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Artificial neural network based inverse design: Airfoils and wings

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ABSTRACT

The numerical search for the optimum shape of airfoil/wing geometry is of great interest for aircraft and turbomachinery designers. However the conventional method of design and optimization, which is to repeat the process of modifying airfoil/wing geometry data based on the flow field calculation of initial geometry, is computationally intensive and time-costly. In lieu of this, this article introduces an applicable airfoil/wing inverse design method with the help of Artificial Neural Network and airfoil/wing database, so that a properly trained network should directly provide an airfoil/wing that fits the required aerodynamical features. Repeating the process itself being avoided, the design efficiency improves. This article will present the detail of setting up the airfoil/wing inverse design method and provide the verification of the applicability of the approach.

1. Introduction

An advanced aerodynamic layout, which can reduce flight drag of a jet to increase its cruise efficiency and safety, is basically dependent on the design of an airplane's wings or more fundamentally, its airfoils. Wind tunnel was the major airfoil/wing designing tool. The first Boeing 747 took wind tunnel experiments for over 15,000 hours.[1] 1960s saw the introduction of CFD into the field that enhanced the development of airfoil/wing design [2]. The methods brought by CFD covered linear potential flow equation method, full velocity potential method with boundary layer correction, Euler equation method and Navier–Stokes equation method [12]. However before 1980s most design results involved quite much experience of designers, due to coupling variables in designs. It was hard then to set up a systematic design that was likely to reduce time and sources, because the conventional design requires the repeated process of *design–evaluation–improvement*. Compared with the wind-tunnel experiments, the conventional design methods performed better but still remain the necessary repetition of modifying during which designers' own experiment interferes. In addition, when the options of optimization method or optimizing direction were not selected properly, satisfactory results were hard to get. Therefore a new airfoil/wing design method of higher efficiency is what mechanics as a discipline as well as engineering application has been looking forward to.

Since 1990s, the rise of database technique and artificial intelligence technique has pushed the passenger jet aerodynamical design forward [1]. Aircraft manufacturers have access to their database that is made up of abundant designing experience and experiment data. The database gives proposal in prototype research and modification. Optimization methods including control theory optimization [11,17], Genetic Algorithm [24,26], Particle Swarm Optimization [25], and Artificial Neural Network [8,16] are carried out in the database. Compared with other machine learning methods which have been tried in shape optimization, ANN is able to provide more flexibility in building the calculating model without involving many parameters (e.g. chromosome in GA, or swarm picking in PSO, etc.) that have to be determined in specific cases. The inverse design case in this article could be regarded as one of the examples.

The technique of ANN raised the hopes for designers, for its swiftness and intelligence. There are precedents of ANN application in airfoil/wing design. Scholars make an ANN model of aerodynamical shape as a tool in geometrical analysis [10]. ANN has its reputation in making a nonlinear link between the inputs and outputs (in our case, a link from geometrical shape to its corresponding aerodynamical features, e.g. lift coefficients). The complexity of airfoil/wing shape design (multi-variables and small samples) does require a model that is intuitive, simple and not too specific; ANN can meet this request very well. As it turns out, design methods with ANN reduce calculation amount and time cost. Yet doubts remain on the reliability of the design result due to the unclear physical explanation of the ANN model. Many scholars have been working on that [5,23]. Bernstein introduced RANN (Replicative Artificial Neural Networks) [4] where inputs and outputs have the

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[1] www.thic.org/pdf/Oct01/boeing.jgreen.011009.pdf.

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same numbers of parameters, which is more than the number of neural nodes. Therefore, an effective data compression is available in analysis.

In recent years ANN has entered the inverse design of airfoils where ANN plays a role as a calculator based on a pre-set model. Kharal et al. [13] described the implementation of ANN for airfoil geometry determination. Instead of using full coordinates of the airfoil, Bezier–PARSEC (Parametric Airfoils and Wings, proposed by Sobieczky [20]) parameters were used to describe an airfoil. But Kharal's method has its shortcomings: its lack of full discretization due to the combination of Bezier and PARSEC, which still requires manual interference in parameterization, hindering the application and the optimization thereafter.

This article, in particular, introduces an inverse aerodynamic shape (i.e. airfoil or wing) design method that can directly inverse-design airfoils/wings whose geometry fits the expected/requested aerodynamic features (again, without repetitive process of conventional design–evaluation–improvement), based on an accumulated database of airfoils/wings and a properly trained Artificial Neural Network (time saved by which is of large magnitude, compared with conventional design method). To be specific, this article provides cases of an application of inverse design as a solution to the problem of the design of wings of a cruising passenger jet. In addition, by providing design results more efficiently and more accurately, the new airfoil/wing inverse design lays foundation for the optimization that may come later.

2. Establish the inverse design method of aerodynamic shape

2.1. Roadmap

Aerodynamic design in modern days has two major goals:

(i) Designers should take advantage of airfoil/wing database to accomplish a new approach in fast design.
(ii) The price of convenience should never be the loss of reliability.

Conventional aerodynamical design method Conventional aerodynamical design method, by definition, first gets the aerodynamic feature of a given airfoil under a certain flow condition by CFD or wind tunnel experiments, modifies the geometry of the airfoil according to aerodynamic knowledge and experience, and then repeats the above process until the outcome is satisfactory.

Inverse design method On the contrary, inverse design, by definition, can get the geometry of aerodynamic shape directly from the required aerodynamic features (usually input by designers).

In our case, ANN is used to set up the network linking aerodynamic features and geometry data, where SOM (Self-Organizing Map) network is used as a classifier to reduce the multi-variable problem's impact to the reliability of the ANN model (Fig. 1). Once the network is trained, the result can be obtained very quickly.

The steps to establish airfoil/wing inverse design approach are the following:

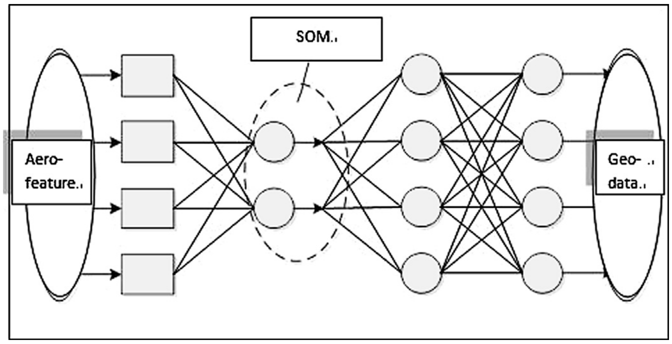

Fig. 1. An ANN model for inverse design.

Step 1 Extract essential geometry data from the parameterized aerodynamic shape. This is necessary for the application of ANN, which resembles the numerical code procedure in Genetic Algorithm.
Step 2 Obtain aerodynamic features from the results of the calculation/experiment of airfoil/wing in a flow condition.
Step 3 The database (its function: to give proposals to the ANN) is built.
Step 4 With SOM as a classifier to reduce the difficulty, ANN now sets up a model, which requires appropriate samples as the model's inputs and outputs.

2.2. Tools

2.2.1. Parameterization

The application of ANN's premise is parameterized database. Many parameterization methods have been used or discussed, e.g. orthogonal basis function method, Dick–Henne form function linear perturbation method [9], B spline method, PARSEC and CST (Class/Shape function Transformation) [14].

Samareh [18] evaluated 9 methods of parameterization with 10 principles. Sripawadkul [22] simplified the research by adding intuitiveness into 5 principles as criteria for parameterization method evaluation (shown in Table 1 with makers ranging from 0.0 to 4.0). The 5 principles:

Parsimony: as few variables as possible
Flawlessness: high uniformity of parameterized and original shapes
Orthogonality: no two aerodynamic shapes share the same set of parameters
Completeness: ensuring no strange/weird shape would appear
Intuitiveness: correlations between parameters and geometrical features

Padulo gave explanation to these five rules [15].

Table 1 tells us (despite the chance of generations of very few strange shapes which include situations where the upper surface crossed the lower surface in the middle of chord. This may be led by the less constraint given by PARSEC for the sake of high parsimony. Airfoils and wings with strange shapes can be detected by naked eyes and can be avoided by adjusting related parameters). PARSEC is generally better than other parameterization methods.

Table 1
Samareh's evaluation to parameterization [18].

Methods	Parsimony	Completeness	Orthogonality	Flawlessness	Intuitiveness
Ferguson's curve	4.0	2.4	0.0	4.0	2.0
Hicks–Henne	1.0	4.0	0.0	4.0	3.0
B-Spline	3.5	3.9	0.0	4.0	3.0
PARSEC	2.9	3.8	4.0	2.9	4.0
CST	2.9	3.7	4.0	4.0	4.0