AI and intelligent automation in aerospace applications

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ABSTRACT OF THE
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The current air traffic control (ATC) system is designed for heavy human controller reliance. While air travel demands are climbing rapidly, limitations in both ATC capacity and supported technologies would sooner or later pose an enormous problem in excessive controllers' workload. Exploiting AI and intelligent automation is an approach to reduce the workload pressure but still maintain or even increase the airspace's safety level. In this thesis, problems and benefits of controlling air traffic with a higher automation level are analyzed to evaluate the automatization idea's feasibility. Up-to-date developed and developing automated systems to avoid aerospace collisions, such as TCAS and ASAS, are also reviewed to provide a general sight of technology applications at present or in the near future. Finally, the thesis presents several directions to automatically solve existing air traffic problems using AI techniques in recent studies.

Keywords: air traffic control, air traffic management, artificial intelligent, human-centered automation, conflict resolution

Preface

I want to thank Professor Jussi Rintanen for his good guidance.

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Abbreviations

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ATC	air traffic control
ATCO	air traffic controller
ATM	air traffic management
TCAS	traffic alert and collision avoidance system
TA	traffic advisory
RA	resolution advisory
ASAS	airborne separation assurance system
ADS-B	automatic dependent surveillance-broadcast
FF	free flight
DP	dynamic programming
ML	machine learning
DL	deep learning

1 Introduction

Given the global Gross domestic product (GDP) growth on a wave of the digital economy and the rapid pace of globalization trends, the air transport industry is calling attention to a substantial rise in air travel demands. In 2019, the Bureau of Transportation Statistics informed that the annual worldwide revenue passenger miles (RPM) had amounted to $1500 billion [1], with a growth rate of over 7.5% per year. To compare with the corresponding increase in the available seat miles (ASM), an airline can divide RPM by ASM to result in the load factor (a low load factor means many seats are still vacant), which has risen from 66% to 84% (1995 – 2019) for the entire industry [2]. This growth is going against both unchanged airspace capacity and limitations in technologies. Sooner or later, the limited facility of the current system, which is encountering regular delays, cancelations, and runway congestions, will most likely be under tremendous pressure to keep up with the number of passengers due to multiple factors, including the following [3].

Firstly, there is the possibility of inefficient airspace utilization. The majority of the flights are following immutable navigation, which is not the optimal pathways in certain circumstances. This deficiency of flexibility limits the airplanes, for example, to utilize benefits from supportive tailwinds.

Secondly, obsolete technologies also exacerbate pressure. The United States (US) air control system has not gone through any considerable shifts for 30 years, especially the computer display technology that might fail to keep the operators properly informed within three to eight seconds [5]. Considering that air travel safety depends crucially on this system, there could be a severe aviation accident every seven to ten days [5].

Finally, and most importantly, heavy Air Traffic Control (ATC) workload should be considered. ATC generally conducts partitions among aircraft from different airports to avoid collisions. Besides, ATC also plays the role of navigators and advisors for pilots when dreadful weather arises. As the current system is designed so that the human factor is irreplaceable, multiple aircraft's coordination to avoid collisions is significantly weakened without ATC services. Therefore, the ATC workload is a relative measure of travelers' safety affairs: the growth of one means reducing the other. The current ATC system requires controllers to perform quite many manual operations. These operations are aided by many technologies that, unfortunately, have not exploited enough the potential capability of many modern techniques. At present, the majority of complex scenarios are often handled by merely human control.

Recently, Artificial Intelligent (AI) has successfully handled many tasks that require human cognitive intelligence, such as face recognition, lung cancer diagnoses, image segmentation, or virtual assistance. Many corporations and productions have benefited from these achievements. As a result, AI and other intelligent automation advancements are highly expected to become a breakthrough for the aviation industry because modern supporting tools would minimize controllers' workload. At the same time, the safety level is maintained or even increased.

Therefore, this thesis aims to propose the guidelines outlining AI and intelligent automation applications in aerospace in three sections. First, it presents a set of advantages and disadvantages of automatizing aviation control and a suggestion to maintain the human-centered automation concept. Second, it identifies developed and developing intelligent automation that helps resolve conflict. Finally, it suggests imminent studies solving air traffic management problems with corresponding AI techniques.

2 Methodology and structure

This thesis provides a general literature review of the study into AI in aviation. The study was conducted by exploring the background information aerospace industry's current situation and possible approaches for technology applications. Most of the data sources are from digital scholarly papers, journals, or books. These sources are discovered through online pages that provide access to technical or scientific research (such as ResearchGate, IEEExplore, ScienceDirect), website of top-notch technology universities (such as Stanford, MIT). For the sake of credibility, the thesis only referred to sources cited at least some dozens of times. Moreover, several documents from leading organizations (such as NASA or ICAO) in the industry were used as a starting point to acknowledge basic concepts.

The thesis contains four sections after the introduction and this section. Section three provides necessary background information about Air Traffic Management and AI technologies. Next, the relationship between humans and machines is modified, and human-centered automation maintenance is recommended in section four. Section five discusses the automation applications that are globally utilized and developed. The sixth chapter presents several potential directions to boost the industry with AI, including weather forecasts, AI search applications, and other ideas. The last chapter concludes and summarizes the whole study.

3 Background

The following subsections will briefly introduce some background information about Air Traffic Management and Artificial Intelligent. Some information is fundamental knowledge necessary for further discussion in successive sections; some are points of view to define such an abstract entity as “intelligent”.

3.1 Air Traffic Management

Air Traffic Management (ATM) is a technical work program that offers secure, organized, economic, and efficient aircraft operations. The system comprises several segments [7] (see Figure 1), including Air Traffic Control (ATC) and Air Traffic Flow Management (ATFM). While ATC continuously maintains separation assurance among aircraft, ATFM sets up the optimization of traffic flows by ensuring maximum ATC capacity and enabling smooth movement in the airspace [7]. Currently administered by the International Civil Aviation Organization (ICAO), this program enables the safe and reliable operation of more than 100,000 daily air flights in the global aviation network.

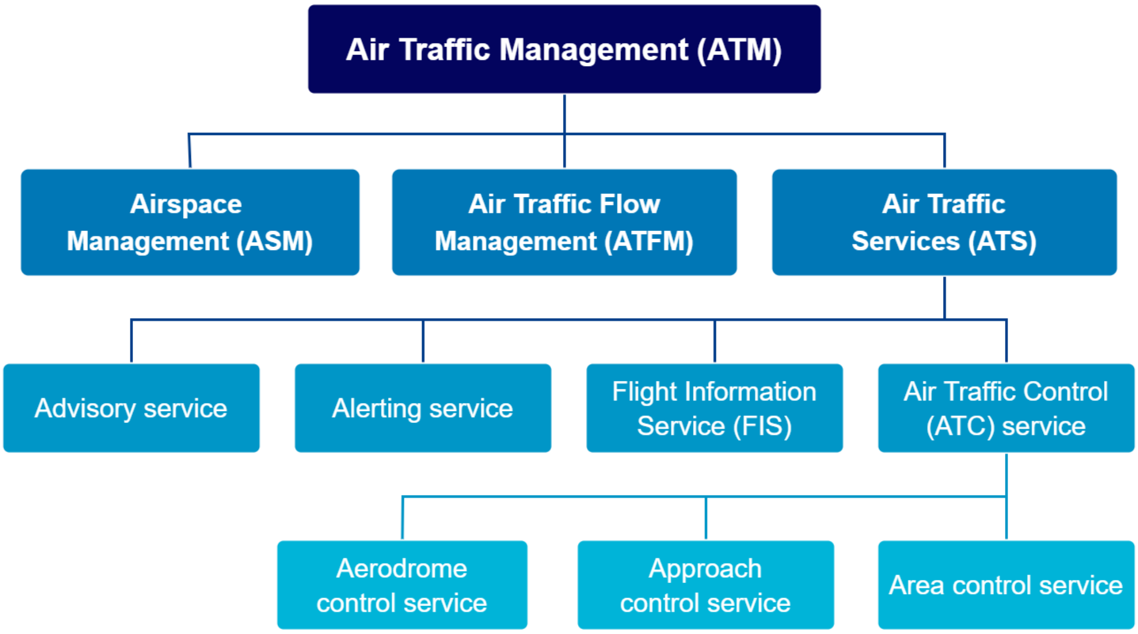

Figure 1: The structure of ATM

In his study of the US aircraft/airspace system, [4] indicated that the Federal Aviation Administration (FAA) was founded in 1958 as the federal agency with a separating authority for civilian and military aircraft within controlled airspace. The FAA has distributed US airspace into 21 air route traffic control centers (ARTCCs) to facilitate the function. Each one supervises an area with the ultimate mission to separate aircraft routes among airports. When a specific region is congested, local ATC offices such as TRACON or RAPCON receive a Letters of Agreement (LOA) from ARTCC to transfer separation responsibilities. An ARTCC is also subdivided into 35 sectors, and these are fundamental units in the US ATM system [4].

[4] also found that, in general, one to three controllers units in a sector are responsible for splitting aircraft within the allocated air space. Three types of controllers [4] are accordingly classified into Flight data controls, Radar controllers, Radar associate / Non-radar controllers. Flight data controls send data to other sectors and help other controllers who directly execute separations. The primary roles of radar controllers are to separate aircraft (i.e., ensure at least a certain minimum amount of space (9 - 18km) around an aircraft) with a radar monitor and manage the tasks in the LOA from an ARTCC. Radar associate / Non-radar controller helps radar controllers when other aircraft are too low or too far away for radar to identity.

In Europe, there is also an intergovernmental organization responsible for separation duty: the European Organisation for the Safety of Air Navigation (EUROCONTROL). Established in 1963, EUROCONTROL currently has 41 European member states with more than 1800 officers and four headquarters in Belgium, France, Luxembourg, and the Netherlands. It provides a variety of cross-border air navigation services in the upper airspace (from FL 245 to FL 660 or 24,500 ft to 66,000 ft), which is operated by the Maastricht Upper Area Control Centre (MUAC) [30]. With professional ATCOs, engineers, and specialists from 30 nations, MUAC could control 1.9 million flights, and 99% of them arrived on time in 2019 [30].

It is also essential to distinguish two kinds of ATC operations when contemplating AI applications: tactical and strategic ATM. Tactical ATM focuses on ensuring a number of aircraft to be separated and to move across the airspace orderly. Strategic ATM is responsible for aggregate traffic flows and adequate utilization of airspace resources with specific demand and capacity [31].

For convenience, the thesis refers throughout to controlled airspace as “the airspace”. Controlled airspace indicates airspace with fixed dimensions that receive ATC services. It contains airways connecting major cities and busy airports with each other. In addition, the thesis only considers “flights” following Instrument Flight Rules (IFR). IFR are rules for aircraft with suitable instruments and navigation equipment to be flown under certain conditions expressed in terms of visibility or distance from clouds and ceiling called Instrument meteorological conditions. IFR flights penetrating clouds or reduced visibility areas are still aided by ATC to remain separated from other IFR aircraft.

3.2 About AI technologies

Unsurprisingly, there are no widely agreed definitions of AI as it is difficult to comprehend “intelligence” entities. Still, it should be noted that fixing a precise description of AI does not allow it to shine brightly and expand as rapidly as it does today. Nowadays, AI has become a hype: Many startups, innovations, or ideas exploiting AI to change the approaching way toward many industries. Recently, the term commonly implies implementations that are not consistent with traditional problem-solving techniques. For people who still find a definition necessary, the contribution of Nils J. Nilsson from Stanford University could be referred:

> Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment [8].

Nowadays, many people regard AI as a machine that can think, act, or feel with a system that functions as humans' brains. However, from this viewpoint, AI is acknowledged in a more general and wider way. Classifying AI is a case of machines being recognized to *function appropriately* and with *foresight* in a particular *environment*. This character is argued to require many capabilities: scale, speed, autonomy, and generality, distinguishing a simple calculator and human brain [9]. Besides, the report [9] also supports Nilsson's point of view by pointing out that the definition can assess other forms of intelligence: humans, animals, and some machines — speech recognition program, smartphone, and thermostats.

Furthermore, the leading textbook "Artificial Intelligence: A modern approach" [10] gathered several concepts in earlier years and divided them into four categories: *Thinking humanly*, *Thinking rationally*, *Acting humanly*, and *Acting rationally* (see Table 1). The authors Russel and Norvig also suggested the superiority of *Acting rationally* based on the precise definition and the total generality of rationality. Through this concept, the intelligent *agents* (objects that observe and execute) perform to maximize the opportunity to achieve objectives. In aerospace applications, human vulnerability currently requires AI precision from the "rationality", rather than human behavior - more likely the adaptability in a particular environment - which is complicated and takes time to perfect. With the same arguments with Nilsson [8], [10] also insisted rationality — never make mistakes — is only possible in a specific environment. In complicated environments, computational demands are excessively high.

Many people view AI as a kind of software or algorithm; however, AI is not merely an input-algorithm-output pattern. Usually, with particular input and output, a proper algorithm[1] has a certain number of steps with linear or polynomial complexity (in terms of the size of the input). The "algorithm" in AI, however, is much more complicated and flexible in computational time and number of iterations.

In [10], the authors also classify AI into several particular categories: Problem-solving, Knowledge and reasoning, Acting logically, Uncertain knowledge and reasoning, Learning, and Communicating, perceiving, and acting. Within the research scope, the following bullets will cover Problem-solving, Uncertain knowledge and reasoning, and Learning, and discuss their connections to aerospace problems.

- Problem-solving: Seeking a sequence of actions to goal states. This is acquired by formulating the relationship between one and successive states, yielding a connection (a reward, a cost). Problem-solving is often referred to as State-space search, and so as in this thesis. Some studies applied this technique for flight plans, for example, to optimize the trajectory.

- Uncertain knowledge and reasoning: An agent might not be able to observe the situation completely. The best solution is non-deterministic and retrieved with

[1] here we do not mention such "blind" algorithms such as Greedy or Brute Force

Systems that think like humans	Systems that think rationally
"The exciting new effort to make computers think . . . machines with minds, in the full and literal sense" (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning..." (Bellman, 1978)	"The study of mental faculties through the use of computational models" (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act" (Winston, 1992)
Systems that act like humans	**Systems that act rationally**
"The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better" (Rich and Knight, 1991)	"A field of study that seeks to explain and emulate intelligent behavior in terms of computational processes" (Schalkoff, 1990) "The branch of computer science that is concerned with the automation of intelligent behavior" (Luger and Stubblefield, 1993)

Table 1: Definitions of AI, organized into four categories [10]

a certain probability. Accordingly, some problems facing uncertainty including flight plan optimization or collision avoidance might be benefited

- Learning: An agent performs more accurately as exposing to the data. Nowadays, learning is rarely accessible in current automation systems, as most of them are complex mathematical structures looking for a deterministic solution. In the aerospace industry, future AI with self-taught and self-evolved capability will make the automated system more trustworthy and helpful for the controllers.

Artificial Intelligent - Machine Learning - Deep Leaning

Many different terms, such as AI, ML, and DL, are often mixed, as they overlap. AI is not a single entity; it combines various technologies, including ML and DL. ML is an algorithm that learns rules from data and improves performance by minimizing a cost function. DL is an ML in a multilayer-based structure, particularly useful when the dataset size is vast.

Being treated as artificial neural networks, DL train the model to become "intelligent" by interacting computational units with each other as if new connections between neurons as learning. A basic neural network, for example, multi-layer perceptrons (MLP), has an input layer, several hidden layers, an output layer. Each layer has several neurons that link to neurons in the next layers. A specific loss function is defined and reduced after each iteration with a particular step size[2]. In other words, the model is updated to fit the training dataset better. The trained model is tested if it predicts well the test data set. Two common results usually happen and require additional tuning: over-fitting and under-fitting. The latter occurs when the model is not sufficiently complex enough to predict the target variable through state variables. The former means the model is overly complicated and does not reflect the data's general trend. As a result, the model performs too well with known data (training dataset) but poorly with unseen data (test set).

State-space search

Having a set of N variables represent solutions for a problem, the task of seeking for these solutions (or determining that no solutions exist) can be viewed as a search in N-dimensional space or simplified to a *search space*. Moreover, some critical decision-making problems in AI might be minimized to searching a path in a graph. Given search spaces, the state-space approach is one of the first choices for such tasks. The state-space algorithms require an initial state and various operators that can be applied to reach a set of new states (successor states) called a path. Here, we denote $G = (V, E)$, where V is a set of elements called vertices or nodes, and E is a set of connection between two distinct vertices called arcs or edges. To represent these problems as graphs, V represents the states (of a process, or a match), E represents different actions (to move from a state to another one), and paths in the graph represent sequences of actions. We are usually interested in paths beginning from an initial state and reaching a goal state, by generating a new state and evaluating if it is the desired goal state. Many famous AI search algorithms can be considered for aerospace applications, including the following:

- Depth-first search (DFS): Find the next state (node) from the deepest state in a single path, establishing and expanding a stack (last in first out) of nodes. Once the stack is popped, the top element is mark visited. The algorithm thereby expands a path until a dead-end (a node has no unvisited successor states) or goal node has been reached.

- Breath-first search (DFS): Construct successor states as a tree structure, and the algorithm visits the node closest to the root first, establishing a queue (first in first out) of nodes.

- Genetic algorithms [24]: An algorithm generates optimal solutions to optimization and search problems inspired by the natural selection process by Charles Darwin. In each iteration, the fitness (usually an objective function) of each individual in a population is calculated. Then we select two random individuals that are likely the fittest one to crossover create two off-springs and mutate them to create a new "generation."

[2] also called learning rate

- Dijkstra algorithm: An algorithm that seeks the shortest path between 2 nodes, providing that the cost of edges (actions) is non-negative. Denotes $d[u]$ is the distance from the start node s. Like other shortest-path search algorithms (such as A*, Ford-Bellman or Floyd), the initiate state of the graph is

  $$d(s) = 0$$

  and

  $$d(u) = +\infty, \forall u \in V \setminus \{s\}$$

  . In each iteration, visit an unvisited node u with smallest $d(u)$ (e.g. using priority queue), and modify

  $$d[v] = min(d(v), d(u) + c(u, v)), \forall v \in V$$

  , where $c(u, v)$ is the cost of action moving from node u to v.

- A* search: An algorithm estimate the cost of a path containing node u by a heuristic function: $f(u) = g(u) + h(u)$, where $g(u)$ is the known path cost from the start node to u, and $h(u)$ is approximated cost of path from u to the goal node. Hence, the outcome is also the optimal solution, i.e., the shortest path in terms of the total cost of actions. The detailed formulation of the A* algorithm is quite similar to the Dijkstra algorithm.

Dynamic Programming

As seen from the above examples of A* and Dijkstra, there are several goal states or several paths to a goal state in some cases. The job turns into finding the shortest path or closest goal nodes (by going through the corresponding path). This then becomes (combinatorial) optimization problem, that we can refer to many classic ones, such as Travelling Salesman Problem (TSP) or Knapsack problem. These problems can be solved by Dynamic Programming (DP). DP is a generic algorithm design technique that follows the "Divide and Conquer" style: The optimal solution of a problem is retrieved from the optimal solution corresponding sub-problem. Note that DP is much faster (and more memory-saving) than recursion due to sub-problem solution reusing capability.

Markov Decision Processes

In AI, many decision-making problems might utilize Search algorithms with the capability to find optimal solutions. However, this assumes certain conditions are satisfied, such as a unique known initial state, or objective is reaching a designated goal state. In many cases, these assumptions do not hold. Uncertainty can be (1) taking actions only produce a reward or a cost instead of heading to a goal state, or (2) the initial state or successor states are (partially) unknown. From there, we often use MDP for (1) and POMDP when both (1) and (2) happen.

4 Human - Machine relationship in air traffic

Automation is allocated responsibility to make up for human deficiencies and boost human resources quality and utilization. However, there exist many challenges that humans should prepare to tackle. On the other hand, with an accurate database and solid supports, practitioners' problem-solving capabilities might outweigh computers where certain challenges need versatility, imagination, and persuasion. In particular, the following subsections present the benefits and drawbacks of machines and suggest that human-centered automation should be designed for aviation applications.

4.1 Automation strength and human weakness

In many industries, including aeronautical applications, the digital revolution's transition has been a prevailing trend to evolve. While we are aware that automation might negatively affect workers' values, the scheme is expected to promote secure and effective operation in the aviation system by air traffic controllers and pilots. Therefore, this subsection concentrates on modifying automation strengths and the ability to compensate for human weaknesses.

It is acknowledged that collaborating with qualified specialists was the best way to address severe problems. Admittedly, they have higher expertise and capacity than ordinary people, but many factors can affect their efficiency in decision-making and consistency on a large scale. Experts in particular and humans in general are prone to perceptual biases that genuinely influence the outcome. For instance, in 2012, a military transport flight from Norway to Sweden operated by Royal Norwegian Air Force cause a fatal accident due to inadequate ATC procedure and erroneous cockpit action [11]. Swedish ATC had authorized the aircraft to fly outside the controlled airspace and below nearby terrain, while the pilots had disabled the terrain warning system. Accordingly, we can see that human weakness is also the machine's strength: they have no feelings. Instead, they function in a computerized, hierarchical manner with absolute discipline, making them far less likely to make errors. Incorporating the AI can eliminate prejudice, faulty inference, the will to ignore complexity and conflict, and the dependence of feelings and motivations.

Many people claim that AI technology is vitiating the productivity of humans. Professor Jeffrey Frankel from Harvard University contended that the advantages of quantity, productivity, and performance are partially balanced by the time people spend learning it [12]. However, the value of AI is distinct from other technologies. AI offers decision-making methods with in-depth analytics by providing guidance and recommendation that are precisely audited (Explainable AI). This attribute saves learning time for the operators. AI can also be used for (mass) automation of endeavors, especially repetitive calculations. This grants time and energy to think creatively about innovations instead of recursive jobs. The preceding argument's evidence can be seen in a report by Michael Chui, James Manyika, and Mehdi Miremadi:

> As roles and processes get redefined, the economic benefits of automation will extend far beyond labor savings. Particularly in the highest-paid

> occupations, machines can augment human capabilities to a high degree, and amplify the value of expertise by increasing an individual's work capacity and freeing the employee to focus on higher-value work [13].

Especially in ATC, people usually treat performance quality over the load for each controller. With the out-performance in arithmetic calculation and multi-tasking, machines in general and AI in particular not only ease the pressure of intensive workload but also offer controllers chances to direct their attention to more complicated tasks. Controllers can focus on flights penetrating adverse weather area or suffering emergencies, or overcrowded airports during rush hours. Rather than an individual working on specific jobs, automation enables multi-tasking by conducting multiple activities that do not require complicated skills. As a result, a sector can be reduced from three to one controller. In cockpits, AI reduces the complexity of manipulations, which means gaining security. When inadvertent incidents - such as sudden weather changes, engine malfunctions, or conflicts with birds - occur, pilots have better chances of coping with the situations when their time is originally not much to waste at all. AI is also essential to ensure enhanced routing, and hopefully, substitute pilots for driving the aircraft automatically in the future.

4.2 Automation issues

The pressure for technologies to boost the ATC system is enormous due to airlines' desire to improve flight performance and reduce cost. However, there remain some challenges to turn this desire into a reality.

Firstly, automation will undoubtedly increase the airspace's complexity due to new directing aircraft methods (e.g., Free Flight concept), leading to significant flow management changes from standard flight routes [32]. For example, the future ATC system will gradually move the focus from tactical decision-making to strategic control of airflow [33]. Therefore, controller selection also prioritizes strategic planning skills.

Besides, automation is considered as a cause to decrease situational awareness in aviation [34]. The severity and frequency of the problem will increase when automation intervenes deeper in ATC operations and cockpits. However, the claim might need to be reconsidered in some specific contexts. For example, ASAS technologies, which we will discuss further below, promote a high level of situation awareness. This benefits the cooperation between ATCOs and pilots thanks to higher joint air traffic awareness, so necessary preparation against potential tragedies is conducted on time.

Moreover, manual techniques of controllers will gradually degrade because of regular practice shortage and forgetfulness [32]. With the current ATM automation system, skill loss is not likely to negatively influence system performance. While the capability of trajectories extrapolating might be faded, controllers may profit in handling conflict-based problems. For example, when predictive modeling is automatic, they would have a better overview of potential conflicts [32]. However, it is necessary to worry about automation's safety issue in the future when it comes to decision-making and active control operations [32].

On the other hand, the controllers require training in new skills to operate new technologies, and inadequate knowledge might lead to performance failure. This also includes pilots as they are exposed to information from automated systems, despite the convenience and precision of autopilot systems. In [33], ATC training is described as playing the "catch-up" role when the job has depended on equipment to result in ideal solutions. The authors also mentioned the problem of a significant difference in resource investment between technology development and human resources, which partially exacerbates "hardware-oriented bias". Consequently, many challenges were posed in order to improve ATC training: Absence of training when necessary, poor staffing recruitment and allocation, poor teaching skills of the instructors.

4.3 Human-centered automation

Despite the explosive growth of machines, it is believed that technology opportunities should not directly lead to automation employment [32]. Only when the technology has the potential to serve the controllers' demand or the system improvement should it be taken into account. We are only (and should remain) using machines as an extension of human powers, leveraging them with higher strength, speed, consistency, and cost-efficiency. Therefore, the thesis highly contends that the theory of human-centered automation will lead the aerospace industry in the future, characterized as follows [32]:

> The choice of what to automate should be guided by the need to compensate for human vulnerabilities and to exploit human strengths. The development of the automated tools should proceed with the active involvement of both users and trained human factors practitioners. The evaluation of such tools should be carried out with human-in-the-loop simulation and careful experimental design. The introduction of these tools into the workplace should proceed gradually, with adequate attention given to user training, to facility differences, and to user requirements. The operational experience from initial introduction should be very carefully monitored, with mechanisms in place to respond rapidly to the lessons learned from the experiences.

This concept of partially automated systems emphasizes the human roles in the aviation environment where most discrete functions will be automated: the commander. Instead of involving in every manual operation or letting the machines take the lead, humans work as supervisors and intervenes when exceptions happen. The reason is that even in an ideal condition, machines can not fully control the whole system, especially for vastly dynamic and unpredictable categories such as the weather system [35]. Also, it is unavoidable that automation can always fail unexpectedly. While absolute reliability is required for systems in such a sensitive field as aviation, even minor bugs or process anomalies will cause different severe problems. These problems need real-time solutions, which is hard to model for automation [35].

In contrast, humans' unique attributes overshadow machines in more complex situations, including the following examples [35]. First, they can separate and detect clear signals out of noises in an excellent way. Second, they can make decisions with uncertain, erroneous, and inconsistent information. This attribute is indispensable, especially when an issue happens unpredictably or can not be visualized so that the automated system does not receive a proper input. Humans can also handle tasks that require creativity, abstraction, negotiation, and collaboration. Hence, humans can control the general situation with their flexibility, which makes the aeronautic system robust. Besides, humans should be responsible for their own lives, especially in such a sensitive industry as aviation that a minor failure might cause many people's deaths. It is unacceptable to explain an accident caused by machines' failure perfunctorily.

From some discussion above, it is self-evident to employ the human the central position in the aerospace system. Thereby, automation only assists specific human demands, and human also needs to be well-trained enough to manage, supervise, scrutinize automation. Naturally, automation would empower human strengths, and their unique attributes also fill the cavities in automated systems. To guarantee the human's position above the machine, the following guidelines should comply with [35]:

1. The human must be the commander.
2. To command effectively, the human must remain involved: No fully automated system, operators must have active control, partially or completely.
3. To be involved, the human must be informed: To maintain the involvement, operators must consistently keep up with data flows.
4. Functions can be automated only if necessary.
5. The human must understand provided automation.
6. As a result, automated must be predictable.
7. The automation must also monitor human operators: Human might also have failures in performance and, therefore, requires monitoring.
8. Each element must know others' intent.

This concept has been accepted in many leading organizations in the aviation industry. To accomplish the goal, [32] also recommended that the FAA ensures the resources for well-trained practitioners and specialists. Both of them should be involved in the early phase to determine the design of the suggested automatons. Finally, the automation designers should consider potential interactions between developing and existing automation, facilitating the operators to combine them and promote the new automation capabilities. To conclude, the human-centered principle is recommended to be the direction and standard for any future automation products in the aviation industry.

5 Current automation in air traffic

Nowadays, most of the operations in ATC are carried on manually. This human-based environment ensures the credibility of provided clearances. However, controllers might have to face issues about workload and productivity without automation assistance. Today, these automation systems already increase airborne safety, although they are expected to be race faster against air travel demands. In this section, some global developed and developing automated systems will be introduced.

Conflict resolution

Conflict in aerospace is defined as a situation when an aircraft trespasses the region that infringes on the minimum separation condition. The minimum separation would rely on several factors, such as the flight phases, the related trajectories, and the airspace regulations. Today's typical ATC separation minima is 5 Nautical Miles (NM) (1NM = 1852m $\approx$ 1.15 miles) and 1000 ft (300m) vertically for IFR flights below Flight Level (FL) 290 and 2000 ft (600m) for ones above FL290 [28]. The designated range is often referred to as the *separation bubble* for a protected area surrounding an aircraft, and is determined by the time of dispute (TTC), not the distance [20].

To confront this collision dilemma, solutions are usually divided into two sections: avoidance and resolution. To avoid, it is necessary to have technologies better than current manual separation from the ATCOs. To resolve, an automated system integrating on aircraft is required to help pilots quickly make a decision. Therefore, the thesis proposes two corresponding typical systems that have been being developed by many leading worldwide organizations: TCAS and ASAS.

5.1 TCAS - Traffic Alert and Collision Avoidance System

The Federal Aviation Administration (FAA) and civil aviation authority (CAA) of several nations have, after many years, developed comprehensive research called Traffic Alert and Collision Avoidance System (TCAS - pronounced tee-kas) to reduce the possibility of collision between aircraft during the en-route phase. This system is also regarded as the Airborne Collision Avoidance System (ACAS) on an international scale [14]. TCAS or ACAS is an aerial system exploited to raise the visibility of surrounding airspace and infrastructure as a final response against aeronautical conflicts. It controls the adjacent area within a certain radius of an aircraft and supplies information to the *transponder* [14]. TCAS performs autonomously without any relations to ground-based facilities to offer pilots instructions about how a possible crash should be stopped. In other words, TCAS is an on-board aircraft dispute identification and settlement program that is used in most IFR flights. Currently, TCAS is the most common airborne safety net technology for conflict prevention and is mandated worldwide, such as in EU or US flights (see Table 2).

As aforementioned, the TCAS system depends heavily on the transponder to perform appropriately. It is noteworthy that the surveillance system of TCAS does not offer any protection against aircraft without a running transponder [14]. ICAO defined a transponder as “a receiver/transmitter which will generate a reply signal upon proper interrogation; the interrogation and reply being on different frequencies.” Note that “interrogation” here means the system interrogates “targets“ and listen for their replies. In other words, this can be seen as one-to-one interactions. Transponders were initially used to locate friendly aircraft with military authority, accompanied by extensive transponders’ usage for civil purposes nowadays. Designating a unique transponder code is also a standard procedure for pilots in controlled airspace for the Air Traffic Controllers (ATCO) to quickly recognize a particular aircraft utilizing the Secondary Surveillance Radar (SSR) full radar screen. In ATM, in addition to aircraft identification, the transponder is also a component of many other ATC mechanisms and safety measures. It is involved in diverse modes equipped in commercial flights (see Table 2).

<table>
<tr><th>Equipment (Target aircraft)</th><th>Capability</th><th>Interrogator aircraft with TCAS II</th><th></th><th></th></tr>
<tr><td>Mode A</td><td>Just send an identifying code</td><td>Does not trace the target</td><td></td><td></td></tr>
<tr><td>Mode C</td><td>Allow the ATCO to instantly see the aircraft altitude and flight level</td><td>Receives Traffic Advisory (TA) and vertical Resolution Advisory (RA)</td><td rowspan="2">Mandatory in busy controlled airspace area</td><td></td></tr>
<tr><td>Mode S</td><td>Capable of selected altitude and also allow data exchange</td><td>Receives TA and vertical RA</td><td>Mandatory for EU Instrument Flight Rule (IFR) flights</td></tr>
<tr><td>TCAS I</td><td></td><td>Receives TA and vertical RA</td><td></td><td>Mandatory for US aircraft 10 - 31 seats</td></tr>
<tr><td>TCAS II</td><td></td><td>Receives TA and coordinated vertical RA</td><td></td><td>Mandatory for US flight >30 seats, EU flight >19 seats</td></tr>
</table>

Table 2: Different modes of transponder and interaction between target aircraft and interrogator aircraft with corresponding modes

TCAS has grown through two commercial versions, corresponding to two systematic complexity stages: TCAS I and TCAS II. TCAS I requires an integral transponder to react to modes A, C, and S [15]. In conjunction with visual and audio updates, TCAS I offers Traffic Advisory (TA) to help pilots detect unexpected intruders in closeby areas. If a TA is released, the pilot shall be informed, but the appropriate collision avoidance protocol must be defined independently. TCAS I is applied in general aviation and especially compulsory in aircraft from 10 to 31 seats. The second-generation technology, TCAS II, offers detailed guidance about mid-air collision prevention methods **in the vertical direction**. These guides are called Resolution Advisories (RAs), instructing guiding the pilots to drop, ascend, or adjust the current vertical gap from an intruder aircraft. In addition to TA that provides a visual scan for intruders aircraft like TCAS I, a RA is delivered when an intruder trespasses a certain level of proximity (see Figure 2). The estimated generation time for a TA is 40 seconds (maximum 48 seconds) when the distance between the Closest Point of Approach (CPA) and the intruder aircraft reaches 3.3 NM. For an RA, the estimated time is 25 seconds (maximum 35 seconds), and the distance is 2.1NM. TCAS II systems can interact and ensure the consistency of separation is maximized by the RA offered for each aircraft [16]. If the target aircraft is also equipped with TCAS II, the two TCAS integrate RAs by Mode S connection, resulting in complementary RAs [14]. For example, aircraft A is below, and in RA protected volume of aircraft B, the complementary RA should advise aircraft A not to ascend faster than a provided speed and aircraft B to maintain the altitude or at least not to descend faster than another provided speed.

The future generation of TCAS is TCAS X, which has been researched formally since 2009 by the FAA TCAS Program Office [41]. An outstanding advantage of TCAS X over TCAS II is the capability to deal with uncertainty in the aircraft's current state, including aircraft variation and corresponding pilot responses. The airborne system generates a new state-space every second. Utilizing MDP's solution, the system finds an optimal action with the lowest expected cost from a numeric lookup table which is the result of a probabilistic model and an optimization process using dynamic programming [41]. The selected action then becomes the basis for warning the flight crews. The advantages of decision-making at a high level with uncertainty technique increased the robustness substantially. Compared to TCAS II, TCAS X could have a lower risk rate by 58.9% [41]. More importantly, TCAS X keeps the same display and announcement ways so that pilots can manage to exploit immediately without further transition to new system. Therefore, it is expected that TCAS X eventually replace TCAS II.

5.2 ASAS - Airborne Separation Assurance System & Free Flight concept

Firstly, ASAS systems utilize a surveillance technique called Automatic Dependent Surveillance-Broadcast (ADS-B). ICAO defined it as "a means by which aircraft, aerodrome vehicles and other objects can automatically transmit and/or receive data such as identification, position and additional data, as appropriate, in a broadcast mode via a data link [7]." Note that "broadcast" here means that the transmitting source has no idea who obtains the data, and there is no interrogation or one-to-one interaction. This is a main automatic gadget for a number of aircraft to interact information with each other. ADS-B is a stepping stone of future applications as it outperforms original radar with advantages such as global interoperability, high performance, cost efficiency, improved safety. [29].

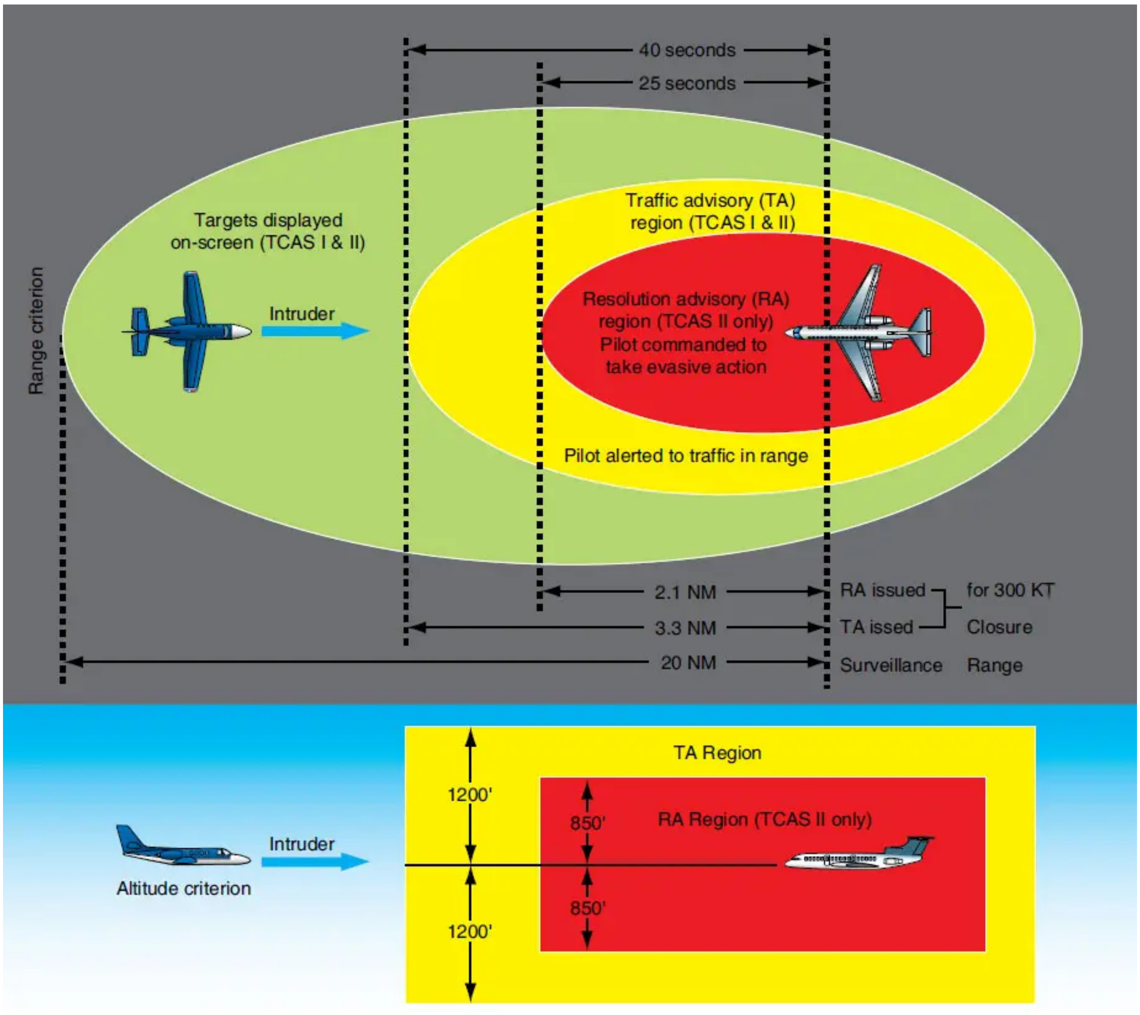

Figure 2: A protected volume of airspace surrounds each ACAS II equipped aircraft [17]

In 1997, the National Aeronautics and Space Administration (NASA), the Dutch Civil Aviation Authority (RLD), and Royal Netherlands Aerospace Center (NLR) raised a concept called Free Flight. The concept allowed aircraft in controlled airspace to fly their optimal routes and still avoid one another without any human-factor intervention from the ground [6]. One of the central motivations and foundations of FF is The Airborne Separation Assurance System (ASAS). ASAS is described as “an aircraft system that enables the flight crew to maintain separation of aircraft from one or more aircraft and provides flight information concerning the surrounding traffic.” [22] The ASAS has been developed with a concentration on ADS-B applications aspects. In [22], FAA and EUROCONTROL have categorized four different ASAS applications including Airborne Traffic Situational Awareness applications, Airborne Spacing applications, Airborne Separation applications, and Airborne Self-separation applications. In FF, Airborne Separation applications play a critical role and indeed are implemented based on the definition of airborne separation standard. These applications' primary objective is for the ATC to assign partly or entirely the traffic separation task in certain airspaces to the aircraft (in cockpits). The work delegation helps minimize manual separations to increase effectiveness and reduce the heavy workload of ATCOs in congested areas. These profits can be converted into throughput growth, cost cutback, and capacity benefits in the current situation. Also, for the sake of workload decline, with Airborne Traffic Situational Awareness applications, ASAS enhances the cockpit understanding of surrounding traffic and minimizes judgemental mistakes. Optimal flight crew decisions help prevent demands from ATC for changes in the flight plan.

At the moment, aircraft are controlled by the ATC to fly as different airways (e.g., four airways A, B, C, D in Figure 3). Through the illustration also in figure 3, [23] has pointed out the drawback of these flight routes as follows. First, it restricts the aircraft flight speed, as one should maintain a certain distance with the other aircraft to the front. This also leads to longer flight time and more fuel consumption. Second, it denies optimal routes as each aircraft could not fly to the destination directly from the departure. Furthermore, most importantly, it wastes a vast amount of the available airspace. Today, this airway-based operating way is shared as it facilitates a large number of aircraft to travel with just a single ATCO for an airway.

In contrast, FF enables safe and efficient flight where the pilots manage to pick an optimized path and speed for the aircraft. Note that this concept leads to an increase in the airspace complexity, which is more complicated to handle due to human-resource limitations. However, with the availability of such automated systems as ADS-B, ASAS, and Cockpit Display of Traffic Information (CDTI), FF becomes feasible. Ideally, all the data broadcast of surrounding aircraft is collected by ADS-B, which is then displayed on the CDTI appropriately for the pilot to catch up with the situation. ASAS could use the data to calculate and generate a maneuver to maintain the separation. Therefore, aircraft are allowed to flight freely with their preferred routes without relying on ATC clearances. Consequently, the drawbacks mentioned above in the conventional way of directing aircraft are overcome, together with a significant decrease in controllers' workload. The procedure is promising but remains conceptual, so it is worth further research in the future.

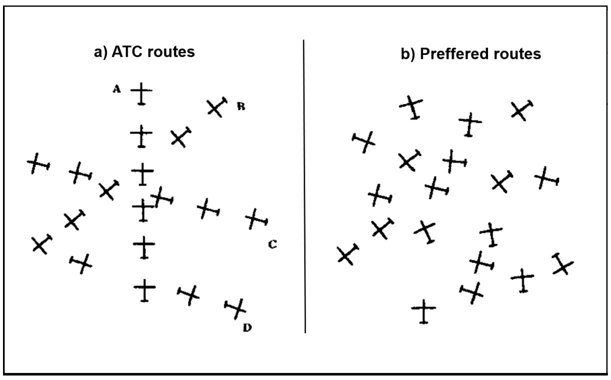

Figure 3: Illustration of route organizes in an airway structure vs preferred route [23]

TCAS vs ASAS

TCAS and ASAS are both created to prevent air traffic conflicts, but with different principles (see Table 3). In the FF concept, ASAS provides the cockpit with vital assistance to maintain the separation standard. Meanwhile, TCAS is capable of generating RA if the safe separation standard is violated, aiding pilots to avoid collisions. In other words, TCAS works as the last protection and can be considered as a backup for the ASAS. However, there is a possibility of co-operations between ASAS and TCAS proposed in [42]. The co-operations could both boost airborne surveillance performance and decrease the number of unnecessary warnings.

	TCAS II	**ASAS**
Purpose	Collision avoidance	Separation maitenance
Surveillance	Transponder - One-to-one interact - Collect data on interrogation - Independent	ADS-B - Broadcast - Collect data automatically - Depend on on-board system
Logic	- Time-to-go to the CPA - Traffic Advisory (TA) (10 - 20 minutes before CPA)	- Distance-to-go to the CPA - Conflict detection (20 - 48 minutes before CPA)
Maneuver	Vertical Resolution Advisory (RA)	Conflict resolution

Table 3: Comparison between TCAS II and ASAS [42]

5.3 Safety net

Safety nets are the last defense system against imminent or actual dangerous events, stopping them from becoming serious incidents or accidents. The whole system indeed contains multiple smaller automation systems, which bolsters the en-route phase of flight and avoids collision of an aircraft with the other, or with nearby terrain or obstacles (see Table 4). Safety nets are either ground-based or airborne:

- Ground-based safety nets: These systems are integrated into the ATM system. The Table 4 refers "promptly" as approximately two minutes. According to the warning, ATCOs are required to assess the situation as quickly as possible and make appropriate decisions.

- Airborne safety nets: Generating warning or RA directly to the flight crew in approximately 40 seconds.

Nowadays, most of the services supplied by Air Traffic Services (ATS), especially ATC service, are human-centered. This includes aircraft separation and tactical plans to maintain the air traffic pattern. While carrying out the plan, the ATCOs might experience mistakes, anomalies, modifications, crises, and distractions, especially during rush hours. Supplementary safety barriers are, in all likelihood, invaluable when the ATCOs overlook possible catastrophes.

	Automation system	**Function**	
Ground-based safety nets	Short Term Conflict Alert (STCA)	Promptly producing a warning about a potential or real violation of separation minima, avoid conflict between aircraft.	Assist the ATCOs
	Area Proximity Warning (APW)	Promptly producing a warning about potential or real unauthorized intrusion of airspace volume	
	Minimum Safe Altitude Warning (MSAW)	Promptly raising awareness about potential threat of controlled flight into terrain (CFIT[3]) or obstacles for aircraft	
	Approach Path Monitor (APM)	Promptly raising awareness about potential threat of CFIT or obstacles for aircraft during final approach[4]	
Airborne safety nets	Airborne Collision Avoidance System (ACAS)	See Section 4.1	Assist the pilots
	Ground Proximity Warning System (GPWS)	Provide information or warning to identify possibly dangerous terrain threat, pilots might accordingly take appropriate measures to avoid CFIT accidents	

Table 4: Current automation systems operated as safety nets [43]

[3]CFIT — Controlled Flight Into Terrain happens when an aircraft completely controlled by pilots flies into terrain, water, or obstacles

[4]Final approach often refers to the landing phase when the aircraft's legs descend

6 Potential AI applications

6.1 Trajectory optimization

In Europe, a future generation of ATM is developed called SESAR (Single European Sky ATM Research) Target Concept [52] indicates the importance of trajectory-based environment altering from the current airspace-based environment. In such an environment, trajectory optimization, which optimizes every single flight's performance, becomes a crucial factor in determining flight performances. Shorter flight routes certainly bring about benefits in travel time, fuel consumption, and environmental friendliness. Typical AI techniques to solve optimization problems is the state-space search and dynamic programming (DP). In particular, the following papers propose experiments to find the optimal trajectory using these techniques.

In [26], Rippel et al. proposed an approach to generate an optimal airborne trajectory between two locations onboard (roughly a few tens of seconds) using the Dijkstra algorithm. By trading off accuracy for speed with modified versions from the original algorithm with reduce-state Dijkstra and A* heuristic, the research looked for sub-optimal routes with significantly decreased runtime, making it entirely feasible for use onboard.

Rippel et al. [26] also mentioned that DP is closely related to state-space search, and it can be applied to some trajectory search problems under certain circumstances. In [27], Harada and Miyazawa also claimed the possibility of utilizing DP as a numerical method in trajectory optimization, with many advantages such as global optimization, predictable run time, feasibility in handling inequality constraints, or simplicity of computer programming.

Another similar experiment from [44] proposed a DP-based trajectory optimization tool. The tool is constructed in four-dimensional state space, including an independent variable: time. In this paper, trajectory optimization also became a foundation for generating a conflict-free trajectory based on the fuel-minimum trajectory with a constraint of arrival time.

However, all three mentioned papers [26], [27], and [44] agreed that "curse of dimensionality" restrict DP's application in high-dimensional space. "Curse of dimensionality" are specific anomalies when analyzing high-dimensional space data but not in low-dimensional one. In an optimization problem, it is often referred to as a massive increasing rate of computational time and memory space over the number of state variables. However, it is expected that current rapid growth in microprocessors will soon remove this constraint.

6.2 Weather forecast

Several recent papers [36] [37] [38] have indicated that weather plays an essential role in the aviation industry. Statistically, there are roughly 40% of delayed flights due to bad weather conditions in 2019 [45]. However, the weather forecast is not an easy computation task due to the enormous amount of data. For example, the National Oceanic and Atmospheric Administration (NOAA) in the US collects daily up to 100 terabytes to feed their supercomputer-based weather forecast engines. At the moment, traditional physics-based models can take up to three hours to make predictions. Therefore, it is not useful to forecast the weather for the next hours, which restricts our awareness of what is happening right now. Fortunately, Google's DL Convolution Neural Network (CNN) [39] model can forecast within ten minutes, called U-Net architectures [51]. This architecture uses images as inputs instead of atmospheric tables. The model contains two phases: encoder and decoder. During the encoder, the image size is squeezed to capture quality and relevant features for the prediction. Without the encoder, high-resolution images going through a sequence of layers could be extremely computationally expensive and could take tons of memory. The decoder phase does the opposite job; it up-samples this compressed data. The final layer produces the images with the original resolution and includes weather forecasting information. An advantage of this ML application is that the predicted result is immediately available. The instant result is convenient for real-time planning, but only for a near-future time range. Hence, it is still better to use the traditional way for long-term forecasting. In addition, a neural network always increases its accuracy as training. Consequently, through the enormous daily amount of real-time data, the technique can be an alternative method in the future.

Weather is the only cause but has a close relation to delayed or late-arrival flights. Modifying this relation would potentially foresee which flight will be late in the future, based on weather forecast data. As a result, ATCOs could recommend flight plan changes or reschedule flight timetable actively. Airlines might avoid flight delay compensations for passengers or additional fuel consumption to gain massive financial savings benefits. This idea was proposed in 2016 by [46]. The study utilized supervise ML[5] algorithms, such as AdaBoost, k-Nearest-Neighbors, and Decision Trees, to classify delayed flights due to adverse weather conditions. The model was expected to classify on time and late flights on unseen data, i.e., scheduled flights that are not launched yet. Unfortunately, the model did not perform well with the test set, as it over-fitted all the input noises. Nevertheless, the study stated the potential possibility to joint two features: flight schedule and weather forecast, to result in a support engine to manage aircraft arrival.

6.3 Other ideas

The flight delay, occurring when a flight takes off or arrives later 15 minutes or more than the schedule, has caused enormous losses for airlines' finance and passengers' convenience. Precise delay prediction would be a stepping stone for the solidity of airlines' business. An appealing approach is using big data and machine learning to predict flight delays. The study [47] compared and evaluated some machine learning models for generalized solutions based on multiple factors rather than just the scope of a single route or airport. The result was a random forest model for binary classification, and one of the most potent recurrent neural network (RNN) called long short-term memory (LSTM) to train the sequence. While the random-

[5]a ML learning task can generate a function mapping an unseen input to an output based on known example inputs and outputs

forest model was up-and-coming (90.2% accuracy for test set), the LSTM model was, unfortunately, over-fitting (99% accuracy of training dataset compared to the abysmal accuracy of the test dataset). The work was claimed to become a better version once over-fitting is solved, and multi-category classification is improved.

Another similar study by [48] using ML to produced a generic assessment for strategic flight schedules, which is conducted in many large European at the present. Strategic flight schedules resolve the imbalance in flight arrangements, causing traffic congestion in busy airports. These schedules allocate slots (arrival and departure time) for flights up to 6 months beforehand. The procedure currently follows several recent studies that have proposed models for optimizing slot allocation in an airport, with the assumption in ideal conditions: No delayed or late-arrival flights in an airport with deterministic capacity. In reality, many unexpectedly late flights would require ATC to adjust the plan many times, as one might influence the others arranged in the next time slot. Therefore, the study [48] contended a model to predict potential delays or cancellations and evaluate ten typical strategic schedules. Three supervised ML algorithms implemented the model: gradient boosting decision tree, neural network, and random forests. As a result, ATCOs and airport coordinators may refer the study to have an insight between delays and strategic schedule, indeed make changes if necessary.

Even though the thesis aims to emphasize the importance of human involvement in aviation, self-driving aircraft draw the attention of many researchers and leading corporations, given the enormous success of Tesla's self-driving car. Safety issues always need to be considered carefully at first, and an automated collision avoidance system is one of them. Therefore, a research direction by [49] formulated this problem as an MDP for precise information about intruders' positions, or as a POMDP for uncertain information. Using solutions from these two formulations' solver, [49] claimed the flexibility of the method for various sensors modalities. Accordingly, the authors suggested the feasibility of avoidance advice generation by state-of-the-art solvers, and the effectiveness of optimizing cost function to minimize flight-plan variations.

In many applications, training a complete model with high accuracy requires a great attempt. Sometimes the available techniques or database is inadequate to build a model performing well in a real-life environment. A method based on human behavior in learning through trial-and-error in real-life situations is called Reinforcement Learning (RL). In ATM, an RL model can be taught to become an assistant for the ATCOs by their decisions in a particular situation. The situation is often formulated to an MDP where each interaction between the system and the ATCOs creates new information, with a corresponding cost or reward. The paper [50] exploited this concept to help ATCOs in conflict resolutions. The authors claimed a promising future of the RF approach as the model yielded more human-like resolutions, which tends to be accepted by ATCOs more. Specifically, 65% of the agent's resolutions are similar to those of ATCOs.

7 Summary

A tremendous and increasing number of air travelers induces both a pressure and a motivation to the aviation industry. The expected scenario is that airlines could become more cost-efficient, punctual, and safer, with a reduction in controllers' excessive workload. This thesis aims to assess the concerns about high-level decision-making and management in air traffic approached by AI and intelligent automation. Through discussed absolute advantages over human, automatizing aerospace is not only feasible but also become an evident tendency soon. However, several issues might need further considerations.

Moreover, developed integrated automated system either on the ground or in the cockpit have played a vital role in preventing unexpected incidents, especially collision avoidance. On the other hand, developing technologies and future generations of developed ones are expected further to not only enhance this capability but also allow separation tasks delegated from controllers to the flight crews. The future of AI applications in aviation is widely opened for many ideas from researchers worldwide. These ideas are so promising that investors and authorities might consider new approaches for the lively aviation market to race against the rapid growth in the aviation market.

The thesis's findings partly indicate that AI techniques have not intervened deeply into the aerospace industry. Most of the studies remain theoretical and require further experiments, research, and validations before becoming practical. This situation might be explained by the complication when integrating an idea into the existing systems. Most of the studies often assume experimental environments that eliminate some uncertainties in reality. Besides, lacking available datasets also challenges model training as it requires tons of data to capture the patterns. It is expected that airlines and leading aerospace organizations would publish more data for the researcher to increase their models' accuracy and avoid over-fitting.

AI applications in aerospace will likely become a trendy topic in the near future, significantly when the technological reforms of the US - NextGen and Europe - SESAR occur. There is plenty of room for improvement in existing studies and the advent of new ones. These studies worth more investment in terms of money, time, and effort. Finally, there are many exciting research directions for this topic that has not been covered in this thesis. One might consider the problem of trust issues, environmental and economic impacts on society.

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