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Aeronautic data analysis

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Abstract. The latest IPCC[1] report shows that the aviation industry is responsible for around 2% of greenhouse gas emissions; this is lower than emissions from many other sectors, but still equivalent to the total emissions of a European country like Germany. Following the recommendations of the International Civil Aviation Organization (ICAO[2]) and its long-term global aspirational goal (LTAG), the aeronautics industry has come together under the Air Transport Aviation Group (ATAG[3]) to converge towards zero greenhouse gas emissions by 2050, such as CO_2 emissions and other radiative effects such as those generated by condensation trails. To achieve this goal, we have a number of levers at our disposal: technical improvements to our engines and aircrafts, the use of new sustainable fuels, and the use of data now accessible thanks to new engineering 4.0 technologies. This document first presents the data we now have at our disposal. The second section briefly recalls the opportunities offered by new renewable fuels. Finally, we present some digital approaches and conclude with details of three central themes illustrated by the contributions to this special session.

1 About data in the aeronautic domain

Aeronautical data is incredibly diverse, as it encompasses various measurements from onboard systems and critical supplementary information. Whether monitoring an aircraft's behavior, managing an airline, or overseeing an airport, understanding this data is essential. It includes not only data collected directly from embedded systems, but also crucial details related to weather, maintenance, safety, fuel consumption, design, development, and industrialization processes — ranging from the large 115000 lbf[4] thrust commercial engines for the Boeing 777 airliner to the smallest sensors.

1.1 Onboard Measurements

When thinking about aeronautical data, the first thing that comes to mind is the measurements acquired during flights. These measurements are typically taken at frequencies ranging from 1 to 100 Hz, and in some cases, at several tens of kHz for data

[1] IPCC – Intergovernmental Panel on Climate Change (https://www.ipcc.ch/) – *(GIEC in French)*.
[2] ICAO – LTAG – https://www.icao.int/environmental-protection/Pages/LTAG.aspx.
[3] ATAG – Air Transport Aviation Group (https://atag.org).
[4] lbf (pounds) 1 lbf ~ 4.5 N

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from vibration sensors like accelerometers and tachometers. However, these data are not the easiest to retrieve. Currently, it is possible to access data from about 30% of flights at a maximum frequency of 100 Hz, with a few short segments of about ten seconds collected at 50 kHz.

Vibrational data is preprocessed onboard through frequency analysis, and what is retrieved are mainly power dissipation information and rotational speeds of various engine shafts. These data are transmitted as approximately forty curves, which can be retrieved intermittently when the aircraft lands at a hub (a primary airport) of the airline. Other measurements are sent via satellite, but these are only summaries (ACARS[5] files). Subscribing to this transmission system is possible, but due to its cost, it is generally used only by airlines with a maintenance contract.

These systematically collected data often include calculated information, such as Health Indicators (HIs) identified by Prognostic and Health Management (PHM) teams. In any case, this data is highly relevant [1], containing critical information from both the engines and the aircraft.

1.2 Contextual Data

To understand the measurements acquired during flights, it is essential to observe them in the context of their acquisition [2]. Every flight is different, so it is necessary to gather mission-related information such as the aircraft's route, departure and arrival airports, weather, local atmospheric conditions, air quality, and fuel status. These contextual measurements are easily accessible from external databases like Metar[6] for international weather, FlightAware or FlightRadar[7] for commercial operations and Satavia[8] for pollution related data. Weather forecast, though subject to uncertainties, despite the accuracy of satellite observation, is necessarily used for all aircraft operations.
Atmospheric information can also be obtained from complex systems, such as hyperspectral measurements taken by satellites (Copernicus[9] in the EU). Statistics of weather and atmospheric conditions are available from public databases generated thanks to Copernicus observations and ECMWF[10] reanalysis tools (ERA5[11] database). These measurements and analyses are particularly useful for detecting phenomena like

[5] ACARS - Aircraft Communication Addressing and Reporting System.
[6] METAR – METeorological Aerodrome Report (https://aviationweather.gov).
[7] FlightAware (https://www.flightaware.com/) and FlightRadar (https://www.flightradar24.com/) are Live Flight Trackers.
[8] SATAVIA – "transform the relationship between aviation and the atmospheric environment" (https://satavia.com/).
[9] Copernicus – Sentinel satellite constellation (https://www.copernicus.eu/en/access-data)
[10] ECMWF – European Centre for Medium-Range Weather Forecasts (https://www.ecmwf.int/).
[11] ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate covering (https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5).

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the formation of contrails [3], [4]. Making accurate predictions with respect to contrail formation is under development, but still difficult, because it depends on local atmospheric conditions forecast, which still relies on research in progress.

1.3 Equipment Management and Maintenance

Aircraft and engines undergo continuous maintenance. Strict regulations imposed by aviation authorities (FAA[12], EASA[13]…) dictate maintenance requirements based on the characteristics of onboard systems. These rules often lead to scheduled replacement operations. However, obtaining detailed information about these procedures can be challenging due to their confidentiality. Nevertheless, monitoring the behavior of components, such as engine temperature, allows us to detect the impact of maintenance operations. By analyzing digital data, we can observe changes resulting from maintenance activities.

To determine the specific maintenance performed, we rely on specialized databases made available to airlines. These include Enterprise Resource Planning (ERP) systems used by airlines and service providers (suppliers or repair facilities) about maintenance tasks. After repair, similar systems record details about the maintenance operation. However, interpreting these narratives, often written in technical English with abbreviations and codes, can be challenging. Fortunately, NLP (Natural Language Processing) technics can assist in interpreting these technical descriptions, language model being promising for that purpose [5]. By refining language models for specific domains (with technics such as retrieval augmentation for example), we can extract valuable insights from maintenance records. Let us also note that some classic chatbots are already not bad at interpreting the symptoms reported by operators [6].
The data gathered for the monitoring of the behavior of components and onboard systems is also studied and analyzed in order to pave the way for maintenance and operations optimization (section 3.2).

1.4 Airport and Airline Management

No aviation operation can occur without an airport, which necessitates managing the flow of aircraft during departures and landings, gate assignments, passenger flow, security, customs, and scheduling. Similarly, airline management requires attention to fleet management, planning replacements, anticipating fuel cost fluctuations, and optimizing routes to maximize passenger and cargo loads.

By analyzing flight data, airlines can derive best practices that inform them about the efficiency of their operations. This allows the development of pilot assistance tools aimed at minimizing fuel consumption (Safran SFCO2[14] service is such a tool).

[12] FAA – Federal Aviation Administration (https://www.faa.gov/).
[13] EASA – European Union Aviation Safety Agency (https://www.easa.europa.eu/en).
[14] SFCO2 – Save Fuel and reduce operation costs (https://www.safran-group.com/products-services/sfco2).

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1.5 Design, Development, and Industrialization

The development of a technological system, such as an aircraft, involves several critical stages: design, development, and industrialization. Each of these stages introduces specific measurements and constraints that must be managed carefully.

During the design phase, detailed drawings of individual parts are created, and manufacturing standards are established. This phase ensures that every component meets precise specifications and adheres to industry regulations.

The development stage focuses on testing these components and systems as they evolve. Continuous testing and iterations are essential to validate the performance, safety, and reliability of the aircraft systems.

The industrialization phase involves optimizing production processes to achieve efficiency and consistency in manufacturing. This includes supply chain agility, setting up production lines, refining assembly procedures, and implementing quality control measures. Metrology plays a crucial role at this stage, as each part and assembly must be evaluated to ensure it meets the design specifications, sampling measurements is key to the serial process optimization.

Acceptance testing is the final step, where the fully assembled aircraft undergoes rigorous testing to confirm its quality and performance. This process guarantees that the aircraft is ready for operational use and complies with all regulatory standards. The entire lifecycle from design to industrialization requires meticulous planning, execution, and continuous monitoring to ensure the highest standards of quality and safety.

1.6 Conclusion about data collection

The integration of diverse data types underscores the complexity of aviation operations. From the meticulous design and development phases to the continuous monitoring during flight and maintenance, every aspect of aircraft operations relies on comprehensive data collection and analysis. Engineers and analysts derive critical insights into system health, operational efficiency, and environmental impact from these interconnected datasets. This holistic approach not only ensures the safety and reliability of flights but also supports efforts to optimize fuel consumption and reduce environmental footprint. Ultimately, the interconnected nature of these data types underscores their collective importance in shaping the future of aviation.

2 Aeronautic operations and decarbonation

2.1 Fleet and Environmental Impact

According to the latest IPCC report [7], the aviation industry contributes around 2% of global greenhouse gas emissions across all sectors, including design, operations, and industrialization (12% of the transportation sector, see also [8] for details on greenhouse

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gas emissions in the aviation sector). However, with pre-pandemic traffic levels having been quickly regained in just two years, and airlines planning to double their fleets by 2040, it is crucial to manage emissions diligently. To address this, the Air Transport Action Group (ATAG) has committed the aviation sector to achieving net-zero CO_2 emissions by 2050 and has defined the needed levers to reach this goal [9]. This ambitious goal requires significant efforts from all stakeholders, with research programs now mandated to contribute 75% towards decarbonizing the aviation industry [10].

In-flight operations are scrutinized in order to develop piloting practices and crew decision-aid tools that can help reducing fuel consumption, atmospheric emissions and environmental impact for each aircraft mission.

Aircraft contrails are studied, which can affect the climate in addition to CO_2 emissions, by increasing radiative forcing [11], like other greenhouse gases. Contrails can evolve into persistent ice clouds that have varying effects depending on the time of day; when at nighttime, they typically warm the atmosphere by greenhouse effect, while at daytime they can have a cooling effect similar to natural clouds. There is today a very high uncertainty on the level of the warming effect of contrails and of other non-CO_2 emissions.

2.2 System optimization and alternative fuels

Manufacturers are innovating with new systems, including more fuel-efficient engines and alternative fuels such as Sustainable Aviation Fuels (SAF), hydrogen and new technologies for aircraft with improved aerodynamics and weight reduction such as additive manufacturing, ceramics and woven carbon fiber blades and casings. Ground operations are also targeted, with initiatives like using electric traction systems for aircraft towing and optimizing braking with new carbon materials.

Sustainable Aviation Fuels (SAFs) are a viable solution for all flights, an in particular long-haul flights which require energy density fuels, which remains comparable to that of kerosene [12]. Today aircraft and engines are certified to operate with up to 50% SAF blended with classic jet fuel. Nine SAF production pathways are qualified. They use various types of feedstock such as recycled oil, waste or plants, or they can be synthesized with captured CO2, hydrogen and low carbon electricity (e-fuels). Today's major challenge lies in the industrial production of these fuels to meet the growing demand. The industry is very confident in its ability to achieve this objective, notably thanks to international initiatives such as RefuelEU[15] in Europe and the Inflation Reduction Act (IRA[16]) in the United States.

[15] RefuelEU - https://www.consilium.europa.eu/fr/press/press-releases/2023/10/09/refueleu-aviation-initiative-council-adopts-new-law-to-decarbonise-the-aviation-sector/

[16] IRA - https://home.treasury.gov/policy-issues/inflation-reduction-act

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Hydrogen presents another promising alternative and can be utilized in several ways. Hydrogen-powered fuel cells can be used in small light aircrafts, air taxis (VTOLs) and potentially in the future in regional short-range commercial aircrafts, while hydrogen can also be used as a fuel in dedicated engines. Although there are challenges such as storage management, cryogenic temperatures, and material compatibility associated with liquid hydrogen. Replacing kerosene with hydrogen in current turbofan engines is technically feasible. Commercial applications remain to be validated: the mass energy content of hydrogen is 3 times higher than that of jet fuel, which makes it a very interesting fuel for aviation (even more so, no doubt, than for terrestrial use!). Of course, its volumetric energy content is 4 times higher, which therefore poses enormous challenges for the development of aircraft and the propulsion system. It should also be noted that while hydrogen reduces CO_2 production, it increases the amount of water vapor, which justifies an in-depth study of condensation trails.

3 Numeric applications

3.1 Automation of Quality Controls

Numerical analysis is making a strong entry into the aeronautics industry. Today, all machine tools funnel their data into digital databases, enabling the optimization of production processes. Manufactured parts are achieving higher precision, and quality controls are becoming more automated.

For raw materials, quality standards are becoming increasingly strict. Microscopic images of material cross-sections are analyzed to construct quality indicators, such as the size and geometry of grains in alloys. Information obtained automatically through image analysis using neural networks allows us to correlate these indicators with the robustness of the parts, as measured in specimen tests. These tests are then analyzed statistically, and predictive techniques are used to construct conservative curves that guarantee the risks of creep rupture or crack formation.

Machined parts are also inspected through tomographic acquisitions. For instance, automated neural network controls can detect weaving defects in the new carbon fiber fan blades.

3.2 Optimization of Maintenance and Operations

In the realm of maintenance, Bayesian troubleshooting techniques are implemented to analyze symptoms observed by operators. Regular inspections generate technical reports written in specialized language. NLP and information technics, including language models are utilized to infer keywords, enabling automatic understanding of the observations reported. These data are then categorized and leveraged for decision support.

Visual observations are gaining increasing importance in maintenance, particularly with the automatic analysis of endoscopic images and the integration of miniature

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cameras within systems. For instance, gearboxes, actuators, and cables on certain helicopters are monitored in this way[17].

Fleet-wide observations are also employed to supervise neural networks designed to build potential counters based on the operational experiences of systems. Inputs to these networks include all contextual flight data and specific measurements from the systems, while outputs are driven by indicators of specific degradation modes, such as corrosion, blade erosion, or crack formation. These indicators are typically used in a statistical reliability model, like a Weibull distribution, whose parameters are learned concurrently with those of the neural network to estimate a remaining life [13], [14].

Though these indicators are not identified yet by civil aviation authorities (FAA, EASA…) as qualified maintenance indicators or means of compliance to safety requirements for aircraft operations, they can be taken into consideration in order to optimize both maintenance and aircraft operations in order to guarantee a better aircraft operational availability or optimize the dispatch among the assets of a fleet: this is the first step toward predictive maintenance.

3.3 The Digital Twin

In the industrial context, digital twins refer to the comprehensive collection of information about an asset from its conception to its operation. Algorithmically, a digital twin is a model that utilizes part of this data to simulate the behavior of a specific asset, aircraft or system.

When a simulator uses a state vector that is updated after each flight, it is called a digital twin. This is because the knowledge of this vector, combined with the digital model, allows for the simulation of any flight. Typically, the neural model is configured for a particular type of system, such as a specific engine type, and the latent state vector represents the specific engine of interest [15]. By inputting this vector into the simulator along with the context data of a test flight, one can generate the engine's response.

Such a model enables the comparison of systems. For instance, it becomes possible to rate similar machine tools for differently processed or managed parts. Additionally, it allows for the comparison of engines installed on different aircraft by simulating their respective behaviors in virtual test flights. This capability is particularly useful for assessing the effectiveness of maintenance operations. It can also be used as an aircraft or system health record for maintenance and operations optimization.

4 Selected Contributions to the Session

Among the contributions submitted to this special session on aeronautical data analysis, we have retained three fundamental themes.

[17] Odysight propose AI-driven embedded sensors (https://www.odysight.ai/).

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One study focuses on the environment, proposing the **monitoring of contrails** produced by engines, which, as mentioned earlier, contribute to climate change. This forward-looking study paves the way for complex analyses, ranging from the automatic collection of data using hyperspectral satellite observations to precise measurements of their effects on the atmosphere, including mitigation strategies. Managing contrails may require optimizing certain flight trajectories while avoiding an increase in greenhouse gas production due to higher fuel consumption. This study also falls within the framework of programs aimed at exploiting hydrogen as an alternative fuel: the direct combustion of hydrogen in fact creates a potentially significant production of water vapor.

Another critical aspect in our field is the connection between physical understanding and numerical models, which we address through the classical problem of **model inversion**. Aeronautical systems are typically designed using physical simulators that involve known equations, often approximated with finite element methods. These simulators are both computationally intensive and highly approximate.
For the thermodynamic performance of engines, simulations exist that can predict temperature, pressure, shaft rotation speeds, fuel consumption, and other parameters during stabilized phases, given the known characteristics of various modules such as the fan and low-pressure (LP) booster, high-pressure (HP) compressor, combustion chamber, HP turbine, and LP turbine. The inverse problem involves determining the coefficients for each module based on observed data.
This problem is generally ill-posed, and one solution involves using the temporal evolution of these measurements to adaptively correct the inferred parameters by minimizing the discrepancy between the simulation and the observation. The presented solution first replaces the physical simulator with a neural model and then uses a Kalman filter for parameter adaptation.

Finally, the recent utilization of generative models enables the construction of engine behavior simulators that not only observe static phases but also accurately reproduce the observed dynamic of temporal measurements. Such a simulator can be adjusted with a corrector that adapts it to each individual, thus providing us with a **digital twin**. The results are very promising, but several open issues remain.

- For instance, identifying the physical states of the engine is challenging because, unlike the previous model, learning does not leverage a physical model.
- Utilizing the digital twin as an anomaly detector still requires a measure of uncertainty in the simulations. Specifically, we need to ensure a confidence interval that with high probability contains at least one physically plausible flight.
- Additionally, rating engines to trace back to missions and infer wear conditions is essential. This scoring method allows us to characterize the use of engines by each airline, thereby better managing maintenance and the costs associated with contracts.

We are only at the beginning of systematically exploiting data from our factories, test benches, and aircrafts. The full benefits of these methods have yet to be identified. As we continue to develop and refine these data-driven approaches, we anticipate uncovering significant insights and efficiencies that will enhance the performance, safety, and sustainability of aerospace operations.

References

[1] O. Fink, Q. Wang, M. Svensén, P. Dersin, W. J. Lee, and M. Ducoffe, "Potential, challenges and future directions for deep learning in prognostics and health management applications," *Eng. Appl. Artif. Intell.*, vol. 92, no. January, p. 103678, 2020, doi: 10.1016/j.engappai.2020.103678.

[2] J. Lacaille, "Standardized Failure Signature for a Turbofan Engine," in *IEEE Aerospace Conference*, Big Sky (USA, Montana): IEEE Aerospace society, Mar. 2009. doi: 10.1109/AERO.2009.4839670.

[3] J. P. Hoffman, T. F. Rahmes, A. J. Wimmers, and W. F. Feltz, "The Application of a Convolutional Neural Network for the Detection of Contrails in Satellite Imagery," *Remote Sens.*, vol. 15, no. 11, 2023, doi: 10.3390/rs15112854.

[4] A. Rose and L. Sherry, "Aviation Sustainability Through Hyperspectral Image Analysis Methodology for Aircraft-Induced Clouds," in *Integrated Communications Navigation and Surveillance (ICNS) Conference*, 2022. [Online]. Available: https://catsr.vse.gmu.edu/pubs/ICNS2022_HyperspectralImagingContrails_Final.pdf

[5] M. Stewart, M. Hodkiewicz, and S. Li, "Large Language Models for Failure Mode Classification: An Investigation," 2023. [Online]. Available: http://arxiv.org/abs/2309.08181

[6] S. Lukens and A. Ali, "Evaluating the Performance of ChatGPT in the Automation of Maintenance Recommendations for Prognostics and Health Management," *Proc. Annu. Conf. Progn. Heal. Manag. Soc.*, vol. 15, no. 1, pp. 1–18, 2023, doi: 10.36001/phmconf.2023.v15i1.3487.

[7] K. Calvin *et al.*, *IPCC, 2023: Climate Change 2023: Synthesis Report.* 2023. [Online]. Available: https://www.ipcc.ch/report/ar6/syr/

[8] J. E. Penner, D. H. Lister, D. J. Griggs, D. J. Dokken, and M. McFarland, "IPCC special report: Aviation and The Global Atmosphere," 1999. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2018/03/av-en-1.pdf

[9] Air Transport Action Group (ATAG), "Waypoint 2050 Second Edition," 2021. [Online]. Available: www.atarg.org

[10] E. Tiirinki, "Carbon Reducing Initiatives as a Strategy to Achieve Sustainable Competitive Advantage : case study of the airline industry," 2022. [Online]. Available: http://www.theseus.fi/handle/10024/753342

[11] D. S. Lee *et al.*, "The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018," *Atmos. Environ.*, vol. 244, no. July, 2021, doi: 10.1016/j.atmosenv.2020.117834.

[12] M. Kousoulidou and L. Lonza, "Biofuels in aviation: Fuel demand and CO2 emissions evolution in Europe toward 2030," *Transp. Res. Part D Transp. Environ.*, vol. 46, pp. 166–181, 2016, doi: 10.1016/j.trd.2016.03.018.

[13] J. Lacaille and R. Langhendries, "Corrosion Risk Estimation and Cause Analysis on Turbofan Engine," *Annu. Conf. PHM Soc.*, vol. 14, no. 1, Oct. 2022, doi: 10.36001/PHMCONF.2022.V14I1.3254.

[14] R. Langhendries and J. Lacaille, "Operability forecasting combining neural network and survival analysis with an application to hot corrosion in turbofan," in *International Conference on Maintenance, Condition Monitoring and Diagnostics (MCMD)*, 2020.

[15] R. Langhendries and J. Lacaille, "Turbofan exhaust gas temperature forecasting and performance monitoring with a neural network model," in *European Conference on Safety and Reliability (ESREL)*, Dublin, 2022. doi: 10.3850/981-973-0000-00-0.

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