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A Comprehensive Review of Modern Aerodynamic Optimization Techniques

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Abstract

In order to improve performance, efficiency, and sustainability in energy, automotive, and aerospace systems, aerodynamic optimization is an essential part of contemporary engineering design. Current advances in aerodynamic optimization are covered in this paper, including gradient-based methods such adjoint techniques for efficient sensitivity analysis in high-dimensional design spaces and gradient-free and evolutionary algorithms for complex and nonlinear situations. The increased incorporation of machine learning and surrogate modeling has reduced the computing cost of high-fidelity CFD simulations, enabling faster and more efficient design exploration. The essay also discusses multidisciplinary and multi-objective optimization frameworks for aerodynamics, propulsion systems, and structures. We examine high-dimensional design spaces, computational costs, uncertainty quantification, and novel research avenues like physics-informed models and hybrid CFD-AI techniques. This page compiles trends and methods for aerodynamic optimization.

Keywords

Aerodynamic Optimization, Adjoint & Evolutionary Methods, Machine Learning & Surrogate Modeling, Multidisciplinary Design Optimization

1. Introduction

The relentless pursuit of increased performance, efficiency, and safety in the automotive, aerospace, and other fluid-flow-dependent industries has put aerodynamic optimization at the forefront of modern engineering design [1]. Aerodynamic form design used to primarily rely on empirical methods, intuition, and extensive physical testing. This method was often expensive, time-consuming, and unable to completely explore the vast design space [2] [3]. However, significant advancements in processing power and numerical techniques—particularly in processing Fluid Dynamics (CFD) [1]-[5]—have made aerodynamic shape optimization a difficult field. This shift has made it feasible to methodically discover novel, often counterintuitive designs that are far better than those that can be produced with more traditional techniques.

Computational advancements in both hardware and numerical schemes, particularly in CFD, have enabled a rigorous study of complex aerodynamic design spaces, resulting in the discovery of better and often counterintuitive designs. Efficient gradient computation algorithms, especially those based on the adjoint approach, have greatly enhanced optimization studies in higher-dimensional aerodynamics and are discussed in detail in Sections 3 [6]-[8]. The method allows for form optimization at high fidelity even when dealing with design problems comprising millions of design variables by creating a "sensitivity map" for optimizing purposes [7] [9] [10].

The adjoint approach is a revolutionary development since it efficiently computes the gradients of an objective function with respect to several design factors at a computational cost that is essentially independent of the number of these variables [6] [7]. This stands in stark contrast to finite-difference methods, which are impractical for complex geometries with many parameters since they require a separate simulation for every design variable [7]. Simplifies complex restricted optimization problems into smaller unconstrained ones using Lagrange multipliers and the calculus of variations, providing a "sensitivity map" that identifies the design elements most important to performance [7] [11]. High-fidelity aerodynamic shape optimization for turbomachinery and other applications has made substantial use of this method [12].

Advancements in experimental, computational, material science, and flow control technologies are leading to major improvements in aerodynamic design and performance. The integration of AI and ML techniques, including deep reinforcement learning and evolutionary algorithms, has led to new approaches for optimizing aerodynamic shapes [2]-[14]. These AI-powered approaches may learn from optimization experiences, manage multidimensional design environments, and enable quick design exploration, resulting in more efficient and imaginative solutions. For example, deep reinforcement learning can automatically learn optimization strategies based on interactions with the environment, solving issues such as data waste and the need to re-run entire optimization processes when starting shapes change.

Figure 1 depicts the latest innovations in aerodynamic tools, techniques, technologies, and applications [15]. Experimental aerodynamics, including sub-scale and full-scale testing and flight experiments, will advance with advanced sensors, equipment, and measuring systems. The future of time-resolved PIV will be defined by technological breakthroughs in imaging, data processing, and integration with new approaches. Future improvements could enable researchers to study flows at several scales simultaneously, connecting small-scale turbulent dynamics to large-scale flow patterns and improving our understanding of turbulence across all scales.

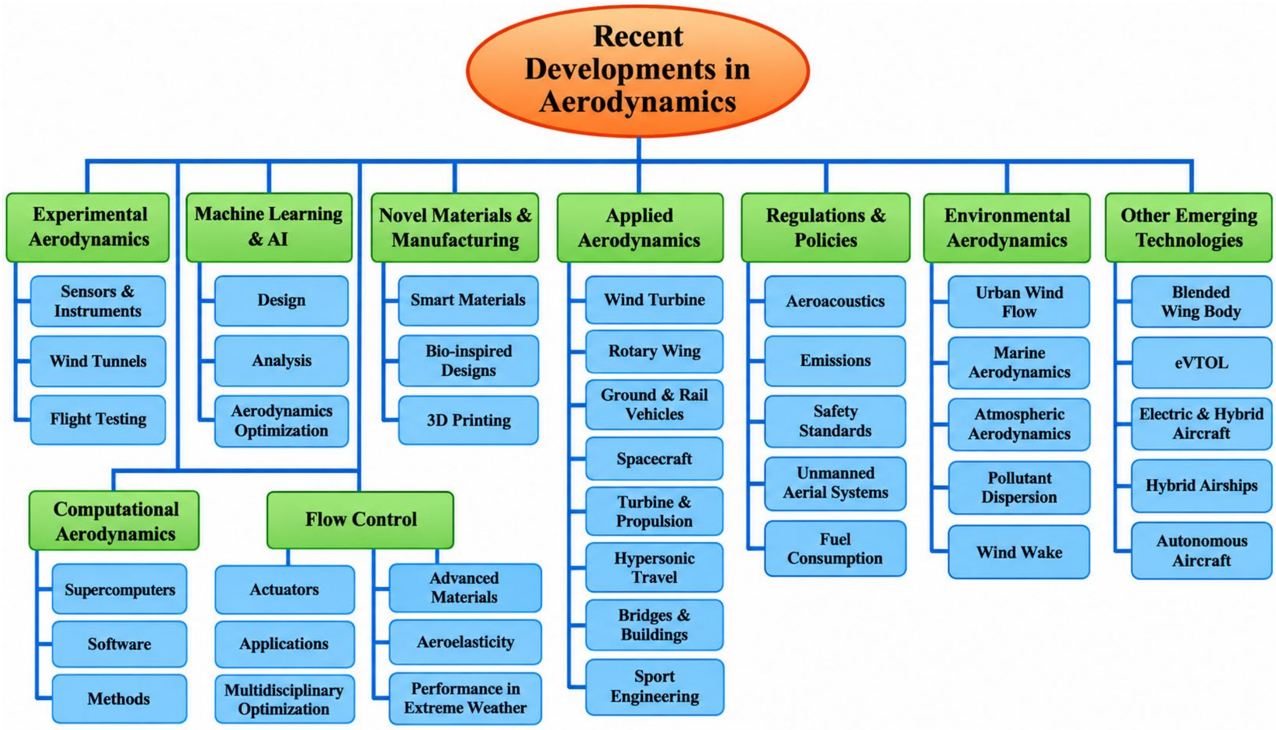

Figure 1. Diagram depicting the main areas of study in the field of aerodynamics as it has evolved recently [15].

Aerodynamic optimization takes into account multidisciplinary trade-offs, resilient design under uncertainty, and geometric and physical restrictions in addition to minimizing drag [16] [17]. Modern methods seek to develop designs that function consistently across a range of operating situations rather than merely at a single optimal point by addressing problems including structural integrity, thermal loads, and noise attenuation. This study will closely investigate these developments as well as the theoretical foundations, computational techniques, and practical applications that characterize the state-of-the-art in contemporary aerodynamic optimization.

In this review, the optimization techniques in aerodynamic flows have been reviewed in terms of external aerodynamics (which comprises airfoil, wings, ground vehicle aerodynamics, etc.) and internal flow geometries (compressors, turbines, etc.). The focus of the review lies on the optimization of subsonic and transonic flow conditions, which find significant applications in industry and aerospace technology, but some advances in the area of supersonic and turbulent flow optimizations have also been highlighted when deemed necessary. It should be noted that in the context of this review, optimization techniques based on computation and data analysis are preferred over those employing only experimental methods, especially in cases involving complex design parameters and multidisciplinary methods.

This paper is based on a systematic survey of literature regarding aerodynamic optimization. Several scientific databases such as Scopus, Web of Science, Google Scholar, and ScienceDirect have been thoroughly reviewed to find relevant articles. Relevant key terms used during the search include "aerodynamic optimization," "computational fluid dynamics (CFD)," "adjoint method," "evolutionary algorithms," "surrogate modeling," "machine learning in aerodynamics," and "multidisciplinary design optimization (MDO)."

2. Fundamentals of Aerodynamic Optimization

Improving the performance characteristics of objects moving through air or other fluid media, such wind turbines, vehicles, and airplanes, is the aim of the complex engineering field of aerodynamic optimization [1]. By carefully altering the object's shape, the primary objective is typically to improve efficiency, decrease drag, boost lift, or regulate thermal and acoustic characteristics. The interaction of sophisticated computer techniques and fluid dynamics ideas is crucial to this process [1] [18]. The advancement of aerodynamic optimization has been greatly influenced by increases in computer power. Early methods relied on basic analytical models and empirical data. Modern computational fluid dynamics (CFD) methods evolved progressively over several decades, with significant advances in numerical schemes, turbulence modeling, and computational power enabling their widespread application in aerodynamic design [19]. Compared to manual design approaches, CFD-based optimization significantly reduced design time by facilitating the evaluation of previously unmanageable complicated designs [18] [19]. Large design spaces can now be explored by automated design processes thanks to the advancement of optimization algorithms and numerical solvers in recent decades, which would not be feasible using conventional experimental techniques [20]. To improve fuel efficiency, reduce emissions, and boost agility across industries, aerodynamic design must keep evolving. Because traditional design approaches frequently depended on linear methods, important coupling effects were overlooked and disciplines like aerodynamics and control were artificially separated. Modern aerodynamic optimization uses multidisciplinary design analysis and optimization (MDAO) to manage these intricate interactions, especially in challenging situations such as hypersonic flight.

One of the main problems in aerodynamic optimization is the high computational cost of analyzing several design modifications using high-fidelity computational fluid dynamics (CFD) simulations. Brute-force optimization is not feasible for complex geometries with numerous design parameters because a single CFD simulation may need a large amount of time and computer resources. This computing limitation has led to the development of numerous sophisticated methods to expedite optimization without compromising accuracy. One of the main obstacles to aerodynamic optimization is the computational cost of running costly CFD simulations on a regular basis.

To address this, numerous approaches have been devised:

Gradient-Based Optimization:

Aerodynamic optimization relies heavily on gradient-based techniques for situations with several design variables [21]. These methods depend on the efficient computation of the sensitivity (gradients) of the target function with regard to the design factors.

Adjoint approach:

The computing cost of the adjoint approach, an effective gradient calculation methodology, is largely unaffected by the number of design variables [19] [21]. This makes it incredibly effective for high-dimensional design spaces and complex geometries, such as those seen in turbomachinery [6] [17]. The adjoint technique is a common option in aerodynamic design optimization because it can turn insoluble problems into ones that can be solved, despite the fact that it takes careful thought [17]. In the face of flow uncertainty, adaptive polynomial chaotic expansion (PCE) in conjunction with a discrete adjoint framework may allow for robust aerodynamic optimization of turbomachinery, therefore overcoming the "curse of dimensionality." The adjoint approach has been a key topic of research for aerodynamic optimization in turbomachinery due to its efficacy in upgrading designs to meet growing sustainability criteria [6].

Finite Differences:

Although conceptually more straightforward, finite difference approaches need the individual perturbation of each design variable and the subsequent re-execution of the flow solver, rendering them computationally impractical for problems with numerous variables [19].

Derivative-Free Optimization (DFO):

For problems of intermediate dimensionality, derivative-free optimization techniques can be competitive. These approaches do not necessitate gradient information, hence facilitating implementation when adjoint solvers are unavailable or challenging to construct. Nevertheless, their efficacy may diminish in exceedingly high-dimensional settings [21].

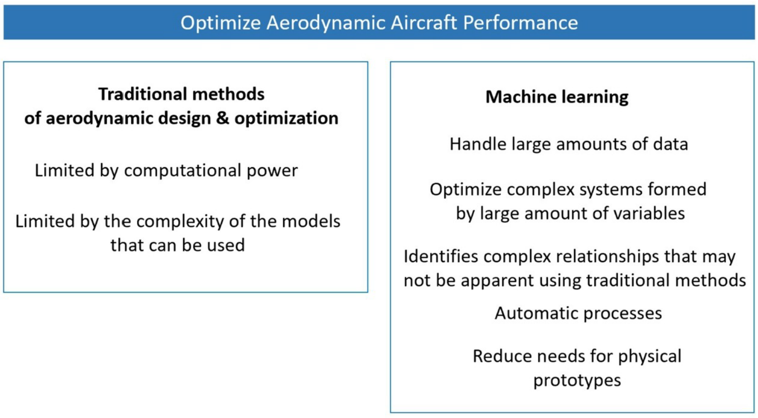

Figure 2. A comparison of machine learning-based and conventional aerodynamic optimization techniques.

Figure 2 compares modern machine learning-based methods with traditional aerodynamic design and optimization methods. It is shown that existing approaches' ability to explore large design domains is limited by their computational limitations and model complexity. However, machine learning methods enable the handling of large datasets, the optimization of complex systems with many variables, the discovery of hidden connections, the automation of processes, and a reduction in the need for physical prototyping.

3. Gradient-Based Optimization Techniques

Gradient-based optimization techniques are one of the most potent and extensively utilized methods in current aerodynamic optimization because they are good at solving high-dimensional design issues. These methods depend on calculating the sensitivities (gradients) of objective functions like drag, lift, or lift-to-drag ratio in relation to design variables. This makes it possible to quickly find the best solutions. In aerodynamic applications, the objective function usually depends on the solution to the equations that regulate fluid flow. Because of this, evaluating the gradient is an important part of the optimization process. Traditional finite-difference methods for calculating gradients are expensive because they need a lot of flow simulations, which are based on the number of design factors. Because of this, advanced methods like the adjoint method have become the basis for gradient-based aerodynamic optimization. This is because they can quickly compute gradients at a cost that is almost independent of the number of design variables [22]. **Figure 3(a)** and **Figure 3(b)** illustrate the adjoint-based aerodynamic optimization loop. CFD analysis, objective function assessment, adjoint equation solution, sensitivity computation, geometry parameterization, and iterative design update till convergence follow.

Modern aerodynamic design makes extensive use of gradient-based optimization techniques due to their ability to effectively manage optimization problems involving several design variables. In order to incrementally enhance aerodynamic performance, these methods utilize sensitivity information, which is represented by gradients of the objective function with respect to design variables. For high-fidelity computational fluid dynamics (CFD) simulations used in aerodynamic optimization, gradient-based approaches are preferable since they demand a lot fewer function evaluations than gradient-free methods like particle swarm optimization or evolutionary algorithms [23]. When solving aerodynamic optimization problems, the objective function usually stands for performance measures like reducing drag, increasing lift, or decreasing the ratio of lift to drag. Gradient-based algorithms change the design variables in the direction of the goal function's negative gradient until the problem is solved. When optimizing the shape of an airplane wing, an airfoil, or a vehicle, these methods work especially well in high-dimensional design spaces [23]. The adjoint approach mathematically creates a Lagrangian formulation in which the objective function is limited by the governing equations. Solving the adjoint system allows for the efficient expression of the gradient of the objective function concerning design variables, eliminating the need to differentiate the flow solution with respect to each variable directly. Computational expenses are greatly decreased as a result, especially for multi-dimensional optimization problems. For instance, the adjoint technique simplifies the process of determining sensitivities for thousands of geometric parameters while developing aerodynamic forms. As a result, it is crucial to the design of modern aircraft. Recent research suggests that gradient-based techniques can be used with reduced-order and surrogate models to significantly speed up optimization without compromising accuracy [24]. In conclusion, gradient-based optimization methods—especially those that use adjoint approaches—are the most important component of contemporary aerodynamic optimization. Because of their capacity to accurately offer sensitivity information and manage a wide range of design elements, aerodynamic design has greatly improved. Current research focuses on building hybrid methodologies, integrating machine learning techniques, and fortifying systems in order to overcome current problems and further improve optimization performance.

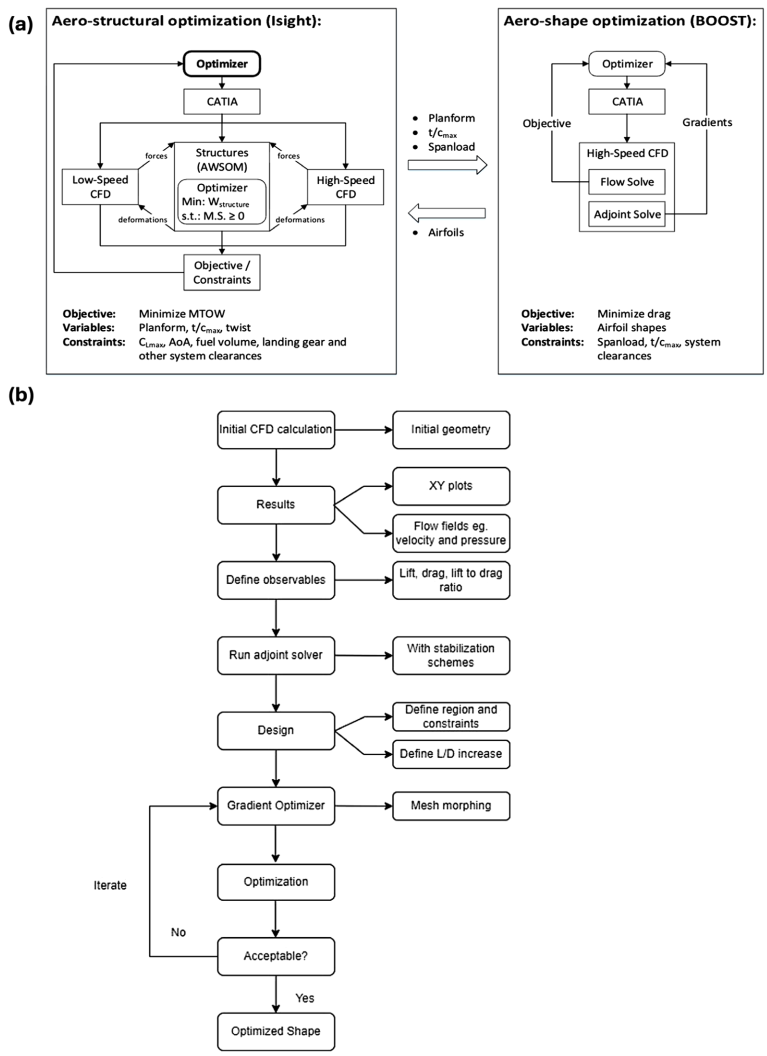

Figure 3. (a) and (b) An adjoint-based aerodynamic optimization approach that includes CFD analysis, adjoint solution, sensitivity evaluation, and iterative design update [7] [19].

Principle of Gradient-Based Optimization

Gradient-based optimization is based on the idea that you may use first-order derivative (gradient) information about an objective function to iteratively move the design variables closer to the best solution. Optimization challenges are usually set up so that a cost or objective function is minimized (or maximized) while still meeting certain conditions. Gradient-based approaches figure out which way to search by looking at how minor changes in design factors affect the objective function. They then alter the variables to get closer to the best solution. When the gradient of the objective function becomes close to zero, it usually means that the optimal solution has been found [25].

In real-world applications, gradient-based optimization works by using the gradient to find a search direction and then updating the design variables over and over again using first-order knowledge. This iterative approach can be seen as solving a series of linearized optimization problems, where the goal function is approximated and improved in small steps. This method speeds up convergence compared to methods that only use function evaluations since gradients give instantaneous information about how sensitive the objective function is. A fundamental need of gradient-based optimization is the accurate calculation of the gradients (sensitivities) of the objective function with respect to design elements. For complex engineering problems like aerodynamic optimization, it is often challenging to estimate these gradients because the objective function is based on governing equations (like CFD equations). Finite-difference and other traditional techniques are expensive to compute since they have to repeatedly evaluate the goal function. The adjoint approach is a well-liked solution to this problem. It enables you to rapidly compute gradients without appreciably raising calculation costs, regardless of the number of design variables [26]. The adjoint approach uses additional variables (adjoint variables) to solve an additional set of equations in order to obtain all sensitivities simultaneously. Additionally, more recent gradient-based optimization techniques usually include more complex strategies to speed up and stabilize the process, such as conjugate gradient approaches, quasi-Newton methods, and cumulative gradient updates. Cumulative gradient techniques, for example, use gradient information from several iterations to increase the search direction and stability [5]. For high-dimensional optimization problems, where rapid convergence is essential, these advances are especially important. In conclusion, gradient-based optimization uses gradient information to choose which direction to improve and repeatedly modifies design factors to obtain the optimal solution. Thanks to the development of effective gradient calculation algorithms, particularly the adjoint approach, gradient-based optimization is now a crucial part of complicated engineering optimization issues and current aerodynamic design.

4. Gradient-Free and Evolutionary Optimization Methods

Gradient-free and evolutionary optimization techniques have become essential tools in aerodynamic design optimization, especially when gradient data is hard to get or calculate. The target function in many aerodynamic issues may be very nonlinear, discontinuous, or noisy due to complicated flow dynamics and numerical simulations. In some circumstances, traditional gradient-based methods may either fail to converge or become too computationally costly to employ. Gradient-free approaches overcome these constraints by exploring the design space using heuristic or stochastic methods instead of depending on derivative knowledge [21]. These methods are especially helpful when employing high-fidelity simulations, such as Large Eddy Simulation (LES) or Reynolds-Averaged Navier-Stokes (RANS) models, in the optimization process. Because of the adjoint technique's potential instability and implementation problems in such simulations, derivative-free techniques offer a workable substitute for aerodynamic form optimization [27]. Gradient-free methods often use stochastic search tactics to gradually enhance a huge number of possible solutions. Because these algorithms can avoid local optima and explore complex design spaces, they are appropriate for airfoil design, aircraft wing optimization, turbomachinery blades, and UAV aerodynamic configurations. Evolutionary algorithms (EAs), a popular class of gradient-free techniques, are based on biological evolution and natural selection. These methods work on a group of possible solutions that change over time through processes like selection, crossover, and mutation. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) are some of the most used evolutionary algorithms used to improve aerodynamics. These methods work best for global optimization since they look at the design space as a whole and are less prone to get stuck in local optima than gradient-based methods. For example, NSGA-II has been used successfully to solve multi-objective airfoil optimization issues by maximizing both lift and drag at the same time, which increased aerodynamic performance [28]. One of the best things about evolutionary optimization approaches is that they can solve multi-objective and constrained optimization problems without needing gradient information. In aerodynamic design, population-based methods can be used to optimize multiple goals at the same time, such as maximizing lift, minimizing drag, and making sure that structural limits are met. Also, these methods can readily include both discrete and mixed design variables, which is hard to do with gradient-based methods. Surrogate models (metamodels) have also been effectively integrated with evolutionary algorithms to lower the cost of computing by approximating expensive CFD simulations. This makes it possible to efficiently explore enormous design spaces [29].

Figure 4 illustrates the fundamental concepts of evolutionary optimization approaches. Panel (a) shows the workflow of a genetic algorithm, including population initialization, evaluation, selection, crossover, mutation, and convergence. In addition to highlighting convergence and variety preservation as well as potential and unfeasible solution locations, Panel (b) displays a Pareto front that illustrates the trade-off between competing aims [21] [28] [29].

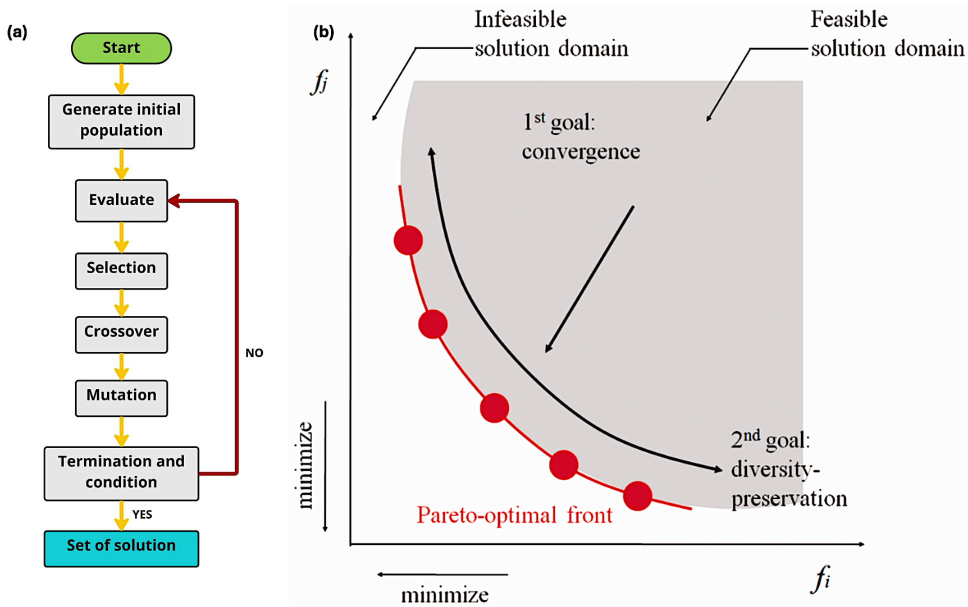

Figure 4. The evolutionary optimization framework, which includes the multi-objective trade-off Pareto front and the genetic algorithm process [21] [28] [29].

5. Surrogate Modeling and Data-Driven Approaches

The high computational cost of high-fidelity computational fluid dynamics (CFD) simulations has made surrogate modeling and data-driven approaches indispensable tools in contemporary aerodynamic optimization. Thousands of simulations are frequently needed for aerodynamic optimization in order to assess performance parameters like lift, drag, or pressure distribution. When calculating the Reynolds-Averaged Navier-Stokes (RANS) equations for complicated geometries, these simulations can be computationally costly. An effective substitute is offered by surrogate models, which use statistical or machine-learning models trained on a small dataset produced from CFD simulations to approximate the relationship between design variables and aerodynamic performance [30]. In order to substitute costly CFD evaluations with quick forecasts, surrogate models are frequently incorporated into optimization frameworks. This method maintains adequate accuracy for design exploration while drastically lowering computational costs. Surrogate models are often used in conjunction with optimization algorithms and design-of-experiments (DOE) techniques to effectively search the design space in aerodynamic design optimization [31].

Figure 5 illustrates the classification of machine learning (ML) models used in aerodynamic optimization and surrogate modeling [2] [13]. Supervised, semi-supervised, and unsupervised learning are the three categories into which the framework classifies machine learning methods. Supervised learning methods for aerodynamic response prediction include neural networks, random forests, support vector machines, and k-nearest neighbors. To achieve adaptive optimization, semi-supervised approaches include reinforcement learning techniques like Markov decision processes and Q-learning. Unsupervised learning methods such as Principal Component Analysis (PCA), Proper Orthogonal Decomposition (POD), and clustering are used to extract features and reduce dimensionality. The illustration also shows artificial neural network (ANN) architectures such as multilayer perceptrons (MLP) and deep learning models such as convolutional neural networks (CNN), recurrent neural networks (RNN), and physics-informed neural networks (PINNs).

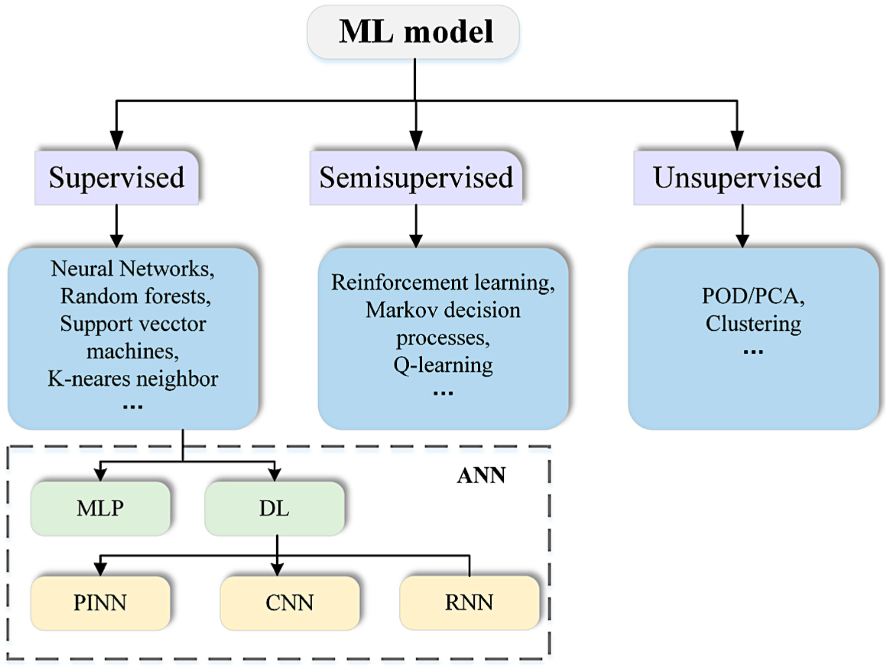

Figure 5. Common machine learning models and neural network architectures utilized in aerodynamic optimization, include supervised, semi-supervised, and unsupervised learning approaches [2] [13].

Surrogate Modeling in Aerodynamic Optimization

The real aerodynamic response function that comes from CFD studies is close to being represented by a surrogate model. In math terms, this estimate can be written as

$$J\wedge(x)=f_s(x)$$

where

x stands for the vector of design factors,

$J(x)$ is the real objective function that we got from the CFD simulations,

$J\wedge(x)$ is the answer that the surrogate model thinks will happen, and

$f_s(x)$ is the function for surrogate estimate.

The dataset for the surrogate model comes from CFD simulations that were run at certain sample places in the design space. To make sure that the design space is covered enough, these steps are usually made using Design of Experiments (DOE) methods like Latin hypercube sampling or factorial design. The surrogate model is developed from a dataset derived from CFD simulations conducted at specific sample points within the design space. These points are generally produced utilizing Design of Experiments (DOE) methodologies, including Latin hypercube sampling or factorial design, to guarantee adequate representation of the design space. Surrogate modeling substantially alleviates the computing demands of aerodynamic optimization. Rather than repeatedly resolving the governing flow equations, the optimization method assesses the surrogate model, which can forecast aerodynamic performance in a significantly reduced computing timeframe [32].

Figure 6 illustrates a surrogate modeling (SM) framework for data-driven aerodynamic flow prediction [30]-[32]. The input consists of flow field variables such as velocity components (u_x, u_y) and spatial descriptors (e.g., signed distance function, sdf). These inputs are divided into localized blocks in order to extract characteristics. Next, dimensionality is reduced and a smaller set of important characteristics is produced using Principal Component Analysis (PCA). A machine learning model, such as a multilayer perceptron (MLP), is trained using these features to predict the reduced-order form of the output field. The expected features are rebuilt using inverse PCA, and the whole flow field (including the pressure distribution p_t) is assembled using local predictions. This approach significantly reduces computational costs while maintaining accuracy in aerodynamic models.

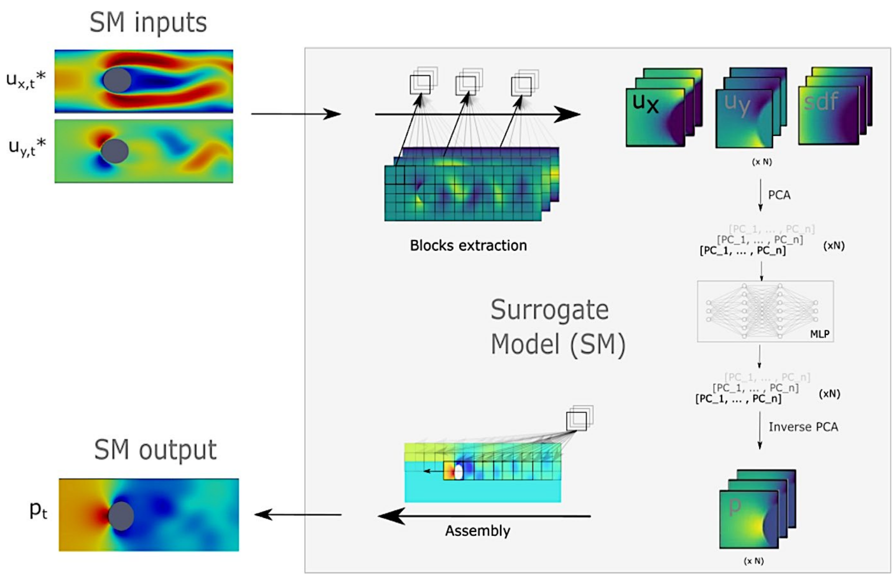

Figure 6. A surrogate modeling framework for aerodynamic flow prediction uses machine learning (MLP), block-based feature extraction, and PCA-based dimensionality reduction for efficient flow field reconstruction [30]-[32].

6. Multi-Objective and Multi-Disciplinary Optimization

Modern aerodynamic design challenges involve a number of conflicting goals and connections across several technological fields. Improving aerodynamic efficiency may lead to increased structural weight or lower aircraft stability. Multidisciplinary Design Optimization (MDO) and Multi-Objective Optimization (MOO) frameworks are widely used in aeronautical engineering to solve complicated problems. These approaches allow engineers to concurrently evaluate a variety of physical domains, including aerodynamics, structural integrity, propulsion, and control systems [33]. Multi-objective optimization aims to simultaneously optimize many objectives, whereas multidisciplinary design optimization incorporates analyses from multiple engineering domains into a cohesive optimization framework. When trade-offs between a variety of performance factors need to be carefully examined, these methods are crucial for the conceptual and fundamental design of aircraft [34].

Multidisciplinary Design Optimization (MDO)

Multidisciplinary Design Optimization amalgamates many engineering disciplines into a unified optimization framework. In aeronautical systems, these fields often encompass:

Aerodynamics

Structural Mechanics

Propulsion mechanisms

Flight dynamics and control

Finding a design that either maximizes performance or lowers total system cost while satisfying performance standards across all pertinent disciplines is the aim of MDO.

Aircraft design is intrinsically multidisciplinary since modifications to aerodynamic arrangement can impact structural loads, propulsion efficiency, and aircraft stability. Because of this, integrated MDO frameworks that integrate aerodynamic research with structural and performance models are becoming increasingly crucial for the development of contemporary aircraft [35].

7. Method Selection and Comparative Synthesis

The choice of an adequate method of aerodynamic optimization depends significantly on the nature of the design task. Methods that employ gradients are best suited for optimizing high-dimensional designs, which have smooth and differentiable objective functions and whose sensitivity information is easy to extract, especially using adjoint approaches. The use of such methods allows for computational efficiency when dealing with large-scale problems, although such problems might pose certain challenges if the design space is highly nonlinear or exhibits some kind of discontinuity.

On the contrary, gradient-free methods, as well as evolutionary approaches, prove to be much more effective at dealing with problems that include non-smooth, noisy or multi-modal objective functions for which the information on the gradients of those objective functions is not available. While these approaches allow for greater robustness when exploring a complicated design space and overcoming any local optima, they typically require considerably larger computational effort. Surrogate-based approaches serve as a good compromise for situations when simulations require extensive computation resources. Using approximate objective functions constructed from data allows for fast design exploration, especially in situations with limited computational resources.

The MOO and MDO paradigm becomes very crucial whenever more than one conflicting objective and interdisciplinary constraints need to be simultaneously addressed. In such cases, the above techniques become especially relevant, because the engineering system under consideration requires the balancing of aspects like aerodynamic properties, structural robustness, power production, and control. However, these paradigms increase the difficulty of the problem, which might require hybridization involving all three major types of optimization techniques. On the whole, the choice of the optimization technique depends on how the above factors interact with each other.

8. Challenges, Applications, and Future Research Directions

In engineering and aerospace design, modern aerodynamic optimization techniques are essential instruments that provide notable gains in economy, performance, and sustainability. These strategies include computational fluid dynamics (CFD), evolutionary algorithms, adjoint-based techniques, and, more recently, data-driven models and artificial intelligence (AI). In order to improve the lift-to-drag ratio, delay flow separation, and boost overall aerodynamic efficiency, aerodynamic optimization techniques are frequently employed in airfoil and wing design. The application of computational fluid dynamics and optimization algorithms has greatly decreased design cycles and increased precision when compared to conventional experimental techniques [36]. Aerodynamic optimization is used to improve the wings, fuselage, and power systems of aircraft and unmanned aerial vehicles (UAVs) in order to minimize fuel consumption and pollution. Multidisciplinary design optimization (MDO) frameworks allow for the simultaneous optimization of aerodynamics, structures, and propulsion, which is essential for advanced aircraft configurations and contemporary distributed propulsion systems [37]. Aerodynamic optimization is also essential in turbomachinery, which includes turbines, compressors, and turbo-engines. The goal is to increase the efficiency of these devices while decreasing aerodynamic losses. By applying machine learning and artificial intelligence [38], it is now possible to estimate flow fields more quickly and enhance optimization methods in these kinds of systems. Professionals in the automotive business frequently employ aerodynamic optimization to lower drag and boost vehicle energy efficiency. They consequently use less gasoline and produce less pollution. Improved designs can increase efficiency and lower drag coefficients by up to 30% - 50%, according to recent studies. Aerodynamic optimization can also help green energy systems, especially when constructing wind turbine blades to maximize wind output under various situations. AI-driven design frameworks, real-time aerodynamic prediction, and surrogate modeling are a few new uses. They expedite and enhance optimization operations by eliminating the need for expensive simulations [36].

Aerodynamic optimization methodologies rely on uncertainty analysis, surrogates' accuracy, and geometry parameterization. Since uncertainties exist in operation conditions and input data, it is imperative to adopt optimization algorithms that tolerate uncertainties, particularly those employed in gradient-based and MDO schemes, in which minor changes have significant effects on sensitivities and convergence. Regarding the surrogate modeling approach, error tolerance and model generalization are highly important in preventing the misleading of optimization due to erroneous predictions, for which reason an adaptive sampling scheme is necessary. Besides, geometry parameterization is an important aspect, influencing the numerical behavior of any optimization methodology, whether gradient-based or evolutionary. An incorrect representation might limit design possibilities and lead to numerical errors, thus playing a vital role in optimization methodology performance.

CFD, adjoint techniques, evolutionary algorithms, and AI-based technologies are all used in modern aerodynamic optimization. Despite these advancements, there are still a number of significant obstacles. High-fidelity CFD simulations are necessary for aerodynamic optimization, but they are costly and time-consuming to compute. Nonlinear Navier-Stokes equations may need to be solved for each design assessment. High-performance computing (HPC) is necessary for large-scale optimization (3D turbulent flows). According to recent studies, computing cost is still a significant challenge, particularly for transdisciplinary and multi-objective problems [19]. Nonlinear behavior in aerodynamic systems is caused by flow physics, including separation, shock waves, and turbulence. The design area contains several local optima. Gradient-based methods might not be able to find global optima.

Evolutionary algorithms improve global search, but they also raise computer costs [1]. Because manufacturing tolerances, operational conditions, and environmental factors are not always understood, robust optimization approaches are also necessary. These make calculations and modeling even more difficult [39]. One of the main problems is that high-fidelity CFD simulations need a lot of computing power and multiple evaluations during the optimization process. This is due to their use of complex, nonlinear governing equations. This difficulty becomes critical when there are several objectives and a large optimization assignment. In some circumstances, thousands of models may be needed [19]. Another important problem is that aerodynamic design spaces are nonlinear and have several modes. These regions often display a range of local ideal circumstances due to complicated flow dynamics such as turbulence, shock waves, and flow separation. This makes it more difficult for gradient-based methods to find the global optimal solutions and raises the need for global optimization procedures, which are very time- and computer-intensive. Because contemporary aerodynamic optimization takes into account several design factors pertaining to mesh generation, geometry parameterization, and operating circumstances, the problem is made worse by the curse of dimensionality. As a result, surrogate models become less helpful and the search space grows exponentially [36]. Measuring uncertainty and making sure designs are sturdy are two more important concerns. This is because real-world aerodynamic performance is influenced by manufacturing tolerances, ambient factors, and fluctuations in operating conditions. The optimization procedure is made more difficult by the inclusion of these unknowns. As a result, models and computation become more challenging. Multidisciplinary connections make things more difficult because propulsion systems, structural mechanics, and aerodynamics can all affect one another and lead to problems with convergence and competing goals in optimization methodologies. Despite their potential, data-driven and AI-based systems are limited by the need to interface with physics-based models, the lack of high-quality training data, and their inability to generalize. These models may be challenging for computers to train, especially when the problems are significant. As a result, they are less useful in daily life [38]. Mesh distortion and geometry parameterization are still problems. Inadequate parameterization can limit the flexibility of designs, while mesh distortion can result in numerical instability and incorrect findings. Future aerodynamic optimization research will increasingly concentrate on developing more precise, scalable, and effective approaches by fusing modern computational and data-driven methodologies with physics-based models.

Improving the integration of artificial intelligence (AI) and machine learning (ML) with traditional CFD systems is a very intriguing path. Hybrid CFD-ML approaches can significantly reduce processing costs without compromising accuracy, according to recent research, enabling faster optimization of complex systems like transonic aircraft wings [40]. Future research should focus on physics-informed machine learning models, which directly include governing equations and physical restrictions into learning algorithms to improve dependability and interpretability, given the current limitations in generalization and physical consistency. One of the main areas of research is improving surrogate modeling and reduced-order modeling methods. Surrogate models like Kriging, neural networks, and Gaussian processes have proven effective in speeding up optimization by imitating costly CFD simulations. The goal of the upcoming research is to enable adaptive sampling methods that improve accuracy in high-dimensional design spaces and effectively explore complicated design domains. Recent research highlights the creation of adaptive surrogate-based optimization frameworks, where models are continuously modified with new data to boost global search efficiency and reduce uncertainty [30]. Furthermore, it is anticipated that the integration of surrogate models with multi-objective optimization approaches will improve real-time design exploration and decision-making in complex engineering systems. Additionally, research will continue to be heavily focused on multidisciplinary and multi-objective optimization. Future aerodynamic optimization frameworks must concurrently address aerodynamics, structural integrity, thermal performance, acoustic emissions, and environmental effect. This necessitates the creation of multidisciplinary design optimization (MDO) algorithms that are more reliable, scalable, and capable of managing intricate coupling effects and competing goals. Large-scale simulations and optimization processes are anticipated to be made practical by advancements in parallel computing and high-performance computing (HPC) architectures [41]. Future research is therefore expected to focus on reliability-based design, resilient optimization, and uncertainty quantification. To provide real-world applicability, optimization frameworks must consider uncertainties related to production processes, material properties, and operational conditions. To create reliable aerodynamic designs that maintain performance under a variety of circumstances, sophisticated probabilistic approaches and stochastic optimization techniques will be required. Aerodynamic optimization is expected to undergo a revolution with the introduction of digital twins and data-driven design ecosystems, which enable ongoing monitoring, forecasting, and improvement throughout the engineering system lifecycle. By increasing their effectiveness and efficiency, modern aerodynamic optimization techniques have significantly improved engineering design, particularly in the domains of automobiles, aviation, turbomachinery, and renewable energy. The main issues with these approaches are high computer costs, transdisciplinary interaction, nonlinear and high-dimensional design environments, and challenges in controlling uncertainty. Although efficiency has increased because of AI and surrogate models, issues with data availability and generalization still exist. Optimization techniques are still employed in real-time applications and smart design despite these issues. Future studies are expected to focus on multi-fidelity and adaptive optimization frameworks, as well as hybrid approaches that combine machine learning and physics-based models. All things considered, the objective of current advancements is to offer more reliable, effective, and flexible aerodynamic design options.

9. Conclusions

This paper has covered the recent developments in aerodynamic optimization including gradient-based, gradient-free and evolutionary algorithms, surrogate modeling, and MDO/MOO. All of the aforementioned categories of optimization algorithms have their own benefits based on the properties of each problem. Gradient-based methods are known to be highly efficient when applied to large-size and smooth optimization problems. At the same time, evolution strategies are characterized by robustness when used to solve complicated optimization problems. Moreover, surrogate modeling and machine learning models are currently considered very promising because of their ability to lower the cost of computation.

Nevertheless, many aspects pertaining to aerodynamic optimization continue to remain problematic despite the progress made in this domain. The aforementioned aspects include expensive calculations due to the employment of highly accurate CFD algorithms, utilization of methods for uncertainty quantification and robust optimization, inaccuracy of surrogate models, and the issues associated with geometric parameterization and meshing. Future studies must concentrate on hybrid optimization techniques that are based on the integration of both physics and data-driven techniques, uncertainty-aware optimization approaches, and scalable multidisciplinary optimization methods. High performance computing technologies, along with the development of physics-informed machine learning, are believed to provide solutions for overcoming the existing drawbacks.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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