ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 7:

AVIATION

Colin McCormick

November 2024

ICEF
Innovation for Cool Earth Forum

CHAPTER 7:
AVIATION

Colin McCormick

The aviation industry is a major sector of the global economy, with almost $1 trillion in revenue in 2024.[1] After a steep decline during the COVID pandemic, airline traffic returned to pre-COVID levels in 2024.[2,3] The sector has consistently grown faster than the global economy, with an average annual growth rate of 5% over the past 30 years.[4]

CO_2 emissions from the aviation sector were approximately 800 Mt in 2022, roughly 80% of pre-pandemic levels.[5] Emissions from aviation grew faster over recent decades than emissions from shipping, road or rail.[5] Member states of the International Civil Aviation Organization (ICAO) have adopted an aspirational goal of achieving net-zero carbon emissions by 2050.[6] In addition to CO_2, the industry is paying increasing attention to non-CO_2 impacts, including NO_x and methane (CH_4) emissions. This also includes persistent contrails.[7,8] While significant uncertainties remain, there is growing scientific consensus that aviation contrails result in an equivalent or greater amount of climate radiative forcing as that caused by aviation CO_2 emissions, making contrails a particularly important area of focus for mitigation efforts.[9,10]

The aviation industry is no stranger to artificial intelligence (AI) and has adopted AI in many areas. However, these uses of AI have primarily focused on areas such as customer satisfaction and cost reduction.[11,12] Specific uses of AI for emissions mitigation are relatively recent and limited in comparison, but they are growing and may have a significant impact in the future.

A. Use of AI For Emissions Mitigation in Commercial Aviation

i. Improving aircraft design

Aviation's CO_2 emissions are overwhelmingly driven by burning fossil-derived aviation fuel in jet engines. The fuel efficiency of new commercial jet aircraft has steadily improved over the past four decades (see Figure 7-1), but AI can help to continue this trend. One key approach is using AI/machine learning (ML) methods to enhance computational modeling of jet engine combustion physics and chemistry, potentially enabling engine designs with improved combustion efficiency.[13] Similar AI/ML techniques can also improve modeling of the advanced methods used to cool critical jet engine components (partly replacing the need for intensive computational fluid dynamics (CFD) calculations). This can enable development of designs that better balance fuel efficiency with engine longevity.[14] A related challenge in jet engine design is efficiently predicting the performance of novel engine concepts—designed by humans or AI systems—without expensive physical testing. AI/ML methods have been used to rapidly develop these performance assessments for next-generation turbofan concepts, accelerating the ability of aerospace design teams to efficiently iterate through novel designs.[15]

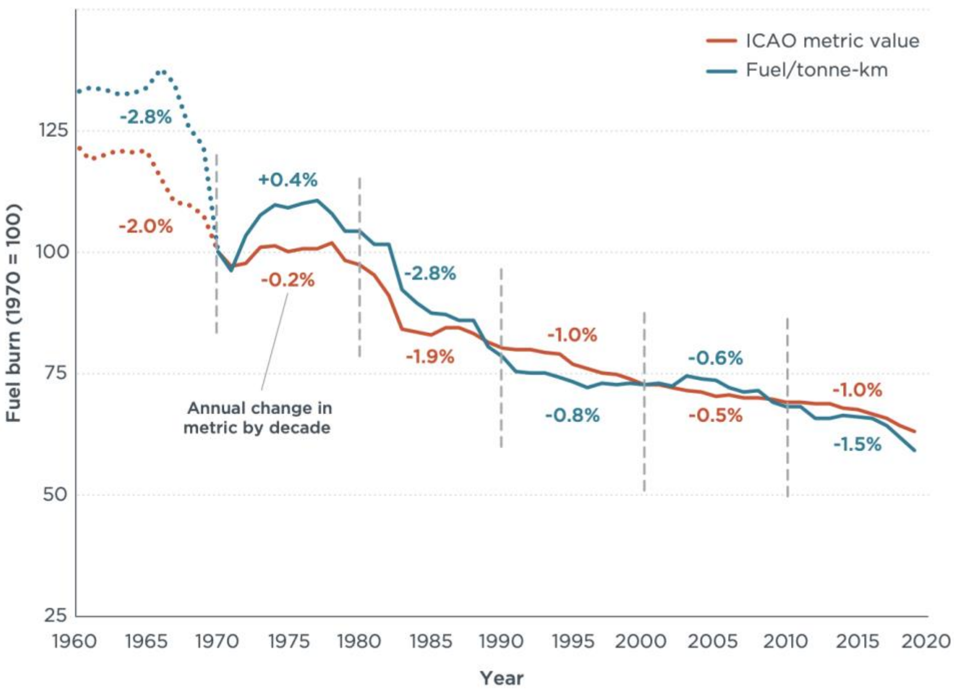

Figure 7-1. *Improvement in fuel efficiency of new commercial jet aircraft, 1980-2020. Credit: The International Council on Clean Transportation.*[21]

While engine efficiency is a crucial component of overall aircraft fuel efficiency, the shape of components, such as wings, fuselage and engine nacelles, can also have a major impact by reducing drag. AI/ML methods can help with aerodynamic shape optimization problems, such as designing highly efficient airfoil (wing) shapes that provide high lift and low drag and designing optimal engine nacelles to reduce drag.[16-18]. The design cycle for aircraft traditionally includes computational simulations that look at how both component shape and turbulent airflow (which often occurs during take-off/landing and in some atmospheric conditions) would affect lift and drag, prior to performing expensive physical testing in a wind tunnel. Conventional CFD methods are accurate but extremely compute-intensive/costly. AI/ML methods can dramatically reduce the computational requirements for modeling turbulent (highly complex) flows[19,20] and the lift and drag of different component designs, arriving at equivalent solutions more quickly and easily. This allows much more experimentation and iterative design-test cycles.

The structural materials used in aircraft, such as aluminum alloys, must meet high performance specifications because they are subject to high stresses under flight conditions. Understanding these stresses quantitatively is challenging. AI/ML methods can increasingly be used to calculate stresses/loads throughout an aircraft during flight and to predict the performance of various alloys used in aircraft construction.[22] The primary use of this method is to ensure aircraft safety, but it could potentially lead to the use of lighter-weight materials and/or novel designs that reduce the total amount of structural materials required, reducing aircraft weight and thus improving fuel efficiency.

ii. Optimizing air operations

Another approach to minimizing emissions from aviation is to optimize the use of the existing aircraft fleet, matching specific aircraft to specific routes and passenger demand as efficiently as possible. A closely related issue is ensuring optimal airport operations, given changing wind conditions, impacts of weather at other airports, and constrained runway count. AI/ML methods have been tested as part of the pre-planning phase of air operations, helping assess demand-capacity balancing for various runway configurations for US airports.[23] NASA and the US Federal Aviation Administration (FAA) have begun implementing an AI/ML-based air traffic management planning tool (the Collaborative Digital Departure Reroute tool) that can improve projections of runway availability and reduce on-tarmac airplane idling time.[24] Carriers such as Alaska Airlines and SWISS have begun using AI/ML-based systems to optimize real-time flight route planning and general flight operations.[25,26] Other carriers, including TUI Airlines, have begun using AI/ML methods calibrated to individual aircraft to develop customized climb rates and speed profiles for lift-off and climb phases of a flight, helping reduce unnecessary fuel burn.[27]

iii. Reducing aviation-induced contrails

When aircraft fly through regions of the atmosphere that are particularly cold, they can form condensation trails ("contrails"), which are essentially artificially induced cirrus clouds. Under specific meteorological conditions, these contrails can persist for many hours and can spread, resulting in a net climate warming effect by blocking thermal radiation (heat) that would otherwise radiate out into space. This effect is quite large, roughly the same as warming effects from the CO_2 emitted by burning jet fuel, although uncertainties remain.[8,10]

Projections for contrail radiative forcing in future years are uncertain but could rise significantly, given increased air traffic and an overall shift in flight altitudes.[28]

One method for reducing this warming effect is "navigational avoidance," which involves predicting where contrail-forming meteorological conditions will occur before or during specific flights and then redirecting aircraft to different altitudes to avoid those atmospheric regions. (Because only a small fraction of flights generates contrails, the use of this method would be limited to a small number of flights annually.) The majority of contrail radiative forcing can be avoided with navigational changes that add only ~0.1% additional cost and fuel burn.[29,30]

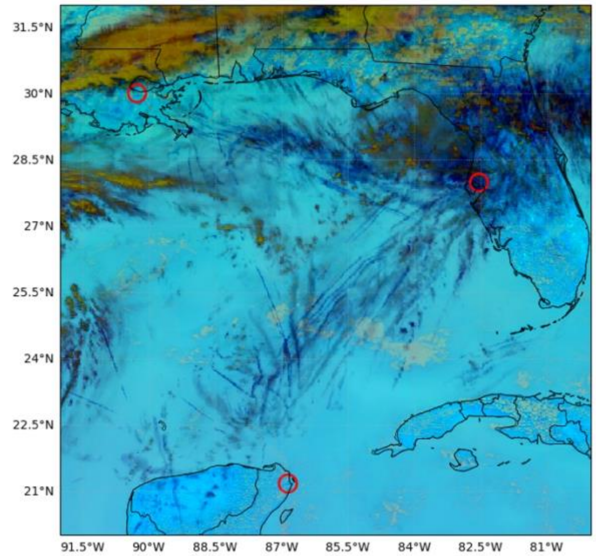

Figure 7-2. False-color image of aviation-induced contrails in the Gulf of Mexico, derived from GOES-16 imagery. Red circles are major airports (MSY, TPA, CUN) and contrails appear as thin, dark-blue lines between them. (Credit: Colin McCormick).

Research is underway to evaluate the use of advanced conventional algorithms and remote sensing imagery to predict where contrail-forming regions will occur. This would support navigational avoidance (Fig. 7-2). However, AI/ML methods may be able to improve on the performance of these conventional algorithms, particularly by leveraging AI-enabled improvements in meteorological forecasting. AI/ML methods have already been developed that can detect contrails in satellite imagery, as well as estimate their altitude, using a variety of deep learning methods.[31-33] Data pipelines based on these methods of detecting contrails can form the basis of validation systems to confirm in near-real-time whether a particular flight successfully avoided forming a contrail, in some cases leveraging aircraft position data via Automatic Dependent Surveillance-Broadcast (ADS-B).[34,35]

Google, Breakthrough Energy and American Airlines recently collaborated to demonstrate AI-based contrail navigational avoidance in a series of 70 test flights, confirming the ability of this approach to avoid contrail formation at a very low cost.[36,37] Because contrail navigational avoidance is entirely an operational change—there are no capital costs for modified equipment or new supply chain requirements—it has the potential to be implemented extremely rapidly.

iv. Advancing Sustainable Aviation Fuel (SAF)

A key strategy for decarbonizing aviation is adopting sustainable aviation fuel (SAF), a (mostly) drop-in replacement fuel for aviation kerosene that is based on non-petroleum feedstocks. As the industry assesses novel chemical compositions of various types of SAF, AI/ML methods can be used to predict key physicochemical properties, such as flash point, density and heat capacity, to identify specific fuel blends that have high enough technical potential for synthesis and physical testing.[38,39] One important barrier to using SAF in conventional aviation fuel systems is the presence of nitrile O-ring seals in many fuel lines, which are designed to swell in the presence of specific conventional jet fuel components. This issue has led to a 50% blend limit of SAF in most current aircraft.[40] However, AI/ML methods have been used to better understand how different O-ring materials would swell in the presence of various different compositions of SAF, potentially helping resolve this issue and eliminating the need for the blend limit.[41,42]

B. Barriers

The multiple regulatory frameworks and industry standards in commercial aviation are a potential barrier to AI/ML adoption. These frameworks have been developed to ensure safety throughout the process of aircraft design, manufacture and operations and are updated on timescales that tend to be significantly slower than the rapid pace of advances in AI/ML. If key regulations do not keep up with advances in AI, they may slow the industry's ability to adopt these emerging technologies.

Another potential barrier is a lack of technical familiarity with modern AI/ML methods within key regulatory agencies, such as the US FAA, the European Union Aviation Safety Agency (EASA) and the Japan Civil Aviation Bureau (JCAB). These agencies may lack staff capacity to assess emerging AI/ML methods, as well as the resources to train existing staff or hire new talent.

Encouragingly, some of these regulators have begun actively considering how AI/ML can be used within aviation through roadmaps[43] and webinars.[44] The work to date has principally focused on safety, which is appropriate given their core mandates.[45] However, if regulators focus exclusively on AI/ML safety issues, this may obscure or preclude consideration of opportunities for emissions reductions, creating an additional barrier to their use in this context.

C. Risks

As with all aerospace design processes, any novel designs for engines, airframe components or structural materials that are developed by AI must be rigorously tested to meet safety criteria. However, if AI/ML methods identify highly novel designs or configurations, it may be challenging to fully test them within existing protocols. If these protocols are not appropriately updated to accommodate an expanded range of designs that may result from AI/ML methods, this could create safety risks.

When using AI for planning and operations, an AI model may identify highly efficient solutions that have less available margin for error than current operational strategies (for example, very tight timing for aircraft turn-around or runway reconfiguration). These solutions could make the overall system more “brittle” or vulnerable to any unanticipated disruptions. Minimizing the effects of these disruptions and fully recovering from them may therefore be more difficult in scenarios in which air operations are guided by AI/ML models.

The use of AI in real-time operations may also introduce cybersecurity risks because of increased complexity in the data systems used.[46] This is a similar challenge to that encountered when using AI in other industries, in the context of real-time decision making for physical assets. Improved testing and cybersecurity response protocols are likely needed to manage this risk.

D. Recommendations

1. *National governments should expand public research and development (R&D) funding for applying AI/ML methods to aircraft design, engine design and aircraft operations, with a focus on improving fuel efficiency, enabling the use of SAF, and reducing non-CO_2 impacts (including contrails). To ensure this funding targets priority areas, the relevant funding ministries should enhance the AI/ML expertise of program management staff through training and/or hiring.*
2. *Aviation technical societies, associations and standards development organizations should expand technical resources available for AI/ML-enabled aircraft design and operations, including developing benchmark datasets, releasing sample algorithms and publishing standard performance metrics.*
3. *National governments should increase the coverage and quality of publicly available meteorological data (temperature, pressure, humidity) in commonly traveled air spaces to enable improved modeling of the non-CO_2 climate impacts of aviation, including contrail formation.*
4. *National governments, philanthropy and private companies should collaborate to improve the state of the art on digital modeling of atmospheric contrail formation by aircraft, including use of advanced AI/ML techniques. High-quality models should be made publicly available.*
5. *National governments should require all commercial and private aircraft to track and report non-CO_2 impacts, including contrail formation. This should be through public-facing data portals or similar methods that minimize the burden of data collection and computation on the private actors covered by these requirements. Aggregated results should be publicly released.*
6. *Carbon accounting bodies should update accounting rules to include the full set of climate impacts of aviation, including contrails. Private companies with aviation-based supply chains should adopt the use of these updated rules in measuring supply chain greenhouse gas (GHG) emissions.*
7. *National governments should ensure that the regulatory frameworks for approving novel aircraft and engine design are compatible with using AI/ML methods and should update them accordingly if necessary. Aviation regulatory bodies should collaborate directly on these topics to ensure that regulations are harmonized as much as possible across national borders.*

E. References

1 International Air Transport Association (IATA). Industry Statistics: Fact Sheet; https://www.iata.org/en/iata-repository/pressroom/fact-sheets/industry-statistics/ (2024).

2 International Civil Aviation Organization (ICAO). Passenger air traffic surpasses pre-pandemic levels; ICAO Newsroom, Montréal, Québec, Canada, https://www.icao.int/Newsroom/Pages/Passenger-air-traffic-surpasses-pre-pandemic-levels.aspx (2024).

3 International Air Transport Association (IATA). Air Passenger Market Analysis; https://www.iata.org/en/iata-repository/publications/economic-reports/air-passenger-market-analysis-february-2024/ (2024).

4 International Civil Aviation Organization (ICAO). Facts and Figures: World Aviation and the World Economy ICAO – Economic Development of Air Transport, Montréal, Québec, Canada, https://www.icao.int/sustainability/pages/facts-figures_worldeconomydata.aspx (Accessed August 2024).

5 International Energy Agency (IEA). Aviation; Paris, France, https://www.iea.org/energy-system/transport/aviation (Accessed August 2024).

6 International Civil Aviation Organization (ICAO). States adopt net-zero 2050 global aspirational goal for international flight operations; ICAO Newsroom, Montréal, Québec, Canada, https://www.icao.int/Newsroom/Pages/States-adopts-netzero-2050-aspirational-goal-for-international-flight-operations.aspx (2022).

7 Richard C. Miake-Lye & Didier Hauglustaine. Impacts of Aviation NOx Emissions on Air Quality, Health, and Climate (within Chapter 3: Local Air Quality) in ICAO Environmental Report Ch. 3, 74–76 (International Civil Aviation Organization (ICAO), Montréal, Québec, Canada, 2022, https://www.icao.int/environmental-protection/Documents/EnvironmentalReports/2022/ENVReport2022_Art18.pdf).

8 International Air Transport Association (IATA). Aviation contrails and their climate effect: Tackling uncertainties and enabling solutions; https://www.iata.org/contentassets/726b8a2559ad48fe9decb6f2534549a6/aviation-contrails-climate-impact-report.pdf (2024).

9 D. S. Lee et al. The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. Atmospheric Environment 244, 117834 (2021). https://doi.org/10.1016/j.atmosenv.2020.117834.

10 R. Teoh et al. Global aviation contrail climate effects from 2019 to 2021. Atmos. Chem. Phys. 24, 6071-6093 (2024). https://doi.org/10.5194/acp-24-6071-2024.

11 Amina Zaoui et al. Impact of artificial intelligence on aeronautics: An industry-wide review. Journal of Engineering and Technology Management 71, 101800 (2024). https://doi.org/10.1016/j.jengtecman.2024.101800.

12 Julie Weed. Did You Make Your Connecting Flight? You May Have A.I. to Thank.; NY Times, New York, NY, https://www.nytimes.com/2024/05/10/travel/airlines-artificial-intelligence.html (2024).

13 Soledad Le Clainche et al. Improving aircraft performance using machine learning: A review. Aerospace Science and Technology 138, 108354 (2023). https://doi.org/10.1016/j.ast.2023.108354.

14 Argonne National Laboratory. Accelerating Gas Turbine Engine Design by Fusing Physics-Guided Machine Learning and Supercomputing; Lemont, Illinois, https://www.anl.gov/aet/accelerating-gas-turbine-engine-design-by-fusing-physicsguided-machine-learning-and-supercomputing (Accessed August 2024).

15 Michael T Tong. Machine learning-based predictive analytics for aircraft engine conceptual design; NASA – Glenn Research Center, Cleveland, Ohio, https://ntrs.nasa.gov/citations/20205007448 (2020).

16 Jichao Li, Xiaosong Du & Joaquim R. R. A. Martins. Machine learning in aerodynamic shape optimization. Progress in Aerospace Sciences 134, 100849 (2022). https://doi.org/10.1016/j.paerosci.2022.100849.

17 Thomas P. Dussauge et al. A reinforcement learning approach to airfoil shape optimization. Scientific Reports 13, 9753 (2023). https://doi.org/10.1038/s41598-023-36560-z.

18 Zilan Zhang et al. An adaptive machine learning-based optimization method in the aerodynamic analysis of a finite wing under various cruise conditions. Theoretical and Applied Mechanics Letters 14, 100489 (2024). https://doi.org/10.1016/j.taml.2023.100489.

19 H. Jane Bae & Petros Koumoutsakos. Scientific multi-agent reinforcement learning for wall-models of turbulent flows. Nature Communications 13, 1443 (2022). https://doi.org/10.1038/s41467-022-28957-7.

20 Ricardo Vinuesa. Perspectives on predicting and controlling turbulent flows through deep learning. Physics of Fluids 36 (2024). https://doi.org/10.1063/5.0190452.

21 Sola Zheng & Dan Rutherford. Fuel burn of new commercial jet aircraft: 1960 to 2019 (White Paper); The International Council on Clean Transportation (ICCT), https://theicct.org/publication/fuel-burn-of-new-commercial-jet-aircraft-1960-to-2019/ (2020).

22 Chenxi Sun et al. A multi-model architecture based on deep learning for aircraft load prediction. Communications Engineering 2, 47 (2023). https://doi.org/10.1038/s44172-023-00100-4.

23 Christopher J. Lloyd et al. Operationalizing Machine Learning Models for Strategic Planning in AIAA AVIATION 2023 Forum (https://arc.aiaa.org/doi/abs/10.2514/6.2023-4213).

24 Hillary Smith. NASA Machine Learning Air Traffic Software Saves Fuel; NASA, https://www.nasa.gov/centers-and-facilities/ames/nasa-machine-learning-air-traffic-software-saves-fuel/ (2023).

25 Alaska Airlines. Alaska Airlines and Airspace Intelligence announce first-of-its-kind partnership to optimize air traffic flow with artificial intelligence and machine learning; https://news.alaskaair.com/newsroom/alaska-airlines-and-airspace-intelligence-announce-first-of-its-kind-partnership-to-optimize-air-traffic-flow-with-artificial-intelligence-and-machine-learning/ (2021).

26 Google Cloud. SWISS: Making air travel more sustainable and improving operational quality with Google Cloud; Mountain View, California, https://cloud.google.com/customers/swiss (Accessed October 2024).

27 The Weather Network. Airline uses Ai to cut carbon emissions during flight take-off; Deutsche Presse-Agentur GmbH via Reuters Connect, Berlin, Germany, https://www.theweathernetwork.com/en/news/climate/solutions/airline-uses-ai-to-cut-carbon-emissions-during-flight-take-off (2023).

28 D. K. Singh, S. Sanyal & D. J. Wuebbles. Understanding the Role of Contrails and Contrail Cirrus in Climate Change: A Global Perspective. EGUsphere 2024, 1-50 (2024). https://doi.org/10.5194/egusphere-2024-127.

29 Denis Avila, Lance Sherry & Terry Thompson. Reducing global warming by airline contrail avoidance: A case study of annual benefits for the contiguous United States. Transportation Research Interdisciplinary Perspectives 2, 100033 (2019). https://doi.org/10.1016/j.trip.2019.100033.

30 A. Martin Frias et al. Feasibility of contrail avoidance in a commercial flight planning system: an operational analysis. Environmental Research: Infrastructure and Sustainability 4, 015013 (2024). https://dx.doi.org/10.1088/2634-4505/ad310c.

31 Luke Kulik. Satellite-based detection of contrails using deep learning, Massachusetts Institute of Technology, Department of Aeronautics and Astronautics, (2019; https://dspace.mit.edu/handle/1721.1/124179).

32 Rémi Chevallier et al. Linear Contrails Detection, Tracking and Matching with Aircraft Using Geostationary Satellite and Air Traffic Data. Aerospace 10, 578 (2023). https://doi.org/10.3390/aerospace10070578.

33 Vincent Meijer, Sebastian David Eastham & Steven R H Barrett. A31D-2428 Contrail Height Estimation Using Geostationary Satellite Imagery; American Geophysical Union (AGU) at AGU23, San Francisco, CA and Virtual, https://agu.confex.com/agu/fm23/meetingapp.cgi/Paper/1430793 (2023).

34 Federal Aviation Administration (FAA). Automatic Dependent Surveillance-Broadcast (ADS-B); US Department of Transportation (DOT), Washington, D.C., https://www.faa.gov/air_traffic/technology/adsb (Accessed August 2024).

35 Scott Geraedts et al. A scalable system to measure contrail formation on a per-flight basis. Environmental Research Communications 6, 015008 (2024). https://dx.doi.org/10.1088/2515-7620/ad11ab.

36 Google Research. Project Contrails; https://sites.research.google/contrails/ (Accessed August 2024).

37 Breakthrough Energy. How Breakthrough Energy's Contrails Team is helping to reduce aviation's climate impact; Kirkland, Washington, https://www.breakthroughenergy.org/news/contrails/ (2023).

38 Clemens Hall et al. Predictive Capability Assessment of Probabilistic Machine Learning Models for Density Prediction of Conventional and Synthetic Jet Fuels. Energy & Fuels 35, 2520-2530 (2021). https://doi.org/10.1021/acs.energyfuels.0c03779.

39 Ji-Hun Oh et al. Learning to predict sustainable aviation fuel properties: A deep uncertainty quantification viewpoint. Fuel 356, 129508 (2024). https://doi.org/10.1016/j.fuel.2023.129508.

40 Conor Faulhaber et al. Measurements of Nitrile Rubber Absorption of Hydrocarbons: Trends for Sustainable Aviation Fuel Compatibility. Energy & Fuels 37, 9207-9219 (2023). https://doi.org/10.1021/acs.energyfuels.3c00781.

41 Shane Kosir, Joshua Heyne & John Graham. A machine learning framework for drop-in volume swell characteristics of sustainable aviation fuel. Fuel 274, 117832 (2020). https://doi.org/10.1016/j.fuel.2020.117832.

42 Benoit Creton, Benjamin Veyrat & Marie-Hélène Klopffer. Fuel sorption into polymers: Experimental and machine learning studies. Fluid Phase Equilibria 556, 113403 (2022). https://doi.org/10.1016/j.fluid.2022.113403.

43 Federal Aviation Administration (FAA). Roadmap for Artificial Intelligence Safety Assurance: Version I; US Department of Transportation (DOT), Washington, D.C., https://www.faa.gov/aircraft/air_cert/step/roadmap_for_AI_safety_assurance (2024).

44 Scot Campbell, Andrés Bucchi & Abdulla Al-Asam. AI in International Civil Aviation (Webinar); International Civil Aviation Organization (ICAO), Montréal, Québec, Canada, https://www.icao.int/Meetings/innovation-series/Pages/AI-in-International-Civil-Aviation.aspx (2024).

45 Rebecca Heilweil. In deploying AI, the Federal Aviation Administration faces unique challenges; Scoop News Group – Fedscoop, Washington, D.C., https://fedscoop.com/in-deploying-ai-the-federal-aviation-administration-faces-unique-challenges/ (2024).

46 Anna Ribeiro. Aviation industry faces rising cybersecurity risks as new technologies drive adoption, says Aviation ISAC survey; Industrial Cyber, https://industrialcyber.co/reports/aviation-industry-faces-rising-cybersecurity-risks-as-new-technologies-drive-adoption-says-aviation-isac-survey/ (2024).