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A PCA–ANN-based inverse design model of stall lift robustness for high-lift device

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ABSTRACT

The concept of stall lift robustness for high-lift device (HLD) measures the stability of lift values under a series of angles of attack (AoA) around stall, which plays a significant role in flight safety. In this article, a stall lift robustness design with the consideration of aerodynamic constraints (stall AoA, average lift, etc.) is carried out, where design targets are set as a series of lift values on Lift-AoA curve. A Principle Component Analysis (PCA)–Artificial Neutral Network (ANN)-based inverse design model is introduced. The design targets are transformed by PCA for data dimension reduction. Then, the new set of design targets are input into the surrogate model of ANN, and corresponding geometry of new HLD is predicted. The ANN is constructed through database and sample points are screened considering lift unsteadiness. The design procedure is iterated to meet the design accuracy. The process of stall lift robustness design with the proposed model is discussed in this article, and the design results are validated by Detached-Eddy Simulation (DES).

1. Introduction

Aircraft stall refers to a sudden drop in lift and a sharp decline in stability at high angles of attack (AoA), which is caused by flow separation on the upper wing surface [1]. This phenomenon may lead to serious aircraft accidents [2]. Therefore, it is necessary to carry out the design of stall lift robustness, which measures the stability of lift values under a series of AoAs around stall. With design constraints, for example, stall AoA, average lift, etc., stall lift robustness design is a comprehensive process, and is related to a set of lift values on the entire Lift-AoA curve. This makes it mathematically a multi-objective problem with a large number of design targets, which gives rise to difficulty in applying design model with the increasing problem dimensions [3,4].

Conventional methods of multi-objective design are mainly weighted-average method and Pareto solution-set evolutionary method [5]. As for weighted-average method, Drela [6] carried out a multi-state aerodynamic design for cruise airfoil. Nemec et al. [7] developed a gradient-based Newton–Krylov algorithm for the aerodynamic shape optimization of single- and multi-element airfoil configurations. However, design results based on weighted-average method are sensitive to preassigned weight coefficients that strongly relies on the designer's subjective intention. As for Pareto solution-set method, Mastroddi and Gemma [8] worked on the design of a wing/horizontal tail/fuselage aircraft configuration. Elham and van Tooren [9] performed multi-objective designs to find the Pareto front between the wing aerodynamic drag and the wing structural weight for a wing equipped with a winglet. However, Pareto solution-set method is suitable only for problems with few design targets in that the convergence of the evolutionary algorithm will deteriorate for multi-objective problems of higher dimensions [10].

Aerodynamic design concerning stall for HLD has been a research focus [11]. Xu [12] worked on the lift optimization under an angle near stall for high-lift system based on Conservative Chimera technique. Soulat et al. [13] utilized Genetic Algorithm and constructed the Pareto front to maximize the lift and minimize the drag. Moens and Dandois [14] studied on passive flow control of multi-element airfoil via Pareto solution-set method, in order to maximize the lifts under two AoAs. However, the above researches were limited in the design for lift enhancement. In comparison, there are few studies in the area of stall lift robustness design. Tang et al. [15] worked on stall lift robustness design by transforming the problem into a two-objective problem, but only several pre-stall lift values were taken into consideration.

For the purpose of stall lift robustness design in consideration of constraints, the authors propose a new design model in this article. The design object is set as the entire Lift-AoA curve, since

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the characteristics of both stall lift robustness and design constraints are comprehensively reflected in the curve. Design targets are set in the form of the discrete lift values on Lift-AoA curve. The model of inverse design is adopted where design targets are given in advance and the corresponding HLD shape is predicted afterwards, with advantages in efficiency, pertinence and credibility [16]. In early researches, inverse design was a method applied in airfoil shape optimization with given target pressure distribution [17,18]. By taking aerodynamic targets as input and geometric shape as output, Sun et al. [19] developed the method and established an Artificial Neutral Network (ANN)-based inverse design model, which is constructed through database, to carry out aerodynamic designs of airfoil and wing. However, the database size of ANN increases with the number of input and output parameters [20]. The large number of design targets of stall lift robustness implies a large size of database, which will cost large amounts of computing resource. Therefore, a data processing technique, Principal Component Analysis (PCA) [21], is applied to reduce data dimensions. PCA decreases the number of variables while preserving data information, which is widely used in many fields [22] such as data mining, information compression, image coding and simulation recognition.

This article is organized as follows. In Section 2, computational fluid dynamics (CFD) method based on Detached-Eddy Simulation (DES) is introduced and validated. In Section 3, the database of HLD configurations is established in preparation of model construction, alongside given are the design targets for stall lift robustness. In Section 4, with data dimension of aerodynamic parameters reduced by PCA and geometry predicted by ANN, the process of stall lift robustness design is performed and iterated with the PCA–ANN-based inverse design model. In Section 5, aerodynamic performance of the design result is presented and discussed. Section 6 draws some conclusions about the proposed model according to the whole work.

2. CFD method and validation

2.1. CFD method

The flow field of HLD under high AoAs is complicated. Among the common CFD methods, Reynolds Averaged Navier–Stokes (RANS) model can simulate attached boundary layer flow, but not applicable for conditions with flow separation of large scale. Large Eddy Simulation (LES) is of great accuracy and cost-effective with integral wall model [23], yet requires large amount of grids to simulate flow separation area. In view of large flow separation, Spalart et al. [24] proposed the DES method, which combines the advantages of both RANS and LES to improve numerical simulation of flow separation at high AoA. The idea of DES is to carry out RANS in the near boundary layer (since RANS can effectively simulate the flow in this region without large demand for computing resource) and LES in the separation area away from the surface.

The integral form of the Spalart–Allmaras equation model is

$$\frac{\partial}{\partial t}\int_{\Omega}\tilde{v}d\Omega+\oint_{\partial\Omega}(F_{c,\mathrm{T}}-F_{v,T})dS=\int_{\Omega}Q_{T}d\Omega \tag{1}$$

where $F_{c,\mathrm{T}}, F_{v,T}$ and Q_T are the convective flux, the viscous flux and the source term of the turbulent eddy viscosity, respectively, represented as:

$$F_{c,\mathrm{T}}=\tilde{v}V_r \tag{2}$$

$$F_{v,T}=\frac{1}{\sigma}\left(\frac{\mu_L}{\rho}+\tilde{v}\right)\left(n_x\frac{\partial\tilde{v}}{\partial x}+n_y\frac{\partial\tilde{v}}{\partial z}\right) \tag{3}$$

$$Q_T=(c_{b1}S+\Delta V)-c_{w1}f_w\left(\frac{\tilde{v}}{d}\right)^2+\frac{c_{b2}}{\sigma}(\Delta\tilde{v})^2 \tag{4}$$

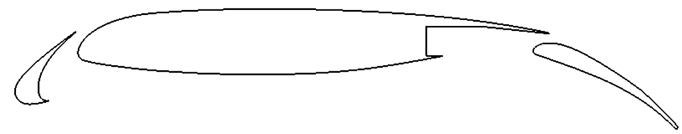

Fig. 1. Schematic of EET three-element airfoil [25].

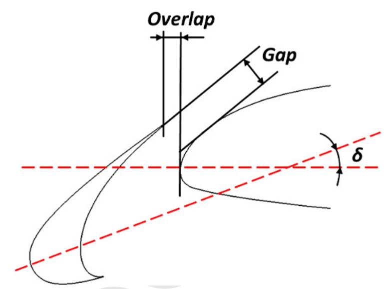

Fig. 2. Geometric parameters of leading edge.

where $\bar{v}$ is the strain, μ_L is the viscosity coefficient, ρ is the density, n_x, n_y represent the normal directions, d is the nearest distance to wall, and c_{b1}, c_{b2}, c_{w1}, σ, f_w, S are the coefficients obtained by dimensional analysis and Galileo invariance analysis.

The S–A-based DES method modifies d (nearest distance from local grid center to wall surface) according to the following formula:

$$d^*=min(d, C_{DES}\Delta) \tag{5}$$

where C_{DES} is a constant 0.65, and Δ is the maximum size of local grid. For structured grids, Δ is generally taken as the maximum distance from local grid to neighboring grid centers.

In the nearby region of wall surface, $d < C_{DES}\Delta$, so $d^*=d$. Here, DES method is equivalent to S–A model. With the increment of d, $d > C_{DES}\Delta$, so $d^*=C_{DES}\Delta$. Here, the attenuation of turbulent eddy viscosity coefficient is determined by local grid scale. When the source term and the attenuation term of the turbulent eddy viscosity coefficient reach equilibrium, $\tilde{v}$ is proportional to Sd^2. If $d^*=c_{DES}\Delta d$, $\tilde{v}$ is proportional to $S\Delta^2$, which is equivalently Smagorinsky subgrid model. Therefore, in regions far from the wall, DES model is shown as the subgrid model required by LES; otherwise, it is characterized by the RANS model.

2.2. Computation validation

The authors select an Energy Efficient Transport (EET) high lift model [25] to validate the accuracy of DES, as is shown in Fig. 1. The geometric parameters of leading edge are: $Gap = 2\%c$; $Overlap = -0.32\%c$; $\delta = 30°$ (see Fig. 2).

The CFD simulation of EET is based on structured grids. The O-grids are divided around slat, main wing, and flap. Y-plus is set to be around 1. Grid isotropy and smooth transition of grid size at the junction of each topology part are ensured. Fig. 3 shows the global view of the grids and local grids at leading and trailing edge, respectively. The grid amount of the entire computational domain is about 600,000. The simulations are conducted at Mach number 0.20 and Reynold number 9×10^6.

Fig. 4 shows the Lift-AoA curve of the computational results compared with the experimental lift results [25] for baseline configuration. The curve corresponding to angles larger than 16° is amplified in the subplot. As can be seen, the lift coefficients along the variation of angles are basically the same between CFD and experiment result: stall angles are both 23°, and maximum lift coefficients of the two curves are close to each other, where the relative error between experiment and CFD simulation is within 1%.