REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Information Technology

THE ROLE OF TECHNOLOGY IN AIRLINE MANAGEMENT AND THE QUALITY OF SERVICES FOR PASSENGERS

Mustafa Mones HATO

Master's Thesis

Supervisor

Prof. Dr. Osman Nuri UCAN

Istanbul, 2023

THE ROLE OF TECHNOLOGY IN AIRLINE MANAGEMENT AND THE QUALITY OF SERVICES FOR PASSENGERS

Mustafa Mones HATO

Information Technologies

Master's Thesis

ALTINBAŞ UNIVERSITY

2023

The thesis titled THE ROLE OF TECHNOLOGY IN AIRLINE MANAGEMENT AND THE QUALITY OF SERVICES FOR PASSENGERS prepared by MUSTAFA MONES HATO and submitted on 03/04/2023 has been **accepted unanimously** for the degree of Master of Science in information technology.

Prof. Dr. Osman Nuri UCAN

Supervisor

Thesis Defense Committee Members:

Prof. Dr. Osman Nuri UCAN	Electrical and Electronics Engineering, Altinbas University,	__________
Prof. Dr. Adil Deniz DURU	Physical Education and Sports, Marmara University,	__________
Asst. Prof. Dr. Sefer KURNAZ	Faculty of Computer Engineering, Altinbas University,	__________

I hereby declare that this thesis meets all format and submission requirements of a Master's thesis.

Submission date of the thesis to Institute of Graduate Studies: ___/___/___

I hereby declare that all information and data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

MUSTAFA MONES HATO

Signature

DEDICATION

I devote and pledge this research work to my supervisor who is salient for guiding me through the whole research work as well as my family for always assisting me in my hard time.

PREFACE

First and foremost, I want to express my gratitude to Prof. Dr. Osman Nuri UCAN, my dissertation supervisor, for his advice and assistance. I found it really helpful to grasp the reasoning behind the research to regularly discuss my progress, issues, and suggestions with my advisor, Prof. Dr. Osman Nuri UCAN. It helped me understand the research's technical requirements better.

ABSTRACT

THE ROLE OF TECHNOLOGY IN AIRLINE MANAGEMENT AND THE QUALITY OF SERVICES FOR PASSENGERS

HATO,Mustafa Mones Hato

M.Sc., Information Technologies, Altınbaş University,

Supervisor: Prof. Dr. Osman Nuri UCAN

Date: April / 2023

Pages: 75

The continuous search for improvements in our Airports is essential, both in technologies and in more innovative processes that aim to guarantee the improvement of the efficiency of the operational network, aiming at a better customer experience, adequate costs and higher numbers of hours in aircraft flights. In addition, the globalized world brings more and more people from all corners of the planet and this study also aims to reduce the difference between national processes and those practiced in the most efficient airports in the world. The papers objective is to develop a model that improves the performance of the airplane scheduling process using artificial intelligence, with immediate and indirect effects on the construction of operating results for airline companies. Being a relevant subject where the consequences impact both the operational management of results and customer satisfaction.

Keywords: AI, Aircraft, Airports, Optimization, Cake Algorithm.

TABLE OF CONTENTS

LIST OF TABLE

Pages

LIST OF FIGURES

Pages

ABBREVIATIONS

CNN	:	Convolutional Neutral Network
AI	:	Artificial Intelligence
SVM	:	Support Vector Machine
UCXAI	:	User-Centric eXplainable Artificial Intelligence
XAI	:	Explanable Artificial Intelligence
ATC	:	Air Traffic Control
ICAO	:	International Civil Aviation Organization
FAA	:	Federal Aviation Administration
NAS	:	National Airspace System
NM	:	Nautical Miles
TAS	:	True Airspeed
CAS	:	Calibrated Airspeed
ANSPs	:	Air Navigation Service Providers
VFR	:	Visual Flight Rules
IFR	:	Instrument Flights Rules
FIR	:	Flight Information Region
UIR	:	Upper Information Region
FAB	:	Functional Airspace Blocks
ATM	:	Air Traffic Management
TMA	:	Terminal Maneuvering Area
TCA	:	Terminal Control Area
CTR	:	Control Zone Rules
SIA	:	Aeronautical Information Service
FMS	:	Flight Management Systems

LIST OF SYMBOLS

μ	:	Mobility of electron
λ	:	Wave length
ω	:	Angle frequency

1. INTRODUCTION

It is one of the most prevalent mistakes that can be found in the aviation business that airplanes can only produce money when they are in the air. This widespread myth is one of the most common misunderstandings that can be discovered in the industry. From the perspective of the airline, the objective should be to increase the amount of time that is spent on flying activities while simultaneously limiting the amount of time that is spent on ground operations. During the course of a flight, a variety of activities may take place, two examples of which are the carrying of both passengers and cargo. A group of ground operations chores that need to be finished in order to get an airplane that has been parked ready for its next flight is referred to as a "turnaround," and this is the meaning of the term "turnaround." This word is used when discussing the operations that take place on the ground. [2] As a consequence of this, the ability of an airline to get the most out of a single aircraft is dependent on a procedure that is both quick and effective when it comes to turning it around. According to [3], the amount of time needed to complete a turnaround might vary due to the stochastic nature of the many subprocesses that compose a turnaround. This is because a turnaround is comprised of many different processes. This is due to the fact that a turnaround requires the completion of a variety of processes.

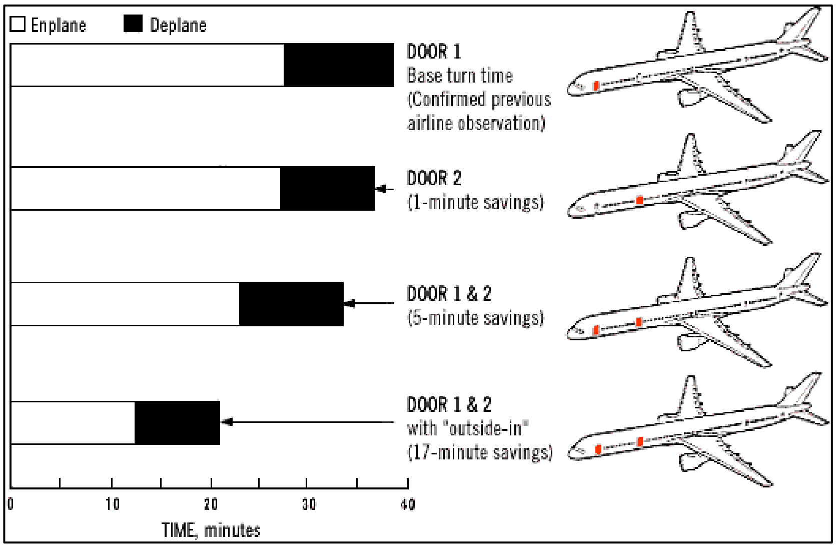

Figure 1.1 : Amount of Time Needed to Deplane [5]

The loading of cargo, the boarding of passengers, the supply of food and drink, and the refueling of the vehicle are all examples of these subprocesses. Other examples include the provisioning of food and drink. The length of time that must be allotted for a single turnaround has an effect on the timetable that must be adhered to by an airline. This is because there is a strict schedule that must be followed for the departure of the airplanes. [4] There is a potential that the departure of the next flight leg will be delayed as a result of the fact that turnaround timings may vary from airport to airport. This risk is the product of the fact that a turnaround is inherently unpredictable and that it is necessary to strictly adhere to a timeline. A strict adherence to a timetable is required due to the presence of both of these elements. Even while quick turnarounds are necessary for optimal aircraft utilization, there is still a chance that the following flight leg will get a late start as a result of them. This is because quick turnarounds take more time. As a result of the trade-off, airlines need an accurate estimate of the turnaround time in order to design a schedule that is both short and provides enough buffer time to absorb any possible deviations in the subprocesses of a turnaround without compromising the departure time. This is necessary in order to design a schedule that is both short and provides enough buffer time to absorb any possible deviations in the subprocesses of a turnaround. This is important in order to construct a schedule that is both short and offers enough buffer time to absorb any possible deviations in the subprocesses of a turnaround. This is a necessity because it is necessary to design a schedule that is both short and provides enough buffer time. This is important in order to construct a schedule that is both short and offers enough buffer time to absorb any possible deviations in the subprocesses of a turnaround. This is a necessity because it is necessary to design a schedule that is both short and provides enough buffer time. This is something that must be done since it is essential to create a schedule that is concise while yet allowing for a sufficient amount of buffer time. The problem is that airlines typically prepare their schedules months in advance [5] of when the flight will be executed, but the factors that impact the turnaround time, such as the weather or the passenger quantity, are decided at the earliest on the day that the turnaround is scheduled to take place. This creates a problem for the turnaround time. Because of this, there will be a delay in the completion of the task. Because of this, there will be a delay in the task that needs to be completed. In addition to the lengths of time that are necessary for particular activities like as boarding and fueling, late-arriving aircraft from the prior trip could possibly cut into the real amount of time that is available for turnaround [6].

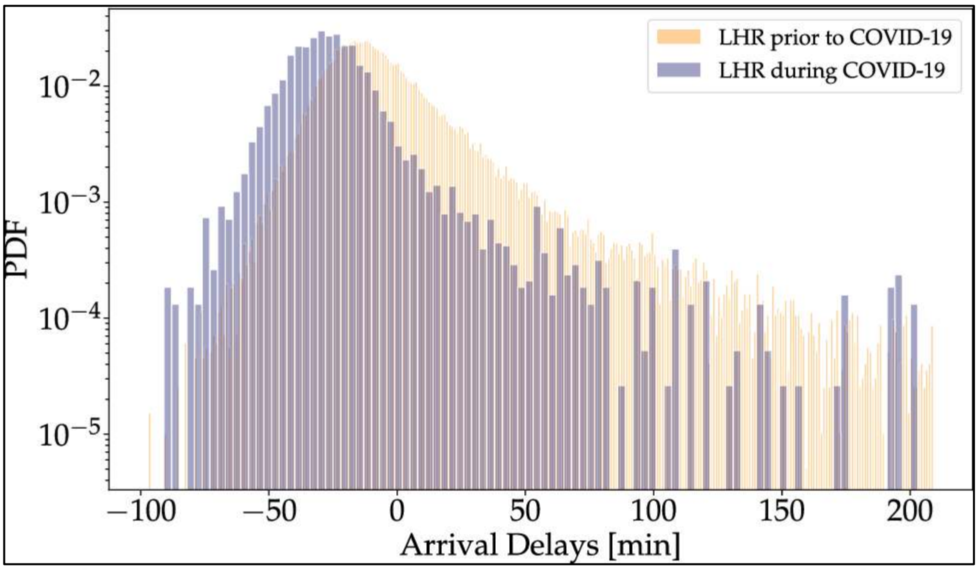

Figure 1. 2 Delay Time Before and After Covid-19 [9]

As a consequence of this, it is advantageous for airlines to have an accurate estimate of the actual duration of the turnaround duration all the way up until the turnaround has been completely finished. This is because airlines may make decisions such as which subsequent operations the aircraft can be used for or how much time is available for passengers who have connecting flights.

1.1 PROBLEM STATEMENT

The continuous search for improvements in our Airports is essential, both in technologies and in more innovative processes that aim to guarantee the improvement of the efficiency of the operational network, aiming at a better customer experience, adequate costs and higher numbers of hours in aircraft flights. In addition, the globalized world brings more and more people from all corners of the planet and this study also aims to reduce the difference between national processes and those practiced in the most efficient airports in the world. According to [13] the frequency of flights is a favorable instrument not only for price reductions, but for improving the quality of the service offered, with emphasis on punctuality, on-board services and differentiated service. Examples such as the American and European stand out. Among the requirements that appear to be fundamental for companies to obtain competitive success in their markets is the need to successfully react to demands, in addition to influencing the environment in which they are inserted [14].

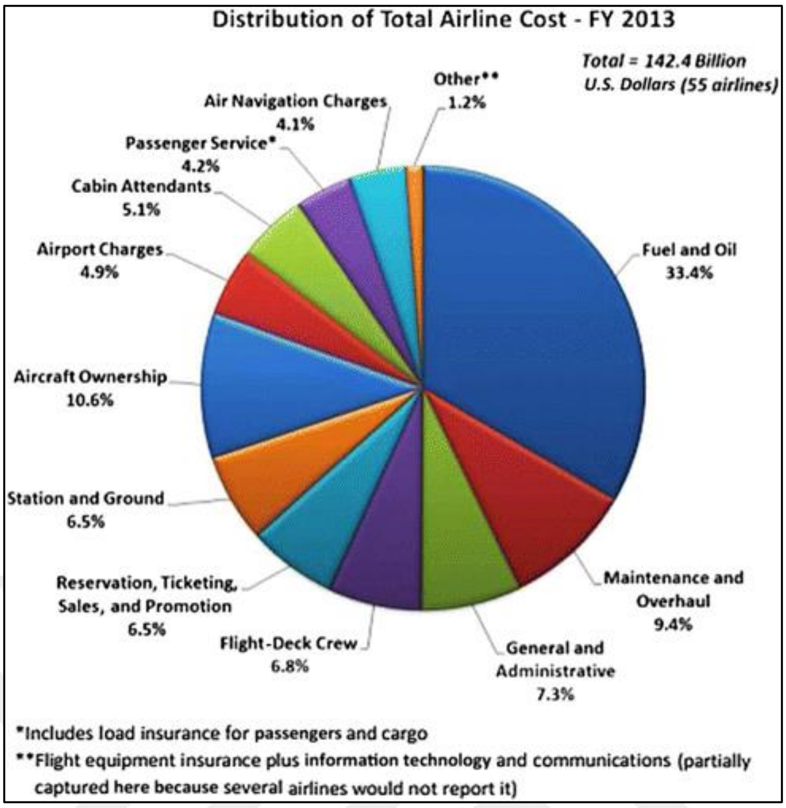

Figure 1.3: Airline Cost Estimation Distribution [14]

Belief in this claim has long lent relevance to the innovation construct [15] already highlighted this importance, emphasizing that innovation is one of the essential functions for the company to achieve its superior objective: customer satisfaction. Therefore, the evolution of these environments does not stop, with innovative and functional processes, proposing solutions that can increase service speed, offer and guarantee safety and sustainability, integrating interests of all interested parties. We have great opportunities to improve check-in processes, checked and hand luggage, aircraft disembarkation processes, with the aim of improving the customer experience and making airlines more efficient, increasing productivity and reducing costs. Another point that we can highlight is the reduction of the shortest time possible for aircraft on the ground, making companies more profitable in the business. According to [16] the average savings corresponding to a 1-minute reduction in the time to board and disembark planes ranges from US$30 to U$ $250. Assuming the example of a large airline, which makes an average of 5,000 flights per day, the most conservative calculation implies savings of almost U$55 million per year when the boarding time of all its passengers is reduced by just one minute flights. This explains why researchers and airlines seek to improve the boarding method, to minimize ground time and operational costs. In this context, we raise the following research question: how to improve the performance of the air process, increasing operational efficiency and consequently user satisfaction?

1.2 MOTIVATION OF THIS THESIS

Due to the growing option of passengers for air transport, it has become essential to know the process of boarding and disembarking at airports in order to create alternatives to reduce the time of the aircraft on the ground. Several studies conducted by the World Bank indicate that a substantial advantage for the growth of the aviation market in the world is related to the reduction of costs and prices per kilometer flown, being a competitive advantage for companies, with economies of scale due to the distances made. At the same time, companies that have been adopting new technologies in their planes, with on-board services with internet access, videos and online reservation systems, have competitive advantages. An article published on the Pan Rotas website, by the author [17] shows that the most efficient airports in the world, such as Detroit (USA), Melbourne (Australia), Incheon (South Korea), Atlanta (USA) and Dusseldorf (Germany), invested in technologies (high-speed conveyor belts with individual trays, supply with fixed hoses instead of tank trucks, luggage with a tag for tracking with RFID technology to speed up availability and speed in both the check-in and check-in flow).

Table 1.1: Most Efficient Airports in The World [7]

Rank 2018	Rank 2017	Airport City / Country / Code	Passengers (Enplaning and deplaning)	% Change
1	1	Atlanta GA, US (ATL)	107,394,029	3.3
2	2	Beijing, CN (PEK)	100,983,290	5.4
3	3	Dubai, AE (DXB)	89,149,387	1.0
4	5	Los Angeles CA, US (LAX)	87,534,384	3.5
5	4	Tokyo, JP (HND)	86,942,794	4.4
6	6	Chicago IL, US (ORD)	83,245,472	4.3
7	7	London, GB (LHR)	80,126 320	2.7
8	8	Hong Kong, HK (HKG)	74,515,927	2.6
9	9	Shanghai, CN (PVG)	74,006,331	5.7
10	10	Paris, FR (CDG)	72,229,723	4.0
11	11	Amsterdam, NL (AMS)	71,053,147	3.7
12	16	New Delhi, IN (DEL)	69,900,938	10.2
13	13	Guangzhou, CN (CAN)	69,743,211	5.9
14	14	Frankfurt, DE (FRA)	69,510,269	7.8
15	12	Dallas/Fort Worth TX, US (DFW)	69,112,607	3.0
16	15	Istanbul, TR (ISL)	68,360,648	6.6
17	19	Incheon, KR (ICN)	68,350,784	10.0
18	17	Jakarta, ID (CGK)	65,667,506	4.2
19	18	Singapore, SG (SIN)	65,628,000	5.5
20	20	Denver CO, US (DEN)	64,494,613	5.1
		TOTAL	1,537,949,380	4.8

They also invested in more efficient processes. In this way, we will propose a model for airports with innovative solutions in processes, mainly to improve the performance of national structures.

1.3 OBJECTIVES

The project's objective is to develop a model that improves the performance of the loading and unloading process, with immediate and indirect effects on the construction of operating results for airline companies. Being a relevant subject where the consequences impact both the operational management of results and customer satisfaction.

1.3.1 Specific Objectives

a. Analyze current processes
b. Identify the main points of improvement
c. Find solutions that reduce aircraft ground time
d. Generate greater operational efficiency and consequently greater profitability for companies

2. LITRITAURE REVIEW

2.1 RELATED WORKS

In the field of computer science, the phrase "artificial intelligence" refers to any system or machine that makes an effort to learn from its earlier experiences and interact intelligently with its surroundings. This includes making decisions based on the information it receives from its environment. The phrase "artificial intelligence" has been in circulation ever since it was coined in the 1950s and dates back to that era. The concept that we now refer to as "artificial intelligence" was initially conceived upon by its namesake, John McCarthy.

2.1.1 Face Recognition In Airports

Face recognition is a biometric technique that can be used to determine a person's identity by analyzing their distinctive facial characteristics, which are sometimes referred to as "nodal points." This examination of a person's face can be carried out with the assistance of a biometric tool, and the results of this analysis can be used to verify the person's identity. On the other hand, when it comes to issues of security, facial recognition is most helpful in confirming, approving, and identifying individuals (Omoyiwola 2018). Face recognition is useful because it enables you to recognize a person without needing to first establish a relationship with that person. In other words, you can recognize someone just by looking at their face. Because of this, being able to recognize faces is a very valuable talent. CNN (Convolutional Neutral Network) algorithms, which are utilized in machine learning for the purpose of facial recognition, are essential for the training and learning processes associated with picture categorization. These methods are applied for facial recognition; hence large datasets are necessary in order to apply them (Trigueros et al. 2018). Face detection is a reliable method for locating human faces inside an image, which is a key stage in the face recognition process. Face recognition relies heavily on face detection. Face recognition cannot take place unless face detection first takes place. This is owing to the fact that recognizing human faces inside a photograph is one of the most important aspects of the face recognition process (Tantak et al. 2017). Face recognition technology allows an employer to determine the times that an employee entered and exited a building by using an image of the employee's face that was captured by a camera. This information is gleaned from the image of the employee's face that was acquired by the camera (Al-bakeri 2016). Studies on student attendance registration systems have also been carried out in a manner akin to the one that has been described here in an effort to cut down on the amount of time that is spent on administrative responsibilities. Taking images of the youngsters is the initial step that needs to be done in order to finish the procedure. This is an absolutely necessary step. The students are not given their names until after the images have been developed and processed. When a student walks into a classroom, the system immediately begins the student identification process that it has been configured to carry out. This happens almost instantaneously. When a student checks in at the beginning of a class, the system will mark them as "present" if they are present for the rest of the session if they are physically present during the entire period. This applies only if the student was physically present throughout the entire period. Only if the student was there and checked in at the beginning of the class does this apply to them. On the other hand, if the student does not show up for class, nobody will be able to say for certain whether or not he or she was present, and the absence will be recorded. However, the absence will be recorded even if the youngster comes to school on the day they were absent (Akshara Jadhav and Tushar Ladhe 2017). Facial recognition can also be accomplished through the utilization of a visitor notification system, which is still another approach that can be used. This device has the capability to recognize the person who is ringing the doorbell, as well as to send a notification as well as a photograph of that person to the person who owns the home where the doorbell is located. Intelligent technologies, which are able to provide support in this area, can help with the organization of people (passengers) within an airport, which is a vital area due to the enormous concentration and variety of people that are present. This can help with the organization of people (passengers) within an airport. Intelligent technology may be able to be of assistance in this domain. At least one airport in the United States has begun using an innovative biometric verification system that scans passengers' faces using facial recognition technology rather than their boarding passes. This system is considered to be on the cutting edge of biometric technology. It should be noted that the airport in question can be found in the United States (CNN newspaper, Street 2019).

2.1.2 Passenger Satisfaction Detection

As a direct result of the gradual increase in the number of passengers that has taken place over the course of the past few years, Muscat International Airport has quickly become one of the busiest and most important airports in all of the world. In fact, it is now considered to be among the busiest and most important airports in the entire world. When there is a high number of passengers present, the check-in lines at the airport are infamous for being quite lengthy for the length of time they take to move. During the process of checking in, we will review any identity documents that you have brought with you, as well as verify any airline reservations that you have made. In addition, we will check the status of your checked bags. Because checking in takes a significant amount of time, travelers have a tendency to be critical of the amount of time they are required to wait there. This is because checking in requires them to wait there. During the process of checking in for a flight, there are a number of different things that could potentially go wrong, and each of those things has the ability to create a delay on its own. When there are a greater number of individuals present, there is an increased possibility that there will be a queue of clients waiting to be attended to. One of the most common reasons for delays is because airports and airlines do not have a sufficient number of staff operating at their respective sites. This can cause a variety of problems, including missed connections and cancelled flights. One hundred different guests were questioned, and twenty-five of them said that when they arrived at the check-in desk, there was no one there to assist them. This information was gleaned from the results of a survey. It is vital that employee absences be kept to a minimum as much as feasible in order for the airline to maintain a safe atmosphere for both its customers and its workers. This can be accomplished by keeping employee absences as low as possible. People who took part in the research were of the opinion that the implementation of a system would help to cut down on the number of aircraft delays seventy-five percent of the time. Face recognition algorithms, which have their roots in the subfield of machine learning known as artificial intelligence, are something that can be utilized to provide assistance with issues of this nature and are one solution that can be pursued. These algorithms are able to recognize the individuals who are working behind the counter simply by looking at their faces. The staff will start monitoring the planes before the flights actually take off officially in order to ensure that everything goes smoothly. If the technology begins monitoring the issue and determines that there is no people available to manage it, it will send an alert to the airline with flight-specific information in the event that this occurs.

2.1.3 Machine Learning And Datamining

Artificial intelligence (AI), also known as machine learning, is the basis of the completed product and serves as its primary foundational component. The finished product will include unique characteristics such as the ability to learn from and make sense of data, as well as the capability to recognize the faces of specific individuals. The following are some of the objectives of this study that have arisen as a direct result of this finding: Construct an automated facial recognition system that makes use of machine learning to track the availability of staff members, and then ensure that it is ready to be put into action after it has been completed. Second, there should be a reduction in the amount of time and money that is wasted as a result of employee absenteeism during check-in periods. This waste occurs because employees fail to show up for work when they are scheduled to do so. This waste arises as a direct result of employees failing to report to work at the times when they were scheduled to do so. In the third and last stage of this investigation, we test the accuracy with which facial recognition software can differentiate between a variety of individuals. Examines what it means to be smart as well as thoughtful (Genc 2019). Already, AI is being put to use in a variety of different businesses, and the technology is swiftly becoming adaptable to an increasing number of facets of human existence as well as culture (Aich 2019). The aviation sector has made considerable investments in the technology of artificial intelligence in order to better satisfy the demands of airlines and customers. These investments were made in order to improve customer service (AI). These investments have been made with the primary objective of improving the level of service that is offered to consumers (Sims 2019). It is now possible for machines to learn new things and make decisions just as quickly as people can learn new things and make decisions thanks to a notion that is known as "machine learning." Beginning in the 1980s with the intention of giving computers the ability to mimic human thought and behavior, the term "machine learning" has since come to mean "teaching" a computer to function independently, without any prior instruction. This shift in meaning occurred as a result of the original goal of giving computers the ability to imitate human thought and behavior. This change in meaning came about as a direct consequence of the primary objective, which was to endow computers with the capacity to emulate human cognition and behavior. This shift in connotation came about as a direct consequence of the goal of programming computers with the ability to replicate human behavior and cognition. The basic objective of machine learning is to provide assistance with difficult problem-solving in a way that is not feasible with conventional computers and other types of systems (Alex and S.V.N. 2009). Learning can be broken down into three categories: supervised learning, unsupervised learning, and reinforcement learning. Machine learning is an umbrella term that incorporates all three of these types of schooling. Each of these subfields can be thought of as a distinct form of education. The most popular type of machine learning is called supervised learning, and you can recognize it by the fact that the data are labeled and the outcome that is sought is already specified. This kind of learning is used to train computers to perform specific tasks more effectively. This sort of learning is distinguished from others by the fact that it is the type of machine learning that has the highest success rate. The system acquires the ability to recognize new inputs by comparing those inputs to a set of instances that it has already identified. This allows the system to learn how to detect new inputs. Because of this, the system is able to develop the capability of recognizing new inputs. This is the case since there are a huge variety of well-known algorithms for supervised learning, such as the decision tree, SVM (Support Vector Machine), linear regression, and k-nearest neighbors, amongst many more (Aich 2019). Unsupervised learning, on the other hand, makes use of a much larger number of data sets than supervised learning does in order to learn how to classify and associate data in order to better anticipate the outcome of an operation. This is in contrast to supervised learning, which makes use of only a small number of data sets. On the other hand, learning that is directed by a teacher is referred to as supervised learning, and this is in contrast to unsupervised learning. The computer needs to rely on its own observations in order to find out how to recognize the various components during the training process. This is due to the fact that the data do not have any labels connected to them in any way. Clustering techniques are commonly utilized by unsupervised learning algorithms such as k-means clustering to organize data into meaningful categories. In this method, the data are first clustered, and then, during each iteration, the local maxima are identified. First, the data are clustered (Genc 2019).

2.1.4 Ai In Flight Scheduling

In 1956, at the first "Dartmouth Summer Research Project on Artificial Intelligence," the term "artificial intelligence" (AI) was used for the first time to characterize robots that demonstrate cognitive capacities that are typically associated with humans. This project was the first to take place at Dartmouth College. The phrase had never been utilized prior to the completion of this project. Since that point in history, the sector has had a succession of "summer" periods, which are characterized by high enthusiasm, followed by "winter" times, which are distinguished by apathy and pessimism [8]. Following each "summer" phase is a "winter" phase in this pattern. The recent resurgence in interest in artificial intelligence (AI) in the 2010s can be partially attributed to the accessibility of large data sets and the discovery that graphics processing units (GPUs) can be used to rapidly calculate learning algorithms [9]. Both of these developments occurred in the past few years. This blossoming is due, in large part, to public achievements that have captured the attention of people all around the world and encouraged increased investment. These achievements include, but are not limited to, the following: IBM's IA Watson's triumph over two Jeopardy! Champions in 2011 [10], Google X's achievement in training an AI to recognize cats in videos in 2012 [11], and AlphaGo and its successor AlphaGo Zero's victory over a world-class Go player in the 2010s [12]. [10] [11] The accomplishment of Google X's artificial intelligence training program to identify cats in video [11] Explainable Artificial Intelligence, or XAI for short, is a collection of methodologies and strategies that, when combined, make it possible for humans to understand either I the AI algorithm itself (also known as global explanation or interpretability) or (ii) the answers that it produces. XAI is abbreviated from its full name, Explainable Artificial Intelligence. XAI, which is currently in its third generation of operation, is following this pattern, which it is currently in (i.e., local explanation or justification). The artificial intelligence in A.T.M. stuck, for the most part, to the same patterns even if there was a very slight delay in terms of time. The following demonstrates how, over the course of the past decade, artificial intelligence in ATM has progressed from systems used to optimize traffic to systems used to anticipate diverse objects, such as forecasting 4D trajectories. This progression can be traced back to the beginning of the decade when these systems were used to optimize traffic. This development may be traced back to the beginning of the decade, when these technologies were utilized to maximize the efficiency of the flow of traffic. This progression may be traced back to the beginning of the decade, when these technologies were utilized to optimize the efficiency of the flow of traffic in an effort to reap the potential benefits of the advancement. A researcher who encounters a problem in the ATM domain will not discover a general guide that describes how to handle the problem (or problems like it), nor will they discover the limitations of the current work, which is detrimental to the domain and its progression. This is the case despite the significant amount of background work that has been done in AI for ATM. There are a few reviews accessible, but they are either out of date [18], they focus on the methodology rather than the integration for end users, or they are written by experts in a certain type of artificial intelligence algorithm (such as meta-heuristics [14,15] or multi-agent systems [16]). Even though a considerable amount of research has been done in the direction of applying AI to the ATM industry, the technology is not yet "fully operational" and is not providing any noticeable benefits to end users at this time. This is despite the fact that a significant amount of research has been done in this direction. It is possible that the fact that the ATM domain is a "life-or-death" domain, in which the highest priority is always placed on maintaining the safety of both passengers and crew members, is to blame for the tardy acceptance of AI in that domain. The use of AI has proceeded at a rather modest pace as a direct consequence of this factor. It is typically required for there to be a person present within the ATM system in order to guarantee the safety of both the passengers and the employees. This is done to ensure that no one gets hurt. This person takes the form of an air traffic controller most of the time; however, this is not always the case (ATCO). The authors suggest that in the not-too-distant future, safety will be obtained through the design of systems that lay a far bigger focus on the human aspect. In order for these systems to be successful, the end-user will need to be able to comprehend them, and the systems themselves will need to be able to adapt to the mental and physical characteristics of the user, in addition to the user's mental and emotional state. It is possible for the system to automatically detect the operator's cognitive state and then utilize this evaluation to carry out operations autonomously along an ascending scale of automation (also known as adaptive automation) [19, 20]. For instance, the system may be able to automatically recognize the operator's cognitive state in situations such as when the operator's workload exceeds their cognitive capacity or when there is some form of incapacitation taking place. In this scenario, the system might be able to carry out tasks on its own while traveling along an escalator. Within the parameters of this scenario, the computer system may make use of this evaluation in order to carry out operations independently along a rising scale of automation.

2.2 CONCLUSION

The increased interest in employing AI to assist humans in making high-stakes decisions in other sectors, such as healthcare and criminal justice, was the impetus for the development of XAI and User-Centric eXplainable Artificial Intelligence (UCXAI) [21]. UCXAI stands for User-Centric eXplainable Artificial Intelligence. XAI stands for Explanable Artificial Intelligence. User-Centric eXplainable Artificial Intelligence is what UCXAI is an abbreviation for. Explainable Artificial Intelligence is what we mean when we refer to XAI. UCD is used during the process of designing new systems for end users in order to assist the testing and verification of innovative algorithmic workflows, interface styles, and workflow styles [22-25]. This is accomplished through the use of a workflow simulator. In spite of the growing emphasis [26, 27], this critical component of ATM has not yet been examined in further detail. This is an activity that absolutely must be carried out.

3. AI AND AIRPORT MANAGEMENT

3.1 INTRODUCTION

The objective of this chapter is to present as clearly and succinctly as possible the current air traffic management system, which will sometimes be abbreviated later by using the initials of the Anglo-Saxon term ATM. In professional jargon, we speak of ATM to refer to the management of air traffic as a whole, and of Air Traffic Control (ATC) for the specific activity air traffic control. For more detailed information, particularly on the regulatory plan and on the organization of services, the reader may refer to the documentation [36, 37] of the International Civil Aviation Organization (ICAO). Or air traffic regulations [49].

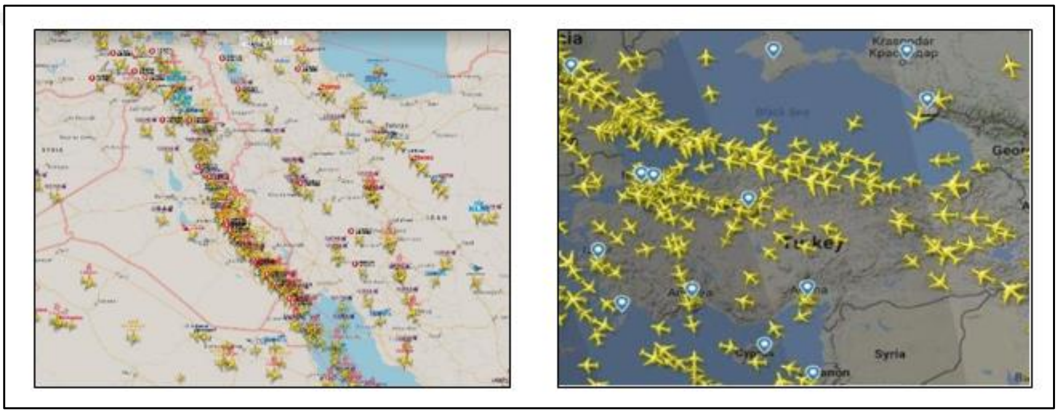

Figure 3.1: Examples of air Traffic in Iraq (left) and Turkey (right). [22]

This complex ATM/ATC system, which we will briefly present in this chapter, currently handles up to 33,000 commercial flights per day in Europe. The order of magnitude is similar in the United States. The Federal Aviation Administration (FAA) estimates the number of flights simultaneously supported by the National Airspace System (NAS) in the United States at between 4,000 and 6,000 in rush hour. Figure 3.1 illustrates the number of aircraft in flight over the two continents.

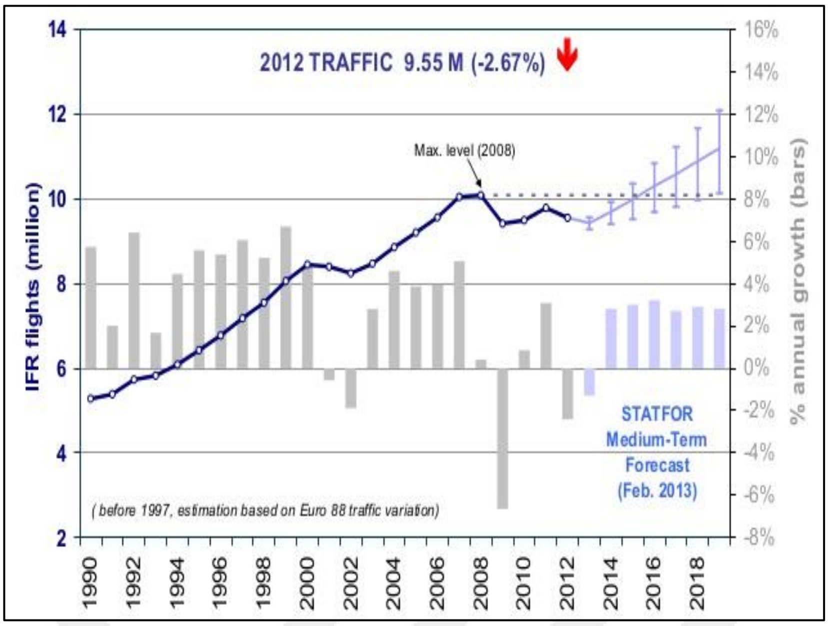

Figure 3.2: Evolution of Traffic in Europe.[23]

In terms of trends, air traffic is increasing rapidly in the Asia-Pacific region. Peaceful. North America and Europe are seeing a slowdown in traffic growth but the forecast schemes still assume an increase (see Figure 3.2).

3.2 VOCABULARY AND UNITS OF MEASUREMENT

The aviation community uses very specific vocabulary and measurement units, which we are going to introduce here, before going into the description of the air traffic management system. A glossary of terms and acronyms is also available at the beginning of this document. Altitudes are expressed in feet (ft), or in flight levels (FL, for Flight Level), with 1FL = 100ft. The altitude most used in aviation is in fact a geopotential pressure altitude (see Appendices D and E) determined using the static pressure p measured at On board the plane. The flight levels are defined with respect to a reference which is the isobaric surface 1013.25 hPa. Distances are expressed in nautical miles (NM), 1 nautical mile equaling 1852 meters. Speeds are expressed in knots (kts), with 1 kts equaling 1 NM/h. The speed of the aircraft in the air is measured by dynamic pressure sensors (see appendix F). The true airspeed (TAS) is the speed of the aircraft in the air mass. The calibrated airspeed is equivalent to the true airspeed which would be necessary at mean sea level, in standard atmospheric conditions, to have the same dynamic pressure as that measured on board the aircraft. . Ignoring instrument errors, the calibrated airspeed (CAS) is the speed read by the pilot on his on-board instruments. The Mach number is the ratio between the true airspeed (TAS) and the speed of sound in the air. The CAS and the Mach number are the two speeds used by the pilot to operate his aircraft, for example by following segments at constant CAS, then at constant Mach, during the climb. The plane evolves in a mass of air itself moving relative to the surface of the terrestrial globe. We therefore also define a speed relative to the ground (ground speed), expressed in knots.

3.3 MISSIONS AND ACTORS

The mission of the current air traffic management system is to ensure the smooth and safe flow of traffic, whether in the air or on airport taxiing surfaces. This mission is carried out by various organizations which provide a set of services to airspace users.

The users can be of various natures: general air traffic, with commercial flights, tourist flights, geographical survey missions, model aircraft, drones, or military air traffic, with training flights, specific missions, etc.

The air traffic services provided to these users are of different types ([48]):

A. The air traffic control service, which is responsible for:

i. To prevent collisions between aircraft;
ii. To prevent collisions between aircraft on the maneuvering area and obstacles on that area;
iii. To speed up and organize air traffic.
   a. The flight information service, the purpose of which is to provide advice and information useful for the safe and efficient execution of flights;
   b. The alerting service, the purpose of which is to alert the appropriate organizations when aircraft need the help of search and rescue organizations, and to lend these organizations the necessary assistance.

A key difference between “control service” and “flight information service” relates to the responsibility for traffic separation. In the context of control, it is the body responsible for air traffic control, and therefore ultimately the controller at his workstation, who is responsible for avoiding collisions between aircraft. To do this, it gives instructions to change heading or altitude, or speed regulation, which the planes must imperatively follow. When only flight information service is provided, aircraft pilots are responsible for avoiding collisions with surrounding traffic. These various services are provided to users by service providers known as ANSPs (Air Navigation Service Providers). For providing the services of air traffic to aircraft. Other actors intervening in the system or interacting with it include the airlines that operate commercial flights in the airspace, the army for military air traffic, meteorological services. In order to avoid overloading in certain portions of the airspace or at certain airports, it is increasingly necessary to regulate and organize air traffic over a large area ladder. This role of Network Manager is now provided in Europe by a service of Eurocontrol, a European inter-state agency. Similar organizations exist in most other regions of the world where the traffic is sufficiently dense.

3.4 VISUAL FLIGHT AND INSTRUMENT FLIGHT

Flights can be classified into two categories, depending on the level of equipment of the aircraft and the qualifications of the pilots: visual flight (VFR for Visual Flight Rules), or instrument flight (IFR for Instrument Flight Rules). In visual flight rules (VFR), the pilot must keep a certain distance from obstacles and clouds and only fly in weather conditions compatible with visual flight, in particular with regard to the visibility. It is a type of flight more suited to tourist aviation, where the basic rule for separation between aircraft and obstacle avoidance is "see and avoid". Instrument flights rules (IFR) are less constrained by weather conditions. Because they can fly in degraded weather conditions, with reduced visibility, IFR flights generally benefit from ATC service. air, which ensures their separation from other flights (IFR or VFR).

3.5 CLASSIFICATION OF AIRSPACES

a. Airspaces are categorized into several classes (from A to G) which make it possible to distinguish which services are provided to which types of flights.
b. For example, in class a airspace, only instrument flights rules (IFR) are admitted, the control service is provided to all IFR flights, the only ones authorized, and separation is ensured between all. In class B airspace, instrument (IFR) and visual (VFR) flights are permitted; a screening service is provided to all flights and separation is ensured between all.

c. In class C airspace, instrument (IFR) and visual (VFR) flights are permitted; separation is only ensured between IFR/IFR or IFR/VFR flights. VFR flights are separated from IFR flights and receive traffic information relating to other VFR flights.
d. The definitions of the other airspace classes can be found in [48], up to class G where only the flight information service is provided, for flights which require it.

3.6 AIRSPACE ORGANIZATION

3.6.1 Flight Information Regions And Functional Space Blocks

The largest unit for dividing airspace into distinct units is the FIR (Flight Information Region). An FIR is a region of airspace in which flight information and alerting services are provided. Any portion of the atmosphere belongs to an FIR. Some countries in the world see their entire airspace constitute a single FIR, even for the smallest, to be included in an FIR extending beyond their borders. Other countries have divided their territorial space into several FIRs. The size and limits of the FIRs result from choices made by the administrations of the countries concerned. Some FIRs are bisected vertically. In this case, the lower part keeps the name of FIR, and the upper part becomes a UIR (Upper Information Region). Figure 3.3 shows the division of European airspace into FIRs. At European level, efforts to harmonize air traffic control procedures and resources through a “Single European Sky” legislative package have led to the creation of functional airspace blocks (FAB Functional Airspace Blocks) grouping the FIRs of several national airspaces. The objective of this initiative is to provide more homogeneous ATM (Air Traffic Management) services in the European area, less dependent on national borders. Figure 3.4 shows the spatial functional blocks defined in Europe. At present, these FABs essentially result in enhanced cooperation between the various national ANSPs (Air Navigation Services Providers).

3.6.2 Vertical Division Of Space

In Europe, airspace is divided vertically into a lower space and an upper space. The border between the two is generally at flight level (or FL for Flight Level) 195, that is to say at 19500 feet of pressure altitude above the isobaric 1013.25 hPa. However, there may be regional variations. For example, the UIR (Upper Information Region) at Maastricht Center, which controls space over Belgium, Luxembourg, and North West Germany, begins at FL 245.

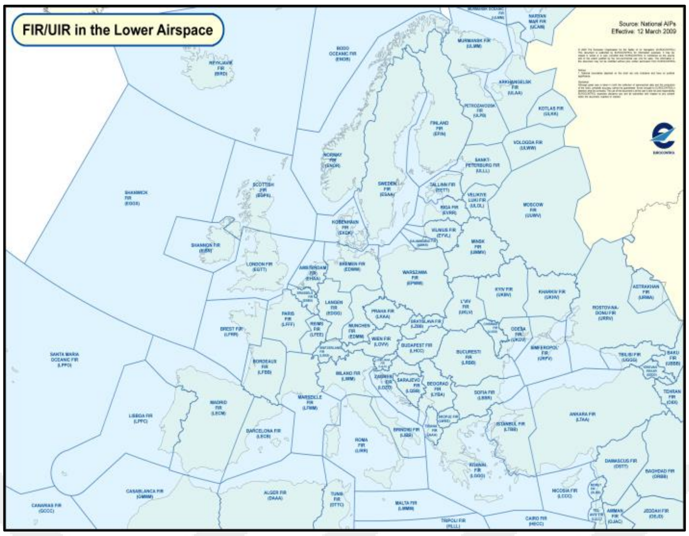

Figure 3.3: FIRs in Europe

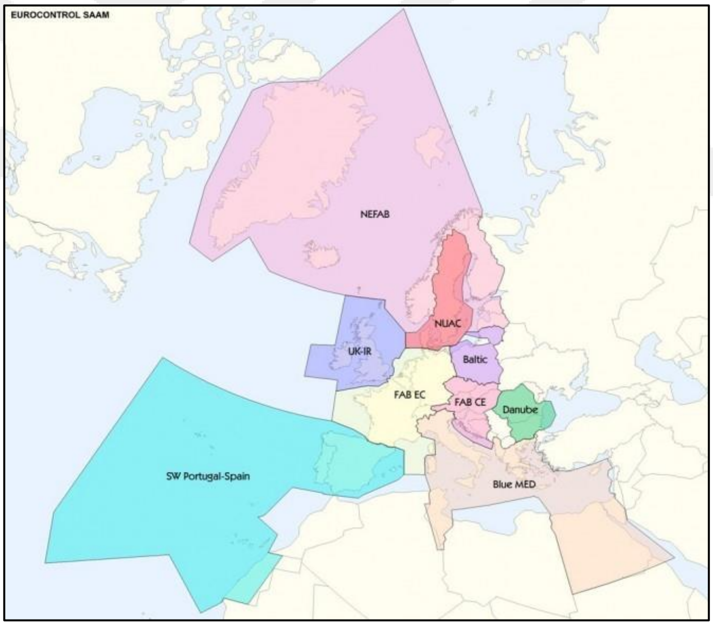

Figure 3.4: FABs (Functional Space Blocks) in Europe. [31]

3.6 AIRSPACE ORGANIZATION

In the United States, there is no actual UIR, but in-rout upper airspace air sectors typically begin at FL 240. As we saw at the very beginning of this section (see Figure 3.3), the lower airspace, below FL 195, is split horizontally into five FIRs (Flight Information Region), each managed by a regional control centre. In the upper airspace, only one region is defined, UIR even if in practice the regional centers each manage the upper airspace portion. Located above or near their FIR.

3.6.3 Controlled Airspaces: In-Rout, Approach, Aerodrome Control

In the airspaces where control services are provided, certain volumes of space are rather dedicated either to the control of aircraft around the airports, or to the control of aircraft in-rout between their airports. Departure and destination airports. Each airport is included in a control zone rules (CTR) dedicated to air traffic in the immediate vicinity of the runway. Above the CTR, and with a wider radius around the airport, there is another area dedicated to maneuvers and procedures for approaching or departing from the airport. Such an approach zone may possibly concern several airports, in particular around large cities. This is referred to as TMA (Terminal Maneuvering Area) or TCA (Terminal Control Area). Figure 3.5 shows a top view and a sectional view of the TMA, with the space classes associated with the space volumes.

Approach areas like the TMA are transition spaces between airports and the airways network defined in the in-rout space. In the end, we therefore distinguish three types of air traffic control, depending on the volume of space considered (see [49]):

a. in-rout control,
b. approach control,
c. and aerodrome control

These three types of control are illustrated in Figure 3.6, where some of the technical means of communication, localization, or radio-navigation essential to air traffic control are also represented. Also represented are the watchtower of a control tower, in charge of managing landings, take-offs and aircraft taxiing, and a regional air navigation center (CRNA), in charge of in-rout traffic. Approach control can be located at the airport or nearby, for the largest of them, or be handled by the regional center, depending on the case.

3.6.4 The air route network and sectorization

Airplanes flying in "in-rout" controlled airspace, lower or upper, operate on airways. The route network may be different depending on whether you are in the lower or upper airspace. In order to be able to be managed by human operators, this space is also divided into aerial sectors, which can be seen as the finest unit for dividing up the space. 'space. These sectors are assigned to the workstations of air traffic controllers (sometimes commonly referred to as 'air traffic controllers').

Figure 3.7 shows both the network of air routes in Europe, and the division into air sectors. Figure 3.8 shows the air route network defined in

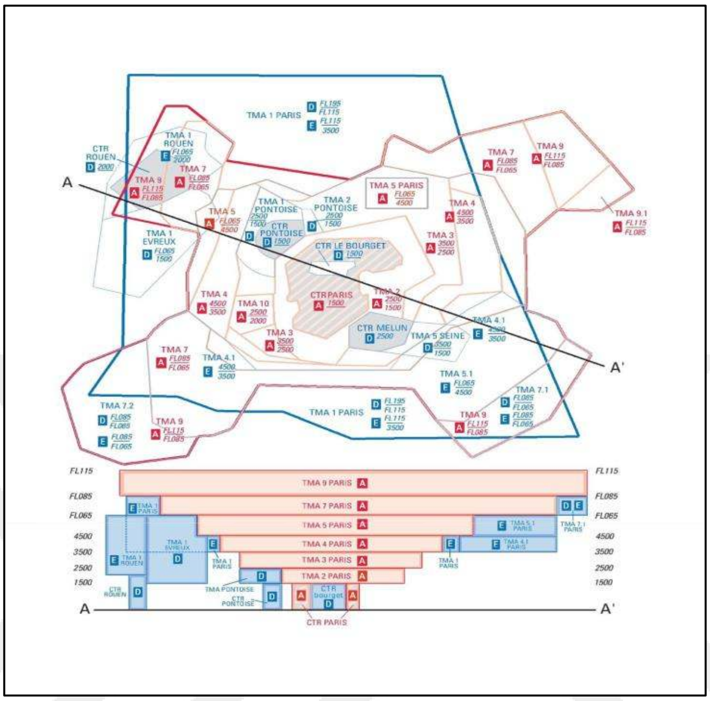

Figure 3. 5 Top View And Sectional View of TMA (2011) [12]

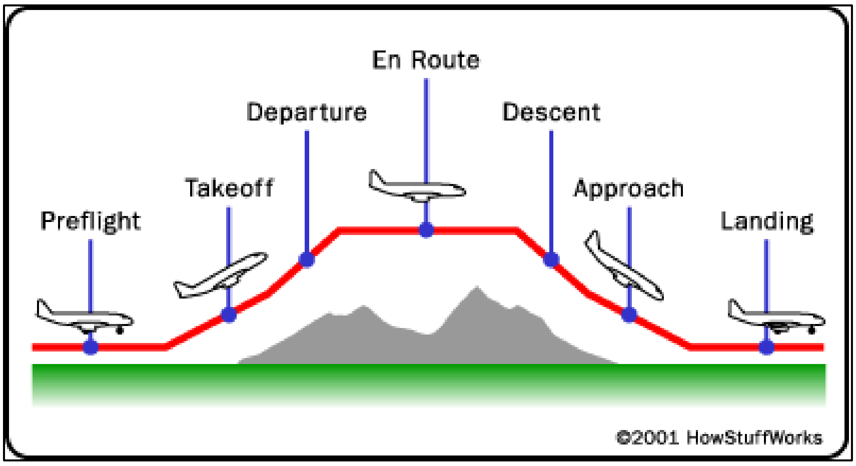

Figure 3.6: In-Route Control, Approach Control, and Aerodrome Control [12]

There are also a number of areas (TSA, D areas, etc.) which, when active, are reserved for military training flights or other deployment activities. Air defense.

3.7 THE WORK OF AIR TRAFFIC CONTROLLERS: TRAFFIC SEPARATION

3.7.1 Separation Standards, Separation Losses

One of the essential tasks of the air traffic controller consists in avoiding collisions between planes. From a regulatory point of view, it must ensure that aircraft maintain a minimum distance between them, expressed in the form of "standard separations" or "separation standards". Two planes must always be separated either laterally by at least a distance δ`, or vertically by at least a distance δz. These two distances may vary depending on the type and level of equipment for radar coverage of the airspace considered. Typically, the minimum radar separation standard in European in-rout airspace is 5 nautical miles in the horizontal plane, and 1000 feet in the vertical plane. These distances, which may seem significant, take into account the inaccuracies of aircraft navigation equipment and radars, as well as the processing times of radar information between actual detection and display on the controller screen. We speak of non-standard separation when the horizontal and vertical distances between two aircraft fall below the standard defined by regulation.

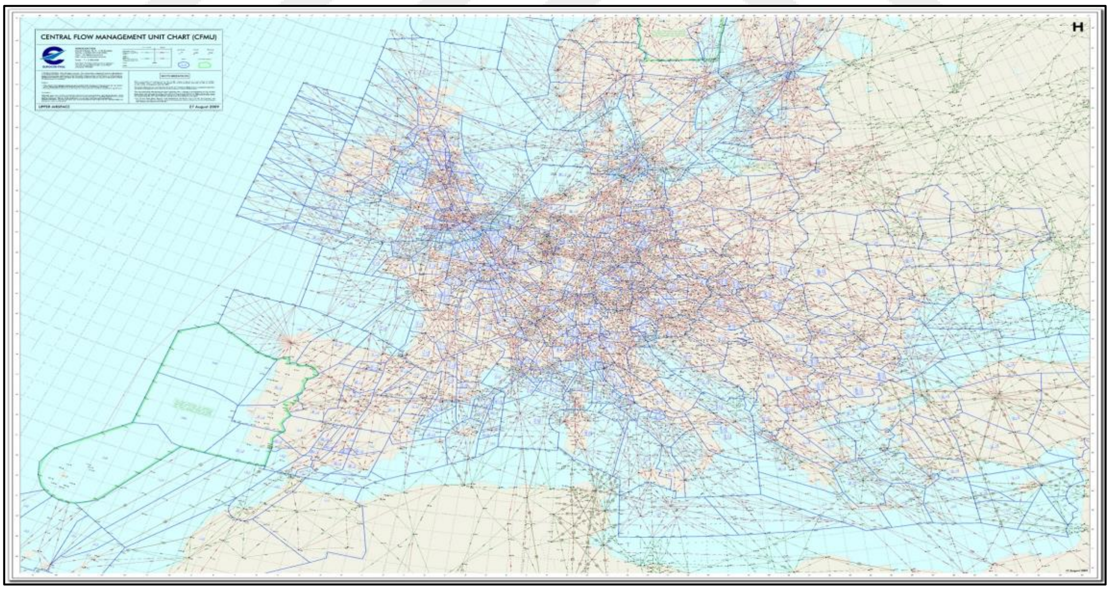

Figure 3.7: Routes and air sectors in Europe (2009) in the upper space [15]

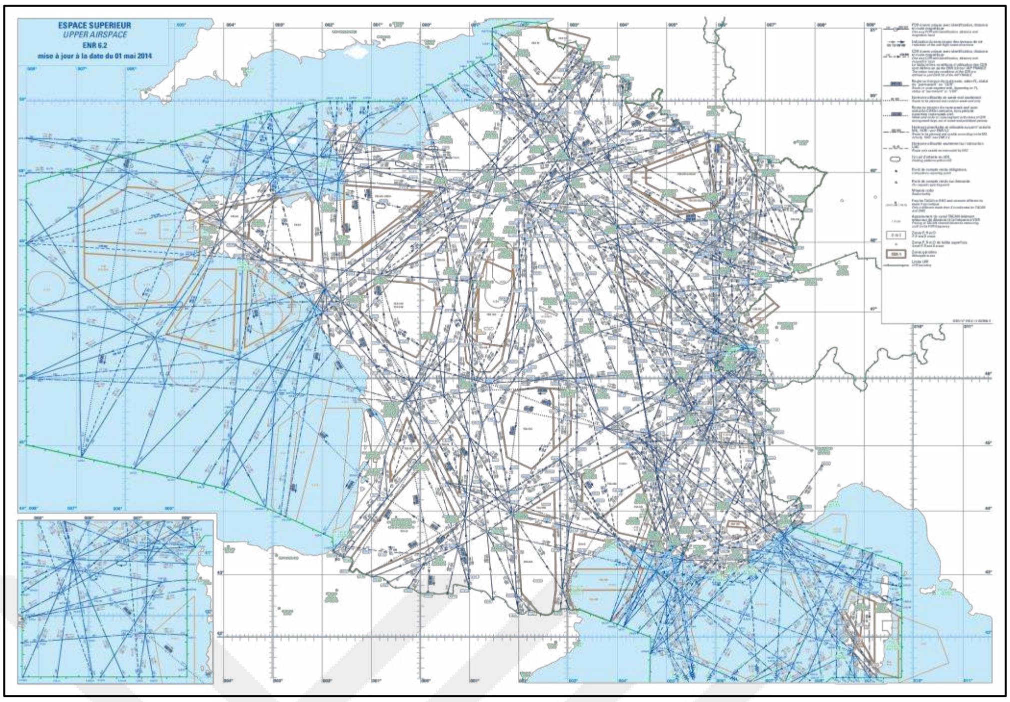

Figure 3.8: Source SIA (Aeronautical Information Service) [46]

In-route area UIR (2014) the "safety net" feature is defined in the controller's IT tools in order to alert him to the risks of non-standard reconciliation. These losses of separation are carefully monitored by the air navigation authorities. DSNA publishes two indicators each year (see [46]) concerning separation losses: the "HN70" when the separation is less than 70% of the standard, and the "HN50" when 'it is less than 50% of the norm. In 2012, the HN70 was 0.64 per 100,000 controlled flights, and there was no loss of separation less than 50% of the standard. The culture of safety is a central element in the professional environment of Civil Aviation. When they believe that the safety of a flight has or could have been jeopardized, ground agents must complete an incident notification form. Pilots, for their part, can file safety reports, commonly called "airprox". These incidents are systematically analyzed in detail, locally and nationally, in order to continually improve procedures and guarantee flight safety. The number of airproxes collected by DSNA in 2012 was 1 per 100,000 flights, for flights involving at least one IFR aircraft and not involving any military flight, and 0.3 per 100,000 for flights involving a military aircraft and a civilian plane.

3.7.2 Detection and resolution of air conflicts

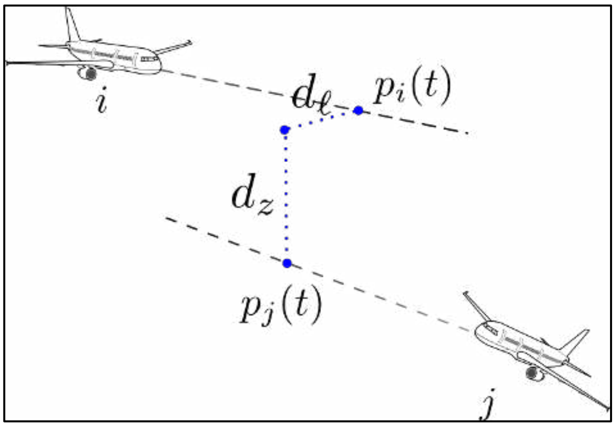

Figure 3.9: Air Conflict [22]

In order to avoid loss of separation, air traffic controllers anticipate aircraft trajectories and give preventive maneuvers to aircraft when they detect a possible loss of separation. The notion of air conflict is therefore defined as a loss of separation between two planned trajectories, as illustrated in Figure 3.9. Formally, there is a conflict between two planes i and j if∃*you*such as:

$$Of\,(i,j,t) \leq \delta` \quad \wedge dz(i,j,t) \leq \delta z$$

Where `δ` and δz are the regulatory minimum separation standards between aircraft (e.g. 5 nautical miles laterally, 1000 feet vertically)

In operational practice, this notion is extended to more than two aircraft, when an aircraft is in conflict with a second aircraft, itself in conflict with another, etc. We then speak of "conflict in aircraft" (see Figure 3.10), n being the number of aircraft involved in the conflict situation. More formally, a certain number of publications introduce the notion of cluster (group) of conflicts as being a transitive closure of the relation "is in conflict with". The notion of conflict then remains reserved for potential losses of separation between two aircraft only, and the notion of cluster is used for conflict situations involving more than two aircraft.

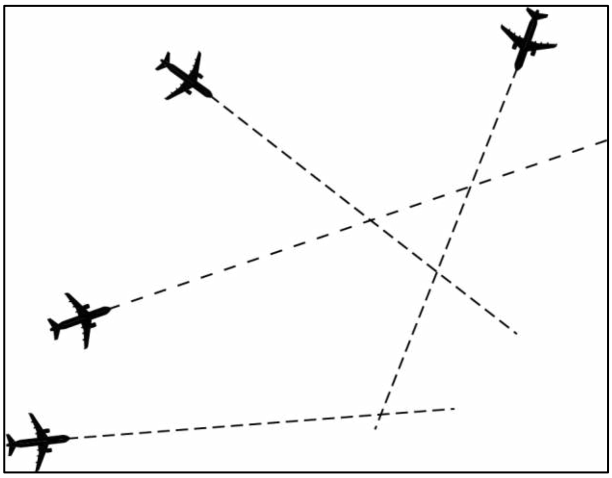

Figure 3.10: Conflict With 4 Planes (Cluster). [22]

The maneuvers given by the controllers to resolve the conflicts can be of several types: change of heading or altitude of the planes, stabilization at an intermediate level during a climb or a descent, cruise control, holding circuit (when approaching airports). Today, these instructions are transmitted to pilots by radio.

3.7.3 Distribution Of Tasks Between Controllers On Their Workstation

The controller who monitors aircraft on a 'radar screen' and gives instructions to pilots by radio is called a 'radar controller'. It is aided by an 'organic controller' which pre-detects potential conflicts and coordinates traffic with adjacent sectors. Anglo-Saxon nomenclature uses the terms “radar-controller” (R-side), “tactical controller” or “executive controller” for the radar controller, and “data-controller” (D-side) or “planning controller” for the organic controller. Typically, radar and organic controllers operate in tandem at their workstation (see Figure 3.11), which is referred to as the control position. Before the automation of transmissions of flight information from one center to another, a control position could be manned by three controllers, a radar, an organic, and an assistant to help with communications telephones. With the appearance of IT tools to aid control, a new distribution of tasks is envisaged, both on the European side within the framework of the Single European Sky ATM Research (SESAR) program and on the United States as part of the Next Generation´ Air Transportation System (NextGen) program. A new role, still under study, is envisaged: that of multi-sector planner, which could either play the role of organic controller for several.

Figure 3.11: Control Position, With A Radar Controller and an Organic Controller Radar Positions, or Plan and Organize Traffic Upstream For Several Workstations, Based on Medium-Term Forecasts [43]

3.7.4 The controller tools

As shown in Figure 3.11, the controllers' workstation (control position) has “radar screens” to display aircraft positions, area geography and major routes. There is also a table of “strips”, which allows them to manipulate strips of paper (strips) containing the essential information relating to each flight. Many countries have now switched (or are in the process of doing so) to a system of electronic strips. The other essential equipment is the radio and telephone systems, the terminal for automatic flight coordination, and the screens for displaying weather information or other useful information. Each sector of space is assigned a radio frequency. Radio frequencies and telephone lines can be dynamically assigned to control positions, which makes it possible to group together several sectors of space on the same workstation.

3.8 REGULATING THE WORKLOAD OF CONTROLLERS

A crucial element for traffic safety is to ensure that the workload of air traffic controllers does not exceed certain acceptable limits. These limits determine the capacity of the operational system to absorb traffic under given conditions (weather, type of traffic, level of equipment, etc.). In this section, we briefly present the different mechanisms put in place to regulate this workload, by best balancing the capacity of the system and the traffic demand. These mechanisms can be set up with several time horizons. A distinction is made between strategic planning (e.g. definition of routes, sectorization of space), pre-tactical preparation (planning of the duty lap, allocation of take-off slots), and real-time tactical traffic management.

3.9 AI AND METAHEURISTICS

The term metaheuristic was introduced by Glover in the mid-1980s, in connection with Taboo Search. In [77], Glover describes his method as a higher level heuristic for solving optimization problems, designed to guide other methods to get out of the pi age of the local optimum. Many other methods are now grouped under this general name, many of which existed before the appearance of the term "metaheuristic", such as evolution strategies ([22]), genetic algorithms ([90, 79]), or simulated annealing ([40]). Metaheuristics are a collection of very diverse methods aimed at solving difficult problems for which "classical" optimization methods no longer work. These are iterative algorithms, as a general rule stochastic, in the sense that the exploration of the space of admissible points involves a random walk, and which seek a global optimum but no guarantee of finding it. In principle, these methods sample iteratively (and more or less randomly) the space of admissible points, being guided by a heuristic which directs the search for good quality solutions. This sampling can explicitly call on probability distributions, as in the case of distribution estimation algorithms, or rely on other mechanisms, as in the case of genetic or genetic algorithms. ` New individuals are produced by crossbreeding and mutation.

All these methods are based, to varying degrees, on three types of mechanisms, sometimes concurrent: random movements, where one allows oneself to degrade the crit `ere-objective f and which make it possible to diversify the search by leaving local optima; a "greedy" search aiming to intensify the search in the interesting areas by improving the objective function f; and an archive allowing to memorize the zones already explored, in order either to avoid returning to them (eg: Taboo method), or on the contrary to define "attractors" indicating interesting areas to explore (eg best positions found, for particle swarms). Beyond their various sources of inspiration (Darwinian selection, physical phenomena, etc.), the effectiveness of metaheuristics is due to the combination of these three mechanisms, which sets a compromise between diversification and intensification, in the search for optima. For a presentation of metaheuristics in general, see the work of Talbi [57], or the works of Siarry ET. Para. [45, 15]. For evolutionary algorithms in particular, we can refer to [55].

3.9.1 Evolutionary algorithms

Evolutionary algorithms are inspired by natural evolution and the Darwinian process of selection and survival of individuals best suited to their environment. Here, this environment is simply the landscape of the function whose optimum is sought. Because of their analogy with the natural process, we speak more readily of maximizing the adaptation (fitness) of individuals, than of minimizing an objective function. However, if one seeks to minimize a function f, it suffices to choose as the fitness of an individual x the opposite of f(x) to reduce oneself to the initial minimization problem. The general principle of an evolutionary algorithm, given by Algorithm 8, is to initialize a population of a certain size, for example by drawing random points in the search space, then to make this population evolve by selection, crossing, and mutation of its individuals.

a. Algorithm 1: General principle of evolutionary algorithms.
b. Require: Popsize population size, probabilities of crossing Pc and mutation Pm
   i. Pop0 ←initiate (popsize)
   ii. while not (Stop (k,Popk)) do
   iii. Evaluate the raw value of the adaptation of Popk's elements
   iv. Edit raw adaptations (ex. *scalingand* sharing)
   v. Select a pool of parents, according to the new adaptations
   vi. Create a new population by crossing, mutation, or duplication of some parents
   vii. *k*←k+1
   viii. end while
   ix. Return the best elements of the population

Among the very first algorithms of this type, the genetic algorithms introduced by Holland [90] and popularized by Goldberg [79] adopt a binary coding, in their canonical version. With this coding, an individual is represented by a sequence of bits, the crossing between two individuals is done by exchanging part of the bits of the sequence, and the mutation by modifying one or more bits. Depending on the problems dealt with, the coding of individuals can however take other forms. In particular, in the case where we optimize a function with real variables, we adopt a real coding and specific crossover and mutation operators (eg barycentric crossover). Beyond their basic principle, which is quite simple, the proper functioning and efficiency of evolutionary algorithms rely on numerous refinements, concerning for example the definition of the operators of scale (scaling), or rebalancing (sharing) for the modification of the raw adaptation, or even the choice of the principle of selection (with or without elitism, random drawing of the parents), or the choice of crossover and mutation operators. Their performance also depends on their correct parameterization. These different aspects are detailed in [55].

3.9.2 Metaheuristics for continuous domain optimization

Particle swarms and differential evolution, briefly presented in this section, are two other examples of population metaheuristics. They were initially designed for the optimization of functions with continuous variables.

i. Optimization By Particle Swarms (Particle Swarm Optimization)

Particle swarm optimization (PSO), proposed by Kennedy and Eberhart [99, 53, 150], is inspired by the living world and its self-organization processes, and in particular the displacements of flocks of birds or schools of fish. The basic idea is that a group of agents provided with simple rules can make emerge an “intelligent behavior”, at the level of the group. Here, we set rules on the individual movement of agents, characterized by their position and their speed, hoping to bring out a global behavior where the swarm converges towards an optimum that we hope global. The steps of the PSO are described in Algorithm 9. The initial positions and velocities of the swarm are generated randomly. The algorithm then updates the velocity vectors, at each iteration, taking into account an inertia factor (parameterized by ω), and attraction factors (c1 and c2) towards the best position found by the considered particle, and towards the best position found by the swarm.

A. Algorithm 2: Particle swarm optimization (PSO)
B. Require: popsize, ω, c_1, vs2. Parameters of the PSO algorithm
   i. 1: P0 ←InitPop(popsize). Initialize positions xi and velocities vi, for each individual i of the population
   ii. 2: repeat
   iii. 3: for*I*= 1 to popsize do
   iv. 4: v_I← ωvi + u (0, c1) ⊗ (bi − xi) + u (0, c2) ⊗ (g−xi)
   v. 5: x_I← xi + vi
   vi. 6: bi ←UpdatePrivateBest(bi,xi) . Best point on the path of the i particle

vii. 7: end for

viii. 8: g ←UpdateGlobalBest (g, b1,...,bpopsize).Best point encountered by the swarm

ix. 9: untilStop( )

x. 10: return g

In Algorithm 9, u (0, c) represents a random vector of dimension n whose components are drawn at random, independently, between 0 and c. The operation⊗denotes the term-by-term multiplication between two vectors. FunctionUpdatePrivateBestevaluates the current position xi of particle i, and replaces bi by xi if f(xi) < f(bi). FunctionUpdateGlobalBestupdates the best g-point found by the swarm. In its original version, the algorithm tends to converge too quickly towards a local optimum, due to the attraction towards the best point g found by the swarm. A classic improvement consists in no longer using g, the best point found by the whole swarm, and replacing it with several attractors defined by subsets of the swarm. We therefore define a "local" attractor gi for each particle i, which corresponds to the best point found by a subgroup not including i. This subgroup is defined by a fixed "topology" of the swarm. For example, for a ring topology, we take the best point found by particles i − 1 and i + 1 (modulo the number of particles). Moreover, in order to prevent the accumulation of successive modifications of the velocity vectors from resulting in displacements that are much too large, or on the contrary too small, we limit the velocity of each particle: kvik∈ [Vmin,Vmax]. In order not to add additional parameters, the choice of Vmin and Vmax is made automatically, depending on the size of the domain in which we are looking for an optimum (knowing that we do not necessarily refrain from leaving temporarily from this area). Parameter tuning (here, popsize, ω, c1, c2) is crucial for the performance of the algorithm. For the dynamics of the particle swarm to be favorable to a convergence without excessive oscillations towards attractors, the parameters must imperatively lie within certain limits (see [36, 162]). Within these limits, the setting of the parameters may be different depending on the problem treated. The reader can refer to [33] for a more complete overview of the different mechanisms and variants of the PSO algorithm, and their analysis. The differential evolution algorithm (DE: differential evolution), introduced by Storn and Price [55] is also a population algorithm, of remarkable simplicity. Starting from an initial population of randomly generated vectors xi, it consists in constructing, for each element xi, a candidate vector yi, which replaces xi in the population if f (yi) < f (xi). To construct the candidate vector yi, we replace, with a probability CR, each coordinate of the vector xi by a combination of 3 vectors taken at random from the population, making sure that there is always at least one coordinate of xi which is modified. The recombination operator calls on a parameter F, which is an amplification factor of the difference between two of the three vectors. Algorithm 10 summarizes the steps of the method.

3.9.3 Consideration of constrains

Constraints can be taken into account in various ways, among which we can cite the following methods

a. reject individuals who do not satisfy the constraints,
b. penalize individuals who do not satisfy the constraints,
c. maintain the feasibility of solutions, by specific representations or operators (e.g.: barycentric crossing in a convex domain),
d. fix inadmissible solutions,
e. consider separately feasible solutions and infeasible solutions (e.g. multi-objective optimization, with a criterion for f(x) and a criterion for the violation of the constraints),
— favor the exploration of the boundary of the admissible domain

The choice of one method or another largely depends on the problem being treated. In some cases, it will for example be relatively easy to initialize a population of points satisfying the constraints, then to maintain the feasibility of the solutions in the successive populations, either by using specific operators, or by repairing the solutions. In other cases, the simple fact of finding a solution satisfying the constraints can turn out to be a difficult problem in itself, independently of the objective of finding an optimal solution. In the latter case, a penalization approach may be preferred.

3.9.4 Hybrid metaheuristics

In addition to the multitude of metaheuristics that can be found in the literature, with their canonical versions and their many variants, there are also hybrid methods [26, 25] combining either several metaheuristics, or metaheuristics and exact methods. We characterize these hybrid metaheuristics according to several criteria (see [98, 136]), according to the type of combined methods (exact, metaheuristics, methods specific to the problem, etc), how the hybridization is carried out (low level, or high level), the order of execution of the methods (in sequence, interleaved, or in parallel ele), and according to the control strategy adopted (integrative or collaborative). In this context, we have proposed a parallel cooperative method [7, 18] hybridizing an evolutionary algorithm and an exact method of branch & bound by intervals (see [82] for the m interval methods, or section 2.3.4 for a short presentation). This approach combines a metaheuristic, capable of exploring the space of admissible points and finding very good solutions (although without guaranteeing them), with an exact method by intervals, capable of reducing the domain eligible. This reduction of the admissible domain is done by eliminating the "boxes" (interval vectors) whose image by an inclusion function is less good than the best solution found, this one being set to up-to-date both by metaheuristics and by the interval method. The cooperation of the two methods makes it possible to prove the optimality of solutions to difficult optimization problems, for functions with real variables, non-convex, strongly multimodal. This preliminary work, where the method by intervals was particularly basic, was subsequently continued and greatly improved by the thesis work of Charlie Vanaret.

3.10 APPLICATION TO SOME AIR TRAFFIC PROBLEMS

To close this chapter on optimization methods, this section 2.6 briefly describes our work on the application of some of these methods to some air traffic problems. Some of this work is detailed in a chapter of the book M´etaheuristiques [5], coordinated by Patrick Siarry, or is discussed in more depth in other chapters of this memoir (optimal partitioning into control sectors, in Chapter 4). Only a few exploratory works on the application to aerial conflict resolution of metaheuristics for continuous domain optimization are therefore a little more developed here. However, most of the contributions that are the subject of this dissertation are presented in chapters 4 and 5.

3.10.1 Network of separate 3d-roads

The work presented in the publications [71, 69, 70, 62], focused on the construction of a network of separate 3D-roads ("tubes") dedicated to bigger flow of traffic. The method used was an evolutionary algorithm, hybridized with an A^*. This is a low-level hybridization, where the A^* is integrated into the mutation operator of the evolutionary algorithm. A variant of the hybrid algorithm, including a greedy method, was also tested. This work, essentially carried out during my doctoral thesis, is not the subject of this thesis, and is therefore not detailed here. They are only recalled as an illustration of an application to air traffic management of the methods presented earlier in this chapter.

3.10.2 Optimal airspace partitioning

It is therefore a matter of constructing a partition of the set of space sectors, so as to balance the workload between the control positions, while respecting a certain number of constraints (respecting the maximum number of working positions, avoiding overloads, etc.). This application is very close to the example of Figure 2.2, except that it is also possible to cut certain branches of the tree, during the construction of the partitions, when certain nodes do not respect the fixed constraints. This application also requires a model of the air traffic controllers' workload, which can be learned using supervised learning techniques (see chapter 3). Our contributions on this application are detailed in chapter 4.

3.10.3 Air conflict resolution

A centralized approach is adopted here, where the maneuvers are given by an actor having full visibility on all the traffic. In this context, the existing works presenting methods capable of dealing with instances of the order of about twenty planes in conflict, are essentially limited to [30], with methods mixed linear programming, and to [51, 52, 49], with evolutionary algorithms. A constraint programming approach is also proposed, and compared to evolutionary algorithms, in [4]. In the mixed linear programming approach, such as [30], the assumptions on the speed of aircraft are strong and unrealistic in the context of operational use: constant speeds for resolutions by lateral avoidance, or instantaneous speed changes for resolutions in speed. In [51], a genetic algorithm evolves a population of individuals encoding lateral deviation maneuvers for aircraft initially in conflict. The proposed model is based on discrete variables: the start and end times of maneuvers are chosen with a fixed time step, and the deviation angles are taken from among discrete values. In [49], a similar modeling is used, with an ant colony algorithm. The evolutionary algorithms give very convincing results, with relatively realistic hypotheses, allowing in particular the taking into account of uncertainties on the speeds of the planes. However, the equipment present today in control centers and on board aircraft is not designed to manage maneuvers defined in time. Consisted in adopting a distance rather than a time model for aircraft maneuvers, and in modeling the problem of conflict resolution as an optimization problem under constraints in continuous domain, rather than in discrete domain. We apply the equipment currently present in control centers and on board aircraft is not designed to manage maneuvers defined in time. We apply to this problem of metaheuristics for continuous domain optimization: real coding evolutionary algorithm, particle swarm optimization, and differential evolution algorithm. For this first approach with these methods and this modelling, we confined ourselves to the resolution in the horizontal plane, for aircraft flying at the same flight level, without uncertainties on the speed. Lateral aircraft maneuvers are defined by distances, which can be translated directly into geographical points directly usable by current Flight Management Systems (FMS), rather than by times.

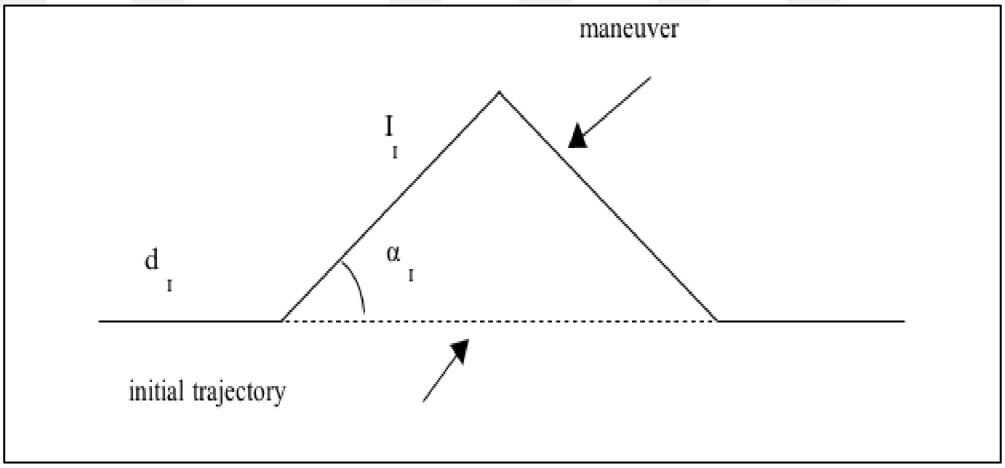

Figure 3.12: Modeling A Lateral Manoeuvre, in Distance and in Angle.

A maneuver imposed on an aircraft i is totally determined by a triplet xi = (di, αi,li) where di is the distance (along the initial route) at which the maneuver begins. Maneuver, αi is the deflection angle, and li is the length of the first deflection segment. The return segment is made by a new angle deviation (−2αi) until interception of the initial route. The modeling provides a sequence of geographical points (Fig. 2.4). The models in time or in distance are of course totally equivalent, knowing the speeds of the planes, if only the nominal trajectory is considered. On the other hand, if we consider the uncertainties around this nominal trajectory, the two models lead to completely different volumes, as shown in Figure 2.5.

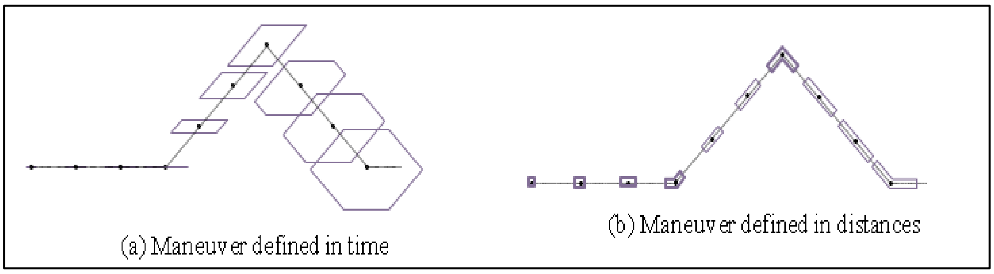

Figure 3.13: Zones of Uncertainty, With Modeling of Maneuvers In Time (on The Left) Or in Distance (on The Right). [43]

We did not take these uncertainties into account in our exploratory work, but this is what motivates this choice of distance modeling. We assumed that the lateral maneuvers would no longer be transmitted by radio as currently, but that the turning points of the maneuvers would be transmitted by data link.

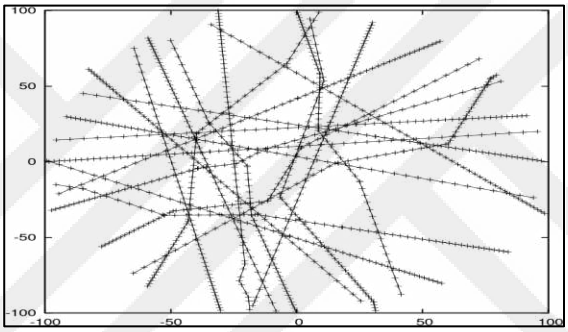

Figure 3.14: Example of A Conflict With 20 Planes Solved by The Differential Evolution Algorithm [43]

The details of each of the methods applied to this problem, as well as the comparative results, are given in [64]. Figure 3.14 gives an example of resolving a conflict

4. PROPOSED METHOD

It is assumed that a new airline called Westpoint Airways, whose hub is in London, has recently started. Throughout this report, optimization methods will be implemented in order to achieve successful results in this new airline for the incoming years. That implies a correct network and frequency plan, together with an adequate fleet plan, which are presented afterwards. Assumptions and results will be commented and explained, taking into account the references included in the Bibliography section, specially the lecture slides provided in the course [1]. Finally, all necessary data and programs to replicate the results are included attached to the report.

4.1 PARAMETERS MODELLING

Common parameters that will be used along the various problems to face are explained here, computed as stated in the problem statement appendices:

4.1.1 Revenue

Yield (or Revenue per RPK -Revenue per Passenger Kilometer-) is divided two different types, depending on if the flight is intra-European or not.

a. Yield for Intra-European Passengers:

$$YEURij = 5.9 \cdot d{-}ij0.76 + 0.043 \tag{4.1}$$

where Y_{EURij} is the yield between origin 'i' and destination 'j', expressed in e and d_{ij} is the distance in km between origin 'i' and the destination 'j'.

b. Yield for flight with US origin or destination:

$$Y_{USij} = e\ 0.05 \tag{4.2}$$

4.1.2 Load factors

Average Load Factors expected are estimated as follows:

i Load Factor for Intra-European Passengers: $LF = 75\%$

ii Load Factor for flight with US origin or destination: $LF = 85\%$

4.1.3 Costs

Costs are subdivided in two different types: Leasing Costs and Operating Costs. Those are explained in detail here:

a. Leasing Costs (C_{Lea}): All aircraft operated are leased, and their leasing costs depend on the Aircraft type and can be found on assignment data provided[1].

b. Operating Costs (C_{OP}): those can be divided as well into three different costs:

i Fixed Operating Costs (C_X^k): costs per flight leg; which includes landing rights, parking fees and fixed fuel costs. They depend on aircraft Type k (assignment data).

ii Time-Based Costs (C_T^k): costs defined in e per flight hour, and account for any cost which is time-dependent (cabin crew, flight crew...). Find below how those costs are modelled:

$$C_{T_{ij}}^k = c_T^k \frac{d_{ij}}{sp^k} \tag{4.3}$$

Where $C_{T_{ij}}^k$ is the time cost between two different airports 'i' and 'j', flown by an aircraft of type 'k'; c^k_T is the time cost parameter for an aircraft of type 'k', d_{ij} represents the distance between two airports and sp^k the aircraft speed (assignment data).

iii Fuel Costs (C_F^k): they depend on the distance flown (d_{ij}), and are modelled as:

$$C_{F_{ij}}^k = \frac{c_F^k \cdot f}{1.5} d_{ij} \tag{4.4}$$

where $C_{F_{ij}}^k$ is the fuel cost between two given airports 'i' and 'j' for a specific flight 'k'; c^k_F is the fuel cost parameter that depends on aircraft type (assignment data) and f is the fuel cost (f = 1.42 USD/gallon in 2017 and f = 1.6 USD/gallon in 2022).

As a result, total cost is computed as:

$$C_{ij}^k = C_{Lea}^k + C_{OP_{ij}}^k \tag{4.5}$$

where C_{OP} should be computed by flight leg between airports 'i' and 'j' (when a flight to/from the hub, operating costs is are assumed to be 30 per cent less) and per aircraft type 'k' as follows:

$$C_{OP_{ij}}^k = C_X^k + C_{T_{ij}}^k + +C_{F_{ij}}^k \tag{4.6}$$

4.1.4 Distance between two points

Distance between two points is necessary to compute, as many factors directly depend on it. To do, it is possible to apply Equation 7 by using the position of two points, given by their respectively latitude and longitude:

$$d_{ij} = 2R_e \cdot \arcsin\sqrt{\sin\left(\frac{\varphi_i - \varphi_j{}^2}{2}\right) + \cos\varphi_i \cos\varphi_j \sin\left(\frac{\lambda_i - \lambda_j{}^2}{2}\right)} \qquad (4.7)$$

where d_{ij} represents that distance between points 'i' and 'j', and ϕ_i, ϕ_j, λ_i and λ_j are the latitude and longitude respectively of airports 'i' and 'j'.

a. Problem 1

Firstly, it is supposed that Westpoint Airways has leased a certain amount of aircraft (assignment data). Therefore, it is necessary to develop an optimal network and frequency plan, in order to maximise Westpoint Airways profit. As a result, an optimisation problem should be solved.

b. Mathematical Model

Before going into the optimisation model itself, it is necessary to specify the notation of the problem. That is: what are the set used, the decision variables, and the different parameters that play an important role in the model.

It is noted that parameters explained in Section II will be used as well. The reader is redirected to that section when any of them appear in the optimisation model.

At the end, optimisation problem is addressed: Network and Frequency plan optimisation model is divided into the objective function (the one that should maximise -in this case in order to get a numerical solution that allows for the desired plan), and the constraints which this objective function is subjected to.

c. Sets

i N: set of airports, where 'h' is the hub

ii K: set of aircraft types

d. Decision Variables

All decision variables have a lower bound at 0.

i w_{ij}: passengers from airport *i* to airport *j* that transfer at the hub ii x_{ij}: direct passengers from airport *i* to airport *j*

iii z_{ij}^k : number of flights from airport *i* to airport *j* with aircraft type *k*.

e. Parameters

i q_{ij}: travel demand between airport *i* to airport *j*

ii g_h: binary parameter: $g_i = 0$ if a hub is located at airport *i*; $g_i = 1$ otherwise

iii d_{ij}: distance between airport *i* to airport *j*

iv *Y* : revenue per RPK flown (Yield)

v s^k: number of seats per aircraft type *k*

vi $C_{OP}{}^k{}_{ij}$: Cost of operating a flight from i to j

vii sp^k: speed of aircraft type *k*

viii $Slot_i$: available slots of each airport type *i*, (unlimited slots in hub airport are considered according to assignment guidelines).

ix BT^k: aircraft type *k* average utilisation time

x RW^k: runway length needed for each aircraft type *k*

xi RW_i: runway length of an airport *i* • RA^k: maximum range of each aircraft type *k*

xii AC^k: number of aircraft of each type *k*.

xiii δijk: runway binary parameter: $\delta ijk = 1$ if $RW^k \leq RW_i$ and $RW^k \leq RW_j$; $\delta ijk = 0$ otherwise.

xiv Ψij: range binary parameter: $\Psi ij = 1$ if $d_{ij} \leq RA^k$; $\Psi ij = 0$ otherwise.

f. Objective Function

$$\sum_{i \in N} \sum_{j \in N} \left[Y \cdot d_{ij}(x_{ij} + w_{ij}) - \sum_{k \in K} C^k_{OP_{ij}} \cdot z^k_{ij} \right] \tag{4.8}$$

The objective function represents the profit obtained in a week of operation, given as the revenues from passenger minus the operating costs. As leasing costs are fixed in this case, they do not need to be included in the objective function. Constraints the different constraints that apply in Problem 1 are:

Demand Constraint

$$x_{ij} + w_{ij} \leq q_{ij}, \forall i,j \in N \tag{4.9}$$

This constraint means that the sum of direct and connecting passengers between two airports *i* and *j* should not be greater than the demand.

Transfer Passengers Constraint

$$w_{ij} \leq q_{ij} \cdot g_i \cdot g_j, \forall i,j \in N \tag{4.10}$$

This constraint means it is not possible to have connecting passengers if the origin or destination airport is the hub (so either g_i or g_j will be zero in those cases). This constraint means that the flow of passengers in each leg *ij* (composed by direct and indirect passengers if the origin or destination is the hub) cannot be higher than the actual capacity, defined as the frequency times the number of seats multiply by the aircraft load factor. Inside this capacity constraint, there are two conditions that the aircraft should comply. Otherwise, the capacity of this aircraft in this leg is zero. This constraint means that the time spent by an aircraft, either on ground or flying, should be lower than the block time of this aircraft.

4.2 ANALYSIS OF RESULTS

After implementing in MATLAB the mathematical model explained previously, it is optimised with CPLEX looking for the maximum profit of WestPoint Airways, considering all constraints mentioned above and a typical week of operations with 10 operating hours per day on average (70 hours on a week). Key performance indicators of the airline (KPI's), network routes, number of flights per route, expected passengers and use of different types of aircraft can be obtained from the solution obtained. In Table 1 the values of KPI's of this airline and its operative results are listed. ASK and RPK are according to a new company operating in Europe with 14 different destinations, mainly short flights. Its CASK is similar to the one of another ULCC (Ultra Low Cost Carrier) as WizzAir, 0.05e represents low costs per ASK [2], and its marginal profit around 13% is also in similar values of this type of airlines. A load factor of 74.90 is quite low in comparison with them but more usual in new companies, and a BELF of 64.68 represents a good business model. Finally, this affirmation is verified with a weekly profit of 70,127e.

Table 4.1: KPI's and Operative Results Exercise 1

Key Performance Indicators	
Available Seat Kilometer (ASK)	8,565,155 ASK
Revenue Passenger Kilometer (RPK)	6,414,930 RPK
Cost per ASK (CASK)	0.0518e/ASK
Revenue per ASK (RASK)	0.0600e/ASK

Yield per RPK	0.0802e/RPK
Average Network Load Factor (ANLF)	74.90%
Break-Even Load Factor (BELF)	64.68%

Table 4.1: KPI's and Operative Results Exercise 1 "Table Continued".

As it is shown on Figure 4.1, there are 14 European destinations from London, without operating any direct flight between other cities but with some transfer passengers. They are just few people (15-30 people each transfer route) for whom is profitable travelling at the longest possible routes of the network, as revenue is based on distance. Also, it is worth mention that the hub lies close to the line joining the origin and destination of connecting passengers, e.g. Dublin-Munich or Madrid-Helsinki.

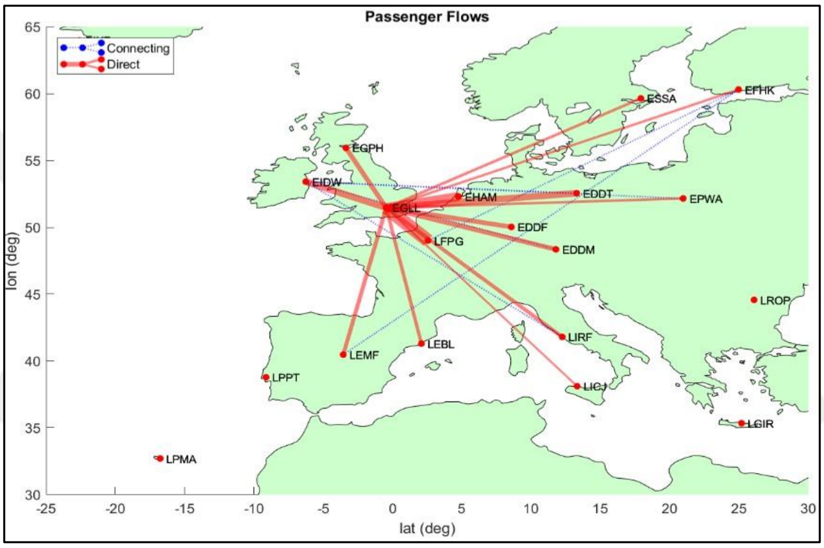

Figure 4.1: Passengers Flows on Westpoint Airways

All flights available from London are represented in Figure 2[2], with their respective passengers and number of flights according to the type of aircraft. Main destinations are Paris, Amsterdam and Dublin, with estimated passengers of 968, 626 and 433, respectively. These routes are also the closest from London, having lower operational costs with the smallest aircraft (regional turboprop, i.e. ATR-42). In that way, it is possible to offer a good number of daily connections, up to 4 in the case of Paris with just regional turboprop. Another type of regional aircraft (regional jet, i.e. Bombardier CRJ-700) is used for destinations with considerable demand and short-mid range, as German cities or Edinburgh. In these airports usually two types of aircraft are used, a combination of regional jet with turboprop or with single-aisle jet (i.e. Boeing 737-700). This last type of aircraft is used for furthest routes of the network, as Warsaw or Rome, with just 1 or 2 weekly services. Finally, the use of aircraft is divided among 2 turboprops, 1 regional jet and 1 single-aisle jet and presented together with its productivity in Figure 4.3. A remarkable aspect is how precise the optimisation is, having a utilisation of 139.92 out of a maximum of 140 on turboprops or 69.98 out of 70 on regional jet, which is a 99.97% of use. Also, it shows how is the importance of Single-aisle jet on productivity with more than 50% of this indicator, meanwhile, in hours used, it is the less used with 24.95%.

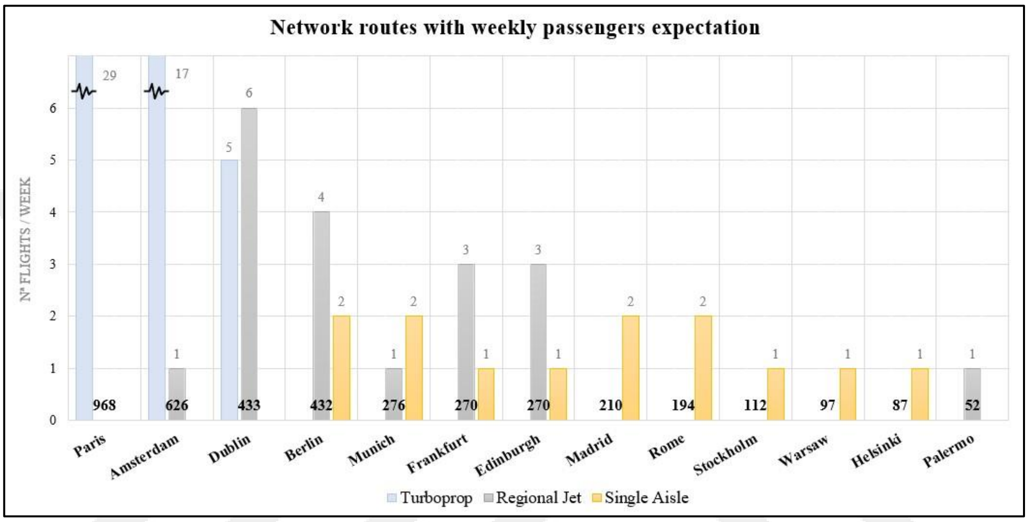

Figure 4. 2 Routes from Westpoint Airways' Hub (London)

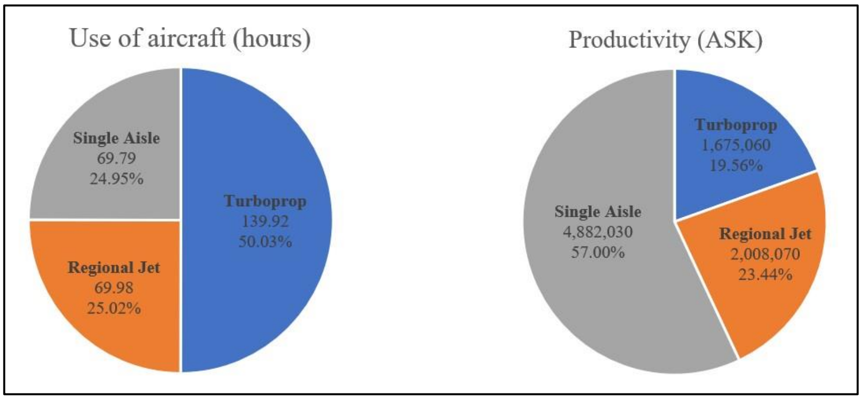

Figure 4.3: Utilization of Aircraft

4.3 IN CASE OF FLEET EXPANSION

In this problem, a demand forecast will be assessed. The results obtained here will be used in next problems to evaluate new results using a fleet expansion; which will be needed to fly to US destinations.

Demand can be modelled using the following gravity model:

$$D_{ij} = k\frac{(pop_i pop_j)^{b1} \cdot (GDP_i GDP_j)^{b2}}{(f \cdot d_{ij})^{b3}} \tag{4.11}$$

Where D_{ij} is the demand between airports i and j; pop_i and pop_j are the population in thousands of cities i and j; GDP_i and GDP_j is GDP of airports i and j; f is the fuel cost (see Parameters Modelling section, Costs), and d_{ij} is the distance between two airports in km. The main goal here will be to obtained the demand for each leg in 2022. Making use of the data about the population (in the correct units), distance and GDP between all set of legs between two points ij in the year 2017, it is possible to compute the parameters k, $b1$, $b2$ and $b3$ using Non-Linear Regression of multiple variables. Notice that it is supposed that this model only differs from European to US models into a factor of 10 of the coefficient k. As a result, those coefficients can be taken from the European data and then apply this scaling factor when computing the demand in US flights.

Where N = Number of European Airports, and that can be solved in this way:

$\Phi = \left(X^T X\right)^{-1} X^T Y$. By doing so, it is obtained:

i k = 0.00376136

ii b1 = 0.539187

iii b2 = 0.560755

iv b3 = 1.32012

Now that this coefficient is known, it is necessary to forecast both, population and GDP to obtained the demand in 2022 by using Equation 14. A linear variation is assumed to do so. As population and GDP values are known in both 2010 and 2017, it is now a linear single variable regression problem, in order to obtained the fitting line between those two values. Afterwards, this trend line will give us the new values at the following years.

To calibrate linear single variable regression line, a similar approach as done before can be performed:

$$\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

Where a_0 and a_1 are the coefficients of the linear fit line $y = a_0 + a_1x$, x_1 and x_2 are the values of the two years 2010 ($x_1 = 0$) and 2017 ($x_2 = 7$), and finally y_1 and y_2 are the population/GDP values in the years 2010 and 2017. Once the fitting line is obtained, just by evaluating this equation with the New Year 2022 ($x_3 = 12$), the new forecast values of GDP and Population are obtained. Finally, by introducing those new values in 2022 of population and GDP in each airport, together with the gravity coefficients, it is possible to forecast the new demand in 2022 by using Equation 14.

4.3.1 Analysis of results

Due to differences in GDP and population expectation in each airport, there are positive and also negative growing on demand, mainly around + or - 20%. Focusing on our hub, London, these higher growths are on the routes with more demand (Paris, Amsterdam and Dublin), and a significant decrement is concentrated on Spain (Madrid and Barcelona) and Italy (Rome) because of lower expectations on GDP and population for 2022.

Top 3 Positive Growth	**Top 3 Negative Growth**
Paris126 (+13%)	Madrid36 (-15%)
Dublin106 (+20%)	Barcelona31 (-16%)
Amsterdam71 (+11%)	Rome 24 (-12%)

Nevertheless, the principal change on demand respect before is the opening of flights to US, even more, due to a scaling factor of 10, which gives a considerable demand from the whole European network to US destinations, especially New York. In these cases, demand goes up to 830 potential passengers. All US cities have a demand between them higher than 1000, but the airline cannot operate those as it lacks the required Air Services Agreement with the US. By making use of the demand forecast in 2022, here new results obtained by flying to US destinations with a fleet expansion are studied.

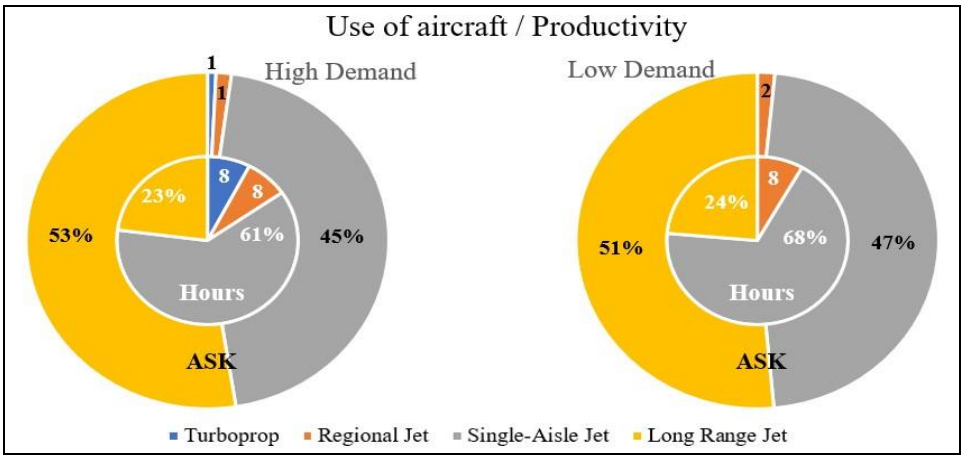

Figure 4.4: Use of Aircraft and Aircraft Productivity - High/Low Demand

Which it produces a maximum-revenue solution, from which the market share is calculated and the process repeated until convergence. In that structure, the optimiser does not *know* that the frequency solution changes the demand, and therefore produces a frequency plan that does not take into account the fact that a high frequency produces better demand. To overcome that problem, a better model can be developed in future studies: demand can be considered (for both high and low season) as a decision variable, adding a new constraint linking the demand to the frequency via a first order Taylor expansion of the market share, so that the problem would still be linear. Then, iteration would still be necessary to adjust the constants in the Taylor expansion until convergence is reached, probably to a solution with better profits.

4.4 CHOOSING HUB CITIES IN CASE OF TRANSIT FLIGHTS

The SHORT-HOP airline is planning to provide transportation service in North Central USA, between 9 different cities, include: Dayton, Fort Wayne, Green Bay, Grand Rapids, Kenosha, Marquette, Peoria, South Bent and Toledo. In order to minimize the cost for the company, it is required to route flights through hub cities, and the number of hub cities should be as small as possible, since we want to reduce the flight distance between any two cities, so that passengers can also get a better experience. In our project, we want to set up a flight network to minimize the number of hub cities, given the pairwise distances between the nine cities. We will be mainly using graph theory to show that when this is possible, and we will prove a theorem to solve the problem. Finally, we are going to develop three different algorithms to solve such problem with any number of cities, and demonstrate the algorithms using MATLAB on a randomly generated situation with 100 cities.

Formulation of the Problem

Let G be a graph of order 9. The adjacent matrix of G is given by:

$$A \quad \begin{bmatrix} 0 & 102 & 381 & 232 & 272 & 494 & 294 & 170 & 134 \\ 102 & 0 & 279 & 133 & 175 & 395 & 235 & 72 & 91 \\ 381 & 279 & 0 & 159 & 134 & 143 & 273 & 215 & 298 \\ 232 & 133 & 159 & 0 & 115 & 262 & 255 & 94 & 139 \\ 272 & 175 & 134 & 115 & 0 & 275 & 156 & 103 & 229 \\ 494 & 395 & 143 & 262 & 275 & 0 & 416 & 341 & 387 \\ 294 & 235 & 273 & 255 & 156 & 416 & 0 & 186 & 320 \\ 170 & 72 & 215 & 94 & 103 & 341 & 186 & 0 & 139 \\ 134 & 91 & 298 & 139 & 229 & 287 & 320 & 139 & 0 \end{bmatrix}$$

A hub is a vertex of degree ≥ 2.

The goal is to find a subgraph $H \subseteq G$, such that:

i H is connected;

ii For all edges $e \in E(H)$, $w(e) \leq 200$;

iii The number of hubs in H is minimized.

Solution

First we need to verify that H exist. Form a graph G' by removing all edges of weight > 200 in G, so G' already satisfy condition 2), plot G' using Matlab:

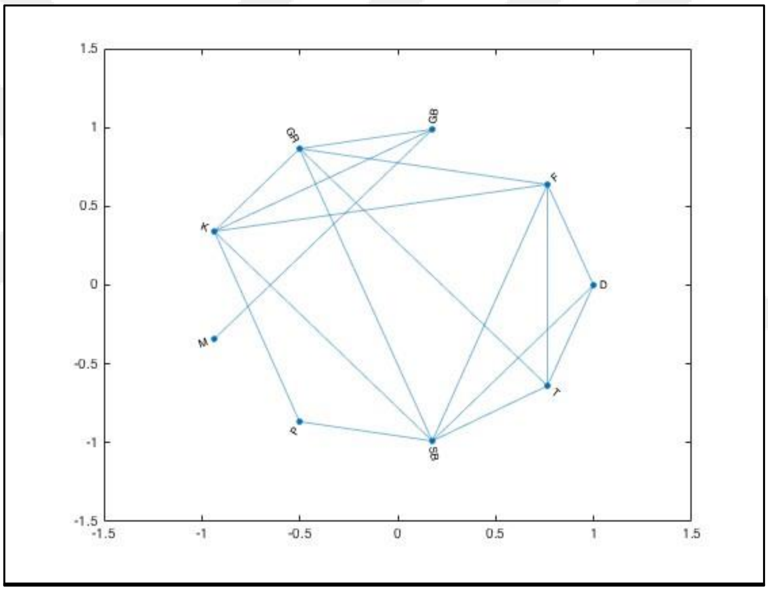

Figure 4.5: Choosing G According to the Hub H

Observed that G' is connected, satisfy condition 1), therefore, we confirm that H exist. We can now limit our searching for H on G'.

<u>Theorem</u>: The minimum number of hubs in H is 3.

<u>Proof</u>: We want to start choosing hub with the highest degree, since in the best case, we only need one hub to connect all other vertices, in which case the degree of the hub is 8.

By observation, the vertex SB has the maximum degree in G', which is 6. Connect SB to all other possible vertices, there are still two vertices M, GB unconnected, therefore 1 hub is not possible. Also by observation, vertex M is incident with only GB. So in order to make

H connected, we need to make GB a hub for M. We still need one more hub to connect with GB, so that H is connected. Therefore, the minimum number of hubs is 3.

We can generalize this idea with G of any order n, by the following algorithm:

<u>Algorithm1</u>

i Given a connected graph G, form a subgraph $G' \subseteq G$ by removing all edges of weight > 200;

ii If G' is connected, proceed, otherwise, stop running;

iii Let H be a graph where $V(H) = V(G^{=})$ and $E(H) = \emptyset$;

iv Let $B = V(G^{=})$;

v For each vertex $v \in B$, calculate how many adjacent vertices in G' are not in the same component in H with v;

vi Choose the one vertex with the highest number, and connect it to all adjacent vertices in H while do not creating loop;

vii Remove that vertex from B;

viii Repeat 5 to 7 until H is connected.

<u>Algorithm2: degree</u>

i Given a connected graph G, form a subgraph $G' \subseteq G$ by removing all edges of weight > 200;

ii If G' is connected, proceed, otherwise, stop running;

iii Let H be a graph where $V(H) = V(G^{=})$ and $E(H) = \emptyset$;

iv Generate an ordered list L, with the degree of vertices in $V(G')$ in decreasing order;

v For each number $d_C \in L$, find the corresponding vertex $v_C \in V(G^{=})$, and add all incident edges of v_C to H, while do not creating loops;

vi Repeat 5 until H is connected.

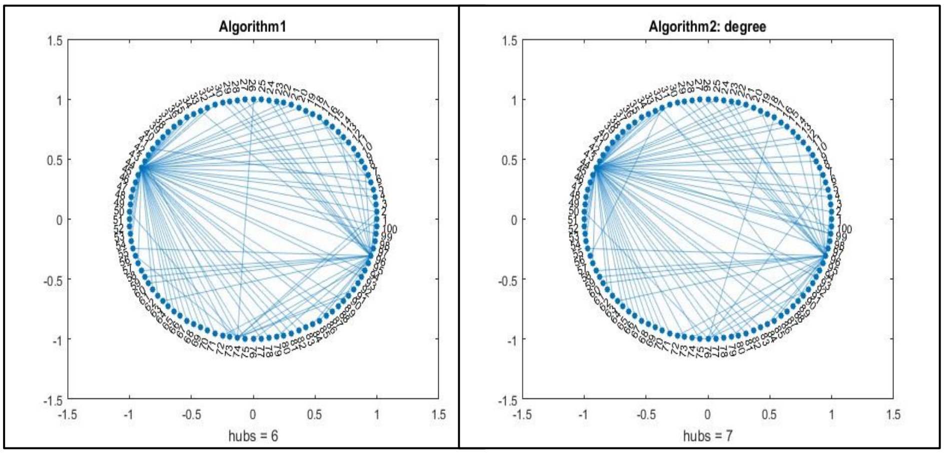

Figure 4.6: Choosing Hubs According to The Hub Selection Algorithms

4.5 WEEKLY FLIGHT SCHEDULE FOR A NEW AIRLINE

The aim of this assignment is to find the optimal solution for a new airline to successfully grow in the coming years. For each problem, an optimization on a different sector will be done. This new airline will operate flights between 19 different European destinations and its hub, which is the Paris Charles de Gaulle Airport (LFPG) in France. To achieve this objective, the assignment is divided into two parts. In the first one, it is developed a network and fleet plan for one standard week on operations based on demand forecast for the year 2019 following a gravity model. The model generated is aimed to maximize the profit of the airline. In the second part, given a daily flight schedule, a passenger mix flow solution is computed that seeks maximizing the revenue of the company. Both models have been implemented in a Matlab code, which can be found in a separate attached file. This paper is divided into three sections: Methodology, Results and Conclusion. In the Methodology, the different steps followed to obtain the results for each of the problems are explained, as well as the developed mathematical models and the considered assumptions. In the Results section, different figures and tables are portrayed to adequately present the solution obtained with both models. Finally, in the Conclusion section, a brief description of the results is given together with final comments regarding what has been found conducting this study. Figure 4.7 shows the type of airplane chosen per flight leg. It can be observed that the shortest flights are connected with the regional turboprop, while the longest with the regional jet. Moreover, the twin aisle twin engine jet is not used. The reason for this is that the hub is located close to the centre of all other airports, reducing considerably the length of all flight legs. Consequently, big aircraft are not required since they will only add significant operational cost. The distribution of aircraft leased by the airline is shown in the following table:

Table 4.2: Distribution of Aircraft Leased by The Airline

Type	Regional		Twin engine jet	
	Turboprop	Jet	Single aisle	Twin aisle
Leased	3	1	1	0

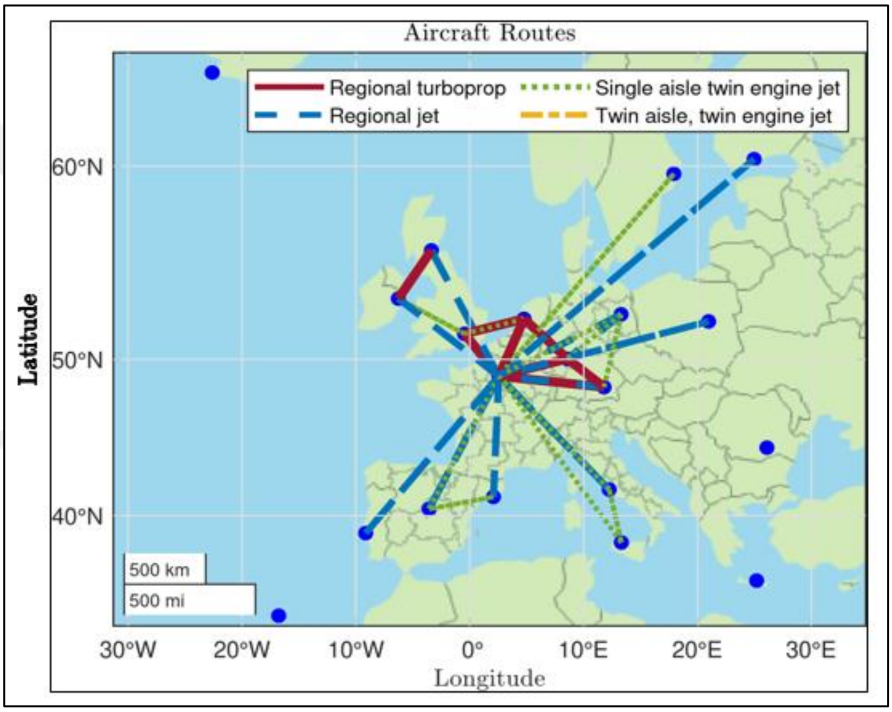

Figure 4.7: Map Displaying The Type of Aircraft Per Flight Leg.

In this section, the results of the passenger mix flow problem are displayed. The solution obtained is shown for both the initial Restricted Master Problem (RMP) and the global problem. In addition, the already mentioned verification of the solution has been carried out to make sure that the results obtained are correct.

4.5.1 Initial RMP

As commented in the section “Methodology”, the initial RMP of a column generation algorithm is solved for an initial set of columns which leads to a feasible solution. The set of columns selected starts with the “fictitious” itinerary (with a null fare) as the only option to reallocate from other itineraries. This itinerary works as a buffer for spilled passengers. The number of columns employed for the first iteration of the column generation algorithm is therefore $(P + 1) = 432$, where P represents the number of itineraries provided at the data sheet. The optimal objective value for the initial RMP is 1.7562E6 e. As a sample, the optimal decision variables associated with the first 5 passengers itineraries, i.e., the number of passengers reallocated (spilled) to the fictitious itinerary, are: 0,12,0,10,50. The total number of passengers spilled is 11765, it must have a high value since there is no reallocation of passengers to other actual itineraries offered by the airline. The optimal dual variables associated with the first 5 flights for the first iteration are π = 62,41,47,69,69, and the ones associated with the first 5 passengers itineraries are σ = 0,0,0,0,0.

4.5.2 Global problem

The passenger mix flow problem has been solved to the end. The number of final columns is 496, so 64 more columns have been added through the process of column generation. This means that the majority of the decision variables are not used in the final solution, and therefore present a null value in the solution obtained. The number of iterations required to converge is 49. This number is lower than the number of columns added because when the pricing problem finds out that there are more than one columns which share the highest (negative) value of "slackness", all the mentioned columns are added as decision variables. The optimal objective value for the global problem is 1.7192E6 e. The decision variables associated with the first 5 passenger itineraries are displayed in Table 3 where the third row indicates first the desired itinerary and the itinerary in which the passengers have been reallocated. It has to be mentioned that since in the data the itineraries started with a 0 value, in the matlab code, one extra unit has been added to all the itineraries. So, in fact those values would be substracting 1 (example: 7-5 for the first case). The table shows non-null values of passengers reallocated to other itineraries from the first 5 and non-null values of passengers reallocated from other itineraries to the first 5. The number of spilled passengers for the global solution is 10321. The optimisation run time is 2974.9 s. Furthermore, the value of the dual variables for the first 5 flights is displayed in Table 4.3.

Table 4.3: Table Displaying The Values of The Non-Zero Objective Values of The First 5 Passenger Itineraries.

Passenger Itinerary	1	2	3	4	5
Pax reallocated:	24	85	41	36	13
Reallocated to:	8-6	16-6	19-17	135-23	195-23

Table 4.4: Table Displaying The Values of The Dual Variables For The First 5 Flights.

Flight	1	2	3	4	5
Dual variable π:	62	41	47	69	66
Dual variable σ:	0	0	0	0	0

In Figure 4.8 the passengers spilled per column added is displayed. Each iteration corresponds to a point in the graph. In the graph it can be observed that the number of columns added per iteration varies. It must be said that the line itself does not provide any information since the approach is discrete.

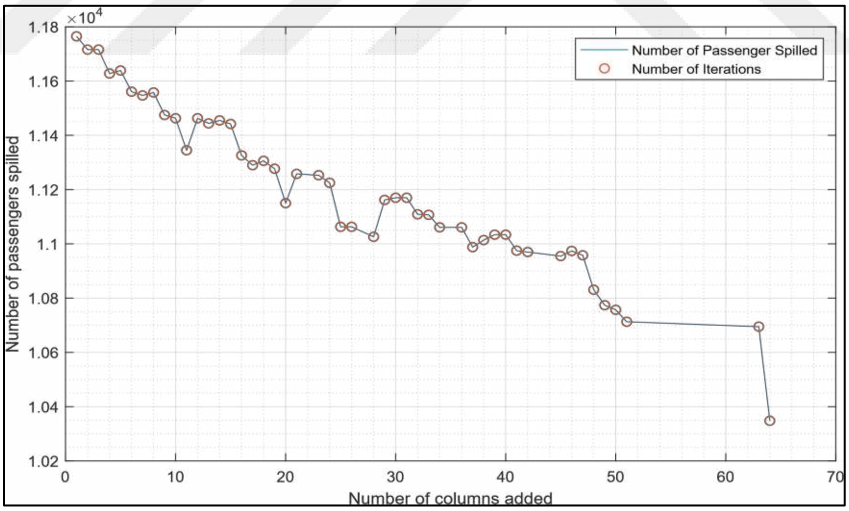

Figure 4.8: Number of Passengers Spilled Per Column Added.

The results obtained when using the optimization for the found number and position of columns match the ones obtained by the column generator algorithm. This means that the while loop is well implemented, and there are no variables wrongly updating the solution. When the program described in class was ran, the results were satisfactory. The number of passengers spilled make sense as well. There is a total demand of 18143 and the total capacity of the flights is 11300. This means that a total of 6843 passengers will be spilled for sure. Furthermore, accounting for the recapture ratio, if the average recapture ratio (0.295) is multiplied by the flight capacity, the average spilled passengers should be 3336, which added to 6843 gives a total of 10179 spilled passengers, quite close to the solution given by the program of 10321. This one is higher because we are not accounting for the specific flights, but gives a good overview if the recapture rate is random. It is important to note that, although this value does not have a clear sense (since we are not taking into account that some passengers fly in the desired schedule, thus the recapture ratio is 1), the order of magnitude should be similar, and it is.

i Given that the airports considered in this problem are all located in Europe, there are no long distance connections (transatlantic flights, connections with Asia...). Therefore, it makes sense that the solver has decided not to lease any twin aisle twin engine jet. Its lease, fixed, time and fuel costs are significantly higher than for the other aircraft. With a load factor of 75%, the spoilage of passengers in the flight legs performed by the twin aisle jet would be too high. Moreover, there are no profitable flights which require a range greater than 6300 km. Thus, it is not necessary to use the twin aisle aircraft to perform flight legs that the single aisle twin engine jet could not.

ii The employed load factor for this problem, 75%, does not differ a lot from the average value that airlines usually have in reality. We wanted to study the influence of this factor in the results. Of course, the different flight legs and aircraft used would present different values of load factor in reality, making some combination of flight schedules more profitable than others. For the employed load factor, only 5 aircraft are leased: 3 regional turboprop, 1 regional jet and 1 twin engine single aisle jet. If we increase the load factor to a value of 90% and run the solver again, suddenly it is much more profitable to perform more flight during the week, the value of the objective function is increased by 500%. Consequently, the number of aircraft leased increases a lot, a total of 9 aircraft are leased: 3 regional turboprop, 2 regional jet, 4 twin engine single aisle jet and again no twin aisle jet. We even notice that the distribution changes, it is now more profitable to lease more twin engine aircraft, which present a much higher number of seats. In Figure 4.9, it is represented the percentage of flights flown by each type of aircraft for the two different load factors analysed.

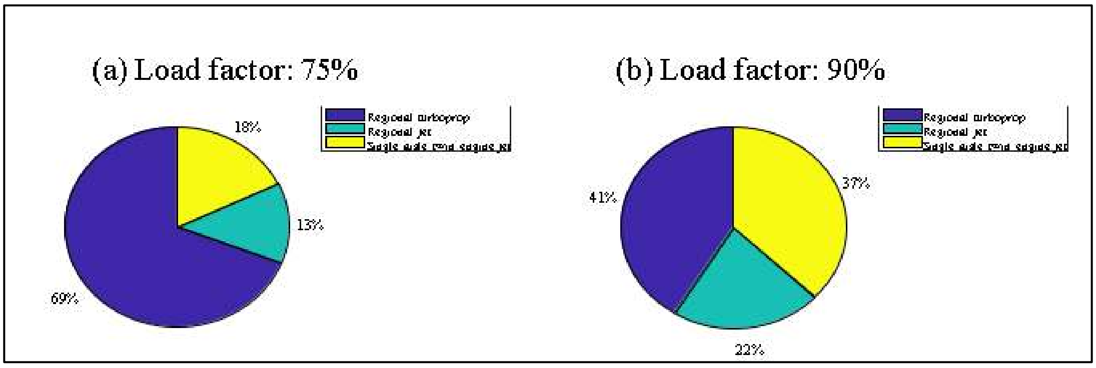

Figure 4.9: Percentage of Flights Flown By Each Type of Aircraft.

iii Another parameter of which we wanted to study its influence on the results was the price of fuel, which has been set at 1.42 USD/gallon for this problem. If we reduce the fuel cost by 15% (1.2 USD/gallon), the objective function value is incremented by approximately a 91%. It is interesting to study what happens with the distribution of leased aircraft in this case. The number of leased aircraft is increased to 8: 3 regional turboprop, 1 regional jet and 4 twin engine single aisle jet. The benefits of using the twin engine aircraft, which can carry many more passengers, are triggered taking into account that it presents a really high fuel cost parameters when comparing with the other 2 aircraft: 2 times the value of the regional jet and 4 times the value of the regional turboprop. Once again, the twin aisle aircraft is not used by the solver, making it clear that it makes no sense to use this aircraft for the routes considered.

Passenger mix flow problem:

a. The recapture ratios and the flight prices do not reflect reality. This allows for the optimizer to redirect the passengers to a multi stop flight since the fare charged to the passenger is higher. That is why multi stop flights are more filled than direct flights. It is difficult to believe that passengers present similar recapture ratios when they are forced to stop over at an airport in their itinerary.

b. Since the demand is very low for the first itineraries, the reallocation of the passengers is as well negligible.

c. The spillage of passengers for the final solution is at first glance intolerable high: 10321 passengers. Taking into consideration that the total unconstrained demand for all itineraries is 18143, approximately 57% of passengers are spilled. In spite of the outrageous results, is has to be observed that the total capacity of the weekly flights (summing the capacity of each flight without considering anything related to timetables or passenger itineraries) is 11300, meaning that ideally only 62% of passengers could actually fly with the airline.

d. The total optimization run time for the second problem is too high: 2974.9 s. Once we got all the results of the problem, we believe we found the source of error in the code that was causing this high computational time. We had included all the information related to all the possible columns of the global problem in each iteration. By means of another variable obtained through the pricing problem in each iteration, the columns added as decision variables from the total set of decision variables were selected. The reason for this way of working is that cplex eliminates all columns from the vector of decision variables which are not considered, computing the same number of columns and rows for the simplex method as if the columns of the vector of decision variables were added in each iteration. Nevertheless, this does not hold true for the other functions which were implemented in the code, which are too time consuming due to the fact that they have to take into account information regarding all other itineraries provided in the data sheet as for example, the time that it takes to complete constraint 1 is 50s each time a new column is added.

4.5 AIRPORT CHECK-IN TIME ESTIMATION

The check-in of an airport consists of 6 parallel desks. For a departure, 140 passengers have tickets, the inter-arrival times of the passengers to the check-in follow an exponential distribution so that the expected number of incoming passengers in an hour is 100. At the check-in, passengers are put in one queue and guided from it to the desk that is first free. The service time of each desk is between 1 and 5 minutes. Suppose that the first passengers start arriving to the check-in at the same time as the desks are opened. The question is “How much time before the departure the check-in should be opened, so that all passengers get served 20 minutes before the departure?” To solve this problem, we run the simulation process with 1500 iterations, written in Matlab program. After the simulation, the maximum time when check-in desks have served all the passengers and can be closed is 1.67 hour. So, addition to 20 minutes the passengers get served, the total time before departure the check-in should be open is 1.67 hour + 20 minutes = 2.01 ~ 2 hours.

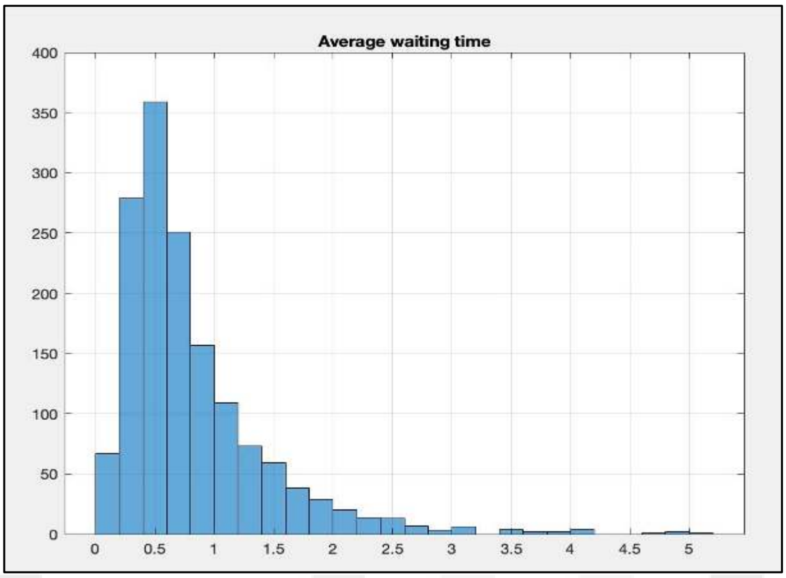

Figure 4. 10: The Average Waiting Time of Passengers of 1500 Iterations. 0.5 Hour (= 30 Minutes) is The Most Frequent Waiting Time of Passengers

5. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

It is essential to gain an understanding of how passengers embark upon and disembark from airplanes at airports in order to devise methods that will cut down on the amount of time spent sitting idle on board aircraft given the growing number of people who opt to travel by air. This is because more people are choosing to travel by air. According to a number of studies conducted by the World Bank, one of the key reasons for the expansion of the aviation business has been the continual reduction in operating expenditures spent per kilometer. This has been one of the primary reasons for the expansion of the aviation industry. This new discovery has been regarded as one of the key reasons that the sector has been expanding over the past several years. Because of this, firms now have a significant advantage over their rivals because to the economies of scale that they have implemented. In the meantime, firms who have been implementing cutting-edge technologies into their aircraft, such as Wi-Fi, multimedia, and online booking, have a competitive advantage over those businesses that have not been doing so. According to the data that has been provided by the United States Department of Transportation so far in the year 2020, 14.69% of all flights have had their departures either delayed or entirely canceled. This percentage accounts for the total number of flights that have been affected. 19% of the flights were required to make an emergency landing as a result of unforeseen circumstances (the plane landed at a unique airport than the planned airport) When flights are delayed, not only do they make passengers irritable, but they also cause airlines to suffer significant financial losses. In addition to the enforcement of monetary fines on the businesses that are guilty for the infraction, a number of countries have enacted laws that mandate airlines pay customers whose flights are delayed due to situations that are beyond the control of the airline. The passing of these legislation was done with the intention of reducing the impact of the aforementioned problem. Despite the existence of these restrictions, it is nevertheless exceedingly frequent for flights to be either delayed or entirely canceled for various reasons. There are many different things that might lead to flight delays, the most common of which include inclement weather, heavy traffic, airport capacity (number of passengers, runways, bridges, etc.), technical and mechanical faults, national aviation systems, and insufficient security. The International Air Transport Association (IATA) has developed standardized departure delay codes for use with regard to commercial passenger flights. There is a widespread misunderstanding in the aviation business that airplanes can only generate revenue while they are actually in the air. This is not the case. This is not even close to being the case at all. This commonly held misconception is an excellent example of one of the most common misunderstandings that can be found in the world of business. When considered from the perspective of the airline, the goal should be to spend as little time as possible on the ground while at the same time maximizing the amount of time that is spent in the air. This will allow for the most efficient use of the airline's resources. During the course of a flight, there is the opportunity for a number of operations to take place, including the transfer of passengers as well as cargo. The sequence of ground operations tasks that must be completed in order to get a parked airplane ready for its next journey is referred to as a "turnaround," and the phrase "turnaround" is used to describe this sequence. A "turnaround" is also the name of the sequence itself. The sequence is also known by its name, which is a turnaround. It is intended that this remark be understood as a reference to the activities that take place on stable ground. If we want our airports to see an increase in the number of flying hours, keep their prices at competitive levels, and improve the quality of service they provide to consumers, we need to be on the constant lookout for innovative methods to conduct business, and we need to do this regularly. The purpose of this study is to find ways to bridge the gap between existing national practices and the international standards that are the most effective for maximizing airport productivity. This is important in light of the fact that globalization has resulted in an increase in the number of people traveling to other parts of the world. This study will concentrate its attention This project aims to build a model that will aid airlines in boosting the efficiency of their loading and unloading procedures so that they may better serve their customers. In turn, this will have both direct and indirect consequences on the growth of the operating results that are produced by those airlines. This is an extremely important topic since its implications have an effect not only on the effective operational management of outcomes, but also on the degree of satisfaction that is felt by customers.

5.2 FUTURE WORK

In the future, increasing flight frequency is an effective tool for lowering fares and improving the quality of service provided by placing more attention on punctuality, on-board services, and differentiated service. This can be accomplished by increasing the number of flights that are operated each day. Increasing the total number of flights that take place on a daily basis is one method for achieving this goal. One approach that might be taken in the direction of accomplishing this objective is to raise the overall number of flights that are operated on a daily basis. Because they are such striking departures from the norm, the cultures of North America and Europe stand out as particularly distinctive.

REFERENCES

[1] Erdi, P. Complex systems: The intellectual landscape. In *Complexity Explained*; Springer: Berlin/Heidelberg, Germany, 2008; pp. 1–23. ISBN 3540357777.

[2] Allignol, C.; Barnier, N.; Flener, P.; Pearson, J. Constraint programming for air traffic management: A survey1: In memory of Pascal Brisset. *Knowl. Eng. Rev.* **2012**, *27*, 361–392. [CrossRef]

[3] International Civil Aviation Organization. *Air Traffic Management: Procedures for Air Navigation Services*; International Civil Aviation Organization: Montréal, QC, Canada, 2007.

[4] Pouzenc, C. Cartes des Secteurs de Contrôle de L'espace Aérien Civil Français. 2017. Available online: https://www.cypouz. com/article/150203/cartes-des-secteurs-controle-espace-aerien-civil-francais (accessed on 2 December 2021).

[5] EUROCONTROL. EUROCONTROL Forecast Update 2021–2024. 2021. Available online: https://www.eurocontrol.int/ publication/eurocontrol-forecast-update-2021-2024 (accessed on 1 June 2021).

[6] Davies, L.; Vagapov, Y.; Grout, V.; Cunningham, S.; Anuchin, A. Review of Air Traffic Management Systems for UAV Integration into Urban Airspace. In Proceedings of the 2021 28th International Workshop on Electric Drives: Improving Reliability of Electric Drives (IWED), Moscow, Russia, 27–29 January 2021; pp. 1–6. [CrossRef]

[7] Degas, A.; Kaddoum, E.; Gleizes, M.P.; Adreit, F.; Rantrua, A. Cooperative multi-agent model for collision avoidance applied to air traffic management. *Eng. Appl. Artif. Intell.* **2021**, *102*, 104286. [CrossRef]

[8] Marquis, P.; Papini, O.; Prade, H. *A Guided Tour of Artificial Intelligence Research: Volume I: Knowledge Representation, Reasoning and Learning*; Springer Nature: Cham, Switzerland, 2020.

[9] Council of Europe. *History of Artificial Intelligence*; Council of Europe: Strasbourg, France, 2020. 10. Ferrucci, D.A. Introduction to "this is watson". *IBM J. Res. Dev.* **2012**, *56*, 1–15. [CrossRef]

[10] Markoff, J. How many computers to identify a cat? 16,000. *New York Times*, 26 June 2012.

[11] Silver, D.; Schrittwieser, J.; Simonyan, K.; Antonoglou, I.; Huang, A.; Guez, A.; Hubert, T.; Baker, L.; Lai, M.; Bolton, A. Mastering the game of go without human knowledge. *Nature* **2017**, *550*, 354–359. [CrossRef] [PubMed]

[12] Mueller, S.T.; Hoffman, R.R.; Clancey, W.; Emrey, A.; Klein, G. Explanation in human-AI systems: A literature meta-review, synopsis of key ideas and publications, and bibliography for explainable AI. *arXiv* **2019**, arxiv:1902.01876.

[13] Durand, N.; Gianazza, D.; Gotteland, J.B.; Alliot, J.M. *Metaheuristics for Air Traffic Management*; John Wiley & Sons: Hoboken, NJ, USA, 2015.

[14] Shone, R.; Glazebrook, K.; Zografos, K.G. Applications of stochastic modeling in air traffic management: Methods, challenges and opportunities for solving air traffic problems under uncertainty. *Eur. J. Oper. Res.* **2021**, *292*, 1–26. [CrossRef]

[15] Emami, H.; Derakhshan, F. An overview on conflict detection and resolution methods in air traffic management using multi agent systems. In Proceedings of the 16th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP 2012), Shiraz, Iran, 2–3 May 2012; pp. 293–298. [CrossRef]

[16] Weigang, L.; Leite, A.F.; Ribeiro, V.F.; Fregnani, J.A.; de Oliveira, I.R. Towards Intelligent System Wide Information Management for Air Traffic Management. In *Security, Privacy, and Anonymity in Computation, Communication, and Storage*; Lecture Notes in Computer Science; Wang, G., Atiquzzaman, M., Yan, Z., Choo, K.K.R., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 584–593. [CrossRef]

[17] Wu, C.L.; Caves, R.E. Research review of air traffic management. *Transp. Rev.* **2002**, *22*, 115–132. [CrossRef]

[18] Aricò, P.; Reynal, M.; Di Flumeri, G.; Borghini, G.; Sciaraffa, N.; Imbert, J.P.; Hurter, C.; Terenzi, M.; Ferreira, A.; Pozzi, S.; et al. How Neurophysiological Measures Can be Used to Enhance the Evaluation of Remote Tower Solutions. *Front. Hum. Neurosci.* **2019**, *13*, 303. [CrossRef]

[19] Aricò, P.; Borghini, G.; Di Flumeri, G.; Colosimo, A.; Bonelli, S.; Golfetti, A.; Pozzi, S.; Imbert, J.P.; Granger, G.; Benhacene, R.; et al.
Adaptive Automation Triggered by EEG-Based Mental Workload Index: A Passive Brain-Computer Interface Application in Realistic Air Traffic Control Environment. *Front. Hum. Neurosci.* **2016**, *10*, 539. [CrossRef]

[20] Wang, D.; Yang, Q.; Abdul, A.; Lim, B.Y. Designing Theory-Driven User-Centric Explainable AI. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems—CHI '19, Glasgow, Scotland, UK, 4–9 May 2019; ACM Press: New York, NY, USA, 2019; pp. 1–15. [CrossRef]

[21] Sedlmair, M.; Meyer, M.; Munzner, T. Design study methodology: Reflections from the trenches and the stacks. *IEEE Trans. Vis. Comput. Graph.* **2012**, *18*, 2431–2440. [CrossRef]

[22] Munzner, T. *Visualization Analysis and Design*; CRC Press: Boca Raton, FL, USA, 2014.

[23] Beaudouin-Lafon, M.; Mackay, W.E. Prototyping tools and techniques. In *Human-Computer Interaction*; CRC Press: Boca Raton, FL, USA, 2009; pp. 137–160.

[24] Vredenburg, K.; Mao, J.Y.; Smith, P.W.; Carey, T. A survey of user-centered design practice. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems–CHI02, Minneapolis, MN, USA, 20–25 April 2002; ACM Press: New York, NY, USA, 2002; pp. 471–478.

[25] Kistan, T.; Gardi, A.; Sabatini, R. Machine Learning and Cognitive Ergonomics in Air Traffic Management: Recent Developments and Considerations for Certification. *Aerospace* **2018**, *5*, 103. [CrossRef]

[26] Xie, Y.; Pongsakornsathien, N.; Gardi, A.; Sabatini, R. Explanation of Machine-Learning Solutions in Air-Traffic Management. *Aerospace* **2021**, *8*, 224. [CrossRef]

[27] McInnes, M.D.; Moher, D.; Thombs, B.D.; McGrath, T.A.; Bossuyt, P.M.; Clifford, T.; Cohen, J.F.; Deeks, J.J.; Gatsonis, C.; Hooft, L.; et al. Preferred reporting items for a systematic review and meta-analysis of diagnostic test accuracy studies: The PRISMA-DTA statement. *JAMA* **2018**, *319*, 388–396. [CrossRef] [PubMed]

[28] Google Scholar. Top Publications: Categories, Engineering & Computer Science, Transportation.Availableonline: https: //scholar.google.com/citations?view_op=top_venues&hl=fr&vq=eng_transportation (accessed on 10 April 2021).

[29] Le Tallec, C.; Taurino, D.; Lancia, C.; Verstraeten, J. Predicting the future location of a general aviation aircraft. In Proceedings of the ICRAT 2014, 6th International Conference on Research in Air Transportation, Istanbul, Turkey, 26–20 May 2014.

[30] Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V. Scikit-learn: Machine learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.

[31] Abadi, M.; Barham, P.; Chen, J.; Chen, Z.; Davis, A.; Dean, J.; Devin, M.; Ghemawat, S.; Irving, G.; Isard, M. Tensorflow: A system for large-scale machine learning. In Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), Savannah, GA, USA, 2–4 November 2016; pp. 265–283.

[32] Chollet, F. *Deep learning with Python*; Apress: Berkeley, CA, USA, 2018; Volume 361.

[33] Alligier, R. Predictive Distribution of the Mass and Speed Profile to Improve Aircraft Climb Prediction. *J. Air Transp.* **2020**, *28*, 114–123. [CrossRef]

[34] Alligier, R.; Gianazza, D.; Durand, N. Predicting aircraft descent length with machine learning. In Proceedings of the ICRAT 2016, 7th International Conference on Research in Air Transportation, Philadelphia, PA, USA, 20–24 June 2016.

[35] Kovarik, S.; Doherty, L.; Korah, K.; Mulligan, B.; Rasool, G.; Mehta, Y.; Bhavsar, P.; Paglione, M. Comparative Analysis of Machine Learning and Statistical Methods for Aircraft Phase of Flight Prediction. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[36] Dalmau Codina, R.; Belkoura, S.; Naessens, H.; Ballerini, F.; Wagnick, S. Improving the predictability of take-off times with Machine Learning: A case study for the Maastricht upper area control centre area of responsibility. In Proceedings of the SID 2019, 9th SESAR Innovation Days, Athens, Greece, 2–6 December 2019; pp. 1–8.

[37] Tran, T.N.; Pham, D.T.; Alam, S.; Duong, V. Taxi-Speed Prediction by Spatio-Temporal Graph-Based Trajectory Representation and Its Applications. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[38] Liu, Y.; Hansen, M.; Ball, M.; Lovell, D. Predicting Aircraft Trajectory Choice—A Nominal Route Approach. In Proceedings of the ICRAT 2018, 8th International Conference on Research in Air Transportation, Castelldefels, Catalonia, Spain, 26–29 June 2018.

[39] Dubot, T. Predicting sector configuration transitions with autoencoder-based anomaly detection. In Proceedings of the International Conference on Research in Air Transportation, Castelldefels, Catalonia, Spain, 26–29 June 2018.

[40] Pham, D.T.; Alam, S.; Yi-Lin, S.; Duong, V.N. A machine learning approach on past ads-b data to predict planning controller's actions. In Proceedings of the ICRAT 2018, 8th International Conference on Research in Air Transportation, Castelldefels, Catalonia, Spain, 26–29 June 2018.

[41] Le, T.H.; Tran, P.; Pham, D.T.; Schultz, M.; Alam, S. Short-Term Trajectory Prediction Using Generative Machine Learning Methods. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[42] Xu, Z.; Zeng, W.; Chu, X.; Cao, P. Multi-Aircraft Trajectory Collaborative Prediction Based on Social Long Short-Term Memory Network. *Aerospace* **2021**, *8*, 115. [CrossRef]

[43] Guleria, Y.; Cai, Q.; Alam, S.; Li, L. A Multi-Agent Approach for Reactionary Delay Prediction of Flights. *IEEE Access* **2019**, *7*, 181565–181579. [CrossRef]

[44] Rantrua, A. Simulation Massive de Monde Virtuel par Système Multi-Agent Auto-Adaptatif. Ph.D. Thesis, Université de Toulouse, Université Toulouse III, Paul Sabatier, Toulouse, France, 2017.

[45] Dieumegard, P.; Chaimatanan, S.; Delahaye, D. Large Scale Adaptive 4D Trajectory Planning. In Proceedings of the 2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC), London, UK, 23–27 September 2018; pp. 1–9. ISSN 2155-7209. [CrossRef]

[46] Durand, N.; Gotteland, J.B. Genetic Algorithms Applied to Air Traffic Management. In *Metaheuristics for Hard Optimization Methods and Case Studies*; Springer: Berlin/Heidelberg, Germany, 2006; Chapter 9, pp. 277–306. [CrossRef]

[47] Degas, A.; Kaddoum, E.; Gleizes, M.P.; Adreit, F.; Rantrua, A. Dynamic Collision Avoidance using Local Cooperative Airplanes Decisions. *CEAS Aeronaut. J.* **2018**, *11*, 309–320. [CrossRef]

[48] Breil, R.; Delahaye, D.; Lapasset, L.; Féron, E. Multi-agent Systems for Air Traffic Conflicts Resolution by Local Speed Regulation. In Proceedings of the ICRAT 2016, 7th International Conference on Research in Air Transportation, Philadelphia, PA, USA, 20–24 June 2016.

[49] Ma, J.; Delahaye, D.; Sbihi, M.; Mongeau, M. Merging flows in terminal maneuvering area using time decomposition approach. In Proceedings of the ICRAT 2016,

7th International Conference on Research in Air Transportation, Philadelphia, PA, USA, 20–24 June 2016.

[50] Zhou, J.; Cafieri, S.; Delahaye, D.; Sbihi, M. Optimization of arrival and departure routes in terminal maneuvering area. In Proceedings of the ICRAT 2014, 6th International Conference on Research in Air Transportation, Istanbul, Turkey, 26–20 May 2014.

[51] Ma, J.; Delahaye, D.; Sbihi, M.; Scala, P.M. Integrated Optimization of Arrival, Departure, and Surface Operations. In Proceedings of the ICRAT 2018, 8th International Conference on Research in Air Transportation, Castelldefels, Catalonia, Spain, 26–29 June 2018.

[52] Breil, R.; Delahaye, D.; Lapasset, L.; Féron, E. Multi-agent systems to help managing air traffic structure. *J. Aerosp. Oper.* **2017**, *5*, 119–148. [CrossRef]

[53] Tang, J.; Alam, S.; Lokan, C.; Abbass, H.A. A multi-objective evolutionary method for Dynamic Airspace Re-sectorization using sectors clipping and similarities. In Proceedings of the 2012 IEEE Congress on Evolutionary Computation, Brisbane, QLD, Australia, 10–15 June 2012; pp. 1–8. ISSN 1941-0026, [CrossRef]

[54] Ligny, L. FPCA applied to flight paths optimization. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[55] Marcos, R.; Ros, O.G.C.; Herranz, R. Combining Visual Analytics and Machine Learning for Route Choice Prediction Application to Pre-Tactical Traffic Forecast. In Proceedings of the SID 2017, 7th SESAR Innovation Days, Belgrade, Serbia, 28–30 November 2017.

[56] Olive, X.; Basora, L.; Viry, B.; Alligier, R. Deep Trajectory Clustering with Autoencoders. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[57] Andrienko, G.; Andrienko, N.; Fuchs, G.; Garcia, J.M.C. Clustering Trajectories by Relevant Parts for Air Traffic Analysis. *IEEE Trans. Vis. Comput. Graph.* **2018**, *24*, 34–44. [CrossRef]

[58] Olive, X.; Grignard, J.; Dubot, T.; Saint-Lot, J. Detecting Controllers' Actions in Past Mode S Data by Autoencoder-Based Anomaly Detection. In Proceedings of the SID 2018, 8th SESAR Innovation Days, Salzburg, Austria, 3–7 December 2018.

[59] Oualil, Y.; Klakow, D.; Szaszák, G.; Srinivasamurthy, A.; Helmke, H.; Motlicek, P. A context-aware speech recognition and understanding system for air traffic control domain. In Proceedings of the 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), Okinawa, Japan, 16–20 December 2017; pp. 404–408.

[60] Degas, A. Auto-Structuration de Trafic Temps-Réel Multi-Objectif et Multi-Critère Dans un Monde Virtuel. Ph.D. Thesis, Université de Toulouse, Université Toulouse III, Paul Sabatier, Toulouse, France, 2020.

[61] Mouillet, V. *User Manual for the Base of Aircraft Data (BADA) Revision 3.14*; Technical Report; EUROCONTROL Experimental Centre: Brétigny, France, 2017.

[62] Fricke, H.; Förster, S.; Vogel, M. Using agent-based modeling to determine collision risk in complex TMA environments: The turn-onto-ILS-final safety case. *Aeronaut. Aerosp. Open Access J.* **2018**, *2*, 155–164. [CrossRef]

[63] Rantrua, A.; Chabrier, S.; Gleizes, M.P. Adaptive Air Traffic with Big Data Analysis. In Proceedings of the 1st EWG-DSS International Conference on Decision Support System Technology: Big data analytics for decision-making (ICDSST 2015), Belgrade, Serbia, 27–29 May 2015; Volume 1, pp. 46–52.

[64] García Vasco, I.; Valero García, M.; Prats Menéndez, X.; Delgado, L. Agent-based simulation framework for airport collaborative decision making. In Proceedings of the 6th International Congress on Research in Air Transportation (ICRAT), Istanbul, Turkey, 26–20 May 2014.

[65] Shah, S.R.; Campbell, A.; Campbell, A. Analyzing Pilot Decision-Making Using Predictive Modeling. In Proceedings of the ICRAT 2018, 8th International Conference on Research in Air Transportation, Castelldefels, Catalonia, Spain, 26–29 June 2018.

[66] Scarselli, F.; Gori, M.; Tsoi, A.C.; Hagenbuchner, M.; Monfardini, G. The graph neural network model. *IEEE Trans. Neural Netw.* **2008**, *20*, 61–80. [CrossRef] [PubMed]

[67] Mollinga, J.; Hoof, H. An Autonomous Free Airspace En-route Controller using Deep Reinforcement Learning Techniques. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.

[68] Legrand, K.; Delahaye, D.; Rabut, C. Wind and Temperature Networking Applied to Aircraft Trajectory Prediction. In Proceedings of the ICRAT 2016, 7th Edition of the

International Conference on Research in Air Transportation, Philadelphia, PA, USA, 20–24 June 2016.

[69] Rantrua, A.; Maesen, E.; Chabrier, S.; Gleizes, M.P. Learning aircraft behavior from real air traffic. In Proceedings of the ATCA 2015, 60th ATCA Annual Conference & Exposition (2015), Washington, DC, USA, 8–9 February 2015.

[70] Gurtner, G.; Delgado, L.; Valput, D. An agent-based model for air transportation to capture network effects in assessing delay management mechanisms. *Transp. Res. Part C Emerg. Technol.* **2021**, *133*, 103358. [CrossRef]

[71] Campanelli, B.; Ramasco, J.J.; Fleurquin, P.; Eguíluz, V.M.; Etxebarria, I.; Arranz, A. Data-driven modelling of the Tree of Reactionary Delays. In Proceedings of the ICRAT 2014, 6th International Conference on Research in Air Transportation, Istanbul, Turkey, 26–20 May 2014.

[72] Fleurquin, P.; Ramasco, J.J.; Eguiluz, V.M. Systemic delay propagation in the US airport network. *Sci. Rep.* **2013**, *3*, 1159. [CrossRef]

[73] Kravaris, T.; Spatharis, C.; Blekas, K.; Vouros, G.A.; Garcia, J.M.C. Multiagent Reinforcement Learning Methods for Resolving Demand—Capacity Imbalances. In Proceedings of the 2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC), London, UK, 23–27 September 2018; pp. 1–10. [CrossRef]

[74] Maas, J.; Sunil, E.; Ellerbroek, J.; Hoekstra, J. The effect of swarming on a voltage potential-based conflict resolution algorithm. In Proceedings of the ICRAT 2016, 7th International Conference on Research in Air Transportation, Philadelphia, PA, USA, 20–24 June 2016.

[75] Pallottino, L.; Scordio, V.G.; Bicchi, A. Decentralized cooperative conflict resolution among multiple autonomous mobile agents.

[76] In Proceedings of the 2004 43rd IEEE Conference on Decision and Control (CDC) (IEEE Cat. No.04CH37601), Paradise Island, Bahamas, 14–17 December 2004; Volume 5, pp. 4758–4763. ISSN 0191-2216. [CrossRef]

[77] Ribeiro, M.; Ellerbroek, J.; Hoekstra, J. The Effect of Intent on Conflict Detection and Resolution at High Traffic Densities. In Proceedings of the ICRAT 2020, 9th International Conference on Research in Air Transportation, Virtual Event, 15 September 2020.