INTERNATIONAL ASSOCIATION FOR GREEN AVIATION

WXP | World Experience and Innovation Impact Journal

Theme: Leveraging Artificial Intelligence to Make Aviation Greener

Leveraging AI to Make Aviation Greener

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Article Type: Case Study

Collaboration: A cross-institutional collaboration and cross-industry collaboration

Citation: (to be generated)

Academic Editor:
Samie Ly
Cameron Welsh

Received: May 10, 2024
Accepted: November 4, 2024
Published: December 17, 2024

Publisher's Note: WXP stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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Abstract

Growing concern about aviation's environmental impact gives rise to the emergency of the concept of Green Aviation. This paper proposes a general definition of Green Aviation based on an overview of early efforts and initiatives aimed at reducing aviation's environmental impact. Crucial issues faced in achieving Green Aviation are analyzed, which are categorized into four aspects, namely design tech, sustainable fuels, management, and awareness. Based on the analysis of these key challenges, two AI solution examples for Green Aviation are provided, that are, visual landing guidance system for general aviation aircraft and 4D flight trajectory prediction for transport aircraft. These examples demonstrate the great potential of AI applications in implementing Green Aviation practices.

Keywords: Green Aviation, Environmental, Climate, Sustainable, Artificial Intelligence

1.0 Introduction

With the rapid development of globalization, the demand for air travel has also increased significantly. The tradeoff for this increased global connectivity is climate impact, which is drawing growing attention. Aviation accounts for about 2~3% of global CO2 emissions (Dobruszkes & Ibrahim, 2021; IATA, 2013; Le Quéré et al., 2018), which is a small amount. However, the emissions occur at high-altitudes, typically between 30,000 and 40,000ft, where their impact on climate is amplified. At these altitudes, emissions contribute to the greenhouse effect by trapping heat. Besides the carbon emissions, the non-CO_2 effects of aviation are also significant. For instance, nitrogen oxides emissions change ozone and methane levels in the atmosphere, leading to deterioration of local air quality (Terrenoire et al., 2022). The high-altitude nature of these emissions exacerbates their contribution to global warming. Moreover, the rapid increase in air travel also causes social disruptions, such as noise pollution (Correia et al., 2013).

Given these environmental impacts of aviation, the concept of Green Aviation (GA) has emerged, aiming to make aviation more environmentally sustainable (Zhang et al., 2024). However, the precise definition of GA and the strategies to realize this vision remain ambiguous. With the rapid development of Artificial Intelligence (AI) nowadays, its application across various domains of aviation have gained growing interest, particularly regarding its potential contributions to GA. Therefore, a comprehensive exploration of AI-based solutions for GA is urgently needed.

The objective of this paper is to provide a clear definition of green aviation and, based on an analysis of the key challenges involved in making aviation sustainable, highlight the critical role that AI can play in implementing green aviation practices. The rest of this paper is organized as follows: **Section 2.0** proposes a general definition of Green Aviation based on an overview of early efforts and initiatives aimed at reducing aviation's environmental impact. **Section 3.0** analyzes the crucial issues faced in achieving Green Aviation, which are categorized into four aspects, namely design tech, sustainable fuels, management and awareness. **Section 4.0** provides two AI solution examples for Green Aviation, namely visual landing guidance system for general aviation aircraft and 4D flight trajectory prediction for transport aircraft, both of which reflect the potential of AI applications in implementing green aviation practices. **Section 5.0** draws the conclusions.

2.0 Definition of Green Aviation

Awareness of aviation's climate impact gives rise to the emergency of the concept of GA. 'Green' refers to the environment characterized by friendly development, energy conservation, and protection to reduce negative influences (Hagmann et al., 2015; Qiu et al., 2021). The term 'green' applied to aviation is a concept that has been used interchangeably with sustainability (Baker, 2023). Some have even used it loosely to elaborate on the notion of sustainability, or net-zero greenhouse gas emissions (Zhang et al., 2024). The reduction of carbon emissions is a top concern for the aviation industry. In October 2016, the 39th ICAO (International Civil Aviation Organization) assembly established CORSIA (Carbon Offsetting and Reduction Scheme for International Aviation) (IATA, 2024). The industry further demonstrated its focus on decarbonization in 2021, when the 77th IATA (International Air Transportation Association) Annual General Meeting in Boston approved a resolution for the global air transport industry to achieve net-zero carbon emissions by 2050. In addition to carbon emissions, other environmental impacts of aviation are increasingly being recognized as critical parts of Green Aviation practices. ICAO concentrates the international aviation environmental collaboration on three core areas, namely climate change and aviation emissions, aircraft noise, and local air quality (ICAO, 2024). NASA perceives Green Aviation as an approach identified by the pursuit of enhanced aircraft efficiency via reduction of noise levels, greenhouse gas emissions, and lower carbon emissions (Proponent, 2017). GlobeAir supposes that Green Aviation refers to the practices, technologies, and policies aimed at reducing the environmental impact of aviation, including decreasing greenhouse gas emissions and noise pollution and improving fuel efficiency (GlobeAir, 2024).

The key principles of these efforts and initiatives aimed at reducing aviation's environmental impact include reducing greenhouse gas emissions and noise pollution, and improving fuel efficiency. The core of Green Aviation is sustainability, that is, the development of aviation should be no more than the presence of assimilate capacity of the ecological system while continuing to support economic growth and global connectivity. Hence, we propose a general definition of Green Aviation: it refers to the practice of making aviation activities more sustainable by implementing technologies and strategies that minimize damage to the environment and build resilience to climate challenges. It encompasses a range of initiatives, including advancements in aircraft designs, the use of sustainable aviation fuels, optimization of flight routes and operations, and efforts in policy making, etc.

3.0 Core Elements of Green Aviation

IATA initially addressed environmental targets through its "Four-pillar Strategy", namely "Design Tech", "Sustainable Fuels", "Management", and "Economic Measures" (Dhara & Muruga Lal, 2021). Here, we propose a slight modification to replace "Economic Measures" with "Awareness of Green Aviation (GA)." We believe that fostering a broader understanding of GA will create a stronger foundation for progress. Accordingly, we categorize the crucial issues in achieving green aviation into four aspects, as shown in **Figure 1**.

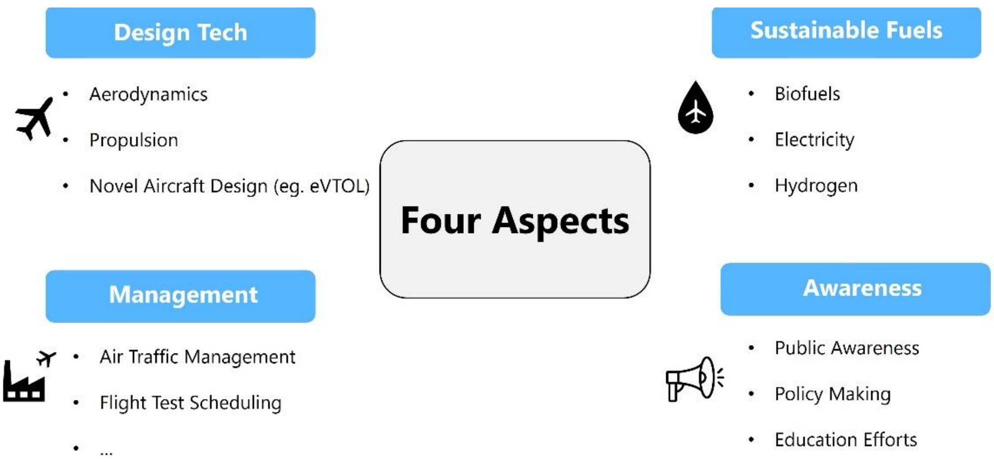

Figure 1 Four aspects of crucial issues faced in making aviation industry green

3.1 Design Tech

Design of aircrafts is the core of the aviation industry. Aerodynamics, propulsive framework are the most significant ways to improve design effectiveness in the aviation industry. Besides the traditional design, some novel configurations are tending to lead the direction of Green Aviation by reform the whole system.

3.1.1 Aerodynamics

The shape of an aircraft is intrinsically linked to its flight efficiency through its aerodynamic performance. A design that enables drag minimization or lift-to-drag maximization compared to a conventional configuration is thus sought to minimize aviation's environmental and noise footprint.

(1). Aerodynamic Structure

a. High Aspect-Ratio Wings (HARWs)

By increasing the aspect ratio of a wing (as shown in **Figure 2**), the lift-induced drag can be reduced, potentially leading to fuel savings. However, designing wings with higher aspect ratios can present structural challenges, particularly at lower airspeeds. Specifically, the dynamic interaction between airflow and the wing structure can give rise to flutter, which poses a risk to the structural integrity of the wing if the structure is designed to be as light as possible (Gao & Zhang, 2020).

Figure 2 Example of a HARW (Afonso et al., 2023)

b. Non-planar wings

With the exception of the near universal adoption of winglet designs to current aircraft configurations, other ideas for non-planar wing extensions have resulted in more complex wing tip structures, as shown in **Figure 3**. Configurations with the main and aft lifting surfaces joined at their tips have claimed benefits of reduced drag coefficients, increased structural robustness, and improved performance levels over conventional Wing–Body–Tail (WBT) designs (Garcia-Benitez et al., 2016). However, practical use of such aircraft configurations in commercial aviation applications has yet to be demonstrated.

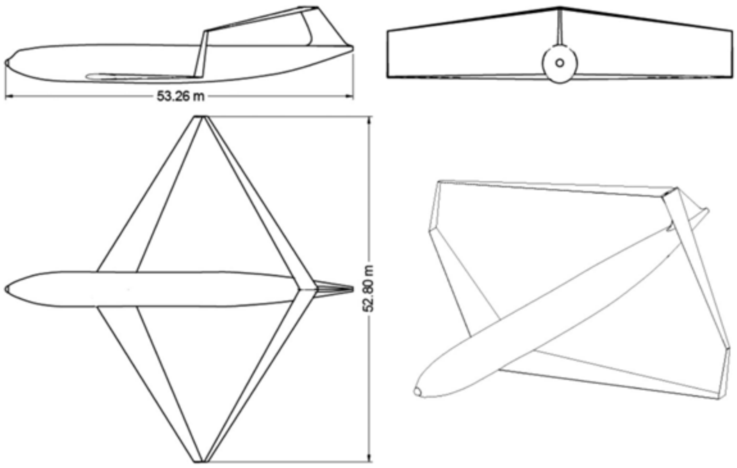

Figure 3 Example of non-planar wing (Garcia-Benitez et al., 2016)

(2). Aerodynamic shape optimization

Aerodynamic shape optimization (ASO) is an approach that is now available for aerodynamic designers to explore the design of lifting. Surfaces and other devices where lift and drag are important. Especially when coupled with computational fluid dynamics (CFD), ASO is an essential procedure in modern aircraft design and other design applications of CFD. Nevertheless, because of the iterative and costly simulation-based evaluations within optimization steps, ASO still cannot effectively satisfy some practical demands, such as fast interactive design optimization. When leading machine learning to ASO, some problems occur (Li et al., 2022):

a. Most prediction models used in ASO inherently interpolate the data and are thus generally incapable of extrapolation. This limitation leads to the need for a large volume of training data to avoid extrapolations.

b. It is expensive to obtain high-fidelity simulation data, and the interpolation feature increases the requirement for large volumes of training data.

c. Most studies in ASO with ML lack a coupling of different data sources, such as simulation and experimental data. Aerodynamic design with no support from experiments may lack practicality from an industrial view, but experimental data depends on specialized facilities and is inaccessible to most academic researchers.

3.1.2 Propulsion

The efficiency of the propulsive system has a critical impact on the efficiency of the entire aircraft, hence the imperative to minimize engine efficiency losses. Considerable effort has been expended over the past decades, with substantial progress achieved in terms of fuel consumption, a reduction of around 75% per passenger-kilometer. Modern turbofan engines in jetliners are thus substantially more energy efficient than the older turbojet engines, thanks to advancements in propulsion system design. These advancements have been achieved either by (a) introducing significant changes to the thermodynamic cycle or (b) incorporating several new components, integrations, mechanisms, or reactions not previously seen. However, these additions either increase the engine's complexity or reduce its availability, etc (Afonso et al., 2023).

If we consider abandoning the traditional propulsion system altogether, the paradigm sought for aviation is to enable all-electric flights in all segments; however, the challenges associated with this approach increase as the desired payload and range values increase. Several all-electric aircraft have been proposed for the envisioned Urban Air Mobility (UAM) segment, with some already undergoing flight testing. However, only a small number of commercial aviation concepts have been presented, mostly with low payload and reduced range capabilities. Moreover, certain issues, such as the energy density challenge for direct electrical energy storage, are further compounded by heat dissipation issues in electric motors and high-power electrical systems when operating electric propulsion systems (Gnadt et al., 2019).

3.1.3 Novel aircraft configuration

(1). eVTOL

Recently, Advanced Air Mobility (AAM) has emerged as a topic of growing global interest. AAM, a novel aviation concept introduced by the National Aeronautics and Space Administration (NASA), envisions the development of an air transportation system capable of safely connecting underserved and previously inaccessible regions, spanning local, regional, intraregional, and urban areas. The burgeoning AAM landscape has witnessed the formation of a multifaceted ecosystem encompassing advanced aircraft technologies, urban infrastructure systems, airspace management strategies, regulatory frameworks, and diverse application scenarios (Xiang et al., 2024). Among them, electric Vertical Takeoff and Landing aircraft (eVTOL) is no doubt one of the best choices to achieve green AAM because of the advantages of energy conservation when cruising, point-to-point trips, reduced noise, and the convenience of free runway requirements (Zhou et al., 2018).

For the propulsion is driven by electricity, the complex and heavy mechanical transmission system is abandoned by eVTOL. The rotor, which is the main driver for taking off and landing, could be deployed more freely. There are four main types of structure: Tilt-Wing, Lift + Cruise, Tilt-Rotor, and Multi-Rotor (Palaia et al., 2021), as shown in **Figure 4**.

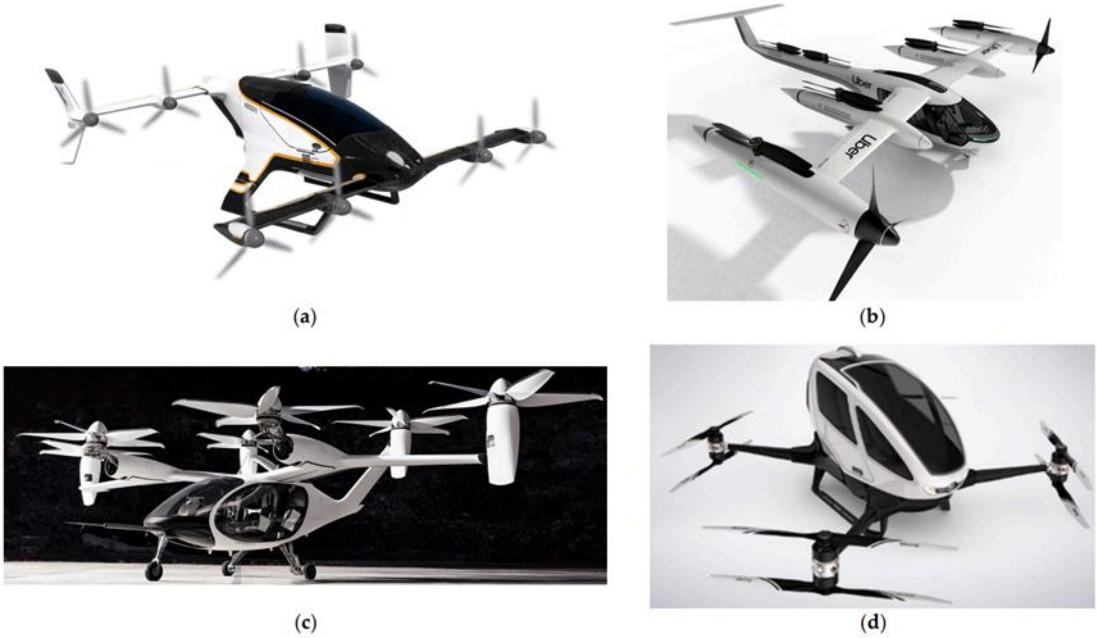

Figure 4 Four main types of eVTOL structure: (a) Tilt-Wing; (b) Lift + Cruise; (c) Tilt-Rotor; (d) Multi-Rotor (Palaia et al., 2021)

Among these, the most widely used is the Lift + Cruise for its simple structure. The advantages and challenges of each structure are listed in the following chart:

Chart 1 Comparison of four configurations

Name	Advantages	Challenges
Tilt-Wing	1. Based on the multi-rotor control strategy, the logic is relatively simple 2. The propeller continues to work, and there will be no problem of stall leading to loss of control 3. High starting efficiency in hover mode, less power consumption under the same working conditions	1. Full oblique power, need to look up first when taking off, need to bow first when entering cruise, the wing needs to be large installation Angle 2. When flying flat, the propeller flow field is relatively complex 3. Full vector control without control rudder surface is less verified on conventional aircraft

Lift + Cruise	1. Simple structure 2. Fusion of fixed wing and rotor advantages, both can be optimized for use conditions	1. The take-off and landing rotors become dead weight and generate additional drag during cruising 2. Efficiency waste, cannot reach the fastest speed
Tilt-Rotor	1. In the hover state, the airflow is the least blocked by the wing; The rudder surface on the wing is efficient enough to be used for yaw control 2. Lighter weight, larger thrust 3. Ability to achieve more posture adjustment ability	1. The mechanical design of the tilting system is complex 2. For the combination of multiple wing tilts, there are vibration and interference problems, fault modes, and high control complexity
Multi-Rotor	1. Simple structure (tends to be helicopter), high hovering state efficiency 2. Mature technology, both control and guidance are similar to existing multi-rotor UAVs	1. All power comes from the rotor, with high power consumption, and the shortest range 2. More rotors improve manufacturing complexity 3. The cruise requires a pitch roll to provide power, and the ride experience is poor

(2). Blended Wing Body

The concept of Blended Wing Body is another suggested novel configuration recently, as shown in **Figure 5**. The body is used as lifting surface as well and the tail is dispensed as the stability is controlled by the main wing.

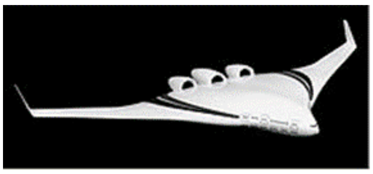

Figure 5 Illustrative example of a Blended Wing Body

Some studies have claimed potentials of this configuration to substantially reduce the aerodynamic drag and reduce further the environmental footprint such as flow control and distributed propulsion. However, two main problems need urgent solutions: (i) balance between ensuring static stability and lowering drag; and (ii) maximum aerodynamic performance occurs for higher cruise altitudes and lift coefficients. The former is one of major challenges of such aircraft design, while the latter have implications of the engine and field performance (altitude and lift coefficient, respectively) (Lyu & Martins, 2014).

3.2 Sustainable Fuels

The aviation industry has committed to reducing its environmental impact and achieving net-zero emissions in order to comply with increasingly stringent environmental regulations. For decades, engine manufacturers have been working to make sustainable aviation fuels (SAF) viable for use in aircraft. Various aerospace technologies, as shown in **Figure 6**, are being explored to enhance aero-engine efficiency, including architectural modifications, all-electric aircraft, hybrid-electric systems, and SAF (Bauen et al., 2020).

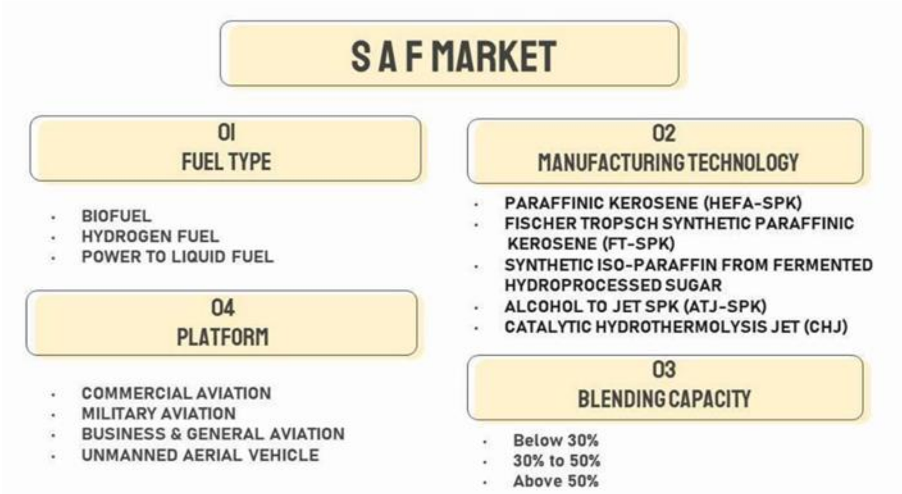

Figure 6 SAF market segments (Dhara & Muruga Lal, 2021)

Aviation fuel demand is projected to continue growing in the coming decades, with jet engines continuing to rely heavily on kerosene-based fuel. While efficiency and operational improvements can help reduce greenhouse gas (GHG) emissions, decarbonization will require a significant shift towards low-carbon, drop-in kerosene alternatives. Currently, sustainable aviation fuels (SAF) account for a very small fraction of fuel used in aviation. Electrification is emerging as a potential solution for aircraft propulsion, either in pure form for smaller aircraft or in hybrid configurations for larger aircraft (Bauen et al., 2020).

3.2.1 Biofuels

Biokerosene is a complex bioadditive for diesel fuels and some other bioproducts. Some researchers suggested technologies for the generation of sustainable aviation fuel from oil and fat and vegetable raw materials. In the process of refining oil and fat raw materials by transesterification, hydrodeoxygenation, isodeparaffinization, and glycerolysis, a whole list of high-quality low-carbon products is formed, as shown in **Figure 7**. However, the biokerosene obtained using this technology will not meet the existing specifications and will need a certification procedure. In addition, due to these numerous bio-based raw materials, the pre-processing is significantly complicated and the cost of the entire process will increase. For direct processing of bio-oil in any type of catalytic process, problems of high coke formation and rapid deactivation of the catalyst will have to be solved (Ershov et al., 2023).

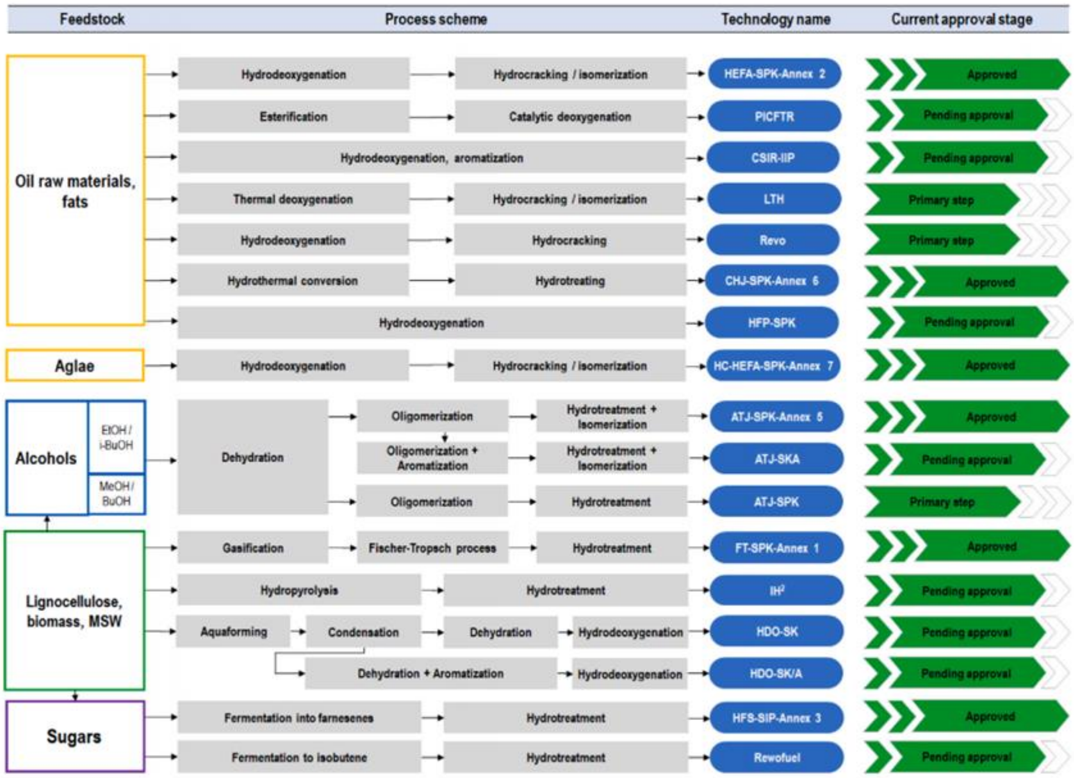

Figure 7 Technologies for the SAF production from different groups of raw materials (Ershov et al., 2023)

3.2.2 *Electrical and hydrogen energy*

(1). Electrical Power

The aviation industry is still in the early stages of developing all-electric aircraft (AEA) capable of operating commercial passenger flights. This is primarily due to challenges associated with the aircraft's electric power system (EPS). Current power electronics technology is insufficient to handle the tens of megawatts of power required for takeoff while simultaneously meeting aviation industry constraints on size, weight, and cost.

While more electric aircraft (MEA) and all-electric aircraft (AEA) offer potential advantages over conventional aircraft, such as reduced noise, energy consumption, emissions, and increased reliability and convenience for diagnostics and prognostics, it is important to note that some perceived benefits, such as lower energy consumption and greenhouse gas (GHG) emissions, may be overstated when considering the entire electricity generation process. These benefits can only be fully realized if renewable electricity generation is assumed. Furthermore, achieving commercial viability for large AEA capable of operating commercial missions remains a significant challenge with current technologies. Critical obstacles lie in the development of electric propulsion system components, particularly in generating tens of megawatts of electric power, distributing it through the aircraft's electric power system (EPS), and converting it into thrust power using electric motors (EM). To address these challenges, satisfactory solutions must be found in the following areas (Barzkar & Ghassemi, 2022):

- Electric power system (EPS), also known as power distribution system;
- Protection devices;
- Electrochemical energy unit (EEU);
- Electric machine (EM);
- Power electronics (PE) converters;
- Wiring and insulation system

(2). Hydrogen Power

The key advantage of hydrogen is that it produces no in-flight CO_2 emissions and is carbon-free throughout its life cycle. It can be employed to power fuel cells (FC) and turbine engines, and its combustion not only eliminates CO_2 emissions but NO_x and particulate emissions, as well. In addition, the energy–mass ratio for H_2 is three times that of jet fuel: 142 MJ/kg versus 43.3 MJ/kg. When compared to another contender, lithium batteries, H_2 have a vastly superior gravimetric energy density. This indicates that H_2 is much better suited for aircraft since less of it would be necessary.

At the same time, the challenges of H_2 powered aircraft are also significant (Gao et al., 2022):

- H2 Storage: Because it has a much lower volumetric energy density, storing enough H2 for a flight requires a lot of volume, which brings a huge challenge for high-pressure tanks, such as materials, lifespan, and space occupancy.
- Safety Concerns: Hydrogen is a reactive gas, meaning it is highly explosive. New safety regulations should be set.
- H2 Production: H2 is more expensive to produce than kerosene. The cost is forecast to approach those of kerosene until 2050, at scale, by 2040, H2 production in Europe may cost as little as US$2.60–3.50/kg, and this price even will be impacted by production location.

3.3 Management

Aircraft operation and infrastructure measure variants of services like maintenance of aircraft, controlling through the air traffic controller, carrying out different airport duties from ground level, and ensuring safety (Shrestha et al., 2021). So the optimization of both flight and ground operations is a way to improve aviation efficiency and reduce its environmental footprint.

3.3.1 Air Traffic Management (ATM)

As mentioned before, due to the complex structure of airport terminal airspace and the high density of flight flow, to optimize flight scheduling and improve operational efficiency, traffic prediction is extensively studied to support ATM, including flight delay prediction, fuel consumption prediction, and flight trajectory prediction (FTP) (Kulida & Lebedev, 2020).

(1). Safety and Security Issues in ATM

Safety in ATMs is the protection of air vehicles from collisions or unintentional accidents. Security in ATMs is the protection or defense of air vehicles from unintentional cyber-attacks. Privacy in ATMs is the protection of the pilots' or air vehicles' private information from hackers or cyber-attacks. The UAV pilots may endanger the civil aircraft by flying near commercial aircraft, while UAVs often face security risks of different sorts, such as sending malicious messages to UAVs, tampering with ECUs by hackers, and trying to reverse engineer their microcontrollers, applications, etc. Therefore, the traffic management system should collect all available traffic information (position, heading, and speed), weather, and geofencing information and send alerts to aircraft as necessary in time (Shrestha et al., 2021).

(2). Optimization of Flight Routes of Aircraft in The Airport Area

Effective trajectory optimization necessitates accounting for multiple conflicting parameters characterized by significant uncertainty. These parameters include collision avoidance, air conditions, noise emissions, optimal engine operation, pollutant emissions, and mission completion time. Consequently, different researchers have adopted varying optimal targets, such as minimizing time, noise, or fuel consumption, and have focused on specific flight stages. Research findings suggest that optimizing trajectories has the potential to enhance aircraft efficiency and environmental performance, particularly in terms of fuel efficiency, contrail generation, and NO_x production. However, implementing these optimizations remains a challenge due to the stringent safety requirements imposed by the aviation industry (Afonso et al., 2023).

Some researchers also came up with the migration to Trajectory-Based Operations (TBO) under which each flight is represented with a trajectory that is shared, managed, and used as a common plan for the flight. TBO seeks to address the present-day information sharing and coordination problems through the provision and consumption of shared information through System Wide Information Management (SWIM), as depicted in **Figure 8**. One fundamental question for TBO is whether flight-specific knowledge of uncertainty should be deliberately incorporated into decision-making because inaccurate input parameters are a source of trajectory prediction uncertainty. This is largely due to ground-based predictors lacking information and assuming one value for all aircraft of a certain category. Research has also not provided a comprehensive, extensively validated method for obtaining changes in aircraft intent resulting from trial changes to flight intent (Mondoloni & Rozen, 2020).

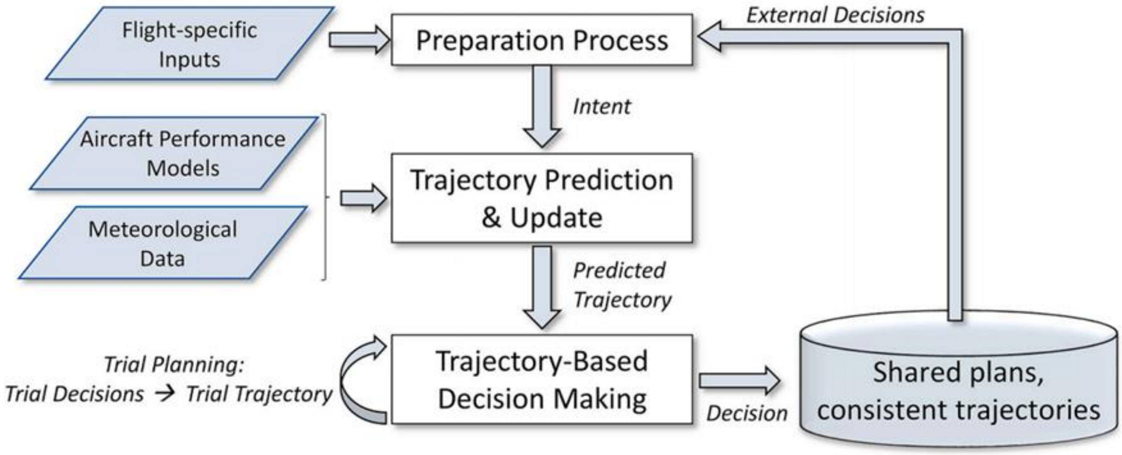

Figure 8 Using trajectories for decision-making in TBO (Mondoloni & Rozen, 2020)

3.3.2 Flight Test Scheduling

A flight test is a scientific experiment carried out under real flight conditions, it is an important part of aviation product design and development. The civil aircraft flight test technology is complex, involving many disciplines and systems. The efficiency and rationality of the flight test task planning have become one of the key factors affecting the flight test duration and cost. However, the relevant automated auxiliary algorithms or software tools have not been found in the domestic public information.

Return to the essence of the problem, test scheduling is a typical multi-objective optimization, which is suitable for every kind of meta-heuristic algorithms, such as Genetic Algorithm, Particle Swarm Optimization (PSO) algorithm, etc. The most significant issues are as follows:

- The logical relations between different test subjects are complex (as shown in **Figure 9**).
- Some subjects need to be tested during some special time window.
- Due to the complicated reality, the subjects need to be adjusted dynamically.

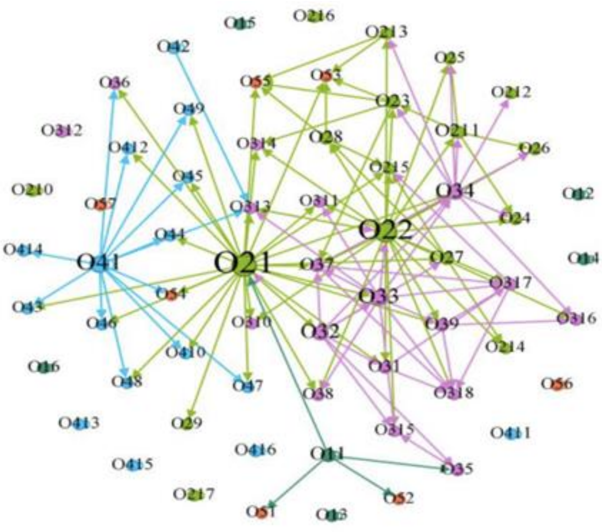

Figure 9 Example of the logical relationship between some test flight subjects of a certain type of aircraft (Mi et al., 2024)

3.4 Awareness

As we mentioned before, one of the most significant drivers is the awareness of the GA of the general public. Only if more and more people have a deeper understanding of the meaning of green aviation than just hearing the word, more resources and efforts can be investigated for it. According to an online interview on awareness of Green Aviation, less than half of the interviewees said they know about Green Aviation and trust it. More people's answers are neutral, as shown in **Figure 10**.

Figure 10 Understanding Degree of Green Aviation (IAGA, 2024)

However, when questions come to some specific details and applications of GA, most replies are negative like "No knowledge" or "Little knowledge", just very few interviewees think they are experts about it, as shown in **Figure 11**.

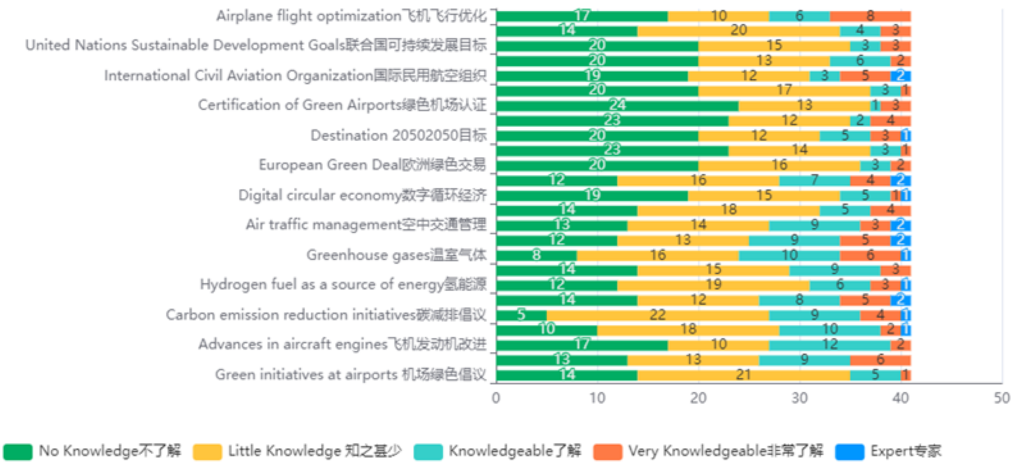

Figure 11 Understanding of details about Green Aviation (IAGA, 2024)

It shows that the participants' overall understanding and belief in green aviation are low from the result of this interview. Because of lacking publicity and education, most people are in the state of "only heard the concept, but not deeply understood". There is no doubt that a challenge for extending Green Aviation. To address this problem, it is important to develop educational and political campaigns and work with airlines or technology companies to provide more information to the public about green aviation practices. By increasing understanding and belief in green aviation, we can encourage more people to make choices that are better for the environment.

4.0 AI solution examples for green aviation

With the rapid development of AI, it has gradually been applied in many fields of aviation. Its applications can be classified into six levels as shown in **Figure 12**. Can AI be a potential solution to these issues faced in making aviation green? It is worth noting that AI is just applicable in certain areas, not omnipotent. It may be a potential solution in areas of aircraft design, aircraft operation, air traffic management, flight training, policy making, and education efforts. To further understand how AI can contribute to green aviation, we show some examples in this section.

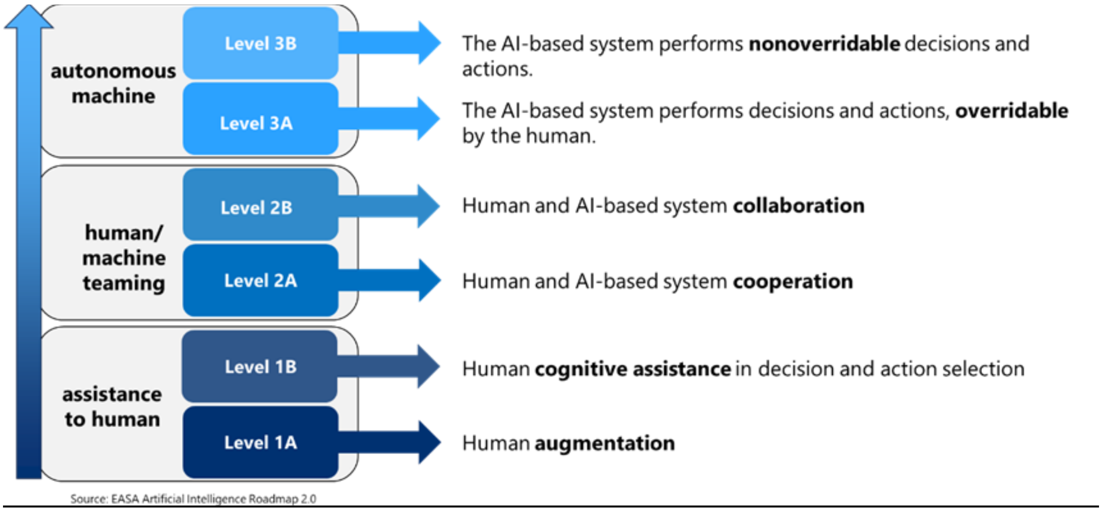

Figure 12 Classification of AI applications (EASA, 2023a)

4.1 Visual landing guidance system for General Aviation Aircraft

4.1.1 Background

Visual Landing Guidance Systems (VLS) for general aviation are gaining attraction as an alternative to traditional landing guidance methods, especially in airports that lack the infrastructure for instrument-based systems like the Instrument Landing System (ILS) (Kügler et al., 2019). VLS systems typically use forward-facing high-resolution cameras to capture the surrounding view of the airport runway, then they leverage advanced image-processing algorithms or other AI techniques to provide real-time guidance during the final approach and landing phases of flight. In the "C2Land" project, researchers at the Technical University of Munich (TUM) and their project partners have demonstrated a fully automatic landing with optically assisted navigation (Krammer et al., 2020; Kügler et al., 2019; Wolkow et al., 2017). This vision-based augmentation using cameras for optical positioning in combination with traditional GNSS/IMU navigation systems. These technologies allow general aviation aircraft to perform precise landings without the need for extensive ground-based infrastructure. Another significant development comes from the joint projects between the Daedalean AG and FAA (Balduzzi et al., 2021), and EASA (EASA, 2023b; EASA & AG, 2020). This system, designed specifically for general aviation under VFR conditions, uses a forward-facing camera to identify and track runways. It offers pilot assistance by providing in-cockpit visual cues, similar to ILS but independent of radio or satellite signals. There are ongoing researches that apply recent advancements of AI, such as deep learning neural networks, to enhanced real-time runway detection (Akbar et al., 2019; Li et al., 2024; Pal et al., 2024). These advanced AI models show promise in making visual-based landing systems more robust, accurate, and adaptable to varying environmental conditions.

4.1.2 Example Solution

A representative example of a VLS system is derived from previous projects introduced above. The system is composed of three main components: perception (camera), AI-based image processing, and a display interface, as illustrated in **Figure 13**.

1. Perception. The primary sensor is a high-resolution forward-looking camera mounted on the aircraft's nose or other places with a good field of view. This camera captures real-time images of the runway as the aircraft approaches. Multiple camera sensors may be installed to provide redundancy for safety. This system is illustrated in

2. AI-based Image Processing. The core of the system is a neural network model that processes the camera feed to detect and extract the runway. The neural network extracts runway geometry and computes the relative position and attitude of the aircraft with respect to the runway. A filtering component ensures that noisy

data is smoothed, and the final output provides critical information, such as the runway corner coordinates, horizontal and vertical deviations from the glide slope.

3. Display. The output is displayed to the pilot, showing runway information, glide slope deviations, and a camera view of the approach. In a fully autonomous scenario, this information would be fed directly to the autopilot system to guide the landing.

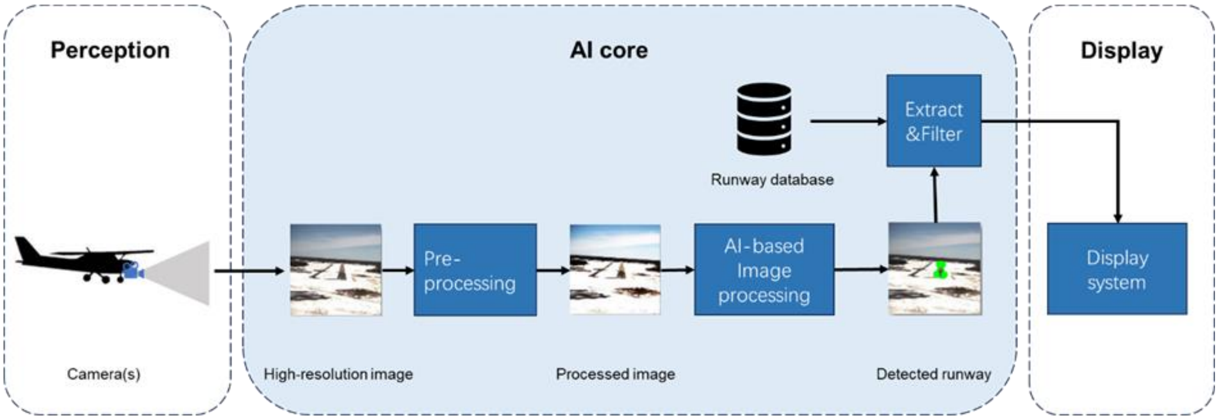

Figure 13 The architecture of an exemplary visual landing guidance system

4.1.3 Benefit and Feasibility Analysis

This VLS design enhances the traditional navigation system by providing additional visual cues and backup solutions when GPS or other external signals are lost. According to the FAA, approximately 43% of general aviation accidents occur during the landing phase of flight, often due to poor situational awareness. The VLS could potentially reduce the accident rate by providing visual guidance in conditions where pilots rely solely on their vision, especially in cases of poor visibility or unfamiliar airports. At the same time, more precise landing guidance reduces fuel consumption and emissions by minimizing go-arounds and unnecessary holding patterns during landing approaches, contributing to greener aviation.

The feasibility of this system is analyzed from different perspectives.

(1). Technical Feasibility. The use of camera-based perception systems and CNNs is well-established in other industries (such as automotive self-driving systems), meaning the core technology is mature. General aviation aircraft typically have simpler avionics compared to commercial jets, so adding an AI-based landing assistance system is feasible with modest hardware upgrades, particularly in glass cockpit systems. The technical feasibility of a VLS system is well-supported by existing research and trials. Projects like "C2Land" have demonstrated the operational capability of vision-augmented systems. However, technical challenges remain, including processing power requirements and maintaining real-time performance under various lighting and environmental conditions. The computational loads for real-time runway detection, filtering, and tracking must be managed efficiently.

(2). Regulatory Feasibility. From a regulatory perspective, AI-based VLS systems are still being evaluated for certification. The FAA and EASA are actively developing frameworks to assess the safety and reliability of such systems and they have published reports that outline the process for certifying machine learning in safety-critical applications (EASA, 2023b). Key regulatory challenges include ensuring explainability of AI decisions, handling uncertainties in real-time, and proving system robustness under different flight. If the VLS system operates as an advisory tool, meaning it does not take over control from the pilot but rather enhances situational awareness, then this system falls into the 1A artificial intelligence level in **Figure 12**. This operation scenario makes certification easier compared to fully automated systems.

4.2 4D Flight Trajectory Prediction for Transport Aircraft

4.2.1 Background

Trajectory-Based Operations (TBO) (Enea & Porretta, 2012) represent a fundamental change in Air Traffic Management (ATM), transitioning from route-based systems to using precise 4D trajectories—defined by latitude, longitude, altitude, and time (ICAO, 2005) —for managing air traffic. Trajectory prediction is a key element of TBO. Accurate prediction of the trajectory can mitigate airspace congestion, improve conflict detection, and ensure that aircraft operate efficiently within their planned airspace.

The accuracy of trajectory prediction relies on sophisticated algorithms that model aircraft dynamics, performance, and environmental factors. Various methods are used to predict trajectories, and these methods can be broadly classified into physics-based models and data-driven models. Traditional trajectory prediction utilized the physics-based models, which rely on aircraft performance data and equations of motion. These models are commonly used for short-term predictions and often suffer from reduced accuracy over time (Zeng et al., 2022). In recent years, researchers have shifted focus to data-driven models due to their ability to handle large datasets and uncover complex, nonlinear relationships. Some examples are feedforward neural networks (Wu et al., 2019), Long Short-Term Memory (LSTM) networks (Jia et al., 2022; Shi et al., 2018), and more complex Generative Adversarial Networks (Hashemi et al., 2023; Zhang & Liu, 2024).

4.2.2 Example Solution

Here the proposed solution leverages the LSTM network, a type of Recurrent Neural Network (RNN) known for handling sequential data, to predict aircraft trajectories. LSTMs are particularly well-suited for time-series predictions, making them ideal for capturing the complex, dynamic patterns in aircraft movement over time (Lin et al., 2022). The system uses historical flight data, environmental conditions, and aircraft performance characteristics to predict the future state of an aircraft. The system is designed with the following components and architecture, as shown in **Figure 14**.

Inputs to the model include real-time and historical data points such as:

- Position (Latitude, Longitude, Altitude): 3D spatial coordinates.
- Time Stamp: To handle temporal relationships.
- Speed, Heading: Kinematic properties of the aircraft.
- Weather Data: Information on wind speeds, temperature, and air pressure.
- Flight Phase: Different flight phases such as takeoff, climb, cruise, descent, approach, etc.

The architecture of the LSTM Model is described as follows:

- Input Layer: Takes sequential time-series data, including both historical data and real-time flight data. This data can be fed into the LSTM using sliding windows, which allow the model to continuously update its predictions as new data becomes available.
- LSTM Cells: The LSTM cells are the core of the network. Each LSTM cell maintains its own internal state, which allows it to remember information from previous time steps.
- Stacked Layers: Multiple LSTM layers are often stacked to allow the network to learn more abstract representations of the data. For example, the first layer may focus on short-term dependencies, while deeper layers capture more complex, longer-term patterns in the trajectory.
- Attention Mechanism (optional): An attention mechanism can be added after the LSTM layers to focus on the most relevant parts of the trajectory sequence. The attention layer weighs the importance of each time step and passes this information to the final prediction layer.
- Output Layer: The final output layer provides the predicted 4D trajectory (latitude, longitude, altitude, and time) for a given prediction horizon. This output is updated as new input data becomes available. For the prediction of future trajectory in multiple steps, the closed-loop prediction of the LSTM neural network is utilized. This is achieved by feeding the predicted trajectory at the current time stamp to the neural network to predict the next step, as shown in **Figure 14**.

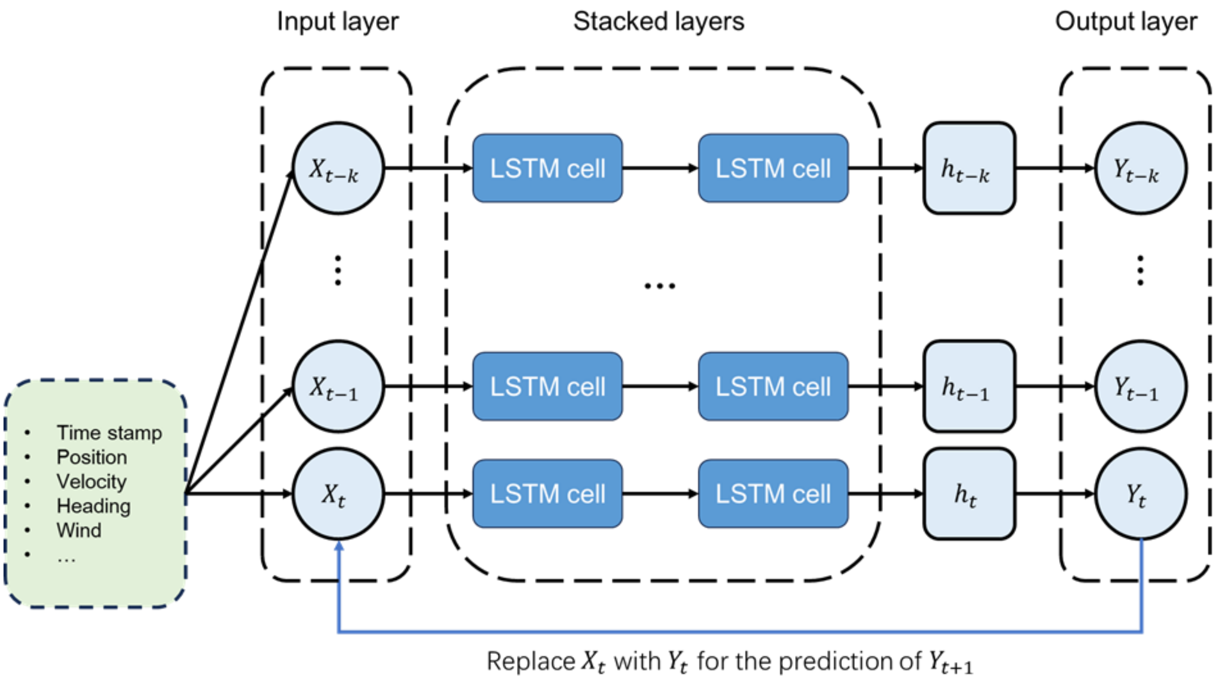

Figure 14 Neural network designed for aircraft trajectory prediction

4.2.3 Benefit and Feasibility Analysis

The deployment of trajectory prediction systems can significantly benefit aviation operation. More accurate trajectory predictions allow for better air traffic management and conflict detection. By reducing the uncertainty in aircraft positions, air traffic controllers can react proactively to potential conflicts, reducing mid-air collision risks and improving separation standards. Improved trajectory predictions would enable more efficient use of airspace, reducing delays and allowing for better traffic flow. Airlines could see fuel savings from optimized flight paths. Moreover, more accurate trajectory predictions reduce unnecessary holding patterns and rerouting, leading to more fuel-efficient flights. This could contribute to an overall reduction in carbon emissions from aircraft.

The feasibility of this trajectory prediction system is analyzed from different perspectives.

(1). Technical Feasibility. First of all, data feasibility. Aircraft GPS data, weather data, and performance data are widely available from various sources such as ADS-B (Automatic Dependent Surveillance-Broadcast) systems, satellite data, and radar tracking. Advanced neural network models such as LSTMs have already demonstrated success in time-series predictions across various industries. Their ability to learn long-term dependencies makes them particularly well-suited for trajectory prediction. However, deep neural networks such as LSTM models are computationally intensive. Given the recent advancements in AI hardware, it might be feasible to run the LSTM model efficiently in operational ATM systems.

(2). Regulatory Feasibility. Adoption of AI-based systems in aviation is subject to rigorous regulatory approval. Compared to less-complex machine learning methods, there has been concerns on deep neural networks over the learning assurance, explainability, and security against adversarial attacks (Hashemi et al., 2020). Since the LSTM-based system serves as an advisory tool for air traffic controllers (not directly controlling aircraft), the regulatory barriers are lower. Actually, this system falls into the 1A or 1B artificial intelligence level in **Figure 12**. The system can be integrated into existing ATM frameworks following certification standards.

4.3 Discussion

These examples show how AI can contribute to Green Aviation. First, AI can reduce accidents caused by human factors which improved aviation safety. Second, it enables more efficient use of airspace and better traffic flow which makes flight more economical. Third, AI enables more fuel-efficient flight and reduce the emissions, making aviation more environmentally sustainable.

In the future, how will AI solutions for Green Aviation develop? First, we believe that it will be more intelligent. In the above examples AI only provides assistance to human or cooperates with human. Higher-level AI systems, termed as autonomous machines, have yet to materialize. Second, we believe that with development of AI, more advanced aircraft design, more efficient aircraft operation and air traffic management will make aviation greener. Third, AI holds great potential to contribute to green aviation across many aspects of the aviation industry. However, it is important to recognize that aviation focus more on safety over efficiency, leading to a more cautious and reluctant approach to AI adoption compared to other industries.

5.0 Conclusions

Compared with other sectors, aviation's climate impacts are introduced. Not only the carbon emissions of aviation, its non-CO_2 effects, including nitrogen oxides emissions and noise pollution should be considered as well. Although aviation emissions are a relatively small proportion compared to other sectors, the high-altitude nature of these emissions exacerbates their contribution to global warming. Based on the overview of early efforts and initiatives aimed at reducing aviation's environmental impact, we propose a general definition of Green Aviation. Then we categorize the crucial issues faced in achieving green aviation into four aspects, termed design tech, sustainable fuels, management and awareness. Examples of AI solutions for Green Aviation are given to show that AI enables safer, more economical, and greener flight. Based on the analysis, we are convinced that AI solutions for Green Aviation have a promising future.

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