DESIGN and be SMART

Eleven engineering challenges to achieve sustainable air transportation under safety assurance in the year 2050

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DESIGN and be SMART: Eleven engineering challenges to achieve sustainable air transportation under safety assurance in the year 2050

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ABSTRACT

The aviation industry faces various challenges in meeting long-term sustainability goals amidst surging demand for air travel and growing environmental concerns of the general public. The year 2050 is set as an ambitious goal for net zero emissions, a substantial reduction in carbon dioxide emissions per passenger kilometer flown, major improvements in aircraft energy efficiency, and a development towards autonomous, intelligent operations. This review explores the pivotal role of advancements in engineering for achieving sustainability in aviation. Through a comprehensive review of existing literature and case studies, our work highlights how innovations in all aspects of aircraft engineering coupled with operations-related technologies, offer promising solutions to mitigate environmental impact, enhance efficiency, and ensure long-term sustainability in aviation operations. To discuss the necessary advances, we promote the so-called 'DESIGN and be SMART' framework, consisting of eleven complementary engineering challenges towards reaching sustainability. To address the high safety levels reached in air transportation, our DESIGN and be SMART framework also addresses the safety assurance challenge that is overarching each of the eleven engineering challenges. We believe that through an orchestrated integration of hardware advancements with innovative software solutions, and novel safety assurance methods, the aviation industry can realize synergistic benefits that drive sustainable growth of air transportation. Our review contributes to such an orchestration by describing the status quo and research challenges ahead.

1. Introduction

Achieving sustainable aviation by the year 2050 is presumably one of the most pressing goals for the air transportation industry (Åkerman, 2005; Gössling, Humpe, Fichert, & Creutzig, 2021; Grimme, Maertens, & Bingemer, 2021; Köves & Bajmócy, 2022). There is an increasing global demand for air travel, driven by economic growth, globalization, and population expansion — only temporally interrupted by the COVID-19 pandemic (Sun, Wandelt, & Zhang, 2023a, 2023b). Given that air transportation is a significant contributor to greenhouse gas emissions, there is a need to reduce aviation's environmental footprint; otherwise, future operations could exacerbate climate change and undermine global sustainability targets. Thus, achieving sustainable aviation is crucial not only for mitigating environmental impacts but also for ensuring the long-term viability of the aviation industry in

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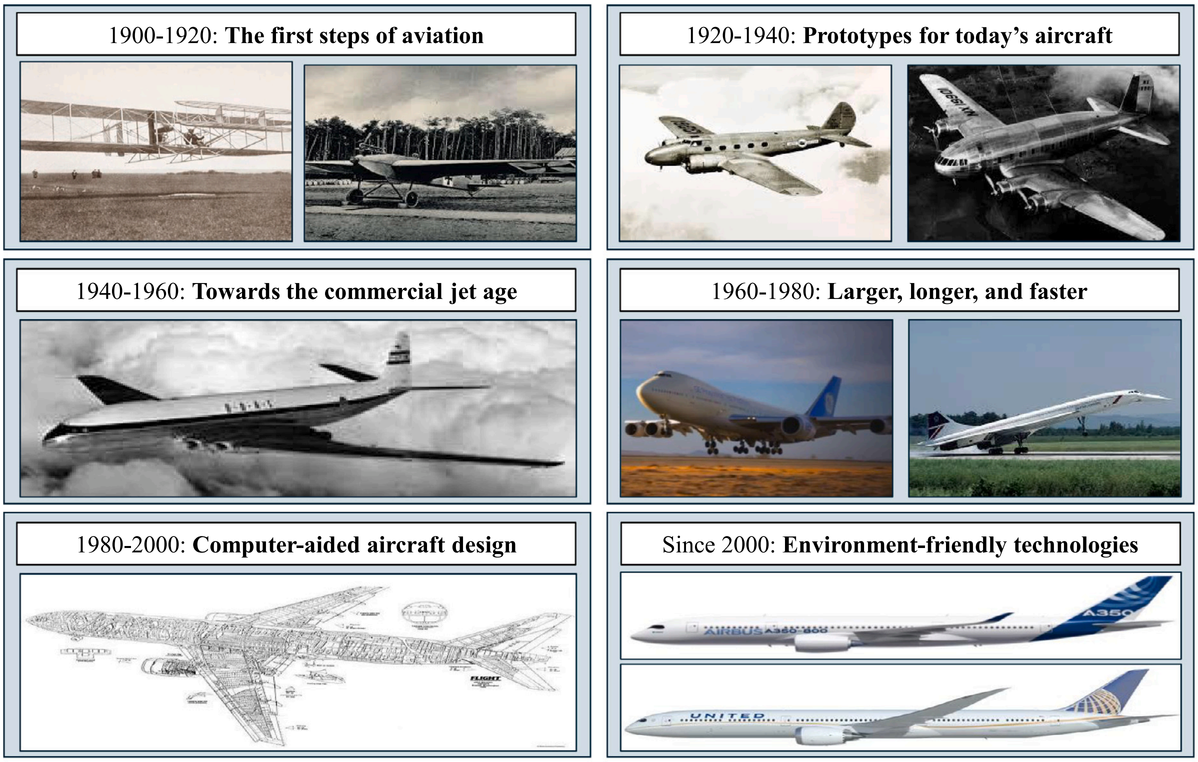

Fig. 1. Six air transportation development phases with different engineering foci.

a rapidly changing world. A key role of this transformation will be taken by intelligent systems, which can significantly contribute to sustainability. Intelligent air transportation encompasses a wide range of technologies, including artificial intelligence (AI), machine learning, big data analytics, and autonomous systems, all of which can optimize flight operations, air traffic management, and aircraft design (Wandelt & Zheng, 2024). These technologies hold the potential to prepare air transportation by reducing fuel consumption, improving operational efficiency, and enhancing the safety and reliability of flights, all while contributing to a lower carbon footprint. Achieving sustainable aviation by 2050 is not merely an environmental necessity; it is essential for the future competitiveness and resilience of the aviation industry. Fig. 1 summarizes the key developments in the history of air transportation; coming decades are expected to see a strong focus on sustainability and intelligent systems. Advances in engineering have always been instrumental for air transportation as they drive the design, development, and implementation of technologies and systems that make air travel safer, more efficient, and more widely accessible to people around the world (Petrescu et al., 2017). To assure compliance with the high safety levels reached in air transportation, the DESIGN and be SMART objectives also pose an overarching safety assurance challenge.

In this study, we review engineering-related challenges which lead to more sustainable aviation in the year 2050.[1] The eleven challenges at the heart of our review are visualized in Fig. 2. Six of these challenges are rather aircraft-oriented and five challenges have a stronger focus on operational aspects. The engineering challenges in our study are complementary to the air transport management challenges presented in Wandelt et al. (2024). In the present study, the focus is put on engineering challenges related towards preparing aviation for a more sustainable operation in the future. Given that these engineering challenges require coordinated efforts from all stakeholders, we believe that discussing and summarizing these aspects in a review provides ample opportunity for other researchers in the community to work on the induced challenges. Particularly engineers will have to play a central role in addressing these challenges through the development of innovative solutions that enable the aviation industry to thrive in a sustainable and socially responsible manner.

The remainder of this study is structured as follows. Section 2 discusses six aircraft-related engineering challenges. Section 3 reviews five operations-related engineering challenges with focus on intelligence. Section 4 addresses the overarching safety assurance challenges in air transportation. Section 5 concludes the study, discusses a set of limitations, and provides an aggregated guideline for future research.

2. Engineering-based aircraft improvements

The following section presents a discussion of six aircraft-related engineering challenges, which we believe will be essential for ensuring a sustainable development of air transportation until the year 2050 and beyond. These challenges include aircraft design (Section 2.1), electrification (Section 2.2), sustainable aviation fuels (Section 2.3), maintenance procedures (Section 2.4), coordination and standardization (Section 2.5), as well as noise reduction techniques (Section 2.6).

2.1. Developing future aircraft designs

The earliest human exploration of flight was inspired by the concept of bionics, which is still a pivotal topic in advanced aircraft design nowadays (Han, Hui, Tian, & Chen, 2021). Traditional aircraft are subject to constraints of their fixed aerodynamic configurations, which bound their potentials of flight performance (Clainche et al., 2023). Morphing aircraft technology, motivated by current bionics, has induced various design concepts such as morphing wings (Li et al., 2018), reconfigurable aircraft (Lingling et al., 2022), and flexible flapping-wing aircraft operating at low Reynolds numbers in small scales. A number of studies have demonstrated that by altering the aerodynamic

[1] While not each of the challenges can solely by attributed to engineering, our study focuses on the engineering aspects and how engineers can contribute towards the common goal of making aviation more sustainable in the future.

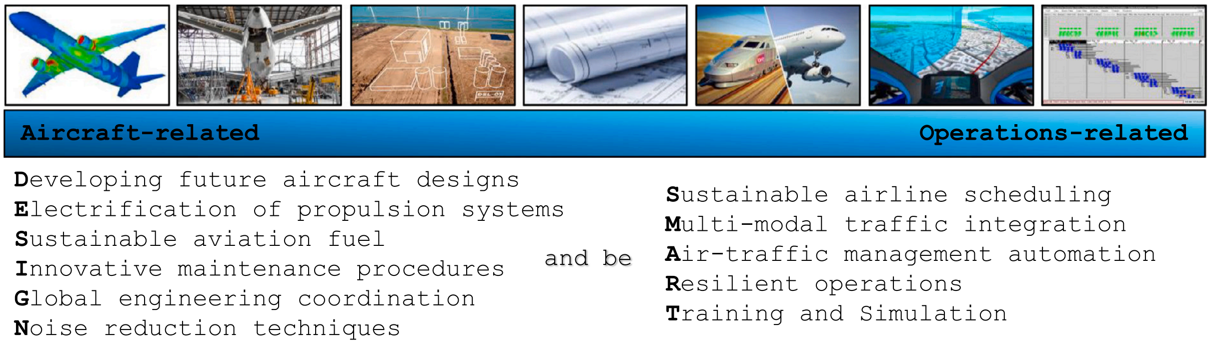

Fig. 2. Framework of engineering challenges for aviation: DESIGN and be SMART.

configuration of structure, e.g., variable wingspan (Di Luca, Mintchev, Heitz, Noca, & Floreano, 2017), variable camber wings (Vale, Leite, Lau, & Suleman, 2011), and variable sweep wings (Aleisa, Kontis, Pirlepeli, & Nikbay, 2023), overall flight performance can benefit under a variety of flight conditions. Although the concept of morphing aircraft has been proposed for years, its practical application in aircraft design remains limited mainly due to structural stiffness and integrity requirements, as well as flight safety and control issues, which result in complex multi-scale unsteady phenomena, high-load deformation materials/structures, and difficulties in cross-coupling verification among aerodynamics, control, structure. It is envisioned that with advancement of machine learning and data-driven approaches, knowledge from experimental and simulation data can be extracted more effectively (Dong, Tao, Zhang, Lin, & Ai, 2021), and with improvement of smart materials (Liu, Du, Liu, & Leng, 2014), intelligent design methodologies (Dong et al., 2021; Clainche et al., 2023), and digital twin technologies (Tao, Zhang, & Zhang, 2024), multi-physics and multidisciplinary intelligent fusion design will offer promising solution for bionic morphing applications.

The propulsion system provides driving force of an aircraft, which not only ensures reliable and sustained flight but also constraints the aircraft's weight, dimensions, and operational environment. The rapid advancements in novel energy and propulsion system have updated the state of art in aircraft design, which have enabled many novel flight missions. For instance, the application of solar energy technology has enabled unmanned aerial vehicles (UAVs) to achieve long-endurance, round-the-clock flights (Zhu, Guo, & Hou, 2014). Besides, cutting-edge power and energy sources such as electrostatics, piezoelectrics, and ionic wind have brought revolutionary changes to aircraft design. Electrostatic energy harnesses the accumulation and release of charges to generate power, and its potential for high energy density and low noise characteristics offers a unique option for micro- and nano-scale aircraft (Graule et al., 2016). Piezoelectric energy utilizes the piezoelectric effect of materials to generate electricity when subjected to mechanical stress, providing a self-sufficient and environmentally adaptive energy solution for aircraft (Jafferis, Helbling, Karpelson, & Wood, 2019). The ionic wind technology, by ionizing air to produce thrust, eliminates the need for traditional mechanical components. Being frictionless, low-noise, and high-efficiency, the ionic wind technology is attracting more and more attentions in the field of micro- and nano-scale aircraft as well as UAVs (Zhang, Jiaming, Zhiwei, Mingjing, & Xiaojun, 2023). These innovative power sources are reshaping the framework of aircraft design, enabling a new era of versatile and efficient aerial platforms.

With the rapid advancements in computation and communication technologies as well as intelligent and autonomous control technologies, the trend towards intelligent and unmanned aircraft becomes increasingly prominent. The challenges of intelligent flight stem primarily from uncertainties of aircraft dynamics and mission environments (Zuo, Liu, Han, & Song, 2022). Common sources of uncertainties in dynamics include morphing aircraft configurations (Sziroczak & Smith, 2016), bio-inspired micro aerial vehicles (Eldredge & Jones, 2019), and hybrid unmanned aerial vehicles (Rohr, Studiger, Stastny, Lawrance, & Siegwart, 2021). Flying in unpredictable and dynamic environments requires intelligent maneuvers to avoid obstacles and other potential threats. The design and implementation of advanced sensors, coupled with estimation and control technologies, enable autonomous flight missions, reducing human workload and enhancing flight safety. Meanwhile, multi-agent coordination or heterogeneous collaboration is a prominent direction, considering the limitation of a single-agent aircraft in diverse and complex missions. Aircraft design needs to transcend traditional metrics like flight efficiency and payload capacity, incorporating the requirements of multi-agent coordination for a paradigm shift in design philosophy.

For future aircraft design, with smart materials/structures that are highly load-bearing, highly deformable, and capable of real-time response, integrating them effectively into engineering models to ensure stable and durable aircraft performance is required, and thus **precise multi-disciplinary coupling models** should be constructed to optimize aerodynamic performance, structural strength, and flight stability. It is also envisioned that the future aircraft design need to accommodate the characteristics of novel propulsion systems, and thus the **deep integration of aircraft design and novel propulsion technology** will be a prominent direction. Moreover, the development of **multi-agent coordination capability** is envisioned to be a critical metric in future aircraft design, which renders aircraft more effective in diverse and complex missions.

2.2. Electrification of aircraft/propulsion systems

A huge potential for reducing climate impact of aviation without controlling air traffic growth is seen in establishing new energy carriers. The first all-electric aircraft commercial flight took place in 2019 in Vancouver, Canada, conducted by a joint venture between Harbour Air Seaplanes and MagniX (Harbour Air, 2019). Rather than relying on fossils fuels, an electric motor is used to propel the aeroplane for this type of aircraft. There are emission benefits of powering an aircraft from electricity, particularly if it comes from renewable sources, but there is the challenge of getting enough power from the battery. Using the two aircraft prototypes assessed in 2021 for emissions impacts in Baumeister, Leung, and Ryley (2024), all-electric aircraft are likely to exhibit the following characteristics. The Heart Aerospace ES-19 has a battery power of 575kWh which allows to carry 19 passengers up to 400 km while the Eviation Alice has a battery power of 900kWh allowing to carry 9 passengers up to 1046 km. They may be a niche air transport option, but a Finnish case study (Baumeister, Leung, & Ryley, 2020) showed that first generation electric aircraft can provide an effective alternative for short-haul flights in terms of travel time as well as emissions. Such locations, where surface transport alternatives are less competitive, say due to challenging mountainous terrain or large bodies of water, are particularly suitable for electric aviation.

Substantially higher efficiencies of electric aircraft systems and electric motors, independent of propulsion unit scale and therefore possibly distributed over the airframe were supposed to contribute to e.g. vertical take-off and landing (VTOL) capability, drag reduction (through placing units at wing tips or boundary layer ingestion with units placed in rear part of the fuselage), noise mitigation and less maintenance efforts (Brelje & Martins, 2019; Pelz, Leise, & Meck, 2021). Electric taxiing on ground and even shutting off propulsion units during approach (possible due to near-zero spool-up time of electric motors) were seen as beneficial options. However, quite closely following Gartner's hype cycle (Fenn & Linden, 2005), electric flying finds itself nowadays beyond the *peak of inflated expectations*. Accordingly, the potential use cases have to be clearly distinguished: the field of advanced air mobility (AAM) most likely has to rely on electric concepts since no other option is currently on the research agenda that would be accepted by the public (Schäfer, 2018; Sun, Wandelt, Husemann, & Stumpf, 2021). The other use case is regional to short range air transport. In Germany, several research consortia, e.g. DLR-EXACT (Hartmann & Nagel, 2021) or the university alliance GNOSIS Electra (Zumegen et al., 2022), investigated novel aircraft configurations with electric propulsion architectures and payload capacities beyond 50 passengers. If the aim is to match the top-level aircraft requirements (at the least transport performance, i.e. payload, range and speed) of conventional fossil fuel reference aircraft designs all-electric aircraft alternatives fail, given the present and short-term battery technology constraints (Aigner, 2024; Strathoff et al., 2022). If, however, a relaxation of requirements is accepted, feasible all-electric aircraft concepts can be found (e.g. with lower payload and range capability). Elysian Aircraft, a spin-off of Technical University of Delft, recently published results for a battery-powered 90-seat aircraft with a useful range of 800 km and an energy consumption of 167Wh per passenger-kilometer (de Vries, Wolleswinkel, Hoogreef, & Vos, 2024; Wolleswinkel, de Vries, Hoogreef, & Vos, 2024). Operational agility used to be a request by airlines and leasing companies influencing the fleet composition and route network, ultimately dominating the purchase decision (Husemann, Schäfer, & Stumpf, 2018). Constraint aircraft layouts (this applies to all-electric as well as hydrogen-powered versions) will increase logistic complexity of aircraft operation.

The existing kerosene-based air transport vehicles are hard to beat in terms of performance and operational efficiency. Especially in light of this fact, the advantages of electrified aircraft need to be convincing and gain acceptance by the general public. The following challenges remain. Current battery technology has **limitations in energy density**, which affects the range and payload capacity of electric aircraft; also resource depletion is a concern in battery–electric aircraft (Peters & Weil, 2016). Advances in battery chemistry and energy storage are needed to make electric aviation viable for longer flights (Wolleswinkel et al., 2024). The existing airport infrastructure is not equipped to handle the unique requirements of electric aircraft, such as charging stations and maintenance facilities. Significant **investment and modification of airport facilities** are required (Liang, Mouli, & Bauer, 2023). While electric aircraft reduce carbon emissions, the **environmental impact of battery production and disposal**, as well as the source of electricity (renewable vs. fossil fuels), must be considered to assess the overall environmental benefits (Thonemann et al., 2024).

2.3. Sustainable aviation fuel implementation

Sustainable aviation fuel (SAF) is an alternative aviation fuel made from sustainable feedstock resources. It presents a promising solution for reducing greenhouse gas emissions and mitigating the environmental impact of air transportation in the pursuit of sustainability (ICAO, 2023[2]). Large-scale, long-distance air transportation has no credible near-term fuel alternative due to the energy density required, although aviation fuel can be used in fuel cells to produce electricity locally in dispersed applications (Oakleaf et al., 2022). Current jet fuel production processes require large facilities that are complex to operate while using fossil oil as feedstock (Shahriar & Khanal, 2022; Vozka & Kilaz, 2020; Watson et al., 2024). Improved aircraft fuel efficiency and better air traffic control have led to less than 15% carbon emission reduction. Compared to these non-fuel approaches, the use of SAFs can achieve a further 50%–80% reduction in carbon emission and is therefore considered to be the most efficient way to achieve carbon neutral aviation operation. Thus, addressing the source of fuel for the aviation industry is an essential part of the answer to achieving a material reduction in greenhouse gas emissions (Ng, Farooq, & Yang, 2021; Voigt et al., 2021). Sustainable aviation fuels can reduce contrail formation and the overall carbon footprint of aviation, and help meet the net carbon neutrality policy of the United Nations. Most market-available SAFs are synthesized using plant- and animal-derived lipid feedstocks (Bai, Zhang, Zhang, Wang, & Ma, 2021; Karatzos, van Dyk, McMillan, & Saddler, 2017; Lu, Ma, & Zhao, 2018; Rana et al., 2013; Verma, Kumar, Rana, & Sinha, 2011). The limited availability of these feedstocks is not able to meet expected future demand on SAFs. It is commonly agreed that a multitude of challenges are ahead to meet the 2050 goal (Lee et al., 2021; Ng et al., 2021) (Air Transport Action Group, 2021[3]).

As of now, there are six ASTM (American Society for Testing and Materials) International D7566-approved SAFs suitable for use in blends ranging from 10% to 50% (Dahal et al., 2021; Kosir, Heyne, & Graham, 2020; Kouhgardi, Zendehboudi, Mohammadzadeh, Lohi, & Chatzis, 2023; Okolie et al., 2023; Yang et al., 2022). Initially, SAFs were composed primarily of n- and iso-alkanes, but now they include all four hydrocarbon families such as cycloalkanes, aromatics, and olefins. These fuels are produced from various sources, such as synthesis gas, fats, oils, greases, sugars, and alcohols (Holladay, Abdullah, & Heyne, 2020). Currently, numerous technologies are being explored and studied to advance SAF production.

One promising research direction is the **development of new sustainable feedstock resources** like Biomass-to-Jet Fuel (BtJ) (Shen, Tao, & Yang, 2019; Yang & Laskar, 2016; Yang & Wang, 2018), renewable Power-to-Liquid (PtL) (Male, Kintner-Meyer, & Weber, 2021) and greenhouse Gas-to-liquid (GtL) (Li et al., 2023) technologies, which offer significant potential to reduce lifecycle greenhouse gas emissions. Another research focus is on **searching for new fuel molecules**, such as cycloalkanes, which could complement iso-alkanes by providing similar functional benefits to aromatics. Cycloalkanes can help fuels meet density requirements and potentially offer the seal-swelling capacity that aromatics provide (Graham, Striebich, Myers, Minus, & Harrison, 2006; Kosir, Heyne, & Graham, 2020; Kramer et al., 2022; Muldoon & Harvey, 2020; Romanczyk et al., 2019). Combined, iso-alkanes and cycloalkanes could enhance fuel value by enabling a high specific energy and energy density while reducing emissions (Ruan et al., 2019; Yang et al., 2022). However, it is crucial to recognize that **commercializing new SAF technology** presents challenges even more formidable than those previously encountered in aviation technology development, requiring immense dedication, persistence, and financial resources (Zhang, Butler, & Yang*, 2020). Additionally, the aviation industry faces an increasingly stringent regulatory compliance environment, primarily due to international carbon emission regulations related to emission quantification and renewable fuel credits (Wang, Yang, Zhang, & Zhu, 2020; Zhang et al., 2020). The uncertainties inherent to present challenges, coupled with decreasing oil reserves and volatile fuel pricing, underscore the need for strategic alliances among SAF stakeholders to collaborate and advance viable alternatives to conventional jet fuel.

[2] Environmental Policies on Aviation Fuels. https://www.icao.int/environmental-protection/GFAAF/Pages/Policies.aspx (accessed 2022-06-14).

[3] WAYPOINT 2050.

2.4. Innovative maintenance procedures

Modern aircraft are equipped with on-board sensors that continuously monitor aircraft components, systems and/or structures. This has increased the availability of sensor data. As an example, for a Boeing 787, approximately 1000 parameters are continuously monitored for the engine alone, leading to a total of 20 terabytes of data per flight hour (Badea, Zamfiroiu, & Boncea, 2018). The continuous streams of measurements/observations have been used to detect anomalies, diagnose faults (diagnostics) and predict (prognostics) the remaining useful lifetime of assets (Kordestani, Orchard, Khorasani, & Saif, 2023; Zonta et al., 2020). The increased availability of health condition monitoring data has incentivized the transition from traditional maintenance strategies such as time-based maintenance (Lee & Mitici, 2020), when assets are periodically maintained at fixed time intervals, to data-driven predictive maintenance for components (Wen & Liu, 2011), systems (Berri, Dalla Vedova, & Mainini, 2021; Mitici, de Pater, Barros, & Zeng, 2023) and/or structures (Katunin, Dragan, & Dziendzikowski, 2015). Here, the aim of predictive maintenance is to timely identify anomalies, anticipate failures, and prescribe appropriate maintenance actions (e.g., inspections, tests, repairs, replacements). As such, predictive aircraft maintenance has the potential to significantly reduce operational and maintenance costs, increase availability of assets, support a sustainable use of assets, reduce workload, as well as to ensure safety (Sutharssan, Stoyanov, Bailey, & Yin, 2015).

The three building blocks of data-driven predictive maintenance for aircraft are: (i) data acquisition and processing, (ii) data-driven algorithms for diagnostics and prognostics, and (iii) decision-making models (Jardine, Lin, & Banjevic, 2006). Data acquisition and processing consists of data collection, feature extraction, and statistical/data analytics methodologies to extract signals from recorded health monitoring measurements (Wen & Liu, 2011). The majority of published papers on predictive maintenance focus on aircraft engines, aircraft auxiliary power units, and aircraft actuators (Wen & Liu, 2011). Diagnostics for aircraft components, systems and/or structures map such signals to fault modes. Common methodologies for diagnostics are statistical approaches (e.g., text statistics), machine learning (e.g., neural networks), Kalman filters, or a hybrid approach (Jardine et al., 2006). Prognostics for aircraft components, systems and/or structures make use of the extracted signals to estimate the remaining useful lifetime or the time to failures of these assets. Some of the commonly used methodologies for prognostics are stochastic processes, e.g., Gamma processes (Lee & Mitici, 2020), machine learning (e.g., neural networks (Kordestani et al., 2023), physics-based models (Stringer, Sheth, & Allaire, 2012)), or a hybrid approach (Berri et al., 2021; Chao, Kulkarni, Goebel, & Fink, 2022). Predictive maintenance planning further makes use of diagnostics or/and prognostics to predictive (near-) optimal times and (near-) optimal actions for the maintenance of components, systems and/or structures. Some of the main methods used for maintenance planning are (stochastic) linear programming (Kordestani et al., 2023; Wang, Chen, Zhao, & Xiang, 2024), stochastic processes (Jardine et al., 2006; Lee & Mitici, 2020; Mitici et al., 2023), machine learning, particularly reinforcement learning (Hu, Miao, Zhang, Liu, & Pan, 2021), and simulation (Lee & Mitici, 2020).

Recently, a transition from predictive maintenance to prescriptive maintenance can be observed (Ansari, Glawar, & Nemeth, 2019; Bertsimas & Kallus, 2020). Seen as the highest level of maturity for maintenance planning, prescriptive maintenance relies on **machine self-diagnosis, and self-scheduled, automated maintenance**. Compared to predictive maintenance, the diagnostics and prognostics are further enriched with causality detection, pattern recognition, learning from former experiences, and semantic-based learning and reasoning. Despite recent advances, the implementation of predictive/prescriptive maintenance in practice is tardive; mainly due to large investments required to build appropriate **infrastructures to acquire and process the data**, the need to educate the workforce, and the necessity to align with existing **safety requirements and regulations for aviation**.

2.5. Global engineering coordination

Advancing sustainability and safety in aviation requires a coordinated standardization of engineering practices, common evaluation principles, and component compatibility (Gudmundsson, 2013). Air transportation is widely regarded as one of the safest transportation modes of transportation when considering accidents per billion passenger kilometers travelled (Barnett, 2020). Statistically, air travel boasts a significantly lower accident rate in comparison to other modes, e.g., road, rail, or maritime transport. This can mainly be attributed to stringent safety regulations, advanced technology, rigorous training of personnel, and a strong safety culture within the aviation industry (Oster, Strong, & Zorn, 2013). The perceptions of safety, however, can vary based on media coverage of accidents, as the recent examples around incidents involving Boeing aircraft have shown: Until the end of the year 2023, events like cracked wind-shields and minor engine problems hardly turned up in the news, despite being happening. That changed significantly in January 2024, when a panel blew off an Alaska Airlines flight 16,000 ft above Oregon.[4] Since that time, media coverage on aviation's smaller incidents or near-misses have significantly increased; leading to several FAA expert panel hearings charged with reviewing Boeing safety culture.

Advancing the public perception of aviation safety requires a resilient standardization of engineering practices based on intelligent systems, fostering interoperability and collaboration among stakeholders; across companies and countries (Dmitriev & Mitroshkina, 2019; Yildirim & Abanteriba, 2012). Here, global standardization is ensuring the reliability, efficiency, and sustainability of aircraft systems; see Ryapukhin (2023) for a recent review. Central to the concept of standardized engineering practices is the development and adoption of common specifications and electronic documents that govern the development and certification of aircraft components and systems in different parts of the world (Fernández-Hernández, Walter, Alexander, Clark, Châtre, Hegarty, Appel, & Meurer, 2019; Seamster & Kanki, 2017). There is a need for making use of intelligent systems and information technology to more effectively develop and disseminate robust regulatory frameworks (Dijkstra, 2007; Enrico, Mengfei, Zhiguo, & Rui, 2019).

In light of existing geopolitical conflicts and their impact on aviation (Standfuss, Fichert, Hirte, & Fricke, 2023; Wang, Zhang, & Wandelt, 2023), there is a need to **retain a notion of aviation diplomacy** (Lin, 2021; Nguyen, 2021) in order to maintain resilient engineering practices. Standardized design encompass aspects such as materials selection, structural analysis, and performance testing, enabling engineers to develop aircraft components that meet stringent safety, reliability, and environmental criteria. Ensuring component and operation compatibility – even under the seemingly increasing threat of geopolitical conflicts (Wang, Zhang, & Wandelt, 2023) – is paramount for optimizing aircraft performance and reliability while minimizing environmental impact. Furthermore, the development of **common interface standards and protocols**, such as ARINC standards for avionics systems (Prisaznuk, 2008) and SAE standards for aircraft components (Gordon, 2000), enables interoperability and compatibility among different suppliers and manufacturers, facilitating the adoption of new technologies and the evolution of aviation systems. By aligning engineering standards and compatibility requirements with **modern, formal language models** (Stewart et al., 2021), the aviation industry can catalyze the development and adoption of next-generation aviation technologies, ensuring that future aircraft are not only safer and more efficient but also more environmentally sustainable. We believe that large-language models can play a key role in all these challenges; see Liu (2024) for a recent review on the use of large language models in air transportation research and applications.

[4] https://www.reuters.com/graphics/ALASKAAIR-BOEING/klvydkrlopg/

2.6. Noise reduction technologies

Aircraft noise has been an issue for more than 50 years now (Armstrong & Williams, 1976; Paullin & Miller, 1971); yet, it is becoming increasingly significant in densely populated areas, reflecting not only the growth in air traffic but also an excessive form of urbanization (Khardi, 2009). As air transportation has expanded to meet the rising demand for connectivity, more flights are taking off and landing, often at airports located near residential neighbourhoods, in an attempt to improve the accessibility of airports and its neighbourhood (Addie, 2014; Van Wijk, Brattinga, & Bontje, 2011). This surge, on the other hand, has led to heightened noise pollution, adversely affecting the quality of life for millions of people (Batard & France, 2005). Noise from aircraft operations, particularly the noise during takeoff and landing, can be disruptive, penetrating homes and schools, interrupting sleep, and contributing to a range of health issues such as stress, cardiovascular problems, and impaired cognitive function. While technological advancements have led to quieter aircraft (Huff, 2006), i.e., it is estimated that individual aircraft have become 75% quieter over the last three decades, these improvements are often outpaced by the sheer volume of flights. In addition, the introduction of air traffic control systems (e.g. NextGen in the United States), which optimizes flight paths for efficiency, has led to concentrated noise corridors, intensifying the impact on certain neighbourhoods. Accordingly, there is a need for further improvement of noise pollution at global airports.

The International Air Transportation Association's (IATA) has proposed a so-called *Balanced Approach*, which consists of four pillars; see Ehmer, Leipold, and Murphy (2012), King (2019) for discussions. The first pillar, commonly described as reduction at source, refers to the reducing the noise emissions by incorporating new technology on aircraft. From an engineering and design perspective, this option is most important to follow up. Then second pillar, referred to as land use, concerns the effective planning and management of the surrounding areas around airports; including the establishment of zoning laws, building insulation and prioritizing industrial and commercial lands around airports to minimize residential disturbance. The third pillar, operational procedures, aims to optimize airline and airport operating procedures, such as flight paths and takeoff and landing procedures. Finally, the fourth pillar, operational restrictions, is the last resort: this entails restricting the number of flights or banning noisier aircraft at an airport. There exist various critical discussion on these pillars and their evaluations, including the lack of background noise considerations (Scatolini, Alves, & Eller, 2016), the impossibility to enforce effective land-use restrictions around airports (da Silva, Santos, & de Arantes Gomes, 2020), under-explored interdependencies (Ganic, Dobrota, & Babic, 2016), the influence of dynamic working patterns (Ang & Cui, 2022), as well as legal consideration (Langlade, 2017).

The most promising engineering aspect for noise reduction is the design of quieter aircraft engines, such as **geared, high-bypass ratio engines** that optimize the airflow and allow the turbine to operate at different speeds (Blech, Appel, Ewert, Delfs, & Langer, 2020; Magrini, Benini, Yao, Postma, & Sheaf, 2020). Another engineering aspect at the source include the **incorporation of noise-reducing modifications into airframes**, e.g., chevrons, and other aerodynamic designs that reduce the drag. Finally, the development of **better aircraft noise models** under consideration of accurate departure characteristics – and the dissemination of public data and codes – is an important direction for future work (Giladi & Menachi, 2024).

3. Innovative operations-related engineering solutions

The following section presents a discussion of five operations-related engineering challenges, which will be essential for ensuring a sustainable development of air transportation until the year 2050 and beyond. These challenges include airline scheduling (Section 3.1), multi-modal integration (Section 3.2), automation (Section 3.3), resilience (Section 3.4), and training/simulation (Section 3.5).

3.1. Sustainable airline scheduling

Airlines are typically profit-driven unless they satisfy other national interests, e.g., aiming either to maximize market share or to establish a prominent market presence. According to Schön (2008), the central product of airlines are their schedule: The schedule establishes which airports are served in their network via direct flights or transfers. Thus, it determines the itineraries — all offered connections which include one or multiple specific flight legs from origin to destination for a specified price and condition. The schedule has the largest influence on fuel burn and the environmental impact of an airline as it determines the overall operation. Schedules can be built from scratch or iteratively improved. Various Operations Research models in the literature solve the schedule design problem by choosing the legs to operate from a set of candidates and build the offered itineraries. Instead of solving the problem isolated, integration with multiple planning steps from the Airline Planning & Scheduling process by Belobaba, Odoni, and Barnhart (2016) is state-of-the-art. Fleet assignment associates the chosen legs to aircraft types; it has a high influence on the overall costs and fuel burn of the airline and is almost always included as in Xu, Adler, Wandelt and Sun (2024); see also (Xu, Wandelt, & Sun, 2024) for a broad literature review on airline scheduling optimization.

On one hand, successful airline operations and environmental considerations are often in conflict, given that every additional flight has a direct impact on the environment. On the other hand, fuel belongs to the biggest expenses of airlines, providing them with a significant incentive to lower fuel burn and emissions. For these two reasons, sustainability considerations have not been actively addressed in the past models but are receiving more attention recently. These new models have the ability to consider the tradeoff between the profit and sustainability objectives; Krömer, Topchishvili, and Schön (2024) provide an overview of the different model results including emission and profit reduction. Furthermore, they specify four influence factors used for their schedule design model to manage total fuel burn in their network: Aircraft selection & assignment (Proesmans, Morlupo, Santos, and Vos 2023, Morrell 2009), network design (Sun, Tian, Zhang, Nadeem and and Xu 2021), cruise speed (Sobieralski 2023), and aircraft utilization. The latter factor represents the relationship of higher load factors resulting in lower per passenger fuel burn; it is not main focus of any reference due to its strong dependence on the other factors. In the literature, most models use multiple influence factors but focus on a specific one, e.g. Noorafza et al. (2023) focus on network design. Additionally, some optimization models such as Wang, Yuan, Zhu and Li (2023), Parsa, Nookabadi, Flapper, and Atan (2019), and Sun et al. (2024) focus on the more strategic planning stages of network or fleet planning. They do not provide a feasible schedule as output but fix strategic long term decisions.

We suggest three further improvements for schedule design models to provide further sustainability insights: From the regulator's perspective, **different regulation designs and their effects should be analysed**. Krömer et al. (2024) only consider a carbon cap policy (CCP – limit of emissions). Other options suggested by Rahmati, Neghabi, Bashiri, and Salari (2024) are a carbon tax policy (CTP – per emission unit), a carbon offset policy (COP – purchase of emission rights) or a carbon cap-and-trade policy (CCTP – purchase and sell of emission rights). A distance-based passenger tax could also be considered as mentioned by Larsson, Elofsson, Sterner, and Åkerman (2019). Next to the airlines profit and network, also the **influence on ticket prices and travel volumes** should be taken into account to estimate the impact of the regulation on consumers. Additionally, **customer preferences in regard to green product attributes** of travel such as in Hagmann, Semeijn, and Vellenga (2015) or Evangelinos, Tscharaktschiew, and Mietzner (2022) have not been included in schedule design models. Using these findings as input for customer behaviour, the higher willingness to pay for greener itineraries might be able to offset some higher costs for sustainable itineraries.

3.2. Multi-modal traffic integration

The integration of air transportation with other modes is pivotal for advancing sustainability in the wider transportation context. For instance, inter-modal and multi-modal transportation options combining air and rail products are increasingly popular in Germany, significantly reducing the necessity to use domestic flights towards the two Lufthansa hubs in Frankfurt and Munich (Wandelt & Sun, 2022). Leveraging modern machine learning techniques and vast datasets, unprecedented capabilities emerge to optimize multi-modal transportation networks, enhance operational efficiency, and minimize environmental impact, while passengers enjoying seamless intermodal connectivity (Raghunathan, Bergman, Hooker, Serra, & Kobori, 2023) and more resilient transport systems (Xu, Wandelt, & Sun, 2023).

At the forefront of such efforts lies the concept of anticipatory analytics, which enables stakeholders to accurately forecast travel demand, optimize routing and scheduling, and improve resource allocation across different modes of transport. By analysing historical data, weather forecasts, and other relevant variables, AI and big data analytics enable transportation planners and operators to identify trends, patterns, and anomalies, facilitating proactive decision-making and dynamic resource allocation to maximize system efficiency, minimize environmental impact, and reducing the downstream effects of disruptions. Existing research using AI-based approaches are mostly on the unimodal transport demand forecasting and operation optimizations (Javanmard, Tang, & Martínez-Hernández, 2024; Rajendran, Srinivas, & Grimshaw, 2021); Banerjee, Morton, and Akartunalı (2020) conducted a systematic review of the methods for aviation demand forecasting, especially highlighting the advancement and merits of AI-based methods. Hejji, Talib, Nassif, Nasir, and Bouridane (2021) offered a comprehensive review on how the AI-based approaches to improve aviation operations, planning and resource allocation. Similarly, the AI-based methods have been widely adopted to forecast demand and suggest operational improvements for other transport modes, including taxi (Wei, Sun, & Tseng, 2021), and public transit (Park, Choi, Kim, & Yoo, 2022). The multimodal transport demand and the operational improvements have not been well explored to date, not to mention the inherent difficulties with increasing sustainability. AI-driven mobility-as-a-service (MaaS) platforms enable travellers to plan, book, and pay for multi-modal journeys with ease, convenience, and affordability, while optimizing travel times, costs, and environmental impacts. For example, Abedalla et al. (2019) proposed a multi-modal transport recommender system using deep learning and tree models, suggesting the passenger's transport mode combinations and routing for OD travel. This deep learning approach utilizes the big data of all travellers' historical OD travel records and the transport system operation parameters. Duan, Tay, Molla, and Deng (2022) utilized an artificial neural network method to predict MaaS use for different trip categories. However, given the rise of the AI-based methods and the concept of MaaS, the application in the multi-modal transport coordination involving air transport has been quite scanty.

Despite existing advances, the integration of air transportation with other modalities presents various future challenges, notably in luggage handling, cross-country ticketing, and coordination during disruptions. Implementing **through-checking and advanced luggage tracking** technologies could mitigate issues such as redundant checks, delays, and lost baggage (Babić, Kalić, Janić, Dožić, & Kukić, 2022). **Effective cross-country, cross-operator ticketing**, particularly between air travel and high-speed rail (HSR), is complex due to disparate operational standards and ticketing systems. Aligning schedules, fare structures, and reservation platforms necessitates extensive collaboration among international transportation authorities and service providers (Sun, Zhang, & Wandelt, 2017). Lastly, **coordination of multi-modality under disruptions** are critical yet challenging, given the different regulatory frameworks and contingency plans of air transport and each complementary mode (Xu et al., 2023). Effective communication, real-time data-sharing, and robust protocols are essential for managing passenger flows, rerouting services, and providing timely information during such events, thereby enhancing system resilience, passenger satisfaction, and sustainability. Combining air and ground transport effectively improves resilience, optimizes resources, reduces carbon emissions, and enhances the overall passenger experience while contributing to a more sustainable transportation ecosystem.

3.3. Air traffic management automation

Current ATM critically depends on the high performance of human controllers throughout the worldwide control centres, and their effective coordination and communication with crews on-board of aircraft that are transporting passengers and cargo around the world. In contrast to road traffic, where each car driver is able to make its own driving decisions, in air traffic, for their decision-making pilots critically depend on controller instructions. The advantage of this centralized approach is that it has worldwide been proven to work well. A disadvantage of this centralized approach is that controller workload forms a bottleneck in increasing air traffic capacity. This explains why the focus of automation in ATM is on reducing the workload of controllers.

In ATM common practice is to organize air traffic control in fixed geographical sectors. Although this way of organizing air traffic control has proven to work well, its disadvantage is that within this sector-based organization there is hardly room for introducing automation support for controllers, e.g. Strauch (2018). This finding has motivated studies to modify the organization of air traffic control. The two main concepts under investigation are Flight-centric operations (Gerdes, Temme, & Schultz, 2018) and Flow-centric operations (Schultz, Tominaga, Itoh, & Duong, 2023). In Flight-centric operations, the sector-based ATM concept is replaced by a decentralized approach where one each individual flight is controlled by the same air traffic controller along the entire trajectory. Hence each air traffic controller is responsible for supporting a number of individual flights throughout the duration of each flight. This flight-centric approach makes it possible to allocate easy flights to an automated system or flight crew (Howell, Tran, King, Rodriguez, & Arbuckle, 2023), and to leave demanding flights under control of a human controller. de Rooij, Stienstra, Borst, Tisza, van Paassen, and Mulder (2023) have developed and evaluated a support system that determines which flights can be allocated to the automated system, and which should be allocated to a human controller. The concept of flow-centric operations (Schultz et al., 2023) goes further, by also organizing flight trajectories in such a way that the level of potential conflicts between different flights is reduced. Hence, flow-centric operations is an enabling technology to address the challenges of free route airspace, and to maximize airspace utilization. The idea behind this concept is that the less heterogeneous and the more ordered the traffic flows are, the easier it is for a controller to manage the traffic scenario. Where flight-centric operations completely work without sectors, flow-centric operations can be combined with dynamically moving sectors. Moving sectors that align with the traffic flows will enable the provision of safe, user-oriented, and prioritized air traffic services by an air traffic controller per sector. Ma, Alam, Cai, and Delahaye (2023) have developed a machine learning method for the coordination framework in support of flow-centric ATM approach.

A central role in air traffic management automation is played by the development of optimization methods for the joint and conflict-free optimization of 4-dimensional trajectory plans for the air traffic flights. Ribeiro, Ellerbroek, and Hoekstra (2020) give a recent overview of the literature on joint trajectory optimization, both for conventional air traffic and for UAS traffic in lower airspace. Recent developments address the use of deep reinforced learning in joint trajectory optimization (Groot, Ellerbroek, & Hoekstra, 2023; Taylor, Vargo, Manderfield, & Heitin, 2023; Wang, Pan, Li, Wang, & Zuo, 2022). This challenge extends to surface and departure management. With the vast number of agents typically involved (including aircraft, pilots, air traffic controllers, ground staff, and automated systems), significant improvements have been demonstrated through research on multi-agent optimization of autonomous surface movement (von der Burg & Sharpanskykh, 2023) and integration with departure traffic operations (Itoh & Schultz, 2023).

Thanks to deep neural network learning technology, significant progress has made in complementary areas that are of great value to ATM: Weather prediction, speech recognition, and surveillance. Novel techniques in learning from data allow to significantly improve the prediction of crucial weather phenomenon, and to use this information in traffic optimization (Dalmau, Attia, & Gawinowski, 2023; Jones & Ellenbogen, 2023; Malfliet, Sun, & Hoekstra, 2023; Nunez-Portillo, Valenzuela, Franco, & Rivas, 2023; Reynolds, Matthews, Enea, & Cushnie, 2023; Sanchez et al., 2023). Automatic speech technology has been further developed in the recently completed SESAR project HAAWAII (Bhattacharjee et al., 2023; Motlicek et al., 2023), and it has been demonstrated that this methodology can effectively reduce the workload of controllers (Helmke, Kleinert, Ahrenhold, et al., 2023; Helmke, Kleinert, Linß, et al., 2023). Novel techniques in computer vision are ready for effective use in air traffic control. Thai, Alam, and Lilith (2023) develops an approach that significantly improves the visual surveillance of aircraft from a tower under low visibility conditions. Ali, Pham, and Alam (2023) develops an approach to improve the processing of multi-camera observations for use in a remote tower. Huang, Zhang, Zhang, Zhang, and Yin (2023) applies deep learning on trajectory images for the prediction of landing time on the airport.

To summarize, there are great opportunities for the successful advancement of ATM automation. First, the introduction of **machine learning methods to weather prediction, speech recognition and surveillance**. Second, **integrated optimization of surface and departure traffic operations** promises significant benefits for all stakeholders. Third, safely increasing air traffic capacity by relaxing the current controller workload limitation through **introducing flow-centric operations in combination with optimization support tools**.

3.4. Resilient operations

The aviation industry operates within a dynamic and complex environment characterized by various risks and uncertainties, including weather disturbances, technical failures, and geopolitical events, which can have significant impacts not only on safety, but also efficiency and environmental sustainability (Cardillo et al., 2013; Muecklich, Sikora, Paraskevas, & Padhra, 2023; Thompson & Tran, 2019). At the heart of understanding and improving the resilience of air transportation rests the concept of inter-connectivity and down-stream effects, given that networked structures within air transportation is paramount for enhancing its resilience. A few common examples for such network structures are described below. Airports are connected via aircraft through direct flights, leading to airport networks (Sun, Wandelt, & Zhang, 2020; Wandelt, Sun, & Zhang, 2023b). Flights are usually operated and managed along routes/corridors, leading to air route networks (Gopalakrishnan & Balakrishnan, 2021). Airlines optimize flights and aircraft movements through airports and maintenance facilities, leading to a connection network (Xu, Wandelt, & Sun, 2024). In light of such network representations, a frequent question is: Which nodes are the most important/vulnerable in the networks? Various studies have addressed this question via methods from statistical physics and operations research; see Sun and Wandelt (2021), Zanin and Wandelt (2023) for reviews. Through a comprehensive analysis of the interconnectedness across airports, airlines, and air traffic management systems, we can identify vulnerabilities and develop strategies to mitigate disruptions. Furthermore, leveraging network theory allows to optimize route planning, resource allocation, and contingency management, ultimately bolstering the robustness of the air transport system in face of unforeseen challenges.

In recent years, aviation stakeholders have enhanced their ability to detect, react, and recover from disruptions, thereby minimizing adverse impacts, enhancing operational resilience, and fostering sustainable practices within the industry. One primary application is the development of predictive models for identifying and forecasting potential risks and hazards, including weather patterns and potentially disruptive flight schedules (Tselentis, Papadimitriou, & van Gelder, 2023; Zhou, Yu, Zhu, Zhou, & Qi, 2023). Big data analytics can integrate information from various sources, such as social media, news feeds, and regulatory databases, to provide early warnings and situational awareness of emerging risks and crisis events (Li & Ryerson, 2019; Martínez-Prieto, Bregon, García-Miranda, Álvarez-Esteban, Díaz, & Scarlatti, 2017). Furthermore, monitoring systems can provide real-time insights into airspace congestion, adverse weather conditions, potential safety hazards (Tang, Liu, & Pan, 2022), as well as deriving robust optimization solutions (Xu, Wandelt, & Sun, 2021). Finally, AI and big data technologies together enable aviation stakeholders to enhance communication and collaboration in response to disruptions, fostering a culture of transparency, accountability, and continuous improvement within the industry.

To further provide resilience operations by air transport, various research challenges remain. One of the major challenges for resilient air transportation will be the **adaptation to the wide-ranging impact of climate change**, with an increasing impacts of extreme weather events along routes as well as around airports, such as increased turbulence, stronger storms, and dynamic wind patterns, as well as changed patterns of wildlife (Gratton, Williams, Padhra, & Rapsomanikis, 2022). Another important aspect is the **identification and mitigation of vulnerabilities from external intruders**, driven by the increasing digitalization and connectivity of aviation systems, which create numerous potential entry points for cyber-attacks. The sheer complexity and sophistication of these integrated systems, along with the presence of legacy infrastructure, make this task tremendously difficult (Dave, Choudhary, Sihag, You, & Choo, 2022). Finally, **mitigating the impact of excessive air transportation delays and cancellations** - caused by multitude of factors, needs to be addressed using modern optimization techniques, e.g., reinforcement learning (Ding, Wandelt, Wu, Xu, & Sun, 2023).

3.5. Training and simulation

Artificial intelligence and big data technologies have enormous potential for revolutionizing training and simulation in all domains (Fiok, Farahani, Karwowski, & Ahram, 2022; Mirchi et al., 2020; Wei, Huang, Li, Liu, & Zou, 2021), including air transportation (Wandelt, Sun, & Zhang, 2023a; Wandelt & Zheng, 2024). Through advanced data analytics, machine learning algorithms, and virtual simulation environments, these technologies enable the development of immersive training programs that replicate real-world scenarios, providing pilots, air traffic controllers, and aviation personnel with hands-on experience and decision-making skills in a safe and controlled setting (Jones et al., 1999; Sprockhoff, Gupta, Durak, & Krueger, 2024; Yang, Yu, Lammers, & Chen, 2021). This not only improves training effectiveness, but also reduces training costs, enhances operational performance, and fostering a culture of continuous learning and improvement in the aviation industry. Particularly the development of adaptive training systems that tailor learning experiences to the individual needs and preferences of trainees promises to be essential. By analysing vast amounts of training data, including performance metrics, physiological responses, and behavioural patterns, AI-powered adaptive training systems can personalize training programs to optimize learning outcomes and improve retention rates. Moreover, the integration of real-time performance monitoring and feedback mechanisms enables trainees to receive immediate guidance and corrective actions during training sessions, facilitating skill acquisition and proficiency development in a dynamic and interactive learning environment (Conceição, 2021; Johnson, Rickel, Lester, et al., 2000; Sabry & Barker, 2009).

Through the use of AI and big data in adaptive training systems, aviation stakeholders can optimize training efficiency, reduce training time, and minimize environmental impact by conserving resources associated with training activities (Zhai et al., 2021). Furthermore, AI and big data-driven simulation technologies can play an important role in enhancing operational readiness and crisis preparedness in air transportation, leading to more sustainable aviation practices (Liu & Wen, 2024; Sridhar & Bell, 2022). A wide range of emergency scenarios can be simulated, including equipment malfunctions, weather disruptions, and airspace congestion. Through the use of big data analytics, simulation systems can analyse historical data on incident response times, error rates, and safety outcomes to identify trends, patterns, and areas for improvement in crisis management procedures. Moreover, AI and big data-driven training and simulation technologies facilitate knowledge transfer and skill retention among aviation personnel. The integration of immersive simulation environments, virtual reality (VR) headsets, and gamification techniques enhances engagement and motivation among trainees, leading to higher levels of knowledge retention and skill transfer to real-world scenarios (Wandelt & Wang, 2024).

Implementing AI into air transportation training and simulation presents significant open research challenges, particularly in creating realistic and complex simulation environments, developing effective human–AI interaction and trust, and ensuring adaptability and personalization of training programs. Simulations must **accurately mimic real-world scenarios**, including dynamic and unpredictable conditions, which requires advancements in virtual and augmented reality technologies, as well as sophisticated algorithms for scenario generation and real-time data integration (Meister et al., 2024). Additionally, AI systems must **effectively interact with human trainees and instructors**, providing transparent and explainable feedback to ensure trust and acceptance, which involves research in human–AI interaction design and explainable AI (Xin et al., 2024). Finally, AI-driven training programs need to **adapt to individual trainee needs and learning styles**, necessitating machine learning techniques for personalized learning, performance assessment algorithms, and adaptive learning systems (Aguilar Reyes, Wozniak, Ham, & Zahabi, 2023).

4. The safety assurance challenge

Sections 2 and 3 have explained several engineering challenges of promising changes in air transportation. Prior to introducing a change, assurance is needed that the safety level of commercial air transportation will not be compromised. First, Section 4.1 explains the challenge posed by the long tail of rare emergent behaviours that may be induced by a change in the design of safety-critical operations. Next, Section 4.2 reviews safety analysis methods on their capability in identifying such long tail of rare emergent behaviours. Section 4.3 discusses the application of novel safety analysis methods to the engineering challenges of Section 2 and Section 3.

4.1. Long tail of rare emergent behaviours

In complexity science a behaviour is called “emergent”, or “systemic” if it results from interactions between the constituting elements of a system. In designing a system, emergent behaviour is both a friend and a potential enemy. It is a friend in designing interactions that yield positive emergent behaviour. It is a potential enemy if a design also produces unintended emergent behaviour, which typically will be negative. As soon as such negative emergent behaviour is identified, then it can be mitigated by improving the design. The latter works well for negative emergent behaviour that happens frequently, though poses challenges for rare emergent behaviour.

The problems that rare emergent behaviour can cause in a novel socio-technical design, has been experienced in the development of autonomous driving in road transportation. Allowing experimental autonomous cars to drive amidst other road traffic, created the opportunity to identify novel emergent behaviour from incidents and accidents, and to use this learning for the improvement of the self-driving system designs. The expectation was that this retrospective learning curve would be such steep that only a few years of driving experience would be needed. However, in practice, the tail of rare emergent behaviour appears to be much fatter and longer than expected (Jiang, Najibi, Qi, Zhou, & Anguelov, 2022; Makansi, Çiçek, Marrakchi, & Brox, 2021). As a result of this, the time schedules in realizing autonomous driving have experienced large delays.

The introduction of promising changes in air transportation will also have to deal with a long tail of rare emergent behaviours. The good news is that in commercial aviation, retrospective safety analysis of accidents and feedback to the operation, is a well-developed method that is worldwide applied. Since the successful introduction of Jet airliners, i.e. Boeing 707 in 1958 and the larger Boeing 747 in 1968, commercial aviation has increased by two orders in magnitude. During the same period, fatal accident rate has decreased by two orders in magnitude (Boeing, 2023). Retrospective learning has played a key role in reaching this high safety level. Hence, the initial idea might be to use this retrospective learning approach also for the identification and mitigation of the long tail of rare emergent behaviours that might come with the introduction of smart design challenges. The problem with this initial idea is that both traffic volume and safety levels of commercial aviation are such high that this is not an option. This means we are in need of a prospective approach in identifying the long tail of rare emergent behaviours, i.e. an approach that can be applied during the design of the novel challenges. Hence, the three follow-on questions are:

- Which prospective safety analysis methods exist?
- How well can these methods identify rare emergent behaviour?
- Can these methods be applied to the engineering challenges of this study?

The first two questions are addressed in the next subsection. Subsequently, the latter question is addressed in Section 4.3.

4.2. Prospective safety analysis methods

In commercial aviation, it is a well-established practice to systematically apply prospective safety assessment methods like Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA), and Event Tree Analysis (ETA) during the design of complex technical systems. By conducting Hazard Analysis, and modelling a pilot or controller as a system that can make errors, external influences and human interactions are also taken into account. To complement this failure/error directed safety analysis, it is also common practice to conduct human-in-the-loop simulations. In addition to these two main types of methods, for mid-air collision risk assessment between air traffic flows the Reich mid-air collision risk model is widely used. For these three types of methods, worldwide standards and regulations have been developed, e.g. ICAO, FAA, EASA.

The subsequent question is how well these methods can identify rare emergent behaviour during the design phase of an improved operation. Since the Reich mid-air collision risk model does not capture the interactions within the system, it is not able to identify unknown emergent behaviour. The technical systems directed methods, like FTA, FMEA, and ETA are perfectly able to identify rare emergent behaviour due to failures in a complex system. However, their simplistic modelling of socio-technical interactions make them unfit for identifying rare emergent behaviours that are not of failure type. Human-in-the-loop simulation has proven to be effective in identifying unexpected emergent behaviours that happen during the conducted simulation sessions. The need to have an trained human-in-the-loop poses a serious limit on the duration and amount of these sessions, and therefore does not allow to systematically identify a long tail of rare emergent behaviours.

Since the mid-eighty's, simulation-based methods have been developed to assess the reduction in collision risk by an Airborne Collision Avoidance System (ACAS) (Kochenderfer, Edwards, Espindle, Kuchar, & Griffith, 2010). The current state-of-the-art is to develop a Dynamic Bayesian Network (DBN) for a random encounter between two (correlated) aircraft, and to train its parameter settings on a large set of collected aviation surveillance data. Such dynamic Bayesian simulation models have been developed for airspaces in USA and in Europe (Dean et al., 2022; Underhill et al., 2018). At MIT Lincoln Laboratory, an earlier dynamic Bayesian model for USA airspace has been used to conduct Monte Carlo simulation of a novel airborne collision avoidance system design (Holland, Kochenderfer, & Olson, 2013). One limitation of this approach is the simulation of the last phase of an encounter only. Another limitation is the use of a simplistic human model, which means that it cannot identify rare emergent socio-technical behaviour.

In the ninety's, the wider safety research community recognized that established safety thinking has critical shortcomings to support technological change, e.g. Woods and Dekker (2000). As a result, the spectrum of safety research has widened to "Resilience Engineering" (Hollnagel, Woods, & Leveson, 2006). The central theme is that human operators should not be considered as systems that make errors; though as resolvers of strange problems that pop up during an operation and being able to learn and improve future response. In support of mobilizing human factors feedforward input to a design change in a safety-critical operation, Hollnagel (2012) developed the Functional Resonance Analysis Method (FRAM). FRAM is a qualitative and graphical method that allows human factors experts to reason about emergent behaviour of a socio-technical system. So far, FRAM has mainly been applied in retrospective analysis of accidents (Patriarca et al., 2020).

In this "resilience engineering" stream, at MIT, Nancy Leveson started the development of novel hazard analysis methods that apply to complex socio-technical systems. The resulting method is STPA (Systems-Theoretic Process Analysis) yields significant improvements in prospective safety analysis methods (Leveson, 2012). For a specific operation considered, STPA develops a system theoretic model of the socio-technical interactions, and subsequently identifies emergent behaviours through a systematic reasoning about all interactions. Because STPA does not conduct simulations with the system theoretic model, it has serious limitations in identifying the full spectrum of emergent behaviours. For developments in civil aviation, Leveson, Wilkinson, Fleming, Thomas, and Tracy (2014) make the prospective safety feedback value of STPA specific through a systematic comparison with established Prospective safety analysis methods. The key added value is that STPA makes it possible to derive functional requirements to novel socio-technical design. Recently, Poh, Leveson, and Neogi (2024) have shown how STPA can be used as basis for the systematic development of architecture options for an ATM design improvement.

In parallel to the "Resilience Engineering" developments, NASA developed the fast time simulation platform Man-Machine Integrated Design and Analysis System (MIDAS) (Hoecker, Corker, Roth, Lipner, & Bunzo, 1994). MIDAS enables fast time simulation of cognitive behaviour and performance of pilots and their interaction with technical systems during a flight. To accomplish this, MIDAS makes use of human cognition and behaviour modelling within Agent Based Modelling and Simulation (ABMS). In the sequel we refer to ABMS+ for this non-trivial extension of ABMS. The MIDAS results have shown that ABMS+ can identify unknown emergent behaviour during the design of a novel human–machine interface in the cockpit. To also address changes in air traffic management, Corker (2000) developed the Air-MIDAS extension. The positive Air-MIDAS findings have stimulated other researchers in aviation to adopt and further develop this ABMS+ approach for the identification of unknown emergent behaviour, e.g. Shah et al. (2005).

Stimulated by NASA's achievements in ABMS+, and its own experience with ICAO's collision risk model, in the nineties, NLR has started to work on the extension of the ABMS+ approach to Agent-Based Dynamic Risk Modelling and Simulation (ABDRMS). Throughout this development, the objective has been to get grip on the modelling and risk assessment of rare events. An important motivation was the lack of adequate safety analysis methods to evaluate the design of novel air traffic operations for Amsterdam airport. Due its complex runway and taxiway layout, existing methods only worked under very restrictive traffic flow conditions. The first step was a generalization of the ICAO collision risk model to dynamic aircraft encounters (Bakker & Blom, 1993). Within a subsequent series of European research projects (MUFTIS, VAPORETO, RHEA, GENOVA, ARIBA), this basic collision risk model has been combined with ABMS+, i.e., ABMS that includes models of human cognitive behaviour and performance (Blom et al., 1998), and to the development of a method to identify "unimaginable hazards" (de Jong, Blom, & Stroeve, 2007). To further improve the integration of the developed methods, active collaboration with university researchers has been realized through a sequence of international projects: NASA safety modelling, Hybridge, iFly and MAREA. The collaborations within NASA safety modelling led to further insight in human cognitive behaviour modelling within ABMS+ (Corker, Blom, & Stroeve, 2005). The collaboration within Hybridge and iFly made it possible to firmly embed the novel approach within the general theory of stochastic hybrid systems (Blom & Lygeros, 2006), and to rare event simulation based collision risk estimation (Blom, Bakker, & Krystul, 2009). The collaboration within MAREA led to a more complete modelling of various disturbances and uncertainties within ABMS+ (Bosse, Blom, Stroeve, & Sharpanskykh, 2013; Stroeve & Blom, 2012). Without these disturbances and uncertainties, a large subset of rare emergent behaviour cannot be identified. An overview of the ABDRMS methodology is given in the FAA/Eurocontrol white paper (Everdij, Blom, Stroeve, & Kirwan, 2014); this includes references to the various methods used.

4.3. Application of novel prospective methods to the engineering challenges

Of the methods mentioned in the previous subsection, STPA, ABMS, ABMS+ and ABDRMS are most promising for prospective identification of unknown emergent behaviours. STPA can effectively be used during the socio-technical design phase for each of the eleven challenges. Subsequently, ABMS, ABMS+ and ABDRMS can effectively be used to identify and analyse complementary emergent behaviours through simulations. Because ABMS is capable in identifying other key performance characteristics than safety alone, its application is of effective use for each of the eleven challenges from Sections 2 and 3. Examples are (Lee & Mitici, 2020; Lee, Mitici, Blom, Bieber, & Freeman, 2023) for the challenge "Innovative maintenance procedures"; Delgado et al. (2023) for the challenge "Multi-modal traffic integration", (Bouarfa, Müller, & Blom, 2018) and Gurtner, Delgado, and Valput (2021) for the challenge "Resilient operations". However, as has been in-depth explained by Feigh, Pritchett, Mamessier, and Gelman (2014), Pritchett, Feigh, Kim, and Kannan (2014), Ribeiro et al. (2020), these ABMS applications do not include human cognitive behaviour models of ABMS+. As has been shown by MIDAS and Air-MIDAS, the ABMS+ capabilities are particularly needed for the challenges "Air Traffic Management automation" and "Developing future aircraft designs". These challenges will further benefit from the additional rare emergent behaviour simulation capabilities of ABDRMS. Therefore, we give an overview of ABDRMS applications for these two challenges, and describe the consequences this has for the challenge "Global engineering coordination".

Air Traffic Management automation. The ABDRMS methodology has been applied to various ATM operational design changes for Amsterdam airport. Each design change typically involved multiple ABDRMS cycles, with feedback of the novel identified emergent behaviour to the design team after each cycle. If a design team expresses doubts regarding the correctness of an identified emergent behaviour, then the

Developing future aircraft designs	1. Comprehensive, multidisciplinary coupling analysis based on intelligent algorithms 2. Better integration of aircraft design and innovative propulsion systems 3. Intelligent flight technology with multi-aircraft platform capabilities
Electrification of aircraft / propulsion systems	4. Address limitations in energy density, which limit range and payload capacities 5. Invest into and redesign airports and maintenance facilities 6. Reduce the environmental impact of battery production and disposal
Sustainable aviation fuel implementation	7. Develop new sustainable feedstock resources to minimize lifecycle emissions 8. Research on new fuel molecules, including cycloalkanes, to complement iso-alkanes 9. Explore pathways for the successful commercialization of SAF technology
Innovative maintenance procedures	10. Improve machine self-diagnosis and self-scheduled, automated maintenance 11. Build appropriate infrastructure to acquire and process the data 12. Align with existing safety requirements and regulations in air transportation
Global engineering coordination	13. Try to maintain a notion of international aviation diplomacy through engineering 14. Develop common interface standards and protocols for interoperability 15. Integrate modern formal (large) language models into the development of standards
Noise reduction technologies	16. Design quitter geared engines with high-bypass ratios to optimize airflow 17. Incorporate noise-reducing modifications into the airframe 18. Devise better aircraft noise models with accurate departure characteristics
Sustainability-oriented optimization	19. Investigate the effects of different regulation designs in airline scheduling 20. Enhance regulation analysis by inclusion of ticket prices and travel volumes 21. Investigate the role of customer preference and acceptance to green product attributes
Multi-modal traffic integration	22. Implement through-checking and advanced luggage tracking technologies 23. Design and implement effective cross-country, cross-operator ticketing 24. Enhance multi-modal coordination capabilities under disruptions
Air traffic management automation	25. Machine learning for weather prediction, speech recognition and surveillance 26. Integrated optimization of surface and departure traffic operations 27. Introducing flow-centric operations in combination with optimization support tools
Resilient operations	28. Adaptation to the wide-ranging, dynamic impacts of climate change 29. Early identification and mitigation of vulnerabilities from external intruders 30. Mitigating the impact of excessive air transportation delays and cancellations
Training and Simulation	31. Advance the degree of realism for training simulations with augmented reality 32. Ensure an effective interaction between human trainees and instructors 33. Investigate how to adapt to individual trainee needs under data privacy constraints
Safety assurance	34. Embrace STPA within the socio-technical design for each engineering challenge 35. Use of ABMS+ for novel emergent behaviours of a proposed socio-technical design 36. Use of ABDRMS for rare emergent behaviours and safety risks of a proposed socio-technical design.

Fig. 3. Overview on 33+3 open challenges within DESIGN and be SMART under safety assurance.

design team is invited to take a look at simulation runs that show this emergent behaviour. There are two possible outcomes: (i) Something is wrong with the simulation model, and the ABDRMS experts will resolve this; or (ii) Design team accepts the identified emergent behaviour, and develops an improved design. For an improved design, the ABDRMS application should be done again to be sure that the previous emergent behaviours have indeed been improved, and that the design change does neither result in new rare emergent behaviour(s). For one of these operations, i.e. an active runway crossing design, the ABDRMS results have been compared to an established safety assessment (Stroeve, Blom, & Bakker, 2013). The ABDRMS methodology has also been applied to a sequence of Free Flight designs, i.e. ATM designs where aircraft crew are responsible for keeping safe separation with other aircraft. Hence, a Free Flight design also involves the challenge of “Design of future aircraft”. For Free Flight in en-route airspace, within the European research projects Hybridge and iFly, three ABDRMS assessments and design improvement cycles have been applied. The outcome of the third ABDRMS assessment is described in Blom and Bakker (2015). These results demonstrate that ABDRMS can identify rare emergent behaviour, and at the same time can assess safety risk, human performance and flight efficiency. Another ATM application of ABDRMS that involved the aircraft side is to assess the safety effect of introducing a novel ACAS design. The main finding is that the role of pilots goes beyond the problems addressed by the existing and the novel ACAS designs (Stroeve, 2023), and that this aspect has not been identified through simulations conducted with a DBN-based safety analysis (Holland et al., 2013).

Developing future aircraft designs: Many of the promising directions in developing future aircraft designs imply socio-technical changes. By conducting ABDRMS on a proposed design, rare emergent behaviours can be identified and assessed on their safety risk during the design. For aircraft design this assessment concerns quantification of probabilities of accident types like Loss of Control In-flight (LOC-I) and Controlled Flight Into Terrain (CFIT). In an MSc report (Jaberi, 2017) it has been demonstrated that ABDRMS is effective in identifying unknown rare emergent behaviour and assessing the risk of Loss of Control In-flight (LOC-I) during final approach.

Global Engineering Coordination: As explained in recent National Academies study report (National Academies of SEM, 2022), emerging developments in commercial aviation pose safety challenges that cannot be addressed by the worldwide accepted aviation safety assurance methodology. In parallel (Macrae, 2022) has conducted a systematic study in learning from failures experienced in the development of autonomous and intelligent systems in various domains. In a subsequent report (National Academies of SEM, 2024) an overview is given of the improvements that are needed in the aviation safety assurance methodology. Of the novel methods identified in Section 4.2, STPA and ABDRMS include the identification and analysis of socio-technical hazards. Hence, STPA and ABDRMS are the logical candidates for the development of a novel safety assurance methodology in commercial aviation. A key difference between these two methods is that STPA conducts a qualitative analysis of socio-technical hazards, whereas ABDRMS conducts a quantitative simulation based analysis of the interaction of socio-technical hazards within ABMS+. This difference implies that STPA and ABDRMS can play complementary roles in aviation safety assurance. STPA is particularly effective in providing feedforward input through identifying design options for the improvement of a socio-technical system (Poh et al., 2024). Once a specific improved socio-technical design has been selected, then ABDRMS is effective in identifying the full spectrum of (rare) emergent behaviours, and in conducting a quantitative safety risk assessment, and to feedback these results to the design team. Subsequently the design team can decide if how the socio-technical design will be further improved. Based on experience for ATM design changes around Amsterdam airport and the Free Flight research projects, for a significant socio-technical design improvement, this typically leads to one of more cycles of further improvement of the socio-technical design and subsequent ABDRMS-based assessment. The reward is that the long tail of emergent behaviours is learned and mitigated during the design phase.

5. Conclusions

In this paper, we have reviewed the major engineering challenges for air transportation on the way towards sustainability in the year 2050. Addressing these challenges is – we believe – paramount for the air transport research community due to its profound impact on global environment, economic stability, and societal well-being; all driven by a healthy air transportation system. The research community plays a crucial role in developing innovative solutions to mitigate potential impacts listed in our review. The pursuit of sustainable solutions in air transport also sets a precedent for other sectors, driving a broader transition towards sustainability across industries. In Fig. 3, we summarize the identified key engineering challenges and trust that other researchers will find them useful in the ongoing need to reshape our global air transportation system to be 2050-ready. To comply with the high safety levels reached in air transportation, we have also addressed novel methods that are able to address the overarching safety assurance challenge. It is clear that to overcome these challenges there is a need for comprehensive and orchestrated efforts.

CRediT authorship contribution statement

Sebastian Wandelt: Writing – review & editing, Writing – original draft, Conceptualization. **Henk Blom:** Writing – review & editing, Writing – original draft. **Marius Magnus Krömer:** Writing – review & editing, Writing – original draft. **Daochun Li:** Writing – review & editing, Writing – original draft. **Mihaela Mitici:** Writing – review & editing, Writing – original draft. **Tim Ryley:** Writing – review & editing, Writing – original draft. **Eike Stumpf:** Writing – review & editing, Writing – original draft. **Kun Wang:** Writing – review & editing, Writing – original draft. **Bin Yang:** Writing – review & editing, Writing – original draft. **Massimiliano Zanin:** Writing – review & editing, Writing – original draft. **Xiaoqian Sun:** Writing – review & editing, Writing – original draft.

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