A SIMPLIFIED MODEL FOR PROPAGATING AIRCRAFT-LEVEL PERFORMANCE TO AVIATION SYSTEM LEVEL

P. Bertram, P. Ratei, L. Weber, and P. Shiva Prakasha
German Aerospace Center (DLR), Institute of System Architectures in Aeronautics,
21129 Hamburg, Germany

Abstract

Global climate change poses major challenges for the aviation industry for the coming decades. This is compounded by rising passenger demand projections. In response to these challenges, aviation stakeholders focus on research of novel aircraft technologies and novel designs, that could be possible game changers with regards to aircraft technology. The advancements are not only at domain level or at novel vehicle/technology aspects, but also at operational, fleeting and energy mix aspects which could translate towards net-zero aviation. To consider a broader holistic system of systems perspective of all these areas, aviation impact assessment expanded from classic aircraft design to a global fleet level assessment incorporating global flight operations. This study evaluates the impact of emerging aircraft technologies and designs on reducing global energy consumption in aviation. By employing a comprehensive fleet network methodology, we project future global fleet compositions and operations, the research analyses efficiency improvements across various routes, coupled with varying entry-into-service timelines, and operational scenarios. This is complemented by using linear fleet optimization techniques and a statistical aircraft retirement approach, to model fleet turnover. Such an approach enables a dynamic multilevel assessment of the impact of disruptive aircraft technologies-vehicle-operational strategies together from a system-of-systems perspective, reflecting the interplay between technology advancement, fleet integration timing, and overall operational improvements.

Keywords

Aircraft Technology Assessment · Aviation System Modelling · Aircraft Performance · Energy Consumption

1. INTRODUCTION

The aviation industry stands at a critical crossroads as it grapples with the dual challenges of mitigating its environmental impact and accommodating an ever-growing demand for air travel. The urgency to address global climate change has spurred ambitious climate goals from public and private stakeholders, as well as governmental and non-governmental organizations, all aiming to significantly reduce global emissions. Notably, the aviation sector was responsible for approximately 3.5% of human-induced global warming in 2019 [1]. Even though CO_2 emissions from aviation accounted for just 2.5% of the total, the operations themselves in the higher atmosphere lead to a greater impact compared to emissions within the lower atmosphere [2]. While other industries, such as the automotive sector, have made significant strides toward achieving net-zero emissions, the aviation industry is under pressure to follow suit and push the transition to sustainable air transportation. Projected growth further complicates this scenario, with passenger demand expected to double by 2040 compared to 2010 levels [3–5]. To decouple this increasing demand from stringent emission requirements, aviation stakeholders are focusing on innovative aircraft technologies that could revolutionize the industry. These advancements span a range of areas, including enhanced structures and aerodynamics, the development of sustainable fuels, new propulsion systems, and more climate-friendly operational strategies. To comprehensively address these diverse areas, environmental assessments in aviation have evolved from traditional aircraft design/mission level assessment to global fleet-level perspectives. This shift encompasses not only single-mission assessments but also holistic fleet network assessments. By doing so, it becomes possible to account for industry-wide factors that influence the development of concept aircraft and acquisition strategies with respect to both economic and ecological footprints. Additionally, this approach considers the significant impact of geographical and altitude-dependent CO_2 and non- CO_2 emissions on global warming. The complexity of this holistic approach lies in balancing the need for accurate models of the air transport system and its future developments with the practicality of usability and computational efficiency. The ultimate goal is to provide a reliable assessment of aviation fleet and emissions, aiding decision-makers in identifying critical measures to mitigate the climate impact of civil aviation. This study proposes a tool that addresses the complex aspects of the Air Transport System (ATS) through a structured system of systems approach, with a focus on the rapid assessment of its environmental impact. Building on insights from a conducted scientific literature review concerning the global impact of future aircraft technology, the proposed tool and its interconnected models will be briefly described. Finally, we will present the tool's capabilities in assessing how varying technology levels and entry-into-service timelines influence the adoption rate of new technologies and the potential for reducing environmental impacts.

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2. LITERATURE REVIEW

To identify relevant state-of-the-art frameworks for long-term aircraft technology impact assessment, a systematic literature review was conducted. From 11 reviewed frameworks, six unique bottom-up approaches were selected for detailed investigation, in regards to aircraft technology injection modeling, aircraft performance modeling, geographical scope, technology considerations, and other key metrics. The following section provides a brief description of each selected framework.

Fleet Systems Dynamic Model (FSDM), Technical University of Munich:

The FSDM, developed by the Technical University of Munich, is part of an aircraft technology assessment framework designed to evaluate the impact of technological advancements on global fleet performance, with a focus on fuel consumption and CO_2 emissions. This dynamic model simulates fleet size and performance by considering aircraft allocation, production rates, and network demand. It uses a global route network divided into six world regions and 21 route groups, modeling traffic flows and stage lengths for each aircraft type. Demand is captured using metrics such as Available Seat Kilometers (ASK), Revenue Passenger Kilometers (RPK) and Revenue Ton Kilometers (RTK), which are projected to grow by employing compound annual growth rates (CAGR). The model utilizes nine representative aircraft classes, including new generation models with fuel efficiency improvements. Aircraft assignment is optimized for fleetwide reduction of fuel burn or Direct Operating Costs (DOC), while retirements are modeled using statistical retirement curves and later an economical approach by using a Net Present Value analysis. Aircraft performance is calculated using EUROCONTROL's BADA, with improvement factors applied for new technology generations. [6, 7]

Fleet-Level Environmental Evaluation Tool (FLEET), Purdue University:

FLEET, developed by Purdue University, is designed to evaluate the environmental impact of new aircraft technologies and aviation policies over a long-term period, from 2005 to 2050. It simulates US airline operations with a focus on optimizing aircraft assignment and retirement decisions to maximize airline profitability while considering demand growth, fuel efficiency, and evolving technology. The model forecasts future demand on an airport/city pair level, based on macroeconomic indicators such as GDP growth and price elasticity of air travel, meaning it estimates how sensitive demand is to changes in ticket prices. Aircraft retirement decisions are modeled using NPV analysis, which compares the cost of keeping older aircraft in service to the potential savings of replacing them with newer, more fuel-efficient models. The fleet is categorized into six seat classes, ranging from small regional jets to large wide-body aircraft, and includes both current and future generations of aircraft equipped with technological advancements aimed at reducing fuel consumption and emissions. Aircraft assignment is optimized based on route demand, with aircraft strategically allocated to routes that maximize operational profit. The model also incorporates technological progress by simulating future aircraft generations, considering improvements in fuel efficiency, based on advancements in aerodynamics, and engine technology. Aircraft performance is typically modeled using the Flight Optimization System (FLOPS), a tool that calculates detailed flight performance characteristics such as fuel burn, range, and emissions based on specific aircraft configurations. Overall, FLEET provides a comprehensive framework for assessing how new aircraft technologies and policies, such as emissions regulations or fuel taxes, can influence the global fleet's environmental performance and profitability over time. [8–11]

Passenger and Flight Forecast Model, German Aerospace Center (DLR):

This model, developed by the German Aerospace Center (DLR), integrates passenger demand forecasts, flight volume projections, airport capacity constraints and fleet development to provide detailed fleet, traffic and emission forecasts. It focuses on specific airport(city) pairs rather than aggregated regions, which allows for more accurate projections by incorporating individual airport capacity limitations. Passenger demand is generated using a gravity model, which accounts for variables such as GDP, population density, and others to estimate the demand for air travel between different locations. These factors influence the number of passengers likely to travel between two cities, with higher GDP or population often leading to increased demand. Based on this demand, the model projects flight volumes for the future, ensuring that capacity limitations at airports are respected. One of the key features of the model is its consideration of airport capacity constraints. Many major airports are facing traffic limitations especially in terms of runway availability, reducing the number of total possible movements per hour. As these airports are reaching its capacity limits, the model forecasts necessary adaptations, such as using larger aircraft, rerouting flights to less congested airports or runway expansions. Aircraft assignment is based on both the projected passenger demand and the capacity constraints of each airport. Aircraft are assigned to routes in a way that optimizes fleet utilization while ensuring that operations remain efficient within the limitations of each airport. The model also accounts for aircraft retirements using ICAO statistical survival curves, which statistically predict when aircraft will be removed from service based on their age and usage. New aircraft are introduced into the fleet based on the demand gap created by retiring aircraft and increasing traffic needs. For aircraft performance, the model uses tools like PIANO-X or BADA. These tools calculate fuel consumption, emissions, and performance characteristics for different aircraft types under varying operational conditions. This allows the model to estimate fuel burn and emissions (CO_2 and NO_x) for the entire fleet over time. [12, 13]

Fast Forward (FFWD), German Aerospace Center:

The Fast Forward (FFWD) model, developed by the German Aerospace Center (DLR), forecasts the evolution of the global commercial aircraft fleet and the impact of new aircraft technologies on CO_2 emissions from 2016 to 2050. The model categorizes aircraft by seat class and technology group, ranging from current models like the A320neo/ceo to future N+2 and N+3 concepts incorporating advanced technologies. Aircraft demand is driven by long-term traffic growth, with new aircraft allocations guided by

ICAO's retirement curves and market segment growth projections based on data from ICAO and IATA. Fixed demand is constrained by historical production rates, while unfixed demand is production unconstrained and includes future technologies from N+1 and N+2 aircraft generations. Aircraft performance, including fuel consumption is modeled using the EUROCONTROL BADA tool. Fuel burn reduction scenarios are integrated, accounting for improvements in propulsion, aerodynamics, and materials. Two key metrics—fleet intensity (CO_2 emissions per RPK) and relative CO_2 emissions compared to 2015—are used to assess the environmental impact of new technologies. This framework offers a robust prediction of aviation's potential to reduce emissions through the adoption of future aircraft technologies. [14, 15]

Bottom-Up Dashboard, University of Toulouse:

The Bottom-Up Dashboard, developed by the University of Toulouse, is an interactive tool for evaluating the impact of aircraft technology advancements on the global fleet from 2019 to 2050. The framework uses logistic functions to model fleet renewal, replacing older aircraft with new designs across four categories: short, medium, long-range, and freighters. Users can adjust parameters such as technology injection speed and market share saturation. Aircraft performance is modeled using energy consumption per ASK, with improvement factors for new technologies and downgrades applied for hydrogen-powered aircraft due to structural mass penalties (hydrogen tank mass). The dashboard is a relative simply tool, but due to its rapid nature it can give a quick first estimate of the emission mitigation potential of new disruptive technology on a fleet-level. [16]

Modular Assessment Framework of WeCare-Project, German Aerospace Center (DLR):

To assess the climate impact of aviation, including non-CO_2 effects, within a context of globally diverse socio-economic growth, it is essential to model the future evolution of the ATS. Within the DLR project WeCare, a modular, four-layer assessment framework has been developed and implemented using the AIRCAST (Air Travel Forecast) model chain to project generic global passenger air traffic networks with a high level of detail. This framework uses a global network architecture at the city-pair level, allowing for detailed quantitative scenarios that encompass anticipated passenger flows between specific city pairs, preferred route choices, and the number and size of aircraft that will operate on each segment worldwide. Collectively, this model provides comprehensive insights into future air traffic patterns and environmental impacts. [48,44]

The first layer, the Origin-Destination Passenger Demand Network, forms the foundation by estimating the volume of passengers expected to travel between specific city pairs in future years. This demand is projected using socio-economic scenarios, including forecasts from Randers (2012) and the International Futures Global Modeling System (IFs), which offer various pathways based on potential global conditions. [45]

Building on this demand data, the second layer, the Passenger Routes Network, models the routes that passengers are likely to choose. Historical data from Sabre Airport Data Intelligence (ADI) is used to calculate route probabilities, capturing preferred travel paths and creating a realistic view of passenger flow patterns. This network is organized into two sub-layers: the passenger route network, representing overall demand on primary routes, and the passenger segment network, which focuses on specific segments within each route. This layer gives insight into how passengers are distributed across routes and segments, which is critical for accurately simulating global air traffic flows. [48]

The third layer, the Aircraft Movements Network, focuses on determining the types of aircraft and the frequency of flights needed to satisfy demand on each route. This calculation is achieved through the DLR's FoAM (Forecast of Aircraft Movements) model and the fleet renewal model FFWD, which together estimate the share of aircraft sizes and service frequencies required to efficiently meet passenger needs. This network also consists of two sub-layers: one classifying movements by seat categories and another by aircraft type and generation. Modeling the structural evolution of global air passenger flows and aircraft movements over time is essential for quantifying future changes driven by diverse growth patterns across world regions and shifts in airline and passenger behavior. These anticipated changes may significantly impact the climate effects of non-CO_2 emissions in the future. Achieving an early and detailed understanding of these structural shifts is strategically important for effectively addressing climate change. [49,50]

With the modeled aircraft movements, GRIDLAB (Global Air Traffic Emissions Distribution Laboratory) enables trajectory simulations under realistic operational conditions, allowing for detailed calculations of emissions' quantity, location, and timing. This capability opens up the possibility for GRIDLAB to provide a precise understanding of aviation emissions and their potential climate impacts. This output feeds into the AirClim chemistry-climate response model, which is integrated through the RCE framework. Since aviation's climate impact depends heavily on emission quantity, species, altitude, and latitude, future ATS simulations require a geo-spatial model suite of global air traffic to produce relevant, quantitative scenarios extending to 2050. [46,47]

Summary:

In conclusion, this review of six distinct frameworks highlights the varied approaches to air transport system modeling, particularly in the scope of fleet development, aircraft assignment, and the evaluation of aviation technology for emissions reduction, as well as the consideration of environmental impact assessment. While each framework provides valuable insights, certain gaps remain, particularly in capturing dynamic operational practices, airline decision-making, and environmental assessments beyond only CO_2 emissions consideration. Furthermore, the trade-off between accuracy and rapid evaluation lays mostly in network scope as well as network resolution, depth and flexibility(dynamically) of modelling approaches. Based on these insights this study proposes a framework which tries to capture a dynamic low-fidelity approach of modeling air transport system with relatively short computation times.

3. IMPACT ASSESSSMENT TOOL

In general, the air transport system is comprised of four primary entities: airports, operators, aircraft, and air navigation services [4]. Most existing frameworks have focused on airlines or operators, with aircraft flying within specific route networks, generating the actual transport performance. Airport-level considerations have largely been neglected (except *DLR: Passenger and Flight Forecast Model*), while air traffic management scenarios have been simplified through efficiency improvements, such as shortening flight route distance. Forecasting of the air transport system has mainly been addressed by calculating the capacity gap caused by aircraft retirements and network growth in the following year. The main differences between existing approaches lie in the scope of the network and the modeling of aircraft assignment and retirement processes.

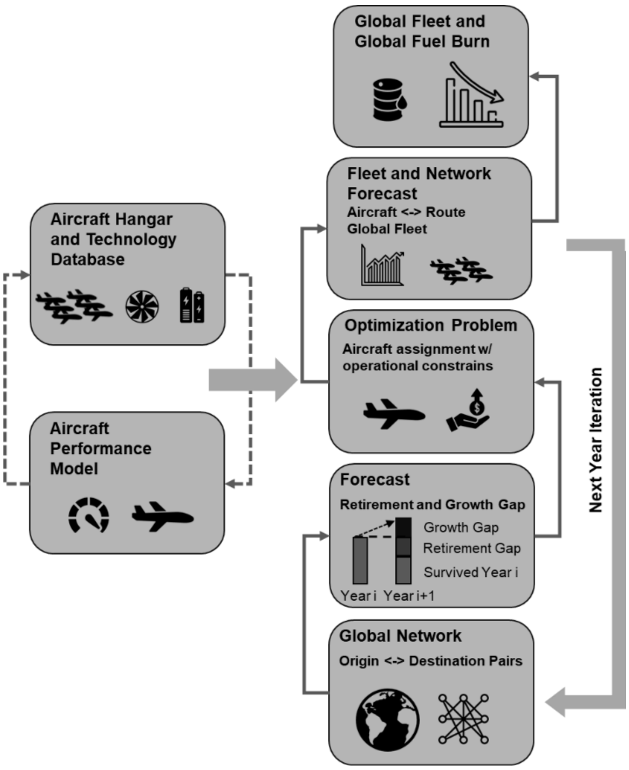

FIG 1: Proposed workflow for aircraft technology impact assessment

These findings have shaped the development of the framework presented here, which incorporates all major entities to model and forecast the effect of aircraft technology on the air transport system (Fig. 1). The tool adopts a bottom-up approach, using airport pairs as the foundation. This allows for more accurate reflection of route length variety, geographic dependencies, and airport-level constraints such as runway length, while also accounting for varying regional demand evolutions scenarios. Future capacity gaps are predicted by applying region-specific compound annual growth rates per route, capturing different socio-economic developments across the globe. Additionally, capacity gaps resulting from aircraft retirement are modeled using a statistical retirement approach. Aircraft technology injection is modeled as an optimization problem, simulating a monolithic global airline that allocates new aircraft to minimize global fleet-wide operating costs. This chapter breaks down the tool into four main sections, namely *Aircraft and Technology Modelling*, *Global Aviation System Model* and *Aircraft Retirement* and *Aircraft Allocation Modelling*. Following we will dive deeper into the different tool-components and explain their interconnections.

3.1. Aircraft and Technology Modelling

This chapter introduce the representation of the global fleet with a reduced number of representative aircraft. Based on a user-defined selection, the global fleet can be clustered into n-different aircraft types (n_{max} = 125), reducing the scope and complexity of the global fleet. The proposed aircraft types, will then be modeled in terms of aircraft performance, generations as well as other characteristics such as, EIS market segment, or utilization characteristics.

3.1.1. Reference Aircraft

As mentioned earlier, a user-defined clustering approach was employed to select representative aircraft types for modeling the global commercial fleet (above 19 seats). Specifically, a k-means clustering method was used, grouping aircraft based on key operational parameters such as payload, range, and seat capacity. Each aircraft's payload-range capability was defined by key data points: maximum payload at zero range, maximum payload at maximum range, maximum fuel at maximum range, and ferry range, provided from public available sources [17–20]. This objective is to reduces the complexity of the global fleet by creating a manageable set of representative aircraft, while still preserving their essential performance characteristics.

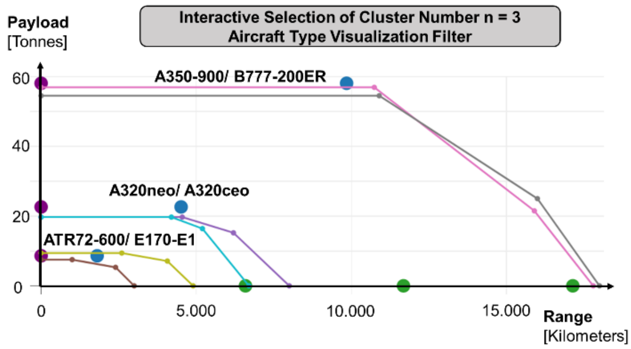

FIG 2: Global fleet clustering tool with representative aircraft (n=3)

As a first step of the global fleet clustering, the user determines the number of representative aircraft, and the tool calculates the centroids for each cluster, identifying the optimal aircraft to represent the group [21, 22]. In this study, a number of three representative aircraft types was selected to model the global fleet. The tool identified the ATR72-600/E170-E1, A320ceo/A320neo, and B777-200ER/A350-900 as the best fit to represent the regional, narrow-body, and wide-body categories, respectively to operational capabilities and seating capacity (Fig. 2). In the following sections, these aircraft will be used to represent the global fleet in the global ATS. Therefore, an identifier list is then created to map these selected representative types to real-world aircraft in the global fleet and network. This user-centric and flexible approach ensures precise and efficient modeling of the global fleet without requiring extensive user expertise. Additionally, it allows for quick adjustments to higher-resolution aircraft fleet representations when needed.

3.1.2. Aircraft Performance

Based on the selection of reference aircraft, performance values and other factors necessary for modeling and integrating the representative aircraft into the ATS are generated. This process includes modeling direct operating costs (DOC), flight time, and fuel burn across the operational range of each representative aircraft. To accomplish this, the in-house tools OpenAD and AMC were employed. These tools use digitized versions of aircraft as inputs. The aircraft modeled include the ATR72-600 (regional), A320neo (narrow-body), and A350-900 (wide-body), which are represented by similar digitized models in terms of performance, operational capabilities, and geometry, as shown in Fig. 3.

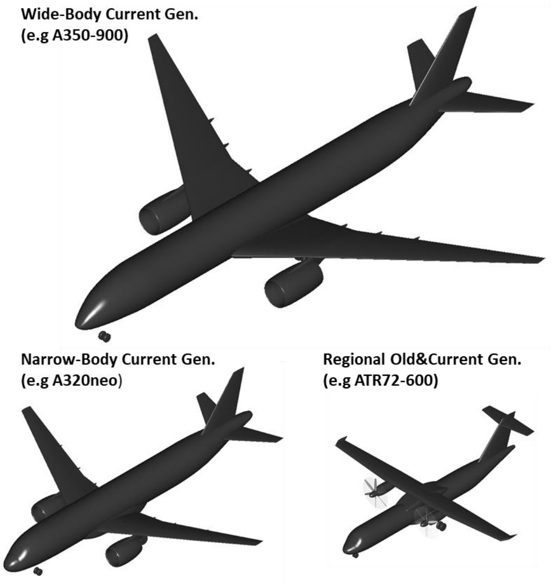

FIG 3: Digital baseline aircraft for representative global fleet

Specifically, OpenAD was used to calculate the direct operating costs per block hour (DOC/bh) of the selected aircraft based on key parameters such as payload, passenger numbers, and flight distance. OpenAD, originally developed as a preliminary aircraft design tool, utilizes well-established and publicly available handbook methods to provide consistent and reliable evaluations of aircraft performance. While its design space covers a wide range of aircraft sizes—from small 19-passenger aircraft, like the Dornier Do 228, to large 800-passenger aircraft, such as the Airbus A380—our focus was not on designing new aircraft but on analyzing the mission performance of existing, in-service aircraft. In this context, OpenAD calculates DOC by dividing costs into two main categories: route-independent costs (e.g., depreciation, insurance, and crew costs) and route-dependent costs (e.g., fuel, maintenance, and landing fees). Since aircraft typically do not operate at full capacity, we assumed an average seat load factor of 85%, which is in line with the current industry average of 83% and expected to increase in the coming years. We also accounted belly freight in the total payload mass ranging from 5-15% based on the max. payload. [23, 24]

The Aircraft Mission Calculator (AMC) models flight time and mission fuel consumption by generating 2D flight trajectories based on propulsive and aerodynamic performance inputs, as well as weight and balance data. This tool simulates all phases of flight—taxiing, take-off, climb, cruise, descent, approach, and landing—providing detailed outputs such as fuel burn, energy flow, drag/lift ratios, thrust, mass properties, and emissions. AMC optimizes the cruise altitude for each aircraft configuration and employs step-climbs during the cruise phase to improve fuel efficiency over longer distances. To calculate the mission points, the same payload assumptions as those used in the DOC calculations were applied. The outputs of the individual mission point calculation from OpenAD and AMC were incorporated into a linear interpolation model to predict flight time, fuel burn, and direct operating costs (DOC) for distances between those points. To improve the accuracy of these predictions, a non-equidistant grid was employed, offering higher resolution for shorter flight distances where the gradients of fuel burn and DOC tend to be steeper. [25, 26]

	Unit	Regional	Narrow-Body	Wide-Body
Baseline	-	ATR72-600	A320neo	A350-900
Design Range	km	1.550	5.450	14.850
Design Payload (95kg per PAX)	kg	6.650	17.100	30.900
Design Ma. No.	-	0.44	0.78	0.85
No. of PAX	-	70	189	325
Max. Payload	kg	7.500	20.000	53.900
Mission Payload (SLF=85%)	kg	6.000 - 5.600	17.500 - 14.500	45.000 - 29.000
TOFL (ISA+0 at SL, SLF=85%)	m	1 (assumption)	1.500	2.100

TAB 1: Baseline fleet performance characteristics

We also included other aircraft-specific information, such as the ICAO/IATA designator, market segment, and production windows. Additionally, utilization values specific to each aircraft or market segment were considered. These utilization parameters account for aircraft downtimes due to maintenance, ground handling, night curfew, and turnaround times, as well as the average operating hours of each aircraft type per day or year (UH). Such factors effectively reduce the total transport performance that an aircraft can provide, as it is not operational 24 hours a day (UH_{max}). From this data, aircraft productivity, which depends on flight distance or block hours, can be calculated (Eq. 1). This information is later used to determine the number of aircraft required to accommodate unfulfilled demand, which is essential for predicting future fleet sizes and delivery needs. [6, 9, 27]

$$(1)\quad f_{max,annual} = \frac{UH_{max}}{UH} * 365{,}25$$

Additionally, performance parameters such as Take-Off Field Length (TOFL) were considered for the modeling of representative aircraft, which will later be used for airport specific runway length constrains. The aircraft performance characteristics of these representative aircraft types, consisting of our baseline aircraft, have been displayed in Tab. 1. For the smallest aircraft, the regional one, we considered the TOFL to be just sufficient for operation at any airport in the network. This assumption simplifies the model by ensuring that all regional aircraft can operate at any airport in the network, to account for all operations. Additionally, we assumed that the TOFL remains constant, regardless of greater flight distance and the corresponding increase in takeoff weight (TOW). However, in reality, a higher TOW typically leads to an increased TOFL requirement. Similarly, the required landing distance depends on the actual landing weight, which varies based on factors such as payload and reserve fuel. Since landing distances are generally shorter than take-off distances, only TOFL was considered in the analysis as a restricting operational factor to conduct a flight between two airports.

3.1.3. Aircraft Generations

The global fleet consists of various aircraft generations, each exhibiting distinct performance characteristics, particularly in terms of fuel burn and direct operating costs (DOC). For this study, the fleet is categorized into four generations: old, current, novel aircraft. Tab. 2 outlines these categories for the old and current generations, with examples of our representative fleet such as the ATR72-600, A320neo, and A350-900, which serve as baseline models for generational performance evaluation. These aircraft were selected based on fleet clustering and the availability of digitalized models, providing the necessary input files for OpenAD and AMC to perform performance calculations, as aforementioned. To model older generation aircraft, percentual deterioration factors were applied to fuel burn and DOC. The primary metric for assessing technological influence on performance was mission fuel burn, with advancements in airframe and engine technologies directly affecting fuel consumption. Historical data was used to account for the fuel burn increase in older aircraft, primarily due to outdated engine, airframe, and wing technologies.

Market Segment	Old Generation	Detoriation Factor	Current Generation
Regional	***ATR72***, ERJ or CRJ	-	***ATR72***, ERJ or CRJ
Narrow-Body	B737NG, MD80 or A320ceo	+15%	***A320neo***, B737 MAX, A220
Wide-Body	B777, A330 or B747	+15%	***A350***, A330neo or B787

TAB 2: Fuel performance assumptions for aircraft generation modeling [28–30]

In the regional aircraft market segment, we did not differentiate between old and new generations since most models entered service in the 1980s. Exceptions, such as the newer Embraer E-Jets (EMB-E2), were classified as narrow-body aircraft due to their higher seat capacity and, as such, were performance-wise represented within the narrow-body market segment [31]. It should be noted that we use these generic aircraft to model a variety of different aircraft types, each with different entry-into-service times and varying technology levels within a generation. Therefore, these generic aircraft must accurately represent the performance of different aircraft types within their respective generation (old, current, or novel) and category (e.g., regional, narrow-body, or wide-body). However, our selection is constrained by the availability of data, requiring us to prioritize aircraft with the highest market share within each category and generation, while also considering the availability of digitized aircraft models. This approach leads to greater uncertainty in the performance predictions for older aircraft generations, which can be better assessed and refined in future iterations of the model.

To model novel aircraft generations, we are considering potential engine retrofits and advanced technological improvements—including airframe, propulsion, aerodynamics, and systems—for the N+1 and N+2 generation aircraft. The approach developed by Weber et al. [32] provides the foundation for modeling these novel aircraft generations, utilizing a systematic framework to assess the environmental impact of advanced technologies [32]. This methodology begins with the development of a comprehensive database of aircraft technologies, informed by literature studies and expert insights. The coupling of aircraft design and mission assessment tools, such as OpenAD and AMC, is then employed to evaluate the performance and environmental impacts of these technologies on baseline aircraft across various market segments and operational ranges. These baseline models include aircraft similar to the ATR72-600 (regional), A320/321neo (narrow-body), and A350-900/1000 (wide-body), fitting well within our represented fleet covering analogic aircraft sizes. Particularly, the technology trendlines have been used to model the narrow- and wide-body market segments. As part of this, technology packages are derived for conceptual aircraft, considering entry into service (EIS), compatibility, and the level of technology integration. Based on this, specific technology factors are employed for each package during the design phase. These factors influence various parameters such as propulsive efficiency, operating empty weight, and lift-over-drag ratio, considering both improvements and potential deteriorations due to the integration of disruptive technologies. In the prescribed study by Weber et al. [32], two distinct scenario build-ups—namely conservative and progressive scenarios—were assessed for narrow- and wide-body concept aircraft. These scenarios differ in technology integration and EIS timelines. One key outcome is the potential reduction in mission fuel burn due to the integration of disruptive technologies, which we will use as our key metric to model new technological improvements. It should be noted that this study also assesses the potential for non-CO_2 emission reductions of novel aircraft technologies [32]. Currently, this capability is not implemented in our proposed tool, but already includes all the essential features needed for future non-CO_2 emission assessments. Tab. 3 presents the conservative scenario build, highlighting the key assumptions and levels of technology integration for the narrow- and wide-body aircraft concepts. This scenario reflects a more cautious approach to adopting advanced technologies, characterized by slower technological progress and later EIS dates. For the N+1 generation, improvements are limited to enhanced engine technologies. In contrast, the N+2 generation incorporates disruptive innovations, including ultra-high-bypass ratio (UHBR) engines, geared turbofans, hybrid laminar flow, high aspect ratio wings, and advanced carbon fiber reinforced polymer (CFRP) structures. A linear interpolation approach was used to predict future mission fuel burn reduction for varying EIS dates, based on the technology trendlines. These values refer to potential mission fuel burn reduction in regards to the current aircraft generation.

Market Segment	Current Generation	N+1 Reduction Factor	N+2 Reduction Factor
Regional	***ATR72***, ERJ or CRJ	-50% EIS: **2035**	-100% EIS: **2050**
Narrow-Body	***A320neo***, B737 MAX or A220	-4,1% EIS: **2035**	-17,6% EIS: **2050**
Wide-Body	***A350***, A330neo or B787	-4,3% EIS: **2035**	-17,2% EIS: **2050**

TAB 3: Conservative scenario build-up based on technology trendlines from [32]

In Tab. 4 the progressive scenario assumptions has been displayed with earlier entry into service dates as well as technological improvements, based for the technology trendlines. In this scenario, the N+1 generation incorporates the same disruptive technologies as the N+2 generation from the conservative scenario: UHBR engines, geared turbofans, hybrid laminar flow, high aspect ratio wings, and advanced CFRP structures. The N+2 generation in the progressive scenario introduces additional advancements, such as an advanced engine concept, aero-elastically optimized wings, further developments in polymer structures, lightweight cabin interiors, and wireless flight control systems. For both scenarios, we made specific assumptions for the regional market segment

Market Segment	Current Generation	N+1 Reduction Factor	N+2 Reduction Factor
Regional	***ATR72***, ERJ or CRJ	-50% EIS: **2030**	-100% EIS: **2045**
Narrow-Body	***A320neo***, B737 MAX or A220	-12,5% EIS: **2030**	-20,3% EIS: **2045**
Wide-Body	***A350***, A330neo or B787	-12,6% EIS: **2030**	-22,6% EIS: **2045**

TAB 4: Progressive scenario build-up based on technology trendlines from [32]

We assumed that advanced technologies, such as hybrid-electric propulsion systems, could be implemented more rapidly in smaller aircraft, given their lower power requirements. In general, the development of hybrid-electric propulsion systems is progressing faster for smaller aircraft, as these platforms are expected to serve as testbeds before scaling up to the mid-range market segment. By 2045, we anticipate that the regional market segment will be capable of operating fully electric vehicle without compromising operational range or seating capacity, leading to a 100% reduction in the use of conventional propellants. Another important factor in modeling aircraft generations is the trend of increasing seat capacity per aircraft. Over the past decades, manufacturers like Boeing and Airbus have increased seat capacity to meet growing passenger demand, improving airline profitability without adding additional flight frequencies. Tab. 5 illustrates this historic growth, with next-generation aircraft expected to continue this trend, increasing seat capacity by 7-8%. In our model, users can adjust seat capacity for successor aircraft generations, with a baseline assumption of an 8% increase in capacity for regional, narrow-body, and wide-body aircraft. [33, 34]

Airframe OEM	Predecessor	Successor	Seat Capacity Predecessor	Seat Capacity Successor	Dev.
Boeing	B737-800NG	B737 MAX 8	189 (1-class)	210 (1-class)	+11%
Airbus	A320ceo	A320neo	180 (1-class)	189 (1-class)	+5%
Boeing	B777-300ER	B777-9	396 (2-class)	426 (2-class)	+7%
Airbus	A340-300	A350-900	300 (2-class)	325 (2-class)	+8%

TAB 5: Historic seat capacity evolution from predecessor to successor generation [18, 35]

3.2. Global Aviation System Model

This chapter will delve into the dynamic aspects of our framework, starting with the initial network build-up and the handling of the network within the simulation loop. The network is designed to represent global transport performance by capturing all flight connections through airport origin-destination pairs. Each pair includes key parameters such as distance, operated aircraft type and demand, measured in Revenue Passenger Kilometers (RPK) and Available Seat Kilometers (ASK), which are essential for evaluating the network's capacity and performance.

3.2.1. Initial Fleet and initial Network

The initial network and fleet reconstruction are based on pre-processed historic 2020 data, serving as the foundation for forecasting future operations. This dynamically handled process begins by loading the pre-processed historic network, which includes flight connections represented by origin-destination pairs. An identifier list is then used to replace the historic operated aircraft with their respective representative models, selected through the fleet clustering approach. This replacement is applied to each flight connection. Following this, identical combinations of origin-destination pairs and aircraft types are clustered together. Specifically, the clustering process aggregates RPK and ASK values to simplify the network and reduce complexity, ultimately resulting in a global network representation by the new representative fleet. Due to differences in seating capacities and performance characteristics between the original and representative aircraft, such as seat capacity and cruise speed, flight cycles are recalculated to accurately meet the annual demand (Eq. 2).

(2) $$flights_{req} = \frac{RPK}{passenger_{per\,flight} * distance} = \frac{RPK}{seat\ capacity * seat\ load\ factor * distance}$$

To bridge the gap between network operations and fleet, a utilization model was applied to predict the global initial fleet size. Based on the required flights to meet the demand for each route, the utilization model was used to determine the yearly productivity for each route and aircraft type, allowing for the calculation of the number of necessary aircraft units. This process was repeated for all route combinations, resulting in the total number of aircraft units required per aircraft type (Eq. 3). This, in turn, serves as the foundation for generating the initial fleet size.

(3) $$Number\ of\ aircraft = \frac{flights_{req}}{f_{max,annual}}$$

After calculating and validating the initial global fleet size by adapting aircraft-specific utilization factors, the size and market shares within the global fleet can be accurately reflected. The key importance of the initial global fleet lies in ensuring that the correct age distributions are represented across all aircraft types, as these are critical for predicting future aircraft retirements. To achieve this, historic fleet data is used to align the age distribution of the newly generated representative fleet with that of the historic fleet. The historic age distribution is normalized for each aircraft type. By mapping the historic aircraft types to their corresponding representative models, the normalized age distribution of the historic fleet is applied to construct the age distribution for the representative fleet. This approach ensures that the age characteristics of the new representative fleet closely mirror those of the historic fleet, maintaining consistency across all aircraft types, which is essential for accurate future aircraft retirement predictions.

3.2.2. Future Operations and Fleet Forecasting

As previously mentioned, the initial fleet and network serve as the foundation for forecasting future operations. To achieve this, the ICAO macro approach for long-term fleet planning has been applied [6, 36]. This method specifically addresses capacity gaps resulting from passenger growth and aircraft retirements. Furthermore, the approach has been adapted to account for seat load factor deterioration and improvements in ATM through more direct routing. As a first step, we calculated the growth gap, which represents the increase in capacity required to meet rising passenger demand for the following year. This was achieved by utilizing region-specific CAGR per route, in conjunction with the passenger demand metric RPK, to forecast regionally dependent passenger growth (Fig. 4). The growth rates were derived from Airbus's Global Market Forecast 2023 (GMF2023), which encompasses 22 distinct world regions [37]. These projections consider regional socio-economic factors, including Gross Domestic Product (GDP) and population growth. This approach enables us to forecast future flight demand not only at the global average level but also at more granular levels, such as specific world regions, countries, or airport pairs. To apply the appropriate growth factors, the origin and destination airports were used to identify the corresponding world regions.

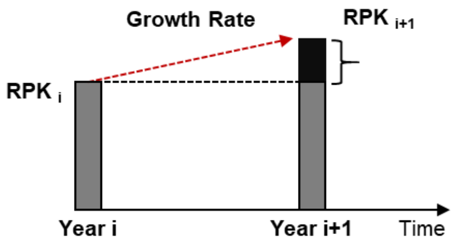

FIG 4: Forecasting of RPK for next year adapted from [6, 36]

The second component of the capacity gap is the retirement gap, which arises from aircraft being phased out of the global fleet. Once retired, these aircraft can no longer contribute to transport performance within the ATS. In the following *Aircraft Retirement Modelling* section, we describe the general approach to modeling aircraft retirement and the connection between the phase-out of individual aircraft and the corresponding reduction in operational capacity within the network. After calculating both the retirement and growth gaps, collectively referred to as the capacity gap, we apply our *Aircraft Allocation Model*. This model assigns and allocates suitable aircraft to the route network, aiming to minimize fleet-wide operational costs

3.3. Aircraft Retirement Modelling

The aircraft retirement model is crucial for predicting how many and which aircraft will be retired during the simulation. The phasing out of aircraft leads to a corresponding retirement gap, as these aircraft exit the air transport system, impacting both operations and fleet size. To model this effect, a connection between aircraft retirement and capacity reduction within the network must be established. We approached this problem by first determining how aircraft leave the fleet using a statistical, age-related retirement model. The model employs survival curves forecast, which are based on the International Civil Aviation Organization Committee on Aviation Environmental Protection (ICAO CAEP/12) approach [12, 13, 37]. Aircraft retirement is modeled through modified S-curves derived from historical retirement data, which provide survival rates as a function of aircraft age (Fig. 5). These survival rates represent the ratio of active aircraft to the number of aircraft built in the same year, offering insight into aircraft survivability within the fleet (Eq. 4).

(4) $$Survival\ Rate\ (age) = \frac{No.\ of\ active\ Aircraft\ (age)}{No.\ of\ build\ Aircraft\ (age)}$$

Aircraft are categorized into turboprop, regional jet, narrow-body jet, and wide-body jet, each represented by differently shaped S-curves with varying half-lives. This demonstrates that the economic lifespan of an aircraft is not solely determined by its structural age limitations but also by several additional factors, including airline business models, fleet planning, geographical operations, and economic conditions. These factors may lead to an earlier retirement and subsequent scrapping of aircraft. The reliance on historical data limits statistical approaches, particularly as future trends are influenced by unpredictable events such as economic crises, global pandemics, and changes in airline operations. For instance, the COVID-19 pandemic accelerated the retirement of older aircraft due to prolonged low demand [38]. Furthermore, production capacity shortages—such as those related to the ongoing Boeing crisis and Airbus's supply chain constraints—have affected retirement patterns, with airlines like Lufthansa continuing to operate older aircraft models to meet post-pandemic strong demand surge [39, 40]. Therefore, using historical survival curves for forecasting may be affected by future economic developments and policy decisions, which could alter the long-term retirement patterns considered in our study, as these patterns are based on historical data.

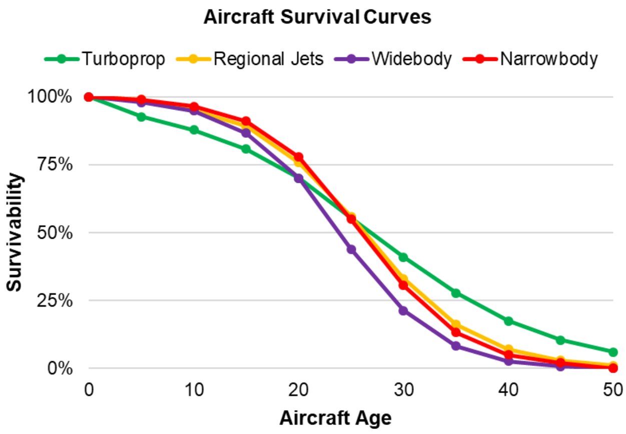

FIG 5: Statistical survival curves adapted from [37]

In our current implementation, we apply static optimistic-adjusted survival curves that represent the economic retirement of aircraft over the past 50 years, based on DLR's retirement forecast model (Fig. 5). For each aircraft-age combination in a given year-iteration, we determine its position on the survival curve by modeling the logistic function through aircraft category-specific sigmoid functions (Fig. 5). This provides the survival probability for each aircraft, which is then inverted to the retirement probability. The retirement probability reflects the statistical fraction of aircraft units that are likely to leave the system. In reality, entire aircraft units leave the fleet not fractions, in turn this statistical fraction offers an indication of the capacity loss associated with aircraft age on a fleet-wide level. Based on this, we estimate the number of aircraft per age that will leave the fleet annually by summing the retirement rate fractions for each aircraft unit within the fleet for specific aircraft type and age. After determining the number of retired aircraft, we calculated the resulting unfulfilled capacity in operations. Assuming a global network operated by a single, monolithic airline, the aircraft within the fleet are scheduled across various routes. The retirement of an aircraft on specific routes creates a capacity gap, which must be addressed by replacement aircraft. In this model, we assume that the retirement of aircraft leads to a uniform reduction in capacity across all routes served by that aircraft type, effectively assuming a uniform capacity reduction across the entire route network.

3.4. Aircaft Allocation Modelling

The core of the aircraft assignment and allocation process is formulated as a linear mixed-integer programming (MIP) optimization problem. Based on the previously calculated retirement and growth gaps, the optimizer is used to determine the appropriate aircraft types for each route and calculate the number of aircraft required to meet demand. The primary objective of the optimizer in selecting an aircraft is to minimize fleet-wide operational costs. [6, 9]

Two distinct assignment strategies were considered. Firstly, the assignment of aircraft to routes is described based solely on constraints, including runway length limitations, operational range capabilities, aircraft availability (in production), and coverage constraints per route. The optimizer then calculates which aircraft will be operated on which routes, and thus the number of aircraft that must be allocated. The underlying philosophy is to determine the optimal fleet size required to accommodate future demand and anticipated retirements, without enforcing any production limitations. In the second approach, additional constraints on the production of aircraft are introduced, limiting the number of aircraft per type that can be produced each year. This limitation may result in a redistribution of aircraft utilization due to production constraints on the more optimal aircraft. Furthermore, the extent to which demand can be met is calculated based on the specific number of aircraft produced within a given timeframe. Consequently, this may lead to a reduction in the actual number of transported passengers due to a lack of offered capacity (aircraft), which is a consequence of the current rate of aircraft production. Currently, feedback regarding the impact of reduced demand when aircraft production is low is not integrated. As a result, the current assessment is limited to the redistribution of aircraft types operated within the network. For this study, we will focus solely on the production-unconstrained aircraft allocation. Therefore, the following section will present the optimization process for unconstrained aircraft allocation.

Production-Unconstrained Optimization Problem

The primary objective of this optimization problem is to minimize the total direct operating cost by assigning the optimal aircraft types, while satisfying operational and aircraft availability constraints (Eq. 5). The total DOC is a function of our decision variable (Eq. 6), which is the percentage fraction of ASK acquired by each aircraft type per route. To calculate the total DOC, we take the fraction of ASK covered by each aircraft type and use the aforementioned models to determine the required number of flights for the assumed ASK. Based on this, we calculate the total flight hours needed. The total DOC per block hour is then used to compute the total annual DOC for specific aircraft type, considering its ASK coverage and distance. The mathematical formulation of our objective function incorporates an additional parameter that mimics a price value. Typically, airlines aim to maximize overall profit by assigning aircraft types to their route network. While other factors also play a role in profit maximization, we attempt to account for this by introducing an additional parameter α that captures the effect of preferred high-capacity aircraft utilization, which can carry more passengers per flight and potentially increase profits. This, in turn, can lower costs, as it counteracts the total direct operating costs function. In our case this additional factor is designed to favor larger aircraft, as they can reduce costs more significantly, by carrying more passengers. By tuning the α parameter we can influence and control the assignment of bigger aircraft. However, for the current optimization, we have set this parameter to zero, so it does not affect the optimization process. We implemented coverage constrain, range limitation constraints and the availability of aircraft to complete our assignment model (Eq. 7-10).

Objective function:

(5) $Minimize \sum_{i \in I} \sum_{ft \in F} totalDOC_{i,ft(x_i,ft,\,t)} - \alpha * \sum_{i \in I} \sum_{ft \in F} (x_{i,ft,t} * MaxPax_{ft})$

Decision variable:

(6) $x_{i,ft,t}$

Coverage constraint:

(7) $\sum_{ft \in F} x_{i,ft,t} = 1, \forall i \in I$

Range limitation constraint:

(8) $\sum_{ft \in F} x_{i,ft,t} = 0,$ *if* $MaxRange_{ft} < Distance_i, \forall i \in I, \forall ft \in F$

Runway length constraint:

(9) $\sum_{ft \in F} x_{i,ft,t} = 0,$ *if* $TOLF_{ft} > min(max(RunwayLenght))_i, \forall i \in I, \forall ft \in F$

Aircraft availability constraint:

(10) $\sum_{ft \in F} x_{i,ft,t} = 0, \ \forall i \in I, \forall ft \in F, \forall t \in T: t < EIS_{ft} \text{ or } t > EOS_{ft}$

Parameters:

- I*: Set of routes*
- F*: Set of aircraft types*
- T*: Set of simulation years*
- $Distance_i$*: Flight distance on route* i
- $MaxRange_{ft}$*: Maximum range of aircraft type* ft
- $RunwayLenght_i$*: Runway length on route* i
- ASK_i*: Available seat kilometers on route* i
- EIS_{ft}*: Entry into service for aircraft type* ft
- EOS_{ft}*: End of service for aircraft type* ft

The coverage constraints ensure that the total demand (ASK) on each route is fully covered by the assigned aircraft. Additionally, this constraint ensures that no more capacity is transported than necessary (Eq. 7). The range limitation constraint ensures that aircraft can only be assigned to routes if they have the necessary range capabilities (Eq. 8). If an aircraft's maximum range is less than the route distance, it cannot be assigned to that route, and the decision variable is set to zero, meaning no ASK can be covered by this aircraft on that route. Another critical operational constraint is the runway length constraint. Similar to the range limitation, we set the covered fraction of aircraft types to zero if the runway length is smaller than the TOFL of the aircraft type (Eq. 9). We assume that the TOFL is a crucial factor because, during takeoff, aircraft operate at their maximum weight during that mission phase, making the takeoff process more demanding. To determine the limiting runway length for the route, we retrieve the maximum available runway length at both origin and destination airports and use the shorter one as the constraint. The aircraft availability constraint ensures that only aircraft currently in production are considered and assigned to our network (Eq. 10). This constraint guarantees that the optimization process only includes feasible and currently available aircraft options. By incorporating these constraints, the optimizer ensures that all routes are adequately covered by appropriate aircraft types. The optimizer iteratively searches the solution space, adjusting the fraction of ASK covered by each aircraft type on each route $x_{i,ft,t}$, to find the optimal solution that minimizes total fleet-wide operating costs while satisfying all constraints.

The optimization problems were implemented using the ‘PuLP’ library in Python. We defined the optimization problem, introduced decision variables, set up various constraints (including the new production constraints), formulated the objective function, and used the ‘PULP_CBC_CMD’ solver to find the optimal solution. The ‘CBC_CMD’ stands for "coin-or branch and cut". The problem is first branched into subproblems and then cut to only include feasible solutions which hold the optimal solution. This was setup using a linear programming model, which is commonly used for aircraft assignment and allocation problems due to its ability to efficiently handle large and complex problems while guaranteeing the optimal solution. We used a standard laptop equipped with an Intel i7 10th generation processor with 6 physical cores, providing up to 2.7 GHz per core, and 32 GB of RAM. The optimization problem is solved within 2 to 10 seconds, depending on the selected optimization scenario and the varying constraints, whereas the whole process, including data loading and output generation, takes around 1 to 1.5 minutes

4. RESULTS

Before presenting the results of the aircraft technology assessment simulations, we will briefly describe and summarize all the required inputs. Specifically, the tool requires the simulation time horizon, growth rate scenario, seat load factor scenario, and the specifications of novel aircraft generations, including general aircraft performance as well as production windows. The input data is summarized in Tab. 6. In particular, we will conduct three different studies, primarily varying in terms of aircraft performance, specifically focusing on the inclusion of novel generation aircraft. To establish a solid baseline, the "Technology Freeze" scenario will illustrate the development of the global ATS if only 2020 generation aircraft, such as the B737 MAX/B787 or A320neo/A350, remain available. This scenario reflects the impact on the ATS assuming no further advancements in aircraft technology beyond 2020 levels. It serves as a benchmark for evaluating the effects of introducing disruptive aircraft technologies into the global ATS, which is explored through the following scenarios. The conservative and progressive scenarios have been thoroughly described in the *Aircraft Generations* section, featuring different EIS dates as well as technological improvements reflected in mission fuel burn reduction, adapted from Weber et al. [32] (Tab. 3 and Tab. 4). Other input parameters, such as the time horizon, growth rate scenario, fleet split, and seat load factor, remain consistent across all studies to adequately compare the results and focus solely on the effects of new aircraft technologies and EIS timing on the global ATS.

Input Matrix	Technology Freeze	Conservative Scenario	Progressive Scenario
Simulation Identification	TF-Base	CON-SC	PROG-SC
Time Horizon	2020-2070	2020-2070	2020-2070
Growth Rate Scenario	Airbus GMF-CAGRs (2023)	Airbus GMF-CAGRs (2023)	Airbus GMF-CAGRs (2023)
Seat Load Factor	2020-2023 (Historic) 83% (2024) to 90% (2070)	2020-2023 (Historic) 83% (2024) to 90% (2070)	2020/2023 (Historic) 83% (2024) to 90% (2070)
Fleet Split	Regional, Narrow- & Wide-Body	Regional, Narrow- & Wide-Body	Regional, Narrow- & Wide-Body
Novel Aircraft Generations	None Only 2020 Generation Fleet	N+1 (EIS: 2035) N+2 (EIS: 2050) Perf. (cf. Tab. 3)	N+1 (EIS: 2030) N+2 (EIS: 2045) Perf. (cf. Tab. 3)

TAB 6: Input matrix for conducted studies

The assessment of novel aircraft technologies on a global scale has been structured into three primary domains: Traffic, Emission, and Fleet Forecast. The introduction of future aircraft into the fleet is primarily governed by capacity gaps, which are dependent on retirements and projected growth in demand. A critical preliminary step in this process is the quantification of future demand, as this serves as one of the principal drivers for aircraft injection. Future demand has been projected using CAGR from the Airbus GMF 2024 report, extrapolated from 2043 through 2070. By 2042, global demand is expected to reach 20 trillion RPK, corresponding to a global CAGR of approximately 3.6% (see Fig. 6), which is line with Airbus and Boeing estimates [41, 42]. The years 2020-2024 were significantly affected by the COVID-19 pandemic, necessitating the use of historical seat load factor values and growth rates for this period. It is assumed that pre-pandemic traffic levels will be restored by the end of 2024, with demand reaching approximately 9 trillion RPK. From 2025 onwards, the CAGRs provided by Airbus have been applied to model future growth per route based on the geographical location of origin and destination airport. Figure 6 presents the global aggregated values for RPK, ASK, and the number of flights, obtained by summing these metrics across all routes.

It is important to note that this represents a highly progressive demand scenario, which may not be very likely. Given the scarcity of studies providing long-term forecasts until 2070, we employed a simple extrapolation approach to evaluate the impact of aircraft technologies with an EIS starting around 2045/2050. Currently, the German Aerospace Center (DLR) is conducting a high-level study to address this gap, utilizing high-fidelity tools for passenger and flight forecasting, as well as considering the performance of both current and future aircraft (concepts) within the project ‘Development Pathways for Aviation up to 2070’ (DEPA 2070) [43].

As previously mentioned, the impact of COVID-19 and the subsequent recovery are evident across all metrics, with exponential growth becoming apparent from 2025 onwards, driven by the applied CAGRs from Airbus. Since the same operational scenario (including Air Traffic Management and Seat Load Factor) was used across all projections, RPKs and ASKs remain consistent across scenarios. However, the number of annual flights differs depending on the scenario. It is evident that the number of flights differ significantly between the ‘Technology Freeze’ scenario and the progressive scenario. This stems from the aircraft seating capacities increase assumptions for N+1 & N+2 generation, which are not included in the 'Technology

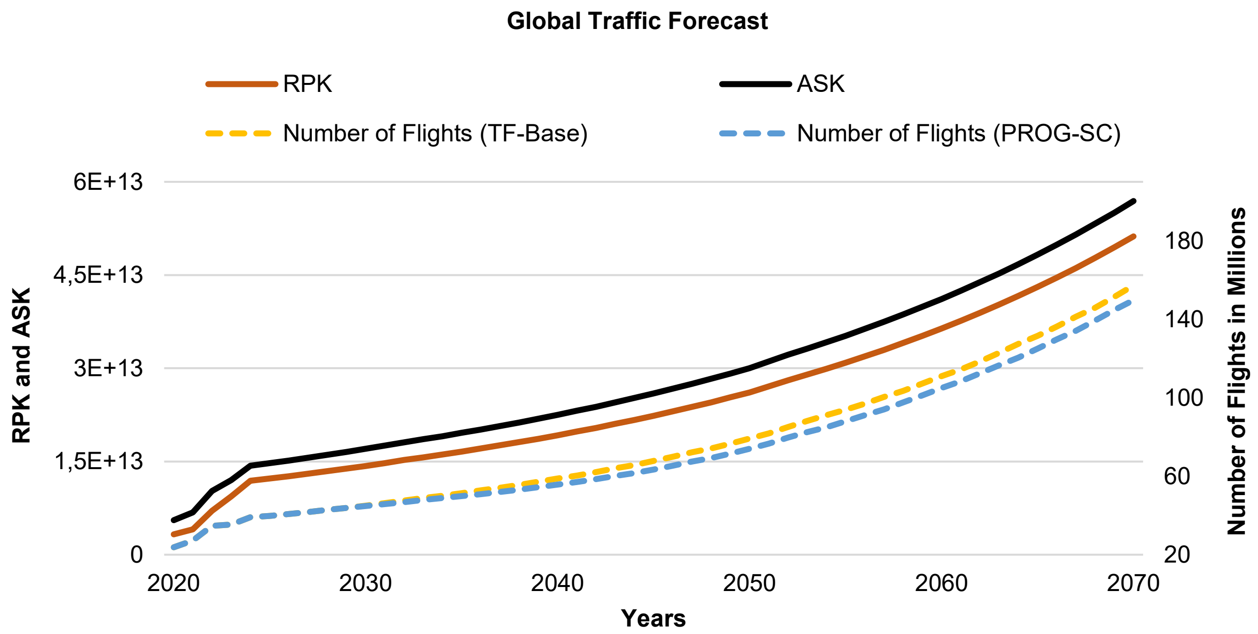

FIG 6: Global traffic forecast, including ASK, RPK and Flights

Freeze' scenario, where only current and older-generation aircraft are considered. As the simulation progresses, current-generation aircraft gradually replace older aircraft in the fleet. Across all generations, we assumed changes in seating capacity, specifically an increase of 6% from older to current-generation aircraft and further to N+1 & N+2 aircraft, resulting in more seats per flight. Since the baseline 'Technology Freeze' scenario does not incorporate N+1 & N+2 aircraft, the number of flights increases throughout the simulation due to the lower average seating capacity of the global fleet. Consequently, the other scenarios that include N+1 & N+2 aircraft require fewer flights to meet the projected future demand. This change becomes evident from 2030 onwards, with the EIS of N+1 generation aircraft. Between 2020 and 2030, no significant changes in the number of flights are observed, as only current-generation aircraft are available in all scenarios. Throughout the simulation, novel aircraft generations gradually take a larger share of the fleet starting from 2030/2035, further reducing the required number of flights compared to the 'Technology Freeze' scenario. Once a specific saturation point is reached—where N+1 & N+2 aircraft make up 100% of the fleet—the average seating capacity stabilizes, and the number of flights is offset by a constant factor. The increase in aircraft seating capacity can lead to a reduction in the number of flights, which in turn directly impacts annual fuel consumption and, consequently, CO_2 emissions.

A less obvious factor is the influence of the EIS timing. The impact of higher seating capacity aircraft is diminished with a later EIS, as these aircraft will represent a smaller share of the global fleet in the early years, resulting in a more limited effect on the average seating capacity. Over time, this effect will lower as these aircraft gradually make up a larger portion of the fleet, eventually converging when they account for nearly 100% of the global fleet. Since the difference between the progressive and conservative scenarios is relatively minor, we have opted not to visualize this effect.

Figure 7 illustrates the global fleet composition for both scenarios, emphasizing the impact of the previously described EIS timing on the generational evolution of the fleet up to 2070. Specifically, the translucent areas with red dashed frames illustrate the global fleet composition and generational breakdown for the conservative scenario, which assumes a five-year delay in the EIS and more modest performance improvements compared to the progressive scenario. By 2042, the model predicts a total fleet of approximately 45,000 aircraft, with market shares of 72% narrow-body, 24% wide-body, and 4% regional aircraft, closely aligning with forecasts from Airbus and Boeing [41, 42]. Furthermore, we observe an exponential increase in the aircraft fleet, driven by rapidly growing demand, ultimately reaching a significant total of approximately 109,000 aircraft by 2070. Aircraft retirement becomes evident with the introduction of new aircraft generations, as the production of their predecessors ceases, and the aircraft within those older generations are phased out according to their respective survival curves. A relatively rapid retirement scenario has been applied, where older-generation aircraft are phased out more quickly. This assumption is based on adjusted retirement curves reflecting an accelerated retirement of older jets, an optimistic assumption that has been consistently applied across all scenarios. The impact of COVID-19 and the subsequent recovery is also apparent in the fleet forecast, with a sharp increase in the number of active aircraft between 2020 and 2025. Both scenarios show the introduction of new aircraft generations, with the progressive scenario beginning in 2030 and the conservative scenario in 2035. Due to the later introduction of new aircraft generations in the conservative scenario, the share of these aircraft is lower in a given year compared to the progressive scenario. This is because the introduction of new aircraft is driven solely by growth rates and retirements. Currently, no mechanism has been implemented to prioritize new aircraft, which could potentially lead to the early retirement of in-service aircraft for economic or environmental reasons. A similar pattern of aircraft injection is observed for the N+2 aircraft generations.

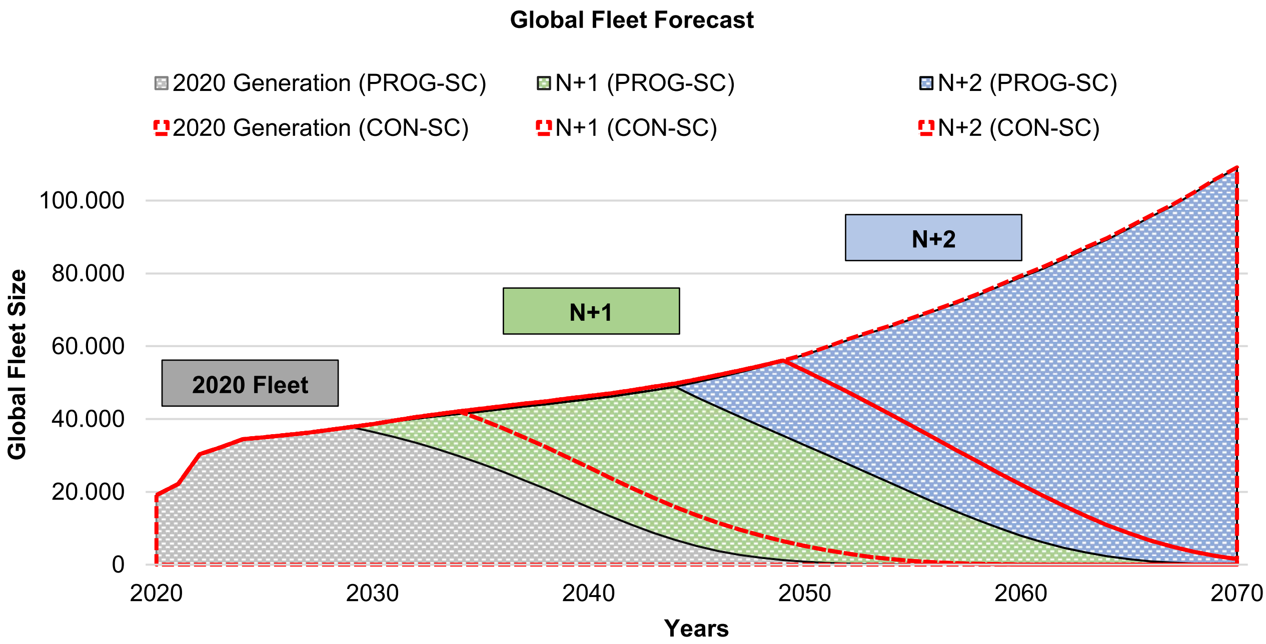

FIG 7: Global fleet forecast, showing generational development for progressive and conservative scenario

As mentioned earlier, the generational composition of the global fleet not only impacts the average seating capacity and, consequently, the number of flights required to meet demand, but also affects overall fleet performance. The introduction of new aircraft generations with advanced performance characteristics—particularly improved fuel burn—plays a significant role. Therefore, we assessed the impact of novel aircraft generations on CO_2 emissions, as these advancements directly contribute to reduced fuel burn and emissions (Fig. 8). The figure illustrates the CO_2 emission reduction potential of the progressive and conservative scenarios compared to the 'Technology Freeze' scenario. The light green area represents the emission mitigation potential of the progressive scenario, while the dark green area reflects the additional mitigation potential of the conservative scenario. The dashed lines represent the percentual mitigation potential of the active fleet of both scenarios, with color markings corresponding to each.

It is evident that the progressive scenario achieves the highest emission reductions, as it assumes greater performance improvements and an earlier introduction of new aircraft generations by five years. Conversely, the conservative scenario shows a lower mitigation potential due to delayed introduction and reduced performance gains from new aircraft generations. Since emissions are also tied to the number of flights, both scenarios benefit from increased seating capacity, which reduces the number of flights needed, further lowering CO_2 emissions compared to the emissions of the 2020 state-of-the-art fleet.

Breaking this down, from 2020 to 2030, neither scenario shows any emission mitigation, as all three scenarios (including 'Technology Freeze') utilize the same aircraft generations. However, starting in 2030, we see the first changes with the introduction of N+1 aircraft. As more of these aircraft enter the fleet, emission mitigation potential increases due to their growing share. In contrast, the conservative scenario does not show emission reductions until 2035, when N+1 aircraft are introduced five years later than in the progressive scenario. From that point onward, the emission mitigation potential increases as the share of N+1 aircraft grows, though the progressive scenario continues to outperform due to its earlier introduction and higher performance improvements.

The dynamic shifts slightly in favor of the conservative scenario with the introduction of N+2 aircraft. Although the progressive scenario introduces N+2 aircraft in 2045 and the conservative scenario follows in 2050, the differences in CO_2 mitigation by 2070 are relatively minor. This is due to two main factors: the performance improvements between the two scenarios vary by only 2-4%, and by 2070, both scenarios exhibit a high share of N+2 aircraft in the global fleet. Consequently, fleet performance improvements and emission mitigation potential are driven more by the performance characteristics of the aircraft themselves rather than the timing and fleet composition. The reason for this is the relatively optimistic retirement patterns assumed across all aircraft generations. These patterns lead to a faster introduction of new-generation aircraft, thereby reducing the overall impact of technology introduction timing.

The effect of EIS timing and generational share is most pronounced between 2045 and 2055, where the progressive scenario shows a higher share of N+2 aircraft compared to the conservative scenario, as indicated by the wider dark green area in the figure. However, even with relatively optimistic performance assumptions, a significant amount of CO_2 emissions remains unmitigated. This is especially evident under the high-demand scenario used in this study, where CO_2 emissions exhibit strong exponential growth starting from 2050 onwards. To better assess the impact on a global scale, future analyses should

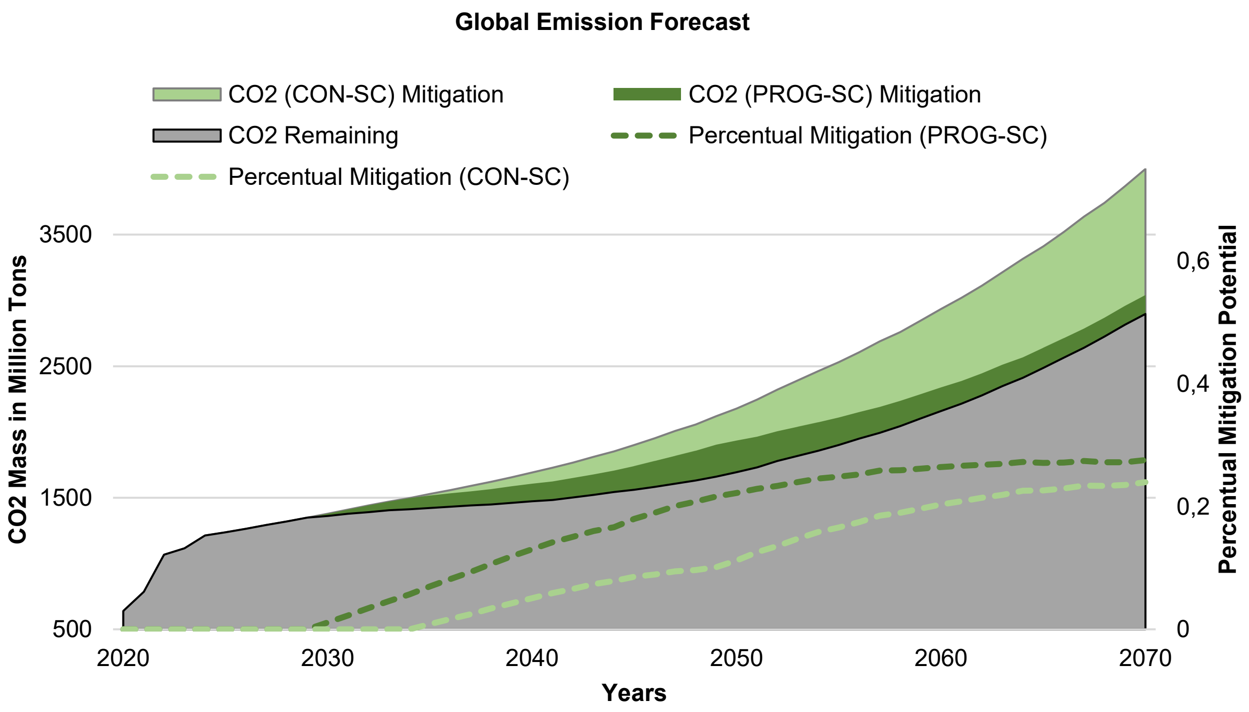

FIG 8: Global emission forecast, showing mitigation potential of progressive and conservative scenario compared to technology freeze

incorporate other technologies, such as hydrogen propulsion or sustainable aviation fuels, along with operational improvements and offsetting strategies. As only aircraft technologies are not able to significantly lower CO_2 emissions, for progressive demand predictions.

5. LIMITATIONS

Since this proposed tool relies on low-fidelity methods for modeling the global aviation system, it is crucial to recognize its limitations to ensure accurate interpretation of the results. The key limitations of the tool are summarized in the following:

- **Demand forecast**: Growth rates are sourced from literature at the regional level, but the actual forecasting of these growth rates is beyond the scope of this work.
- **Network**: The origin-destination pairs in the network are fixed based on the input file and do not change according to future demand projections or airline operations.
- **Airports**: The impact of future aircraft operations being constrained by airport-level movement capacity is not considered, which could significantly alter the results.
- **Trajectories**: Trajectories are modeled based on great circle distance with operational factors and mission-level aircraft assessments, but no detailed route planning or trajectory simulations are included.

These limitations are addressed in higher-fidelity models, which should be consulted for more than a preliminary estimation of fleet development at the aviation system level.

6. CONCLUSION

In conclusion, this paper presents a simplified tool that provides a robust baseline for forecasting future demand, flights, fleet composition, and CO_2 emissions using low-fidelity methods. Novel aircraft technologies were modeled by applying technology trend curves derived from Weber et al. [32], which directly influence mission fuel burn. In particular, the major aircraft market segments—regional, narrow-body, and wide-body—were assessed through the introduction of two different aircraft generations, each incorporating varying levels of disruptive technologies. By utilizing statistical survival (retirement) curves, the tool predicts aircraft retirements and projects future growth using compound annual growth rates (CAGRs) from Airbus GMF, extrapolated from 2043 to 2070. Aircraft injection was dynamically modeled through an optimization problem aimed at minimizing fleet-wide direct operating costs, simulating monolithic airline decision-making on a global scale.

This study demonstrates the tool's key capabilities in predicting future aircraft fleets and technology introductions through 2070, across two distinct scenarios that vary in technology introduction timing and aircraft performance improvements. The analysis highlights the critical role of aircraft retirement in fleet turnover, alongside the impact of performance improvements, in striving toward a net-zero aviation system. The study concludes that aircraft technologies alone are insufficient to achieve this goal. Reaching net-zero aviation is a multidisciplinary challenge, requiring collaboration from experts across various fields to develop pathways for sustainable aviation. Therefore, it is crucial to move beyond traditional single-mission assessments of aircraft technologies. To identify key enablers across different sectors, these technologies must be evaluated on a global scale, as changes in aircraft design could fundamentally alter the global ATS and its network structure. For instance, novel propulsion technologies like battery-electric or hydrogen powertrains are highly dependent on airport infrastructure. In the future, airlines may transition from traditional hub operations to more direct or intermediate-stop operations, potentially reshaping the global network structure, effecting the global passenger flows and therefore emissions. Accelerated demand growth could also drive this shift, as increased airport movements further tightening airport capacity constraints, making direct flights more economically viable and necessary.

Corresponding Author

Pascal Bertram
pascal.bertram@dlr.de

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