Table 1 Residual bending and tip plane inclination in forward flight<sup>a</sup>

| Speed, | $\theta_{\mathbf{tp}}$ | $\frac{1}{2}\theta_{tp}$ |          |
|--------|------------------------|--------------------------|----------|
| kn     | deg                    | rad                      | $M_x/Q$  |
| 0      | -4.9692                | -0.04336                 | -0.04327 |
| 10     | -4.5464                | -0.03967                 | -0.03963 |
| 20     | -4.0913                | -0.03570                 | -0.03574 |
| 30     | -3.5879                | -0.03131                 | -0.03142 |
| 40     | -3.0461                | -0.02658                 | -0.02670 |
| 50     | -2.4846                | -0.02168                 | -0.02181 |
| 60     | -1.9201                | -0.01676                 | -0.01693 |
| 70     | -1.3755                | -0.01200                 | -0.01219 |
| 80     | -0.8511                | -0.00743                 | -0.00761 |
| 90     | -0.3485                | -0.00304                 | -0.00311 |
| 100    | 0.1377                 | 0.00120                  | 0.00139  |

Fixed shaft, cyclic input is 5-deg forward.

that, within the range of inclinations allowed in the Robinson R22, Eq. (16) is a very close approximation.

The data plotted in Fig. 2 are for idealized hover. The data were obtained by fixing the shaft, adjusting the collective to eliminate vertical acceleration, and then applying the longitudinal cyclic input. The tip plane followed the swashplate to within 0.1 deg. The residual bending moment is shown non-dimensionalized by  $Q_0$ .

To first-order, Eq. (16) could be replaced with  $\bar{M}_{ry} = \frac{1}{2}\theta_{tp}Q_0$ . What is plotted in Fig. 2 is  $\bar{M}_{ry}/Q_0$ . Equation (16) was left in terms  $\bar{Q}$ , because it turns out that agreement with the computer simulation is even closer that way. Had the Bladehelo results been plotted as  $\bar{M}_{ry}/\bar{Q}$ , the two curves in Fig. 2 would then be indistinguishable.

Table 1 shows that Eq. (16) remains very nearly true in forward flight. The data in Table 1 were computed with the shaft fixed vertical and with a constant forward cyclic input of 5 deg.  $\theta_{\rm up}$  varies with speed because of blowback. Table 1 presents the values of  $\theta_{\rm up}$  that resulted and compares  $\frac{1}{2}\theta_{\rm up}$  to  $M_{\rm x}/\bar{Q}$ .

The inputs into Bladehelo were selected to represent a Robinson R22  $\beta$ . An assessment of the accuracy of the numerical computation in Appendix B of Ref. 1 shows that the moments produced by Bladehelo are accurate to a fraction of a percent. The data presented show that Eqs. (16) and (18) remain very nearly true over a wide range of flight conditions.

## IV. Magnitude and Significance of Residual Bending

In first-order, residual bending, like the normal control moment, is proportional to the tip plane inclination. For teetering rotors, the ratio of the residual bending moment [Eq. (16)] to the control moment that results from tilting the thrust is

$$\zeta_{r,\text{teeter}} = \bar{Q}/2Th \tag{19}$$

When this is applied to the Robinson R22 in out of ground effect (OGE) hover at full takeoff (TO) power (131 hp), residual bending amounts to 7.9% of the normal control moment. This is reduced to 7.5% at the maximum continuous power (124 hp), and is further reduced in proportion to power required under more favorable conditions. (The numbers are based on the assumption that 90% of the engine power reaches the main rotor.)

In the case of offset flapping hinges, Eq. (19) must be replaced by

$$\zeta_r = \frac{\bar{Q}}{2Th + N_b e K \Omega^2} \tag{20}$$

to account for conventional hub moments. Applied to the AH-64, Eq. (20) computes as 4%.

The effect of residual bending is to make the total effective control moment act in a direction that is off (in a conventional American helicopter, to the left) from the direction in which the tip plane is tilted. The difference is

$$\delta \psi_r = \arctan \zeta_r \tag{21}$$

which amounts to 4 deg in the Robinson R22 and 2 deg in the AH-64.

The residual cross-coupling effect may already be embedded in those codes that, like Bladehelo, are based on full and correct blade dynamics. However, it is unfamiliar to the community, as an effect to be anticipated and included in preliminary estimates.

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### Multiobjective Genetic Algorithm for Multidisciplinary Design of Transonic Wing Planform

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#### Introduction

PORMULATION of multidisciplinary optimization (MDO) presents organizational challenges for coupling analysis codes from each discipline. A simple sequential optimization that executes each disciplinary optimization task in sequence cannot take advantage of the benefits from cross-disciplinary tradeoffs. Therefore, MDO requires multiobjective, systemlevel optimization.

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. Conventional optimization techniques seek such solutions one-by-one. Genetic algorithms (GAs), however, 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

Received April 7, 1997; revision received June 11, 1997; accepted for publication June 12, 1997. Copyright © 1997 by the American Institute of Aeronautics and Astronautics, Inc. All rights reserved.

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can be examined quantitatively. These characteristics make Pareto-based GAs very attractive for solving multiobjective problems

GAs are search algorithms based on the mechanics of natural selection and natural genetics. They are different from the conventional optimization algorithms in that they use only objective function information, not derivatives or other auxiliary knowledge. In other words, they are blind to specific problems. This feature also makes GAs attractive for solving system-level optimization.

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. 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 code development, because analysis codes in subproblems may be updated frequently with more sophisticated codes. A system-level optimizer is thus desired to be blind to the auxiliary information of subproblems.

Another advantage of GAs is their suitability to parallel processing. Because the majority of computational time will be consumed by function evaluations (aerodynamic computations), the simple master–slave scheme<sup>2</sup> can be used to improve computational efficiency of the present computation. The master process controls selection, mating, and the performance of genetic operators. The slaves simply perform function evaluations. Because GAs can be parallelized more effectively than conventional optimization methods, they will be more efficient in parallel computing environments.

Therefore, Pareto-based GAs are very attractive for solving MDO problems with parallel architecture. In this paper, a multiple objective genetic algorithm (MOGA)<sup>3</sup> is applied to the simultaneous aerodynamic and structural optimization of a transonic wing. Similar studies have been reported.4-6 Reference 4 provides a more accurate multidisciplinary model including aeroelasticity than the present work, but only one single optimal solution per one proposed objective function was obtained because of the use of the conventional gradient-based approach. Reference 5 employed one of the Pareto-based GAs, but did not take advantage of parallel computation. Reference 6, in contrast, performed a parallel computation. However, its GA was conventional, not Pareto-based. In Refs. 5 and 6, the aerodynamic models were limited to subsonic flows and the structural models were based on a simple beam. Therefore, the present research aims for a transonic wing planform design with a wing-box structure using Pareto-based GAs in parallel computing.

#### **Approach**

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

Because the purpose of the present design is a demonstration of MOGA as a system-level optimizer, the design variables for wing geometry are greatly reduced. First, aircraft sizes were assumed to have a span length of 94.9 ft and a total weight of 95,000 lb, with 156 passenger seats at a cruise Mach number of 0.82. Next, as a baseline geometry, a transonic wing was taken from a previous research. The original wing has an aspect ratio of 9.42, a taper ratio of 0.246, and a sweep angle at the quarter-chord line of 23.7 deg. It has a trailing-edge kink at a 37.7% semispan location. Its airfoil sections are supercritical, and their thickness and twist angle distributions are reduced toward the tip. Then, only three parameters are chosen as design variables: sweep angle, chord length at the kink, and chord length at the tip. These parameters can produce a wide variety of aspect and taper ratios at various sweep angles. In

the following, these three real numbers are regarded as strings of genetic codes of design candidates.

The objective functions and constraints are computed as follows. First, drag is evaluated, using a potential flow solver called FLO22. The code can solve subsonic and transonic flows. From the flowfield solution, lift and drag can be post-processed. Because the flow is assumed inviscid, only a sum of the induced and wave drag is obtained. Second, the wing weight is calculated, using an algebraic weight equation. Third, the fuel weight is calculated directly from the tank volume given by the wing geometry. Finally, the structural model is taken from Ref. 4. 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 constraints' violations are now passed on to the system-level optimizer. MOGA (Ref. 3) is employed as the system-level optimizer. Starting from the initial population, a simple GA proceeds with three operators: 1) reproduction, 2) crossover, and 3) mutation.<sup>2</sup> Reproduction is a process in which individual strings are copied according to their fitness values. This implies that strings with a higher fitness value have a higher probability of contributing one or more offsprings in the next generation. In MOGA, the Pareto-based ranking method is developed so that near-Pareto-optimal solutions are assigned higher fitness values. When any constraint is violated, the rank of a particular design is lowered by adding 10. Furthermore, by implementing the fitness-sharing technique,<sup>2,3</sup> one can expect to evolve a uniformly distributed representation of the global tradeoff surface.

The reproduction process produces a mating pool, then crossover proceeds in two steps. First, members in the mating pool are mated at random, and second, each pair of strings undergoes partial exchange of their strings. This results in a pair of strings of a child generation. Mutation is a random change of a string that occurs during the crossover process at a given mutation rate. Mutation implies a random walk through the string space and it plays a secondary role in simple GA. The arithmetical crossover and nonuniform mutation operators are used here. As the elite strategy, the two best strings in the old generation are copied into the next generation without crossover or mutation.

The present method has been implemented at the Numerical Wind Tunnel (NWT) at the National Aerospace Laboratory, a parallel vector machine with 166 processing elements (PEs) at a peak performance of 279 GFLOPS. A typical FLO22 calculation takes roughly 30 s on a single PE at NWT. Computational costs for GA operators were negligible. In the following case, 50 generations are computed with a population size of 100. By using 100 PEs, the following case took roughly 25 min at NWT.

#### Result

In this research, a number of Rank-1 individuals in the Pareto-ranking method was monitored for convergence. After 23 generations, all 100 individuals became Rank-1. Because the multiobjective optimization does not have a scalar objective function, it is difficult to illustrate convergence in terms of the objective function value. Thus, in the future, a better index for convergence is required.

Figure 1 shows the locus of Pareto solutions in the objective space. All three axes are arranged so that the left lower corner becomes the desired direction. The two-dimensional projection to the design plane of wing—weight vs fuel-weight shows a distinct Pareto front, because less wing weight means less space for the fuel tank. Figure 2 shows the original and optimized wing planform shapes. The minimum-drag wing has a slightly larger taper ratio than expected because the original wing is twisted down. The shapes corresponding to the minimum wing weight and the maximum fuel weight can be distinguished easily. The wing design taken from the center of

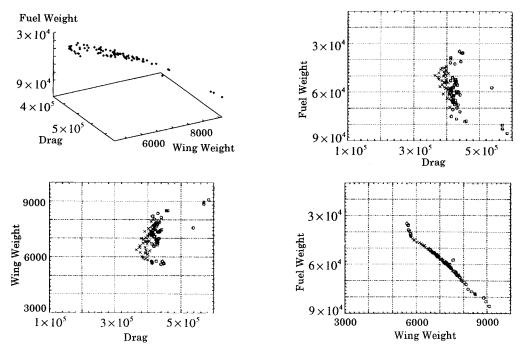


Fig. 1 Pareto solutions in the objective function domain.

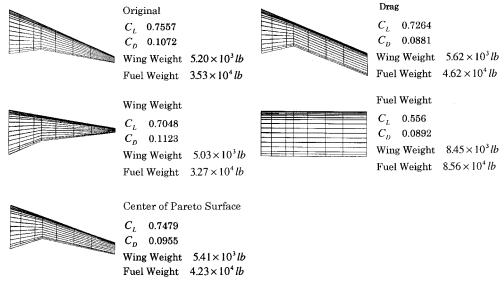


Fig. 2 Planform shapes of Pareto solutions.

the Pareto surface has the most reasonable shape and can be considered as the best compromise between the multiple objectives presented here.

#### **Conclusions**

Multiobjective Genetic Algorithm based on the Pareto ranking has been applied to the multidisciplinary optimization of a transonic wing planform. The present optimizer can find Pareto solutions at a system level in parallel. The method has been implemented at the Numerical Wind Tunnel by using the master–slave concept. Planform shapes with minimum drag, minimum weight, and maximum fuel weight, (tank volume) under constraints of lift and structural strength, were sought by using the analysis model that consisted of potential flow, algebraic weight, and wing–box structure equations. A wide variety of Pareto solutions were obtained, including a good compromised solution. The computational time was about 25 min in the parallel computing environment. These results in-

dicate the feasibility of the present approach for multidisciplinary optimization.

#### Acknowledgment

The first and second authors' work was supported by de Havilland, Inc., Canada.

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# **Vortex Flaps Canard Configuration for Improved Maneuverability**

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#### Introduction

M ODERN design of air-to-air missiles is directly connected to flying at high angles of attack. The needs of maneuverability, as well as improved tracking features, dictate the basic design goals. However, the region of high angles of attack presents many difficulties for canard configurations. The use of such configurations has three main advantages.

- 1) The forward location of the control surfaces enables close and easy connection between the tracking and control systems, as well as the installation of the control servomotors at a convenient location.
- 2) The long distance between the control surface and the c.g. enables the production of large moments by small control forces.
- 3) The forces on the control surfaces are in the same direction as the intended maneuver, which gives a better dynamic response than tail control.

With all of these merits in mind, it is evident that a canard-controlled configuration having the ability to perform at high angles of attack would be desirable; however, experience shows that a loss of controllability occurs in this region. This loss of controllability is attributed to the flow separation over the canard surface. At high deflection angles combined with high angles of attack, it is impossible to maintain a monotonically growing lift force. Another aspect of this problem is connected with the control method that is based on hinge moment control as opposed to direct force control. This method calls for monotonic behavior of the hinge moment. The breakdown of the vortex, in addition to the change in the lift force slope, also causes a forward motion of the c.p., which results in pitch-up of the control surface.

To overcome this situation, a solution is sought that will enable a control surface to achieve high angles of attack, maintaining a monotonically growing lift force, and, preferably, hinge moment. Such a solution was suggested by Katz et al. Their solution was based on a split canard configuration, where part of the canard was free to move around a hinge, and contributed lift only at high combined angles. The results showed improvement in the high-angle-of-attack range, but a low efficient configuration at the low-angle-of-attack range.

The new approach presented in this Note is based on the use of vortex flaps. The vortex flaps technique is common in airplane configurations that have delta wings. The vortex flaps effect is to redirect the leading-edge suction. The leading-edge suction reduces the drag when the flow is attached to the wing; however, delta wings flying at moderate and high angles of attack have a separated flow that generates the leading-edge vortex. This vortex enhances the suction above the wing upper surface, generating an additional lift, referred to as the nonlinear lift. The drag, however, grows as well. Polhamus leadingedge suction analogy<sup>5</sup> supplies a tool to calculate this additional lift, as well as an explanation of how the repositioning of the suction peak above the wing enhances the lift and drag. By implementing the vortex flap, the effective angle of attack on the leading edge is reduced, and the positioning of the leading-edge vortex and the direction of the suction force can be controlled. Rao, 6 as well as other researchers, have shown that an optimization of the lift-to-drag ratio can be obtained, and the airplane performance can be improved. The lift-to-drag ratio has little importance for canard performance, and the difference in the geometry of a typical canard configuration compared to the geometry of a wing in airplane configuration results in no benefits to the lift-to-drag ratio when vortex flaps are attached to thick delta wings. However, Ref. 7 shows that vortex flaps can produce a considerable delay in the stall angle, which is a favorable characteristic sought for canard configurations. The feasibility of this idea was tested experimentally in the current investigation.

#### **Test Model and Apparatus**

Tests were conducted in the  $0.6\times0.8$  m transonic wind tunnel in the Wind Tunnel Laboratory in the Aerodynamic



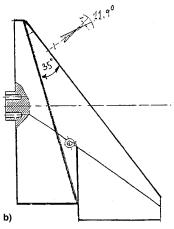


Fig. 1 a) Vortex flap model and b) canard and vortex flap.

Received Aug. 29, 1996; revision received Jan. 8, 1997; accepted for publication May 30, 1997. Copyright © 1997 by the American Institute of Aeronautics and Astronautics, Inc. All rights reserved.

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