Proceedings of CONF-MPCS 2026 Symposium: Theoretic Physics and Plasma Physics
DOI: 10.54254/2753-8818/2026.DL34744

Aerodynamic Characterization of Unmanned Aircraft: A Descriptive Review of Flight-Test and Parametric Approaches

Chen Yuan

Dulwich International High School Hengqin, Zhuhai, China
Yuanchen7737@outlook.com

Abstract. Aerodynamic characterization is a fundamental aspect of aircraft analysis because lift and drag directly govern flight performance, energy efficiency, and operational capabilities. For unmanned aircraft, this analysis is particularly critical, as these platforms often operate under strict energy constraints and are frequently utilized as testbeds for novel configurations. Current engineering practices primarily employ two distinct paradigms: in-flight system identification and parametric numerical modeling. Bergmann, Denzel, Pfeifle, Notter, Fichter, and Strohmayer established a robust framework for estimating aerodynamic coefficients through direct in-flight thrust measurement, effectively capturing real-world operational dynamics. Conversely, Jin, Yu, Meng, Zhang, Cui, He, ... & Musa demonstrated the efficacy of high-dimensional parametric design and numerical simulation in predicting the performance of morphing-wing vehicles. Although these methodologies differ fundamentally in their approach, they offer complementary insights into aerodynamic behavior. This paper provides a comprehensive descriptive review and comparison of these two techniques, ultimately proposing an integrated approach wherein simulation guides initial design and flight testing validates and refines the models, thereby enhancing the overall aircraft development lifecycle.

Keywords: Unmanned aerial vehicle, aerodynamic characteristics, flight test, parametric modeling, system identification, adjoint optimization

1. Introduction

Lift and drag are the first two properties of aerodynamics that need to be considered when designing aircraft; otherwise, it would be impossible to complete such a design. In general, traditional manned aircraft have a large amount of fuel and a high degree of redundancy to offset the relatively small loss in aerodynamic efficiency; however, unmanned aerial vehicles (UAVs), especially electric multi-rotor and fixed-wing drones, have limited power due to the small energy capacity of batteries and often need to perform long-duration hovering or extended flights. Therefore, even a decrease in aerodynamic efficiency of one-hundredth would reduce the flight time and be uncontrollable; it would be unfit for flight. Therefore, to a certain extent, one should acquire and optimise the aerodynamic characteristics of UAVs accurately [1-3].

It is not very easy to acquire the aerodynamic characteristics of unmanned aerial vehicles (UAVs). In the propeller-driven mode, there is an aerodynamic interference between the slipstream

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2026.DL34744

of the propeller and the wings and fuselage. If this interference is not taken into account in the ground wind tunnel test, and only theory or static test data are used, there will be considerable errors in the drag prediction. Thus, the research of System Identification will be performed on the actual flight data to obtain some aerodynamic information from a real-world system.

At the same time, the Method of modern aeroplane design is also changing gradually. The old way of the serial process of "drawing blueprints - building models - testing in wind tunnels" can no longer meet the requirements of high-speed iteration. Engineers are starting to use parametric design methods now, so a small change in the number of design variables can alter the form of an aircraft in an automatic manner. The former was a "single Design", and now the latter is a "multi-dimensional investigation".

The two research paradigms mentioned above are: one is to calculate aerodynamic coefficients based on actual flight data, and the other is to predict and optimise aerodynamic layout during the design stage; although they are different paths, their ultimate goal is to enhance the overall performance of Unmanned Aerial Vehicles (UAVs). The general characteristics of the two kinds of technologies will be introduced in this paper, and how they work together to build a closed-loop structure in the field of current UAV engineering will be examined.

2. Aerodynamic system identification of unmanned aerial vehicles based on flight tests

The final way to obtain the actual aerodynamic characteristics of Unmanned Aerial Vehicles (UAVs) is flight tests. Although there are some initial data from theoretical calculations and numerical simulations (such as CFD), the actual Reynolds number, atmospheric turbulence and other complex dynamic-aerodynamic coupling phenomena will only be known after the aircraft flies.

2.1. Experimental principle and data perception architecture

Stenfelt, Krüger, Ringert, et al. [4] have shown in their study of the flight test of a small Unmanned Aerial Vehicle (UAV) how to obtain aerodynamic parameters by means of on-board sensor fusion technology. At the bottom of this way is Newton's second law and rigid-body dynamics. In the steady-level flight state of a UAV, its mechanical equilibrium equation can be simplified to approximately show that the thrust (T) is equal to the drag (D) and the lift (L) is equal to the weight (W).

To be in a very good condition, the high-precision inertial measurement unit (IMU) and pitot-static tube, angle-of-attack/sideslip-angle sensor, and motor tachometer are needed at all times of measurement. First of all, many scholars will add high-precision thrust sensors, such as six-component force balances, to the propulsion system to obtain the three-dimensional force/moment vector produced by the propeller in real time. At this time, the lift coefficient (C_L) and the drag coefficient (C_D) can be calculated by the following formulas:

$$C_L = \frac{2L}{\rho V^2 S} C_D = \frac{2D}{\rho V^2 S} \tag{1}$$

In this context, ρ denotes the ambient air density, V stands for the aircraft's true airspeed, and S refers to the wing's reference area.

DOI: 10.54254/2753-8818/2026.DL34744

2.2. Power interaction effects and real-time aerodynamic data analysis

A fundamental problem in flight tests is that it is difficult to maintain ideal and well-controlled experimental conditions. The ground-based test environment is relatively fixed and stable, but Unmanned Aerial Vehicles (UAVs) operate in nature, are subject to all sorts of disturbances in acceleration and attitude, etc., and are therefore unstable. Propeller-induced slipstreams can alter the local flow of air over the wing, change the velocity distribution at the surface, and thus cause all kinds of irregular boundary layer separation, especially in the region around the junction of the wing and the fuselage. At the same time, the autonomous flight control system also frequently changes the speed of alteration of actuator commands and rapidly modifies the flight path and height based on the aerodynamic characteristics of the aircraft.

In recent years, many people have used new ways of system identification to separate the clean aerodynamic signal from the noisy actual flight data, such as Maximum Likelihood Estimation (MLE) and Kalman filter framework. The above two ways to build a dynamic state-space model of the UAV and process the sensor time-series data by means of forward prediction and backward smoothing are presented. A two-pass method can separate the effect of control inputs from that of the actual aerodynamic response. Therefore, the refined dataset can be used to reconstruct high-precision lift curves ($C_L - \alpha$) drag polar plots ($C_D - C_L$) , etc., and other necessary parameters such as minimum-drag speed (V_{md}) and optimum endurance operating points can also be determined reliably.

3. Parametric design and aerodynamic optimization of unmanned aerial vehicles

3.1. Geometric parameterization and control of design flexibility

The conventional aerodynamic configuration design of UAVs is based on empirical knowledge, and the wing shape is generally a scale-and-twist variation of a standard airfoil from the NACA series. While this approach is intuitive, it offers a limited design space and constrains further optimization. In contrast, modern parametric design frameworks are mathematically driven, enabling the systematic definition of an aircraft's three-dimensional geometry.

Lee, Kim, and Lee [5] developed a robust parametric model utilizing B-spline curve representation and Free-Form Deformation (FFD) to optimize the aerodynamic shape of low-Reynolds-number UAVs. Within this system, primary wing properties—such as chord distribution, twist distribution, and thickness profile—are treated as continuous functions controllable via the manipulation of control points. Modifying these points generates a wide array of topologically sound aerodynamic shapes. Furthermore, this methodology addresses structural considerations concurrently, facilitating the design of lightweight yet strong structures that integrate favorable aerodynamics with structural integrity.

3.2. Adjoint-based sensitivity computation and high-dimensional gradient evaluation

If the number of Design Parameters is increased to several dozen or even a hundred, the calculation load for the old finite-difference method will be prohibitively high. Therefore, in order to address the above problem, the adjoint method of optimal control theory has been applied for an economical sensitivity analysis [6].

Generally, we solve the Navier-Stokes (N-S) equations in CFD to get the flow field information. In short, the adjoint method can compute the gradient (sensitivity) of the objective function with

DOI: 10.54254/2753-8818/2026.DL34744

respect to all design variables at once by solving an "adjoint equation" that is dual to the original problem.Its mathematical expression can be briefly described as follows: if the objective function is J and the design variable is α, then by solving the adjoint variable ψ, the gradient $\nabla J(\alpha)$ can be directly obtained.

A certain advantage of this way is that it is scalable; that is, even when the number of parameters is large, only one primal-flow-solution plus one adjoint-field-solve needs to be performed for gradient computation. A Gradient-Descent Optimiser, such as Sequential Quadratic Programming (SQP), is employed here to update the solution according to the gradient in the direction of descent and find a good, low-energy design efficiently.

3.3. Surrogate modeling and multi-objective evolutionary optimization

Besides the gradient-based method, other ways that do not use gradients have also been employed to optimise the surrogate model. In order to address the problem of sparse simulation data, some scholars have built continuous approximations known as response surfaces by means of interpolative models, such as radial basis functions (RBF) and Gaussian process regression (Kriging). The above are surrogate functions that are computationally cheap approximations of the true objective function [7].

NSGA-II is a well-known type of population-based evolutionary algorithm that can be combined with population-based evolutionary algorithms to perform joint exploration of the Design Space. It can produce a large number of different Pareto-optimal designs (a Pareto front) that balance various reasons for optimisation in the design of aircraft, such as range and agility. Therefore, according to the demands of different missions, engineers can choose.

4. Comparison and critique: combination of empirical verification and predictive models

The other way to assess the aerodynamics of an unmanned aerial vehicle (UAV) is by flight tests, and there are different types of identification methods; among them, one is based on experimental data, while the other is guided by theoretical analysis.

4.1. Precision origins: convergences and divergences

The first strength of flight testing is its empirical fidelity; that is, without making assumptions about fluid-dynamic simplifications, aerodynamic responses are direct manifestations of physical laws and unfiltered verdicts from nature. There are some problems as well; the uncertainty of the instrument and an unstable atmosphere (such as gust-induced flow distortion) in the original data are relatively large, and numerical instability of post-processing methods, such as data assimilation, is also a problem. Therefore, although the test maneuvers are nominally the same, the lift and drag values will be different due to random fluctuations in the strength and shape of surrounding turbulence.

Parametric optimisation has the advantage of being systematic and comprehensive; that is, in a good mathematical model, it can cover the entire design space of geometric parameters. However, how good it is at predicting will be determined by what needs to be predicted by the computational fluid dynamics (CFD) model in actual operation. The mesh size and topology, as well as the turbulence model used (e.g., Spalart-Allmaras versus k-ω SST) and boundary conditions, are all factors that can affect the accuracy of the gradient and thus the feasibility of the calculated optimum. In addition, although some are mathematically optimal, they may not be practically realised due to fabrication errors, deformation under load, thermal expansion, etc.; thus, the model is not perfect.

DOI: 10.54254/2753-8818/2026.DL34744

4.2. Integrated feedback loop: from prediction to refinement

Contemporary UAV development no longer treats empirical validation and predictive modeling as disjoint activities; rather, they constitute an iterative, self-correcting cycle: model → build → fly → refine → re-model. Parametric CFD models are used to obtain the aerodynamic data needed for the first stage of Design of the flight controller and stability augmentation logic. After the first flight, high-fidelity in-situ measurements will be taken to target model recalibration; that is to say, the coefficients of the actuator disk model in CFD simulations or effective Reynolds number corrections for wind tunnel scaling can be obtained through inverse analysis.

For example, if the drag data in flight is consistently higher than the prediction based on the current parameters by a large amount according to statistical tests, then this difference can be added to the optimisation objective function as a physics-informed regularisation term. Therefore, the revised design based on this feedback has fixed some problems and reduced the difference between simulation and reality in the latest vehicle version. Based on experience, the new model will be more stable in the face of changes in the development environment and can respond to changes in the business environment in a timely manner.

5. Emerging directions: intelligent convergence and adaptive real-time optimization

With the development of artificial intelligence and edge computing in recent years, new trends have emerged in the technology for aerodynamic analysis and optimisation of unmanned aerial vehicles (UAVs), and it is being promoted in the field of intelligence, adaptation and energy efficiency.

5.1. Physics-guided neural networks: bridging data and first principles

Most traditional data-driven machine learning methods are not easy to interpret and are thus "black boxes", so they cannot be used to solve physics problems. In light of the above, Physics-Guided Neural Networks (PGNNs) have incorporated the fundamental laws of nature, such as the Navier-Stokes equations, into the network's loss function to ensure that the training results conform to physical principles [8]. In the future, PGNN will be able to perform high-fidelity full-field flow reconstruction from a small number of low-quality flight-test sensor data (which will act as sparse boundary inputs) without the need for a long calibration period and to reduce the workflow of system identification.

5.2. Real-time digital twins for on-the-fly aerodynamic adaptation

More and more new drones will be based on cloud and on-device digital twin platforms, which are virtual replicas of real objects that can be updated in milliseconds. A very low-latency 5G/6G network will be employed to transmit the real-time telemetry data of the attitude, acceleration and airspeed to the twin for multi-objective optimisation in the embedded part, and then the configuration of the morphing wing will be changed almost immediately. A command will be sent to the plane for changes in aerodynamic conditions at high speed, and thus the plane will continue to fly normally despite alterations in the environment [9].

5.3. Co-optimized aerostructural design enabled by additive manufacturing

Parametric Design is no longer only based on Traditional Geometry. With the development of metal additive manufacturing, UAV airframes will be constructed in monolithic, functionally graded

DOI: 10.54254/2753-8818/2026.DL34744

structures. In the future, the structure of generative Design will be able to construct multi-functional integrated outer skins with lightweight lattice cores that can passively change the shape of the surface under aerodynamic load, such as avian feathers, and reduce vibration and lower the radar cross-section. Aerodynamics, Structure and Functionality have been integrated holistically; no longer is there a separation among them [10].

6. Conclusion

Two main ways to research the aerodynamic features of Unmanned Aerial Vehicles (UAVs) are carried out in this paper, which are the flight-test-driven system identification method and the parametric-model-based adjoint optimisation method.

According to the results of high-precision sensor data and strong state estimation technology for flight-test-oriented system identification, the distortion caused by propulsion-aerodynamics coupling has been reduced, and therefore the lift-to-drag ratio is close to that in actual flight. Therefore, it can be used to conduct experiments and verify the aerodynamic model of a UAV. At the same time, adjoint-based optimisation can be employed to solve the geometry parameterisation problem of B-spline free-form deformation (FFD) and efficiently calculate gradients by solving adjoint equations; thus, it does not have the scaling limitation of traditional design methods. It is fully automatic, and because the high computational cost is relatively small, it can carry out high-dimensional shape refinement.

In short, the above two are in harmony. Parametric modelling has a regular structure, and it is easy to explore the design space and conduct all sorts of flight tests. At the same time, flight tests will be conducted to obtain some actual data and verify the accuracy of the parameters and simulations. In order to achieve good aerodynamic performance for the new generation of UAVs, an all-weather continuous improvement cycle must be formed that integrates the construction of virtual prototypes, real-flight tests and data analysis, etc. In the future, there will be a shift in the direction of research on UAV aerodynamics towards the integration of Physics-Informed Neural Networks (PINNs), digital twin infrastructure and real-time adaptive learning; it will be more sensitive and predictive to meet the demands of new flying technology beyond the limitations of traditional aerodynamics.

References

[1] Bergmann, D. P., Denzel, J., Pfeifle, O., & et al. (2021). In-flight lift and drag estimation of an unmanned propeller-driven aircraft. Aerospace, 8(2), 43. https: //doi.org/10.3390/aerospace8020043

[2] Jin, Z., Yu, Z., Meng, F., & et al. (2024). Parametric design method and lift/drag characteristics analysis for a wide-range, wing-morphing glide vehicle. Aerospace, 11(4), 257. https: //doi.org/10.3390/aerospace11040257

[3] Zhang, J., Li, F., & Wang, L. (2020). Aerodynamic characteristics and endurance performance optimization of small electric UAV. Acta Aeronautica et Astronautica Sinica, 41(8), 123–134. https: //doi.org/10.7527/S1000-6893.2019.23456

[4] Stenfelt, G., Krüger, T., Ringert, J., & et al. (2021). Aerodynamic parameter identification of a small unmanned aerial vehicle. In AIAA Scitech 2021 Forum (p. 1187). American Institute of Aeronautics and Astronautics. https: //doi.org/10.2514/6.2021-1187

[5] Lee, D., Kim, J., & Lee, J. (2023). Aerodynamic design optimization of a small UAV wing considering flexibility using parametric modeling and adjoint method. Aerospace Science and Technology, 138, 108345. https: //doi.org/10.1016/j.ast.2023.108345

[6] Wang, G., Liu, Z., & Yang, Y. (2018). Progress in aerodynamic shape optimization using adjoint method. Advances in Mechanics, 48, 201802. https: //doi.org/10.6052/1000-0992-18-006

[7] Chen, H., Zhang, Y., & Huang, J. (2016). Aerodynamic shape optimization design based on surrogate model and genetic algorithm. Acta Aeronautica et Astronautica Sinica, 37(3), 916–926. https: //doi.org/10.7527/S1000-

DOI: 10.54254/2753-8818/2026.DL34744

6893.2015.0198
[8] Jiang, Z., Ren, J., Xu, H., & et al. (2022). A surrogate model for low-speed flow past airfoils based on physics-informed neural network. Acta Aeronautica et Astronautica Sinica, 43(7), 125–136. https: //doi.org/10.7527/S1000-6893.2021.26125
[9] Valencia, E., Toapanta, F., Oña, G., & et al. (2025). An Open-source UAV Digital Twin framework: A Case Study on Remote Sensing in the Andean Mountains. Journal of Intelligent & Robotic Systems, 111, 71. https: //doi.org/10.1007/s10846-025-02276-7
[10] Khan, N., & Riccio, A. (2024). A systematic review of design for additive manufacturing of aerospace lattice structures: Current trends and future directions. Progress in Aerospace Sciences, 149, 101021. https: //doi.org/10.1016/j.paerosci.2024.101021