MULTI-POINT AERODYNAMIC OPTIMIZATION DESIGN OF A DUAL-AISLE AIRPLANE WING

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Abstract

Industrial supercritical wing aerodynamic design does not solely pursue minimum cruise drag coefficient, but a balance among cruise performances, robustness and geometry limitations. Although optimization methods have been widely applied in optimization designs, different methods can have different performances. In the present study, gradient optimization algorithm and RBF-assisted differential evaluation (RADE) algorithm are used in a beforehand cruise drag optimization to generate initial designs. Then a multi-point multi-objective multi-constraint optimization is carried out to gain the Pareto front of the drag coefficients of 3 flight conditions. Pressure distribution and geometry constraints are used to ensure robustness and industrial applicability.

1 Introduction

Aircraft wing design is a multi-disciplinary problem with robustness considerations. Designing a state-of-art supercritical wing requires comprehensive considerations regarding lift/drag ratio, buffet onset, drag divergence Mach number, geometry constraints, etc. Nowadays, in order to further improve fuel consumption efficiency, it becomes more and more complex to define the purpose of optimization design, and it raised even more difficulties in its realization. [1]

Optimization method has been well developed and applied in the industrial aircraft wing designs in the past few decades. Although various optimization methods have been proposed to achieve robust well-performance designs, the results gained by optimization algorithms are still mostly not feasible for industry usage. It is mainly due to the complexity of the practical application as well as the high modality of the optimization problems. [2,3]

One of the key problems is the definition of objectives and constraints. The supercritical wing aerodynamic design needs to compromise among cruise performances and off-design characteristics under geometry constraints. Usually a multi-point multi-objective multi-constraint optimization is carried out, which has a much lower efficiency due to the increase of problem modality. On the other hand, engineers usually have experiences and requirements that cannot be mathematically described. But they are usually critical to the industrial designing process, without which the optimization usually generates results with unsatisfying robustness or other drawbacks. [4,5] Therefore, in order to achieve these requirements while maintaining efficiency, the objectives and constraints need to be properly defined, and the optimization process may need to be constantly supervised and manipulated.

There have been several methods developed to introduce experiences and judgements into the optimization design, which are often based on pressure distributions. For example, airfoils' pressure gradient should not be too large so that flow separation does not occur, and aft loading should be limited in order to avoid unacceptable nose-down pitching moment. [6-8] One of these methods is "man-in-loop" strategy, it allows manual manipulation of the optimization process to introduce engineers' requirement and judgement. [1] Another one is pressure distribution oriented (PDO) optimization, which uses engineer-proposed pressure distribution considerations to improve robustness while optimizing performances. ZHANG et. al [9,10] studied the performances and robustness of 3 typical supercritical pressure distributions and used pressure distribution constraints to improve cruise performances and robustness while achieving the proposed weak wave pressure distribution. And the PDO method was also used to achieve different favorable pressure gradients for natural laminar airfoils for different desirable performances. [11]

In this paper, initial designs for a dual-aisle aircraft supercritical wing optimization are generated via two beforehand optimizations. Firstly, a gradient optimization based on adjoint method is carried out to reduce cruise drag coefficient. Then a RBF-assisted differential evaluation (RADE) algorithm [12] is used to optimized cruise drag while maintaining robustness using constraints and sub-optimization about pressure distribution considerations, where the sub-optimization on RBF response surface predicts well-performance designs satisfying pressure distribution requirements, and these individuals are added into the DE population to improve optimization efficiency. After that the initial designs are gathered, a 3-point multi-objective optimization is carried out to gain a Pareto front formed by drag coefficients of 3 flight conditions.

2 Modeling and Optimization Methods

2.1 Modeling and Deformation Methods

In the present paper, a 6th order Bernstein polynomial based Class Shape Transformation (CST) method is used to construct upper and lower surfaces of an airfoil. The wing surface is interpolated by 7 span-wise distributed airfoil sections, of which the locations are shown in Figure 1. The ranges of the variables are the same as those in reference [13].

A structural grid is used for CFD evaluation, and only the O-type grids surrounding the wing are updated according to the wing surface deformation. The surface grid deformation is interpolated based on the geometry deformation, and the interior grid cells are adjusted accordingly. Figure 2 shows the O-grid deformation of a wing section.

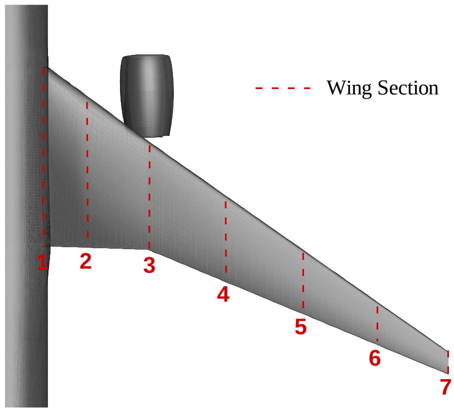


Figure 1 Wing section locations

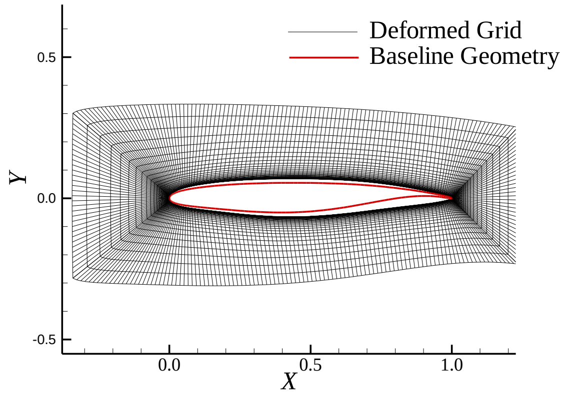
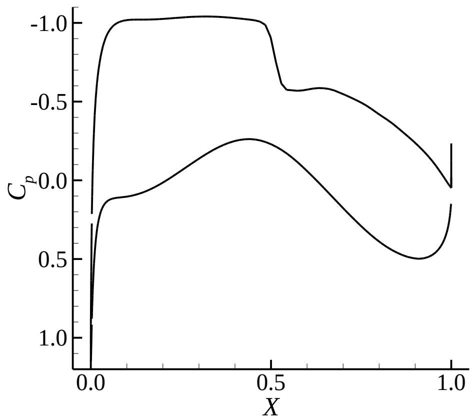


Figure 2 Geometry and grid deformation

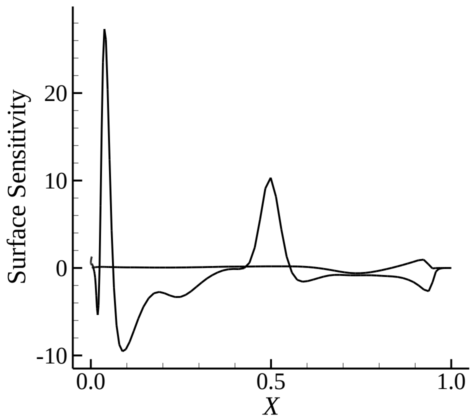
2.2 CFD and Adjoint Methods

The wing aerodynamic performances are evaluated by NSAWET, an in-house cell-centered finite volume compressible Reynolds average Navier Stokes (RANS) solver. The scheme for reconstruction and spatial discretization in the present paper are MUSCL and Roe's scheme, respectively. And LU-SGS is used for time advancing, and sheer stress transport (SST) model is used for turbulence modeling. The solver has been validated and successfully applied in many industrial designs. [9-11,13-15]

A continuous adjoint method solver (NSAWET-ADJ) with frozen viscosity assumption for RANS is developed on NSAWET, of which the formulations are mainly based on reference [16]. In the present paper, it employs 2nd order upwind scheme for reconstruction, Roe's scheme for spatial discretization, and LU-SGS method for time advancing. The pressure and surface sensitivity distributions of a supercritical airfoil evaluated by NSAWET-ADJ are shown in Figure 3. The gradients estimated by adjoint and previous mesh deformation method are validated with the gradients calculated by finite difference method, as shown in Figure 4. The adjoint solver can also be applied to 3D cases, Figure 5 shows the surface sensitivity distributions of a dual-aisle aircraft.



(1) Pressure distribution



(2) Surface sensitivity

Figure 3 Pressure and surface sensitivity distributions of a supercritical airfoil

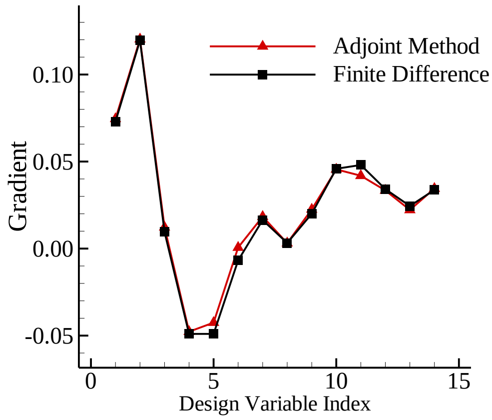


Figure 4 Gradients from NSAWET-ADJ and finite difference method

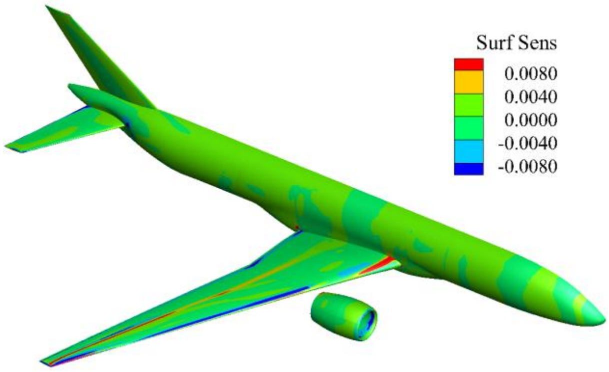


Figure 5 Surface sensitivity distribution of a dual-aisle aircraft

2.3 Optimization Methods

With the development of surrogate models, RADE, Kriging and other models have been widely used to improve optimization efficiency. In previous studies, a RADE algorithm was developed [12] to utilize calculated individual information by RBF, then a beforehand sub-optimization on the RBF response surface was conducted to predict excellent individuals for the DE algorithm. The predicted individuals are added into the current candidate population to participate in consequence DE process, and the CFD evaluations are still adopted. The basic steps can be seen in Figure 6. The sub-optimization on RBF response surface can have different objectives and constraints comparing to the main optimization process, so that the RBF can be used to guide the main optimization to directions engineers prefer.

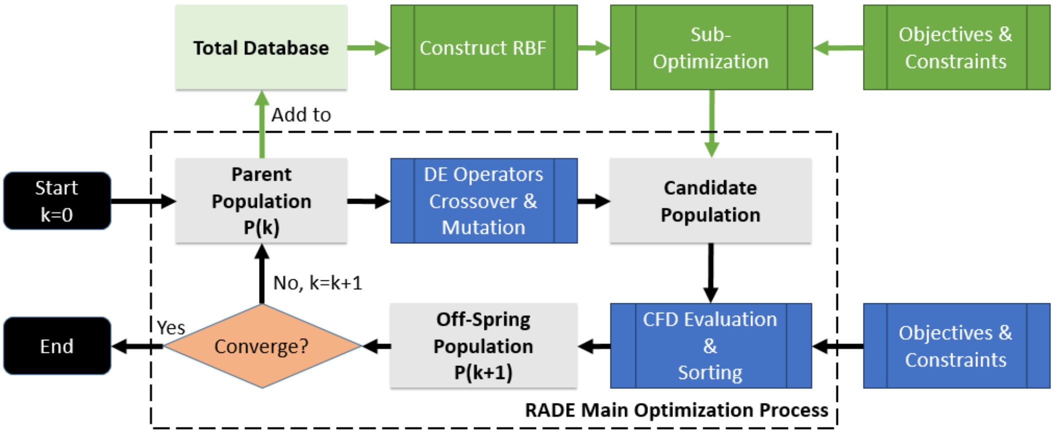


Figure 6 Flow chart of the RADE algorithm

As for the gradient optimization carried out in the present paper, Stanford SNOPT [17] toolbox is used, where the objectives and gradients are evaluated by NSAWET and NSAWET-ADJ, respectively.

3 Optimization Design of a dual-aisle aircraft supercritical wing

The aerodynamic optimization design of a supercritical wing needs to compromise among cruise performances, off-design characteristics and various geometry constraints. Therefore, an expensive multi-point optimization is required. However, it is too time consuming and unwise to conduct multi-objective multi-constraint optimizations in the early stage of a designing process. And it is reasonable to use single objective optimization, such as gradient optimization, to generate baselines for further optimization design.

In the present study, a full wing gradient optimization for cruise drag reduction using SNOPT and NSAWET-ADJ is carried out to generate a baseline design. The gradient optimization shows great efficiency in drag reduction, of which the final result, however, has unacceptable off-design characteristics. Therefore, a single-objective multi-constraint inboard wing optimization based

on RADE algorithm is carried out to generate the baselines, and the outer wing is gained by a previous multi-objective 2.75D airfoil optimization [13], of which the pressure distribution is shown in Figure 3(1). Then a multi-objective multi-constraint full wing optimization is carried out to gain the Pareto front of 3 flight condition drags, where the initial population is constructed by previous optimization results and random generated ones. The flight conditions of 3-point optimization are listed in Table 1.

Table 1 The 3 discussed flight conditions

Cruise (Condition 0)	Drag divergence control (Condition 1)	Buffet onset control (Condition 2)
M=0.85 C_L=0.48 Re=4 $\times 10^7$	M=0.87 C_L=0.48 Re=4 $\times 10^7$	M=0.85 C_L=0.60 Re=4 $\times 10^7$

3.1 Optimization Process

The beforehand cruise drag optimizations, i.e. gradient optimization and single objective RADE optimization, and the 3-point optimization share the same geometry constraints, which can be seen in Table 2. The full wing gradient optimization has no constraints other than the geometry ones. And to gain more robust results, several measures are taken in the single-objective inboard wing optimization. Firstly, the outboard wing sections use the same airfoil gained by previous study, which is well balanced between cruise performances and robustness , details can be seen in reference [13]. Then the inboard wing is optimized by a single-objective optimization with pressure distribution considerations embedded via RADE sub-optimization and constraints, and the detail settings can be seen in Table 2.

Table 2 Inboard wing optimization settings

	Main optimization	Sub-optimization
Objectives	cruise drag C_{d0}	cruise drag C_{d0} Summation of shockwave strengths $\sum \Delta C_{p,i}$ Summation of suction peak absolute pressure coefficients $\sum \left\|C_{p,suc}\right\|_i$
Constraints		
Amount of double shock sections	< 2	< 1
Pitching moment	< 0.065	
Leading edge radius	> critical values for 3 sections, respectively	
Maximum thickness	> critical values for 3 sections, respectively	
Others	Several constraints about pressure distribution considerations [10]	

In order to gain a fully developed Pareto front, the full wing 3-point optimization has no or loosen pressure distribution constraints comparing to the inboard wing optimization. And the convergence history of cruise drag coefficient C_{d0} in 3 optimizations are shown in Figure 7. Only the individuals of which the cruise drag are further reduced during the optimization are shown in the Figure 7, and the 3-point optimization convergence history starts form ID of 150 since its initial population is constructed by results from previous optimizations. And the plateau in the 3-point optimization is mainly the result of the development of Pareto front.

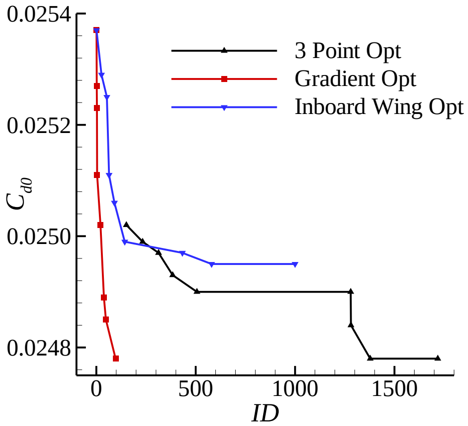


Figure 7 Convergence history of 3 optimization processes

In order to demonstrate the processes of the three optimizations, the optimization process and the Pareto front are plotted in 2 dimensions (Figure 8), i.e. the cruise drag coefficient C_{d0} and the average drag coefficient of the other two flight conditions. The results of two beforehand optimizations are also plotted. Figure 8 shows that the inboard wing optimization with robust outboard wing installed can gain more robust results than the gradient optimization, whereas the gradient optimization has much more efficiency, as shown in Figure 7. The reason that inboard wing optimization could not gain a better result is mainly due to the limitation of the pre-optimized outboard wing. Although 2.75D method can gain an excellent airfoil for the outboard wing in a significantly small cost, the actual 3D effects, such as cross flow, installation effect, etc., still have a quite great influence on the overall performances. Therefore, the outboard wing gained via 2.75D method should only be used as an initial design, and it needs further adjustment in the full wing optimization to improve the performances.

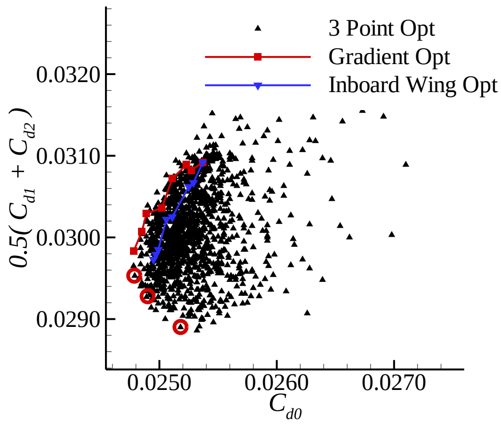


Figure 8 Optimization process and Pareto front of 3 point optimization

3.2 Selected Results and Robustness Analysis

The 3-point optimization is carried out in order to gain a well-balanced design among cruise performances and robustness. Usually, when a Pareto front is gained, engineers can choose the preferred design from these individuals basing on their own judgements. Three designs are selected from the Pareto front, which are flagged by red circles in Figure 8. From left to right, the three designs are named as 001, 002, and 003, and their pressure distributions of cruise condition are compared in Figure 9.

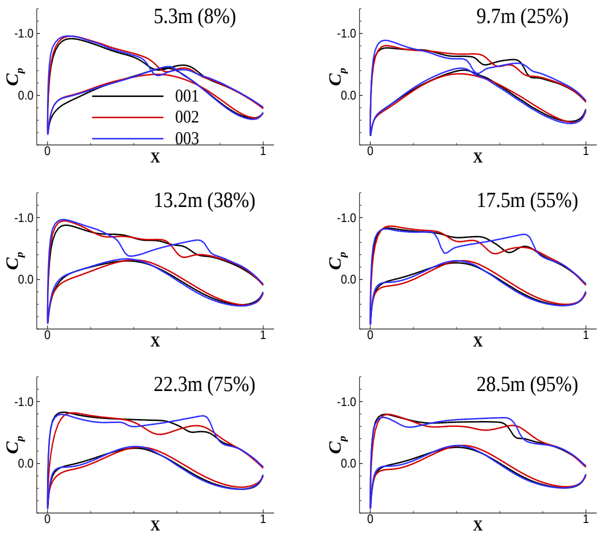
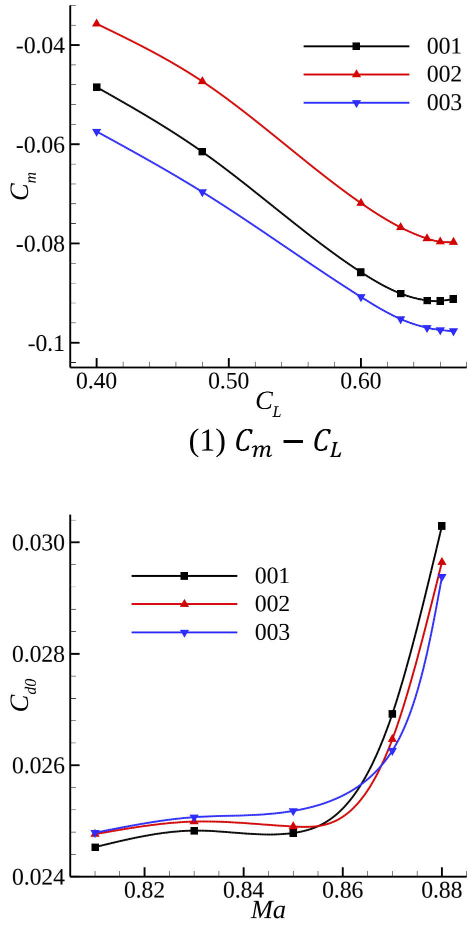


Figure 9 Cruise pressure distributions of 3 designs on Pareto front

Figure 10 (1) shows the $C_m - C_L$ curves of the 3 results. Figure 10 (2) shows the $C_{d0} - M$ curves. The inflection in $C_m - C_L$ curve can be used to define the buffet onset [18], and the $C_{d0} - M$ curve can be used to determine the drag divergence Mach number. The results show that 002 has low drag and good buffet and drag divergence performances. And although the cruise drag coefficient of 001 is slightly smaller than 002, its nose-down pitching moment is much larger, so that the trim drag may compromise its advantage. Furthermore, the buffet and drag divergence robustness of 001 are worse than 002, therefore, it is not always a good idea to pursue the optimized cruise drag coefficient. As for 003, though the design has excellent robustness, the overall drag coefficients are too large, and the pressure distributions are not satisfying, either. Therefore, 002 is the preferred design on the Pareto front.



(1) $C_m - C_L$

(2) $C_{d0} - M$

Figure 10 Buffet and drag divergence characteristics

4 Conclusion

Different optimization methods have different performances in supercritical wing aerodynamic optimization designs. Gradient optimization is most efficient in single objective cruise drag reduction, however, its results tend to have unsatisfying robustness, and engineers have difficulty to manipulate its process to guide the optimization to the preferred direction. RADE algorithm with pressure distribution as constraints and sub-objectives can guide the single objective cruise drag optimization to the preferred direction so that they can ensure the wing robustness.

In the present paper, beforehand single objective optimizations are carried out to generate initial designs. Then, a 3-point multi-objective optimization is conducted to gain the Pareto front. The performances and robustness of the final results on Pareto front are compared, and the results show that weak shockwave pressure distribution is a satisfactory balance between cruise drag and robustness.

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