Aerodynamic Optimization of Transonic Wing Design Based on Evolutionary Algorithm

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ABSTRACT: Evolutionary Algorithm (EA) is applied to a practical three-dimensional shape optimization for aerodynamic design of an aircraft wing. Aerodynamic performances of the design candidates are evaluated by using the three-dimensional compressive Navier-Stokes equations. A structural constraint is introduced to avoid an apparent solution of zero thickness wing for low drag in high speeds. To overcome enormous computational time necessary for the optimization, the computation is parallelized on Numerical Wind Tunnel at National Aerospace Laboratory in Japan, a parallel computer with 166 vector-processing elements. The results ensure the capability of the EA in handling large-scale design optimizations.

KEYWORDS: optimization, evolutionary algorithm, CFD, wing, parallel computing

AMS(MOS) subject classification:

1. INTRODUCTION

The aircraft industry, like others, is increasingly exposed to considerable commercial pressures: Boeing Company and Airbus Industrie are struggling for supremacy on the large-size civil airliner (seating more than 100 passengers) market, while many companies, such as Bombardier, Embraer, Dornier, Dasa, are fighting for a larger share of the expanding regional jet aircraft market. Since the success of such commercial products depends on cost and timeliness as well as quality, the design process is being reengineered to save cost and time scales.

With advances in Computational Fluid Dynamics (CFD) and computer hardware, CFD has become an integral part of the aircraft design process. CFD has contributed to cut aerodynamic design cost and time scales by reducing the number of required wind tunnel tests. However, it is just an instrument for estimating aerodynamic performance of a given aircraft configuration. On the whole, the basis of the design process is trial and error, and the success of the final design depends on the knowledge and intuition of the designer. CFD technology will be able to display its ability to the full when it is coupled with numerical optimization methods by displacing any human interactions in the design procedure.

Yet, despite the fact that numerical optimization methods have been successfully used for a countless number of design problems, an application of numerical optimization to aerodynamic design still remains as a formidable challenge because of the following difficulties: 1) Objective function landscape of an aerodynamic optimization is often multimodal and nonlinear because the flow field is governed by a system of nonlinear partial differential equations 2) Function evaluations using a CFD code, especially a three-dimensional Euler or Navier-Stokes code, are very expensive. Due to the above difficulties, aerodynamic design problems require a numerical optimization tool to be very robust and efficient as well.

The gradient-based methods are well-known optimization algorithms that probe the optimum by calculating the local gradient information. These methods are efficient in searching optimums. Not only that, the optimum obtained from these methods will be a global one, if the objective and constraints are differentiable and convex. Therefore, this approach has been widely used for many design problems including wing design [1], scramjet nozzle design [2], supersonic wing-body design [3], and more complex aircraft configurations [4,5].

Distribution of an objective function of an aerodynamic design problem, however, is usually multimodal, and thus, one could only hope for a local optimum neighboring the initial design point by using the gradient-based methods. Therefore, to find a global optimum, one must start the optimization process repeatedly from a number of initial points and check for consistency of the optima obtained. In this sense, the gradient-based methods are neither efficient nor robust for design automation.

Evolutionary Algorithms (EAs) are emergent optimization algorithms mimicking mechanism of the natural evolution, where a biological population evolves over generations to adapt to an environment by selection, recombination and mutation. When EAs are applied to optimization problems, fitness, individual and genes usually correspond to an objective function value, a design candidate, and design variables, respectively. One of the key features of EAs is that they search from multiple points in the design space, instead of moving from a single point like gradient-based methods do. Furthermore, these methods work on function evaluations alone and do not require derivatives or gradients of the objective function. These features lead to the advantages such as Robustness, suitability to parallel computing and simplicity in coupling CFD codes. Owing to these advantages over the analytical methods, EAs have become increasingly popular in a broad class of design problems (for example, see [6]). EAs have been also successfully applied to aerodynamic shape optimization problems such as airfoil shape design [7,8], Multi-element airfoil shape design [9], subsonic wing shape design [10] and supersonic wing shape design [11].

The previous applications of numerical optimization methods, however, are restricted to more or less simplified problems involving not more than 10-30 design parameters. In contrast to that, in real-world design problems, a large number of design parameters must be handled – for example, a wing shape for a generic transonic aircraft usually parameterized by more than a hundred of design parameters. Since such problem has highly multidimensional search space and extremely complicated objective function distribution, even EAs would fail to find a globally optimum.

The objective of this research is to demonstrate capability of an up-to-date EA in handling real-world large-scale design optimizations. In the present study, the real-coded Adaptive Range Genetic Algorithm (real-coded ARGA) [12] coupled with the structured coding [13] will be applied to a practical transonic wing design optimization. The real-coded ARGA is an emergent EA that can solve large-scale design optimization problems very efficiently by promoting the population toward promising design regions during the optimization process. The structured coding also improves EA search ability by rearranging coding structure by examining interactions between design parameters in advance.

2. FORMULATION OF DESIGN PROBLEM

The objective of the present wing design problem is maximization of the lift-to-drag ratio *L/D* at the transonic cruise design point, maintaining the minimum wing thickness required to stand the bending moment due to the lift distribution. The cruising Mach number and the angle of attack are set to 0.8 and 0 degree, respectively.

The planform of the supercritical wing in the NASA Energy Efficient Transport (EET) Program [14] is selected as the test configuration for the following design case (Fig.1). Wing profiles of design candidates are parameterized by the PARSEC airfoils [15]. A remarkable point of this parameterization technique is that it has been developed aiming to control important aerodynamic features effectively by selecting the design parameters based on the knowledge of transonic flows around an airfoil. It is reported that the PARSEC is the most efficient airfoil shape parameterization technique among typical parameterization techniques for aerodynamic optimization [16]. Similar to 4-digit NACA series airfoils, The PARSEC parameterizes upper and lower airfoil surfaces using polynomials in coordinates *X*, *Z* as,

$$Z = \sum_{n=1}^{6} a_n \cdot X^{n-1/2} \tag{1}$$

where a_n are real coefficients. Instead of taking these coefficients as design parameters, the PARSEC airfoils are defined by basic geometric parameters: leading-edge radius, upper and lower crest location including curvatures, trailing-edge ordinate, thickness, direction and wedge angle as shown in Fig. 2. These parameters can be expressed by the original coefficients a_n by solving simple simultaneous equations. Eleven design parameters are required for the PARSEC airfoils to define an airfoil shape in total. In this paper, ten design variables are used to give an airfoil shape with zero trailing-edge thickness.

The PARSEC parameters and the section angle of attack (in other words, root incident angle and twist angle) are given at seven span sections, of which spanwise locations are also treated as design variables except for the wing root and tip locations. The PARSEC parameters are rearranged from root to tip according to the airfoil thickness so that the resulting wings always have maximum thickness at the wing root. The twist angle parameter is also rearranged into numerical order from tip to root. The wing surface is then interpolated in spanwise direction by using the second-order Spline interpolation. In total, 87 parameters determine a wing geometry. Parameter ranges of the design space are shown in Table 1.

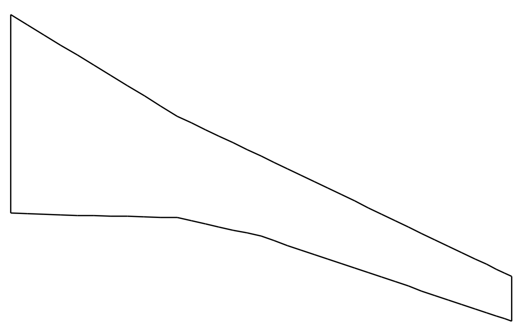


Figure 1 Wing planform

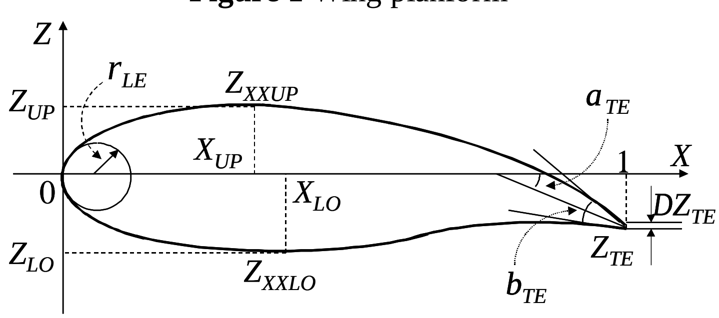


Figure 2 Design parameters for the PARSEC

Table 1 Parameter ranges of the design space

parameters	r_{LE}	Z_{TE}	a_{TE}	b_{TE}	X_{UP}	Z_{UP}	Z_{XXUP}	X_{LO}	Z_{LO}	Z_{XXLO}	twist ang
upper bound	0.030	0.01	-3.00	8.00	0.70	0.18	0.00	0.60	0.02	0.90	7 deg
lower bound	0.002	-0.01	-13.00	4.00	0.30	0.08	-0.30	0.20	-0.04	0.30	-1 deg

3. APPROACH

3.1 Aerodynamic analysis

The flow physics can be represented by a wide range of approximations. Among them, the Reynolds-averaged Navier-Stokes equations provide the state-of-aft of aerodynamic performance evaluation. Although a Navier-Stokes calculation requires large computer resources to estimate wing performances within a reasonable time, the three-dimensional Navier-Stokes equations must be solved because flows around a wing involve significant viscous effects, such as potential boundary-layer separations and shock wave/boundary layer interactions in the transonic regime. In this paper, a three-dimensional thin-layer Reynolds-averaged Navier-Stokes solver will be used to guarantee an accurate model of the flow field to demonstrate the feasibility of EA methodology. This code employs total variation diminishing type upwind differencing[17], the lower-upper symmetric Gauss-Seidel scheme [18], and the multigrid method [19].

3.2 Estimation of required thickness

To estimate the minimum thickness distribution to stand the bending moment due to the spanwise lift distribution, the wing structure is modeled by a thin walled box-beam as shown in Fig. 3. The skin panels of the box-beam are considered to shear the bending moment. For the brevity, the lift distribution is replaced by spanwise concentrated loads. The bending stress at each station is given by

$$s = \frac{\boldsymbol{M}}{\boldsymbol{I}}\frac{\boldsymbol{t}_1}{2} \tag{2}$$

where M represents the moment due to the lift. The second moment of area I is calculated as

$$\boldsymbol{I} = 2\cdot\left(\frac{\boldsymbol{t}_1}{2}\right)^2\cdot\boldsymbol{t}_2\cdot\boldsymbol{c} = \frac{1}{2}\boldsymbol{t}_1^2\cdot\boldsymbol{c}\cdot\boldsymbol{t}_2 \tag{3}$$

The constraint is then given by the local stress to be less than the ultimate shear stress of, say, Aluminum alloy 2024-T351.

$$s < s_{\boldsymbol{ultimate}} \tag{4}$$

Using Eqs. (2) to (4), we obtain the minimum thickness t_{min} at each segment,

$$t_1 > \frac{M}{s_{ultimate}\cdot c\cdot t_2} = t_{\min} \tag{5}$$

Following assumptions are made: the thickness of the skin panels is 2.5[cm] and its ultimate normal stress is $2.74\text{x}10^7$[kgf/m^2]. The length of the chord at wing root C_{root} and maximum wingspan $b/2$ are 10[m] and 18.8[m], respectively.

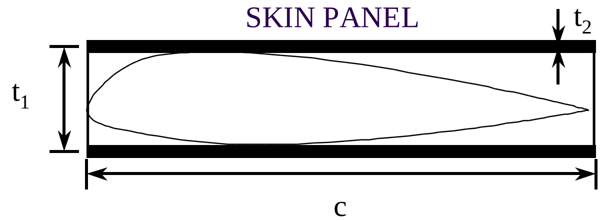


Figure 3 Box-beam modeling

3.3 Optimization using evolutionary algorithm

The real-coded ARGA [12] is used for the present optimization. The real-coded ARGA is an EA that can solve large-scale design optimization problems very efficiently by promoting the population toward promising design regions during the optimization process. The structured coding is incorporated to improve EA search ability further. Appropriate coding structure for efficient recombination is determined in advance by examining interactions between design parameters with experimental design method [20].

The present EA adopts the elitist strategy [21] where the best and the second best individuals in each generation are transferred into the next generation without any recombination or mutation. The parental selection consists of the stochastic universal sampling [22] and the ranking method [23]. Blended crossover (BLX-0.5) [24] is used for recombination. Mutation takes place at a probability of 10% and then adds a random disturbance to the corresponding gene up to 10% of the given range of each design parameter. The population size is kept at 64 and the maximum number of generations is set to 65. The initial population is generated randomly over the entire design space.

The main concern related to the use of EAs coupled with three-dimensional Navier-Stokes solvers for aerodynamic shape designs is the required computational effort. In the present case, each CFD evaluation takes about 100 min. of CPU time even on a vector computer. Because the present optimization evaluates 64 x 65 = 4160 design candidates, sequential evolutions would take almost 7000 h (more than half a year!).

Fortunately, parallel vector computers are now available in many institutions and universities. In addition, EAs are intrinsically parallel algorithms and can be easily parallelized. One of such computers is *Numerical Wind Tunnel* (*NWT*) [25] located at National Aerospace Laboratory in Japan. NWT is a MIMD parallel computer with 166 vector-processing elements (PEs) and its total peak performance and the total main memory capacity are about 280 GFLOPS and 45GB, respectively. In the present optimization, evaluation process at each generation is parallelized using the master-slave concept; the grid generations and the flow calculations associated to the individuals of a generation are distributed into 64 PEs of NWT. This makes the corresponding turnaround time almost 1/64 because the CPU time used for EA operators are negligible.

To handle the structural constraint, the constrained optimization problem is transformed into an unconstrained problem as

$$\textbf{\textit{fitness}}\ \ function = \begin{cases} 100 + L/D & \textbf{\textit{if}} \quad t_1 \geq t_{\min} \\ (100 + L/D)\cdot \exp(t_1 - t_{\min}) & \textbf{\textit{otherwise}} \end{cases} \tag{7}$$

where t_1 and t_{min} are thickness and minimum thickness at the span station of the maximum local stress. The exponential term penalizes the infeasible solutions by reducing the fitness function value. Because some design candidates can have negative *L*/*D*, the summation of 100 and *L*/*D* is used.

4. RESULTS

The optimization history of the present EA is shown in Fig. 4 in terms of *L*/*D*. During the initial phase of the optimization, some members had a strong shock wave or failed to satisfy the structural constraint. However they are weeded out from the population because of the resultant penalties to the fitness function. The final design has *L*/*D* of 18.91 (lift coefficient of 0.2621 and drag coefficient of 0.01386) satisfying the given structural constraint.

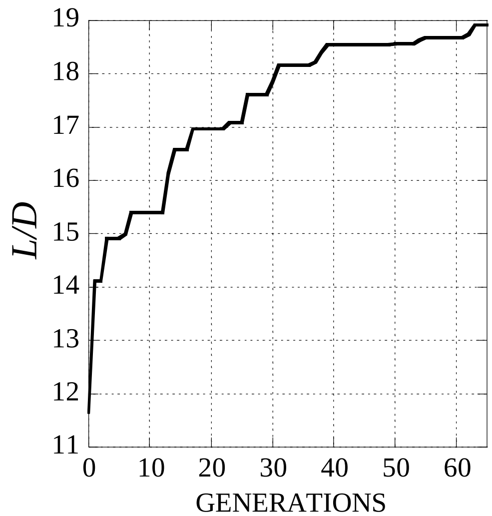


Figure 4 Optimization history in terms of *L*/*D*

The wing thickness distribution of the design is given in Fig. 5. The minimum thickness constraint appears at the kink because the inboard sections of the wing have large chord lengths and allow a large moment. The design satisfies this structural constraint while minimizing its thickness distribution to reduce the wave drag.

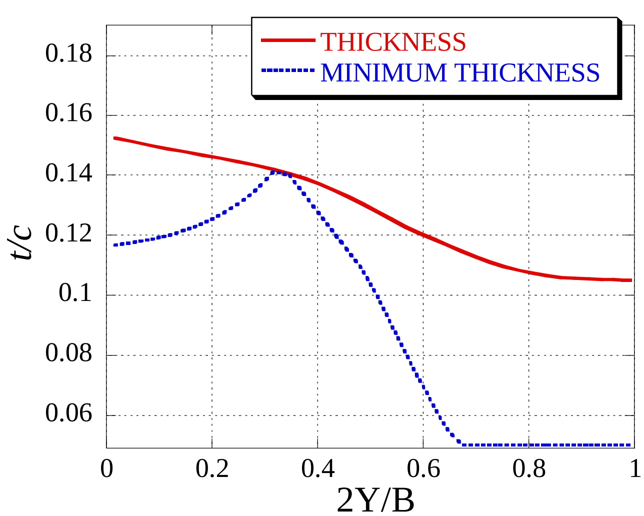
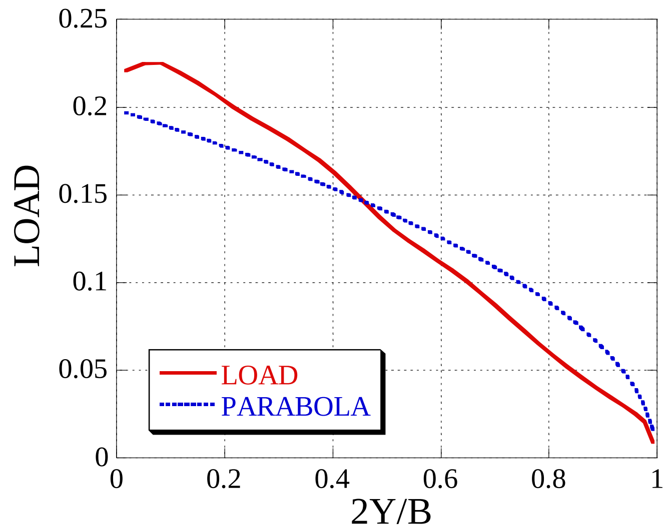


Figure 5 Spanwise thickness distribution

Figure 6 compares the span load distribution of the designed wing with a parabola that is known to give the minimum induced drag when the structural constraint is considered. The design does not have the parabolic span load distribution but a straight load distribution, which helps to reduce the bending moment at the inboard of the wing. The thickness distribution for the corresponding parabolic span load distribution is presented in Fig. 7. This figure shows that a design that minimizes the induced drag would have 18% thickness-to-chord. Such design would result in an unacceptably large wave drag associated with a stronger shock wave. This result indicates the structural constraint imposed a tradeoff between minimizations of induced drag and wave drag. The present straight span load distribution is a compromise of the tradeoff.



Fig**ure 6** Spanwise lift distribution

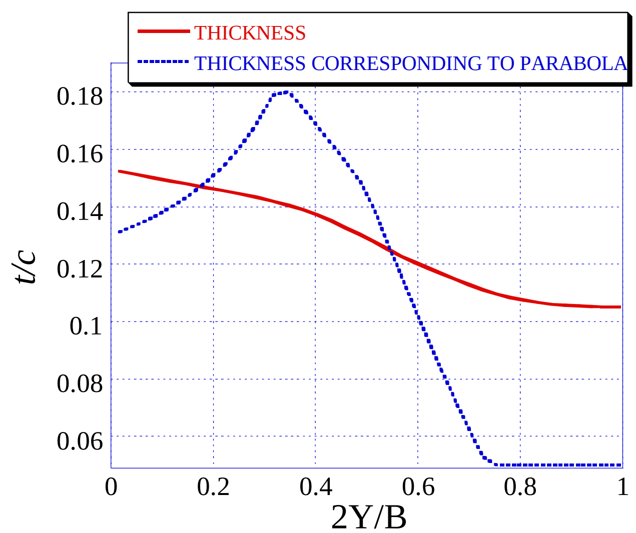


Figure 7 Comparison of thickness distributions between the present design and the minimum induced-drag design

The designed airfoil sections and the corresponding pressure distributions at the 0, 33, and 66% spanwise locations are shown in Fig. 8. In the pressure distributions, neither any strong shock wave nor any flow separation is found. This ensures that the present wing has very little wave drag and pressure drag. At 33 and 66% spanwise locations, the rooftop, front-loading and rear loading patterns are observed, which are typical for the supercritical airfoils [12] used for advanced transport today. The corresponding airfoil shapes are indeed similar to supercritical airfoils. Overall, these detailed observations of the design confirm that the present design is very close to a global optimum expected by the present knowledge in aerodynamics.

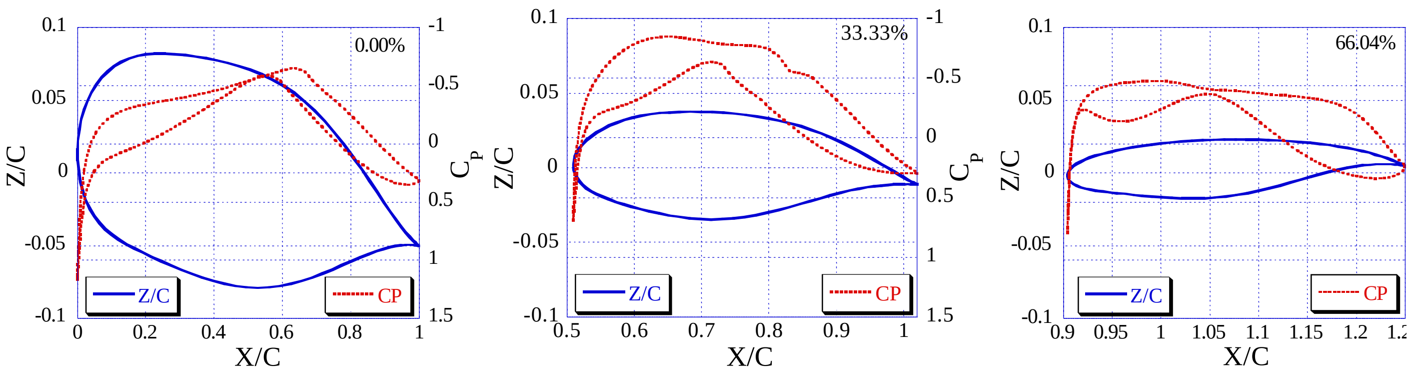


Figure 8 Designed airfoil sections and the corresponding pressure distributions

5. SUMMARY

Aerodynamic design optimization of a transonic wing shape for generic transport aircraft is demonstrated by using the real-coded ARGA coupled with the structured coding. Aerodynamic performances of the design candidates are evaluated by using the three-dimensional compressive Navier-Stokes equations to guarantee an accurate model of the flow field. A practical structural constraint is introduced to avoid an apparent solution of zero thickness wing for low drag in high speeds. To overcome enormous computational time necessary for the optimization, the computation is parallelized on NWT.

The designed wing has a fully attached flow and the allowable minimum thickness so that pressure drag and wave drag are minimized under the present structural constraint. Indeed the resulting wing appears very similar to advanced wing designs based on supercritical airfoils. The design also compromises the tradeoff between minimizations of the induced drag and the wave drag imposed by the structural constraint. These results ensure the capability of the present EA in handling large-scale design optimizations.

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