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Theme: Leveraging Artificial Intelligence to Make Aviation Greener

Leveraging AI to Make Aviation Greener

Xuanyu Chen [1], Tingyu Huang [2], Zhidong Lu [3], Shuyi Jiang [4]

[1,2,4] Shanghai Jiao Tong University, Shanghai, China

[1] xuanyu.chen@sjtu.edu.cn | [2] Huang_Tingyu@sjtu.edu.cn | [4] joker-ke@sjtu.edu.cn

[3] Technical University of Munich, Munich, Germany, zhidong.lu@tum.de

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Abstract

Due to the climate impact of the rapid development of aviation, the notion of Green Aviation is taking hold in the aviation community. Yet there is no clear definition to what it means or implies. In this article, we first overview aviation's climate impact, with both carbon emissions and non-CO_2 effects taken into account. Based on this, we propose the definition of Green Aviation. Then the pain points of making aviation green are analyzed, which can be summarized into four aspects, termed as design tech, sustainable fuels, management and awareness. We then give several examples of Artificial Intelligence in aviation to show that AI may be a potential solution to transition aviation to greener practices.

Keywords: Green Aviation, 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 increasingly attracting 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 do not occur at the ground level but rather in the high-altitude atmosphere. High-altitude emissions insulate heat in the range of 30,000~40,000ft, leading to significant impact on climate change. Besides the carbon emissions, non-CO_2 effect of aviation should be considered as well. The emissions of nitrogen oxides can increase ozone production in the upper troposphere and lower stratosphere, and reduce methane concentrations. Due to the high-altitude characteristic, the emissions of aviation contribute a lot to the greenhouse effect. The exponential increase in air travel not only makes a significant impact on the climate via increased emissions but also on social ecosystem due to such interferences as noise pollution (Correia et al., 2013).

Considering these impacts of aviation, the notion of Green Aviation (GA) is proposed, which contains the desire to make aviation more environmentally friendly. Yet the clear definition of GA and the way to make it a reality are still not explicit. With the rapid development of Artificial Intelligence (AI), it has gradually been applied in many fields of aviation. Much attention has been paid to the role that AI will play in the practice of GA. Further investigation on AI solutions for GA is highly required.

Hence, the purpose of this paper is to give a definition of green aviation and, based on the analysis of the pain points faced in making aviation green, illustrate the important role that AI can play in green aviation practice.

2.0 Definition of Green Aviation

Green Aviation 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 the use of sustainable aviation fuels (SAFs) derived from renewable resources, the conversion toward more electric power in propulsion system, the implementation of hydrogen combustion, the application of hydrogen fuel cells, the combination of hybrid solutions, advancements in aircraft design for increased fuel efficiency, optimization of flight routes and operations, and investment in green airport infrastructure (Ficca et al., 2023).

The key principles of green aviation include the reduction of greenhouse gas emissions, conservation of natural resources, and the promotion of clean energy solutions. These principles are aligned with global efforts to mitigate climate change and meet international commitments to reduce aviation's environmental footprint. By integrating these practices, the aviation industry aims to achieve long-term sustainability while continuing to support economic growth and global connectivity.

3.0 Pain Points of Green Aviation

IATA once addressed environmental targets with a "Four-pillar Strategy", namely “Design Tech”, “Sustainable Fuels”, “Management”, and “Economic Measures” (Dhara & Muruga Lal, 2021). We edited a little of changing the “Economic Measures” to “Awareness of GA” because we believe that economic issues are considered when talking about technologies. Still, it’s the more important part that understanding GA in minds will give a stronger push. Therefore, we summarize the crucial issues faced in making aviation industry green into four aspects in this section, as shown in **Figure 1**.

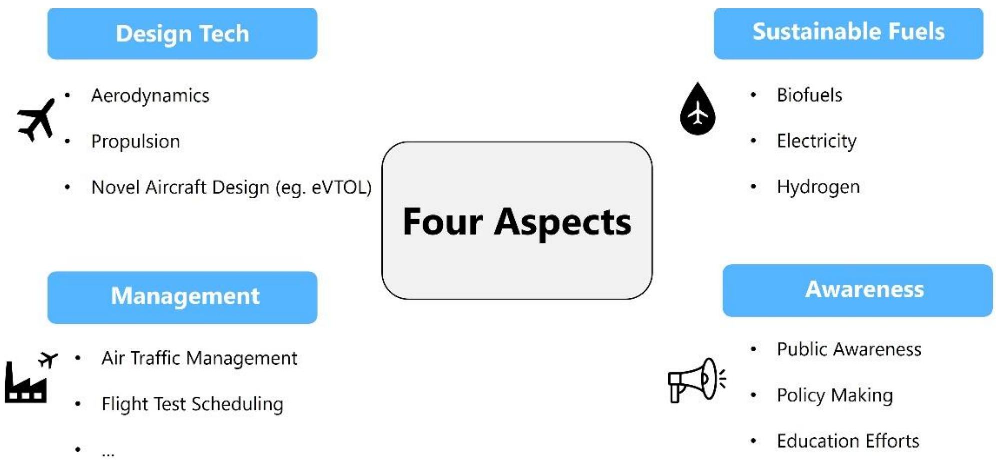

Figure 1 Four aspects of crucial issues faced in making aviation industry green

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. However, **new and unconventional designs are necessary as conventional concepts were optimized over the last decades and reached a state where further improvement is expensive and a steep rise is not expected** (Afonso et al., 2023).

(1). Aerodynamic Structure (Afonso et al., 2023)

a. HARW

By designing a wing with a higher aspect ratio, the lift-induced drag is reduced, which may also translate into a fuel reduction. However, higher root bending moments are expected, thus a proper drag-weight trade-off should be conducted. Additionally, structural issues may occur at a lower airspeed than in a conventional design once the wing’s structure is projected to be the lightest possible, namely those that may arise from the dynamic interaction between airflow and structure such as flutter.

Figure 2 Example of a HARW

b. Non-planar wings

Except for Advances in winglet design which is almost standard in current aircraft designs, other ideas of non-planar wing extension result in more complex wing tip structures, as shown in **Figure 3**. Configurations with the main and aft lifting surfaces joined at their tips claim to provide lower drag coefficients, structural robustness, and better performance levels than the conventional Wing–Body–Tail (WBT). However, a strong interference between the outer wing and the vertical wing connector due to the miniature distance of the surfaces poses additional aerodynamic and structural challenges, possibly jeopardizing the contemplated benefit. A practical use of such aircraft configurations is not yet seen for commercial aviation.

Figure 3 Example of non-planar wing

(2). Aerodynamic shape optimization (Li et al., 2022)

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:

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 (Afonso et al., 2023)

The propulsive system efficiency has a critical impact on the entire aircraft's efficiency, so **the emergency is to reduce the efficiency loss of engines**. A substantial amount of effort has been carried over the past decades with considerable progress achieved in terms of fuel consumption, a reduction of around 75% per passenger-kilometer. Nowadays turbofans in the jetliners are thus substantially more energy efficient than the old turbojet engines thanks to the development of propulsion systems. By (a) adding significant changes to the thermodynamic cycle or (b) several new components, integrations, mechanics, or reactions not previously seen. However, these additions either increase the complexity of the engine or lower the availability of oxygen, etc.

If we change the idea of abandoning the traditional propulsion system, the paradigm sought for aviation is to enable all-electric flights in all segments, however, the challenges associated increase as the desired payload and range values ramp up. Several all-electric aircraft have been proposed for the envisioned Urban Air Mobility (UAM) segment with some already being flight tested. However, only a small number of commercial aviation concepts have been presented, mostly with low payload and reduced range capability. However, some problems, such as the **energy density question** for direct electrical energy storage, are more prone to **heat dissipation issues** during electric motors and high-power electric systems operating when using electrical propulsion systems.

3.1.3 Intellectualized System

Artificial Intelligence (AI) and Machine Learning (ML) applications are currently found across all engineering domains, including the aviation industry. Typical applications of ML could be flight control laws optimization, development of means for detecting and preventing collisions between aircraft and unmanned aerial systems, aviation computer training complexes, diagnostics of airborne components and assemblies (including in real-time), automation and autonomy of management, solving combat missions, etc (Kulida & Lebedev, 2020). Furthermore, AI could also be used to embed complex models onboard aircraft systems, for instance by using surrogate models that are more memory and processing efficient. However, these applications are still in the early stages or only stay in papers, which means there's still a long way to make systems intellectualized totally. Here are some examples.

(1). Integrated health monitoring and engine management systems

Modern turbofan engines utilize Full Authority Digital Engine Control (FADEC) systems to manage thrust control. FADEC interprets pilot input and adjusts fuel flow to maintain engine operation within safety limits. However, current control architectures cannot adapt to changes in engine operating conditions due to factors such as erosion and fouling. To address this, as shown in **Figure 4**, model-based control architectures have been proposed, incorporating engine monitoring units (EMUs) to assist FADEC with thrust control.

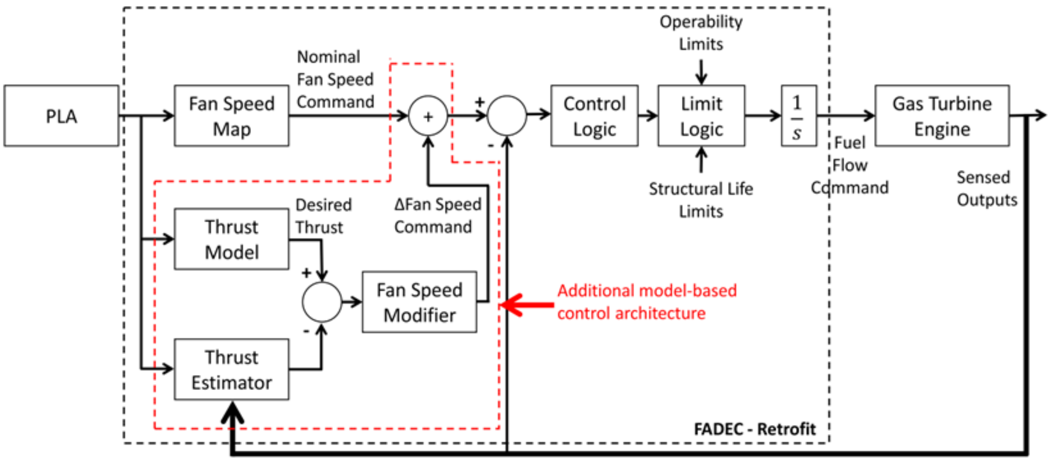

Figure 4 Block diagram of modified engine control loop

As of this point, the only factor involved in the control loop that modifies the engine's operating conditions is the fuel flow; however, this technology could potentially pave the way to other factors such as variable pitch turbofan blades and variable reduction ratio gearbox technology being involved. The **TRL of this technology is still relatively low** and would require more development, testing, and validation to reach the level of technical maturity required for commercial use by engine manufacturers (Ranasinghe et al., 2019).

Determining the optimal thrust value is crucial, as insufficient thrust can compromise flight safety, while excessive thrust leads to increased fuel consumption and potentially uncomfortable vibrations. Researchers use the Velocity, altitude, and ambient temperature values of an Airbus A319 to input the ANN model to get the prediction of thrust. The average percent relative errors and test MSE gotten from the LM algorithm are less than 2%. **To get more accurate results faster, performance analysis of ANN can be made using different intelligent optimization methods and more inputs should be increased** (Yildirim Dalkiran & Toraman, 2021).

(2). Automation of Aircraft

Currently, the main achievements in the field of artificial intelligence are related to success in the development of methods for training deep neural networks. These developments in the future give hope for full automation of the flight control process of the aircraft. However, compared with other DL frontiers such as computer vision or natural language processing, however, **DL-based research works and techniques in the aircraft design, dynamics, and control field are still rare** (Dong et al., 2021).

a. System Identification (Bagherzadeh, 2018)

A high-performance aircraft should be able to perform controlled maneuvers throughout its flight envelope. Therefore, nonlinear aerodynamics should be considered in the design, development, and flight of maneuverable aircraft. Due to the capability to estimate a wide range of functions, the ANN can provide effective non-parametric identification methods for nonlinear systems. ANN is a suitable tool for aerodynamic modeling. Nevertheless, present studies in this field face some difficulties:

- First-order stability and control derivatives are usually used as the predetermined structure for simplification. Although these parametric models are straightforward, it is **not effective to predict complex nonlinear behaviors by predetermined models**.
- **Decoupling longitudinal and lateral-directional dynamics overlooks their coupling**, especially in nonlinear regimes.
- In all studies, the **flight parameters are treated without any preprocessing**.
- Noise is always present in flight tests. Noisy inputs and targets have undesirable consequences for the ANN: **reducing the accuracy and increasing the training time.**

b. Trajectory Prediction (Zeng, Chu, Xu, Liu, & Quan, 2022)

The current fixed airspace sector and route structure exhibit limitations such as rigidity, susceptibility to cascading failures, and constrained capacity. These limitations hinder airspace communication optimization and impede the adoption of future trajectory-based and performance-based airspace operations. Aircraft four-dimensional (4D, encompassing longitude, latitude, altitude, and time) trajectory prediction is crucial for existing automation systems and forms the foundation for future trajectory-based operations. Present challenges and research directions are summarized as follows:

- To make more accurate predictions, it is possible to **strengthen the realtime sharing and transmission of data** such as uncertainty, or **establish a more robust prediction model**.
- **Using multiple models or learners for modeling and using certain rules** to integrate the learning results to build a track prediction fusion model to improve the accuracy and stability of the model for adapting to various scenarios.
- The **complex structure of the airport terminal airspace, the high density of flight flow, and the frequent changes in aircraft flight attitudes** bring challenges to the high-precision and reliable prediction of flight paths. This will be summarized later.

3.1.4 Novel aircraft configuration

(1). eVTOL

To achieve green aviation, electric Vertical Takeoff and Landing aircraft (eVTOL) is no doubt one of the best choices to achieve green aviation because of the advantages of energy conservation when cruising, point-to-point trips, reduced noise, and the convenience of free runway requirements, as shown in **Figure 5**.

Figure 5 tilt-rotor eVTOL

VTOL is a classical over-actuated system, which means the number of control inputs exceeds the number of independent degrees of freedom or the outputs. Due to overactuation and coupling of control surface effects, it is difficult to determine an appropriate method of how to translate a flight control command into a control surface command. When adopting traditional linear control law, the performance may be degraded when dealing with complex nonlinear systems or systems with large delays. To overcome the shortcoming, Nonlinear Dynamic Inversion (NDI) and Incremental Nonlinear Dynamic Inversion (INDI) occur. The core idea of these technologies is to use the dynamic model of the aircraft to reverse the control effect, to achieve accurate control of the aircraft state (**Figure 6**). They adjust the control input through real-time feedback to adapt to external disturbances and changes in system dynamics (Raab et al., 2018).

However, the shortcomings of NDI are also obvious: **this strategy relies on accurate system dynamics, which is impossible to reach**. If we turn to the incremental form of it, we need to calculate the Jacobian matrix, which is a **high load for computers**.

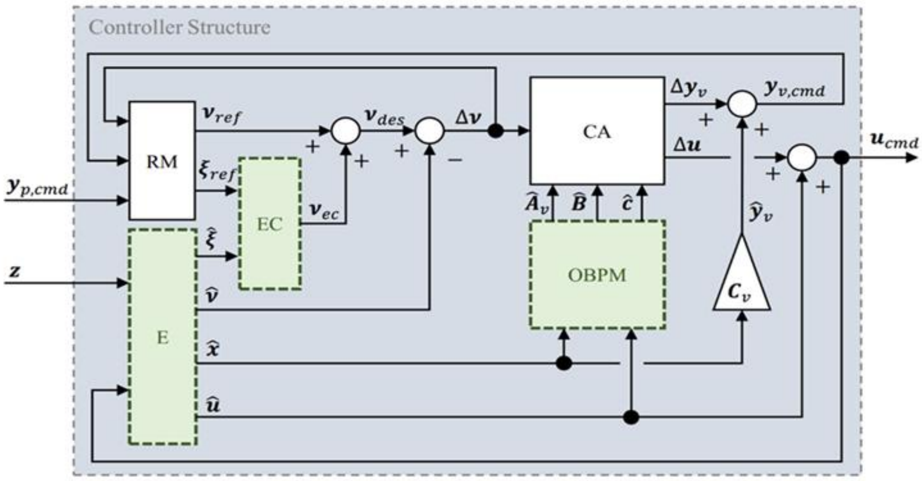

Figure 6 Structure of INDI

The purpose of Control Allocation (CA) is to allocate the desired pseudo-control generated by NDI or INDI to the actuators. At present there are two challenges when allocating control: **efficiency of calculation** and **physical meaning of allocation**.

a. Efficiency of calculation

As mentioned before, eVTOL is an over-actuated system, so the effective matrix **B** in the core equation $\boldsymbol{\nu} = \mathbf{Bu}$ is a fat matrix (the number of columns is more than of rows). That means we need to calculate the pseudo-inverse of the effective matrix. This occupies too much computation resources on computers because the size of the effective matrix is always large. The most common method is to use SVD decomposition, researchers have given some methods to raise the efficiency of calculation (Li et al., 2024), but there's still room for optimization.

b. Physical Meaning

Considering the physical performance, safety comes as the top priority. When the system fails, the backup system takes over and can carry out appropriate switching and control redistribution. Besides that, we want to make the trip more stable, and more comfortable or save more energy during transition mode. Most of the present allocation methods just use Quadratic Programming to find the solution, however. To achieve the goals, we can adopt different allocation strategies. For example, researchers propose an energy-efficient incremental control allocation method for transition flight control (Lu et al., 2023). This is also an important and interesting direction to fly greener.

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: composite wing, tilt-rotor, multi-rotor, and power-forward, as shown in **Figure 7**.

Figure 7 Four main types of eVTOL structure

Among these, the most widely used is the composite wing 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
Composite wing	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, can not 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	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

	3. Ability to achieve more posture adjustment ability	
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
Power-forward	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

(2). Blended Wing Body (Afonso et al., 2023)

The concept of Blended Wing Body is another suggested novel configuration recently, as shown in **Figure 8**. The body is used as lifting surface as well and the tail is dispensed as the stability is controlled by the main wing.

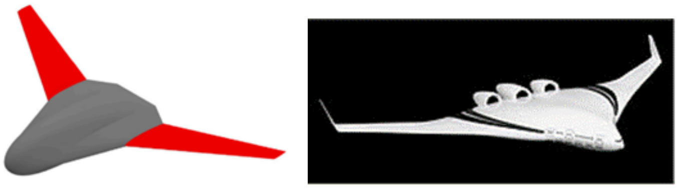

Figure 8 Illustrative example of a Blended Wing Body

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).

3.2 *Sustainable Fuels*

The aeronautics Industry has committed to reducing environmental impacts to create a zero net emission and fulfill robust environmental legal limits. For decades engine manufacturers have been striving to make renewable fuels feasible for use in airplanes. Possible options, such as **enhancing aero-engine effectiveness through architectural adjustments, all-electric aircraft, hybrid-electric systems, SAF**, and many more, would be embraced by different aerospace technologies, as shown in **Figure 9**.

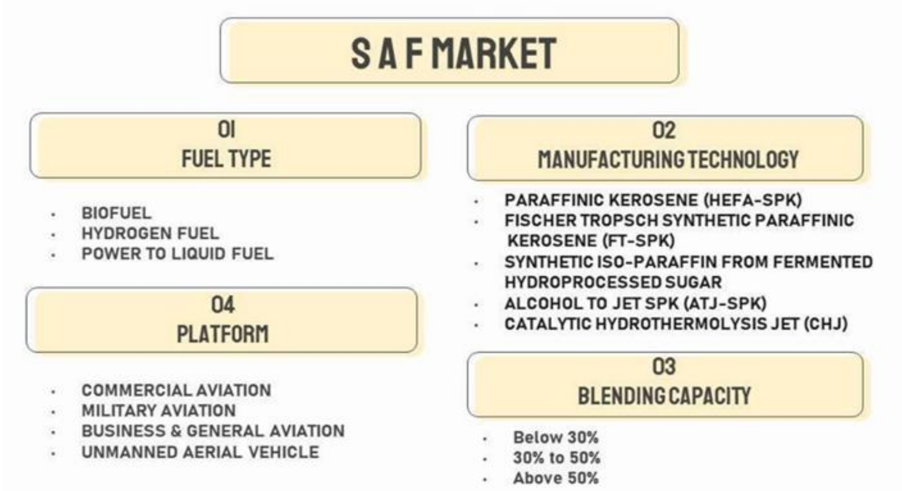

Figure 9 SAF market segments

Take fuel for example, aviation fuel demand is expected to continue to grow over the next decades and continue to rely heavily on kerosene fuel for use in jet engines. While efficiency and operational improvements are possible ways to reduce greenhouse gas (GHG) emissions, de-carbonization will need to heavily rely on low-carbon kerosene drop-in alternatives. Currently, alternative fuels make up a very small share of fuel used in aviation, electrification is emerging as an option for providing propulsion in aircraft, either in pure form in small aircraft or in hybrid mode in 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 10**. 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).

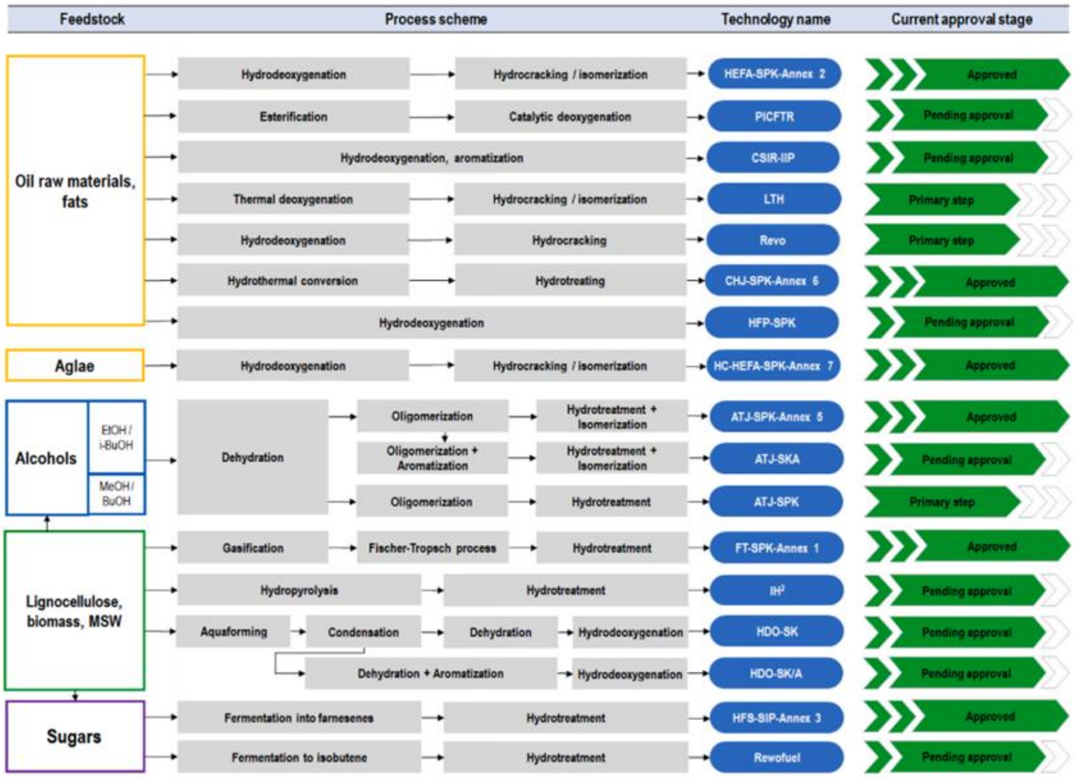

Figure 10 Technologies for the SAF production from different groups of raw materials

3.2.2 *Electrical and hydrogen energy*

(1). Electrical Power (Barzkar & Ghassemi, 2022)

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**:

- 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 (Gao et al., 2022)

The key advantage of hydrogen is that it produces no in-flight CO2 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 CO2 emissions but NOx and particulate emissions, as well. In addition, the energy–mass ratio for H2 is three times that of jet fuel: 142 MJ/kg versus 43.3 MJ/kg. When compared to another contender, lithium batteries, H2 have a vastly superior gravimetric energy density. This indicates that H2 is much better suited for aircraft since less of it would be necessary.

At the same time, the challenges of H2 powered aircraft are also significant:

- 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. 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 NOx 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). 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)**.**

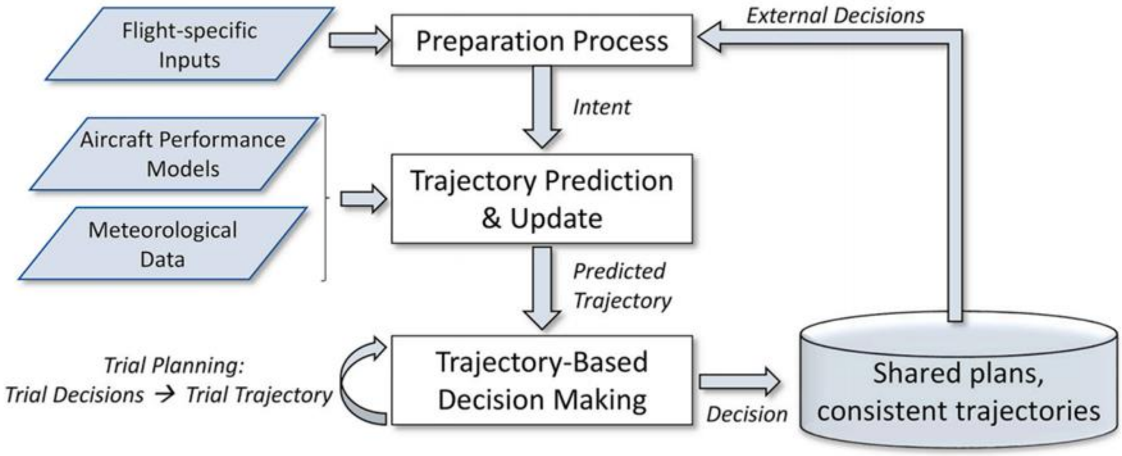

Figure 11 Using trajectories for decision-making in TBO

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.
- Some subjects need to be tested during some special time window.
- Due to the complicated reality, the subjects need to be adjusted dynamically.

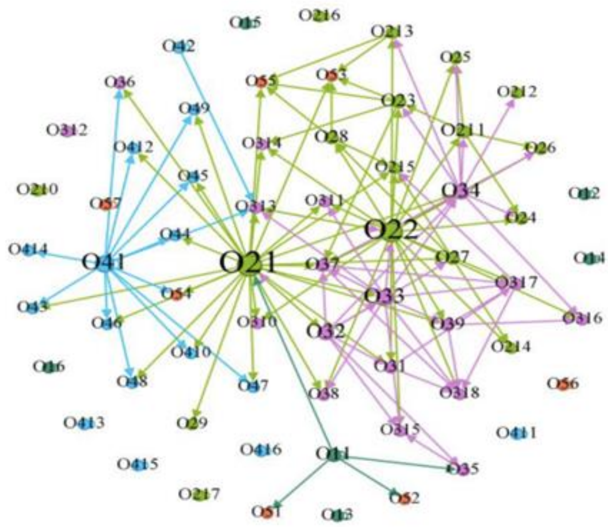

Figure 12 Example of the logical relationship between some test flight subjects of a certain type of aircraft (Mi et al., 2024)

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 13**.

Figure 13 Understanding Degree of Green Aviation

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 14.**

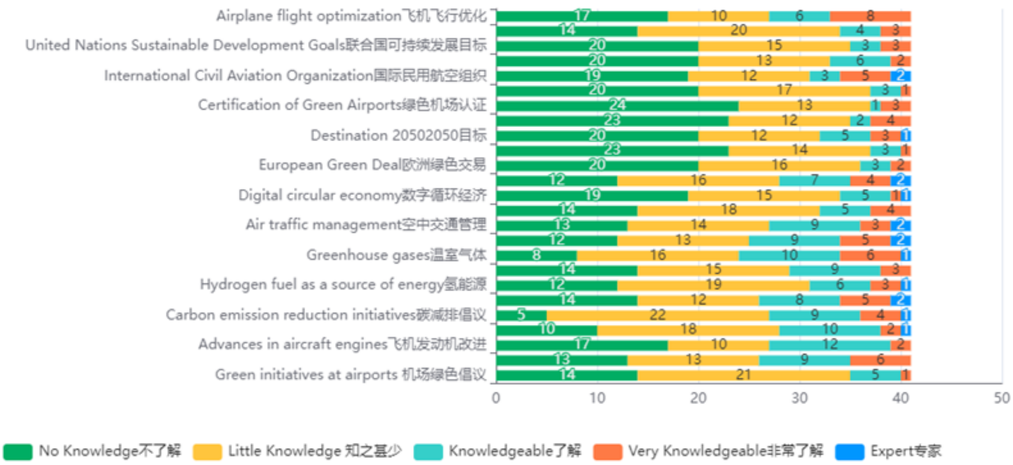

Figure 14 Understanding of details about Green Aviation

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 Artificial Intelligence (AI), it has gradually been applied in many fields of aviation. Its applications can be classified into six levels as shown in **Figure 15**. Can AI be a potential solution to these issues faced in making aviation green? It is worth noting that AI is not omnipotent. It is just applicable in certain areas. We believe that AI has the potential to do better in areas where natural intelligence works. AI 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.

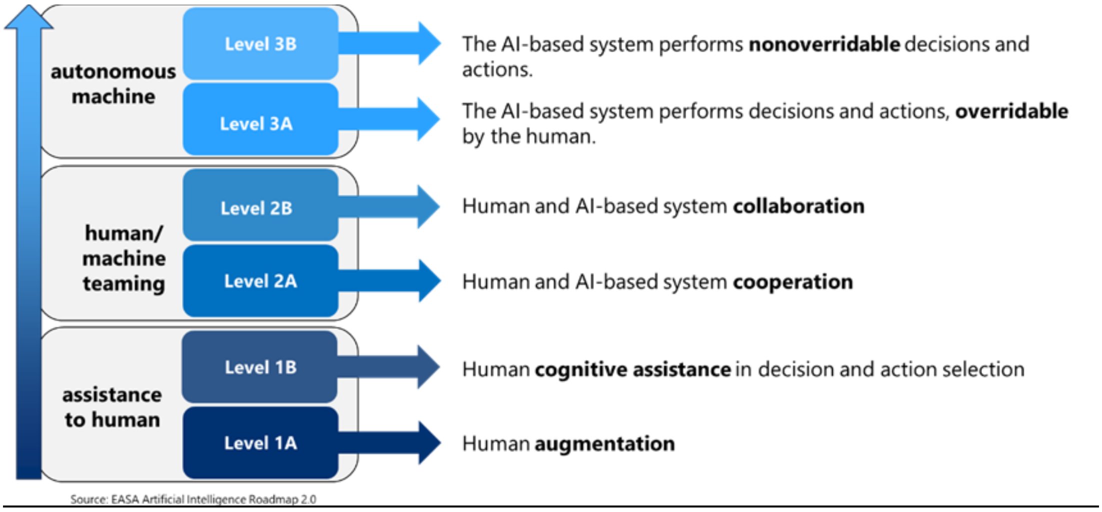

Figure 15 Classification of AI applications (EASA, 2023)

4.1 Visual landing guidance system for General Aviation Aircraft

4.1.1 Description

The Visual Landing Guidance System (VLS) provides real-time visual assistance to pilots of general aviation aircraft during landings. The system is designed to work in daytime Visual Meteorological Conditions (VMC), under Visual Flight Rules (VFR). A forward-facing high-resolution camera captures the runway and surrounding area, and a Convolutional Neural Network (CNN) processes the imagery to identify the runway. The system overlays critical visual landing guidance onto the pilot's display, including the aircraft's position relative to the runway, vertical/horizontal deviations from the glide slope, and runway centerline tracking. The VLS acts as a low-cost, AI-powered alternative to the Instrument Landing System (ILS), providing enhanced situational awareness during the final approach.

4.1.2 Design

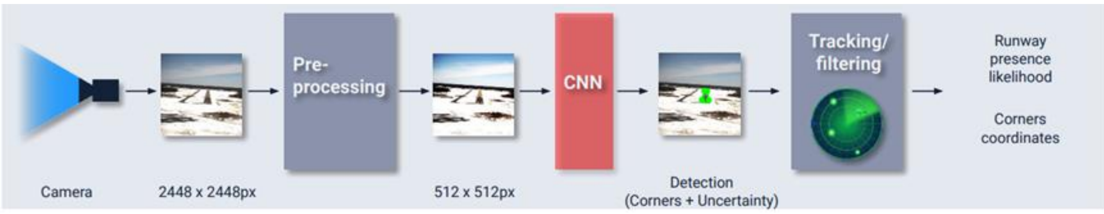

Figure 16 Visual landing guidance system architecture (EASA, 2020)

As shown in **Figure 16**, the system consists of three integrated subsystems (EASA, 2020):

(1). Perception Subsystem. High-resolution cameras mounted on the aircraft's nose continuously capture visual data of the runway environment.

(2). Processing Subsystem. A neural network (CNN) processes the images, detecting runway markers, estimating runway boundaries, and calculating the glide path in real-time. The system utilizes specialized hardware like GPUs or FPGAs for rapid data processing, critical for maintaining real-time feedback to the pilot.

(3). Display Subsystem. The pilot's glass cockpit flight display provides a graphical overlay of the aircraft's position relative to the runway. This includes horizontal and vertical guidance similar to ILS, helping the pilot maintain the correct approach angle and alignment.

The CNN is trained on thousands of landing scenarios and continuously improved via machine learning, updating its capability to adapt to new runway environments.

4.1.3 Feasibility Analysis

(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.

(2). Regulatory Feasibility. The system operates as an advisory tool, meaning it does not take over control from the pilot but rather enhances situational awareness. Actually, this system falls into the 1A artificial intelligence level in **Figure 15**. This limits the regulatory challenges and makes certification easier compared to fully automated systems. The system would need to comply with aviation standards such as DO-254 (for airborne electronic hardware) and DO-178C (for airborne software).

(3). Market Feasibility. With over 300,000 active general aviation aircraft worldwide (NASM, 2022), many of which do not have advanced landing guidance systems, there is a clear market for such technology. General aviation pilots often fly into smaller airports that lack ILS, making a VLS highly valuable for both safety and convenience.

4.1.4 Cost Analysis

(1). Development Costs: The primary costs are associated with developing the CNN and AI models, ensuring hardware compatibility with various aircraft, and rigorous testing. Initial development would focus on training the model with various runway scenarios and optimizing the software for real-time performance.

(2). Hardware Costs: Each installation would require a forward-facing high-resolution camera, a processing unit (GPU/FPGA), and integration into the cockpit display system. Estimated costs for each unit range between $5,000 and $10,000 per aircraft, depending on aircraft type and existing avionics.

(3). Maintenance Costs: Software updates and occasional recalibration of cameras and sensors would be necessary. The low complexity of the system ensures minimal ongoing maintenance compared to more advanced autopilot or landing systems.

4.1.5 Impact

(1). Safety Impact.

a. 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 these accidents by 20-30% by providing visual guidance in conditions where pilots rely solely on their vision, especially in cases of poor visibility or unfamiliar airports.

b. If we estimate that 20% of general aviation accidents are landing-related, the introduction of this system could potentially prevent 50-100 accidents per year, depending on market adoption rates.

(2). Economic Impact. The cost of an aviation accident can vary greatly, but FAA estimates place the average cost of a general aviation accident involving aircraft damage and injury at around $500,000. If the VLS can prevent 50 accidents annually, that would result in potential savings of $25 million annually for the aviation industry in terms of reduced accident costs.

(3). Environmental Impact. More precise landing guidance reduces fuel consumption and emissions by minimizing go-arounds and unnecessary holding patterns during landing approaches.

(4). Scalability. The system can potentially be adapted for commercial aircraft or even autonomous drones in the future, expanding its application beyond general aviation.

4.2 4D Flight Trajectory Prediction for Transport Aircraft

4.2.1 Description

The 4D aircraft flight trajectory prediction refers to the process of predicting an aircraft's future trajectory in terms of latitude, longitude, altitude (3D), and time (4D) (ICAO, 2005). This prediction is critical for air traffic management

(ATM) systems to enhance safety, optimize airspace utilization, and reduce delays. Accurate prediction of the trajectory can mitigate airspace congestion, improve conflict detection, and ensure that aircraft operate efficiently within their planned airspace.

Here the proposed solution leverages Long Short-Term Memory (LSTM) networks, 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.

Problem Addressed. Traditional trajectory prediction methods based on kinematics or estimation models often suffer from reduced accuracy over time (Zeng, Chu, Xu, Liu, & Zhibin, 2022). Machine learning models such as LSTMs can improve prediction accuracy by learning from large datasets of historical trajectories and accounting for various factors, including weather, air traffic, and operational constraints, which are often overlooked in simpler models.

4.2.2 Design

The system is designed with the following components and architecture, as shown in Figure 17.

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

(1). Position (Latitude, Longitude, Altitude): 3D spatial coordinates.

(2). Speed, Heading, and Acceleration: Kinematic properties of the aircraft.

(3). Weather Data: Information on wind speeds, temperature, and air pressure.

(4). Time Stamp: To track the progression of events and handle temporal relationships.

(5). Traffic and Route Information: To account for air traffic control constraints and deviations.

The architecture of the LSTM Model is described as follows:

(1). Input Layer: Takes sequential time-series data (e.g., past 10-20 seconds of flight data).

(2). LSTM Layers: Multiple LSTM layers process the time-dependent data. LSTMs are excellent for learning patterns in sequential data, making them ideal for capturing aircraft trajectory behaviors over time.

(3). Dense (Fully Connected) Layer: Post-LSTM layer to further refine the output.

(4). Output Layer: Predicts the 4D trajectory (future position, and time).

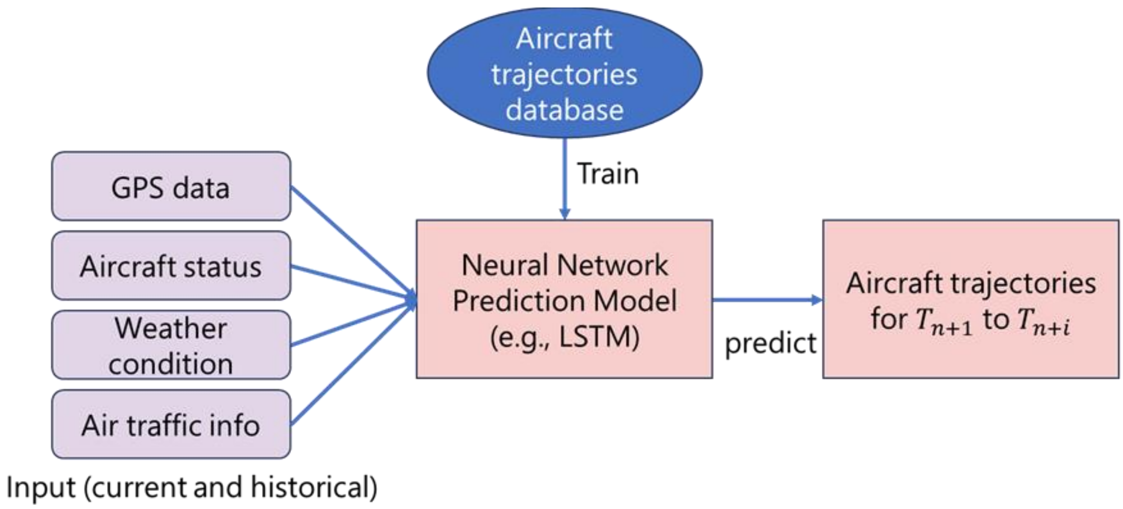

Figure 17 Neural network designed for aircraft trajectory prediction

The LSTM network is trained using large-scale datasets of historical aircraft trajectory data combined with environmental data. The training process involves optimizing the model to minimize prediction error, using a loss function such as Mean Squared Error (MSE). The training dataset would be augmented with various scenarios, including different weather conditions, air traffic situations, and aircraft types, to improve generalization.

Once trained, the LSTM model is deployed in a real-time system that continually takes the latest aircraft data to predict the future trajectory for the future states (e.g., next 5-10 seconds). The system generates a 4D trajectory prediction, including position, altitude, and future timestamps. Uncertainty metrics (confidence intervals) for each prediction are provided to alert ATM systems when predictions are less reliable.

4.2.3 Feasibility Analysis

(1). Technical Feasibility.

a. 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.

b. LSTM models 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.

c. Computation Requirements. LSTM models are computationally intensive but can be executed in real-time with modern GPUs and cloud-based infrastructure. Given the recent advancements in AI hardware, it is 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. 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 15**. The system can be integrated into existing ATM frameworks following certification standards.

(3). Market Feasibility. With increasing airspace congestion and the growth of air traffic worldwide, there is a strong demand for improved trajectory prediction systems. This solution is highly marketable, especially to air traffic control agencies, airlines, and airport authorities looking to optimize their operations.

4.2.4 Cost Analysis

(1). Development Costs.

a. Data Acquisition: Licensing or purchasing aircraft trajectory data from flight tracking sources: $500,000.

b. Model Development: Building and training the LSTM model with historical data, model fine-tuning, and testing: $1 million - $1.5 million.

c. Software Infrastructure: Developing the real-time prediction engine, integrating it with ATM systems, and deploying it: $500,000.

Total Development Cost: Approximately $2 million - $2.5 million.

(2). Operational Costs.

a. Hardware: The LSTM model requires modern GPUs or cloud-based computing for real-time operations. Server rental or hardware costs are estimated at $200,000 per year.

b. Maintenance: Updating the model with new data and re-training: $100,000 per year.

Total Yearly Operational Cost: $300,000.

4.2.5 Impact

(1). Safety Impact. 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.

(2). Economic Impact: 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. With global airline fuel costs exceeding $180 billion annually, a 1% reduction could save the industry $1.8 billion annually.

(3). Environmental Impact. More accurate trajectory predictions reduce unnecessary holding patterns and re-routing, leading to more fuel-efficient flights. This could contribute to an overall reduction in carbon emissions from aircraft.

4.3 Landing Pad Detection for eVTOL Aircraft Night Operation

4.3.1 Description

This solution addresses the challenge of automatic landing of electric Vertical Take-Off and Landing (eVTOL) aircraft under low illumination conditions, such as night operations (Shi, 2024). The proposed design incorporates optical markers on a landing pad, which are detected by an onboard camera using AI-based computer vision algorithms for real-time relative pose estimation in six degrees of freedom (6-DOF).

Problem: Night operations and low-light conditions pose challenges for accurate pose estimation in automatic landings.

Proposed Solution: The landing pad is equipped with active optical markers (light sources) and finder markers to enable accurate detection and pose estimation by the onboard camera.

The system leverages computer vision, which processes images captured by the onboard camera to recognize optical markers and estimate the aircraft's position and attitude (relative pose). The markers use blinking frequencies to uniquely identify the landing pad under low-light conditions.

4.3.2 Design

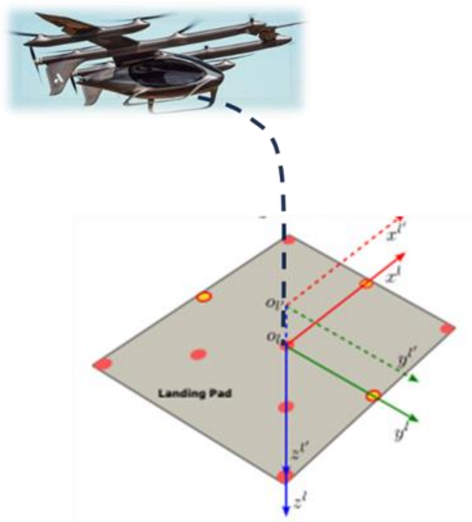

Figure 18 eVTOL Landing pad design, source: (Shi, 2024) and https://www.autoflight.com/

The system is composed of the following key components (Shi, 2024):

(1). Onboard Camera and Computer Vision System:

a. The aircraft is equipped with a high-resolution camera that captures the landing pad and markers during the descent phase.

b. Computer vision algorithms are applied to detect and identify the optical markers in real time.

c. The AI model uses image recognition techniques to process visual inputs, even in low-light conditions, leveraging the blinking light patterns emitted by the active markers.

(2). Optical Markers on Landing Pad:

a. Finder Markers: These are arranged in a structured layout on the landing pad to ensure easy detection from a distance.

b. Active Markers: Blinking light sources with different frequencies help in uniquely identifying the landing pad.

c. The arrangement of the markers is optimized for efficient and reliable detection by the onboard AI system.

(3). Pose Estimation Algorithm. A modified four-point algorithm is applied to estimate the 6-DOF pose (position and orientation) of the aircraft with respect to the landing pad.

(4). AI-Based Processing. AI algorithms, including Convolutional Neural Networks (CNNs), are used for detecting and classifying the markers. These algorithms achieve real-time tracking and updating of the aircraft's position relative to the landing pad using the visual feed.

4.3.3 Feasibility Analysis

(1). Technical Feasibility:

a. Computer Vision: The AI-based vision system is feasible given the advancement of computer vision technologies and real-time image processing.

b. Low-Light Performance: The use of active optical markers with distinct blinking frequencies ensures that the system works effectively in low-light conditions, such as nighttime operations.

(2). Regulatory Feasibility. VTOL aircraft and autonomous landing systems are subject to strict regulatory standards (e.g., FAA, EASA). Since this system primarily aids pilots with landing, regulatory approval is likely, but airworthiness certification may be required for the onboard systems. This system only provide method for landing pad detection and pose estimation, not include automatic landing flight control, therefore, this system falls into the **2A or 2B artificial intelligence level** in **Figure 15**.

(3). Market Feasibility. This system targets urban air mobility (UAM) and commercial drone markets, which are rapidly expanding. The demand for safe, reliable autonomous landing systems, especially under low-light conditions, makes this system highly marketable.

4.3.4 Cost Analysis

(1). Development Costs:

a. AI and Vision System Development: Developing and training the computer vision system to accurately detect and classify markers is estimated at $0.5 million.

b. Hardware and Sensor Costs: High-resolution cameras, processing units (GPUs), and installation on the VTOL are estimated to cost $5,000 per aircraft.

c. Optical Markers: Manufacturing the landing pad with active and finder markers would cost around $3,000 per pad.

d. Software Development and Integration: Integration of the computer vision system with the aircraft's control systems is estimated at $50,000.

(2). Installation and Operational Costs:

a. Installation of Landing Pads: Each landing pad, including infrastructure setup and markers, would cost around $6,000 - $8,000 per unit.

b. Maintenance: Periodic maintenance of optical markers and system recalibration could cost $2,000 per year per landing pad.

4.3.5 Impact

(1). Safety Impact:

a. The system significantly enhances landing safety in low-visibility conditions, such as nighttime operations or fog, by providing accurate real-time pose estimation.

b. The use of AI-based visual recognition ensures reliability and minimizes human error, making it safer for urban air mobility applications.

(2). Economic Impact:

a. Operational Efficiency: The system reduces landing errors, minimizes the need for manual intervention, and reduces the risk of accidents, potentially lowering insurance costs for operators.

b. Cost Reduction: Automated landing systems reduce the need for costly ILS (Instrument Landing Systems) or ground-based radar systems, making it a cost-effective solution for commercial VTOL applications.

(3). Scalability. The design of this system is scalable and can be deployed in urban air mobility networks, commercial drone operations, and emergency response vehicles that require autonomous or assisted landing capabilities, especially in night operations.

(4). Environmental Impact. By ensuring precise landings, the system reduces the need for multiple landing attempts, thereby saving fuel and reducing the carbon footprint of VTOL operations. The active light sources are designed to be energy-efficient, minimizing the environmental impact of continuous marker operations.

4.4 Wind Measurement for Soaring-Capable UAVs

4.4.1 Description

Dynamic soaring is a non-powered flight mode used by albatrosses to actively extract energy from the wind, enabling albatrosses to cover a large distance at low energy cost (as shown in **Figure 19**). Due to its characteristic of saving energy, dynamic soaring may be an option for long-endurance flight missions of Unmanned Aerial Vehicles (UAVs). In the ideal case, soaring vehicles can achieve long-endurance flight by extracting energy from the wind and without additional energy cost.

The energy harvesting of dynamic soaring is achieved by windward climbs and leeward descents (Sachs, 2019). For actively extracting energy from the wind, precise wind measurements are required.

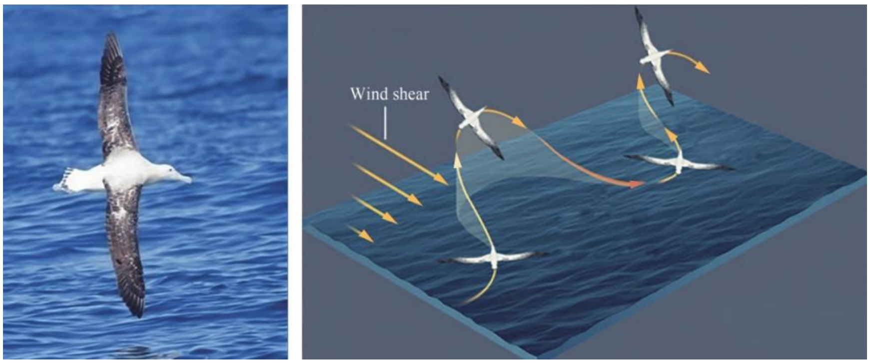

Figure 19 Dynamic soaring of albatross (Richardson, 2011)

4.4.2 Design

A variety of methods can be used for wind vector sensing on aircraft. For small soaring-capable UAVs, typical air data sensing systems are expensive when compared to the cost of small UAVs and will result in weight and drag penalties. A nosecone mounted flush air data sensing (FADS) system may be an option for use on small, low cost, soaring UAVs (Quindlen & Langelaan, 2013). The FADS system uses pressure ports located on the nose of a small sailplane to replace large, damage-prone external vanes or probes (as shown in **Figure 20**).

Single Hidden Layer (SHL) neural networks are used to determine regression models for computing airspeed, angle of attack, and angle of sideslip (Quindlen & Langelaan, 2013). The general structure of the airspeed neural network is shown in **Figure 21** and the remaining two networks for the angle of attack and the angle of sideslip follow the same architecture. The three inputs from the pressure sensors are sent to each network's input layer of N neurons. Each neuron in the input layer is connected to every neuron in the hidden layer as well. The hidden neurons are connected to a single output neuron which outputs the desired wind vector parameter. This structure results in a N x 3 weighting matrix in the input layer, a 1 x N weighting matrix in the hidden layer, a N x 1 bias vector in the input layer, and a 1 x 1 scalar bias in the hidden layer. These networks are trained using input data collected during wind tunnel testing of the aircraft and FADS configuration. The SHL-fitted models can compute realistic wind vector parameters from the measured pressure data.

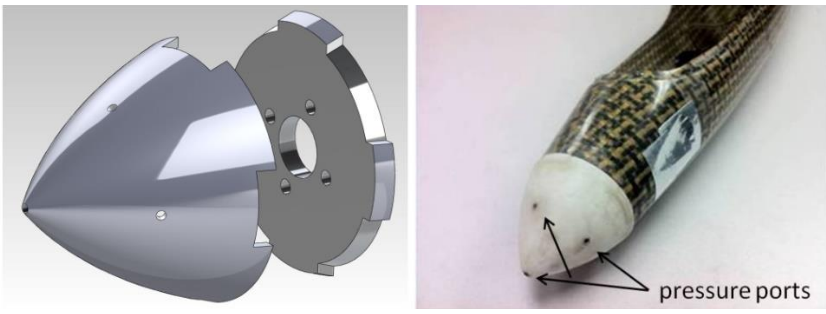

Figure 20 FADS nosecone (Quindlen & Langelaan, 2013)

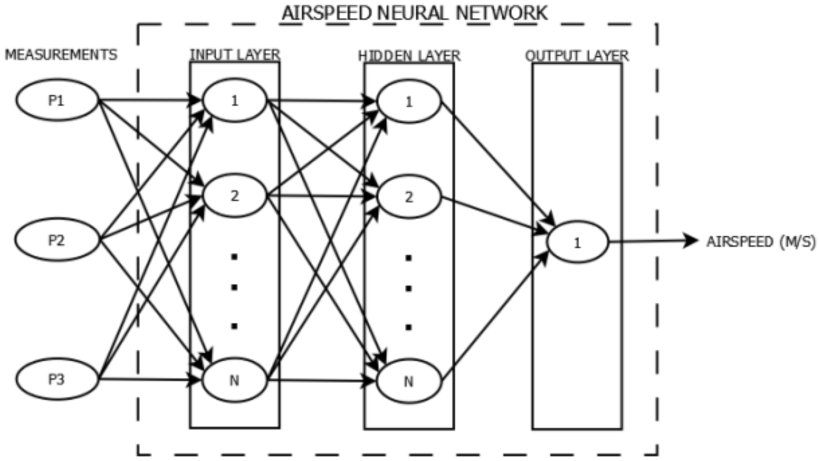

Figure 21 The general structure of the airspeed neural network (Quindlen & Langelaan, 2013)

4.4.3 Feasibility Analysis

(1). Technical Feasibility:

a. Dynamic Soaring: Previous studies on dynamic soaring have proved that energy harvesting from the wind can be achieved by windward climbs and leeward descents in wind shear. In (Bronz et al.), flight test results revealed that, without any complex trajectories, on average, the glider can extract close to 60% of its required power from dynamic soaring, which indicates that the application of dynamic soaring for UAVs has a promising future.

b. Neural Network Based FADS System: There has been extensive research on the FADS system for aircraft and spacecraft. Flight tests on manned aircraft like the F-14 and KC-135 demonstrate the feasibility of the FADS approach even during maneuvering flight. Neural networks have been specifically chosen for the FADS system because they can handle large sets of flight test data without explicit knowledge of the airflow model over the nosecone. Previous studies in neural network based FADS systems have proven its accuracy and usefulness.

(2). Regulatory Feasibility.

Application of AI-based systems in aviation is subject to rigorous regulatory approval. Since the neural network based FADS system serves as an tool sensing information for aircraft control (not directly controlling aircraft), the regulatory barriers are lower. Actually, this system falls into the **1A or 1B artificial intelligence level** in **Figure 15**.

(3). Market Feasibility.

Dynamic soaring is a flight technique that enables flying objects to actively extract energy from the wind. Based on this, UAVs can fly for extended range at low energy cost, which reduces fuel consumption. This solution enables soaring UAVs to achieve long-endurance flight tasks in the fields of searching and environmental monitoring. Thus, it is highly marketable.

4.4.4 Cost Analysis

Compared with typical air data sensing systems which are expensive for small UAVs, the AI-based nosecone mounted flush air data sensing (FADS) system is at low cost. Thus, it is a feasible option for small soaring UAVs.

4.4.5 Impact

(1). Safety impact. More precise wind measurement enables better flight control for UAVs.

(2). Economic impact. More efficient energy harvesting from the wind enables soaring UAVs to achieve low fuel consumption flight. Thus, it is a cost-effective solution for many long-endurance flight tasks, such as searching and environmental monitoring, etc.

(3). Environmental impact. Wind energy is a kind of green energy. Soaring UAVs can exploit wind energy to extend the endurance, which may reduce fuel consumption and emissions significantly. This solution is in line with the green aviation.

4.5 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 friendly.

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 impact is introduced. Not only the carbon emission of aviation, its non-CO_2 effect, including NO_x and SO_x emissions, noise pollution, and contrail formation should be considered as well. Although aviation emissions are a relatively small proportion compared to other sectors, the emissions do not occur at the ground level but rather in the high-altitude atmosphere, leading to significant impact on climate change. Based on the overview of aviation's climate impact, we proposed the definition of green aviation, with all the above effects of aviation taken into account. Then we summarize the crucial issues faced in making aviation green into four aspects, termed design tech, sustainable fuels, management and awareness. Examples are given to show that AI enables safer, more economical, and greener flight. Based on the analysis, we believe that AI solutions for green aviation have a promising future.

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