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Gaps and Opportunities in Aircraft Performance Research

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Abstract. Analysis of aircraft performance underpins the design and certification and safe operation of modern aviation systems. In the past, much of the work in this field relied on simple aerodynamic models, standard atmospheric assumptions, and performance values from primarily controlled flight tests. While these approaches have preserved a degree of inherent safety and compliance with regulatory requirements, the methods used have remained relatively unchanged for decades and are occasionally becoming insufficient for the requirements of modern aviation. This paper reviewed the status quo of methodology, outlined some of the static assumptions on which all these methods rely, and noted some of the limitations born from their failure to adapt in a realistic way. We identified several large gaps in practice, which included a disconnect between high fidelity modelling, real time environmental sensors, in-flight optimizations, and a failure to properly leverage new digital technologies like machine learning and digital twins. We explored how challenges associated with regulatory conservatism, data availability, and computational integration are demonstrable examples of systemic barriers that continue to inhibit innovation. We concluded with a vision for the future where adaptive performance frameworks that incorporates high-fidelity simulation, data-driven methods, and regulation will help to deliver the future of aviation, where innovations on safety, efficiency, and sustainability are common, and performance analysis is more than just a means to safeguard operations from risk but also supports aviation's transformation through technology.

Keywords. Optimization, Deep Neural Network, Aerospace Engineering, Aircraft Design, Aircraft Performance, Data Driven Methods, Machine Learning.

1 Introduction

Performance analysis of aircraft lies in the heart of aerospace engineering and plays a critical role in making design, certification, operations, and maintenance decisions. Despite the success of traditional performance theory based on steady-state characterizations of aerodynamics, propulsion models, and assumptions about an idealized atmosphere [1], [2], [3] has served the industry for decades, enabling safe and efficient operations for both civil and military aviation. However, the aviation world is rapidly changing. The introduction of sustainable propulsion systems [4], [5], growing environmental regulations [6], [7], [8], [9], newly introduced advanced sensing and communication [10], [11], and continued growth of air traffic management complexity [12] are changing how we view the limits of "performance" and how we quantify it.

Although we have made considerable progress, performance analysis in practice tends to be bound by either simple assumption, barriers to data integration and pre-flight optimization instead of truly dynamic, in-flight optimization [13], [14], [15]. For example, manufacturers' performance manuals still typically limit models to idealized flight conditions using test data from certification testing, while operational planning tools do not incorporate transient atmospherics and flight dynamics or are not able to account for all the changes in dynamics that happen over time as an aircraft ages and systems degrade [16], [17], [18]. The difference between theoretical capability and things that actually matter operationally is a challenge, but also an opportunity. Recently, there has been research in new directions such as the use of machine learning assisted performance prediction [19], [20], [21] and adaptive control systems that optimize the burn of fuel [22], [23].

However, the majority of these examples are unvalidated, are disjointed and therefore not for large-scale commercial adoption, and have been poorly integrated within established regulatory, organizational, and operational frameworks. There is a pressing need to systematically map where these gaps are, so more focused research can be conducted where it will have the most meaningful and substantial impact.

The purpose of this paper is to provide such a mapping. In this paper we review the state of aircraft performance analysis, which has included both the aircraft technology capabilities but also what entrepreneurs and researchers have done with this new technology over the past few decades. We identify essential research challenges that must be tackled so that the emerging technologies can be better utilized, and that the needs of next-generation travel, such as air taxis, can be enabled. Both the technological and operational sides of aircraft performance analysis have been emphasized, with a consideration of priority directions for future research.

2 Current Methods and Assumptions

Aircraft performance analysis is an established discipline with established methods in both the academic literature and practice. Although there are some new propulsion technologies, digital tools, and operational methods evolving, a majority of operational performance modeling is based on assumptions rooted in aerodynamic and propulsion theory, primarily pre-1970's assumptions. This section introduces the basic methods used in the industry and research and the assumptions that govern their applicability.

Performance Analysis Framework

In operational and regulatory settings, performance is usually measured in three main performance regimes: (1) Steady-state cruise performance is generally determined from a combination of aerodynamic drag polar models and propulsion system thrust and thrust-specific fuel consumption (TSFC) characteristics, and normally controls endurance, range and fuel burn predictions. Sometimes simple models rely on analytic (layout exhaustions) methods like Breguet range and endurance equations. [24], [25]. (2) Take-off and landing performance is predicted using semi-empirical models validated with certification tests. It takes into account runway length, acceleration/braking capability, and obstacle clearance margins and is heavily influenced by atmospheric conditions and the runway's situation/material and aircraft configuration (flaps, slats, thrust setting) [1], [2], [3], [26]. (3) Climb, descent, and maneuverability performance that is computed from excessive power or thrust-to-weight estimates. These calculations are often simplified to steady descents or climbs-in which transients, real-time atmospheric data, and energy management trade-offs are ignored [2], [27], [28].

2.1 Data Sources and Tools

Performance calculations rely on a combination of: (1) Manufacturers Flight Manuals (AFM/POH) which provides certified performance data, often tabulated for certain weights, altitudes and temperature conditions. Typically, there are no more than a few discrete operating points. (2) Operational Flight Planning Systems that airlines and operators use in route and fuel planning [29], [30]. These systems commonly interpolate AFM data and apply average wind/temperature corrections where there is generally no in-flight adjustments involved for real time conditions. (3) Numerical Simulation Tools such as CFD and flight simulation models are useful in design phases, but not operational phases due to their complexity and computational costs [15], [31], [32]. (4) Simplified Analytical Models: Drag polar estimation, constant TSFC, and perfect atmosphere are typical assumptions used to conduct quick performance calculations for design and pilot training purposes [2].

2.2 Regulatory Context

Authorities that grant certification, specifically European Union Aviation Safety Agency (EASA) and Federal Aviation Administration (FAA), require that for safety critical operations (i.e., takeoff distance, climb gradients), the performance data used must have been taken from flight testing or validated simulations, and conducted in a controlled environment [33], [34], [35]. Although this guarantees safety, it also means that the data is frequently based on idealized, clean airframe conditions and does not take into consideration in-service degradation (such as engine wear, surface roughness from dirt or paint erosion). In rare instances, it also incorporates real-time meteorological data beyond standard atmosphere corrections.

2.3 Operational Decision-Making

Operational performance planning is actually determined by a combination of pilot or dispatcher judgment, atmospheric corrections, and AFM-based data. These techniques are conservative by nature, which frequently results in fuel overestimation, less-than-ideal climb/descent profiles, and underutilization of available performance margins, even though they have been shown to be safe and generally dependable [14], [36], [37]. Despite their sophisticated avionics, modern aircraft are frequently operated with a performance philosophy that hasn't changed much in decades due to the lack of integration between high-fidelity aerodynamic modeling, real-time environmental sensing, and in-flight optimization.

3 Gaps in Aircraft Performance Analysis

Current methods for assessing aircraft performance have kept aviation safe and reliable, but they’re limited and don’t take full advantage of new technologies. That cautious approach makes sense for safety, yet it has left gaps in knowledge that hold back gains in efficiency, sustainability, and adaptability to changing flight conditions. In several key areas, the assumptions behind today’s performance models no longer match the needs of modern and next generation aircraft.

3.1 Real-Time Performance Prediction and Adaptive Optimization

Today, performance analysis is usually treated as a static, pre-flight calculation instead of a dynamic process. Even though we have data from onboard sensors, satellite navigation, and advanced avionics, performance models still rely on pre-computed tables and simple interpolations. Those methods don’t handle changing atmospheric conditions or in-flight aircraft degradation well. Without combining high-fidelity aerodynamic models with real-time sensor data, chances to optimize climb, descent, and routing during flight are often missed, which leads to wasted fuel and scheduling inefficiencies. [38], [39], [40].

3.2 Performance Modelling for Novel Propulsion Systems

Classical formulas for endurance, range, and the trade-offs between payload and fuel were developed with gas-turbine engines in mind. They assume things like how specific fuel consumption changes with altitude and how power changes with operating conditions. Those assumptions don’t apply to hybrid-electric, hydrogen, or distributed propulsion systems, which have more complex efficiency behaviour, battery degradation, and thermal management challenges [41], [42], [43], [44], [45], [46], [47], [48]. As a result, current models can’t accurately capture the real operational limits of next generation aircraft, restricting both design evaluation and comparative performance assessments.

3.3 Integration of Advanced Atmospheric Effects

Most current performance calculations rely on the International Standard Atmosphere (ISA) [49], it uses modest temperature and pressure deviations to represent operational conditions. In reality, atmospheric variability is much more complex, including mesoscale effects like mountain waves, strong crosswinds, turbulence layers, and microbursts, all of which can significantly affect aircraft performance [50], [51], [52], [53], [54]. Environmental factors like contrail formation, localized emissions, and their impact on global warming are rarely taken into account, even though they're becoming increasingly important for sustainable aviation [55], [56]. Closing this gap means adding more advanced weather modelling to both planning and real-time decision-making.

3.4 Unsteady and Transient Flight Conditions

Performance theory is overwhelmingly based on steady state or quasi steady assumptions. In practice, however, aircraft frequently encounter transient regimes such as rapid climb and descent maneuvers, turns in congested airspace, or unsteady thrust settings that directly impact fuel burn, stall margins, and emissions [52], [57], [58]. These effects are typically neglected in operational performance models, leading to discrepancies between predicted and observed outcomes, particularly in short haul and urban air mobility operations where transients dominate [57].

3.5 Performance Degradation Over Time

Operational models almost universally assume an "as-new" aircraft condition, yet degradation over time is unavoidable [59]. Engines lose efficiency due to wear and fouling [60], [61], while aerodynamic drag gradually increases as a result of paint erosion [62], [63], roughness accumulation, and minor structural deformations [64]. Although these phenomena are qualitatively acknowledged, they are not quantitatively represented in routine performance predictions. Advances in machine learning and statistical modeling present an opportunity to forecast degradation and adapt performance expectations dynamically, but these methods have yet to be widely adopted in mainstream operations.

4 Cross-Cutting Challenges in Advancing Aircraft Performance Analysis

If the gaps discussed in the prior section point to places where we are lacking, the obstacles described here illustrate the structural difficulties impeding advancement. We see these limitations in performance analysis as not necessarily tied to a lack of sophisticated models or data-driven approaches, but in more general issues of data availability, certification, validation, and computational feasibility.) If the research opportunities identified are to be realized in operational practice, these cross-cutting barriers must be addressed.

4.1 Data Availability and Accessibility

High-quality data remains one of the most significant bottlenecks in advancing aircraft performance research. Flight test data, engine degradation metrics, and operational sensor outputs are tightly controlled by manufacturers and operators due to proprietary concerns, competitive advantage, and safety regulations. As a result, most researchers outside of major aerospace companies rely on simplified or public-domain datasets that lack the fidelity necessary for realistic performance modeling. Even when data is available, it is often fragmented, with aerodynamic data, propulsion performance, and atmospheric conditions stored in incompatible formats. The absence of open-access, standardized datasets limits both the validation of new performance models and the ability to compare approaches across research groups [65], [66], [67], [68], [69], [70], [71], [72].

4.2 Certification and Regulatory Barriers

Certification frameworks set by authorities such as EASA and the FAA prioritize safety and reliability above all else, which naturally encourages the use of proven, conservative methods. While this approach has been highly successful in ensuring airworthiness, it also slows the adoption of new performance modeling techniques. Any performance method used in certification or operational manuals must be validated through extensive testing, which is both costly and time-consuming. Novel methods such as machine learning–based degradation prediction or real-time optimization algorithms face a high barrier to regulatory acceptance because their behavior is not always transparent or deterministic [69], [70]. As a result, innovation in performance analysis often remains confined to academic or exploratory studies rather than entering operational practice.

4.3 Model Validation and Verification

Developing new models is only one part of the challenge; validating them under realistic conditions is equally critical. High-fidelity CFD [32] or flight dynamics simulations [73], [74], [75] may capture unsteady or degraded performance, but their results require extensive validation against experimental or flight test data before they can be trusted operationally [76], [77], [78], [79], [80], [81]. This creates a feedback loop: lack of data limits validation, while lack of validated models discourages data collection efforts. Moreover, performance models must be robust across the entire operating envelope of the aircraft, including off-design and abnormal conditions. Ensuring such robustness is non-trivial, especially for novel propulsion systems where long-term degradation and failure modes are not yet well understood [82], [83], [84].

4.4 Computational Practicality

Another challenge lies in balancing fidelity with practicality. High-resolution CFD or digital twin simulations are computationally demanding and cannot be executed in real time within current flight management systems [85], [86], [87], [88]. Conversely, the simplified models used in current operations, while computationally efficient, fail to capture the complexities of modern flight environments. Bridging this gap requires innovative approaches such as reduced order models, surrogate modeling, or machine learning approximations that combine fidelity with computational speed. Achieving this balance is particularly important for real-time performance prediction and optimization, where onboard systems must process large data streams under strict time constraints [89], [85], [90], [91], [92], [93], [94], [95].

4.5 Integration into Operational Ecosystems

Finally, even when advanced performance models exist, integrating them into the broader operational ecosystem poses challenges. Airline operations are governed by a combination of regulatory standards, legacy flight planning systems, dispatcher procedures, and cost structures. Introducing new performance models requires not only technical validation but also training for pilots and dispatchers, adjustments to flight planning workflows, and updates to software and avionics platforms [96], [97], [98], [99], [100]. The inertia of existing practices means that even demonstrably superior methods may face slow adoption unless they are introduced in a way that minimizes disruption and clearly demonstrates economic benefit.

5 Future Outlook

The future of aircraft performance analysis will be defined by the extent to which the field can embrace adaptability, integration, and sustainability. The limitations identified in current methods, together with the systemic challenges that hinder progress, underscore the need for a paradigm shift. Instead of viewing performance as a static property to be documented in certification manuals, performance should increasingly be conceived as a dynamic process that evolves with changing flight conditions, technological advancements, and operational demands. Several trends suggest promising directions for this transformation.

One of the most impactful developments is the rise of digital twins and data-driven performance models. By combining high-fidelity aerodynamic simulations, onboard sensor data, and operational histories, digital twins can provide real-time predictions of an aircraft’s performance throughout its life cycle.

Such systems would not only enable optimized flight trajectories but also provide early warnings of performance degradation, supporting predictive maintenance strategies [101], [102], [103], [104]. While regulatory acceptance of such methods remains a challenge, incremental adoption in non-safety-critical domains; such as fuel efficiency tracking or fleet management offers a feasible pathway to integration.

The shift toward sustainable propulsion technologies will also drive innovation in performance modeling. Hybrid-electric, hydrogen, and distributed propulsion architectures fundamentally alter the assumptions that underpin classical performance theory. Future work must therefore focus on developing new analytical frameworks and validated models tailored to these propulsion systems. Such frameworks will need to incorporate nonlinear efficiency profiles, energy storage limitations, and novel failure modes while remaining computationally tractable for operational use [4], [105], [106], [107], [108], [109]. Successful development in this area will be crucial for enabling the certification and widespread adoption of low-emission aircraft.

Another transformative direction lies in the integration of atmospheric and environmental considerations into performance analysis. Next-generation models should move beyond the simplified International Standard Atmosphere to incorporate high-resolution mesoscale weather data, contrail prediction, and localized emissions effects [14], [110], [111], [112]. By doing so, performance analysis could become a powerful tool not only for operational efficiency but also for reducing aviation's environmental footprint. Advances in coupled atmospheric flight modeling, combined with satellite-based sensing, will make such integration increasingly feasible.

The adoption of machine learning and reduced-order modeling will further expand the possibilities for real-time performance optimization. Surrogate models trained on large datasets can approximate the fidelity of high-resolution simulations at a fraction of the computational cost, making them suitable for onboard implementation [113], [114], [115], [116], [117], [118], [119].

These methods could allow flight management systems to continuously adjust trajectories for optimal fuel burn, noise reduction, or emissions avoidance [120], [121], [122]. To build trust in such approaches, however, emphasis must be placed on transparency, explainability, and rigorous validation.

Finally, the evolution of performance analysis will depend on collaborative frameworks between academia, industry, and regulators. Academic research can push the boundaries of modeling fidelity and algorithm development, while industry provides access to data and operational context, and regulators ensure that new methods are introduced without compromising safety. Establishing open-access datasets, shared validation benchmarks, and pre-competitive research consortia would accelerate progress across all fronts.

In summary, the outlook for aircraft performance research is both challenging and promising. The field must move beyond its reliance on static, conservative methods and embrace a more integrated, adaptive, and environmentally conscious approach. Advances in digital twins, sustainable propulsion modeling, real-time optimization, and collaborative data sharing provide the tools needed to achieve this transformation. If pursued with rigor and cooperation, these developments could redefine aircraft performance analysis as a dynamic discipline central to the future of safe, efficient, and sustainable aviation.

6 Conclusion

Aircraft performance analysis has historically relied on assumptions and methodologies that, while robust for certification and safety assurance, are increasingly misaligned with the demands of modern aviation. The reliance on simplified aerodynamic models, static atmospheric assumptions, and fixed operational margins has provided consistency but at the cost of adaptability and accuracy in real-world operations. As shown in this review, the gap between traditional performance practices and the emerging needs of next-generation aviation; particularly in areas such as sustainable propulsion, real-time optimization, and environmental accountability represents a pressing challenge for the field.

At the same time, these challenges open new opportunities. Digital twins, advanced sensing, data-driven modeling, and machine learning offer pathways to dynamic and adaptive performance prediction. Coupled with regulatory innovation and stronger collaboration between academia, industry, and certification authorities, such advances could reshape performance analysis into a discipline that is no longer static and conservative, but responsive and predictive.

The future of aircraft performance research will depend on the community's willingness to embrace integration and innovation. If successful, these efforts could enable safer, more efficient, and more sustainable aviation while maintaining the reliability that has long defined the field. In doing so, performance analysis will not simply keep pace with the rapid evolution of aerospace technology, it will become one of the primary drivers of that transformation. The current practices, gaps, challenges, and opportunities in aircraft performance analysis that are discussed in this paper are briefly summarized in **Table *1***.

Table 1: Summary of Current Practices, Gaps, Challenges, and Opportunities in Aircraft Performance

Gap Area	Current Practice	Limitation	Potential Research Direction
Aerodynamic Modelling	Simplified lift/drag polars, low-fidelity methods validated by flight testing	Limited integration of high-fidelity CFD or wind tunnel data in operational use	Digital twins, adaptive aerodynamic models, real-time recalibration
Atmospheric Assumptions	Standard Atmosphere (ISA), tabulated corrections	Poor adaptability to real-world conditions (winds, turbulence, anomalies)	Onboard sensors, satellite data, ML-based atmospheric modelling-print receipt
Propulsion & Energy Efficiency	Charts from test data, fixed thrust assumptions	No real-time adaptation to degradation, new fuels, hybrid systems	Engine health monitoring, hybrid/electric models, adaptive thrust prediction
Regulatory Framework	Certification driven by FAA/EASA standards, flight test validation	Certification requirements lag behind data-driven methods	Regulatory sandboxing, incremental certification of AI/digital twins
Operational Data Use	Reliance on AFM/POH tables, interpolation by pilots/dispatchers	Limited real-time optimization despite advanced avionics	Cockpit decision-support tools, AI-based trajectory and fuel optimization
Sustainability Metrics	Metrics: distance, fuel, time only	Lack of integrated emissions/eco-performance in assessments	Emissions models, optimization for sustainability, eco-performance standards

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