Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 14
TPCEE 2026

Aircraft Aerodynamic Shape Optimization Through Kriging Surrogate Models

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Abstract. To address the high computational cost and long cycle of traditional aerodynamic optimization under transonic cruise conditions, this paper establishes a multi-objective optimization framework based on Kriging surrogate modeling, aiming to improve lift-to-drag performance of the wing platform with limited computational resources, thereby contributing to aircraft fuel economy. Taking a wing platform with NASA 2412/0012 airfoil sections as the baseline, eight parameterized design variables (including twist angles at five sections, root/tip chord lengths, and sweep angle) are defined. An Advanced Latin Hypercube Sampling (ALHS) generates initial design points, followed by CFD simulations to build a Kriging surrogate model. After achieving the prescribed accuracy, the surrogate model drives a Pareto-front search for maximum lift coefficient and minimum drag coefficient. The optimal design is finally verified by high-fidelity CFD. The selected optimal design shows that the Cl has increased by 4.9% and the Cd has decreased by 21.4%. The proposed surrogate-assisted optimization framework effectively balances accuracy and computational expense, enabling efficient exploration of complex design spaces.

Keywords: Kriging surrogate model; Multi-objective optimization; Surrogate-assisted optimization; Advanced Latin Hypercube Sampling.

1. Introduction

Fuel economy remains the core lifeblood of sustainable development of civil aviation transportation industry. Against the background of fuel costs accounting for a high proportion of total operating expense, enhancing efficiency of aircraft and reducing fuel consumption have emerged as pressing issues in the field of design and manufacturing that demand immediate action. The aerodynamic performance of aircrafts and fuel consumption have positive correlation. Wing, which is the main part that generate lift force, plays a decisive role in the energy efficiency performance of the entire aircraft due to its aerodynamic drag and lift characteristic. Therefore, optimization of aerodynamic shape of the wing is the key approach to improve the fuel economy of aircraft.

Aerodynamic optimization design of aircraft wings is a highly complex systematic engineering [1, 2]. Due to the strong coupling between lift and drag, the aerodynamic performance is extreme sensitive to the change in aerodynamic shape. Traditional design approach often relies on the experiences of engineer and a large number of wind tunnel experiments, which is not only long cycle and high cost, but also difficult to find a truly global optimal solution. With the maturity of Computational Fluid Dynamics (CFD) technology, numerical simulation has gradually become an effective alternative to wind tunnel experiments. However, high-precision CFD calculations are time-consuming, and if directly embedded into optimization loop, the consumption of computational resources would be unbearable [3, 4].

In order to solve the contradiction between computational cost and accuracy, surrogate model technique is introduced into aerodynamics optimization field [5-7]. This paper established a multi-objective shape optimization framework based on Kriging method, aiming to reduce the computational cost during the optimization process and making it possible to explore complex wing design space with limited computational resources. The subsequence chapters will elaborate on specific geometric parameterization, numerical simulation settings, as well as a comparative analysis of aerodynamic performance before and after optimization.

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2. Framework

The framework of shape optimization established in this study is shown in Figure 1. The overall workflow consists of two successive stages: sensitivity analysis and multi-objective optimization. First, the geometry of the wing is parameterized using a python script, so that it can automatically generate the fluid domain. Next, an initial set of Design of Experiments (DOE) is generated using Advanced Latin Hypercube Sampling (ALHS). These DOEs are used to define the parametric geometries, and it will automatically generate the corresponding computational meshes and perform CFD simulations. The simulation data are then used to construct a Kriging surrogate model [1, 4]. The prediction accuracy is evaluated by Coefficient of Prediction (CoP) and its defined as:

$$CoP = 1 - (\frac{SSE_{\text{prediction}}}{TSS})$$

Where $SSE_{\text{prediction}}$ is sum of squares of prediction errors under cross validation and TSS is total square sum. If this criterion is not satisfied, additional DOEs are generated and the CFD–Kriging process is repeated until the required accuracy is achieved. Once a sufficiently accurate surrogate model has been established, it is employed to efficiently search for the Pareto front of the multi-objective optimization problem [3, 4]. The optimal solution is then selected from the Pareto-optimal candidates and finally verified using a high-fidelity CFD simulation.

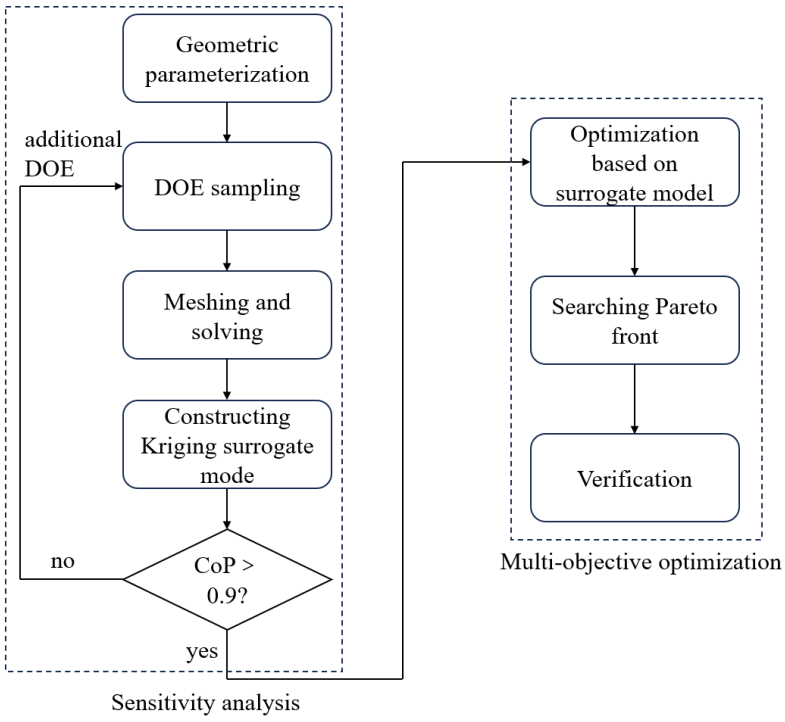

Figure 1. Framework of optimization

3. Test model and approaches

3.1. Parameterized Geometry

The geometry includes the wing and fuselage. The wing features a NASA 2412 airfoil at the root and a NASA 0012 airfoil at the tip, while the fuselage is the NASA Common Research Model as seen in Figure 2.

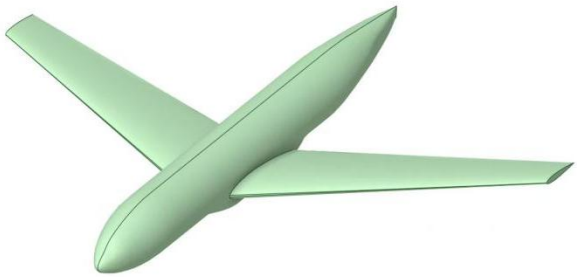

Figure 2. Geometric of the of aircraft

To enable fully autonomous optimization, the wing must be parameterized. In this study, the three-dimensional wing is formed by the lofting of five airfoil cross-sections. The initial and final cross-sections are the wing root and wing tip and the other three cross-sections are evenly distributed between them, each with its own angle of incidence. The root chord length, tip chord length and sweep angle have also been parameterized. The details of those parameters are shown in Table 1.

Table 1. Parameters and ranges of wings

Parameters	Description	Units	Initial Values	Range
$\boldsymbol{\alpha_0}$	Angle of incidence at root	deg	2	$\alpha_0 \in [-1,5]$
$\boldsymbol{\alpha_1}$	Angle of incidence at section 2	deg	2	$\alpha_1 \in [-1,5]$
$\boldsymbol{\alpha_2}$	Angle of incidence at section 3	deg	2	$\alpha_2 \in [-1,5]$
$\boldsymbol{\alpha_3}$	Angle of incidence at section 4	deg	2	$\alpha_3 \in [-1,5]$
$\boldsymbol{\alpha_4}$	Angle of incidence at tip	deg	2	$\alpha_4 \in [-1,5]$
$\boldsymbol{c_1}$	Root chord length	m	0.7	$c_1 \in [0.63,0.77]$
$\boldsymbol{c_2}$	Tip chord length	m	0.3	$c_2 \in [0.27,0.33]$
β	Sweep angle	deg	30	$\beta \in [27,33]$

3.2. Numerical Methods

In this study, ANSYS Fluent is utilized to conduct a three-dimensional, compressible simulation. The fluid field and boundary conditions is shown in figure 3. The diameter of the fluid field d is given by d = 20l, where l is the length of the fuselage. In order to save computing resources, half model is used for calculation. The pressure far-field is set as inlet boundary condition with a velocity of 0.6 Mach and an angle of attack of 10°. The symmetry plane is set as symmetry boundary condition and the aircraft is set to a no-slip wall. In terms of spatial discretization of convective terms, a second-order upwind difference scheme is applied. In addition, the pressure velocity coupling uses the SIMPLEC algorithm. In order to improve the accuracy of simulating high Reynolds numbers and compressible shear flows near aircraft, this study adapts the SST k-ω turbulence model.

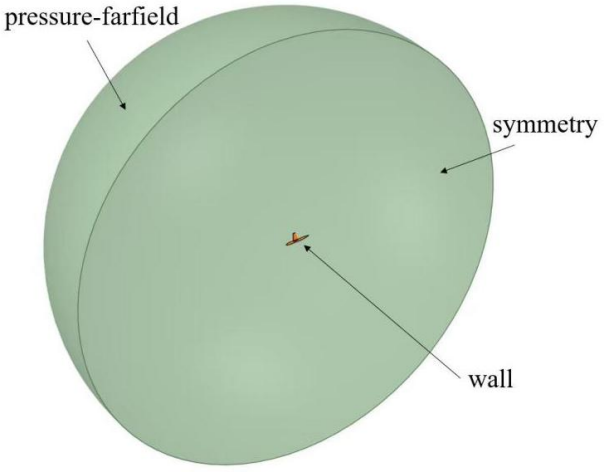

Figure 3. Computational domain and boundary conditions

Figure 4 illustrates the polyhedral mesh of the model. The details of the surface mesh size are shown in Table 2. The aspect ratio of the first boundary layer mesh is set to 5, with a growth rate of 1.2, and the total number of boundary layers is 5. The entire fluid field is divided into 1.5 million cells.

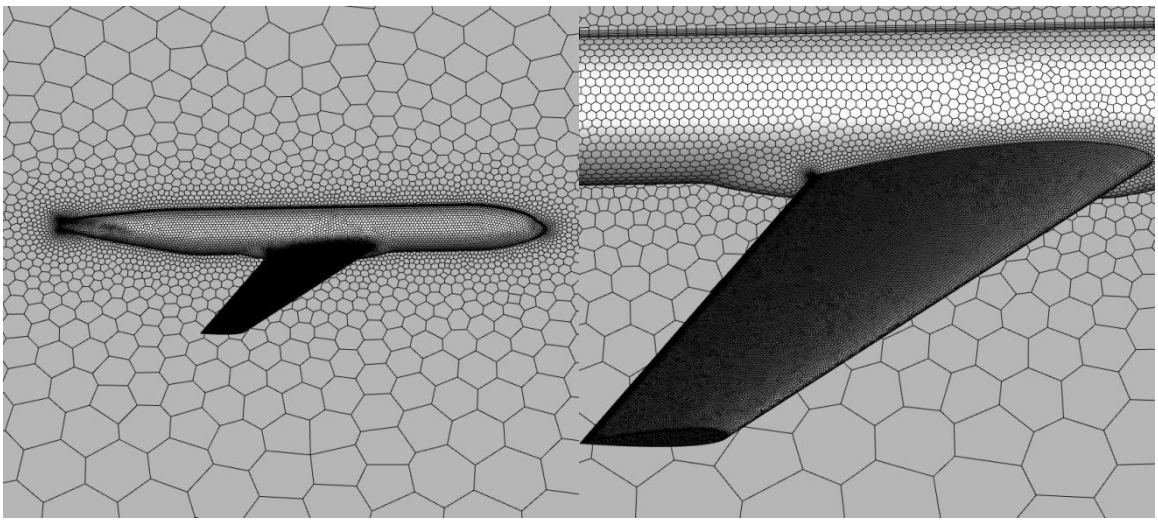

Figure 4. Surface mesh of the model

Table 2. Details of the mesh size

Surface Type	Lower Limits	Upper Limits	Unit
Trailing Edge	0.4	0.4	mm
Tip	0.4	2	mm
Wing	0.4	5	mm
Fuselage	0.4	20	mm

Figure 5 illustrates the lift coefficient (C_l) distributions under three different grid resolutions. The variation of C_l in three different grid numbers is essentially consistent. Therefore, the grid of 1.5 million cells is used as the computational grid of this study.

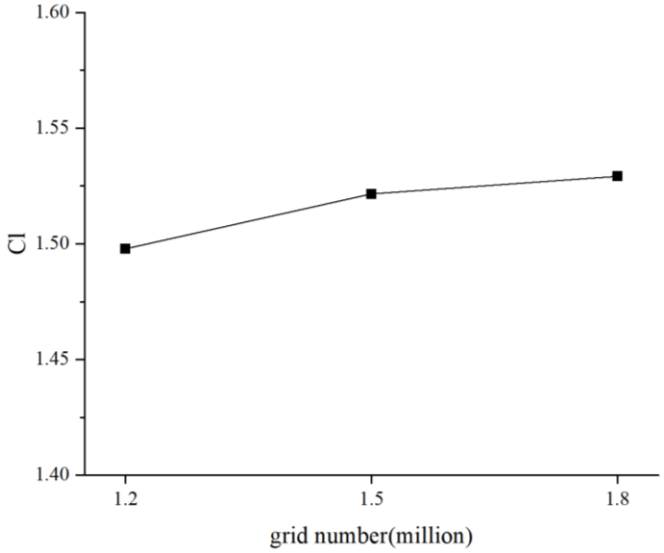

Figure 5. Grid independence

3.3. Optimization Method

The method used in this paper is an optimization method based on the Kriging surrogate model. It first generates initial samples using the DOE (ALHS algorithm) and constructs the Kriging model. Then, it uses the predicted values and prediction errors provided by Kriging to guide new sampling points, gradually supplementing samples, updating the model, and converging to the global optimum. Its advantages lie in significantly reducing the number of calculations required by expensive CFD solvers through error predictors, which is suitable for nonlinear and high-cost engineering problems [4, 8]. At the same time, it can quantify model uncertainty by predicting variance, determine which regions need to be sampled and which regions can trust the model, thereby achieving local refinement while ensuring global optimization capability [4]; This method is particularly suitable for scenarios with high evaluation costs and the need to find the global optimum with the minimum number of design points [3, 9, 10]. The optimization objective is to minimize the drag coefficient and maximize the lift coefficient under the specified operating conditions.

4. Results and Discussion

Figure 6 shows the response surface of Cd, where the x-axis represents angle of incidence 2 and the y-axis represents angle of incidence 3. It can be seen that the surface is smooth and the supporting points are closely distributed on the surface, indicating good fitting quality. Figure 7 shows the pareto plot of multi-objective optimization. The red line in the Figure 7 is the Pareto front, which is the boundary of all optimal solutions. This paper selects a compromise solution that meets engineering preferences from the Pareto front and the design #491 is chosen as the final optimal design. Table 3 compares the geometric parameters between the original design and the optimal design. Table 4 compares Cl and Cd between the original values, kriging predicted optimal values, and CFD validated optimal values. The difference between the predicted Cl and the CFD verified Cl is 4.3%, and the difference in Cd is 8.5%, indicating that the prediction error is relatively small. And finally, the Cl has increased by 4.9% and the Cd has decreased by 21.4% after optimization.

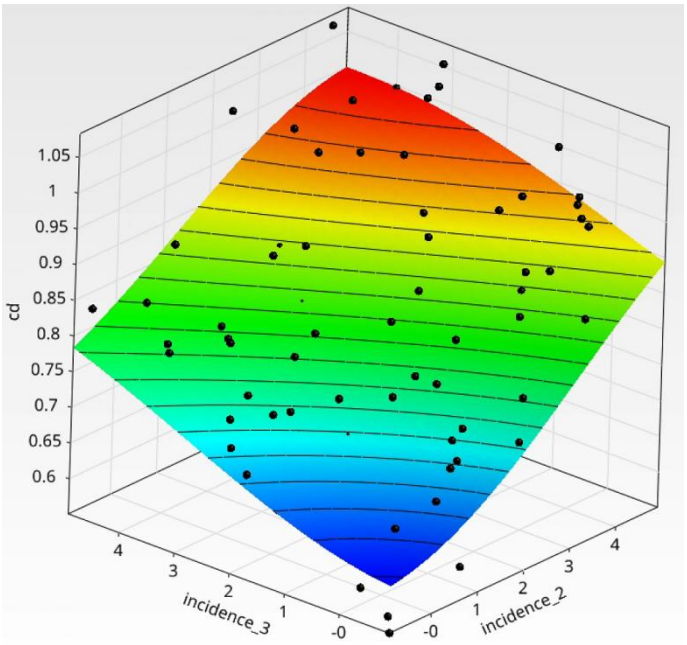

Figure 6. Response surface of cd

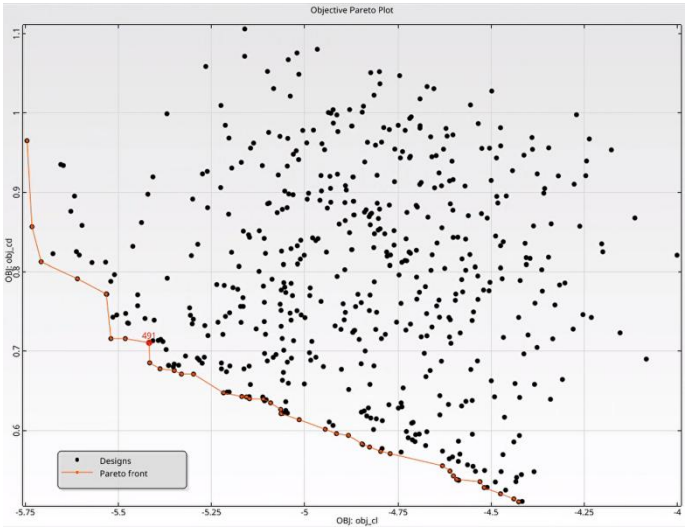

Figure 7. Pareto plot of multi-objective optimization

Table 3. Parameters of original and optimal design

	α_0	α_1	α_2	α_3	α_4	c_1	c_2	β
Original design	2	2	2	2	2	0.7	0.3	30
Optimal design	2.803	0.748	-0.725	-0.708	3.877	0.767	0.312	30.98

Table 4. Lift coefficient and drag coefficient of original and optimal design

	Original	Optimal (Kriging)	Optimal (CFD)
C_l	5.03598	5.52009	5.28497
C_d	0.83361	0.71594	0.65510

Figure 8 shows the pressure distribution on the surface of the aircraft before and after optimization. As shown in Figure 8, after optimization, the low-pressure area at the leading-edge increases, resulting in a decrease in pressure drag and an increase in lift.

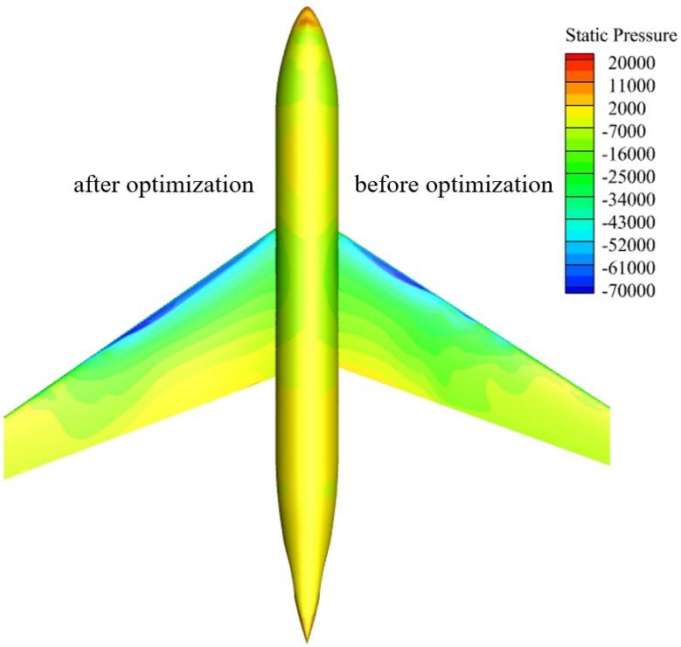

Figure 8. Pressure distribution before and after optimization

5. Conclusion

This study addresses the core requirements of aircraft fuel economy and establishes a multi-objective optimization framework based on Kriging surrogate model and computational fluid dynamics (CFD) technology. This framework constructs initial design space through Advanced Latin Hypercube Sampling (ALHS), utilized kriging approximation to construct a surrogate model, replacing time-consuming CFD solver. After satisfying the preset accuracy tolerance, the efficient search for the pareto frontier with maximum lift coefficient and minimum drag coefficient in a wide design space was successfully developed. The result of this study demonstrate that this "surrogate model-assisted optimization" strategy can significantly reduce computational cost and is a reliable means for aerodynamic optimization.

The ultimately selected Pareto optimal design scheme (Design #491) has achieved a comprehensive improvement in aerodynamic performance compared to the original design. After verification through high-fidelity CFD solver, the Cl has increased by 4.9% and the Cd has decreased by 21.4%. This result indicates that the optimization scheme significantly reduces lift characteristics, making a positive contribution to improving fuel economy of aircraft.

Further analysis of the physical mechanism behind the reduction in drag reveals that although the wing surface area after optimization has increased compare to original design, the drag coefficient has still reduced. This indicates that the primary contribution to the reduction in drag does not come from frictional drag, but rather from optimization of pressure drag. The optimized wing has formed a more noticeable low-pressure area in the leading-edge region, effectively improving the surface pressure distribution.

In general, the aerodynamic optimization method based on Kriging surrogate model proposed in this paper can effectively identify excellent aerodynamic performance wing design in complex design space with low computational cost. Future work can be extended to optimization across multiple operating points, aiming to provide technical support for rapid iterative optimization in future aircraft development.

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