function evaluations (CFD calculations), the simple *master-slave* scheme [1] can be used to improve their computational efficiency. The master process controls selection, mating, and the performance of genetic operators. The slaves simply perform function evaluations. Since GAs can be parallelized more effectively than the conventional optimization methods, they will be more efficient in parallel computing environments.

Furthermore, GAs can search for many Pareto-optimal solutions for a multiobjective optimization problem in parallel, by maintaining a population of solutions [1]. When solving the single-objective optimization problem formulated appropriately from multiple objectives, Pareto-optimal solutions have to be sought on a one-by-one basis. Although GAs require a large number of function evaluations, they can be very efficient if they can sample many solutions from the Pareto-optimal set in parallel. Since GAs are inherently robust, the combination of efficiency and robustness makes them very attractive for solving MO problems. Several approaches have been proposed [6-8] and one of them to be employed here is called Multiple Objective Genetic Algorithms (MOGAs) [7].

In this paper, the single-objective GA and MOGA are applied to optimization problems of supersonic wings and their feasibility is examined. This paper considers two optimization problems: a single-objective aerodynamic optimization and a multiobjective, multidisciplinary optimization. The aerodynamic optimization problem searches for an optimal supersonic wing shape using the Euler equations. The multidisciplinary optimization problem looks for an optimal supersonic wing planform shape using linearized aerodynamics and wing weight algebraic estimation.

2 AERODYNAMIC OPTIMIZATION USING EULER EQUATIONS

An attempt was carried out to optimize an aerodynamic shape of a supersonic wing using the Euler equations. The unstructured grid approach was employed [9]. As an aerodynamic objective, the Lift-to-Drag ratio, *L/D*, was maximized at a cruise Mach number of 2.3.

Instead of introducing complicated constraint functions, a limited design space was considered here. First, the wing planform was fixed. A wing shape is then specified by airfoil sections interpolated by the

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third-order Spline curve in the spanwise direction. The Spline control points are defined at the root, 25, 50, 75, 100 and 125 % spanwise locations. Each airfoil section is assumed to have the same, given thickness distribution as shown in Fig. 1.

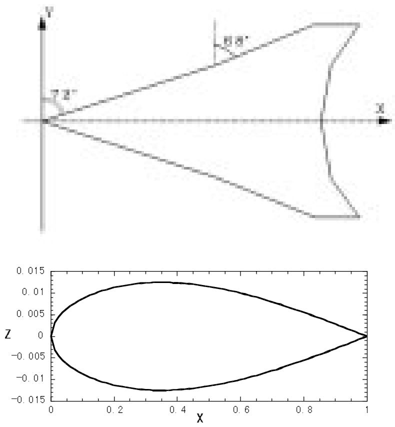

Figure 1. Wing planform and thickness distribution

The maximum camber m ($-0.1c < m < 0.15c$ where c is a local chord) and its chordwise location p ($0.01c < p < 0.95c$) will be optimized as design variables. The camber line is then given by a third-order Spline curve which connects the leading-edge, maximum camber and trailing-edge coordinates. The twist angle of each airfoil sections is also considered as a design variable. In total, 18 design variables are used.

The unstructured grid generation was performed for each design candidate by using the dynamic mesh technique [10]. First, the baseline unstructured grid was generated for a wing without camber or twist. Then, a grid for a wing with specified camber and twist was generated by the dynamic mesh technique. The flow calculation was also accelerated by using the space marching technique [11]. The evolutionary computation was performed for 70 generations using 50 individuals in the population.

Figure 2 shows the optimization history in terms of the performance of the best individual among each generation. It clearly shows the improvements in the design objective. Figure 3 shows the twist angle distribution of the optimal wing. It indicates that the design accounts for the kink.

Figure 4 shows the spanwise loading distribution of the designed wing. It does not show the elliptic loading,

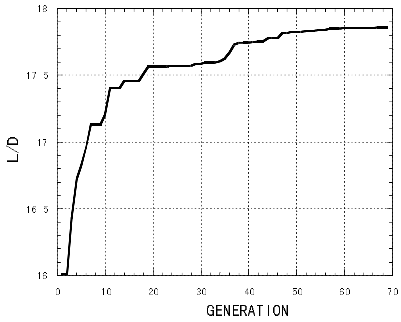

Figure 2. Optimization history

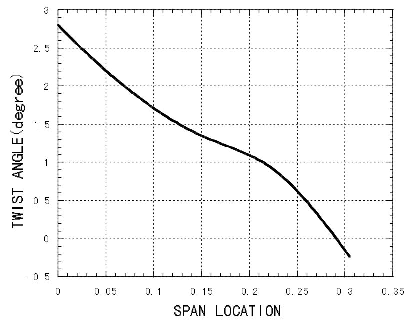

Figure 3. Twist angle distribution of the designed wing

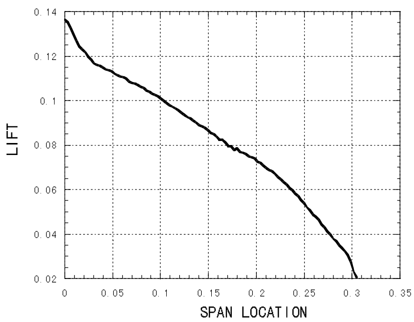

Figure 4. Loading distribution of the designed wing

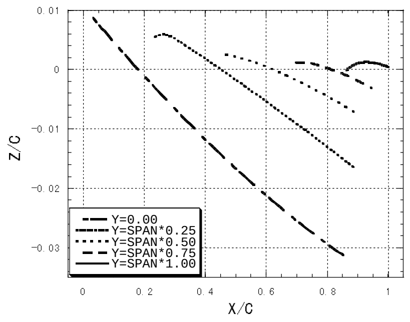

Figure 5. Camber lines of the designed wing

although the elliptic loading corresponds to the minimum induced drag due to the lift. Since the wave drag also depends on the lift in the supersonic flow, the loading pattern corresponding to the minimum drag does not yield the elliptic shape. The designed camber lines are shown in Fig. 5. The root section has a negative camber to compensate the long root chord that would generate a large lift otherwise.

The present computation took 8 hours of computational time, using 25 CPU's of NEC SX-4/128H4 computer at Computer Center of Tohoku University. The designed wing is not practical since the design space is very limited. A large number of design variables and constraints will be needed to produce a practical design. Nevertheless, the present result indicates that such evolutionary computations will be affordable.

3 MULTIDISCIPLINARY OPTIMIZATION OF WING PLANFORM DESIGN

Aerodynamic optimization often has to account for constraints, for example, structural strength. Such structural constraints might be derived from design optimization in the structural discipline. However, a simple sequential optimization that executes each disciplinary optimization task in sequence cannot take advantage of beneficial cross-disciplinary tradeoffs. Therefore, multidisciplinary design optimization (MDO) approach is desired. Formulation of such approach presents organizational challenges for coupling analysis codes in each discipline. Furthermore, MDO requires multiobjective, system-level optimization.

The conventional system-level optimization requires system sensitivity analysis. Although the techniques for sensitivity analysis of disciplinary subproblems are well established, they require expertise in each discipline, especially in CFD. When an analysis code for a discipline is updated, the system sensitivity analysis code must also be changed. This is not cost-effective in terms of the code development, since analysis codes in subproblems may be updated with more sophisticated codes frequently. A system-level optimizer is thus desired to be blind to the auxiliary information of subproblems. GAs use only objective function information, not derivatives or other auxiliary knowledge, and thus they are blind to specific problems. Therefore, GAs are attractive for solving system-level optimization.

MOGAs that can seek multiple Pareto solutions in parallel are very attractive for solving MDO problems with parallel computing. The previous research considered an application of MOGA to MDO of the transonic wing planform design [2]. A similar approach is applied to MDO of supersonic wing planform design in this research.

To show the applicability of MOGA to the supersonic wing planform design, the present multiobjective optimization problem considers to

1. Minimize aerodynamic drag
2. Minimize wing weight
3. Minimize aspect ratio for structure

under a geometric constraint of the semispan-to-length ratio.

The definition of the supersonic wing planform geometry is also simplified here. The planform parameters were assumed as the semispan-to-length (lifting length of the wing) ratio of 0.45 and the root chord of 14.3 *ft* at cruise Mach number of 2.0. The flat-plate wing was assumed. Then, only four parameters are chosen as design variables: inboard and outboard sweep angles, chord length of the kink, and spanwise location of the kink. The tip chord length can be calculated from the specified parameters. These parameters can still produce a wide variety of planform shapes.

The objective functions and constraint are computed as follows. First, drag is evaluated, using the linearized theory for supersonic flows [12]. Second, wing weight is calculated, using the transonic algebraic weight equation [13]. The weight formula will be upgraded to a more adequate model for supersonic wings in future. Third, the aspect ratio is used instead of evaluating the structure, assuming that a lower aspect ratio provides stronger stiffness. Since the present disciplinary models are very simple, 100 individuals are used in the following evolutionary computation. The present supersonic MDO code takes only a few minutes of computational time on the SGI Indy workstation.

In this problem, an average rank of the population due to the Pareto ranking and fitness sharing methods was monitored for convergence as shown in Fig. 6. After several generations, all 100 individuals became Rank-1 because the best *N* selection was used here. The actual rank number still fluctuated afterwards due to the sharing. Since the present problem does not have a scalar objective function, it is difficult to illustrate convergence in terms of the objective function value. Thus in future, a better index for convergence is required.

Figure 7 shows the Pareto front in the objective function space and the planform shapes of the extreme Pareto solutions. The planform shape which gives the minimum drag has the largest aspect ratio. It also has the smallest wing area, and thus it gives the minimum wing weight. One of the compromised solutions is given by the center of the Pareto front. It tries to minimize the drag as well as to maximize the aspect ratio. Although the present disciplinary models are too simple to produce realistic designs, the extreme Pareto solutions are physically reasonable. This confirms the feasibility of the present approach for solving MDO problems of supersonic wing planform shapes.

4 CONCLUSION

Feasibility of evolutionary computations for supersonic wing design optimization was demonstrated by the single-objective aerodynamic optimization and multiobjective, multidisciplinary optimization. The aerodynamic optimization problem seeks an optimal supersonic wing shape using the Euler equations. The multidisciplinary optimization problem seeks an optimal supersonic wing planform shape using linearized aerodynamics and wing weight algebraic estimation.

Coupling the evolutionary approach with CFD codes, for example, the Euler code in this research, requires large computational time due to expensive function evaluations. However, the total computational time will be affordable with recent vector-parallel computers.

MOGA has been applied to MDO problems of supersonic wing planform shapes. Since MOGAs reveal tradeoffs between multiple objectives from a population of Pareto solutions, they will be an efficient system-level optimizer for MDO. MDO researches coupled with nonlinear CFD codes will be performed in the near future.

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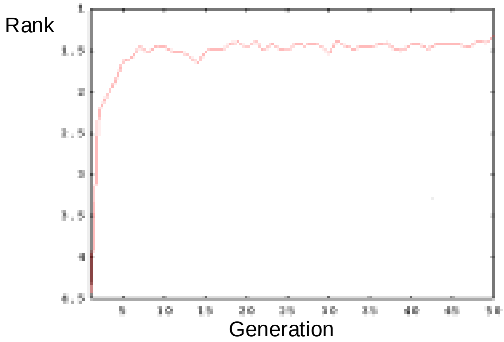

Figure 6. Rank-based convergence history

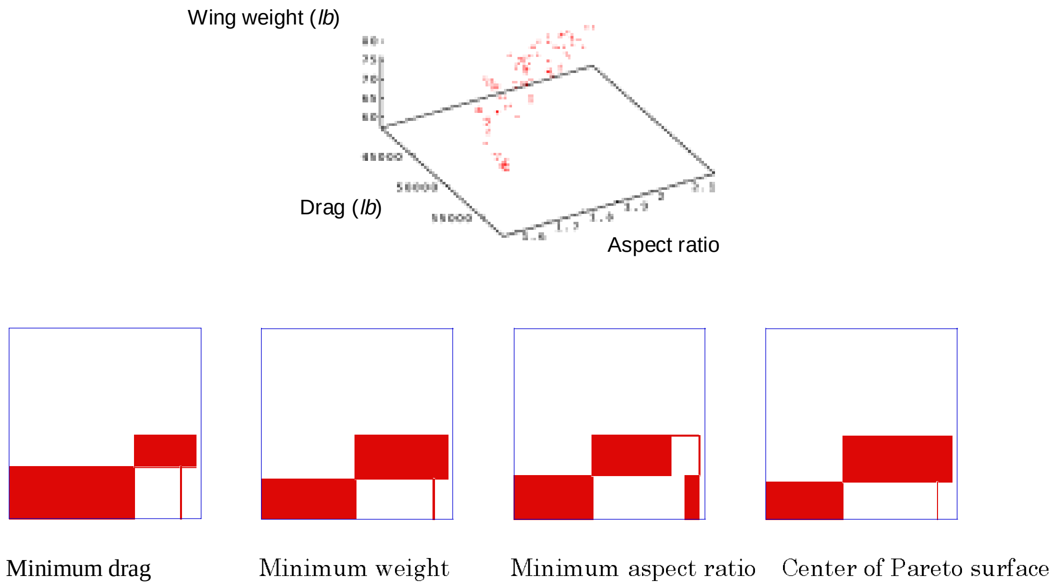

Figure 7. Pareto front and extreme Pareto solutions