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A Review on the Development of Data Driven Aerodynamic Optimization Design Technology for Airfoils

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Abstract. Traditional airfoil optimization generally relies on Computational Fluid Dynamics (CFD) simulations to build aerodynamic models for prediction and combines them with optimization algorithms. However, CFD computations are often computationally expensive and time-consuming, failing to meet the demands of modern aircraft design. In recent years, data-driven methods have gradually been introduced into aerodynamic design, offering new pathways to reduce dependence on expensive CFD calculations and improve airfoil optimization efficiency. This paper reviews research progress in data-driven airfoil aerodynamic optimization, focusing on applications of traditional surrogate models, deep learning models, and intelligent optimization algorithms for aerodynamic performance prediction and optimization. It also analyzes current challenges in data-driven airfoil optimization, including the high cost of acquiring training data, insufficient model interpretability, limited physical consistency constraints, and inadequate generalization across multiple operating conditions. On this basis, this paper discusses future development directions such as multi-fidelity data fusion, Physics-Informed Neural Networks (PINNs), and AI-CFD collaborative optimization, aiming to provide references for further application of data-driven methods in airfoil aerodynamic optimization design.

Keywords: Airfoil optimization, Aerodynamic optimization, Surrogate model, Computational Fluid Dynamics (CFD), PINN

1. Introduction

As a critical component of wings, blades, and propulsion systems, an airfoil directly affects the lift, drag, stability, and economy of an aircraft through its aerodynamic performance. Therefore, rapid and efficient airfoil optimization has long been an important research direction in aeronautical engineering. Traditional airfoil design mainly relies on wind tunnel testing and Computational Fluid Dynamics (CFD) techniques. However, as aircraft performance requirements continue to increase, airfoil design has become more complex, and conventional methods have gradually revealed problems such as high testing costs, long test cycles, and insufficient computational resources [1]. In addition, complex aerodynamic phenomena such as shock waves, boundary layer separation, and stall exhibit strong nonlinearity, further increasing the computational difficulty of predicting and optimizing airfoil aerodynamic performance [2-5].

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Data-driven methods can use latent patterns in existing aerodynamic data to map airfoil geometric parameters to aerodynamic performance, reducing the need for repeated high-cost CFD calculations during optimization and improving efficiency. However, the literature lacks a systematic review of technological development, model applications, and the synergistic relationships between data-driven approaches and traditional CFD methods in airfoil aerodynamic optimization. Therefore, this paper reviews technological development in this field and compares the main characteristics and applicable scenarios of different technical approaches. On this basis, it summarizes current research challenges and future trends, aiming to provide a reference for related research and engineering applications.

2. Fundamental theory of airfoil aerodynamic optimization

2.1. Airfoil aerodynamic optimization process

The core objective of airfoil aerodynamic optimization is to improve overall aircraft performance by adjusting airfoil geometric parameters, for example, to increase lift, reduce drag, or improve the lift-to-drag ratio, while satisfying constraints related to structure, manufacturing, and flight performance. In practice, the primary optimization objectives often include increasing the lift coefficient, reducing the drag coefficient, or improving the lift-to-drag ratio, with corresponding geometric and aerodynamic constraints set according to specific application scenarios. Airfoil aerodynamic optimization typically begins with parametric methods that describe and model airfoil geometry, thereby converting the complex airfoil profile into a finite set of design variables suitable for optimization. Depending on the parameterization method, design variables may include maximum thickness, camber, leading-edge radius, control point coordinates, and other geometric descriptors. The choice of parameterization method directly affects the expressiveness of the design space and the computational efficiency of the subsequent optimization process, so the method should be selected according to specific design objectives.

After completing airfoil parameterization, the aerodynamic performance of airfoils under different combinations of design variables is evaluated. Traditional methods usually use CFD simulations or wind tunnel testing to evaluate aerodynamic performance and obtain key parameters such as the lift coefficient, drag coefficient, and pressure distribution. Optimization algorithms then adjust the design variables based on objective-function feedback, using methods such as gradient-based algorithms, genetic algorithms, or particle swarm optimization to update the airfoil design variables and continuously improve airfoil performance. This iterative process is repeated until preset convergence criteria are met or design objectives are achieved [6, 7].

2.2. Traditional CFD-based airfoil optimization methods and inherent drawbacks

Traditional CFD-coupled optimization primarily combines CFD with optimization algorithms for flow-field computation; these algorithms are typically based on gradient methods or genetic algorithms. The core idea is to run CFD simulations to compute airfoil aerodynamic performance based on parametric models, and then use optimization algorithms to iteratively adjust airfoil geometric parameters to improve performance. Traditional CFD-coupled optimization typically uses methods such as NACA parameterization, Bézier curves, or CST (Class-Shape Transformation) to describe the airfoil shape and determine design variables for subsequent optimization [1, 8, 9].

The commonly used optimization algorithms in airfoil aerodynamic optimization fall into two categories: gradient-based methods and intelligent optimization algorithms. Gradient-based methods

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use sensitivity information of the objective function with respect to design variables to guide the search, offering high computational efficiency and being suitable for continuous optimization problems. Among these, the adjoint method has been widely applied in engineering design optimization, such as in the design of large aircraft wings [10]. Intelligent optimization algorithms mainly include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) [6, 7, 11]. These algorithms do not rely on gradient information and have strong global search capabilities, making them widely applicable to complex nonlinear optimization problems. However, their efficiency is limited by computational cost. As the number of design variables increases or the objectives become more complex, aerodynamic performance evaluation requires numerous CFD calculations during optimization, significantly extending the optimization cycle and increasing computational cost.

2.3. Application of traditional surrogate models in airfoil design

To address the efficiency limitations of repeatedly invoking high-fidelity CFD computations in traditional CFD-coupled optimization, surrogate models have been introduced into airfoil aerodynamic optimization. Surrogate models construct approximate mappings between design variables and aerodynamic performance, replacing expensive CFD numerical simulations with inexpensive computations while maintaining a certain level of prediction accuracy [8]. Early research identified the Kriging model, response surface methodology, and Support Vector Machines (SVMs) as the three most representative traditional surrogate models.

2.3.1. Kriging model

The Kriging model is based on Gaussian process regression and exhibits strong nonlinear fitting capability with high accuracy. It provides not only predicted values but also prediction variance, and its uncertainty estimates can guide adaptive sampling to balance global exploration and local optimization [12]. However, its computational complexity grows cubically with sample size, making training of correlation-function parameters difficult in high-dimensional optimization, and it is sensitive to numerical noise.

2.3.2. Response surface methodology

Response surface methodology typically approximates aerodynamic responses using low-order polynomials (e.g., second-order polynomials). Its advantages include a simple structure and low construction cost, allowing the relationships between design variables and performance to be identified with relatively few experiments and quickly revealing overall trends in the design space, making it suitable for preliminary coarse optimization. However, its drawbacks include poor adaptability; as the design space expands, response-surface prediction error increases. Airfoil aerodynamic performance often exhibits strong nonlinearity with shape changes (e.g., shock-induced drag, separation zones), and low-order polynomials have limited global approximation capability, potentially missing local features or even misleading the search direction.

2.3.3. Support vector machines

Support Vector Machines (SVMs) are based on structural risk minimization and map input variables to a high-dimensional feature space via kernel functions, establishing nonlinear relationships between airfoil design variables and aerodynamic performance. Compared with low-order response

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surface models, SVM generally offers better generalization in small-sample and nonlinear problems, and its ability to capture complex airfoil responses is superior to that of response surface methods. However, SVM performance depends entirely on the quality and quantity of the training dataset and relies heavily on the choice of kernel type and hyperparameters. Moreover, standard support vector regression does not provide prediction uncertainty or probabilistic interpretation.

3. Application of data-driven methods in airfoil aerodynamic optimization

Compared with traditional surrogate models, deep learning can automatically extract airfoil geometric features and generally provides stronger nonlinear fitting capability and higher prediction accuracy. These capabilities make it useful for airfoil design, flow-field reconstruction, and cross-condition prediction.

3.1. DNN for mapping airfoil geometry to aerodynamic coefficients

DNNs are widely used in data-driven airfoil modeling. A DNN usually consists of an input layer, multiple hidden layers, and an output layer, and learns the relationship between airfoil geometric parameters and aerodynamic performance through multilayer nonlinear mapping. In practice, airfoil geometry is often represented by coordinate points, Bézier curve control points, or CST parameters as input features, while the outputs are aerodynamic performance parameters under the corresponding operating conditions. After training, the DNN can rapidly predict the performance of new airfoil geometries without additional CFD calculations, thereby shortening the multi-objective optimization design cycle.

3.2. CNN: reading airfoil profile data

Convolutional Neural Networks (CNNs) are among the most representative neural networks in modern deep learning [14]. Airfoil profiles, pressure distributions, and velocity fields have clear spatial structure, so airfoil coordinates can be represented as two-dimensional data, or pressure contour maps and velocity fields from CFD computations can be used directly as network inputs. Through convolution operations, CNNs automatically extract geometric features such as leading-edge curvature, maximum-thickness location, and trailing-edge shape, and map these features to aerodynamic performance. Compared with manual extraction of geometric parameters, CNNs can more fully use spatial information in the data and thus improve prediction accuracy. CNNs have also been applied to flow-field reconstruction and pressure distribution prediction. For example, given airfoil geometry information, a CNN can rapidly predict the pressure distribution over the airfoil surface, providing richer flow-field information for airfoil design.

3.3. Transformer: multi-condition aerodynamic performance prediction

In recent years, the Transformer, with its self-attention mechanism, has been gradually applied in fluid mechanics and aerodynamics research [15]. Compared with traditional neural networks, the Transformer can capture global correlations among different positions in the input data, making it better suited to aerodynamic data with complex coupling relationships. In airfoil aerodynamic prediction, operating parameters such as Mach number, angle of attack, and Reynolds number can be encoded as condition inputs, and the attention mechanism learns the relationships among different flight conditions, enabling cross-condition aerodynamic performance prediction. Existing studies have shown that the Transformer achieves good prediction accuracy and generalization under

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multi-Mach-number and multi-angle-of-attack conditions [16]. Compared with DNNs and CNNs, the Transformer can handle multi-variable coupling more effectively and provide more stable predictions in complex flow environments. Therefore, it is considered an important direction for intelligent aerodynamic design.

In airfoil aerodynamic optimization, data-driven models can act as CFD surrogates and be combined with genetic algorithms or particle swarm optimization to reduce CFD calls and improve efficiency with acceptable accuracy.

4. Discussion

4.1. Challenges

In recent years, deep learning has significantly reduced numerical computation and improved airfoil design efficiency, showing strong potential for surrogate modeling, rapid prediction, and intelligent optimization. However, owing to factors such as training data, model architecture, and physical constraints, current data-driven methods still face challenges before practical engineering application.

4.1.1. High cost of acquiring high-quality training data

Deep learning models typically require large amounts of high-quality data for training, whereas airfoil aerodynamic data mainly originate from high-fidelity CFD numerical simulations and wind tunnel tests [5]. Compared with typical image datasets, CFD computations are time-consuming and resource-intensive, especially under high-Reynolds-number, transonic, or complex turbulent conditions, where a single high-precision computation may take several hours or longer. Therefore, constructing large-scale datasets covering different airfoils, Mach numbers, and angles of attack is costly, which limits the training effectiveness and widespread application of deep learning models.

4.1.2. Insufficient model interpretability

Most deep learning models are black-box models [17]. Although they can predict airfoil aerodynamic performance with reasonable accuracy, their internal decision-making processes are difficult to interpret, and they cannot clearly explain how changes in airfoil geometry affect flow-field structure and aerodynamic forces. This lack of interpretability reduces researchers' confidence in model predictions and hinders deployment in high-reliability applications such as aeronautical engineering.

4.1.3. Limited model generalization capability

Since deep learning models are primarily trained on specific datasets, their predictions are relatively reliable within the training distribution. However, when applied to new airfoil types or new flight conditions, prediction accuracy decreases markedly. For example, some models may accurately predict the aerodynamic performance of low-speed airfoils, but under transonic, hypersonic, or complex flow conditions, prediction errors may increase noticeably. Moreover, when the number of training samples is small or the sample distribution is imbalanced, models are prone to overfitting, further affecting prediction performance.

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4.2. Future development directions

To address the bottlenecks of high-quality training data acquisition cost, insufficient model interpretability, and limited generalization capability in data-driven aerodynamic optimization design, future efforts should further introduce Physics-Informed Neural Networks (PINNs), Multi-Fidelity Deep Neural Network (MFDNN) methods, and collaborative optimization methods. These approaches have the potential to address current limitations in training cost, interpretability, and generalization.

4.2.1. Physics-Informed Neural Networks

PINNs incorporate the governing equations of fluid mechanics into the training process, enabling models to learn from data while satisfying physical conservation laws [18]. Compared with traditional deep learning, PINNs reduce dependence on large training datasets, improve physical consistency, and enhance prediction capability under unknown operating conditions. In recent years, PINNs have been applied to flow-field reconstruction, pressure prediction, and fluid parameter inversion, and are considered an important development direction in data-driven aerodynamics.

4.2.2. Multi-Fidelity Deep Neural Network (MFDNN) methods

Data from different sources vary in computational accuracy and acquisition cost. For example, low-fidelity data are fast to compute but less accurate, while high-fidelity CFD and wind tunnel test data are highly accurate but costly [19]. In the future, Multi-Fidelity Deep Neural Network (MFDNN) models can fuse data at different fidelity levels to improve model prediction accuracy while reducing data acquisition costs.

4.2.3. AI-CFD collaborative optimization

Future data-driven methods will not completely replace CFD; rather, they are more likely to form an "AI + CFD" collaborative optimization paradigm [15]. In this paradigm, deep learning models rapidly predict and screen design candidates, while CFD performs high-precision verification and refinement of the selected candidates [5]. These two components complement each other, maintaining high computational efficiency while ensuring reliable prediction results, thus enabling intelligent airfoil optimization design.

5. Conclusion

This paper reviews the current state of data-driven airfoil aerodynamic optimization design and summarizes the application status and key technologies of traditional CFD-coupled optimization methods. Models such as Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Transformers can effectively learn the complex relationships between airfoil geometry and aerodynamic performance, enabling rapid aerodynamic performance prediction and cross-condition modeling. They demonstrate good robustness and application prospects in surrogate model construction and intelligent optimization design.

However, owing to cost constraints, the black-box nature of these models, and limited generalization, future efforts should further promote technologies such as Physics-Informed Neural Networks (PINNs), multi-fidelity data fusion, and AI-CFD collaborative optimization. Data-driven

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airfoil aerodynamic optimization is expected to further improve prediction accuracy and engineering applicability, providing more efficient and reliable technical support for intelligent aircraft design.

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